Appendix

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A NOTATIONS

This section summarizes the notations used throughout this paper.

Table 5: Notations used throughout this paper.

Notations	**Definitions or Descriptions**
$\mathbb{G}, \mathbb{G}^c$	Random variable of universal graphs and graphs from domain c
$\mathcal{G}, \mathcal{G}^c$	Set of universal graphs and graphs from domain c
$\mathcal{G}^{\text{Train, Val, Test, c}}$	Set of training/validation/testing graphs from domain c
$P(\mathbb{G}), P(\mathbb{G}^c)$	Distribution of universal graphs and graphs from domain c
$G = (\mathbf{X}^G, \mathbf{E}^G)$	Graph G with node/edge category matrices $\mathbf{X}^G, \mathbf{E}^G$
n_G	Number of nodes in graph G
d_X/d_E	Number of node/edge categories
$\mathbf{Q}_X^t, \mathbf{Q}_E^t$	Node/edge transition matrices
$\bar{\mathbf{Q}}_X^t, \bar{\mathbf{Q}}_E^t$	Node/edge accumulative transition matrices
$\mathbf{m}_X^c, \mathbf{m}_E^c$	Distribution of node/edge categories of graphs from domain c
$t, \mathcal{T}$	Diffusion step t and the set of total steps $\mathcal{T}$
$\widetilde{\mathbb{G}}$	Distribution of graphs from unseen domains
$\widetilde{\mathcal{G}}$	Set of graphs from unseen domains
$S, \phi(S)$	Text with its embedding from the pre-trained textual encoder ϕ
$P(\mathbb{G}, \mathbb{S})$	Joint distribution of graphs and their textual descriptions
$\mathbf{\Theta}$	Parameters of Neural Networks
$\mathbf{\Theta}^{\star}$	Optimal Parameters of Neural Networks after pre-training
$\mathbf{\Theta}^{\star\star}$	Optimal Parameters of Neural Networks after fine-tuning
$\mathbf{\Theta}^{\square}$	Optimal Parameters of Neural Networks after Text2Graph Generation
FB, ASN	Facebook Networks, Animal Social Networks
EMAIL, WEB	Email Networks, Web Graphs
ROAD, POWER	Road Networks, Power Networks
CHEM, BIO	Chemical Networks, Biological Networks
ECON, RT	Economic Networks, Retweet Networks
COL, ECO	Collaboration Networks, Ecological Networks
CITATION	Citation Networks
LGGM-X	Pre-trained LGGM on all other domains except X
Fine-tuned LGGM on X	Fine-tuned LGGM-X on domain X
LGGM-T2G	LGGM trained on graphs paired with texts
LGGM-T2G$^{\text{D}}$	LGGM trained on graphs with texts on domains
LGGM-T2G$^{\text{UP}}$	LGGM trained on graphs with user prompts on domains/names
LGGM	LGGM trained on all graphs from all domains

B SPACE AND TIME COMPLEXITY ANALYSIS

Table 6: Our theoretical/empirical analysis of the DiGress and EDGE graph diffusion models, both with and without our Large Graph Training Scheme (LGGM). Incorporating LGGM only increases complexity linearly due to the added domains, aligning with the theoretical analysis. T - number of diffusion steps, $\mathcal{V}/\mathcal{E}$ - number of nodes/edges, K - number of active nodes, C - number of domains.

Backbone	**Training Strategy**	**Theoretical Time Space Complexity**	**Running Time per Epoch (s) with #Domains/#Graphs** 1/403	2/806	4/1219	8/2837	12/4492
DiGress	Original	$\mathcal{O}(T\|\mathcal{V}\|^2)$	19.12±0.03	–	–	–	–
	LGGM	$\mathcal{O}(CT\|\mathcal{V}\|^2)$	19.14±0.05	36.34±0.21	47.46±0.11	142.14±0.19	224.74±0.23
EDGE	Original	$\mathcal{O}(T\max(\|\mathcal{E}\|, K^2))$	1.02±0.13	–	–	–	–
	LGGM	$\mathcal{O}(CT\max(\|\mathcal{E}\|, K^2))$	1.07±0.18	1.92±0.26	5.42±0.09	11.59±0.20	19.48±0.22

C PROOF OF THEOREMS

Theorem 1. *If the transition matrices $\mathbf{Q}_X^t, \mathbf{Q}_E^t$ are independent of the textual description $\mathbb{S}$, then we have $P(\mathbb{G}^{t-1}|\mathbb{G}^t, \mathbb{G}, \mathbb{S}) \propto P(\mathbb{G}^t|\mathbb{G}^{t-1})P(\mathbb{G}^{t-1}|\mathbb{G})$ and correspondingly, we have the analytical formed solution, i.e., $P(\mathbf{X}^{t-1}|\mathbf{X}^t, \mathbf{X}, S) \propto \mathbf{X}^t(\mathbf{Q}_X^t)^\top \odot \mathbf{X}\bar{\mathbf{Q}}_X^{t-1}$, $P(\mathbf{E}^{t-1}|\mathbf{E}^t, \mathbf{E}, S) \propto \mathbf{E}^t(\mathbf{Q}_E^t)^\top \odot \mathbf{E}\bar{\mathbf{Q}}_E^{t-1}$ following Vignac et al. (2023).*

Proof. Applying the Bayes rule, we have:

$$P(\mathbb{G}^{t-1}|\mathbb{G}^t, \mathbb{G}, \mathbb{S}) \propto P(\mathbb{G}^{t-1}, \mathbb{G}^t, \mathbb{G}, \mathbb{S}) \propto P(\mathbb{G}^t|\mathbb{G}^{t-1}, \mathbb{G}, \mathbb{S})P(\mathbb{G}^{t-1}, \mathbb{G}, \mathbb{S}) \tag{6}$$

$$\propto P(\mathbb{G}^t|\mathbb{G}^{t-1}, \mathbb{G}, \mathbb{S})P(\mathbb{G}^{t-1}|\mathbb{G}, \mathbb{S})P(\mathbb{G}, \mathbb{S}). \tag{7}$$

Given the independence of the transition matrix on the textual description S and also the noise is Markovian Vignac et al. (2023), we have $P(\mathbb{G}^t|\mathbb{G}^{t-1}, \mathbb{G}, \mathbb{S}) = P(\mathbb{G}^t|\mathbb{G}^{t-1})$, $P(\mathbb{G}^{t-1}|\mathbb{G}, \mathbb{S}) = P(\mathbb{G}^{t-1}|\mathbb{G})$, and also the irrelevance of $P(\mathbb{G}, \mathbb{S})$ to $P(\mathbb{G}^{t-1}|\mathbb{G}^t, \mathbb{G}, \mathbb{S})$, we then end up with:

$$P(\mathbb{G}^{t-1}|\mathbb{G}^t, \mathbb{G}, \mathbb{S}) \propto P(\mathbb{G}^t|\mathbb{G}^{t-1})P(\mathbb{G}^{t-1}|\mathbb{G}). \tag{8}$$

Since the distribution of graphs can be decomposed into the distribution of node and edge categories, following Vignac et al. (2023), we similarly have:

$$P(\mathbf{X}^{t-1}|\mathbf{X}^t, \mathbf{X}, S) \propto P(\mathbf{X}^t|\mathbf{X}^{t-1})P(\mathbf{X}^{t-1}|\mathbf{X}) = \mathbf{X}^t(\mathbf{Q}_X^t)^\top \odot \mathbf{X}\bar{\mathbf{Q}}_X^{t-1}, \tag{9}$$

$$P(\mathbf{E}^{t-1}|\mathbf{E}^t, \mathbf{E}, S) \propto P(\mathbf{E}^t|\mathbf{E}^{t-1})P(\mathbf{E}^{t-1}|\mathbf{E}) = \mathbf{E}^t(\mathbf{Q}_E^t)^\top \odot \mathbf{E}\bar{\mathbf{Q}}_E^{t-1}. \tag{10}$$

□

Theorem 2. *Given the decomposition in Eq. (4) that $P(\mathbb{G}^{t-1}|\mathbb{G}^t, \mathbb{S}) \propto \sum_{\mathbb{G}} P(\mathbb{G}^{t-1}|\mathbb{G}^t, \mathbb{G}, \mathbb{S})P(\mathbb{G}|\mathbb{G}^t, \mathbb{S})$, optimizing $\mathbf{\Theta}$ according to Eq. (5) essentially optimizes the variational lower bound of the log-likelihood $P_{\mathbf{\Theta}}(\mathbb{G}^0, \mathbb{S})$.*

