

---

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

---

## Authors' Response to Reviewer RjkE

### Opportunities For Improvement:

**O1.** The discussion regarding the results of the evaluation experiments is shallow. In particular, the high accuracy and speed of NAT for link prediction, as already reported in NAT's paper, do not provide novelty. Also, there is a limited specific discussion on how dataset differences impact accuracy. It would be more interesting if the authors could demonstrate new insights that are not easily inferred from existing papers.

**O2.** The discussion of the experimental results is mainly limited to the aspects listed in Table 1 (Memory, Attention, RNN, TempWalk, Scalability), so they lack detailed analysis. For example, CAWN and NeurTW both leverage TempWalk, but the experiments in Table 3 demonstrate that these two have different strengths and weaknesses on different datasets. Therefore, there should be more discussion on what specific differences in the characteristics between CAWN and NeurTW contribute to these strengths and weaknesses. Similar discussions should be made for other methods to show the correlations between the design of existing methods and the datasets. Regarding the statement "NeurTW introduces a continuous-time operation that can depict evolution trajectory, which is potentially suitable for CanParl with a large time granularity", the meaning is unclear due to the lack of a sufficient description of the correlation between the evolution trajectory and large time granularity.

**O3.** While the difficulty of the inductive New-New setting task is understandable, however, to say "Nevertheless, CAWN, NeurTW, and NAT still perform well due to their structure-aware techniques" is not sufficient. More detailed explanations of the structure-aware techniques should be provided.

**O4.** Regarding the efficiency evaluation, it may be desirable to discuss the elapsed time for users (i.e., per epoch time \ average number of epochs). Then, it would be beneficial to break down the analysis using the per epoch time and average number of epochs, respectively. Also, the paper only reports the execution time and memory usage without conducting in-depth analyses of their correlations with the design of each existing method.

**O5.** Node classification becomes more challenging as the number of labels increases, but the paper only handles binary classification, limiting the benchmark's generality. Performance benchmarks for tasks with multiple label numbers are desired.

**O6.** The statement "MOOC is relatively denser, and the temporal walk mechanism can effectively perceive local structures" is interesting, however, there is insufficient evidence to support the claim. Can the paper demonstrate that the effectiveness of the temporal walk mechanism changes in response to changes in graph density?

**O7.** The proposed technique, TeMP, is only briefly described in seven lines, making it difficult to fully understand its features.

1

### 2 General Response:

3 Thanks for the valuable suggestion! We have updated Section 4.4 in the paper ([https://](https://openreview.net/pdf?id=rnZm2vQq31)  
4 [openreview.net/pdf?id=rnZm2vQq31](https://openreview.net/pdf?id=rnZm2vQq31)). We provide summaries of the state-of-the-art results,  
5 the limitations of existing methods, and discuss future directions of TGNN research.

Submitted to the 37th Conference on Neural Information Processing Systems (NeurIPS 2023) Track on Datasets and Benchmarks. Do not distribute.

6 We have updated Section 4.4 in the paper (<https://openreview.net/pdf?id=rnZm2vQq31>) for  
 7 the discussion differences between CAWN [1] and NeurTW [2]. We have updated the sentence  
 8 in Section 4.2 of the paper (<https://openreview.net/pdf?id=rnZm2vQq31>) and added more  
 9 details of the structure-aware techniques.

10 We have added **the inference time** metric to evaluate the efficiency of methods. We have added  
 11 experiments of the node classification task with multiple label numbers. We have demonstrated that  
 12 the effectiveness of the CAWN based on temporal walk mechanism changes in response to changes  
 13 in graph density. We have added the details of TeMP in Appendix.

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

#### Comment 1

**O1.** The discussion regarding the results of the evaluation experiments is shallow. In particular, the high accuracy and speed of NAT for link prediction, as already reported in NAT’s paper, do not provide novelty. Also, there is a limited specific discussion on how dataset differences impact accuracy. It would be more interesting if the authors could demonstrate new insights that are not easily inferred from existing papers.

#### Response:

17 We thank the reviewer for the suggestions! We have updated Section 4.4 in the paper (<https://openreview.net/pdf?id=rnZm2vQq31>). We provide summaries of the state-of-the-art results,  
 18 the limitations of existing methods, and discuss future directions of TGNN research.

