MiNT: Multi-Network Transfer Benchmark for Temporal Graph Learning

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https://github.com/benjaminnNgo/ScalingTGNs

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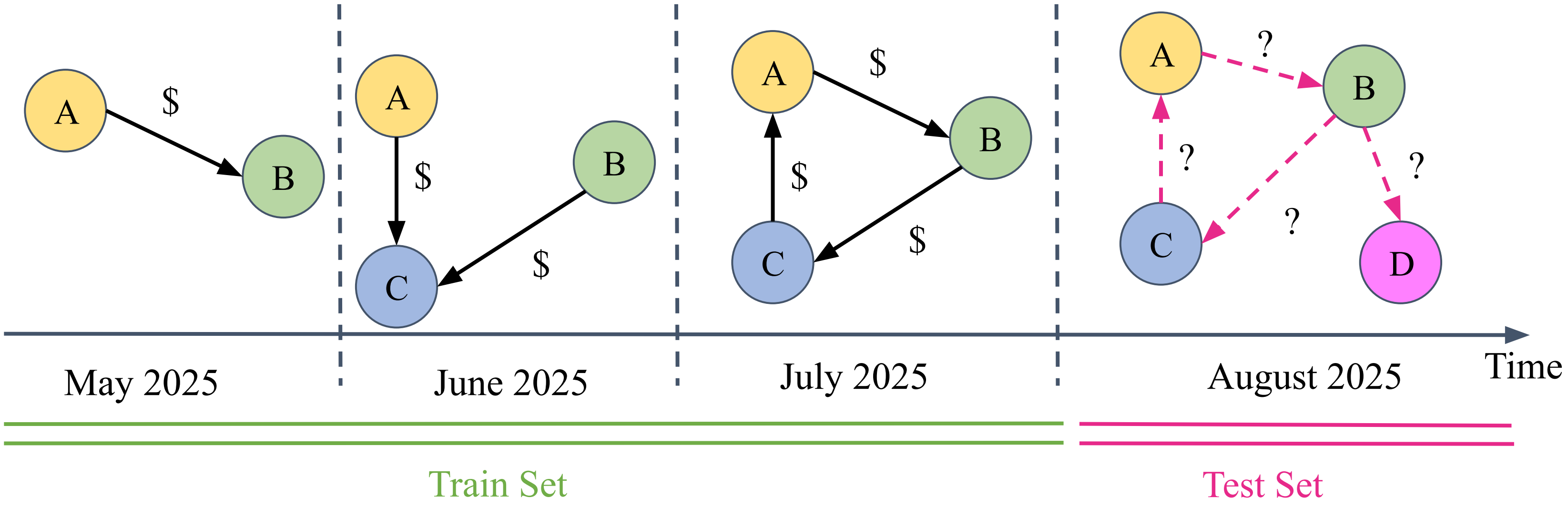
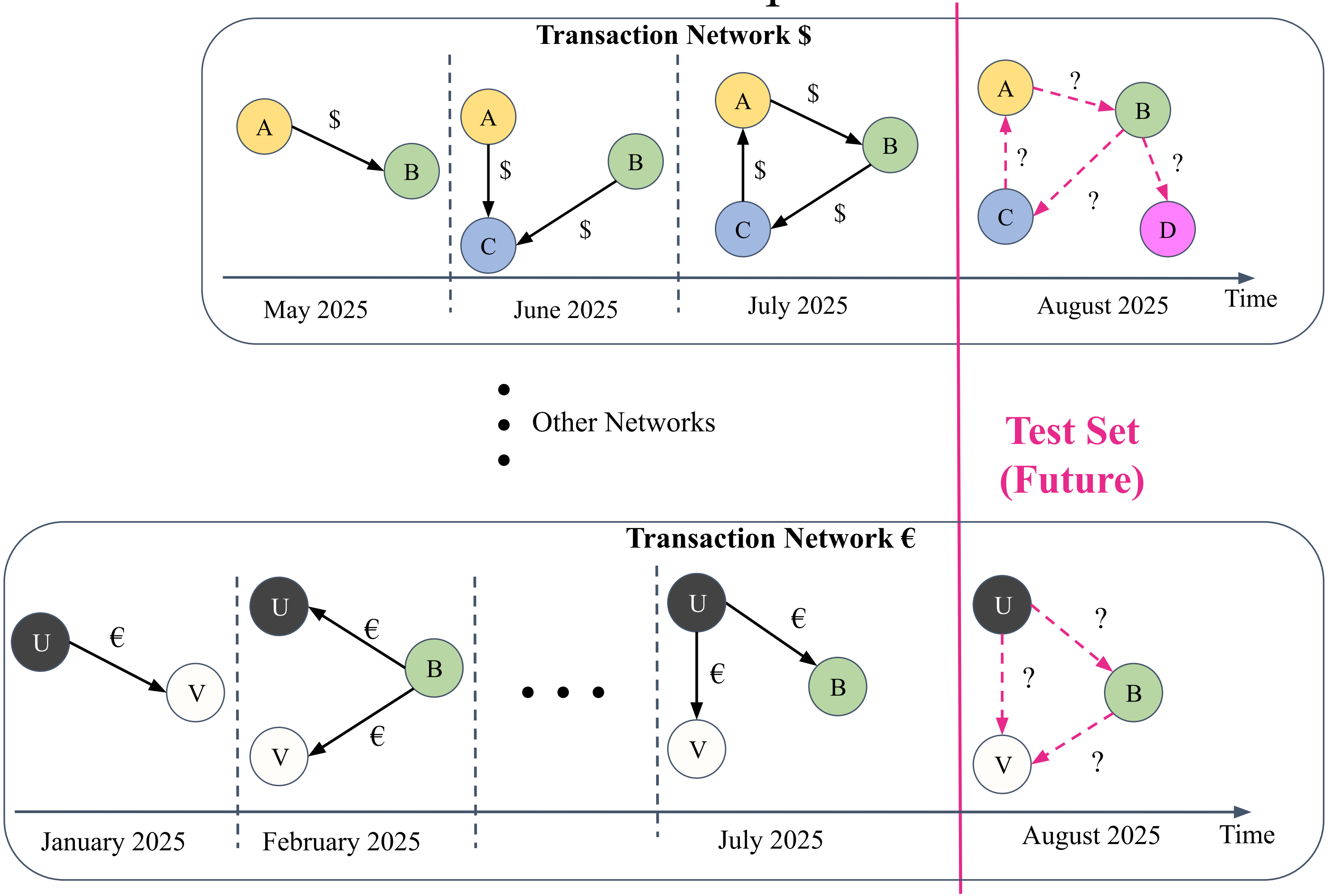
Traditional TGL: Single Network