Proof. We start directly from the log-likelihood of the joint distribution of $P_\Theta(\mathbb{G}^0, \mathbb{S})$:

$$\log P_{\mathbf{\Theta}}(\mathbb{G}^0, \mathbb{S}) = \log \int P_{\mathbf{\Theta}}(\mathbb{G}^0, \mathbb{S}, \mathbb{G}^1, ..., \mathbb{G}^T)d(\mathbb{G}^1, \mathbb{G}^2, ..., \mathbb{G}^T) \tag{11}$$

$$= \log \int \frac{P_{\mathbf{\Theta}}(\mathbb{G}^0, \mathbb{S}, \mathbb{G}^1, ..., \mathbb{G}^T)}{q(\mathbb{G}^1, \mathbb{G}^2, ..., \mathbb{G}^T)} q(\mathbb{G}^1, \mathbb{G}^2, ..., \mathbb{G}^T)d(\mathbb{G}^1, \mathbb{G}^2, ..., \mathbb{G}^T) \tag{12}$$

$$= \log \mathbb{E}_{q(\mathbb{G}^1, \mathbb{G}^2, ..., \mathbb{G}^T)} \frac{P_{\mathbf{\Theta}}(\mathbb{G}^0, \mathbb{S}, \mathbb{G}^1, ..., \mathbb{G}^T)}{q(\mathbb{G}^1, \mathbb{G}^2, ..., \mathbb{G}^T)} \tag{13}$$

$$\geq \mathbb{E}_{q(\mathbb{G}^1, \mathbb{G}^2, ..., \mathbb{G}^T)} \log \frac{P_{\mathbf{\Theta}}(\mathbb{G}^0, \mathbb{S}, \mathbb{G}^1, ..., \mathbb{G}^T)}{q(\mathbb{G}^1, \mathbb{G}^2, ..., \mathbb{G}^T)} \quad \text{by Jensen's inequality} \tag{14}$$

$$= \mathbb{E}_{q(\mathbb{G}^1, \mathbb{G}^1, ..., \mathbb{G}^T)} \log \frac{P(\mathbb{G}^T, \mathbb{S}) \prod_{t=1}^T P_{\mathbf{\Theta}}(\mathbb{G}^{t-1}|\mathbb{G}^t, \mathbb{S})}{q(\mathbb{G}^1) \prod_{t=2}^T q(\mathbb{G}^t|\mathbb{G}^{t-1})} \quad \text{by Markovian} \tag{15}$$

$$= \mathbb{E}_{q(\mathbb{G}^0, \mathbb{G}^1, ..., \mathbb{G}^T)}[\log P(\mathbb{G}^T, \mathbb{S}) + \sum_{t=1}^T \log \frac{P_{\mathbf{\Theta}}(\mathbb{G}^{t-1}|\mathbb{G}^t, \mathbb{S})}{q(\mathbb{G}^t|\mathbb{G}^{t-1})}] + \text{const.} \tag{16}$$

According to the decomposition in Eq. (2), optimizing $\mathbf{\Theta}$ according to Eq. (5) leads to optimizing $P_{\mathbf{\Theta}}(\mathbb{G}^{t-1}|\mathbb{G}^t, \mathbb{S})$, which corresponds to the second term in Eq. (16) and subsequently optimizes the variational lower bound of the log-likelihood $P_{\mathbf{\Theta}}(\mathbb{G}^0, \mathbb{S})$ according to the derivation from Eq. (11) to Eq. (16). Therefore, training Text-to-Graph LGGM according to Eq. (5) enables the model to generate graphs such that the pairs of texts and graphs end up with higher likelihoods.

□

D Data Preparation

D.1 Pre-processed Graphs for Training LGGMs

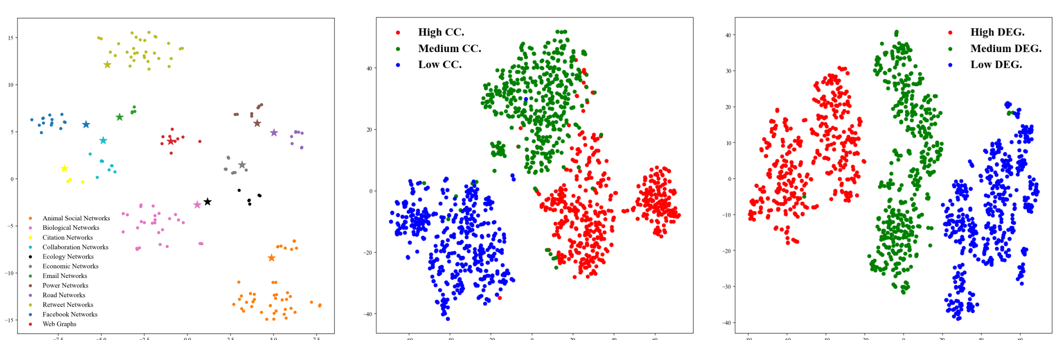
We select graphs from the Network Repository across 13 distinct yet representative domains covering a wide variety of real-world scenarios, including Facebook, Animal Social, Email, Web, Road, Power, Chemical, Biological, Economic, Retweet, Collaboration, Ecological, and Citation. Due to the scalability with diffusion-based graph generative models, we further sample subgraphs for certain domains, and Table 7 presents the comprehensive statistics of the sampled subgraphs, which are used for training LGGMs. We can see that graphs from different domains are statistically different.

Table 7: Summary of Graph Statistics. Facebook (FB), Animal Social (ASN), Email, Web, Road, Power, Chemical (CHEM), Biological (BIO), Economic (ECON), Retweet (RT), Collaboration (COL), Ecological (ECO), Citation.

Category	Num Nodes	Num Edges	Avg Degree	Avg Clustering	Max Nodes	Min Nodes	Max Edges	Min Edges	Num Graphs
ASN	52.47 ± 40.13	77.59 ± 80.95	2.62 ± 1.52	0.395 ± 0.178	283	3	515	2	267
BIO	191.14 ± 43.47	965.71 ± 878.35	9.16 ± 7.69	0.276 ± 0.199	258	109	4392	96	504
CHEM	36.46 ± 20.49	64.61 ± 26.23	3.75 ± 0.63	0.421 ± 0.223	125	2	149	1	646
Citation	235.91 ± 27.25	1287.16 ± 1087.00	10.17 ± 8.14	0.369 ± 0.224	270	175	4474	188	504
COL	174.26 ± 53.82	312.56 ± 176.33	3.41 ± 1.24	0.497 ± 0.203	247	52	996	68	504
ECO	100.67 ± 30.10	1490.00 ± 673.87	27.72 ± 7.00	0.406 ± 0.082	128	54	2106	353	6
ECON	144.18 ± 35.82	3258.76 ± 3540.28	39.76 ± 37.80	0.419 ± 0.296	219	90	11142	188	504
Email	146.67 ± 35.86	681.55 ± 500.28	9.79 ± 7.26	0.389 ± 0.211	213	82	2909	216	504
Power	132.22 ± 20.29	289.32 ± 183.02	4.35 ± 2.31	0.161 ± 0.164	187	81	1332	133	512
Road	265.25 ± 94.31	276.46 ± 79.61	2.70 ± 2.08	0.078 ± 0.134	411	32	456	137	504
RT	104.11 ± 35.23	110.99 ± 46.44	2.11 ± 0.37	0.028 ± 0.038	175	35	295	34	558
FB	219.45 ± 47.05	1863.44 ± 701.53	16.36 ± 6.17	0.315 ± 0.083	259	48	3898	46	504
Web	173.32 ± 24.86	462.21 ± 336.46	5.09 ± 3.06	0.404 ± 0.196	231	119	1607	149	504

D.2 Preparing Graphs and Text Description About Their Domains/Names

Here we thoroughly discuss the process of obtaining graphs and their corresponding text prompts describing their domains/names. As given by the Network Repository, we directly download graphs along with their domains/names. We then prompt GPT3.5 to generate user prompts describing the graph given its domain/name. The concrete prompt template we use here is shown in Listing 1 with exemplary generated user prompts shown in Listing 2. Moreover, we apply the sentence transformer to obtain text embeddings of the generated prompts for each network and perform t-SNE visualization. As shown in Figure 7a, we see prompts for graphs from different domains from different clusters. More importantly, textual similarity can somewhat reflect their network similarity. For example, prompts for road and power networks are very close, and they both belong to infrastructure. Moreover, Facebook Networks, Email Networks, Collaboration Networks, Web Graphs are very close since all these four belong to some sub-variants of social networks. *This inherent relationship between the textual similarity and structural similarity between two graphs demonstrates that the world knowledge encoded in the text could somehow provide useful preference for the graphs to be generated.*



(a) Domain and Name (b) Average Clustering Coefficient (c) Average Degree

Figure 7: t-SNE visualization of textual description about network (a) domain/name (b) average clustering coefficient (c) average degree.