20 For example, the high accuracy and speed of NAT [3] for dynamic link prediction task are already  
 21 reported in NAT’s paper. However, NAT’s original paper did not perform experiments for dynamic  
 22 node classification task. We implement the dynamic node classification task of NAT, the experimental  
 23 results are shown in Table 5 in the paper (<https://openreview.net/pdf?id=rnZm2vQq31>) and  
 24 reveal that *NAT performs poorly on the node classification task. The node classification task does*  
 25 *not rely on structural features as much as the link prediction task, so that the joint neighborhood*  
 26 *mechanism of NAT may be less effective.*

27 Besides, In the original paper of NeurTW [2], the efficiency of NeurTW is not discussed. In  
 28 BenchTeMP proposed by us, we evaluated NeurTW with diverse workloads, including performances  
 29 and efficiency (**runtime** in the paper, **running memory** in the paper, **inference time** shown in Figure  
 30 1 of this response file). We reveal that *NeurTW performs poorly on efficiency.*

31 Furthermore, previous works conduct experiments on datasets with a small number of nodes  
 32 and edges. Thus, in this response file, we have added *six* datasets (eBay-Small, eBay-Large,  
 33 Taobao-Large, DGraphFin, YouTubeReddit-Small, YouTubeReddit-Large), including *four large-*  
 34 *scale* datasets (eBay-Large, Taobao-Large, DGraphFin, YouTubeReddit-Large). The statistics of the  
 35 new datasets are shown in Table 1. The eBay datasets are a collection of the user transactions on  
 36 eBay’s e-commerce platform. We thank our industrial collaborator for sharing their datasets in our  
 37 research.

38 After a discussion with our industrial partner eBay, we are working on sharing the **eBay-Small** and  
 39 **eBay-Large** datasets in a way that ensures availability and justifies the research purpose. We provide  
 40 a Google form for the applicants: <https://forms.gle/bP1RmyVJ1C6pgyS66> (**the applicants can**  
 41 **remain anonymous**).

42 The experimental results on large-scale datasets (eBay-Large, Taobao-  
 43 Large, DGraphFin, YouTubeReddit-Large) may be more convincing. Furthermore, we have  
 44 added **Average Rank** metric for ranking model performances on the newly added large-scale datasets  
 45 (eBay-Large, Taobao-Large, DGraphFin, YouTubeReddit-Large) to evaluate TGNN models on  
 46 dynamic link prediction task and node classification task shown in Table 2 and Table 4.

- **eBay-Small** is a subset of the eBay-Large dataset. We sample 38,427 nodes and 384,677 edges from eBay-Large graph according to edge timestamps.
- **YouTubeReddit-Small** is a collection of massive visual contents on YouTube and long-term community activity on Reddit. This dataset covers a 3-month period from January to March 2020. Each row in the dataset represents a YouTube video  $v_i$  being shared in a subreddit  $s_j$  by some user  $u_k$  at time  $t$  [4]. Nodes are YouTube videos and subreddits, edges are the users' interactions between videos and subreddits. This dynamic graph has 264,443 nodes and 297,732 edges.
- **eBay-Large** is a million-scale dataset consisting of 1.3 million nodes and 1.1 million edges, which comprises the selected transaction records from the eBay e-commerce platform over a two-month period. eBay-Large is modeled as a user-item graph, where items are heterogeneous entities which include information such as phone numbers, addresses, and email addresses associated with a transaction. We select one month of transactions as seed nodes and then expand each seed node two hops back in time to enrich the topology while maintaining consistency in the distribution of seed nodes.
- **DGraphFin** is a collection of large-scale dynamic graph datasets, consisting of interactive objects, events and labels that evolve with time. It is a directed, unweighted dynamic graph consisting of millions of nodes and edges, representing a realistic user-to-user social network in financial industry. Nodes are users, and an edge from one user to another means that the user regards the other user as the emergency contact person [5].
- **Youtube-Reddit-Large** dataset covers 54 months of YouTube video propagation history from January 2018 to June 2022 [4]. This dataset has 5,724,111 nodes and 4,228,523 edges.
- **Taobao-Large** is a collection of the Taobao user behavior dataset intercepted based on the period 8:00 to 18:00 on 26 November 2017 [6]. Nodes are users and items, and edges are behaviors between users and items, such as favor, click, purchase, and add an item to shopping cart. This public dataset has 1,630,453 nodes and 5,008,74 user-item interaction edges.

