SALoM: Structure Aware Temporal Graph Networks with Long-Short Memory Updater

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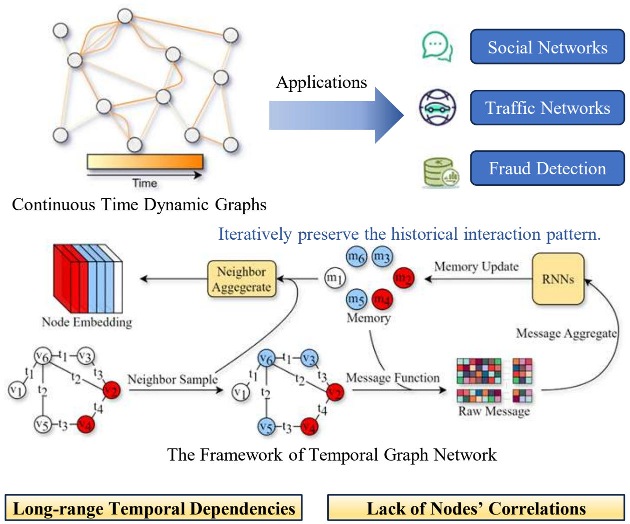
Abstract

Dynamic graph learning is crucial for accurately modeling complex systems by integrating topological structure and temporal information within graphs. While memory-based methods are commonly used and excel at capturing short-range temporal correlations, they struggle with modeling long-range dependencies, harmonizing long-range and short-range correlations, and integrating structural information effectively. To address these challenges, we present SALoM: Structure Aware Temporal Graph Networks with Long-Short Memory Updater. SALoM features a memory module that addresses gradient vanishing and information forgetting, enabling the capture of long-term dependencies across various time scales. Additionally, SALoM utilizes a long-short memory updater (LSMU) to dynamically balance long-range and short-range temporal correlations, preventing over-generalization. By integrating co-occurrence encoding and LSMU through information bottleneck-based fusion, SALoM effectively captures both the structural and temporal information within graphs. Experimental results across various graph datasets demonstrate SALoM's superior performance, achieving state-of-the-art results in dynamic graph link prediction. Our code is openly accessible at https://github.com/wave5418/SALoM.

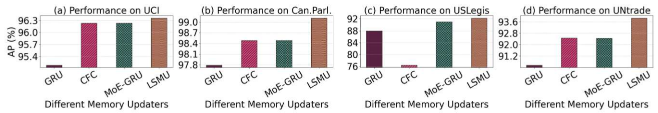
Background

Paradigm of Memory Based Methods



Bottlenecks

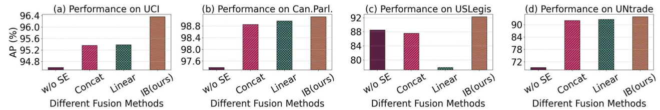
Bottleneck #1: Difficulty capturing complete long-range neighborhood temporal correlations.



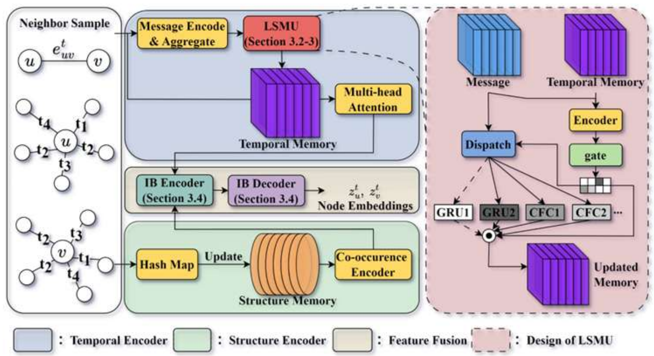
Bottleneck #2: Challenge in balancing long-range and short-range temporal neighborhood features.

	CanParl	USLegis	UCI	Untrade
Concat	96.90	76.93	96.02	92.00
Avg-Voting	98.65	76.06	96.23	92.99
MoE	**99.11**	**92.27**	**96.36**	**93.86**

Bottleneck #3: Hard to integrate long-term temporal and topological structural features.



Methodology



Structure Aware Temporal Graph Networks with Long-Short Memory Updater:
This paper introduce SALoM, a more novel and effective temporal graph network paradigm for dynamic graph learning. SALoM effectively captures long-term, short-term temporal correlation and structural features and adaptively fuses temporal and structural features.

Continuous-Time Memory Module:
This approach effectively captures long-range dependencies in complex graphs by modeling the derivative of the target function rather than a direct input-output mapping.

Long-Short Memory Updater as Temporal Memory Updater:
The optimal balance between long-range and short-range temporal dependencies exhibits dataset-specific and entity-specific characteristics in continuous-time dynamic graphs.