- Learning on a single TG
- Train a model from scratch (i.e. TGN, GCLSTM …)
- Inference only on the test set of such network

ML Question: Given observed history of this network, can we predict the future of this network ?

Can we Learn from Multiple Networks?



Challenges

Challenges:

- Existing TGL training only tells us how to train on single network
- Lack of dataset that contains many temporal network (i.e. > 20)
- Networks might have disjoint set of nodes (potentially share some)
- Networks have different duration
- Networks have different sizes in # of nodes & edges
- Unseen networks might be born after training timestamps

MiNT Dataset

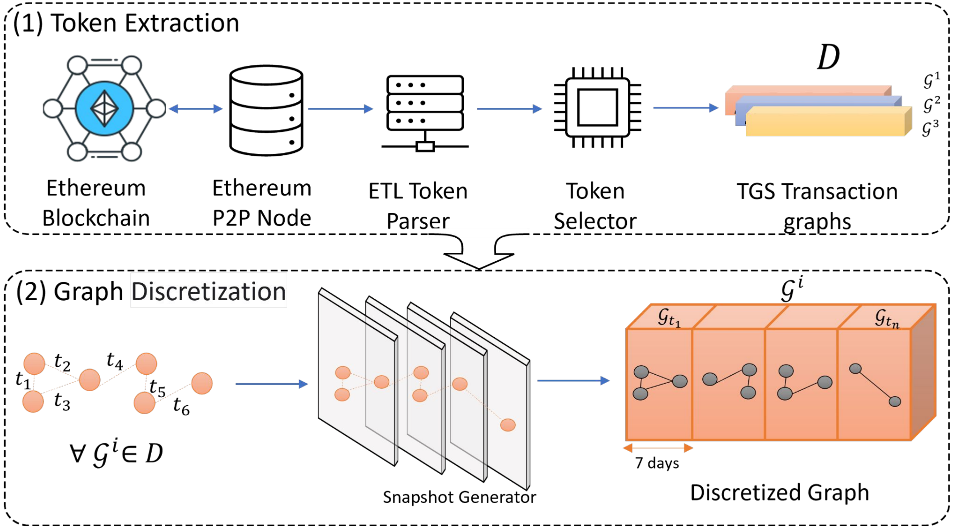
In MiNT for the first time we have:

