Language in the Flow of Time: Time-Series-Paired Texts Weaved into a Unified Temporal Narrative

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Abstract

While many advances in time series models focus exclusively on numerical data, research on multimodal time series, particularly those involving contextual textual information commonly encountered in real-world scenarios, remains in its infancy. With recent progress in large language models and time series learning, we revisit the integration of paired texts with time series through the *Platonic Representation Hypothesis* [11], which posits that representations of different modalities converge to shared spaces. In this context, we identify that time-series-paired texts may naturally exhibit periodic properties that closely mirror those of the original time series. Building on this insight, we propose a novel framework, Texts as Time Series (TaTS), which considers the time-series-paired texts to be auxiliary variables of the time series. TaTS can be plugged into *any* existing numerical-only time series models and enable them to handle time series data with paired texts effectively. Through extensive experiments on both multimodal time series forecasting and imputation tasks across benchmark datasets with various existing time series models, we demonstrate that TaTS can enhance predictive performance without modifying model architectures. Code is available at `https://github.com/iDEA-iSAIL-Lab-UIUC/TaTS`.

1 Introduction

Time series modeling plays an important role in many of real-world applications [30, 49, 7, 16, 18]. While extensive research has focused solely on the numerical values of time series [53, 22, 42, 37], real-world scenarios often involve additional modalities that co-occur with the time series and can provide valuable complementary information [4, 28, 17, 38]. In this work, we focus on **time-series paired with texts at each timestamp**, a common data format in real-world applications where textual descriptions are associated with time series at each timestamp in a parallel manner, as illustrated in Figure 3 (left).

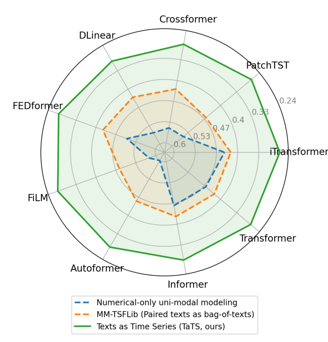
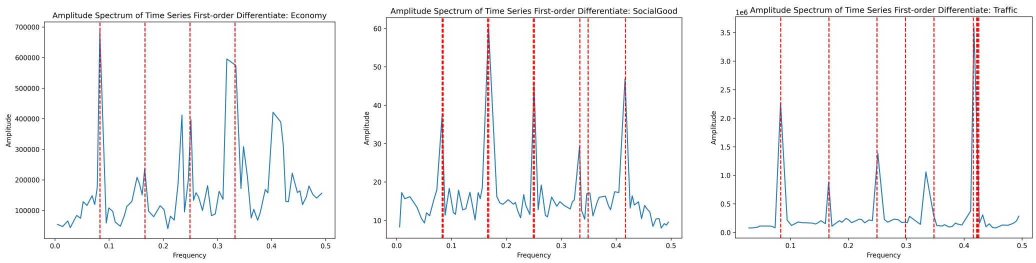


Figure 1: Mean Square Error of modeling frameworks of time series with paired texts on the Environment dataset. Full results in Appendix F.3.

Motivated by the *Platonic Representation Hypothesis (PRH)* [11], we pioneer the exploration of leveraging paired texts to enrich time series analysis. We identify **"Chronological Textual Resonance"** (CTR): depending on data quality, time-series-paired texts may exhibit periodic patterns that closely reflect the temporal dynamics of their corresponding numerical time series. Further, we introduce **TT-Wasserstein**, a new metric designed to measure the level of CTR and quantify alignment quality.

Building on these insights, we propose **Texts as Time Series** (TaTS), a simple yet effective framework for integrating paired texts to enhance multimodal time series modeling. Previous studies have shown that different variables in one multivariate time series exhibit similar periodicity properties [51, 38, 46],

NeurIPS 2025 Workshop on Recent Advances in Time Series Foundation Models (BERT^{2}S).



(a) Economy (b) Social Good (c) Traffic

Figure 2: By overlaying the top frequencies of paired texts (vertical dashed lines) onto the amplitude spectrum of the time series, it is observed that the time-series-paired texts exhibit similar periodic properties that closely mirror those of the original time series. We term this phenomenon *Chronological Textual Resonance*. More Details are provided in Appendix A.

and CTR suggests that time-series-paired texts follow a similar pattern. This observation implies that paired texts can be considered as special auxiliary variables to augment the original time series. TaTS offers two key benefits: (i) it effectively captures the evolving positional characteristics of texts paired with a time series by incorporating their projected representations into time series models; and (ii) it functions as a plug-in module, maintaining compatibility with existing time series models.