Listing 1: Prompt Template for Generating Textual Description about Network Domain/Name.

```
PROMPT: Given a graph called {GRAPH NAME} that is from the DOMAIN {DOMAIN NAME}. Please
    generate a short sentence about the graph.

Note:
* Do not generate more than 20 words.
```

Listing 2: Examples of Textual Description about Network Domain/Name.

```
================================================================================
*DOMAIN: Animal Social Networks
*NAME: reptilia−tortoise−network−sl
*TEXT: The reptilia−tortoise−network−sl graph represents the social connections among tortoises in the
    reptile community.
================================================================================
*DOMAIN: Power Networks
*NAME: power−eris1176
*TEXT: The power−eris1176 graph represents the interconnected nodes and edges of a power network system
================================================================================
*DOMAIN: Economic Networks
*NAME: econ−poli
*TEXT: The econ−poli graph represents the interconnectedness of economic and political factors in a
    network.
================================================================================
*DOMAIN: Ecology Networks
*NAME: eco−evergla
*TEXT: The eco−evergla graph represents the interconnectedness of species in the Everglades ecosystem.
================================================================================
*DOMAIN: Email Networks
*NAME: email−enron−only
*TEXT: The email−enron−only graph represents the network of email communication within the Enron
    corporation.
================================================================================
*DOMAIN: Road Networks
*NAME: road−roadNet−CA
*TEXT: The road−roadNet−CA graph represents the road network in California.
================================================================================
*DOMAIN: Retweet Networks
*NAME: rt_occupywallstnyc
*TEXT: The graph rt_occupywallstnyc represents retweet relationships in the Occupy Wall Street movement
    in New York City.
================================================================================
*DOMAIN: Facebook Networks
*NAME: socfb−Haverford76
*TEXT: The socfb−Haverford76 graph represents the social connections among users in the Haverford
    College community on Facebook.
================================================================================
*DOMAIN: Web Graphs
*NAME: web−wiki−chameleon
*TEXT: The web−wiki−chameleon graph represents the interconnections between web pages, Wikipedia
    articles, and chameleon species.
================================================================================
*DOMAIN: Biological Networks
*NAME: bio−WormNet−v3−benchmark
*TEXT: The bio−WormNet−v3−benchmark graph represents a biological network related to worms.
================================================================================
*DOMAIN: Citation Networks
*NAME: cit−DBLP
*TEXT: cit−DBLP is a graph representing the citation relationships between research papers in the field of
    computer science.
================================================================================
*DOMAIN: Collaboration Networks
*NAME: ca−netscienc
*TEXT: The ca−netscienc graph represents a collaboration network in the field of science.
================================================================================
```

D.3 Preparing Graphs and Their Textual Description about Graph Property

Here we thoroughly discuss the process of obtaining graphs and their corresponding text prompts describing their properties. Our goal is to demonstrate that Text2Graph LGGM can control the statistics of the generated graphs in the full spectrum. However, the graphs obtained directly from the Network Repository do not cover the whole topological space (e.g., Figure 1(a) shows that no networks have a higher average degree while low clustering coefficient). Therefore, we plan to synthesize graphs covering the whole space by Watts-Strogatz Small-world Graph Model. We vary the number of nodes between [10, 110], the number of initial neighbors between [5, number of nodes], and also the probability of rewiring each edge between [0, 1] to ensure the generated graphs span across the full spectrum. After that, we group the generated graphs into low, medium, and high groups in terms of their clustering coefficient and average degree. We implement this using NetworkX.

After we synthesize graphs and divide them into three groups, we generate user prompts paired with these graphs next. Specifically, we prompt GPT4 following the templates in Listing 3/4. To ensure the compatibility between the synthesis graphs and the generated user prompts. We further replace the number output by GPT4 describing the network property with the real statistic calculated from each network.

Listing 3: Prompt Template for Generating Textual Description about Network Property.

```
================================================================================
PROMPT: Please generate a short sentence about the graph, including its clustering coefficient information.

Note:
∗ Do not generate more than 20 words.
∗ Make sure the generated sentence includes the level of clustering coefficient, you can either specify it via
      words like ['low', 'medium', 'high']. or specify it via numbers like [(0, 0.25), (0.25, 0.5), (0.5, 0.75)]"
∗ You can also sometimes specify a concrete application scenario of the generated network.
∗ Please be accurate but also diverse
================================================================================
PROMPT: Please generate a short sentence about the graph, including its average degree information.

Note:
∗ Do not generate more than 20 words.
∗ Make sure the generated sentence includes the level of average degree, you can either specify it via words
      like ['low', 'medium', 'high']. or specify it via numbers like [(0, 20), (20, 50), (50, 100)]"
∗ You can also sometimes specify a concrete application scenario of the generated network.
∗ Please be accurate but also diverse
================================================================================
```

Listing 4: Examples of Textual Description about Network Property.

```
================================================================================
∗ This graph has a high clustering coefficient, suggesting strong node clustering.
∗ Please generate a network with a clustering coefficient around 0.61, indicating strong clustering.
∗ This retirement community's social interaction graph displays a high clustering coefficient of 0.73,
      indicative of close relationships.
================================================================================
∗ With an average degree of 35, this network is ideal for studying urban transportation patterns.
∗ The graph's moderate connectivity level helps in understanding the structure of small to medium−sized
      music bands.
∗ An average degree of 41 makes this network suitable for simulating the collaboration in local artisan
      markets.
================================================================================
```

E Experimental Setting

E.1 Evaluation Metrics

Following Thompson et al. (2022); You et al. (2018), we evaluate the graph generation performance by the standard Maximum Mean Discrepancy (MMD) between generated and reference graphs $\mathcal{G}_g, \mathcal{G}_r$:

$$\mathrm{MMD}(\mathcal{G}_g, \mathcal{G}_r) = \frac{1}{m^2}\sum_{i,j=1}^{m} k(\mathbf{x}_i^r, \mathbf{x}_j^r) + \frac{1}{n^2}\sum_{i,j=1}^{n} k(\mathbf{x}_i^g, \mathbf{x}_j^g) - \frac{2}{nm}\sum_{i=1}^{n}\sum_{j=1}^{m} k(\mathbf{x}_i^g, \mathbf{x}_j^r), \quad (17)$$

where $k(\cdot,\cdot)$ is a general kernel function and specifically we use RBF kernel following You et al. (2018):

$$k(\mathbf{x}_i, \mathbf{x}_j) = \exp(-d(\mathbf{x}_i, \mathbf{x}_j)/2\sigma^2), \quad (18)$$

where $d(\cdot,\cdot)$ computes pairwise distance following Vignac et al. (2023) and MMD is evaluated over the distributions of degree (DEG), clustering coefficients (CC), eigenvalues of normalized Laplacian matrix (Spec) and orbits counts representing the distribution of all substructures of size 4 (Orb).

E.2 Hyperparameter Details

For all experiments, we select the best configuration according to the generation performance on validation graphs and report the final performance on generating testing graphs. We adopt the default hyperparameter settings from DiGress Vignac et al. (2023) with the following exceptions: we generate 100 graphs per domain for each evaluation and set the training epochs at 300 to ensure convergence. Additionally, we implement gradient accumulation, using a mini-batch size of 12 across 4 accumulations, resulting in an effective batch size of 48. For Text-to-Graph Generation, the textual encoder used to obtain textual description embeddings is "all-MiniLM-L6-v2". All experiments are performed on a machine with A100-80G GPU RAM and 128GB RAM.

E.3 Paradigm Setup

Figure 8 comprehensively visualizes the training/evaluation paradigms of the four experiments, the details of which are discussed in Section 5.1.

