Schema-Guided Knowledge Graph Unlearning Appendix

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Abstract

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1 Background on GRPO

GRPO is a reinforcement learning algorithm that compares actions within semantically coherent groups rather than relying on absolute scores. Unlike Proximal Policy Optimization (PPO) [2], GRPO requires no value network, reducing memory cost and improving stability. The method is grounded in the insight that human feedback—and many real-world settings—favor relative preference over absolute reward [1, 3]. GRPO defines a *relative advantage* for each action:

$$A_{\text{rel}}(s, a_i) = R(s, a_i) - \frac{1}{N}\sum_{j=1}^{N} R(s, a_j),$$

where $R(s, a_i)$ is the reward of action a_i in state s, and the second term is the average reward in the group. The GRPO objective is:

$$L_{\text{GRPO}}(\theta) = -\mathbb{E}_{s,a\sim\pi_{\theta_{\text{old}}}}\left[\min\left(r_\theta(s,a)A_{\text{rel}},\ \text{clip}(r_\theta(s,a), 1-\epsilon, 1+\epsilon)\, A_{\text{rel}}\right)\right],$$

where $r_\theta(s,a) = \frac{\pi_\theta(a|s)}{\pi_{\theta_{\text{old}}}(a|s)}$ is the policy ratio, ϵ is the clipping parameter that limits policy updates, and $\pi_\theta(a|s)$ represents the probability of taking action a in state s under policy θ. The objective encourages increasing the probability of actions with positive relative advantage while restricting update magnitude through clipping.

2 Configurations and Hyperparameter Setting

To ensure robust and comprehensive evaluation of SGKU, we adopt a systematic hyperparameter strategy that balances search coverage with computational efficiency. Unless noted otherwise, values are tuned on a validation split at **Time 1** and reused for **Times 2–3**. The main SGKU hyperparameters are summarized in Table 1.

2.1 Sequential Optimization Strategy

Given the expanded hyperparameter space, a naïve full-grid over all dials we considered would be prohibitively large. To navigate this space efficiently, we use a three-phase, coarse-to-fine strategy.

Phase 1: Architectural & Policy Shaping (coarse grid). Fix secondary knobs to stable defaults (α=10^{-3}, batch= 1024, λ_2=1.0, α_{ema}=0.99, K=20, M=5, κ_{hub}=1.0) and search over the levers that most directly shape unlearning behaviour:

- **Triple Grouping Strategy** ∈ {Relation, Entity, Schema, Batch, Random} (5)
- **Group Weight Method** ∈ {Frequency, Degree, Info-theoretic, Uniform} (4)
- **Projection Strength** $\lambda_{\text{proj}} \in \{0.0, 0.25, 0.5, 0.75, 1.0\}$ (5)
- **PPO Clip** $\epsilon_{\text{clip}} \in \{0.10, 0.15, 0.20, 0.25, 0.30\}$ (5)
- **Minimum Temperature** $T_{\min} \in \{0.05, 0.10, 0.15, 0.20\}$ (4)
- **KL Regularization** $\lambda_{\text{KL}} \in \{0.5, 1.0, 1.5, 2.0\}$ (4)

This phase (5×4×5×5×4×4 = 8,000 settings) locks in the core semantics and stability of the GRPO update before any training-dynamics tuning.

Phase 2: Learning Dynamics (conditioned grid). Conditioned on the top Phase-1 candidates, tune the training schedule and statistics:

- **Learning Rate** $\alpha \in \{1\times10^{-4}, 3\times10^{-4}, 5\times10^{-4}, 1\times10^{-3}\}$ (4)
- **Batch Size** ∈ {256, 512, 1024} (3)
- **EMA Momentum** $\alpha_{\text{ema}} \in \{0.95, 0.975, 0.99\}$ (3)
- **Ref. Policy Refresh** $M \in \{2, 5, 10\}$ (3)
- **Projection Interval** $K \in \{5, 10, 20, 50\}$ (4)

This aligns the optimizer's "tempo" with the chosen architecture (4×3×3×3×4 = 432 settings per Phase-1 seed).

Phase 3: Boundary & Robustness Refinement (narrow search). Finally, refine the entity-space regularization around the Phase-2 best:

- **Boundary Weight** $\lambda_2 \in \{0.0, 0.5, 1.0, 1.5, 2.0\}$ (5)
- **Huber Scale** $\kappa_{\text{hub}} \in \{0.5, 1.0, 1.5, 2.0\}$ (4)

We also run a micro-sweep (*e.g.*, {−0.05, 0, +0.05}) around the winning λ_{proj} and λ_{KL} when sensitivity curves indicate a sharp optimum.

2.2 Evaluation Metrics and Configuration Selection

For each configuration we report validation metrics capturing the unlearning trade-off:

- $\mathbf{MRR}_{\text{Avg}}$: overall link-prediction quality post-unlearning,
- $\mathbf{M_f}$: forgetting efficacy on $\cup_{j\le i}\mathcal{T}_j^-$ (lower is better),
- $\mathbf{M_r}$: retention on $\mathcal{T}_i^+$ (higher is better).

We rank configurations using a balanced score:

$$\text{Score} \;=\; \text{MRR}_{\text{Avg}} \;+\; 0.3\cdot(1 - M_f) \;+\; 0.3\cdot M_r. \tag{1}$$

This prioritizes overall utility while assigning symmetric weight to forgetting and retention.

2.3 Optimization and Compute Budget

We apply early stopping on validation Score after 100 iterations and carry the top-k Phase-1 models (default k=10) into Phases 2–3.

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Table 1: Main hyperparameters of the SGKU framework (notation aligned with the method section).

Hyperparameter	Description	Range/Options	Chosen / Optimal
Triple Grouping Strategy	Organizes triples into semantically coherent groups used for policy formation and baselines	{Relation, Entity, Schema, Batch, Random}	**Schema**
Schema/Group Weight Method	Importance weights w_g used in GRPO loss and KL	{Frequency, Degree, **Info-theoretic**, Uniform}	**Info-theoretic**
Projection Strength (λ_{proj})	Strength of conflict-aware gradient projection	$[0.0, 1.0]$	**0.5**
Boundary Preservation (λ_2)	Weight of boundary-entity Huber regularizer	$[0.0, 2.0]$	**1.0**
KL Regularization (λ_{KL})	Pattern-weighted KL term for policy stability	$[0.5, 2.0]$	**1.0** (robust 1.0–1.5)
PPO Clipping (ϵ_{clip})	Trust-region clipping for policy ratio ρ_θ	$[0.10, 0.30]$	**0.20**
Softmax Temperature Floor ($T_{\min}$)	Group temperature: $T_j = \max(T_{\min}, 1/\lvert g_j \rvert)$	$[0.05, 0.20]$	**0.10**
Reference Policy Update (M)	Frequency to refresh θ_{old}	$\{2, 5, 10\}$	**5**
Projection Cadence (K)	Frequency to apply gradient projection	$\{5, 10, 20, 50\}$	**20**
EMA Momentum (α_{ema})	EMA for running (μ, σ) in score standardization	$[0.95, 0.995]$	**0.99**
Huber Threshold Scale (κ_{hub})	Scale for boundary Huber $\delta_{\text{hub}} = \kappa_{\text{hub}} \cdot \text{median}\lVert \mathbf{e}_{\theta_{\text{old}}} \rVert / \sqrt{d}$	$[0.5, 2.0]$	**1.0**
Learning Rate (α)	Adam step size (shared across models unless noted)	$[1\text{e}{-4}, 1\text{e}{-3}]$	5×10^{-4}
Batch Size	Triples per mini-batch; group-aware batching (complete groups per batch)	{256, 512, 1024}	**512** (stable 256–1024)

In practice, this reduces the effective search by $> 99.9\%$ versus the 69.1M full grid while preserving solution quality. The entire sweep required ~200 compute-hours on an Apple M2 Ultra (192GB shared memory).

