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TSNet: a foundation model for wireless network status prediction in digital twins

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Key words: Digital twin; Communication network; Foundation model; Network status prediction

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Motivation

- A digital twin network (DTN) is a virtual representation of a physical communication network.
- Network status prediction is a basic DTN capability.
- In wireless networks, there are many kinds of measurements that characterize the network status, such as radio resource utilization and user equipment (UE) throughput. Network status prediction is fundamentally a problem of time-series forecasting.
- In this paper, we want to propose a general framework for network status prediction in DTNs, to handle numerous and various network measurements.

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Related works

In the literature, many efforts have been devoted to time-series prediction.

- Traditional statistical methods: ARIMA, Holt-winter
  - make strong assumptions on data distribution
- Traditional machine learning methods: using classical regression algorithms, for example random forest and XGBoost
  - require engineers to design effective features carefully to achieve high accuracy
- Deep neural networks: RNN, LSTM, CNN, Transformers
- Foundation models: TimesNet, GPT4TS, LLM4TS, TimesFM
  - directly apply CV/NLP foundation model to time series
  - pure time-series pretrained model

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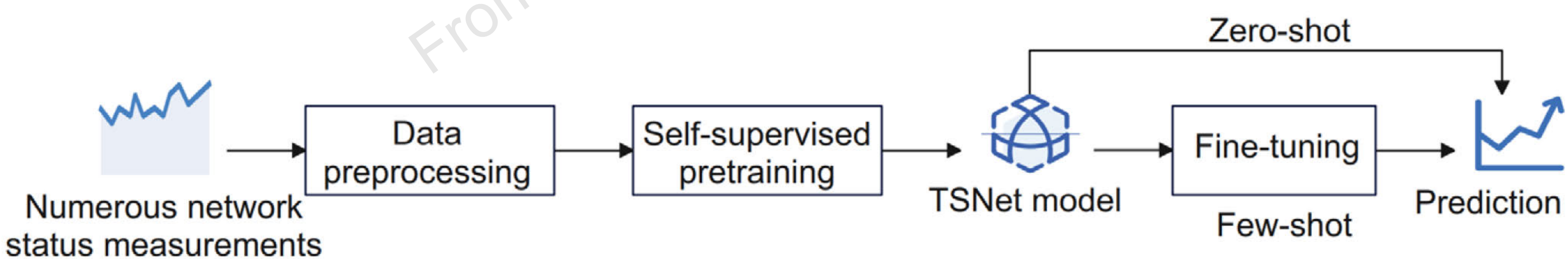
Framework

- Data preprocessing: filter low-quality data and standardize the data
    - Data quality measurement: completeness and variation
    - Data normalization
- Pretraining
    - A novel network architecture for TSNet with 0.1 billion parameters
    - A self-supervised manner using a prediction task with an MSE loss function
- Prediction
    - Zero-shot
    - Few-shot: fine-tuning to freeze the majority of parameters