## A Experiments

We conduct extensive experiments on the tasks of *dynamic link prediction* and *dynamic node classification*. The experimental setup is the same as in the paper <https://openreview.net/pdf?id=rnZm2vQq31>.

### A.1 Link Prediction Task

We run the link prediction task on 7 TGNN models and the new datasets under different settings (Transductive, Inductive, Inductive New-Old, and Inductive New-New). The AUC and AP results for each new datasets are shown in Table 2 and Table 3, respectively. For the four large-scale datasets (eBay-Large, Taobao-Large, DGraphFin, YouTubeReddit-Large), we observe the similar results as in the paper. Specifically, NAT and NeurTW achieve the top-2 performance on almost all datasets under transductive and inductive settings.

Table 1: Dataset statistics of the newly added datasets.

	Domain	# Nodes	# Edges
eBay-Small	E-commerce	38,427	384,677
YouTubeReddit-Small [4]	Social	264,443	297,732
eBay-Large	E-commerce	1,333,594	1,119,454
DGraphFin [5]	E-commerce	3,700,550	4,300,999
Youtube-Reddit-Large [4]	Social	5,724,111	4,228,523
Taobao-Large [2, 6]	E-commerce	1,630,453	5,008,745

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 $\pm$ 0.0033	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>

## A.2 Node Classification Task

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

## A.3 Efficiency

Considering many real world applications and , we add **the inference time** metric to evaluate the efficiency of models. The inference time comparison per 100,000 edges is shown in Figure 1. According to the figure, we can observe the similar model efficiency results as in the paper. In terms of the inference time, JODIE, DyRep, TGN have almost the same efficiency, while NeurTW are much slower. TGAT achieves the second-best efficiency. NAT is relatively faster than temporal walk-based methods through caching and 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

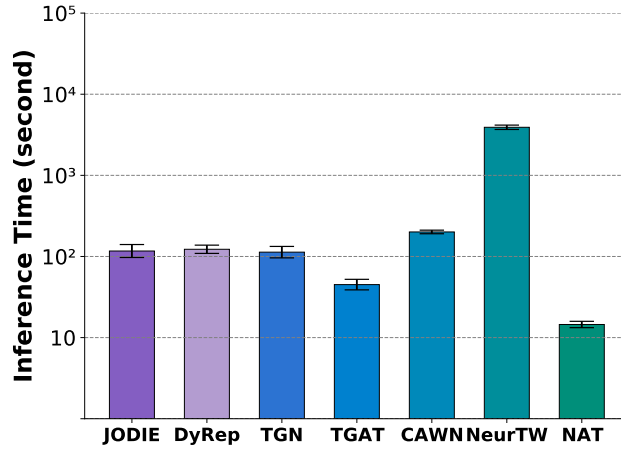


Figure 1: Inference time comparison per 100,000 edges.

## Comment 2

**O2.** The discussion of the experimental results is mainly limited to the aspects listed in Table 1 (Memory, Attention, RNN, TempWalk, Scalability), so they lack detailed analysis. For example, CAWN and NeurTW both leverage TempWalk, but the experiments in Table 3 demonstrate that these two have different strengths and weaknesses on different datasets. Therefore, there should be more discussion on what specific differences in the characteristics

## Comment 2

between CAWN and NeurTW contribute to these strengths and weaknesses. Similar discussions should be made for other methods to show the correlations between the design of existing methods and the datasets. Regarding the statement "NeurTW introduces a continuous-time operation that can depict evolution trajectory, which is potentially suitable for CanParl with a large time granularity", the meaning is unclear due to the lack of a sufficient description of the correlation between the evolution trajectory and large time granularity.