3 Main results with standard deviation

We report the results of the main experiment in the paper including standard deviation.

4 Additional KGE model experiments

Our experimental results reveal remarkable consistency in SGKU's performance advantages across different embedding models, each representing fundamentally different mathematical frameworks. SGKU consistently achieves the best performance among approximate unlearning methods, substantially outperforming SGU, GNNDELETE, MetaEU, and FedLU across all evaluation metrics and architectures. This consistency is particularly significant given the diverse computational approaches: RotatE's rotation operations in complex space and DistMult's bilinear diagonal factorization.

Across both models, SGKU demonstrates superior forgetting efficacy (lower M_f) while maintaining better knowledge retention (M_r) and overall performance. For instance, on FB-20% at Time 3, SGKU achieves consistent performance leadership: $M_f = 0.170/\text{MRR}_{Avg} = 0.615$ (RotatE) and $M_f = 0.183/\text{M}_{avg} = 0.504$ (DistMult), compared to the next-best approximate method FedLU with $M_f = 0.177/\text{MRR}_{Avg} = 0.610$ (RotatE) and $M_f = 0.190/\text{M}_{avg} = 0.499$ (DistMult).

4.1 Model-Specific Performance Characteristics

While maintaining consistent relative rankings, we observe distinct model-specific performance characteristics that reflect the underlying embedding architectures and their computational complexities:

RotatE Performance Patterns. RotatE generally exhibits stronger absolute performance across most metrics, particularly excelling in MRR_{Avg} scores. This advantage is most pronounced on the FB datasets, where RotatE's rotation operations effectively capture complex relational patterns. The model achieves $\text{MRR}_{Avg} = 0.566$ on WN-20% at Time 3 with SGKU, demonstrating robust performance across different knowledge domains.

DistMult Stability Advantages. DistMult demonstrates more stable forgetting performance across time steps, with predictable convergence behavior despite generally lower absolute scores. This stability stems from DistMult's simpler bilinear structure, which provides more interpretable gradient dynamics during the unlearning process. On WN-20%, DistMult achieves $\text{M}_{avg} = 0.561$ at Time 3, showing consistent improvement from $\text{M}_{avg} = 0.506$ at Time 1.

The consistent performance improvements of SGKU across both embedding models provide compelling evidence for our core hypothesis that schema-aware unlearning delivers fundamental advantages regardless of the underlying embedding architecture. Our schema-guided triple grouping and weighted regularization mechanisms successfully leverage structural knowledge patterns across rotation-based (RotatE) and bilinear (DistMult) embedding spaces.

Remarkably, the relative improvement margins of SGKU over competing methods remain substantial across both architectures. For example, SGKU's advantage over SGU on FB-20% at Time 3 shows consistent patterns: $\Delta\text{MRR}_{Avg} = 0.014$ (RotatE) and $\Delta\text{M}_{avg} = 0.021$ (DistMult). Similarly, on WN-20%, SGKU outperforms SGU by $\Delta\text{MRR}_{Avg} = 0.023$ (RotatE) and $\Delta\text{M}_{avg} = 0.020$ (DistMult). This consistency demonstrates that schema-awareness provides architecture-independent benefits, validating the generalizability of our approach.

References

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Table 2: Evaluation results. Bold indicates the best approximate method, underlined indicates second best. Standard deviations shown as subscripts.

KGE (TransE)	FB-10%											
	M_f ↓			M_r ↑			M_{avg} ↑			M_{F1} ↑		
	T1	T2	T3	T1	T2	T3	T1	T2	T3	T1	T2	T3
Retrain	$.125_{.003}$	$.126_{.004}$	$.126_{.003}$	$.231_{.005}$	$.233_{.006}$	$.237_{.007}$	$.553_{.008}$	$.553_{.009}$	$.555_{.010}$	$.365_{.011}$	$.367_{.012}$	$.372_{.013}$
Finetune	$.128_{.004}$	$.130_{.005}$	$.128_{.004}$	$.228_{.006}$	$.231_{.007}$	$.233_{.008}$	$.550_{.009}$	$.550_{.010}$	$.552_{.011}$	$.361_{.012}$	$.365_{.013}$	$.367_{.014}$
SGU	$.217_{.016}$	$.210_{.015}$	$.198_{.014}$	$.185_{.013}$	$.195_{.014}$	$.203_{.015}$	$.484_{.019}$	$.492_{.020}$	$.502_{.021}$	$.299_{.017}$	$.313_{.018}$	$.324_{.019}$
GNNDELETE	$\underline{.156}_{.012}$	$.162_{.013}$	$\underline{.150}_{.011}$	$.181_{.012}$	$.190_{.013}$	$.201_{.014}$	$\underline{.512}_{.017}$	$.514_{.018}$	$.525_{.019}$	$.298_{.016}$	$.309_{.017}$	$.325_{.018}$
MetaEU	$.193_{.015}$	$.185_{.014}$	$.182_{.013}$	$.188_{.013}$	$.196_{.014}$	$.201_{.015}$	$.497_{.018}$	$.505_{.019}$	$.509_{.020}$	$.305_{.017}$	$.316_{.018}$	$.323_{.019}$
FedLU	$.168_{.013}$	$\underline{.158}_{.012}$	$.152_{.011}$	$\underline{.192}_{.013}$	$\underline{.198}_{.014}$	$\underline{.208}_{.015}$	$.512_{.017}$	$\underline{.520}_{.018}$	$\underline{.528}_{.019}$	$\underline{.312}_{.017}$	$\underline{.321}_{.018}$	$\underline{.334}_{.020}$
SGKU	$\mathbf{.141}_{.009}$	$\mathbf{.145}_{.010}$	$\mathbf{.143}_{.009}$	$\mathbf{.197}_{.011}$	$\mathbf{.202}_{.012}$	$\mathbf{.211}_{.013}$	$\mathbf{.528}_{.014}$	$\mathbf{.528}_{.015}$	$\mathbf{.534}_{.016}$	$\mathbf{.320}_{.014}$	$\mathbf{.327}_{.015}$	$\mathbf{.339}_{.016}$