- **Dataset:** **92** temporal graphs (84 financial + 8 social) for transfer learning.
- **Algorithm:** MiNT-train can train a TGNN on distinct networks **at same time**.
- **Scaling:** Clear **neural scaling trend** in temporal graph learning.
- **Generalization:** Strong **zero-shot** transfer within & across domains.

MiNT Token Dataset

Challenge: A **big set of networks** needed to study the possibility and impact of multi-network training.
Solution:

- **84 distinct** ERC20 token transaction networks (2017-2023).
- 3M nodes, 19M edges.
- Discretizing the networks.



MiNT data processing overview

1. **Token extraction:** extracting the token transaction network from the Ethereum node.
2. **Discretization:** creating weekly snapshots to form discrete time dynamic graphs.

MiNT
Methodology

MiNT Framework - Data Split

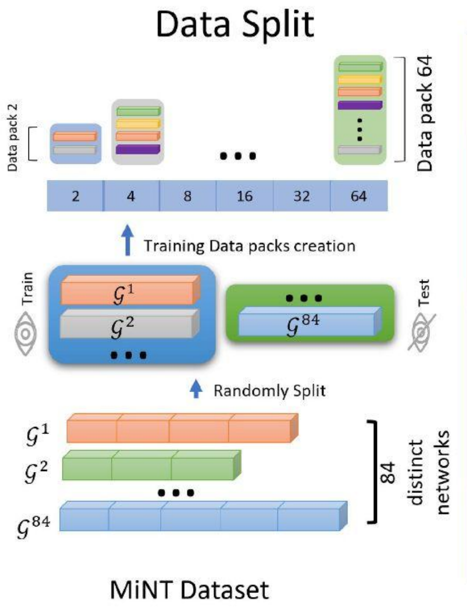
Dataset Splits: The dataset is divided into two parts:

- **Training Split**: 64 token networks used for model training.
- **Holdout Split**: 20 token networks reserved for **evaluation only**, never used in training.

Randomized Allocation: Network splits are **random**.

Variable Training Sizes: Divided into **subsets** of sizes ranging from 2 to 64 networks to evaluate the impact of **increasing training data** on transfer learning performance.

Model Training: Each subset is used **independently** to train the models.



MiNT Framework - Training

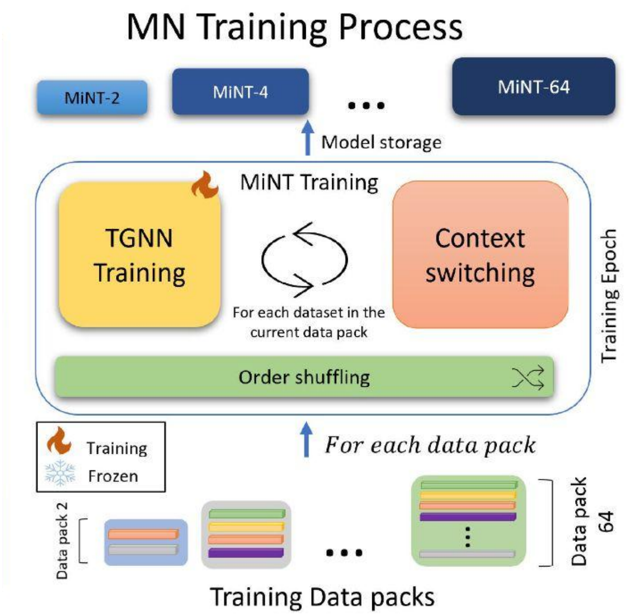
Train a temporal graph model that **generalizes** across multiple train networks.