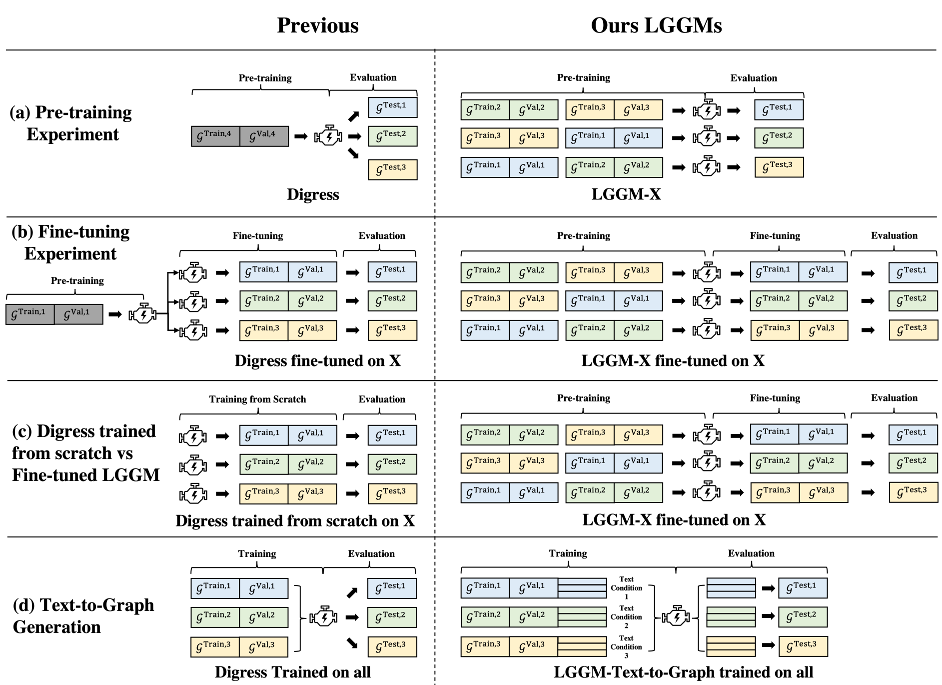


Figure 8: Comprehensive Overview of the Experimental Setup for our LGGMs.

F FULL EXPERIMENTAL RESULTS

F.1 OUT-OF-DOMAIN PERFORMANCE COMPARISON BETWEEN DIGRESS AND LGGM

F.1.1 DOMAIN SPECIFIC TRANSITION STRATEGY

Table 8: Comparing Zero-shot Generation Performance on Unseen Graphs in domain X between DiGress trained on QM9 and LGGM-X pre-trained on all domains except the held-out domain X.

Domain	Method	DEG	CC	Spec	Orb	Domain	Method	DEG	CC	Spec	Orb
FB	DiGress	**0.2695**	**0.3452**	**0.0649**	**0.1489**	BIO	DiGress	0.2419	**0.2993**	**0.1101**	**0.2978**
	LGGM-X	0.4962	0.7625	0.3408	0.7982		LGGM-X	**0.2117**	0.6365	0.1690	0.5156
ASN	DiGress	0.1793	0.4721	0.1751	0.5654	ECON	DiGress	0.2811	0.2042	0.2028	0.2633
	LGGM-X	**0.0220**	**0.4044**	**0.1274**	**0.0505**		LGGM-X	**0.1916**	**0.0917**	**0.1219**	**0.0640**
EMAIL	DiGress	**0.2312**	**0.5444**	**0.0674**	**0.2650**	RT	DiGress	0.4466	0.4170	0.4483	0.4551
	LGGM-X	0.2618	0.8650	0.3013	1.0459		LGGM-X	**0.0721**	**0.0517**	**0.2331**	**0.4085**
WEB	DiGress	0.2575	**0.5955**	0.1907	0.9282	COL	DiGress	0.2393	**0.5341**	0.2247	0.7619
	LGGM-X	**0.1491**	0.9436	**0.1154**	**0.4016**		LGGM-X	**0.1493**	0.9200	**0.1786**	**0.2057**
ROAD	DiGress	0.4111	0.6653	0.3084	0.6530	ECO	DiGress	0.4580	0.4546	0.2144	0.4417
	LGGM-X	**0.0379**	**0.1191**	**0.0759**	**0.0401**		LGGM-X	**0.2049**	**0.2760**	**0.0691**	**0.2107**
POWER	DiGress	0.5292	**0.6083**	0.3556	1.2124	CITATION	DiGress	0.3159	**0.3664**	0.1299	**0.2278**
	LGGM-X	**0.0343**	0.6290	**0.0649**	**0.0228**		LGGM-X	**0.1314**	0.8908	**0.1188**	0.6391
ALL	DiGress	0.3217	**0.4589**	0.2077	0.5184						
	LGGM-X	**0.1635**	0.5492	**0.1597**	**0.3669**						

F.1.2 UNIFORM TRANSITION STRATEGY

Table 9: Comparing Zero-shot Generation Performance on Unseen Graphs in domain X between DiGress trained on QM9 and LGGM-X pre-trained on all domains except the held-out domain X.

Domain	Method	DEG	CC	Spec	Orb	Domain	Method	DEG	CC	Spec	Orb
FB	DiGress	**0.3376**	**0.6298**	**0.0797**	**0.3593**	BIO	DiGress	0.2712	0.5202	0.1127	0.3188
	LGGM-X	0.4723	0.6843	0.2924	0.7555		LGGM-X	**0.1081**	**0.2696**	**0.0900**	**0.2053**
ASN	DiGress	0.1496	0.3258	0.1506	0.4420	ECON	DiGress	0.2987	0.4841	0.2162	0.3834
	LGGM-X	**0.0281**	**0.2440**	**0.0830**	**0.0618**		LGGM-X	**0.1213**	**0.0920**	**0.1120**	**0.1086**
EMAIL	DiGress	0.2192	0.6012	0.0702	0.3416	RT	DiGress	0.4164	0.1327	0.4147	0.5957
	LGGM-X	**0.0751**	**0.2364**	**0.0768**	**0.3089**		LGGM-X	**0.0525**	**0.1429**	**0.1330**	**0.2219**
WEB	DiGress	0.2556	0.6186	0.1877	0.6045	COL	DiGress	0.2473	0.5826	0.2314	0.7679
	LGGM-X	**0.0648**	**0.3961**	**0.0549**	**0.1127**		LGGM-X	**0.0736**	**0.5769**	**0.0895**	**0.0988**
ROAD	DiGress	0.3705	0.8226	0.2801	0.7198	ECO	DiGress	0.5431	0.7915	0.2338	0.6045
	LGGM-X	**0.0713**	**0.2193**	**0.0987**	**0.2986**		LGGM-X	**0.4753**	**0.3904**	0.3194	**0.3934**
POWER	DiGress	0.3726	0.4582	0.3270	1.4732	CITATION	DiGress	0.2527	0.7790	0.1315	**0.4966**
	LGGM-X	**0.0119**	**0.1293**	**0.0373**	**0.0754**		LGGM-X	**0.1348**	**0.7257**	**0.1160**	0.4981
ALL	DiGress	0.3112	0.5622	0.2030	0.5923						
	LGGM-X	**0.1408**	**0.3422**	**0.1253**	**0.2616**						

F.2 PERFORMANCE COMPARISON BETWEEN FINE-TUNED DIGRESS AND FINE-TUNED LGGM

F.2.1 DOMAIN SPECIFIC TRANSITION STRATEGY

Table 10: Comparing Graph Generation Performance between Fine-tuned DiGress and Fine-tuned LGGM on each domain. DiGress-FT: DiGress pre-trained on QM9 and fine-tuned on domain X; LGGM-FT: LGGM pre-trained on all other domains except X and fine-tuned on X under **Domain Specific Transition Strategy**.

Domain	Method	DEG	CC	Spec	Orb	Domain	Method	DEG	CC	Spec	Orb
FB	DiGress-FT	0.0159	0.0564	0.0082	0.0298	BIO	DiGress-FT	0.0391	0.0354	0.0347	0.0291
	LGGM-FT	**0.0065**	**0.0544**	**0.0069**	**0.0282**		LGGM-FT	**0.0036**	**0.0303**	**0.0102**	**0.0342**
ASN	DiGress-FT	0.0189	0.0775	0.0729	0.0886	ECON	DiGress-FT	0.0301	0.0431	0.0372	0.0392
	LGGM-FT	**0.0014**	**0.0509**	**0.0161**	**0.0084**		LGGM-FT	**0.0215**	**0.0330**	**0.0062**	**0.0249**
EMAIL	DiGress-FT	0.0208	0.0448	0.0230	**0.0447**	RT	DiGress-FT	0.0054	0.0464	0.0051	0.0437
	LGGM-FT	**0.0166**	**0.0364**	**0.0104**	0.0463		LGGM-FT	**0.0012**	**0.0075**	**0.0033**	**0.0162**
WEB	DiGress-FT	0.0192	0.0808	0.0664	0.1361	COL	DiGress-FT	0.0255	0.2279	0.0788	0.0731
	LGGM-FT	**0.0116**	**0.0721**	**0.0152**	**0.0656**		LGGM-FT	**0.0202**	**0.1621**	**0.0571**	**0.0631**
ROAD	DiGress-FT	0.0907	0.1404	0.1099	0.1097	ECO	DiGress-FT	0.1370	0.2747	0.0476	0.2109
	LGGM-FT	**0.0088**	**0.1349**	**0.0347**	**0.0125**		LGGM-FT	**0.0196**	**0.2343**	**0.0291**	**0.2100**
POWER	DiGress-FT	0.0104	0.2197	0.1023	0.0445	CITATION	DiGress-FT	0.0363	0.1140	0.0469	0.0423
	LGGM-FT	**0.0008**	**0.1539**	**0.0215**	**0.0081**		LGGM-FT	**0.0078**	**0.0827**	**0.0137**	**0.0316**
All	DiGress-FT	0.0374	0.1134	0.0528	0.0743						
	LGGM-FT	**0.0010**	**0.0877**	**0.0187**	**0.0458**						

