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# BENCHTEMP: A General Benchmark for Evaluating Temporal Graph Neural Networks

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## Authors' Response to Reviewer J4Uw

### Opportunities For Improvement:

**W1.** The novelty and contributions of this work are somewhat limited. No new evaluation tasks or datasets are developed in this work. The evaluation tasks and settings, including the transductive and inductive settings, have been widely used by previous works. Also, the datasets included in the benchmark were created by previous works.

**W2.** The experiments section focuses a lot on presenting and discussing individual methods' performance. It'd be better to provide summaries of the state-of-the-art results and the limitations of existing methods, and in light of that, discuss future directions of TGNN research.

**W3.** This paper defines a temporal graph to be a sequence of temporal "user-item" interactions. However, this is a limited form of a temporal graph as this definition covers only a particular type of bipartite graphs with two types of nodes. I think using a more general definition without such conditions (in both the writing and the code) would be more suitable for a general TGNN benchmark.

**W4.** Datasets are not that large for efficiency evaluation. Most graphs used in the benchmark are not that large. The GPU memory usage for these graphs are mostly 1-3 GB. Larger temporal graphs would be more desirable for evaluating model efficiency. Constructing synthetic temporal graphs with increasing sizes could facilitate more systematic evaluations of TGNN models' efficiency.

**W5.** Node reindexing described in Figure 3 is confusing. In the homogeneous graph, why do two different nodes have the same id? For example, in the rightmost graph in Fig 3, there are a user with id 2 and an item with id 2. In general, nodes should have different ids as they are separate entities.

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### 2 General Response:

3 We appreciate your great feedback! We have presented new datasets with up to several million  
4 edges and nodes. We have carefully through your comments and added *six* datasets (eBay-Small,  
5 eBay-Large, Taobal-Large, DGraphFin, YouTubeReddit-Small, YouTubeReddit-Large), including  
6 **four large-scale** datasets (eBay-Large, Taobao-Large, DGraphFin, YouTubeReddit-Large). We have  
7 reported the corresponding experiments and detailed discussions in the updated paper. The eBay  
8 datasets are a collection of the user transactions on **eBay's e-commerce platform**. We thank our  
9 industrial collaborator for sharing their datasets in our research. Considering user privacy and security,  
10 eBay datasets could only be shared among collaborators. Any researchers who are interested in the  
11 eBay datasets, please email our team (jonnyhuanghnu@gmail.com). For easy access, all datasets have  
12 been hosted on the open-source platform zenodo (<https://zenodo.org/>) with a Digital Object  
13 Identifier (DOI) 10.5281/zenodo.8267846 (<https://zenodo.org/record/8267846>).

14 We have conducted extensive experiments on the six newly added temporal graph datasets, including  
15 the dynamic link prediction task and dynamic node classification task, diverse workloads (transductive,  
16 inductive, inductive New-Old, and inductive New-New scenarios). We have added **the inference**  
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and Benchmarks. Do not distribute.

17 **time** metric to evaluate the efficiency of methods. We have added *Average Rank* metric shown in  
 18 Table 2 and Table 4 for ranking model performances on the newly added large-scale datasets for  
 19 evaluating TGNN models.

20 We have open sourced the codes of preprocessing large-scale datasets at <https://github.com/qianghuangwhu/benchtemp/tree/master/preprocess> with MIT license.

22 We have updated the manuscript in section 4.4 to provide summaries of the state-of-the art results  
 23 and the limitations of existing methods, and the future directions of TGNN research.

24 We have updated a general definition for temporal graph in section 3.1. A temporal graph can be  
 25 represented as an ordered sequence of temporal interactions. Each interaction  $I_r = (u_r, i_r, t_r, e_r)$   
 26 happens at time  $t_r$  between the source node  $u_r$  and the destination node  $i_r$  with edge feature  $e_r$ .  
 27 Considering many real world applications and large-scale temporal graphs, we have added **the**  
 28 **inference time** metric to evaluate the efficiency of methods.

29 We have changed the rightmost graph in Figure 3. In the homogeneous graph shown in Fig 3(b), the  
 30 user with id 2 and the item with id 2 are the same node.