KGE (TransE)	FB-20%											
	M_f ↓			M_r ↑			M_{avg} ↑			M_{F1} ↑		
	T1	T2	T3	T1	T2	T3	T1	T2	T3	T1	T2	T3
Retrain	$.138_{.005}$	$.134_{.004}$	$.133_{.004}$	$.221_{.006}$	$.226_{.007}$	$.245_{.009}$	$.541_{.010}$	$.546_{.011}$	$.556_{.012}$	$.352_{.013}$	$.358_{.014}$	$.382_{.016}$
Finetune	$.139_{.005}$	$.136_{.005}$	$.135_{.005}$	$.217_{.007}$	$.221_{.008}$	$.242_{.010}$	$.539_{.011}$	$.542_{.012}$	$.553_{.013}$	$.347_{.014}$	$.352_{.015}$	$.378_{.017}$
SGU	$.203_{.017}$	$.186_{.016}$	$.174_{.015}$	$.182_{.014}$	$.188_{.015}$	$.205_{.017}$	$.489_{.021}$	$.501_{.022}$	$.515_{.023}$	$.296_{.018}$	$.305_{.019}$	$.328_{.020}$
GNNDELETE	$\underline{.179}_{.014}$	$.172_{.013}$	$.164_{.012}$	$.185_{.013}$	$\underline{.190}_{.014}$	$.213_{.016}$	$\underline{.503}_{.018}$	$.509_{.019}$	$.524_{.020}$	$.302_{.017}$	$\underline{.309}_{.018}$	$.340_{.021}$
MetaEU	$.196_{.016}$	$.182_{.015}$	$.170_{.014}$	$.183_{.014}$	$.186_{.015}$	$.204_{.016}$	$.493_{.019}$	$.502_{.020}$	$.517_{.021}$	$.298_{.017}$	$.303_{.018}$	$.328_{.020}$
FedLU	$.184_{.015}$	$\underline{.168}_{.013}$	$\underline{.159}_{.012}$	$\underline{.187}_{.014}$	$.189_{.015}$	$\underline{.214}_{.017}$	$.501_{.018}$	$\underline{.510}_{.019}$	$\underline{.527}_{.020}$	$\underline{.304}_{.018}$	$.308_{.018}$	$\underline{.341}_{.021}$
SGKU	$\mathbf{.165}_{.011}$	$\mathbf{.154}_{.010}$	$\mathbf{.154}_{.010}$	$\mathbf{.189}_{.012}$	$\mathbf{.191}_{.013}$	$\mathbf{.218}_{.015}$	$\mathbf{.512}_{.015}$	$\mathbf{.518}_{.016}$	$\mathbf{.532}_{.017}$	$\mathbf{.308}_{.015}$	$\mathbf{.312}_{.016}$	$\mathbf{.347}_{.018}$

KGE (TransE)	WN-10%											
	M_f ↓			M_r ↑			M_{avg} ↑			M_{F1} ↑		
	T1	T2	T3	T1	T2	T3	T1	T2	T3	T1	T2	T3
Retrain	$.326_{.015}$	$.268_{.014}$	$.250_{.013}$	$.359_{.018}$	$.361_{.019}$	$.380_{.021}$	$.516_{.022}$	$.546_{.024}$	$.565_{.026}$	$.468_{.025}$	$.484_{.027}$	$.504_{.029}$
Finetune	$.328_{.016}$	$.270_{.015}$	$.252_{.014}$	$.358_{.018}$	$.359_{.019}$	$.376_{.020}$	$.515_{.022}$	$.544_{.024}$	$.562_{.026}$	$.467_{.025}$	$.481_{.027}$	$.500_{.028}$
SGU	$.381_{.027}$	$.324_{.024}$	$.301_{.022}$	$.298_{.020}$	$.305_{.021}$	$.325_{.023}$	$.458_{.030}$	$.490_{.032}$	$.512_{.034}$	$.402_{.027}$	$.420_{.029}$	$.444_{.031}$
GNNDELETE	$.373_{.026}$	$.312_{.023}$	$.292_{.021}$	$.315_{.021}$	$.317_{.022}$	$.335_{.024}$	$.471_{.031}$	$.502_{.033}$	$.521_{.035}$	$.419_{.028}$	$.434_{.030}$	$.455_{.032}$
MetaEU	$.376_{.026}$	$.315_{.023}$	$.296_{.021}$	$.316_{.021}$	$.316_{.022}$	$.333_{.024}$	$.470_{.031}$	$.500_{.033}$	$.518_{.035}$	$.420_{.028}$	$.432_{.030}$	$.452_{.032}$
FedLU	$\underline{.372}_{.025}$	$\underline{.310}_{.022}$	$\underline{.290}_{.020}$	$\underline{.320}_{.021}$	$\underline{.318}_{.022}$	$\underline{.336}_{.024}$	$\underline{.474}_{.031}$	$\underline{.504}_{.033}$	$\underline{.523}_{.035}$	$\underline{.424}_{.028}$	$\underline{.435}_{.030}$	$\underline{.456}_{.032}$
SGKU	$\mathbf{.367}_{.021}$	$\mathbf{.304}_{.019}$	$\mathbf{.283}_{.017}$	$\mathbf{.323}_{.018}$	$\mathbf{.320}_{.019}$	$\mathbf{.340}_{.021}$	$\mathbf{.478}_{.026}$	$\mathbf{.508}_{.028}$	$\mathbf{.528}_{.030}$	$\mathbf{.428}_{.024}$	$\mathbf{.438}_{.026}$	$\mathbf{.461}_{.028}$

KGE (TransE)	WN-20%											
	M_f ↓			M_r ↑			M_{avg} ↑			M_{F1} ↑		
	T1	T2	T3	T1	T2	T3	T1	T2	T3	T1	T2	T3
Retrain	$.194_{.011}$	$.228_{.013}$	$.124_{.008}$	$.359_{.018}$	$.365_{.019}$	$.394_{.022}$	$.582_{.025}$	$.568_{.024}$	$.635_{.028}$	$.497_{.027}$	$.496_{.027}$	$.544_{.030}$
Finetune	$.195_{.011}$	$.230_{.013}$	$.126_{.008}$	$.354_{.018}$	$.363_{.019}$	$.391_{.022}$	$.579_{.025}$	$.566_{.024}$	$.632_{.028}$	$.492_{.026}$	$.493_{.027}$	$.540_{.030}$
SGU	$.227_{.017}$	$.268_{.020}$	$.159_{.013}$	$.298_{.020}$	$.312_{.022}$	$.329_{.024}$	$.535_{.034}$	$.522_{.033}$	$.585_{.036}$	$.430_{.030}$	$.438_{.031}$	$.473_{.033}$
GNNDELETE	$.223_{.016}$	$.263_{.019}$	$.151_{.012}$	$.308_{.021}$	$.320_{.023}$	$.342_{.025}$	$.542_{.035}$	$.528_{.034}$	$.595_{.037}$	$.441_{.031}$	$.446_{.032}$	$.488_{.034}$
MetaEU	$.225_{.016}$	$.265_{.019}$	$.153_{.012}$	$.313_{.022}$	$.317_{.023}$	$.338_{.025}$	$.544_{.035}$	$.526_{.033}$	$.592_{.037}$	$.446_{.031}$	$.443_{.031}$	$.483_{.034}$
FedLU	$\underline{.222}_{.016}$	$\underline{.261}_{.019}$	$\underline{.149}_{.012}$	$.316_{.022}$	$\underline{.321}_{.023}$	$\underline{.345}_{.025}$	$\underline{.547}_{.035}$	$\underline{.530}_{.034}$	$\underline{.598}_{.037}$	$\underline{.449}_{.031}$	$\underline{.448}_{.031}$	$\underline{.491}_{.034}$
SGKU	$\mathbf{.220}_{.014}$	$\mathbf{.258}_{.016}$	$\mathbf{.143}_{.010}$	$\mathbf{.319}_{.019}$	$\mathbf{.325}_{.020}$	$\mathbf{.352}_{.022}$	$\mathbf{.549}_{.030}$	$\mathbf{.533}_{.029}$	$\mathbf{.604}_{.032}$	$\mathbf{.453}_{.026}$	$\mathbf{.452}_{.027}$	$\mathbf{.499}_{.029}$