2 Chronological Textual Resonance (CTR)

The Platonic Representation Hypothesis (PRH) [11] posits that different modalities describing the same object converge towards a shared, latent representation. Extending this hypothesis, if time series and paired text both describe the same changing event, their representations can be seen as dynamic projections from a common underlying source, and should exhibit similar periodic properties. To illustrate this hypothesis for time series with paired texts, we analyze three real-world datasets [20]. For each dataset, we employ the Fourier Transform [25, 31] to analyze the frequency components of time series and the major frequencies of the texts, respectively illustrated by the blue curves and the dashed lines in Figure 2. Detailed process is provided in Appendix A. We find that, for these datasets, the major frequencies of the paired texts closely match those of the time series, which we term CTR.

Of course, we cannot expect every time series with paired texts at each timestamp to exhibit periodicity similarity. To this end, we propose a new metric for CTR, TT-Wasserstein, defined as the Wasserstein distance between the normalized spectra of time series and texts. Formally, based on Wasserstein distance $W(P, Q)$ [13], for time series with paired texts dataset $\mathcal{D} = \{\mathbf{X}, \mathbf{S}\}$, after computing normalized frequencies and amplitudes $\tilde{f}_{\text{texts}}, \tilde{f}_{\text{ts}}, \tilde{a}_{\text{texts}}, \tilde{a}_{\text{ts}}$,

$$\begin{gathered}\text{TT-Wasserstein}(\mathcal{D}) = W(P_{\text{texts}}, P_{\text{ts}}) = \inf_{\gamma \in \Pi(P_{\text{text}}, P_{\text{ts}})} \sum_{i=1}^{n} \sum_{j=1}^{m} \gamma_{ij} \cdot \left| \tilde{f}_{\text{texts}}^{(i)} - \tilde{f}_{\text{ts}}^{(j)} \right| \\ \text{Subject to} \quad \gamma_{ij} \geq 0, \quad \sum_{j=1}^{m} \gamma_{ij} = \tilde{a}_{\text{texts}}^{(i)}, \quad \sum_{i=1}^{n} \gamma_{ij} = \tilde{a}_{\text{ts}}^{(j)}\end{gathered} \tag{1}$$

TT-Wasserstein$(\mathcal{D})$ quantifies the discrepancy between the spectral distributions of paired texts and time series data. By design, a lower value of TT-Wasserstein$(\mathcal{D})$ should indicate a higher alignment.

3 Texts as Time Series

Transforming Concurrent Texts into Variables. Given the dataset $\mathcal{D} = \{\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N\}, \mathbf{S} = \{s_1, s_2, \ldots, s_T\}\}$, we first embed the texts using a text encoder $\mathcal{H}_{\text{text}}$ to obtain text embeddings $\mathbf{E} = \{e_1, e_2, \ldots, e_T\} \in \mathbb{R}^{d_{\text{text}} \times T}$. We reduce the dimensionality of the text embeddings by applying a Multi-Layer Perceptron (MLP) to d_{mapped}.

$$\mathbf{z}_t = \text{MLP}(\mathbf{e}_t; \theta_{\text{MLP}}) \in \mathbb{R}^{d_{\text{mapped}}}, \tag{2}$$

Unifying by Plugging-in a Time Series Model. The resulting mapped embeddings $\mathbf{Z} = \{\mathbf{z}_1, \mathbf{z}_2, \ldots, \mathbf{z}_T\} \in \mathbb{R}^{d_{\text{mapped}} \times T}$ are then treated as auxiliary variables in the time series. Specifi-

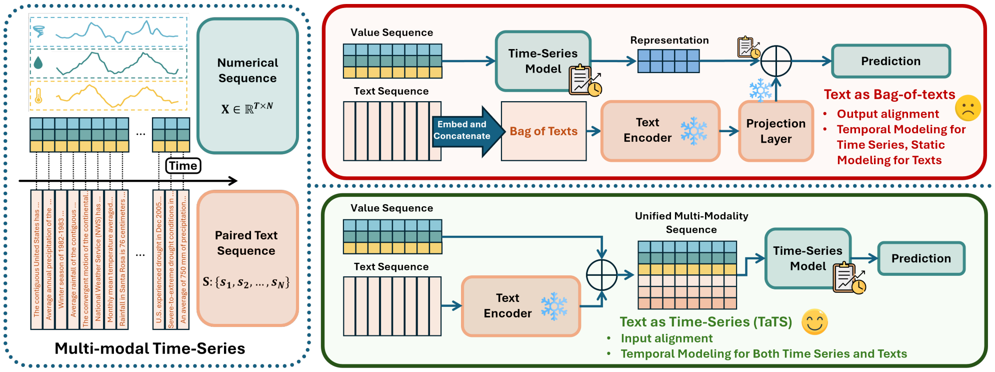


Figure 3: Texts as Time Series (TaTS) framework. As paired texts may exhibit behaviors similar to accompanying variables in a time series, TaTS transforms the paired texts into auxiliary variables. These variables augment the numerical sequence, forming a unified multimodal sequence that can be seamlessly integrated into any existing time series model.