31 **We provide our response to each individual comment below:**

#### Comment 1

**W1.** The novelty and contributions of this work are somewhat limited. No new evaluation tasks or datasets are developed in this work. The evaluation tasks and settings, including the transductive and inductive settings, have been widely used by previous works. Also, the datasets included in the benchmark were created by previous works.

#### Response:

34 We thank the reviewer for the suggestions! Indeed, the evaluation settings have been widely used  
 35 by previous works, which are also adopted by SOTA methods. Our purpose is not to introduce new  
 36 settings; instead, we aim at comparing different TGNN models on the same ground.

37 We have included new datasets with up to several million edges and nodes. We have added *six* datasets  
 38 (eBay-Small, eBay-Large, Taobao-Large, DGraphFin, YouTubeReddit-Small, YouTubeReddit-Large),  
 39 including *four large-scale* datasets (eBay-Large, Taobao-Large, DGraphFin, YouTubeReddit-Large).  
 40 The statistics of the new datasets are shown in Table 1. For easy access, all datasets have been hosted  
 41 on the open-source platform zenodo (<https://zenodo.org/>) with a Digital Object Identifier (DOI)  
 42 10.5281/zenodo.8267846 (<https://zenodo.org/record/8267846>). In our paper, we present  
 43 BENCHTEMP, a general benchmark for evaluating temporal graph neural network (TGNN) models  
 44 over a wide range of tasks and settings. We extensively compare representative TGNN models on  
 45 the benchmark datasets, regarding different tasks, settings, metrics, and especially model efficiency -  
 46 **inference time**.

- 47 • **eBay-Small** is a subset of the eBay-Large dataset. We sample 38,427 nodes and 384,677 edges  
 48 from eBay-Large graph according to edge timestamps.

Table 1: Dataset statistics of the new datasets.

	<i>Domain</i>	<i># Nodes</i>	<i># Edges</i>
eBay-Small	E-commerce	38,427	384,677
YouTubeReddit-Small [1]	Social	264,443	297,732
eBay-Large	E-commerce	1,333,594	1,119,454
DGraphFin [2]	E-commerce	3,700,550	4,300,999
Youtube-Reddit-Large [1]	Social	5,724,111	4,228,523
Taobao-Large [3, 4]	E-commerce	1,630,453	5,008,745

- 49 • **YouTubeReddit-Small** is a collection of massive visual contents on YouTube and long-term  
50 community activity on Reddit. This dataset covers a 3-month period from January to March 2020.  
51 Each row in the dataset represents a YouTube video  $v_i$  being shared in a subreddit  $s_j$  by some  
52 user  $u_k$  at time  $t$  [1]. Nodes are YouTube videos and subreddits, edges are the users' interactions  
53 between videos and subreddits. This dynamic graph has 264,443 nodes and 297,732 edges.
- 54 • **eBay-Large** is a million-scale dataset consisting of 1.3 million nodes and 1.1 million edges, which  
55 comprises the selected transaction records from the eBay e-commerce platform over a two-month  
56 period. eBay-Large is modeled as a user-item graph, where items are heterogeneous entities which  
57 include information such as phone numbers, addresses, and email addresses associated with a  
58 transaction. We select one month of transactions as seed nodes and then expand each seed node  
59 two hops back in time to enrich the topology while maintaining consistency in the distribution of  
60 seed nodes.
- 61 • **DGraphFin** is a collection of large-scale dynamic graph datasets, consisting of interactive objects,  
62 events and labels that evolve with time. It is a directed, unweighted dynamic graph consisting  
63 of millions of nodes and edges, representing a realistic user-to-user social network in financial  
64 industry. Nodes are users, and an edge from one user to another means that the user regards the  
65 other user as the emergency contact person [2].
- 66 • **Youtube-Reddit-Large** dataset covers 54 months of YouTube video propagation history from  
67 January 2018 to June 2022 [1]. This dataset has 5,724,111 nodes and 4,228,523 edges.
- 68 • **Taobao-Large** is a collection of the Taobao user behavior dataset intercepted based on the period  
69 8:00 to 18:00 on 26 November 2017 [4]. Nodes are users and items, and edges are behaviors  
70 between users and items, such as favor, click, purchase, and add an item to shopping cart. This  
71 public dataset has 1,630,453 nodes and 5,008,74 user-item interaction edges.