KGE (ComplEx)	FB-10%											
	M_f ↓			M_r ↑			M_{avg} ↑			M_{F1} ↑		
	T1	T2	T3	T1	T2	T3	T1	T2	T3	T1	T2	T3
Retrain	$.118_{.004}$	$.121_{.005}$	$.119_{.004}$	$.245_{.007}$	$.248_{.008}$	$.251_{.009}$	$.564_{.010}$	$.564_{.011}$	$.566_{.012}$	$.383_{.014}$	$.387_{.015}$	$.391_{.016}$
Finetune	$.121_{.005}$	$.123_{.006}$	$.122_{.005}$	$.239_{.008}$	$.242_{.009}$	$.244_{.010}$	$.559_{.011}$	$.560_{.012}$	$.561_{.013}$	$.376_{.015}$	$.379_{.016}$	$.382_{.017}$
SGU	$.234_{.018}$	$.227_{.017}$	$.215_{.016}$	$.172_{.014}$	$.181_{.015}$	$.189_{.016}$	$.469_{.021}$	$.477_{.022}$	$.487_{.023}$	$.281_{.018}$	$.293_{.019}$	$.305_{.020}$
GNNDELETE	$\underline{.169}_{.013}$	$.175_{.014}$	$\underline{.163}_{.012}$	$.168_{.013}$	$.177_{.014}$	$.188_{.015}$	$\underline{.500}_{.018}$	$.501_{.019}$	$.513_{.020}$	$.280_{.017}$	$.292_{.018}$	$.307_{.019}$
MetaEU	$.206_{.016}$	$.198_{.015}$	$.195_{.014}$	$.175_{.014}$	$.183_{.015}$	$.188_{.016}$	$.485_{.019}$	$.493_{.020}$	$.497_{.021}$	$.287_{.018}$	$.298_{.019}$	$.305_{.020}$
FedLU	$.181_{.014}$	$\underline{.171}_{.013}$	$.165_{.012}$	$\underline{.179}_{.014}$	$\underline{.185}_{.015}$	$\underline{.195}_{.016}$	$.499_{.018}$	$\underline{.507}_{.019}$	$\underline{.515}_{.020}$	$\underline{.294}_{.018}$	$\underline{.303}_{.019}$	$\underline{.316}_{.020}$
SGKU	$\mathbf{.152}_{.010}$	$\mathbf{.156}_{.011}$	$\mathbf{.154}_{.010}$	$\mathbf{.184}_{.012}$	$\mathbf{.189}_{.013}$	$\mathbf{.198}_{.014}$	$\mathbf{.516}_{.015}$	$\mathbf{.517}_{.016}$	$\mathbf{.522}_{.017}$	$\mathbf{.302}_{.015}$	$\mathbf{.309}_{.016}$	$\mathbf{.321}_{.017}$

KGE (ComplEx)	FB-20%											
	M_f ↓			M_r ↑			M_{avg} ↑			M_{F1} ↑		
	T1	T2	T3	T1	T2	T3	T1	T2	T3	T1	T2	T3
Retrain	$.131_{.005}$	$.127_{.005}$	$.126_{.005}$	$.234_{.008}$	$.239_{.009}$	$.258_{.011}$	$.552_{.012}$	$.556_{.013}$	$.566_{.014}$	$.369_{.015}$	$.375_{.016}$	$.398_{.018}$
Finetune	$.132_{.006}$	$.129_{.006}$	$.128_{.006}$	$.228_{.009}$	$.233_{.010}$	$.253_{.012}$	$.548_{.013}$	$.552_{.014}$	$.563_{.015}$	$.361_{.016}$	$.368_{.017}$	$.392_{.019}$
SGU	$.218_{.019}$	$.199_{.017}$	$.187_{.016}$	$.169_{.015}$	$.175_{.016}$	$.192_{.017}$	$.476_{.022}$	$.488_{.023}$	$.503_{.024}$	$.278_{.019}$	$.287_{.020}$	$.311_{.021}$
GNNDELETE	$\underline{.192}_{.015}$	$.185_{.014}$	$.177_{.013}$	$.172_{.014}$	$\underline{.177}_{.015}$	$.200_{.017}$	$\underline{.490}_{.019}$	$.496_{.020}$	$.512_{.021}$	$.284_{.018}$	$\underline{.291}_{.019}$	$.322_{.021}$
MetaEU	$.209_{.017}$	$.195_{.015}$	$.183_{.014}$	$.170_{.014}$	$.173_{.015}$	$.191_{.016}$	$.481_{.020}$	$.489_{.021}$	$.504_{.022}$	$.280_{.018}$	$.285_{.019}$	$.310_{.021}$
FedLU	$.197_{.016}$	$\underline{.181}_{.014}$	$\underline{.172}_{.013}$	$\underline{.174}_{.014}$	$.176_{.015}$	$\underline{.201}_{.017}$	$.489_{.019}$	$\underline{.498}_{.020}$	$\underline{.515}_{.021}$	$\underline{.286}_{.018}$	$.290_{.019}$	$\underline{.323}_{.021}$
SGKU	$\mathbf{.176}_{.012}$	$\mathbf{.165}_{.011}$	$\mathbf{.165}_{.011}$	$\mathbf{.176}_{.013}$	$\mathbf{.178}_{.014}$	$\mathbf{.205}_{.016}$	$\mathbf{.501}_{.016}$	$\mathbf{.507}_{.017}$	$\mathbf{.520}_{.018}$	$\mathbf{.290}_{.015}$	$\mathbf{.293}_{.016}$	$\mathbf{.329}_{.018}$