97

## Response:

99 Thanks for the valuable suggestion! We have updated Section 4.4 in the paper (<https://openreview.net/pdf?id=rnZm2vQq31>) for discussing the differences between CAWN [1] and  
100 NeurTW [2].  
101

102 CAWN [1] and NeurTW [2] perform well on the link prediction task and are both based on motifs  
103 and index anonymization operation. However, NeurTW [2] additionally constructs neural ordinary  
104 differential equations (NODEs). With a component based on neural ordinary differential equa-  
105 tions, the extracted motifs allow for irregularly-sampled temporal nodes to be embedded explicitly  
106 over *multiple different interaction time intervals*, enabling the effective capture of the underlying  
107 spatiotemporal dynamics.

108 In NeurTW [2], The *Continuous Evolution* operation is illustrated in Equation 8 in the original paper  
109 (<https://openreview.net/pdf?id=NqbktPUkZf7>).

$$h'_i = h_{i-1} + \int_{t_{i-1}}^{t_i} f(h_t, \theta) dt, \quad (1)$$

110 where  $f(h_t, \theta)$  is the ODE function, implemented by an autoregressive gated recurrent unit with a  
111 parameter  $\sigma$ . The corresponding ODE function  $\tilde{f}(\tilde{h}_s, s, \theta)$  follows:

$$\begin{aligned} \tilde{f}(\tilde{h}_s, s, \theta) &:= \frac{d\tilde{h}_s}{ds} = \frac{dh_t}{dt} \Big|_{t=s(t_{\text{end}}^c - t_{\text{start}}^c) + t_{\text{start}}^c} \frac{dt}{ds} \\ &= f(h_t, t, \theta) \Big|_{t=s(t_{\text{end}}^c - t_{\text{start}}^c) + t_{\text{start}}^c} (t_{\text{end}}^c - t_{\text{start}}^c) \\ &= f(\tilde{h}_s, s(t_{\text{end}}^c - t_{\text{start}}^c) + t_{\text{start}}^c, \theta) (t_{\text{end}}^c - t_{\text{start}}^c) \end{aligned} \quad (2)$$

112 Thus, Due to the neural ordinary differential equations (NODEs), NeurTW [2] performs better on  
113 datasets with a large time granularity.

114 CanParl is a Canadian parliament bill voting network extracted from open website [7]. Nodes are  
115 members of parliament (MPs), and edges are the interactions between MPs from 2006 to 2019.

116 We illustrate the distribution of temporal edge count for the CanParl dataset in Figure 2. As shown in  
117 Figure 2, CanParl dataset has a large time granularity and NeurTW [2] achieves the best performance  
118 on CanParl dataset. Inspired by the above analysis, we could infer that NeurTW is potentially suitable  
119 for datasets with a large time granularity and time intervals, such as CanParl.

120 We further conduct ablation studies to verify the effectiveness of neural ordinary differential equations  
121 (NODEs) of NeurTW on datasets with a large time granularity and time intervals. The experimental  
122 results are detailed in Table 5.

123 NeurTW without differential equations (NODEs) module performs much poorly on datasets with a  
124 large time granularity and time intervals (such as, CanParl). However, on a tiny time granularity and  
125 time intervals (such as, USLegis, the timestamp of USLegis is only from 0 to 11.), thus, removing the  
126 differential equations (NODEs) module has relatively little negative impact on the performance of the  
127 NeurTW.

Table 5: Ablation studies on neural ordinary differential equations (NODEs) of NeurTW. "- NODEs" means remove NODEs module.

Ablation	Datasets	AUC				AP			
		Transductive	Inductive	New-Old	New-New	Transductive	Inductive	New-Old	New-New
original	CanParl	$0.8920 \pm 0.0173$	$0.8871 \pm 0.0139$	$0.8847 \pm 0.0102$	$0.8882 \pm 0.0045$	$0.8528 \pm 0.0213$	$0.8469 \pm 0.0161$	$0.8417 \pm 0.0132$	$0.8511 \pm 0.0079$
	USLegis	$0.9715 \pm 0.0009$	$0.9708 \pm 0.0009$	$0.9682 \pm 0.0018$	$0.9787 \pm 0.0004$	$0.9713 \pm 0.0013$	$0.971 \pm 0.0009$	$0.9671 \pm 0.0027$	$0.9803 \pm 0.0005$
- NODEs	CanParl	$0.5 \pm 0.0$	$0.5001 \pm 0.0$	$0.5001 \pm 0.0$	$0.5 \pm 0.0$	$0.5 \pm 0.0$	$0.5001 \pm 0.0$	$0.5001 \pm 0.0$	$0.5 \pm 0.0$
	USLegis	$0.898 \pm 0.004$	$0.9186 \pm 0.0018$	$0.9026 \pm 0.0025$	$0.9474 \pm 0.0$	$0.8721 \pm 0.0047$	$0.9037 \pm 0.0034$	$0.8651 \pm 0.0029$	$0.9458 \pm 0.0004$