IB Encoder and IB Decoder:
IB Encoder and IB Decoder can harmoniously integrate temporal and structural encodings, as simple concatenation fails to address modality conflicts.

Experiments

Performance Study

Metrics	Datasets	JODIE	DyRep	TGAT	TGN	CAWN	EdgeBank	TCL	GraphMixer	NAT	DyGFormer	CNE-N	SALoM
Trans-AP	Wikipedia	96.50	94.86	96.94	98.28	98.76	90.37	96.47	97.25	97.50	**99.03**	98.61	**99.03**
	Reddit	98.31	98.22	98.52	98.47	99.11	94.86	97.53	97.31	99.10	99.22	99.26	**99.27**
	MOOC	80.23	81.97	85.84	**93.21**	80.15	57.97	82.38	82.78	87.21	87.52	90.16	92.42
	LastFM	70.85	71.92	73.42	84.36	86.99	79.29	67.27	75.61	88.57	93.00	92.60	**93.14**
	Enron	84.77	82.38	71.12	91.51	89.56	83.53	79.70	82.25	90.81	92.47	92.13	**94.08**
	Social Evo.	89.89	88.87	93.16	89.83	84.96	74.95	93.13	93.37	91.23	**94.73**	94.50	**94.73**
	UCI	89.43	65.14	79.63	92.94	95.18	76.20	89.57	93.25	94.26	95.79	95.64	**96.36**
	Flights	95.60	95.29	94.03	97.94	98.51	89.35	91.23	90.99	97.66	98.91	98.73	**98.94**
	Can. Parl.	69.26	66.54	70.73	96.29	69.82	64.55	68.67	77.04	83.83	97.36	81.84	**99.11**
	US Legis.	75.05	75.34	68.52	78.09	70.58	58.39	69.59	70.74	77.56	71.11	72.58	**92.27**
	UN Trade	64.94	63.21	61.47	68.3	65.39	60.41	62.21	62.61	72.32	66.46	77.97	**93.86**
	UN Vote	63.91	62.81	52.21	64.13	52.84	58.49	51.90	52.11	69.70	55.55	58.10	**86.81**
	Contact	95.31	95.98	96.28	95.00	90.26	92.58	92.44	91.92	97.25	98.29	98.28	**98.53**
	Avg. Rank	7.76	8.61	8.38	4.92	7.07	10.53	9.76	8.38	4.53	3.15	3.61	**1.07**
Trans-AUC	Wikipedia	96.33	94.37	96.67	98.01	98.54	90.78	95.84	96.92	96.72	**98.91**	98.4	98.87
	Reddit	98.31	98.17	98.47	98.32	99.01	95.37	97.42	97.17	99.02	99.15	99.19	**99.2**
	MOOC	83.81	85.03	87.11	**93.56**	80.38	60.86	83.12	84.01	88.38	87.91	91.42	92.52
	LastFM	70.49	71.16	71.59	82.66	85.92	83.77	64.06	73.53	86.94	**93.05**	92.21	92.32
	Enron	87.96	84.89	68.89	90.99	90.45	87.05	75.74	84.38	92.02	93.33	92.77	**95.11**
	Social Evo.	92.05	90.76	94.76	90.36	87.34	81.60	94.84	95.23	93.22	96.3	96.20	**96.36**
	UCI	90.44	68.77	78.53	92.17	93.87	77.30	87.82	91.81	93.02	94.49	94.32	**95.53**
	Flights	96.21	95.95	94.13	97.99	98.45	90.23	91.21	91.13	97.32	98.93	98.74	**98.99**
	Can. Parl.	78.21	73.35	75.69	97.17	75.7	64.14	72.46	83.17	87.70	97.76	84.49	**99.18**
	US Legis.	82.85	82.28	75.84	84.63	77.16	62.57	76.27	76.96	84.68	77.90	79.38	**93.75**
	UN Trade	69.62	67.44	64.01	69.41	68.54	66.75	64.72	65.52	76.76	70.20	79.64	**93.23**
	UN Vote	68.53	67.18	52.83	62.76	53.09	62.97	51.88	52.46	74.44	57.12	60.67	**87.87**
	Contact	96.66	96.48	96.95	95.37	89.99	94.34	94.15	93.94	97.64	98.53	98.62	**98.69**
	Avg. Rank	7.07	8.38	8.69	5.53	7.15	10.15	10.07	8.61	4.30	3.23	3.53	**1.23**
Ind-AP	Wikipedia	94.82	92.43	96.22	97.49	98.24	-	96.22	96.65	95.40	**98.59**	97.76	98.49
	Reddit	96.5	96.09	97.09	97.26	98.62	-	94.09	95.26	98.56	98.84	98.82	**98.93**
	MOOC	79.63	81.07	85.50	**91.86**	81.42	-	80.60	81.41	83.59	86.96	88.71	90.53