Process:

1. **Shuffling per Epoch** – Shuffle the networks order in training.
2. **Context Switching** – Reset historical embeddings at the start of each epoch to prevent cross-network bias.
3. **Model Storage**– Store all packs results for further evaluation.

Why Important:

- Captures **shared** temporal patterns across diverse networks.
- Prevents **overfitting** to a single graph's structure.
- Enables strong transfer to **unseen** temporal networks



MiNT Framework - Transfer Inference

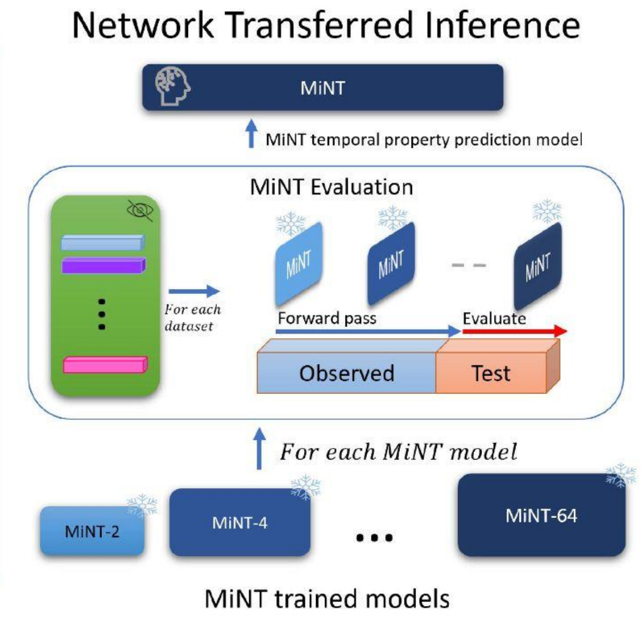
Assess model performance on unseen networks **without** retraining.

Inference Process:

1. Load all pre-trained models.
2. Initialize **fresh historical embeddings** to remove any bias from previous networks.
3. Perform a **single forward pass** on the target network's data to adapt embeddings.
4. Evaluate performance **directly** on the adapted model.

Key Benefit:

- Enables **fast** adaptation to unseen networks.



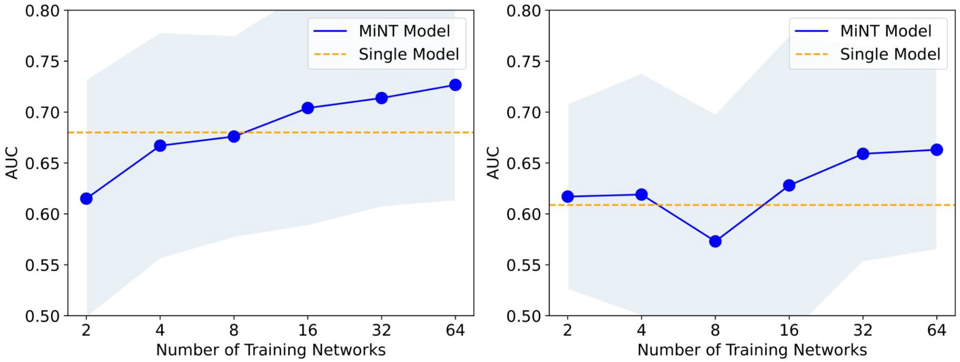
MiNT transfer performance (Network G/S)

- Individual models trained **specifically** on the network and tested on the test split of that network.
- MiNT transfer models trained on 64 train networks and **never** trained on test networks.
- MiNT-64 bits SOTA **without training** in some datasets and get best average rank.