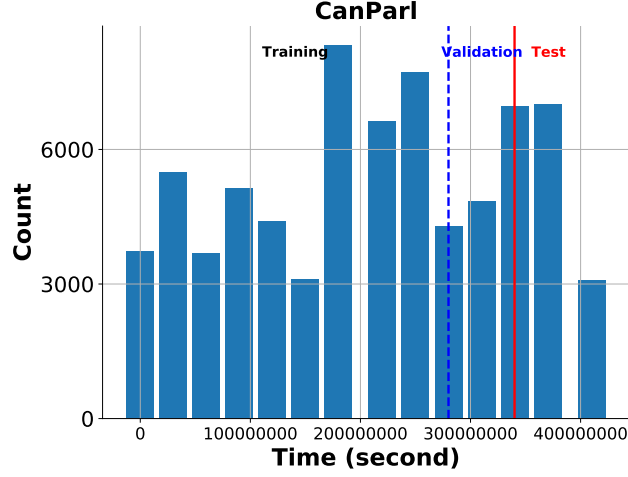


Figure 2: The distribution of temporal edge count for the CanParl dataset, and the illustration on the train-validation-test splitting.

128 Ablation studies on neural ordinary differential equations (NODEs) of NeurTW verify that "NeurTW  
129 introduces a continuous-time operation that can depict evolution trajectory, which is potentially  
130 suitable for CanParl with a large time granularity and time intervals".

### Comment 3

**O3.** While the difficulty of the inductive New-New setting task is understandable, however, to say "Nevertheless, CAWN, NeurTW, and NAT still perform well due to their structure-aware techniques" is not sufficient. More detailed explanations of the structure-aware techniques should be provided.

### Response:

We appreciate this suggestion! We have updated the sentence in Section 4.2 of the paper (<https://openreview.net/pdf?id=rnZm2vQq31>) and added more details of the structure-aware techniques.

CAWN, NeurTW, and NAT still perform well under the inductive **New-New** setting due to their structure-aware techniques. CAWN and NeurTW are both based on motifs and index anonymization operation [1, 2]. NeurTW additionally constructs neural ordinary differential equations (NODEs). NAT relies on joint neighborhood features based on a dedicated data structure termed *N-caches* [3].

### Comment 4

**O4.** Regarding the efficiency evaluation, it may be desirable to discuss the elapsed time for users (i.e., per epoch time \ average number of epochs). Then, it would be beneficial to break down the analysis using the per epoch time and average number of epochs, respectively. Also, the paper only reports the execution time and memory usage without conducting in-depth analyses of their correlations with the design of each existing method.

### Response:

We appreciate the suggestion and totally agree!

In many real world applications, *the inference time (the elapsed time)* of methods might be more important as they are deployed in the real world. Thus, we have added **the inference time** metric to evaluate the efficiency of TGNN models. See Section A.3 for details.

### Comment 5

**O5.** Node classification becomes more challenging as the number of labels increases, but the paper only handles binary classification, limiting the benchmark's generality. Performance benchmarks for tasks with multiple label numbers are desired.

### Response:

Thanks for this valuable suggestion! We have added experiments of the node classification task with multiple label numbers.

In the previous works, only Reddit, Wikipedia, and MOOC datasets have node labels (two labels: 0 and 1) and are used for binary node classification task. Through unremitting efforts, we have found a large-scale temporal dataset - DGraphFin [5] with multiple node labels. DGraphFin consists of 3,700,550 nodes and 4,300,999 edges. 4,300,999 edges.

**DGraphFin** is a collection of large-scale dynamic graph datasets, consisting of interactive objects, events and labels that evolve with time. It is a directed, unweighted dynamic graph consisting of millions of nodes and edges, representing a realistic user-to-user social network in financial industry.