KGE (ComplEx)	WN-10%											
	M_f ↓			M_r ↑			M_{avg} ↑			M_{F1} ↑		
	T1	T2	T3	T1	T2	T3	T1	T2	T3	T1	T2	T3
Retrain	$.318_{.016}$	$.261_{.015}$	$.243_{.014}$	$.372_{.020}$	$.374_{.021}$	$.393_{.023}$	$.527_{.024}$	$.557_{.026}$	$.575_{.028}$	$.481_{.027}$	$.497_{.029}$	$.517_{.031}$
Finetune	$.321_{.017}$	$.263_{.016}$	$.245_{.015}$	$.370_{.020}$	$.372_{.021}$	$.389_{.022}$	$.525_{.024}$	$.555_{.026}$	$.572_{.028}$	$.479_{.027}$	$.494_{.029}$	$.513_{.031}$
SGU	$.394_{.030}$	$.337_{.026}$	$.314_{.024}$	$.285_{.021}$	$.292_{.022}$	$.312_{.024}$	$.446_{.033}$	$.478_{.035}$	$.499_{.037}$	$.388_{.029}$	$.405_{.031}$	$.429_{.033}$
GNNDELETE	$.386_{.029}$	$.325_{.025}$	$.305_{.023}$	$.302_{.022}$	$.304_{.023}$	$.322_{.024}$	$.458_{.034}$	$.490_{.036}$	$.509_{.038}$	$.405_{.030}$	$.419_{.032}$	$.440_{.034}$
MetaEU	$.389_{.029}$	$.328_{.025}$	$.309_{.023}$	$.303_{.022}$	$.303_{.023}$	$.320_{.024}$	$.457_{.034}$	$.488_{.036}$	$.506_{.038}$	$.405_{.030}$	$.418_{.032}$	$.437_{.034}$
FedLU	$\underline{.385}_{.028}$	$\underline{.323}_{.024}$	$\underline{.303}_{.022}$	$\underline{.307}_{.022}$	$\underline{.305}_{.023}$	$\underline{.323}_{.024}$	$\underline{.461}_{.033}$	$\underline{.491}_{.035}$	$\underline{.510}_{.037}$	$\underline{.410}_{.030}$	$\underline{.421}_{.032}$	$\underline{.441}_{.034}$
SGKU	$\mathbf{.378}_{.024}$	$\mathbf{.317}_{.021}$	$\mathbf{.296}_{.019}$	$\mathbf{.310}_{.019}$	$\mathbf{.307}_{.020}$	$\mathbf{.327}_{.021}$	$\mathbf{.466}_{.028}$	$\mathbf{.495}_{.030}$	$\mathbf{.516}_{.032}$	$\mathbf{.414}_{.026}$	$\mathbf{.424}_{.028}$	$\mathbf{.447}_{.030}$

KGE (ComplEx)	WN-20%											
	M_f ↓			M_r ↑			M_{avg} ↑			M_{F1} ↑		
	T1	T2	T3	T1	T2	T3	T1	T2	T3	T1	T2	T3
Retrain	$.187_{.012}$	$.221_{.014}$	$.117_{.008}$	$.372_{.020}$	$.378_{.021}$	$.407_{.024}$	$.593_{.027}$	$.579_{.026}$	$.645_{.030}$	$.510_{.029}$	$.509_{.029}$	$.557_{.032}$
Finetune	$.188_{.012}$	$.223_{.014}$	$.119_{.008}$	$.367_{.020}$	$.376_{.021}$	$.404_{.024}$	$.590_{.027}$	$.577_{.026}$	$.643_{.030}$	$.506_{.029}$	$.507_{.029}$	$.554_{.032}$
SGU	$.240_{.019}$	$.281_{.022}$	$.172_{.015}$	$.285_{.021}$	$.299_{.023}$	$.316_{.025}$	$.523_{.036}$	$.509_{.035}$	$.572_{.038}$	$.415_{.032}$	$.422_{.033}$	$.457_{.035}$
GNNDELETE	$.236_{.018}$	$.276_{.021}$	$.164_{.014}$	$.295_{.022}$	$.307_{.024}$	$.329_{.026}$	$.530_{.037}$	$.516_{.036}$	$.583_{.039}$	$.426_{.033}$	$.431_{.034}$	$.472_{.036}$
MetaEU	$.238_{.018}$	$.278_{.021}$	$.166_{.014}$	$.300_{.023}$	$.304_{.024}$	$.325_{.026}$	$.531_{.037}$	$.513_{.036}$	$.580_{.039}$	$.431_{.033}$	$.428_{.034}$	$.468_{.036}$
FedLU	$\underline{.235}_{.018}$	$\underline{.274}_{.021}$	$\underline{.162}_{.013}$	$\underline{.303}_{.023}$	$\underline{.308}_{.024}$	$\underline{.332}_{.026}$	$\underline{.534}_{.037}$	$\underline{.517}_{.036}$	$\underline{.585}_{.039}$	$\underline{.434}_{.033}$	$\underline{.433}_{.034}$	$\underline{.476}_{.036}$
SGKU	$\mathbf{.231}_{.015}$	$\mathbf{.270}_{.018}$	$\mathbf{.155}_{.011}$	$\mathbf{.306}_{.020}$	$\mathbf{.312}_{.021}$	$\mathbf{.339}_{.023}$	$\mathbf{.538}_{.032}$	$\mathbf{.521}_{.031}$	$\mathbf{.592}_{.034}$	$\mathbf{.438}_{.028}$	$\mathbf{.437}_{.029}$	$\mathbf{.484}_{.032}$

Table 3: Results on FB-10%, FB-20%, WN-10%, and WN-20%. Bold indicates best approximate method, underlined indicates second best approximate method. Results averaged over 5 runs using RotatE as KGE model. Standard deviations shown as subscripts.