F.2.2 UNIFORM TRANSITION STRATEGY

Table 11: Comparing Graph Generation Performance between Fine-tuned DiGress and Fine-tuned LGGM on each domain. DiGress-FT: DiGress pre-trained on QM9 and fine-tuned on domain X; LGGM-FT: LGGM pre-trained on all other domains except X and fine-tuned on X under **Uniform Transition Strategy**.

Domain	Method	DEG	CC	Spec	Orb	Domain	Method	DEG	CC	Spec	Orb
FB	DiGress-FT	**0.0039**	0.0650	0.0090	0.0304	BIO	DiGress-FT	0.0274	0.0845	0.0493	0.0312
	LGGM-FT	**0.0050**	**0.0579**	**0.0059**	**0.0280**		LGGM-FT	**0.0049**	**0.0496**	**0.0056**	**0.0257**
ASN	DiGress-FT	0.0249	0.5604	0.0779	0.0348	ECON	DiGress-FT	**0.0133**	**0.0355**	0.0223	**0.0360**
	LGGM-FT	**0.0058**	**0.1098**	**0.0311**	**0.0101**		LGGM-FT	0.0597	0.0594	**0.0216**	0.0535
EMAIL	DiGress-FT	0.0134	0.0709	0.0223	0.0694	RT	DiGress-FT	0.0418	0.0243	0.0495	0.0583
	LGGM-FT	**0.0120**	**0.0559**	**0.0158**	**0.0444**		LGGM-FT	**0.0032**	**0.0163**	**0.0051**	**0.0227**
WEB	DiGress-FT	0.0327	0.2025	0.0858	0.2033	COL	DiGress-FT	**0.0562**	0.7070	**0.1086**	0.1471
	LGGM-FT	**0.0218**	**0.1398**	**0.0310**	**0.1262**		LGGM-FT	0.1074	**0.4265**	0.1398	**0.0897**
ROAD	DiGress-FT	0.0843	0.1010	0.1873	0.5155	ECO	DiGress-FT	0.1118	0.3016	0.0548	0.2102
	LGGM-FT	**0.0081**	**0.0547**	**0.0573**	**0.0228**		LGGM-FT	**0.0204**	**0.2347**	**0.0404**	**0.2100**
POWER	DiGress-FT	0.0231	0.1029	0.0683	0.0441	CITATION	DiGress-FT	0.0277	0.1622	0.0501	0.0813
	LGGM-FT	**0.0077**	**0.0570**	**0.0134**	**0.0040**		LGGM-FT	**0.0052**	**0.0821**	**0.0221**	**0.0443**
All	DiGress-FT	0.0384	0.2015	0.0654	0.1218						
	LGGM-FT	**0.0218**	**0.1120**	**0.0324**	**0.0568**						

F.3 Performance Comparison between DiGress directly trained on X and Fine-tuned LGGM

F.3.1 Domain Specific Transition

Table 12: Comparing Graph Generation Performance between DiGress and Fine-tuned LGGM on each domain. DiGress: DiGress trained directly on domain X; LGGM-FT: LGGM pre-trained on all other domains except X and fine-tuned on X under **Domain Specific Transition Strategy**.

Domain	Method	DEG	CC	Spec	Orb	Domain	Method	DEG	CC	Spec	Orb
FB	DiGress	0.0423	0.0718	0.0243	0.0298	BIO	DiGress	0.0481	0.1286	0.0487	0.0460
	LGGM-FT	**0.0065**	**0.0544**	**0.0069**	**0.0282**		LGGM-FT	**0.0036**	**0.0303**	**0.0102**	**0.0342**
ASN	DiGress	0.0319	0.0835	0.0679	0.1463	ECON	DiGress	0.0224	0.0361	0.0084	0.0325
	LGGM-FT	**0.0014**	**0.0509**	**0.0161**	**0.0084**		LGGM-FT	**0.0215**	**0.0330**	**0.0062**	**0.0249**
EMAIL	DiGress	**0.0145**	0.0671	0.0143	0.0558	RT	DiGress	0.0035	0.0111	0.0094	0.0207
	LGGM-FT	0.0166	**0.0364**	**0.0104**	**0.0463**		LGGM-FT	**0.0012**	**0.0075**	**0.0033**	**0.0162**
WEB	DiGress	0.0204	0.0778	0.0695	0.1101	COL	DiGress	0.0278	0.2192	0.0669	0.0284
	LGGM-FT	**0.0116**	**0.0721**	**0.0152**	**0.0656**		LGGM-FT	**0.0202**	**0.1621**	**0.0571**	**0.0631**
ROAD	DiGress	0.0333	**0.1342**	0.0932	0.0861	ECO	DiGress	0.0268	0.2356	0.0339	0.2100
	LGGM-FT	**0.0088**	0.1349	**0.0347**	**0.0125**		LGGM-FT	**0.0196**	**0.2343**	**0.0291**	**0.2100**
POWER	DiGress	0.0143	0.2050	0.0776	0.0392	CITATION	DiGress	0.0406	0.1790	0.0677	0.0944
	LGGM-FT	**0.0008**	**0.1539**	**0.0215**	**0.0081**		LGGM-FT	**0.0078**	**0.0827**	**0.0137**	**0.0316**
All	DiGress	0.0272	0.1208	0.0485	0.0749						
	LGGM-FT	**0.0100**	**0.0877**	**0.0187**	**0.0458**						

F.3.2 Uniform Transition

Table 13: Comparing Graph Generation Performance between DiGress and Fine-tuned LGGM on each domain. DiGress: DiGress trained directly on domain X; LGGM-FT: LGGM pre-trained on all other domains except X and fine-tuned on X under **Uniform Transition Strategy**.

Domain	Method	DEG	CC	Spec	Orb	Domain	Method	DEG	CC	Spec	Orb
FB	DiGress	0.0177	0.0698	0.0138	0.0296	BIO	DiGress	0.0179	0.0499	0.0441	0.0526
	LGGM-FT	**0.0050**	**0.0579**	**0.0059**	**0.0280**		LGGM-FT	**0.0049**	**0.0496**	**0.0056**	**0.0257**
ASN	DiGress	0.0337	0.1744	0.0482	0.0243	ECON	DiGress	**0.0229**	**0.0430**	**0.0088**	**0.0427**
	LGGM-FT	**0.0058**	**0.1098**	**0.0311**	**0.0101**		LGGM-FT	0.0597	0.0594	0.0216	0.0535
EMAIL	DiGress	0.0259	0.0901	0.0366	0.0743	RT	DiGress	0.0336	0.0920	0.0432	0.0572
	LGGM-FT	**0.0120**	**0.0559**	**0.0158**	**0.0444**		LGGM-FT	**0.0032**	**0.0163**	**0.0051**	**0.0227**
WEB	DiGress	0.0239	**0.0898**	0.1033	0.2371	COL	DiGress	**0.0252**	0.5156	**0.1171**	0.2060
	LGGM-FT	**0.0218**	0.1398	**0.0310**	**0.1262**		LGGM-FT	0.1074	**0.4265**	0.1398	**0.0897**
ROAD	DiGress	0.1553	0.2788	0.2169	0.0542	ECO	DiGress	0.0263	0.2359	0.0439	0.2100
	LGGM-FT	**0.0081**	**0.0547**	**0.0573**	**0.0228**		LGGM-FT	**0.0204**	**0.2347**	**0.0404**	**0.2100**
POWER	DiGress	0.0348	0.3174	0.1083	0.1393	CITATION	DiGress	0.0217	0.1566	0.0645	0.1235
	LGGM-FT	**0.0077**	**0.0570**	**0.0134**	**0.0040**		LGGM-FT	**0.0052**	**0.0821**	**0.0221**	**0.0443**
All	DiGress	0.0366	0.1761	0.0707	0.1042						
	LGGM-FT	**0.0218**	**0.1120**	**0.0324**	**0.0568**						

F.4 Domain Transferability Analysis

Table 14: Transferability analysis between Chemistry (CHEM) and Society (SOC) domains. The pre-trained LGGM on chemistry demonstrates negative transferability on IMDB-BINARY/MULTI graphs in the SOC domain. LGGM pre-trained on society demonstrates negative transferability on graphs PROTEINS/ENZYMES/MUTAG in CHEM domain.