Nodes are users, and an edge from one user to another means that the user regards the other user as the emergency contact person [5].

There four classes. Below are the nodes counts of each class.

- 0: 1210092
- 1: 15509
- 2: 1620851
- 3: 854098

Nodes of Class 1 are fraud users and nodes of 0 are normal users, and they the two classes to be predicted. Nodes of Class 2 and Class 3 are background users.

We preprocess DGraphFin as the format of temporal graph. We open source the code of preprocessing DGraphFin dataset at <https://github.com/qianghuangwhu/benchtemp/blob/master/DGraphFin/DGraphFin.py>.

DGraphFin dataset has been hosted on the open-source platform zenodo (<https://zenodo.org/>) with a Digital Object Identifier (DOI) 10.5281/zenodo.8267771 (<https://zenodo.org/record/8267846>).

The experimental results for dynamic node classification task on DGraphFin dataset are shown in Table 6. Different evaluation metrics are available, including Accuracy, Precision, Recall and F1.

$$\begin{aligned}
 \text{Precision}_{\text{weighted}} &= \frac{\sum_{i=1}^N \text{Support}_i \times \text{Precision}_i}{\sum_{i=1}^N \text{Support}_i} \\
 \text{Recall}_{\text{weighted}} &= \frac{\sum_{i=1}^N \text{Support}_i \times \text{Recall}_i}{\sum_{i=1}^N \text{Support}_i} \\
 \text{F1}_{\text{weighted}} &= \frac{2 \times \text{Precision}_{\text{weighted}} \times \text{Recall}_{\text{weighted}}}{\text{Precision}_{\text{weighted}} + \text{Recall}_{\text{weighted}}}
 \end{aligned} \tag{3}$$

where  $\text{Support}_i$  is the number of supports for the  $i$ -th class.

Table 6: The experimental results for dynamic node classification task with multiple labels on DGraphFin dataset.

	JODIE	DyRep	TGN	TGAT	CAWN	NeurTW	NAT
Accuracy	0.4396 ± 0.0070	0.4400 ± 0.0117	<b>0.5696 ± 0.0056</b>	<u>0.5529 ± 0.0036</u>	0.4366 ± 0.0068	0.4933 ± 0.0870	0.4131 ± 0.0038
Precision	0.1933 ± 0.0062	0.1937 ± 0.0103	<b>0.4806 ± 0.0053</b>	<u>0.4644 ± 0.0118</u>	0.1906 ± 0.0060	0.3879 ± 0.2849	0.3068 ± 0.0044
Recall	0.4396 ± 0.0070	0.4400 ± 0.0117	<b>0.5696 ± 0.0056</b>	<u>0.5529 ± 0.0036</u>	0.4366 ± 0.0068	0.4933 ± 0.0870	0.4131 ± 0.0038
F1	0.2685 ± 0.0073	0.2690 ± 0.0121	<b>0.4905 ± 0.0063</b>	<u>0.4744 ± 0.0020</u>	0.2654 ± 0.0071	0.3727 ± 0.1588	0.3402 ± 0.0047

As shown in Table 6, TGN achieves the best performance on dynamic node classification task with multiple labels, followed by TGAT. JODIE, DyRep, and CAWN perform poorly.

#### Comment 6

**O6.** The statement "MOOC is relatively denser, and the temporal walk mechanism can effectively perceive local structures" is interesting, however, there is insufficient evidence to support the claim. Can the paper demonstrate that the effectiveness of the temporal walk mechanism changes in response to changes in graph density?

#### Response:

We appreciate your valuable suggestion! We have added experiments to demonstrate that the effectiveness of the temporal walk mechanism changes in response to changes in graph density.