Network	Single Model on Individual Networks					Transfer Model - 64 Networks	
	HTGN	GC-LSTM	EvolveGCN	GraphPulse	ROLAND	GC-LSTM	HTGN
WOJAK	0.479±0.005	0.484±0.000	0.505±0.023	0.467±0.030	0.529 ± 0.005	**0.534±0.020**	0.524±0.027
DOGE2.0	**0.590±0.059**	0.538±0.000	0.551±0.022	0.384±0.180	0.513 ± 0.022	0.551±0.022	0.538±0.038
EVERMOON	0.512±0.023	**0.562±0.179**	0.451±0.046	0.519±0.130	0.349 ± 0.119	0.494±0.047	0.517±0.039
QOM	0.633±0.017	0.612±0.001	0.618±0.002	**0.775±0.011**	0.641 ± 0.003	0.618±0.004	0.647±0.019
SDEX	**0.762±0.034**	0.720±0.002	0.733±0.028	0.436±0.030	0.483 ± 0.254	0.723±0.002	0.614±0.020
ETH2x-FLI	0.610±0.059	0.670±0.009	0.688±0.010	0.666±0.047	0.621 ± 0.023	0.697±0.009	**0.729±0.015**
BEPRO	0.655±0.038	0.632±0.019	0.610±0.012	**0.783±0.003**	0.439 ± 0.125	0.746±0.015	0.782±0.003
XCN	0.668±0.099	0.306±0.092	0.512±0.067	0.821±0.004	0.765 ± 0.015	0.733±0.003	**0.851±0.043**
BAG	0.673±0.227	0.196±0.179	0.329±0.040	**0.934±0.020**	0.418 ± 0.016	0.529±0.023	0.931±0.028
TRAC	0.712±0.071	0.748±0.000	0.748±0.000	0.767±0.001	0.495 ± 0.223	0.742±0.004	**0.785±0.008**
DERC	0.683±0.013	0.703±0.022	0.669±0.009	0.769±0.040	0.405 ± 0.357	0.696±0.011	**0.798±0.027**
Metis	0.715±0.122	0.646±0.023	0.688±0.027	**0.812±0.011**	0.696 ± 0.108	0.697±0.013	0.760±0.025
REPv2	0.760±0.012	0.725±0.014	0.709±0.002	**0.830±0.001**	0.751 ± 0.003	0.733±0.019	0.789±0.020
DINO	0.730±0.195	**0.874±0.028**	0.868±0.029	0.801±0.020	0.497 ± 0.092	0.659±0.039	0.779±0.113
HOICHI	0.807±0.047	**0.857±0.000**	0.856±0.001	0.714±0.010	0.815 ± 0.036	0.847±0.005	0.765±0.018
MUTE	0.649±0.015	0.593±0.030	0.617±0.010	**0.779±0.004**	0.289 ± 0.042	0.636±0.003	0.673±0.013
GLM	0.830±0.029	0.451±0.003	0.501±0.033	0.769±0.018	0.559 ± 0.357	0.501±0.027	**0.831±0.024**
MIR	0.750±0.005	0.768±0.026	0.745±0.015	0.689±0.097	0.228 ± 0.060	0.788±0.022	**0.836±0.016**
stkAAVE	0.702±0.042	0.368±0.011	0.397±0.022	**0.743±0.006**	0.591 ± 0.122	0.650±0.028	0.709±0.022
ADX	0.769±0.018	0.723±0.002	0.718±0.004	**0.784±0.002**	0.761 ± 0.011	0.673±0.022	0.679±0.024
Top rank ↑	2	3	0	**8**	0	1	6
Avg. rank ↓	3.8	4.6	4.6	3.05	5.25	3.9	**2.55**

MiNT scaling behaviour

- MiNT's transfer performance **improves** as the number of training networks increases.
- Showing a **neural scaling trend** in temporal graph learning.
- Training on **more networks** → **better zero-shot performance** on unseen graphs.
- **Diversity & quantity** of pretraining networks directly enhance generalization.
- First empirical evidence of scaling behavior in **temporal graph learning**.



(a). HTGN (b). GCLSTM

Model	Top rank ↑	Avg. rank ↓	Win ratio ↑
Single model	3	4.35	–
MiNT-2	0	6.15	0.25
MiNT-4	2	4.35	0.45
MiNT-8	1	4.45	0.45
MiNT-16	1	3.45	0.65
MiNT-32	2	3.20	0.70
MiNT-64	**11**	**2.15**	**0.80**

MiNT LLC task

- An **additional property task** alongside network growth.
- Zero-shot evaluation after multi-network pretraining.
- **Larger** multi-network pretraining $\Rightarrow$ **better** zero-shot LCC performance on many networks.
- MiNT-64 achieved best avg rank on test networks without any training on test networks.