## 72 A Experiments

73 We have conducted extensive experiments on the six newly added temporal graph datasets, including  
74 the dynamic link prediction task and dynamic node classification task, diverse workloads (transductive,  
75 inductive, inductive New-Old, and inductive New-New scenarios). We have added **the inference**  
76 **time** metric to evaluate the efficiency of methods.

77 The experimental setup is the same as in the paper.

### 78 A.1 Link Prediction Task

79 We run the link prediction task on 7 TGNN models and the new datasets under different settings  
80 (Transductive, Inductive, Inductive New-Old, and Inductive New-New).

81 The experimental results on large-scale datasets may be more convincing. Furthermore, we have  
82 added **Average Rank** metric shown in Table 2 and Table 4 for ranking model performances on the  
83 newly added large-scale datasets for evaluating TGNN models.

84 The AUC and AP results for each new datasets are shown in Table 2 and Table 3, respectively.  
85 For the four large-scale datasets (eBay-Large, Taobao-Large, DGraphFin, YouTubeReddit-Large),  
86 we observe the similar results as in the paper. Specifically, NAT and NeurTW achieve the top-2  
87 performance on almost all datasets under transductive and inductive settings.

### 88 A.2 Node Classification Task

89 The eBay-Small and eBay-Large datasets have node labels, so we conduct dynamic node classification  
90 experiments on both the eBay-Small and eBay-Large datasets. The AUC results are shown in Table 4.  
91 We can observe the similar results as in the paper. NeurTW achieves the best performance on both  
92 eBay-Small and eBay-Large datasets. NAT performs poorly on the node classification task.

Table 2: ROC AUC results of new datasets on the *dynamic link prediction task*. The best and second-best results are highlighted as **bold red** and underlined blue. **Average Rank** are computed by the experimental results of models on four large-scale datasets (eBay-Large, Taobao-Large, DGraphFin, YouTubeReddit-Large). We do not highlight the second-best if the gap is  $> 0.05$  compared with the best result.