Pipeline of TSNet

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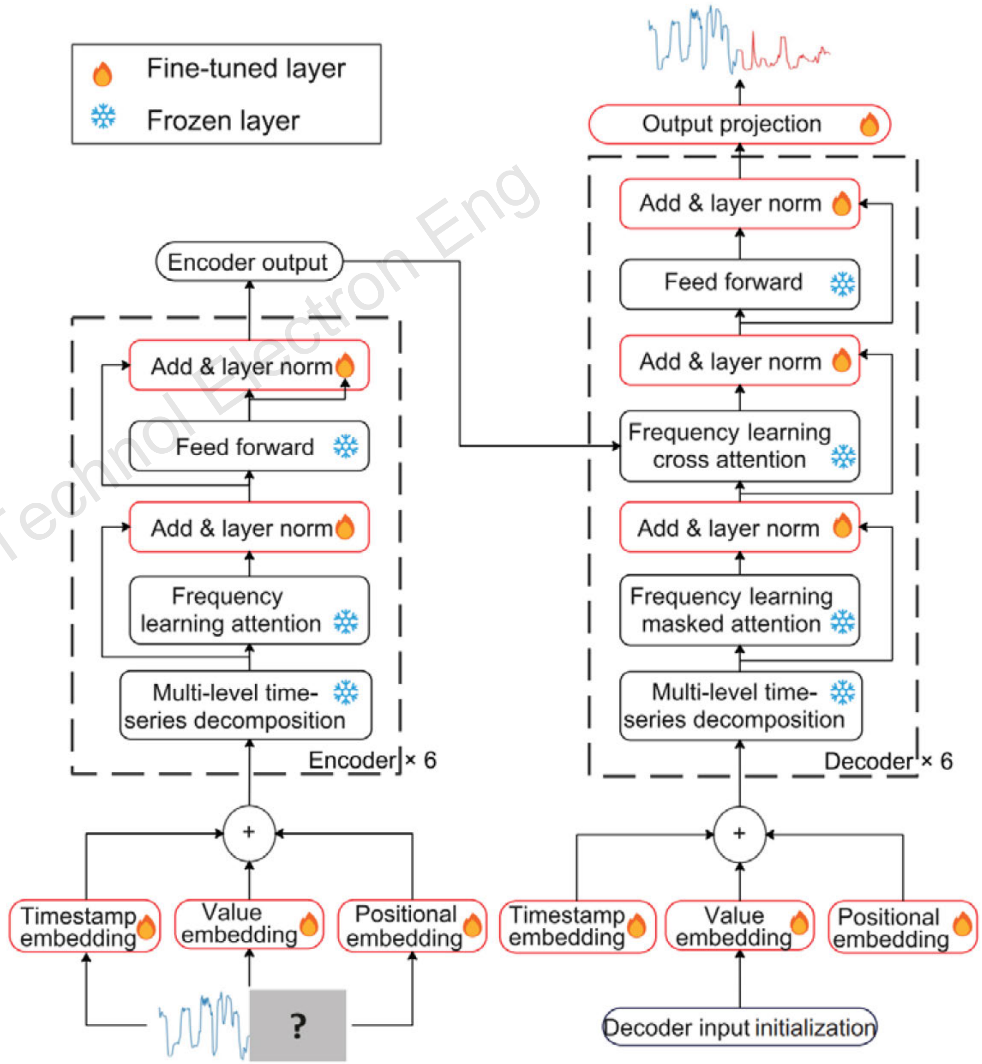
Model architecture

- **Input embedding**: positional embedding and timestamp embedding
- **Channel independence**: multivariate time-series data are processed independently
- **Time-series decomposition**: separate the original time series and hidden states into distinct seasonal and trend components.
- **Frequency learning attention**: implement multi-head attention in the frequency domain to capture implicit features.



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Experiments

TSNet outperforms baseline models in most cases regarding MSE and MAE.