	Time 1				Time 2				Time 3			
$\mathcal{T}^-$: FB-10%	$M_f \downarrow$	$M_r \uparrow$	$MRR_{Avg} \uparrow$	$MR_1 \uparrow$	$M_f \downarrow$	$M_r \uparrow$	$MRR_{Avg} \uparrow$	$MR_1 \uparrow$	$M_f \downarrow$	$M_r \uparrow$	$MRR_{Avg} \uparrow$	$MR_1 \uparrow$
Retrain	$.109_{.003}$	$.258_{.004}$	$.575_{.007}$	$.400_{.008}$	$.112_{.004}$	$.261_{.005}$	$.575_{.006}$	$.403_{.009}$	$.110_{.003}$	$.265_{.006}$	$.578_{.008}$	$.408_{.011}$
Finetune	$.111_{.004}$	$.254_{.005}$	$.572_{.008}$	$.395_{.010}$	$.114_{.005}$	$.257_{.006}$	$.572_{.007}$	$.398_{.012}$	$.112_{.004}$	$.261_{.007}$	$.575_{.009}$	$.403_{.013}$
SGU	$.245_{.015}$	$.169_{.012}$	$.462_{.018}$	$.276_{.014}$	$.238_{.016}$	$.177_{.013}$	$.470_{.019}$	$.287_{.015}$	$.226_{.014}$	$.185_{.014}$	$.480_{.020}$	$.299_{.016}$
GNNDELETE	$.182_{.011}$	$.165_{.010}$	$.492_{.016}$	$.275_{.013}$	$.177_{.012}$	$.174_{.011}$	$.499_{.017}$	$.287_{.014}$	$.165_{.010}$	$.183_{.012}$	$.509_{.018}$	$.300_{.015}$
MetaEU	$.213_{.013}$	$.172_{.011}$	$.480_{.017}$	$.282_{.014}$	$.206_{.014}$	$.180_{.012}$	$.487_{.018}$	$.293_{.015}$	$.202_{.012}$	$.187_{.013}$	$.493_{.019}$	$.303_{.016}$
FedLU	$.195_{.012}$	$.176_{.011}$	$.491_{.016}$	$.289_{.013}$	$.185_{.013}$	$.182_{.012}$	$.499_{.017}$	$.298_{.014}$	$.178_{.011}$	$.192_{.013}$	$.507_{.018}$	$.311_{.015}$
SGKU	**$.171_{.009}$**	**$.181_{.008}$**	**$.505_{.012}$**	**$.297_{.010}$**	**$.165_{.009}$**	**$.186_{.008}$**	**$.511_{.013}$**	**$.304_{.011}$**	**$.162_{.008}$**	**$.195_{.009}$**	**$.517_{.014}$**	**$.316_{.012}$**
$\mathcal{T}^-$: FB-20%	$M_f \downarrow$	$M_r \uparrow$	$MRR_{Avg} \uparrow$	$MR_1 \uparrow$	$M_f \downarrow$	$M_r \uparrow$	$MRR_{Avg} \uparrow$	$MR_1 \uparrow$	$M_f \downarrow$	$M_r \uparrow$	$MRR_{Avg} \uparrow$	$MR_1 \uparrow$
Retrain	$.126_{.004}$	$.241_{.006}$	$.558_{.010}$	$.378_{.012}$	$.122_{.005}$	$.246_{.007}$	$.562_{.011}$	$.384_{.013}$	$.120_{.004}$	$.264_{.009}$	$.572_{.015}$	$.406_{.018}$
Finetune	$.128_{.005}$	$.237_{.007}$	$.555_{.011}$	$.373_{.014}$	$.124_{.006}$	$.242_{.008}$	$.559_{.012}$	$.379_{.015}$	$.122_{.005}$	$.260_{.010}$	$.569_{.016}$	$.401_{.019}$
SGU	$.231_{.018}$	$.160_{.013}$	$.465_{.021}$	$.265_{.016}$	$.212_{.019}$	$.168_{.014}$	$.478_{.022}$	$.277_{.017}$	$.200_{.017}$	$.185_{.015}$	$.493_{.025}$	$.301_{.020}$
GNNDELETE	$.203_{.014}$	$.163_{.011}$	$.480_{.018}$	$.271_{.014}$	$.196_{.015}$	$.170_{.012}$	$.487_{.019}$	$.281_{.015}$	$.184_{.013}$	$.193_{.013}$	$.505_{.021}$	$.312_{.017}$
MetaEU	$.218_{.016}$	$.161_{.012}$	$.472_{.019}$	$.267_{.015}$	$.205_{.017}$	$.166_{.013}$	$.481_{.020}$	$.275_{.016}$	$.193_{.015}$	$.184_{.014}$	$.496_{.023}$	$.300_{.018}$
FedLU	$.210_{.015}$	$.165_{.011}$	$.478_{.017}$	$.273_{.013}$	$.189_{.016}$	$.169_{.012}$	$.490_{.018}$	$.280_{.014}$	$.177_{.014}$	$.194_{.013}$	$.509_{.022}$	$.314_{.017}$
SGKU	**$.187_{.012}$**	**$.167_{.009}$**	**$.490_{.014}$**	**$.277_{.011}$**	**$.172_{.011}$**	**$.171_{.009}$**	**$.500_{.015}$**	**$.283_{.012}$**	**$.170_{.010}$**	**$.198_{.011}$**	**$.514_{.018}$**	**$.320_{.014}$**
$\mathcal{T}^-$: WN-10%	$M_f \downarrow$	$M_r \uparrow$	$MRR_{Avg} \uparrow$	$MR_1 \uparrow$	$M_f \downarrow$	$M_r \uparrow$	$MRR_{Avg} \uparrow$	$MR_1 \uparrow$	$M_f \downarrow$	$M_r \uparrow$	$MRR_{Avg} \uparrow$	$MR_1 \uparrow$
Retrain	$.308_{.012}$	$.378_{.015}$	$.535_{.018}$	$.489_{.022}$	$.247_{.014}$	$.380_{.016}$	$.567_{.020}$	$.505_{.024}$	$.230_{.013}$	$.399_{.018}$	$.585_{.021}$	$.526_{.026}$
Finetune	$.310_{.013}$	$.374_{.016}$	$.532_{.019}$	$.485_{.023}$	$.249_{.015}$	$.376_{.017}$	$.564_{.021}$	$.501_{.025}$	$.232_{.014}$	$.395_{.019}$	$.582_{.022}$	$.522_{.027}$
SGU	$.415_{.025}$	$.276_{.018}$	$.431_{.028}$	$.375_{.021}$	$.358_{.026}$	$.283_{.019}$	$.463_{.030}$	$.393_{.023}$	$.335_{.024}$	$.303_{.020}$	$.484_{.031}$	$.416_{.024}$
GNNDELETE	$.407_{.023}$	$.293_{.017}$	$.443_{.026}$	$.392_{.020}$	$.347_{.024}$	$.295_{.018}$	$.474_{.027}$	$.406_{.021}$	$.326_{.022}$	$.313_{.019}$	$.494_{.028}$	$.427_{.022}$
MetaEU	$.410_{.024}$	$.294_{.017}$	$.442_{.027}$	$.392_{.020}$	$.350_{.025}$	$.294_{.018}$	$.472_{.028}$	$.405_{.022}$	$.329_{.023}$	$.311_{.019}$	$.491_{.029}$	$.425_{.023}$
FedLU	$.405_{.022}$	$.298_{.017}$	$.447_{.025}$	$.397_{.019}$	$.344_{.023}$	$.296_{.017}$	$.476_{.026}$	$.408_{.020}$	$.323_{.021}$	$.314_{.018}$	$.496_{.027}$	$.429_{.021}$
SGKU	**$.399_{.019}$**	**$.301_{.014}$**	**$.451_{.022}$**	**$.401_{.017}$**	**$.338_{.020}$**	**$.298_{.015}$**	**$.480_{.023}$**	**$.411_{.018}$**	**$.317_{.018}$**	**$.318_{.016}$**	**$.501_{.024}$**	**$.434_{.019}$**
$\mathcal{T}^-$: WN-20%	$M_f \downarrow$	$M_r \uparrow$	$MRR_{Avg} \uparrow$	$MR_1 \uparrow$	$M_f \downarrow$	$M_r \uparrow$	$MRR_{Avg} \uparrow$	$MR_1 \uparrow$	$M_f \downarrow$	$M_r \uparrow$	$MRR_{Avg} \uparrow$	$MR_1 \uparrow$
Retrain	$.174_{.008}$	$.378_{.015}$	$.602_{.018}$	$.519_{.022}$	$.206_{.010}$	$.384_{.016}$	$.589_{.020}$	$.518_{.024}$	$.102_{.006}$	$.413_{.019}$	$.656_{.023}$	$.566_{.027}$
Finetune	$.176_{.009}$	$.374_{.016}$	$.599_{.019}$	$.514_{.023}$	$.208_{.011}$	$.380_{.017}$	$.586_{.021}$	$.514_{.025}$	$.104_{.007}$	$.409_{.020}$	$.653_{.024}$	$.562_{.028}$
SGU	$.264_{.020}$	$.276_{.018}$	$.506_{.025}$	$.401_{.021}$	$.305_{.023}$	$.290_{.020}$	$.493_{.027}$	$.409_{.023}$	$.195_{.016}$	$.307_{.020}$	$.556_{.028}$	$.444_{.024}$
GNNDELETE	$.260_{.018}$	$.286_{.017}$	$.513_{.023}$	$.413_{.020}$	$.300_{.021}$	$.298_{.019}$	$.499_{.025}$	$.418_{.022}$	$.187_{.014}$	$.320_{.018}$	$.567_{.026}$	$.459_{.022}$
MetaEU	$.262_{.019}$	$.291_{.017}$	$.515_{.024}$	$.417_{.020}$	$.302_{.022}$	$.295_{.019}$	$.497_{.026}$	$.415_{.023}$	$.189_{.015}$	$.316_{.019}$	$.564_{.027}$	$.455_{.023}$
FedLU	$.258_{.017}$	$.294_{.016}$	$.518_{.022}$	$.421_{.019}$	$.298_{.020}$	$.299_{.018}$	$.501_{.024}$	$.419_{.021}$	$.185_{.013}$	$.323_{.018}$	$.569_{.025}$	$.463_{.021}$
SGKU	**$.255_{.015}$**	**$.297_{.014}$**	**$.521_{.019}$**	**$.425_{.017}$**	**$.294_{.017}$**	**$.303_{.015}$**	**$.505_{.021}$**	**$.424_{.019}$**	**$.178_{.011}$**	**$.330_{.016}$**	**$.576_{.022}$**	**$.471_{.019}$**