Model Dataset	Transductive						
	JODIE	DyRep	TGN	TGAT	CAWN	NeurTW	NAT
eBay-Small	0.9946 $\pm$ 0.0002	0.9941 $\pm$ 0.0006	0.9984 $\pm$ 0.0003	0.9838 $\pm$ 0.0006	0.9985 $\pm$ 0.0	<b>0.9991 <math>\pm</math> 0.0</b>	<u>0.9978 <math>\pm</math> 0.0003</u>
YouTubeReddit-Small	<u>0.8519 <math>\pm</math> 0.0007</u>	0.8499 $\pm$ 0.0012	0.8432 $\pm$ 0.0032	0.8441 $\pm$ 0.0014	0.7586 $\pm$ 0.0031	<b>0.9003 <math>\pm</math> 0.0031</b>	0.8259 $\pm$ 0.005
eBay-Large	0.9614 $\pm$ 0.0	0.9619 $\pm$ 0.0001	<u>0.9642 <math>\pm</math> 0.0003</u>	0.5311 $\pm$ 0.0003	0.9442 $\pm$ 0.0003	0.9608 $\pm$ 0.0	<b>0.9658 <math>\pm</math> 0.0002</b>
DGraphFin	0.8165 $\pm$ 0.0024	0.8171 $\pm$ 0.0016	<b>0.8683 <math>\pm</math> 0.0023</b>	0.6112 $\pm$ 0.0165	0.5466 $\pm$ 0.0103	<u>0.8611 <math>\pm</math> 0.0035</u>	0.8258 $\pm$ 0.0001
Youtube-Reddit-Large	0.8532 $\pm$ 0.0003	0.8529 $\pm$ 0.0006	0.8458 $\pm$ 0.0025	0.8536 $\pm$ 0.0026	0.7466 $\pm$ 0.0012	<b>0.916 <math>\pm</math> 0.0025</b>	<u>0.8605 <math>\pm</math> 0.0009</u>
Taobao-Large	0.7726 $\pm$ 0.0005	0.7724 $\pm$ 0.001	<u>0.8464 <math>\pm</math> 0.0008</u>	0.5567 $\pm$ 0.0047	0.7771 $\pm$ 0.0068	<b>0.859 <math>\pm</math> 0.0091</b>	0.8188 $\pm$ 0.001
<b>Average Rank</b>	4.5	4.5	2.75	5.75	6	2.25	2.25
Model Dataset	Inductive						
	JODIE	DyRep	TGN	TGAT	CAWN	NeurTW	NAT
eBay-Small	0.9696 $\pm$ 0.0007	0.9674 $\pm$ 0.0018	0.9913 $\pm$ 0.0004	0.9698 $\pm$ 0.0006	0.9964 $\pm$ 0.0001	<u>0.9982 <math>\pm</math> 0.0</u>	<b>0.9998 <math>\pm</math> 0.0001</b>
YouTubeReddit-Small	0.7582 $\pm$ 0.0003	0.7545 $\pm$ 0.0009	0.7276 $\pm$ 0.0034	0.7436 $\pm$ 0.0006	0.7533 $\pm$ 0.0016	0.8978 $\pm$ 0.0032	<b>0.9876 <math>\pm</math> 0.0049</b>
eBay-Large	0.7536 $\pm$ 0.0014	0.7515 $\pm$ 0.0006	0.7657 $\pm$ 0.0026	0.5224 $\pm$ 0.0003	0.9459 $\pm$ 0.0001	<u>0.9608 <math>\pm</math> 0.0</u>	<b>0.9999 <math>\pm</math> 0.0001</b>
DGraphFin	0.6884 $\pm$ 0.0051	0.6876 $\pm$ 0.001	0.6439 $\pm$ 0.0089	0.5677 $\pm$ 0.0184	0.5479 $\pm$ 0.009	<b>0.8635 <math>\pm</math> 0.0021</b>	<u>0.7955 <math>\pm</math> 0.0201</u>
Youtube-Reddit-Large	0.7539 $\pm$ 0.0005	0.7554 $\pm$ 0.0003	0.7243 $\pm$ 0.0016	0.7501 $\pm$ 0.0019	0.7327 $\pm$ 0.0016	<u>0.9128 <math>\pm</math> 0.0031</u>	<b>0.9863 <math>\pm</math> 0.006</b>
Taobao-Large	0.7075 $\pm$ 0.0009	0.7042 $\pm$ 0.0006	0.6812 $\pm$ 0.0032	0.5222 $\pm$ 0.0041	0.7787 $\pm$ 0.0103	<u>0.869 <math>\pm</math> 0.010</u>	<b>0.9933 <math>\pm</math> 0.0008</b>
<b>Average Rank</b>	4	4.5	5.5	6.25	4.75	1.75	1.25
Model Dataset	Inductive New-Old						
	JODIE	DyRep	TGN	TGAT	CAWN	NeurTW	NAT