Domain	**Chemistry**						**Social**			
Dataset	**PROTEINS**		**ENZYMES**		**MUTAG**		**IMDB-BINARY**		**IMDB-MULTI**	
Metric	Orb	CC	Orb	CC	Orb	CC	Orb	CC	Orb	CC
CHEM	0.0604	0.0297	0.0593	0.0534	0.0445	0.0340	0.9001	0.4085	0.5511	0.6324
SOC	0.6997	0.0890	0.8028	0.0422	0.5022	0.9439	0.1526	0.2247	0.0605	0.0945

F.5 Equipping Large-scale Training Paradigm with another graph generative backbone EDGE

Table 15: Comparing Graph Generation Performance between EDGE and EDGE equipped with LGGM on each domain. We can still see the performance boost after equipping EDGE with our large-scale training paradigm.

Domain	**Method**	**DEG**	**CC**	**Spec**	**Orb**	**Domain**	**Method**	**DEG**	**CC**	**Spec**	**Orb**
FB	EDGE	0.0031	**0.0609**	0.0079	0.0362	BIO	EDGE	0.0126	**0.0555**	**0.0484**	0.0612
	LGGM	**0.0022**	0.0657	**0.0073**	**0.0354**		**LGGM**	**0.0120**	0.0669	0.0502	**0.0590**
ASN	EDGE	0.0212	0.1416	0.1145	0.1652	ECON	EDGE	**0.0416**	**0.0398**	**0.0078**	**0.0364**
	LGGM	**0.0146**	**0.0783**	**0.0724**	**0.1285**		LGGM	0.0519	0.0817	0.0665	0.0551
EMAIL	EDGE	0.0118	0.0661	0.0249	0.0771	RT	EDGE	0.0340	**0.1760**	0.1242	**0.0331**
	LGGM	**0.0081**	**0.0519**	**0.0237**	**0.0691**		**LGGM**	**0.0288**	0.3088	**0.0366**	0.0938
WEB	**EDGE**	**0.0132**	**0.1062**	0.1094	0.1950	COL	EDGE	0.0042	**0.2161**	0.1325	**0.3049**
	LGGM	0.1225	0.1283	**0.0976**	**0.1840**		**LGGM**	**0.0026**	0.3058	**0.1285**	0.3104
ROAD	EDGE	0.0254	0.1314	0.1313	0.1065	ECO	EDGE	0.0367	0.2424	0.0665	**0.2156**
	LGGM	**0.0222**	**0.0624**	**0.1242**	**0.0867**		**LGGM**	**0.0197**	**0.2406**	**0.0349**	**0.2156**
POWER	EDGE	0.1417	0.2811	0.2568	0.4298	CITATION	EDGE	0.0124	0.0962	0.0460	0.0438
	LGGM	**0.1276**	**0.2276**	**0.2548**	**0.3549**		**LGGM**	**0.0073**	**0.0947**	**0.0448**	**0.0458**

F.6 Text-to-Graph Generation

F.6.1 Domain Specific Transition

Table 16: Comparing the performance of graph generation between LGGM trained on graphs from all domains with and without domain/name as textual conditions.

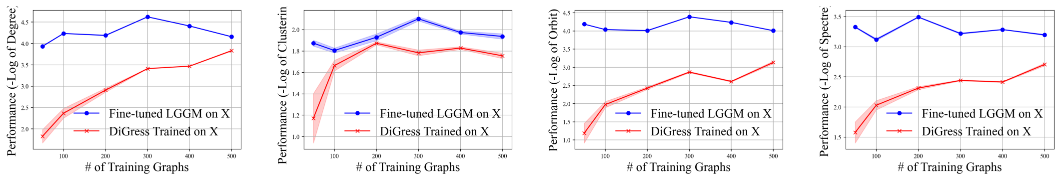
Domain	Method	DEG	CC	Spec	Orb	Domain	Method	DEG	CC	Spec	Orb
	LGGM	0.2566	0.3552	0.0587	0.1614		LGGM	0.2860	0.3275	0.1117	0.2333
FB	LGGM-T2G^{D}	0.1533	0.1894	0.0817	0.0492	BIO	LGGM-T2G^{D}	0.1313	0.5111	0.1340	0.3736
	LGGM-T2G^{UP}	**0.0053**	**0.0576**	**0.0076**	**0.0245**		LGGM-T2G^{UP}	**0.0219**	**0.0251**	**0.0126**	**0.0190**
	LGGM	0.1477	0.3003	0.1551	0.3719		LGGM	0.3540	0.3404	0.2078	0.2740
ASN	LGGM-T2G^{D}	0.0429	0.4742	0.0949	0.0401	ECON	LGGM-T2G^{D}	0.2346	0.1572	0.1550	**0.0579**
	LGGM-T2G^{UP}	**0.0161**	**0.1312**	**0.0344**	**0.0174**		LGGM-T2G^{UP}	**0.0869**	**0.0601**	**0.0412**	0.0592
	LGGM	0.1957	0.2629	0.0646	0.2118		LGGM	0.4355	0.3924	0.4329	0.4966
Email	LGGM-T2G^{D}	0.0874	0.3238	0.1472	0.2869	RT	LGGM-T2G^{D}	0.0050	0.0940	0.0415	0.2870
	LGGM-T2G^{UP}	**0.0077**	**0.0316**	**0.0176**	**0.0365**		LGGM-T2G^{UP}	**0.0034**	**0.0253**	**0.0225**	**0.0869**
	LGGM	0.2461	0.3570	0.1853	0.4832		LGGM	0.2616	**0.3398**	0.2305	0.7090
Web	LGGM-T2G^{D}	0.1253	0.9088	0.1156	0.3884	Col	LGGM-T2G^{D}	0.1301	0.9384	0.1963	0.2032
	LGGM-T2G^{UP}	**0.0771**	**0.2720**	**0.0732**	**0.1251**		LGGM-T2G^{UP}	**0.0845**	0.5070	**0.1378**	**0.1531**
	LGGM	0.4315	0.8107	0.3192	0.6976		LGGM	0.4611	0.3108	0.1932	0.3468
ROAD	LGGM-T2G^{D}	0.0112	0.1611	**0.0298**	0.0120	Eco	LGGM-T2G^{D}	**0.0575**	0.2976	0.0585	0.2580
	LGGM-T2G^{UP}	**0.0097**	**0.1316**	0.0324	**0.0119**		LGGM-T2G^{UP}	0.1070	**0.2913**	**0.0410**	**0.2556**
	LGGM	0.4411	**0.4694**	0.3384	1.3222		LGGM	0.3392	0.5009	0.1295	0.2248
Power	LGGM-T2G^{D}	**0.0194**	0.6031	**0.0286**	**0.0193**	Citation	LGGM-T2G^{D}	0.1636	0.8868	0.2036	0.6142
	LGGM-T2G^{UP}	0.0227	0.4817	0.0330	0.0223		LGGM-T2G^{UP}	**0.0496**	**0.0914**	**0.0669**	**0.0318**
	LGGM	0.3213	0.3973	0.2022	0.4610						
All	LGGM-T2G^{D}	0.0968	0.4621	0.1072	0.2158						
	LGGM-T2G^{UP}	**0.0410**	**0.1755**	**0.0434**	**0.0703**						

F.6.2 Uniform Transition

Table 17: Comparing the performance of graph generation between LGGM trained on graphs from all domains with and without domain/name as textual conditions.