Cell	Metric	TSNet (zero-shot)		LSTM		Nbeats		TFT		NHiTS		TSNet (fine-tuned)	
		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
1	PRB.DL	0.0117	**0.0792**	0.0215	0.1073	**0.0100**	0.0811	0.0175	0.0986	0.0118	0.0845	*0.0084*	*0.0701*
	PRB.UL	0.0171	0.1038	0.0211	0.1078	**0.0132**	**0.0895**	0.0176	0.1057	0.0157	0.0969	*0.0142*	*0.0964*
	Traffic.DL	**0.0118**	**0.0782**	0.0205	0.1021	0.0133	0.0847	0.0413	0.1664	0.0155	0.0919	*0.0091*	*0.0726*
	Traffic.UL	**0.0215**	0.1065	0.0292	0.1172	0.0223	0.1062	0.0248	0.1201	0.0219	**0.1019**	*0.0155*	*0.0883*
	Num.user	0.0072	0.0634	0.0128	0.0822	**0.0036**	**0.0454**	0.0144	0.0854	0.0039	0.0488	*0.0042*	*0.0487*
	Thrp.DL	**0.0192**	0.1062	0.0265	0.1217	0.0203	**0.1010**	0.0389	0.1459	0.0241	0.1105	*0.0106*	*0.0851*
	Thrp.UL	**0.0313**	**0.1339**	0.0514	0.1796	0.0352	0.1482	0.0490	0.1797	0.0452	0.1640	*0.0210*	*0.1184*
	RRC.connect	0.0072	0.0614	0.0441	0.1782	0.0041	0.0505	0.0616	0.2093	**0.0039**	**0.0464**	*0.0049*	*0.0497*
2	PRB.DL	**0.0300**	**0.1143**	0.0579	0.1731	0.0428	0.1426	0.0490	0.1615	0.0425	0.1424	*0.0141*	*0.0892*
	PRB.UL	**0.0346**	**0.1255**	0.1169	0.2846	0.0756	0.2153	0.0871	0.2416	0.0979	0.2586	*0.0156*	*0.0884*
	Traffic.DL	**0.0228**	**0.1050**	0.0398	0.1427	0.0646	0.1974	0.0372	0.1416	0.0296	0.1227	*0.0134*	*0.0841*
	Traffic.UL	**0.0505**	**0.1041**	0.0700	0.1348	0.0594	0.1134	0.0699	0.1362	0.0616	0.1172	*0.0167*	*0.0624*
	Num.user	**0.0596**	**0.1664**	0.1452	0.2942	0.0994	0.2413	0.1403	0.2867	0.1082	0.2500	*0.0162*	*0.0983*
	Thrp.DL	0.0426	0.1553	0.0826	0.2324	0.0396	0.1616	**0.0377**	**0.1365**	0.0483	0.1745	*0.0315*	*0.1355*
	Thrp.UL	**0.0235**	0.0922	0.0252	**0.0879**	0.0247	0.0900	0.0238	0.0881	0.0320	0.1150	*0.0104*	*0.0735*
	RRC.connect	**0.1205**	**0.2151**	0.2839	0.3935	0.2503	0.3567	0.3762	0.4835	0.3245	0.4331	*0.0411*	*0.1242*
3	PRB.DL	**0.0123**	**0.0827**	0.0208	0.1070	0.0150	0.0983	0.0356	0.1542	0.0167	0.1024	*0.0071*	*0.0672*
	PRB.UL	**0.0318**	**0.0956**	0.0490	0.1414	0.0323	0.0999	0.0703	0.1727	0.0430	0.1252	*0.0086*	*0.0713*
	Traffic.DL	**0.0234**	**0.1100**	0.0328	0.1373	0.0249	0.1209	0.0566	0.1982	0.0265	0.1230	*0.0154*	*0.0952*
	Traffic.UL	0.0371	0.0993	0.0505	0.1274	**0.0331**	0.1041	0.0447	**0.0980**	0.0662	0.1319	*0.0092*	*0.0721*
	Num.user	**0.0209**	**0.1164**	0.0626	0.2047	0.0312	0.1381	0.0769	0.2276	0.0388	0.1555	*0.0133*	*0.0962*
	Thrp.DL	**0.0416**	**0.1242**	0.0484	0.1278	0.0427	0.1321	0.0720	0.1622	0.0484	0.1438	*0.0102*	*0.0771*
	Thrp.UL	0.0545	0.0994	0.0609	0.1066	0.0560	0.0916	**0.0542**	**0.0853**	0.0557	0.1046	*0.0074*	*0.0671*
	RRC.connect	**0.0249**	**0.1278**	0.1947	0.3747	0.0590	0.1967	0.3086	0.4989	0.0737	0.2310	*0.0145*	*0.1022*
Average		**0.0316**	**0.1111**	0.0653	0.1694	0.0447	0.1336	0.0752	0.1827	0.0523	0.1448	*0.0139*	*0.0847*

MSE: mean squared error; MAE: mean absolute error. The best score of each group except fine-tuned TSNet is indicated in bold. The performance of TSNet fine-tuned with MinFT is in italics

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Prediction results of TSNet and baseline methods on evaluation datasets

Summary

- In this paper, we propose TSNet, a novel time-series foundation model designed for network status prediction in DTs.
- TSNet demonstrates competitive zero-shot prediction capability on diverse network status measurements, achieving the best prediction results regarding MSE and MAE on average compared with fully supervised prediction models trained with historical data.
- For future endeavors, we plan to explore TSNet’s capability for unified time-series representation, extending to various downstream tasks including time-series classification, anomaly detection, and pattern matching.

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