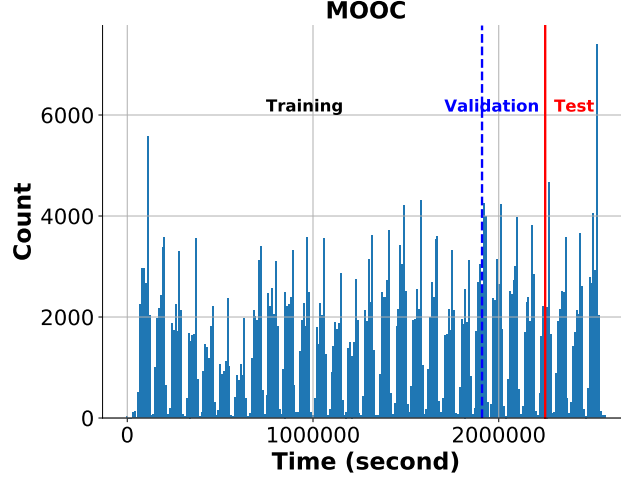


Figure 3: The distribution of temporal edge count for the MOOC dataset, and the illustration on the train-validation-test splitting.

As shown in Figure 3, MOOC is relatively denser and CAWN based on the temporal walk mechanism (motifs) achieves the best performance on this dataset.

To demonstrate that the effectiveness of the temporal walk mechanism changes in response to changes in graph density, we adopt edges sampling strategy. We randomly sample a constant number  $N_e$  of temporal edges  $\{(u_1, i_1), \dots, (u_N, i_N)\}$  each time as a subgraph  $G_S$  of the original temporal graph. The number  $N_u$  of the source nodes is the number of the elements in set  $\{u_1, \dots, u_N\}$ . The number  $N_i$  of the source nodes is the number of the elements in set  $\{i_1, \dots, i_N\}$ .

The graph density  $\sigma_{D_S}$  in our paper is the temoral density of temoral edges  $(u_t, i_t)$ , the calculation formula is as follows:

$$\sigma_{D_S} = \frac{N_e}{N_u \times N_i}. \quad (4)$$

The number of sampled edges is a constant  $N_e$ . Thus, we sampled two subgraphs:  $G_{S_1}$  and  $G_{S_2}$ . The statistics of sampled subgraphs are shown in Table 7. The temoral graph density of  $G_{S_1}$  is 0.6320, while  $G_{S_2}$  0.3127.

Table 7: The parameters of sampled graphs  $G_{S_1}, G_{S_2}$ .

	$N_e$	$N_u$	$N_i$	$\sigma_{D_S}$
$G_{S_1}$	100000	4395	36	0.6320
$G_{S_2}$	100000	4264	75	0.3127

The experimental results of CAWN based on the temporal walk mechanism (motifs) on  $G_{S_1}$  and  $G_{S_2}$  are shown in Table 8.

Table 8: The experimental results of CAWN on  $G_{S_1}$  and  $G_{S_2}$ .

	AUC				AP			
	Transductive	Inductive	Inductive New-Old	Inductive New-Old	Transductive	Inductive	Inductive New-Old	Inductive New-Old
$G_{S_1}$	0.886 $\pm$ 0.0164	0.883 $\pm$ 0.0158	0.8847 $\pm$ 0.0166	0.8701 $\pm$ 0.0134	0.8651 $\pm$ 0.021	0.8601 $\pm$ 0.0219	0.8616 $\pm$ 0.0225	0.8511 $\pm$ 0.0174
$G_{S_2}$	0.8357 $\pm$ 0.0073	0.8353 $\pm$ 0.0105	0.8535 $\pm$ 0.0087	0.7752 $\pm$ 0.0157	0.8172 $\pm$ 0.0088	0.8154 $\pm$ 0.0128	0.8337 $\pm$ 0.0103	0.7535 $\pm$ 0.0197

As shown in Table 8, CAWN performs much better on  $G_{S_1}$  with a larger graph density,  $\sigma_{D_{S_1}} = 0.6320 > \sigma_{D_{S_2}} = 0.3127$ . The experimental results demonstrate that the effectiveness of the CAWN based on temporal walk mechanism changes in response to changes in graph density.

## Comment 7

**O7.** The proposed technique, TeMP, is only briefly described in seven lines, making it difficult to fully understand its features.

### Response:

We are grateful for this suggestion!

TeMP is a novel approach that incorporates GNN aggregation and temporal structure. TeMP performs node pre-initialization as an alternative approach to global memory, and utilizes message passing on temporal subgraphs. Moreover, TeMP runs label propagation to capture evolving local structures, motivated by the temporal walk technique. We provide detail of TeMP at Section E of Appendix ([https://openreview.net/attachment?id=rnZm2vQq31&name=supplementary\\_material](https://openreview.net/attachment?id=rnZm2vQq31&name=supplementary_material)).