Network	Standard Training	Transfer Model				
	HTGN	MiNT-4	MiNT-8	MiNT-16	MiNT-32	MiNT-64
MIR	0.745 ± 0.023	0.570 ± 0.117	0.655 ± 0.012	0.783 ± 0.041	0.766 ± 0.053	**0.845 ± 0.035**
DOGE2.0	0.446 ± 0.164	0.530 ± 0.113	0.548 ± 0.063	0.631 ± 0.027	0.571 ± 0.139	**0.661 ± 0.047**
MUTE	0.574 ± 0.022	0.471 ± 0.014	0.468 ± 0.021	0.509 ± 0.037	**0.592 ± 0.038**	0.582 ± 0.078
EVERMOON	0.494 ± 0.127	0.424 ± 0.059	0.421 ± 0.029	0.376 ± 0.014	**0.542 ± 0.077**	0.527 ± 0.118
DERC	0.717 ± 0.035	0.552 ± 0.015	0.584 ± 0.040	0.554 ± 0.011	**0.733 ± 0.067**	0.689 ± 0.096
ADX	**0.753 ± 0.013**	0.610 ± 0.019	0.635 ± 0.033	0.603 ± 0.019	0.619 ± 0.012	0.587 ± 0.014
HOICHI	**0.746 ± 0.010**	0.738 ± 0.009	0.696 ± 0.072	0.715 ± 0.027	0.592 ± 0.147	0.722 ± 0.034
SDEX	**0.911 ± 0.104**	0.330 ± 0.117	0.425 ± 0.199	0.361 ± 0.113	0.437 ± 0.316	0.382 ± 0.280
BAG	0.493 ± 0.043	0.772 ± 0.213	0.685 ± 0.163	0.892 ± 0.036	**0.952 ± 0.019**	0.893 ± 0.074
XCN	0.566 ± 0.199	0.742 ± 0.039	0.688 ± 0.041	0.802 ± 0.037	0.774 ± 0.144	**0.827 ± 0.025**
ETH2x-FLI	0.561 ± 0.037	0.610 ± 0.015	0.625 ± 0.020	**0.658 ± 0.018**	0.636 ± 0.076	0.618 ± 0.025
stkAAVE	0.623 ± 0.077	0.613 ± 0.041	0.567 ± 0.038	0.668 ± 0.061	0.687 ± 0.045	**0.688 ± 0.019**
GLM	0.761 ± 0.031	0.585 ± 0.144	0.679 ± 0.026	0.698 ± 0.054	0.783 ± 0.031	**0.818 ± 0.074**
QOM	0.658 ± 0.150	0.535 ± 0.036	0.513 ± 0.003	0.566 ± 0.036	**0.696 ± 0.092**	0.645 ± 0.109
WOJAK	0.378 ± 0.028	0.407 ± 0.012	0.362 ± 0.053	0.384 ± 0.024	0.421 ± 0.029	**0.492 ± 0.107**
DINO	0.706 ± 0.120	0.794 ± 0.090	**0.827 ± 0.039**	0.815 ± 0.043	0.753 ± 0.165	0.561 ± 0.006
Metis	0.679 ± 0.039	0.697 ± 0.031	0.671 ± 0.047	0.711 ± 0.028	0.705 ± 0.047	**0.780 ± 0.041**
REPv2	0.730 ± 0.007	0.653 ± 0.014	0.642 ± 0.061	0.694 ± 0.002	**0.765 ± 0.030**	0.742 ± 0.041
TRAC	0.733 ± 0.009	0.658 ± 0.040	0.643 ± 0.052	0.720 ± 0.048	**0.767 ± 0.012**	0.762 ± 0.028
BEPRO	**0.694 ± 0.009**	0.587 ± 0.002	0.604 ± 0.006	0.589 ± 0.018	0.601 ± 0.129	0.628 ± 0.017
Top Rank ↑	4	0	1	1	6	**7**
Avg. Rank ↓	2.80	4.40	4.65	3.45	2.50	**2.20**

Thank you for your attention

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