	LastFM	81.61	83.02	78.63	87.18	89.42	-	73.53	82.11	86.87	94.23	94.00	**94.56**
	Enron	80.72	74.55	67.05	84.53	86.35	-	76.14	75.88	89.03	89.76	87.59	**91.67**
	Social Evo.	91.96	90.04	91.41	82.85	79.94	-	91.55	91.86	91.22	**93.14**	92.70	92.84
	UCI	79.86	57.48	79.54	82.04	92.73	-	87.36	91.19	87.30	**94.54**	93.58	94.36
	Flights	94.74	92.88	88.73	95.03	97.06	-	83.41	83.03	96.59	97.79	97.34	**97.85**
	Can. Parl.	53.92	54.02	55.18	78.75	55.80	-	54.30	55.91	60.62	87.74	65.01	**96.20**
	US Legis.	54.93	57.28	51.00	55.74	53.17	-	52.59	50.71	57.54	54.28	59.54	**68.38**
	UN Trade	59.65	57.02	61.03	77.86	65.24	-	62.21	62.17	69.29	64.55	69.84	**85.46**
	UN Vote	56.64	54.62	52.24	65.67	49.94	-	51.6	50.68	**66.35**	55.93	57.57	62.37
	Contact	94.34	92.18	95.87	88.56	89.55	-	91.11	90.59	96.79	**98.03**	97.58	97.79
	Avg. Rank	7.92	8.69	8.15	5.38	6.38	-	8.53	8.15	5.07	2.84	3.23	**1.53**
Ind-AUC	Wikipedia	94.33	91.49	95.9	97.08	98.03	-	95.57	96.30	94.74	**98.48**	97.45	98.26
	Reddit	96.52	96.05	96.98	96.94	98.42	-	93.8	94.97	97.99	98.71	98.69	**98.85**
	MOOC	83.16	84.03	86.84	**92.02**	81.86	-	81.43	82.77	86.13	87.62	89.94	90.09
	LastFM	81.13	82.24	76.99	85.58	87.82	-	70.84	80.37	83.07	**94.08**	93.62	93.77
	Enron	81.96	76.34	64.63	83.58	87.02	-	72.33	76.51	89.92	90.69	88.24	**92.57**
	Social Evo.	93.70	91.18	93.41	82.04	84.73	-	93.71	94.09	92.11	**95.29**	94.99	95.03
	UCI	78.80	58.08	77.64	86.48	90.40	-	84.49	89.30	83.81	**92.63**	91.31	92.17
	Flights	95.21	93.56	88.64	95.92	96.86	-	82.48	82.27	96.36	97.80	97.20	**97.95**
	Can. Parl.	53.81	55.27	56.51	80.21	58.83	-	55.83	58.32	61.62	89.33	66.51	**96.07**
	US Legis.	58.12	61.07	48.27	58.87	51.49	-	50.43	47.20	62.85	53.21	60.10	**65.56**
	UN Trade	62.28	58.82	62.72	75.70	67.05	-	63.76	63.48	72.56	67.25	71.40	**83.04**
	UN Vote	58.13	55.13	51.83	61.64	48.34	-	50.51	50.04	**66.26**	56.73	58.85	62.44
	Contact	95.37	91.89	96.53	88.87	89.07	-	93.05	92.83	96.67	**98.30**	97.91	97.98
	Avg. Rank	7.76	8.53	8.07	5.46	6.53	-	8.76	8.15	5.00	2.69	3.46	**1.53**

Our SALoM consistently achieves top performance across most datasets, with average rankings ranging from 1.07 to 1.46 for different metrics. Specifically, notable improvements are observed in the USLegis, UNtrade, and Unvote datasets, with enhancements of 14.18%, 15.89%, and 32.48% over its closest competitors, respectively.

Trade-off Between Accuracy and Efficiency

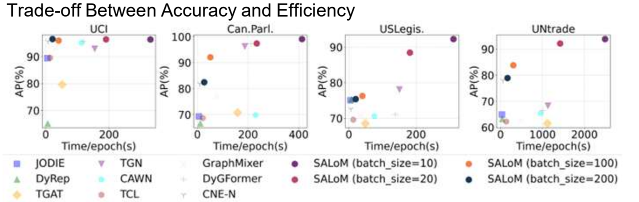


Figure 5: The trade-off between efficiency and performance under different settings of batch sizes.

SALoM is evaluated with different batch sizes, while baseline methods maintain their default settings. SALoM can outperform existing methods with a slight edge in performance at comparable computational costs. When computational constraints are relaxed, setting a small batch size significantly boosts SALoM's performance, largely surpassing existing approaches.