eBay-Small	0.9862 $\pm$ 0.0003	0.9836 $\pm$ 0.0016	0.9947 $\pm$ 0.0009	0.9712 $\pm$ 0.002	0.9985 $\pm$ 0.0	<u>0.9988 <math>\pm</math> 0.0</u>	<b>0.9999 <math>\pm</math> 0.0</b>
YouTubeReddit-Small	0.7695 $\pm$ 0.001	0.7655 $\pm$ 0.0018	0.7396 $\pm$ 0.0034	0.7242 $\pm$ 0.0004	0.7573 $\pm$ 0.0022	<u>0.922 <math>\pm</math> 0.0002</u>	<b>0.9967 <math>\pm</math> 0.0014</b>
eBay-Large	0.6109 $\pm$ 0.0244	0.5906 $\pm$ 0.0087	0.8134 $\pm$ 0.0105	0.6363 $\pm$ 0.0605	<u>0.9569 <math>\pm</math> 0.0007</u>	0.8973 $\pm$ 0.0	<b>1.0 <math>\pm</math> 0.0</b>
DGraphFin	0.5768 $\pm$ 0.0071	0.5735 $\pm$ 0.0007	0.5564 $\pm$ 0.0021	0.5742 $\pm$ 0.013	0.5646 $\pm$ 0.0244	<u>0.7702 <math>\pm</math> 0.0043</u>	<b>0.8693 <math>\pm</math> 0.0066</b>
Youtube-Reddit-Large	0.7844 $\pm$ 0.0015	0.7894 $\pm$ 0.0017	0.7623 $\pm$ 0.0031	0.7457 $\pm$ 0.0062	0.7511 $\pm$ 0.0022	<u>0.9356 <math>\pm</math> 0.0004</u>	<b>0.9958 <math>\pm</math> 0.0025</b>
Taobao-Large	0.7023 $\pm$ 0.0015	0.6953 $\pm$ 0.0022	0.6771 $\pm$ 0.0055	0.5104 $\pm$ 0.0106	0.7674 $\pm$ 0.005	<u>0.8458 <math>\pm</math> 0.0043</u>	<b>0.9965 <math>\pm</math> 0.0005</b>
<b>Average Rank</b>	4.25	5	5.5	5.75	4.25	2.25	1
Model Dataset	Inductive New-New						
	JODIE	DyRep	TGN	TGAT	CAWN	NeurTW	NAT
eBay-Small	0.9388 $\pm$ 0.0009	0.9366 $\pm$ 0.0037	0.9838 $\pm$ 0.0007	0.9556 $\pm$ 0.0007	0.9937 $\pm$ 0.0	<u>0.9975 <math>\pm</math> 0.0</u>	<b>0.9997 <math>\pm</math> 0.0004</b>
YouTubeReddit-Small	0.7436 $\pm$ 0.0015	0.7436 $\pm$ 0.0018	0.7265 $\pm$ 0.0055	0.749 $\pm$ 0.0011	0.7479 $\pm$ 0.004	<u>0.864 <math>\pm</math> 0.0071</u>	<b>0.9868 <math>\pm</math> 0.0049</b>
eBay-Large	0.7526 $\pm$ 0.0013	0.7500 $\pm$ 0.0005	0.7639 $\pm$ 0.0027	0.5196 $\pm$ 0.0002	0.9542 $\pm$ 0.0003	<u>0.9615 <math>\pm</math> 0.0</u>	<b>0.9999 <math>\pm</math> 0.0001</b>
DGraphFin	0.7307 $\pm$ 0.0007	0.7323 $\pm$ 0.0002	0.6843 $\pm$ 0.0131	0.5649 $\pm$ 0.0248	0.5417 $\pm$ 0.0099	<b>0.9051 <math>\pm</math> 0.0028</b>	<u>0.7584 <math>\pm</math> 0.0323</u>
Youtube-Reddit-Large	0.6932 $\pm$ 0.0026	0.7022 $\pm$ 0.0007	0.6703 $\pm$ 0.0024	0.7269 $\pm$ 0.0	0.6942 $\pm$ 0.0028	<u>0.8716 <math>\pm</math> 0.0077</u>	<b>0.9796 <math>\pm</math> 0.0103</b>
Taobao-Large	0.7243 $\pm$ 0.0001	0.7247 $\pm$ 0.0001	0.6885 $\pm$ 0.0024	0.5256 $\pm$ 0.0054	0.7922 $\pm$ 0.0118	<u>0.8906 <math>\pm</math> 0.0088</u>	<b>0.9969 <math>\pm</math> 0.0002</b>
<b>Average Rank</b>	5	4.25	5.5	5.75	4.5	1.75	1.25
Model Dataset	Inductive New-New						
	JODIE	DyRep	TGN	TGAT	CAWN	NeurTW	NAT
<b>Total Rank</b>	4.44	4.56	4.81	5.88	4.88	<u>2.00</u>	<b>1.44</b>