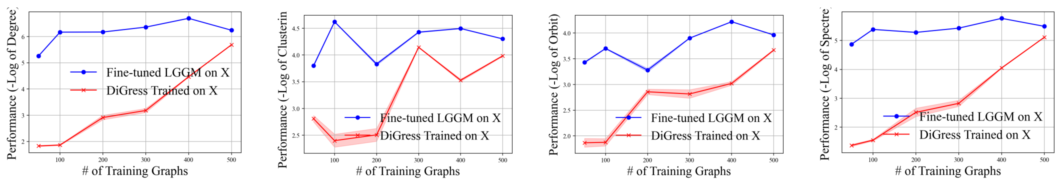
Domain	Method	DEG	CC	Spec	Orb	Domain	Method	DEG	CC	Spec	Orb
	LGGM	0.0321	0.4994	0.0763	0.3117		LGGM	0.2661	0.3120	0.1135	0.3835
FB	LGGM-T2G^{D}	0.1561	0.1639	0.0924	0.0417	BIO	LGGM-T2G^{D}	0.0099	0.1286	0.0303	0.1366
	LGGM-T2G^{UP}	**0.0050**	**0.0545**	**0.0070**	**0.0251**		LGGM-T2G^{UP}	**0.0028**	**0.0287**	**0.0236**	**0.0174**
	LGGM	0.1511	0.4325	0.1875	0.3896		LGGM	0.3828	0.1533	0.2039	0.2583
ASN	LGGM-T2G^{D}	0.0318	0.2821	0.0606	0.0631	ECON	LGGM-T2G^{D}	0.0666	0.0594	0.0650	0.0586
	LGGM-T2G^{UP}	**0.0211**	**0.1191**	**0.0462**	**0.0195**		LGGM-T2G^{UP}	**0.0132**	**0.0257**	**0.0053**	**0.0191**
	LGGM	0.2156	0.2450	0.0666	0.2757		LGGM	0.4395	0.2225	0.4337	0.6641
Email	LGGM-T2G^{D}	0.0469	0.0982	0.0484	0.0505	RT	LGGM-T2G^{D}	0.0468	0.0955	0.0729	0.0393
	LGGM-T2G^{UP}	**0.0073**	**0.0379**	**0.0127**	**0.0437**		LGGM-T2G^{UP}	**0.0286**	**0.0933**	**0.0400**	**0.0312**
	LGGM	0.2725	0.2672	0.1900	0.4368		LGGM	0.3565	0.3554	0.2451	0.7874
Web	LGGM-T2G^{D}	0.0255	**0.0737**	0.0354	0.1856	Col	LGGM-T2G^{D}	0.0395	0.3110	0.1146	0.1823
	LGGM-T2G^{UP}	**0.0105**	0.0941	**0.0206**	**0.0451**		LGGM-T2G^{UP}	**0.0265**	**0.2813**	**0.0895**	**0.0899**
	LGGM	0.4825	0.5373	0.3398	0.7542		LGGM	0.5466	0.6003	0.2257	0.7089
ROAD	LGGM-T2G^{D}	**0.0088**	0.1225	0.0399	0.0155	Eco	LGGM-T2G^{D}	0.2160	0.2917	0.1203	0.2569
	LGGM-T2G^{UP}	0.0177	**0.0437**	**0.0336**	**0.0086**		LGGM-T2G^{UP}	**0.0293**	**0.2885**	**0.0416**	**0.2556**
	LGGM	0.4394	0.4646	0.3473	1.3186		LGGM	0.2624	0.5374	0.1295	0.3419
Power	LGGM-T2G^{D}	0.0162	0.1131	0.0479	0.1786	Citation	LGGM-T2G^{D}	0.0101	0.1025	0.0315	0.0651
	LGGM-T2G^{UP}	**0.0062**	**0.0570**	**0.0111**	**0.0084**		LGGM-T2G^{UP}	**0.0072**	**0.0849**	**0.0115**	**0.0287**
	LGGM	0.3206	0.3856	0.2132	0.5526						
All	LGGM-T2G^{D}	0.0562	0.1535	0.0633	0.1061						
	LGGM-T2G^{UP}	**0.0146**	**0.1007**	**0.0286**	**0.0494**						

F.7 Sensitive Analysis on Number of Training Data under Domain Specific Transition



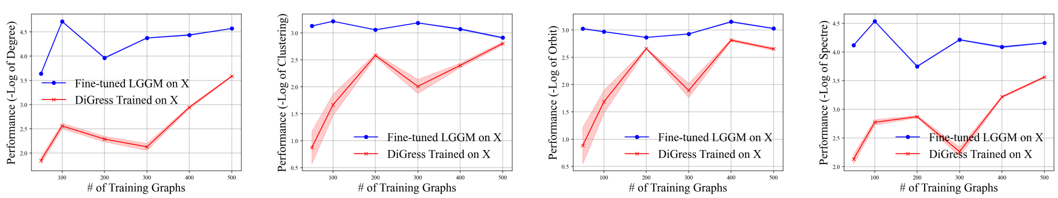
(a) Road-DEG (b) Road-CC (c) Road-Orb (d) Road-Spec

Figure 9: Effect of Number of Training Graphs on Road Networks.



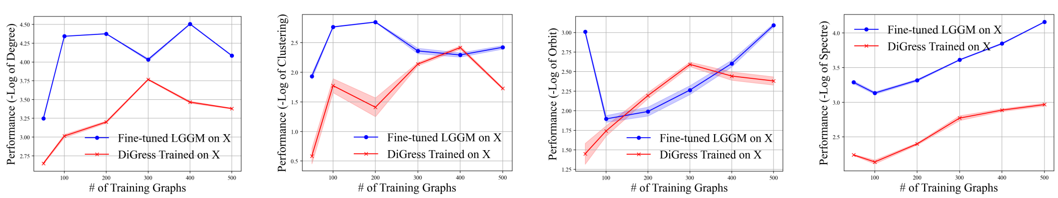
(a) Retweet-DEG (b) Retweet-CC (c) Retweet-Orb (d) Retweet-Spec

Figure 10: Effect of Number of Training Graphs on Retweet Networks.



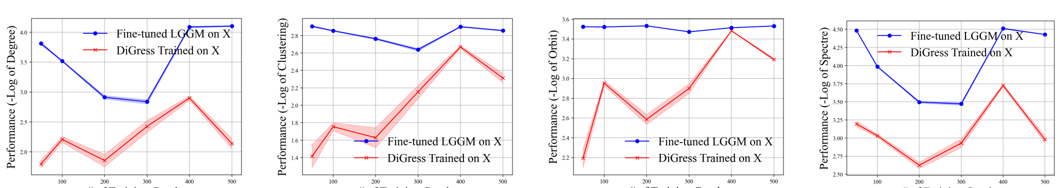
(a) Email-DEG (b) Email-CC (c) Email-Orb (d) Email-Spec

Figure 11: Effect of Number of Training Graphs on Email Networks.



(a) Web-DEG (b) Web-CC (c) Web-Orb (d) Web-Spec

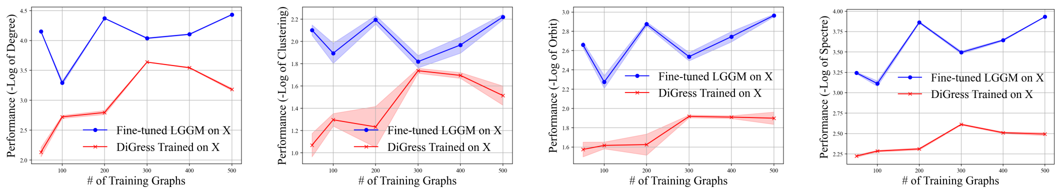
Figure 12: Effect of Number of Training Graphs on Web Graphs.



(a) Facebook-DEG (b) Facebook-CC (c) Facebook-Orb (d) Facebook-Spec

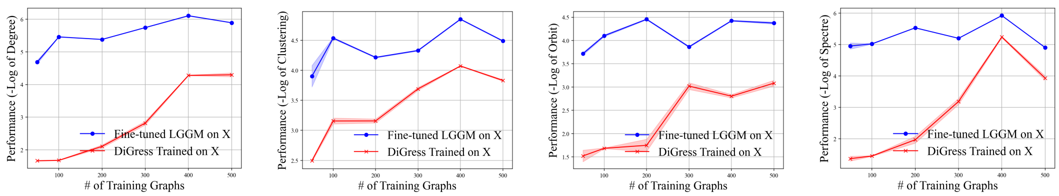
Figure 13: Effect of Number of Training Graphs on Facebook Networks.