Table 4: Results on FB-10%, FB-20%, WN-10%, and WN-20%. Bold indicates best approximate method, underlined indicates second best approximate method. Results averaged over 5 runs using DistMult as KGE model. Standard deviations shown as subscripts.

	Time 1				Time 2				Time 3			
$\mathcal{T}^-$: FB-10%	$M_f \downarrow$	$M_r \uparrow$	$M_{avg} \uparrow$	$M_{F1} \uparrow$	$M_f \downarrow$	$M_r \uparrow$	$M_{avg} \uparrow$	$M_{F1} \uparrow$	$M_f \downarrow$	$M_r \uparrow$	$M_{avg} \uparrow$	$M_{F1} \uparrow$
Retrain	$.115_{.004}$	$.245_{.006}$	$.565_{.009}$	$.384_{.011}$	$.118_{.005}$	$.248_{.007}$	$.565_{.010}$	$.387_{.012}$	$.116_{.004}$	$.252_{.008}$	$.568_{.011}$	$.392_{.013}$
Finetune	$.117_{.005}$	$.241_{.007}$	$.562_{.010}$	$.379_{.012}$	$.120_{.006}$	$.244_{.008}$	$.562_{.011}$	$.382_{.013}$	$.118_{.005}$	$.248_{.009}$	$.565_{.012}$	$.387_{.014}$
SGU	$.258_{.020}$	$.162_{.014}$	$.452_{.022}$	$.266_{.016}$	$.251_{.021}$	$.170_{.015}$	$.460_{.023}$	$.277_{.017}$	$.239_{.019}$	$.178_{.016}$	$.470_{.024}$	$.289_{.018}$
GNNDELETE	$\underline{.195_{.015}}$	$.158_{.012}$	$\underline{.482_{.018}}$	$.264_{.014}$	$\underline{.190_{.016}}$	$.167_{.013}$	$\underline{.489_{.019}}$	$.277_{.015}$	$\underline{.178_{.014}}$	$.176_{.014}$	$\underline{.499_{.020}}$	$.290_{.016}$
MetaEU	$.226_{.017}$	$.165_{.013}$	$.470_{.020}$	$.272_{.015}$	$.219_{.018}$	$.173_{.014}$	$.477_{.021}$	$.283_{.016}$	$.215_{.016}$	$.180_{.015}$	$.483_{.022}$	$.293_{.017}$
FedLU	$.208_{.016}$	$\underline{.169_{.012}}$	$.481_{.017}$	$\underline{.279_{.013}}$	$.198_{.017}$	$\underline{.175_{.013}}$	$.489_{.018}$	$\underline{.287_{.014}}$	$.191_{.015}$	$\underline{.185_{.014}}$	$.497_{.019}$	$\underline{.301_{.015}}$
SGKU	$\mathbf{.184}_{.012}$	$\mathbf{.174}_{.010}$	$\mathbf{.495}_{.014}$	$\mathbf{.287}_{.011}$	$\mathbf{.178}_{.013}$	$\mathbf{.179}_{.011}$	$\mathbf{.501}_{.015}$	$\mathbf{.294}_{.012}$	$\mathbf{.175}_{.011}$	$\mathbf{.188}_{.012}$	$\mathbf{.507}_{.016}$	$\mathbf{.306}_{.013}$
$\mathcal{T}^-$: FB-20%	$M_f \downarrow$	$M_r \uparrow$	$M_{avg} \uparrow$	$M_{F1} \uparrow$	$M_f \downarrow$	$M_r \uparrow$	$M_{avg} \uparrow$	$M_{F1} \uparrow$	$M_f \downarrow$	$M_r \uparrow$	$M_{avg} \uparrow$	$M_{F1} \uparrow$
Retrain	$.132_{.006}$	$.228_{.008}$	$.548_{.012}$	$.361_{.014}$	$.128_{.007}$	$.233_{.009}$	$.553_{.013}$	$.368_{.015}$	$.126_{.006}$	$.251_{.011}$	$.563_{.014}$	$.390_{.017}$
Finetune	$.134_{.007}$	$.224_{.009}$	$.545_{.013}$	$.356_{.015}$	$.130_{.008}$	$.229_{.010}$	$.550_{.014}$	$.363_{.016}$	$.128_{.007}$	$.247_{.012}$	$.560_{.015}$	$.385_{.018}$
SGU	$.244_{.023}$	$.153_{.016}$	$.455_{.026}$	$.254_{.019}$	$.225_{.024}$	$.161_{.017}$	$.468_{.027}$	$.267_{.020}$	$.213_{.022}$	$.178_{.018}$	$.483_{.028}$	$.290_{.021}$
GNNDELETE	$\underline{.216_{.019}}$	$.156_{.014}$	$\underline{.470_{.022}}$	$.260_{.017}$	$\underline{.209_{.020}}$	$.163_{.015}$	$\underline{.477_{.023}}$	$.270_{.018}$	$\underline{.197_{.018}}$	$.186_{.016}$	$\underline{.495_{.024}}$	$.302_{.019}$
MetaEU	$.231_{.021}$	$.154_{.015}$	$.462_{.024}$	$.257_{.018}$	$.218_{.022}$	$.159_{.016}$	$.471_{.025}$	$.264_{.019}$	$.206_{.020}$	$.177_{.017}$	$.486_{.026}$	$.289_{.020}$
FedLU	$.223_{.020}$	$\underline{.158_{.014}}$	$.468_{.021}$	$\underline{.263_{.016}}$	$.202_{.021}$	$\underline{.162_{.015}}$	$.480_{.022}$	$\underline{.269_{.017}}$	$.190_{.019}$	$\underline{.187_{.016}}$	$.499_{.023}$	$\underline{.304_{.018}}$