### 93 A.3 Efficiency

94 Considering many real world applications and , we add **the inference time** metric to evaluate the  
 95 efficiency of models. The inference time comparison per 100,000 edges is shown in Figure 1.  
 96 According to the figure, we can observe the similar model efficiency results as in the paper. In  
 97 terms of the inference time, JODIE, DyRep, TGN and TGAT are faster, while CAWN and NeurTW  
 98 are much slower. NAT is relatively faster than temporal walk-based methods through caching and  
 99 parallelism optimizations, *achieving a good trade-off between model quality and efficiency.*

Table 3: AP results of new datasets on the *dynamic link prediction task*. The best and second-best results are highlighted as **bold red** and underlined blue. We do not highlight the second-best if the gap is  $> 0.05$  compared with the best result.

		Transductive						
Model \ Dataset	JODIE	DyRep	TGN	TGAT	CAWN	NeurTW	NAT	
eBay-Small	0.9938 ± 0.0004	0.9936 ± 0.0006	<u>0.9983 ± 0.0003</u>	0.9819 ± 0.0009	0.9981 ± 0.0	<b>0.9991 ± 0.0</b>	0.9975 ± 0.0002	
YouTubeReddit-Small	<u>0.8612 ± 0.0009</u>	0.8594 ± 0.0012	0.8421 ± 0.0041	0.8515 ± 0.0012	0.7625 ± 0.0042	<b>0.9112 ± 0.0021</b>	0.8325 ± 0.0068	
eBay-Large	0.9318 ± 0.0002	0.9322 ± 0.0002	<u>0.9357 ± 0.0006</u>	0.5239 ± 0.0002	0.9144 ± 0.0004	0.9307 ± 0.0	<b>0.9398 ± 0.0004</b>	
DGraphFin	0.7705 ± 0.0009	0.7705 ± 0.0024	<u>0.8571 ± 0.0009</u>	0.6441 ± 0.0123	0.5431 ± 0.0095	<b>0.8637 ± 0.0014</b>	0.7956 ± 0.0012	
Youtube-Reddit-Large	0.8622 ± 0.0007	<u>0.8632 ± 0.0004</u>	0.8476 ± 0.0022	0.8591 ± 0.0026	0.7475 ± 0.0017	<b>0.9222 ± 0.0013</b>	0.8628 ± 0.0015	
Taobao-Large	0.7164 ± 0.0003	0.7142 ± 0.0008	<u>0.844 ± 0.0011</u>	0.5761 ± 0.0023	0.7616 ± 0.0069	<b>0.8568 ± 0.016</b>	0.7904 ± 0.0008	
		Inductive						
eBay-Small	0.9638 ± 0.0007	0.9619 ± 0.0017	0.9898 ± 0.0005	0.9675 ± 0.0007	0.9953 ± 0.0002	<u>0.9982 ± 0.0</u>	<b>0.9998 ± 0.0001</b>	
YouTubeReddit-Small	0.7866 ± 0.0007	0.7833 ± 0.0009	0.7387 ± 0.0069	0.7551 ± 0.0002	0.7568 ± 0.0031	<u>0.9086 ± 0.0022</u>	<b>0.9872 ± 0.0056</b>	
eBay-Large	0.6989 ± 0.0018	0.6973 ± 0.0007	0.7096 ± 0.0030	0.518 ± 0.0002	0.9174 ± 0.0001	<u>0.9308 ± 0.0</u>	<b>0.9999 ± 0.0001</b>	