F.8 Sensitive Analysis on Number of Training Data under Uniform Transition Strategy



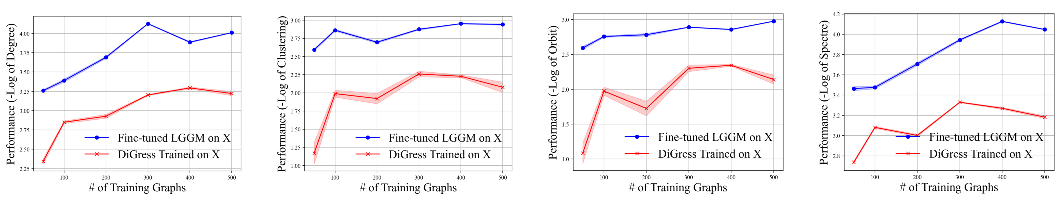
(a) Citation-DEG (b) Citation-CC (c) Citation-Orb (d) Citation-Spec

Figure 14: Effect of Number of Training Graphs on Citation Networks.



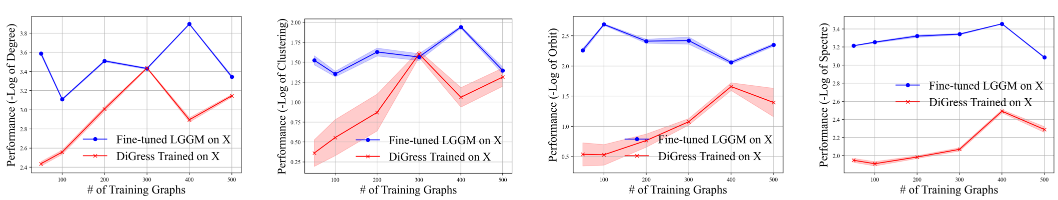
(a) Retweet-DEG (b) Retweet-CC (c) Retweet-Orb (d) Retweet-Spec

Figure 15: Effect of Number of Training Graphs on Retweet Networks.



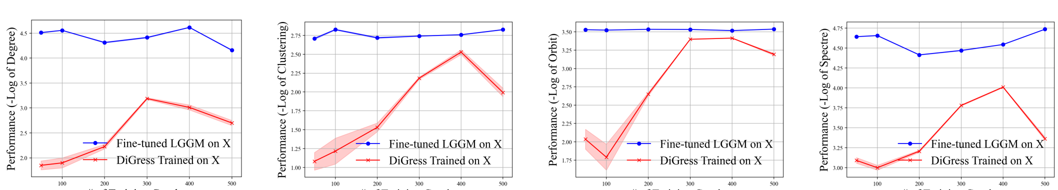
(a) Email-DEG (b) Email-CC (c) Email-Orb (d) Email-Spec

Figure 16: Effect of Number of Training Graphs on Email Networks.



(a) Web-DEG (b) Web-CC (c) Web-Orb (d) Web-Spec

Figure 17: Effect of Number of Training Graphs on Web Graphs.



(a) Facebook-DEG (b) Facebook-CC (c) Facebook-Orb (d) Facebook-Spec

Figure 18: Effect of Number of Training Graphs on Facebook Networks.

F.9 Comparing the Domain as the Textual Condition before/after shuffling

F.9.1 Domain Specific Transition

Table 18: Comparing the performance of graph generation between LGGM trained on graphs from all domains with and without domain/name as textual conditions under domain-specific transition.

Domain	Method	DEG	CC	Spec	Orb	Domain	Method	DEG	CC	Spec	Orb
FB	LGGM-T2G^{D}	**0.1533**	**0.1894**	**0.0817**	**0.0492**	BIO	LGGM-T2G^{D}	**0.1313**	**0.5111**	**0.1340**	**0.3736**
	LGGM-T2G$^{D}*$	0.2323	0.2618	0.1590	0.0923		LGGM-T2G$^{D}*$	0.1762	0.5887	0.1460	0.4929
ASN	LGGM-T2G^{D}	**0.0429**	**0.4742**	**0.0949**	**0.0401**	ECON	LGGM-T2G^{D}	0.2346	**0.1572**	**0.1550**	**0.0579**
	LGGM-T2G$^{D}*$	0.0891	0.5725	0.1446	0.0610		LGGM-T2G$^{D}*$	**0.2029**	0.3393	0.2298	0.0579
Email	LGGM-T2G^{D}	**0.0874**	**0.3238**	**0.1472**	**0.2869**	RT	LGGM-T2G^{D}	**0.0050**	**0.0940**	**0.0415**	**0.2870**
	LGGM-T2G$^{D}*$	0.2169	0.7497	0.2825	0.8397		LGGM-T2G$^{D}*$	0.0240	0.1023	0.1374	0.4123
Web	LGGM-T2G^{D}	**0.1253**	**0.9088**	**0.1156**	**0.3884**	Col	LGGM-T2G^{D}	**0.1301**	**0.9384**	**0.1963**	**0.2032**
	LGGM-T2G$^{D}*$	0.1464	0.9776	0.1460	0.4211		LGGM-T2G$^{D}*$	0.1529	0.9684	0.2313	0.2089
ROAD	LGGM-T2G^{D}	**0.0112**	**0.1611**	**0.0298**	**0.0120**	Eco	LGGM-T2G^{D}	**0.0575**	**0.2976**	**0.0585**	0.2580
	LGGM-T2G$^{D}*$	0.0365	0.2430	0.0605	0.0500		LGGM-T2G$^{D}*$	0.1964	0.3330	0.1438	**0.2574**
Power	LGGM-T2G^{D}	**0.0194**	**0.6031**	**0.0286**	**0.0193**	Citation	LGGM-T2G^{D}	0.1636	**0.8868**	0.2036	0.6142
	LGGM-T2G$^{D}*$	0.0434	0.6721	0.0626	0.0231		LGGM-T2G$^{D}*$	**0.1615**	0.9553	**0.1903**	**0.6078**
All	LGGM-T2G^{D}	**0.0968**	**0.4621**	**0.1072**	**0.2158**						
	LGGM-T2G$^{D}*$	0.1399	0.5636	0.1611	0.2937						

F.9.2 Uniform Transition

Table 19: Comparing the performance of graph generation between LGGM trained on graphs from all domains with and without domain/name as textual conditions under uniform transition strategy.

Domain	Method	DEG	CC	Spec	Orb	Domain	Method	DEG	CC	Spec	Orb
FB	LGGM-T2G^{D}	**0.1561**	**0.1639**	**0.0924**	**0.0417**	BIO	LGGM-T2G^{D}	**0.0099**	**0.1286**	**0.0303**	**0.1366**
	LGGM-T2G$^{D}*$	0.3018	0.4207	0.2069	0.2622		LGGM-T2G$^{D}*$	0.0754	0.2889	0.0881	0.2783
ASN	LGGM-T2G^{D}	**0.0318**	0.2821	**0.0606**	**0.0631**	ECON	LGGM-T2G^{D}	**0.0665**	**0.0594**	**0.0650**	**0.0586**
	LGGM-T2G$^{D}*$	0.0637	**0.1561**	0.1416	0.2351		LGGM-T2G$^{D}*$	0.1035	0.0736	0.0971	0.0922
Email	LGGM-T2G^{D}	**0.0469**	**0.0982**	**0.0484**	**0.0505**	RT	LGGM-T2G^{D}	**0.0468**	**0.0955**	**0.0729**	**0.0393**
	LGGM-T2G$^{D}*$	0.1107	0.2322	0.1315	0.1692		LGGM-T2G$^{D}*$	0.1399	0.3913	0.2441	0.2497
Web	LGGM-T2G^{D}	**0.0255**	**0.0737**	**0.0354**	**0.1856**	Col	LGGM-T2G^{D}	**0.0395**	**0.3110**	**0.1146**	**0.1823**
	LGGM-T2G$^{D}*$	0.0485	0.0830	0.1340	0.2669		LGGM-T2G$^{D}*$	0.0323	0.4972	0.1159	0.5375
ROAD	LGGM-T2G^{D}	**0.0088**	0.1225	**0.0399**	**0.0155**	Eco	LGGM-T2G^{D}	**0.2160**	**0.2917**	**0.1203**	**0.2569**
	LGGM-T2G$^{D}*$	0.0453	**0.1005**	0.1257	0.3803		LGGM-T2G$^{D}*$	0.3722	0.3210	0.2226	0.2771
Power	LGGM-T2G^{D}	**0.0162**	**0.1131**	**0.0479**	**0.1786**	Citation	LGGM-T2G^{D}	**0.0101**	**0.1025**	**0.0315**	**0.0651**
	LGGM-T2G$^{D}*$	0.0225	0.1533	0.1264	0.2957		LGGM-T2G$^{D}*$	0.0375	0.2454	0.0699	0.1363
All	LGGM-T2G^{D}	**0.0562**	**0.1535**	**0.0633**	**0.1061**						
	LGGM-T2G$^{D}*$	0.1128	0.2469	0.1420	0.2650						