SGKU	$\mathbf{.200}_{.016}$	$\mathbf{.160}_{.012}$	$\mathbf{.480}_{.018}$	$\mathbf{.267}_{.014}$	$\mathbf{.185}_{.017}$	$\mathbf{.164}_{.013}$	$\mathbf{.490}_{.019}$	$\mathbf{.273}_{.015}$	$\mathbf{.183}_{.015}$	$\mathbf{.191}_{.014}$	$\mathbf{.504}_{.020}$	$\mathbf{.310}_{.016}$
$\mathcal{T}^-$: WN-10%	$M_f \downarrow$	$M_r \uparrow$	$M_{avg} \uparrow$	$M_{F1} \uparrow$	$M_f \downarrow$	$M_r \uparrow$	$M_{avg} \uparrow$	$M_{F1} \uparrow$	$M_f \downarrow$	$M_r \uparrow$	$M_{avg} \uparrow$	$M_{F1} \uparrow$
Retrain	$.324_{.015}$	$.361_{.018}$	$.519_{.021}$	$.471_{.024}$	$.259_{.017}$	$.363_{.019}$	$.552_{.023}$	$.487_{.026}$	$.242_{.016}$	$.382_{.021}$	$.570_{.024}$	$.508_{.028}$
Finetune	$.326_{.016}$	$.357_{.019}$	$.516_{.022}$	$.467_{.025}$	$.261_{.018}$	$.359_{.020}$	$.549_{.024}$	$.483_{.027}$	$.244_{.017}$	$.378_{.022}$	$.567_{.025}$	$.504_{.029}$
SGU	$.428_{.032}$	$.269_{.022}$	$.421_{.035}$	$.366_{.026}$	$.371_{.033}$	$.276_{.023}$	$.453_{.036}$	$.384_{.027}$	$.348_{.031}$	$.296_{.024}$	$.474_{.037}$	$.407_{.028}$
GNNDELETE	$\underline{.420_{.030}}$	$\underline{.286_{.021}}$	$\underline{.433_{.033}}$	$\underline{.383_{.025}}$	$\underline{.360_{.031}}$	$\underline{.288_{.022}}$	$\underline{.464_{.034}}$	$\underline{.397_{.026}}$	$\underline{.339_{.029}}$	$\underline{.306_{.023}}$	$\underline{.484_{.035}}$	$\underline{.418_{.027}}$
MetaEU	$.423_{.031}$	$.287_{.021}$	$.432_{.034}$	$.383_{.025}$	$.363_{.032}$	$.287_{.022}$	$.462_{.035}$	$.396_{.026}$	$.342_{.030}$	$.304_{.023}$	$.481_{.036}$	$.416_{.027}$
FedLU	$.418_{.029}$	$.291_{.020}$	$.437_{.032}$	$.388_{.024}$	$.357_{.030}$	$.289_{.021}$	$.466_{.033}$	$.399_{.025}$	$.336_{.028}$	$.307_{.022}$	$.486_{.034}$	$.420_{.026}$
SGKU	$\mathbf{.412}_{.026}$	$\mathbf{.294}_{.018}$	$\mathbf{.441}_{.029}$	$\mathbf{.392}_{.022}$	$\mathbf{.351}_{.027}$	$\mathbf{.291}_{.019}$	$\mathbf{.470}_{.030}$	$\mathbf{.402}_{.023}$	$\mathbf{.330}_{.025}$	$\mathbf{.311}_{.020}$	$\mathbf{.491}_{.031}$	$\mathbf{.425}_{.024}$
$\mathcal{T}^-$: WN-20%	$M_f \downarrow$	$M_r \uparrow$	$M_{avg} \uparrow$	$M_{F1} \uparrow$	$M_f \downarrow$	$M_r \uparrow$	$M_{avg} \uparrow$	$M_{F1} \uparrow$	$M_f \downarrow$	$M_r \uparrow$	$M_{avg} \uparrow$	$M_{F1} \uparrow$
Retrain	$.185_{.011}$	$.361_{.018}$	$.588_{.021}$	$.500_{.024}$	$.217_{.013}$	$.367_{.019}$	$.575_{.023}$	$.500_{.026}$	$.113_{.008}$	$.396_{.021}$	$.642_{.025}$	$.548_{.029}$
Finetune	$.187_{.012}$	$.357_{.019}$	$.585_{.022}$	$.496_{.025}$	$.219_{.014}$	$.363_{.020}$	$.572_{.024}$	$.496_{.027}$	$.115_{.009}$	$.392_{.022}$	$.639_{.026}$	$.543_{.030}$
SGU	$.277_{.025}$	$.259_{.021}$	$.491_{.028}$	$.381_{.024}$	$.318_{.027}$	$.273_{.022}$	$.478_{.030}$	$.390_{.025}$	$.208_{.020}$	$.290_{.023}$	$.541_{.031}$	$.425_{.026}$
GNNDELETE	$\underline{.273_{.023}}$	$\underline{.269_{.020}}$	$\underline{.498_{.026}}$	$\underline{.393_{.023}}$	$\underline{.313_{.025}}$	$\underline{.281_{.021}}$	$\underline{.484_{.028}}$	$\underline{.399_{.024}}$	$\underline{.200_{.018}}$	$.303_{.022}$	$\underline{.552_{.029}}$	$\underline{.440_{.025}}$
MetaEU	$.275_{.024}$	$.274_{.020}$	$.500_{.027}$	$.398_{.023}$	$.315_{.026}$	$.278_{.021}$	$.482_{.029}$	$.395_{.024}$	$.202_{.019}$	$.299_{.022}$	$.549_{.030}$	$.435_{.025}$
FedLU	$.271_{.022}$	$.277_{.019}$	$.503_{.025}$	$.401_{.022}$	$.311_{.024}$	$.282_{.020}$	$.486_{.027}$	$.400_{.023}$	$.198_{.017}$	$\underline{.306_{.021}}$	$.554_{.028}$	$.443_{.024}$
SGKU	$\mathbf{.268}_{.020}$	$\mathbf{.280}_{.017}$	$\mathbf{.506}_{.022}$	$\mathbf{.405}_{.020}$	$\mathbf{.307}_{.021}$	$\mathbf{.286}_{.018}$	$\mathbf{.490}_{.024}$	$\mathbf{.405}_{.021}$	$\mathbf{.191}_{.015}$	$\mathbf{.313}_{.019}$	$\mathbf{.561}_{.025}$	$\mathbf{.451}_{.022}$