DGraphFin	0.6563 ± 0.002	0.6567 ± 0.0009	0.624 ± 0.006	0.5866 ± 0.0123	0.5428 ± 0.0082	<b>0.8626 ± 0.0012</b>	<u>0.7053 ± 0.0185</u>	
Youtube-Reddit-Large	0.7796 ± 0.0009	0.7818 ± 0.0009	0.73 ± 0.0029	0.7587 ± 0.0025	0.7353 ± 0.0022	<u>0.9192 ± 0.0022</u>	<b>0.9849 ± 0.0071</b>	
Taobao-Large	0.6763 ± 0.0011	0.6746 ± 0.0011	0.6664 ± 0.0012	0.5315 ± 0.0027	0.7533 ± 0.011	<u>0.8596 ± 0.0205</u>	<b>0.9941 ± 0.0007</b>	
		Inductive New-Old						
eBay-Small	0.9849 ± 0.0007	0.9836 ± 0.0013	0.9931 ± 0.0008	0.9682 ± 0.0028	0.9985 ± 0.0001	<u>0.999 ± 0.0</u>	<b>0.9999 ± 0.0</b>	
YouTubeReddit-Small	0.7963 ± 0.0013	0.7937 ± 0.0014	0.729 ± 0.0086	0.7296 ± 0.0013	0.762 ± 0.0041	<u>0.9244 ± 0.0015</u>	<b>0.9966 ± 0.0016</b>	
eBay-Large	0.5670 ± 0.0186	0.5870 ± 0.0074	0.8024 ± 0.0060	0.6504 ± 0.0385	<u>0.9592 ± 0.0008</u>	0.8458 ± 0.0	<b>1.0 ± 0.0</b>	
DGraphFin	0.6005 ± 0.0048	0.5872 ± 0.0059	0.5753 ± 0.0062	0.5927 ± 0.0058	0.5669 ± 0.0269	<u>0.7572 ± 0.0025</u>	<b>0.8184 ± 0.0088</b>	
Youtube-Reddit-Large	0.808 ± 0.0014	0.8142 ± 0.0019	0.7472 ± 0.0043	0.7526 ± 0.0097	0.7553 ± 0.0025	<u>0.9368 ± 0.0009</u>	<b>0.9953 ± 0.0028</b>	
Taobao-Large	0.7009 ± 0.0013	0.698 ± 0.0014	0.6879 ± 0.0008	0.5254 ± 0.0074	0.7597 ± 0.0053	<u>0.8459 ± 0.0103</u>	<b>0.9969 ± 0.0004</b>	
		Inductive New-New						
eBay-Small	0.923 ± 0.001	0.9226 ± 0.0024	0.98 ± 0.0007	0.9505 ± 0.0009	0.991 ± 0.0001	<u>0.9973 ± 0.0</u>	<b>0.9997 ± 0.0004</b>	
YouTubeReddit-Small	0.7578 ± 0.0015	0.7582 ± 0.0021	0.7564 ± 0.0043	0.7718 ± 0.0023	0.7498 ± 0.004	<u>0.8868 ± 0.0034</u>	<b>0.9861 ± 0.0063</b>	
eBay-Large	0.6976 ± 0.0016	0.6957 ± 0.0007	0.7078 ± 0.0031	0.5154 ± 0.0001	0.93 ± 0.0003	<u>0.9318 ± 0.0</u>	<b>0.9999 ± 0.0001</b>	
DGraphFin	0.6802 ± 0.0005	0.6811 ± 0.0002	0.6526 ± 0.0098	0.5831 ± 0.0184	0.5379 ± 0.0071	<b>0.8977 ± 0.0014</b>	0.6529 ± 0.0249	
Youtube-Reddit-Large	0.7038 ± 0.0024	0.7115 ± 0.0007	0.6979 ± 0.002	0.7414 ± 0.0012	0.6965 ± 0.004	<u>0.8848 ± 0.0023</u>	<b>0.9761 ± 0.0134</b>	
Taobao-Large	0.6738 ± 0.0005	0.6742 ± 0.0005	0.6611 ± 0.0011	0.53 ± 0.0023	0.7521 ± 0.0127	<u>0.8738 ± 0.0145</u>	<b>0.9973 ± 0.0001</b>	