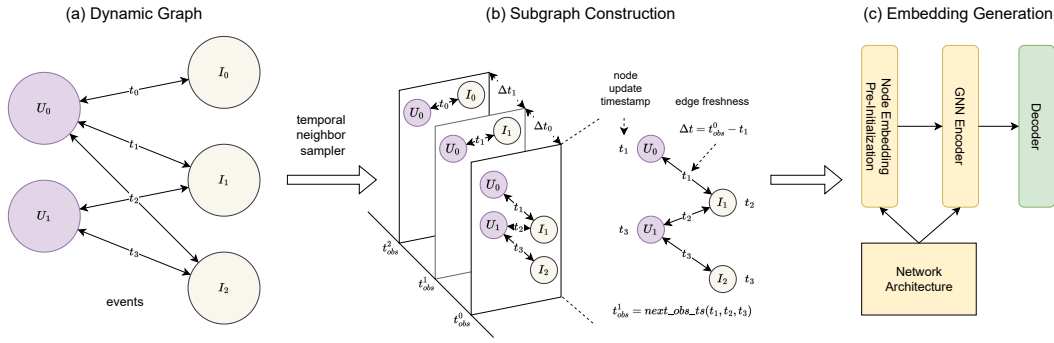


Figure 4: Workflow of TeMP.  $U$  denotes user, and  $I$  denotes item.

As shown in Figure 4, given a dynamic graph (a), the processing of TeMP is as follows:

- *Subgraph Construction (b).*

We construct a subgraph with a temporal neighbor sampler with intervals adaptive to data. We try to find a reference timestamp and sample a subgraph before this timestamp. We have conducted experiments at various quantiles, and chosen the mean timestamp since it obtains the overall best performance.

- *Embedding Generation (c).* Upon subgraph construction, TeMP generates temporal embeddings for nodes and edges. The model architecture consists of three main components: temporal label propagation (LPA), message-passing operators, and a sequence updater. The temporal LPA captures the motif pattern, while the message-passing operators aggregate the original edge features. The sequence updater chooses RNN to update the embeddings with a memory module. Furthermore, TeMP uses a pre-initialization strategy to generate initial temporal node embeddings.

We provide detail of TeMP at Section E of Appendix ([https://openreview.net/attachment?id=rnZm2vQq31&name=supplementary\\_material](https://openreview.net/attachment?id=rnZm2vQq31&name=supplementary_material)).

## References

- [1] Yanbang Wang, Yen-Yu Chang, Yunyu Liu, Jure Leskovec, and Pan Li. Inductive representation learning in temporal networks via causal anonymous walks. In *International Conference on Learning Representations*, 2021.
- [2] Ming Jin, Yuan-Fang Li, and Shirui Pan. Neural temporal walks: Motif-aware representation learning on continuous-time dynamic graphs. In *Advances in Neural Information Processing Systems*, 2022.
- [3] Yuhong Luo and Pan Li. Neighborhood-aware scalable temporal network representation learning. In *The First Learning on Graphs Conference*, 2022.
- [4] Yiqiao Jin, Yeon-Chang Lee, Kartik Sharma, Meng Ye, Karan Sikka, Ajay Divakaran, and Srijan Kumar. Predicting information pathways across online communities. *arXiv preprint arXiv:2306.02259*, 2023.
- [5] Xuanwen Huang, Yang Yang, Yang Wang, Chunping Wang, Zhisheng Zhang, Jiarong Xu, Lei Chen, and Michalis Vazirgiannis. Dgraph: A large-scale financial dataset for graph anomaly detection. *Advances in Neural Information Processing Systems*, 35:22765–22777, 2022.
- [6] Han Zhu, Xiang Li, Pengye Zhang, Guozheng Li, Jie He, Han Li, and Kun Gai. Learning tree-based deep model for recommender systems. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 1079–1088, 2018.
- [7] Shenyang Huang, Yasmeen Hitti, Guillaume Rabusseau, and Reihaneh Rabbany. Laplacian change point detection for dynamic graphs. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 349–358, 2020.