Table 4: ROC AUC results for the *dynamic node classification task* on the eBay datasets. The top-2 results are highlighted as **bold red** and underlined blue.

Model \ Dataset	JODIE	DyRep	TGN	TGAT	CAWN	NeurTW	NAT
eBay-Small	0.9274 $\pm$ 0.0017	0.8677 $\pm$ 0.0356	0.913 $\pm$ 0.0025	<u>0.9342 <math>\pm</math> 0.0002</u>	0.9305 $\pm$ 0.0001	<b>0.9529 <math>\pm</math> 0.0002</b>	0.6797 $\pm$ 0.0115
eBay-Large	0.7244 $\pm$ 0.0002	0.7246 $\pm$ 0.0	0.6586 $\pm$ 0.0129	0.672 $\pm$ 0.0016	<u>0.7710 <math>\pm</math> 0.0002</u>	<b>0.7859 <math>\pm</math> 0.0</b>	0.5304 $\pm$ 0.0011
Average Rank	4	4.5	5.5	3.5	<u>2.5</u>	<b>1</b>	7

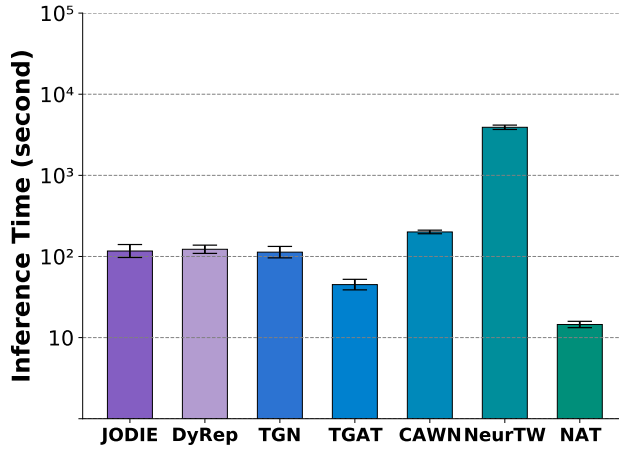


Figure 1: Inference time comparison per 100,000 edges.

#### Comment 2

**W2.** The experiments section focuses a lot on presenting and discussing individual methods' performance. It'd be better to provide summaries of state-of-the-art results and the limitations of existing methods, and in light of that, discuss future directions of TGN research.

101 **Response:**

102 We appreciate this suggestion! We have updated the paper (<https://openreview.net/pdf?id=rnZm2vQq31>) in section 4.4 to provide the summaries of the state-of-the-art results and the limitations  
103 of existing methods, and the future directions of TGNN research.  
104

**Comment 3**

**W3.** This paper defines a temporal graph to be a sequence of temporal “user-item” interactions. However, this is a limited form of a temporal graph as this definition covers only a particular type of bipartite graphs with two types of nodes. I think using a more general definition without such conditions (in both the writing and the code) would be more suitable for a general TGNN benchmark.

105

106 **Response:**

107 Thanks for your comment! We have updated a general definition for temporal graph in section 3.1.  
108 A temporal graph can be represented as an ordered sequence of temporal interactions. The  $r$ -th  
109 interaction  $I_r = (u_r, i_r, t_r, e_r)$  happens at time  $t_r$  between the source node  $u_r$  and the destination  
110 node  $i_r$  with edge feature  $e_r$ .

**Comment 4**

**W4.** Datasets are not that large for efficiency evaluation. Most graphs used in the benchmark are not that large. The GPU memory usage for these graphs are mostly 1-3 GB. Larger temporal graphs would be more desirable for evaluating model efficiency. Constructing synthetic temporal graphs with increasing sizes could facilitate more systematic evaluations of TGNN models’ efficiency.

111

112 **Response:**

113 Thanks for this valuable comment!

114 We have included new datasets with up to several million edges and nodes. We have added *six* datasets  
115 (eBay-Small, eBay-Large, Taobao-Large, DGraphFin, YouTubeReddit-Small, YouTubeReddit-Large),  
116 including *four* **large-scale** datasets (eBay-Large, Taobao-Large, DGraphFin, YouTubeReddit-Large).  
117 The statistics of the new datasets are shown in Table 1. For easy access, all datasets have been hosted  
118 on the open-source platform zenodo (<https://zenodo.org/>) with a Digital Object Identifier (DOI)  
119 10.5281/zenodo.8267846 (<https://zenodo.org/record/8267846>). Furthermore, considering  
120 many real world applications and large-scale temporal graphs, we have added **the inference time**  
121 metric to evaluate the efficiency of TGNN models. See Section A for details.

**Comment 5**

**W5.** Node reindexing described in Figure 3 is confusing. In the homogeneous graph, why do two different nodes have the same id? For example, in the rightmost graph in Fig 3, there are a user with id 2 and an item with id 2. In general, nodes should have different ids as they are separate entities.

122

123 **Response:**

124 We appreciate the suggestion and totally agree. In the homogeneous graph shown in Figure 3(b), the  
125 user with id 2 and the item with id 2 are the same node. Therefore, we have updated the Figure 3(b)  
126 in the paper by replacing the labels "user" and "item" with "node".

## References

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