cally, $\mathbf{Z}$ is concatenated with $\mathbf{X}$ to form a unified multimodal sequence:

$$\mathbf{U} = [\mathbf{X}; \mathbf{Z}^\intercal]_{\text{dim}=1} \in \mathbb{R}^{T \times (N + d_{\text{mapped}})}, \tag{3}$$

The unified sequence $\mathbf{U}$ is then passed into an existing time series model for downstream tasks. Here, we formulate the example of forecasting the next H steps of the time series

$$\widehat{\mathbf{X}}_{T+1:T+H} = \mathcal{F}\left(\mathbf{U}_{1:T}; \theta_{\text{forecast}}\right)[: N] \in \mathbb{R}^{H \times N}, \tag{4}$$

where $\mathcal{F}(\cdot; \theta_{\text{forecast}})$ denotes the time series forecasting model with parameters θ_{forecast}, and $[: N]$ extracts the first N variables corresponding to the original time series.

Finally, we train the time series model θ_{forecast} as well as the mapping MLP θ_{MLP} using MSE loss.

$$\mathcal{L}_{\text{forecast}}(\mathbf{X}, \widehat{\mathbf{X}}) = \frac{1}{H \cdot N} \sum_{t=T+1}^{T+H} \sum_{i=1}^{N} \left(\mathbf{X}_{t,i} - \widehat{\mathbf{X}}_{t,i}\right)^2, \tag{5}$$

where $\mathbf{X}_{t,i}$ and $\widehat{\mathbf{X}}_{t,i}$ represent the ground truth and predicted values of the i^{th} variable at time step t, respectively. TaTS for imputation follows a similar process and is omitted here due to space constraints. Detailed algorithms for both forecasting and imputation are provided in Appendix D.

4 Experiment

We empirically validate the effectiveness of the proposed TaTS framework. We use GPT2 [27] encoder to embed the paired texts. We also validate the performance of TaTS with other text encoders in section F.2 and Appendix F.8. Implementation details are in Appendix E.4.

Datasets. We evaluate our framework on 9 real-world datasets from a recent benchmark [20]. Further details about the datasets are in Appendix E.1.

Time Series Models and Baselines. We integrate TaTS with 9 widely used models across different categories, including transformer-based models [22, 24, 51, 40, 53, 34], linear models [47], frequency-based models [55, 54].

4.1 Main Results

Time Series Forecasting. Table 1 presents the performance results for the time series forecasting task. The full results for each prediction length are provided in Appendix F. From the results, our TaTS consistently achieves the best performance across all datasets. Notably, by plugging in TaTS to various existing time series models, it achieves an average performance improvement of over 5% on 6 out of 9 datasets. The results also demonstrate that TaTS is highly compatible with a wide range of existing time series forecasting models, consistently delivering performance improvements across all of them in both long-term forecasting and short-term forecasting tasks. We provide a visualization of the performance boost in Appendix F.3.

Table 1: Performance of time-series forecasting task. The results are averaged across all prediction lengths. Full results in Appendix F.4. *Promotion* (positive or negative) denotes the percentage reduction (or increase) in MSE or MAE achieved by TaTS compared to the best-performing baseline.

Models		iTransformer [2024]		PatchTST [2023]		Crossformer [2023]		DLinear [2023]		FEDformer [2022]		FiLM [2022]		Autoformer [2021]		Informer [2021]		Transformer [2017]	
Metric		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Agriculture	Uni-modal	0.122	0.251	0.120	0.247	0.323	0.406	0.223	0.354	0.138	0.286	0.139	0.256	0.158	0.297	0.599	0.630	0.354	0.434
	MM-TSFLib	0.112	0.230	0.114	0.233	0.218	0.313	0.218	0.355	0.131	0.275	0.140	0.258	0.158	0.288	0.313	0.414	0.249	0.352
	TaTS (ours)	0.109	0.229	0.114	0.235	0.212	0.312	0.214	0.351	0.131	0.276	0.135	0.251	0.125	0.266	0.255	0.348	0.191	0.313
	Promotion	2.7%	0.4%	0.0%	-0.9%	2.8%	0.3%	1.8%	0.8%	0.0%	-0.4%	2.9%	2.0%	20.9%	7.6%	18.5%	15.9%	23.3%	11.1%
Climate	Uni-modal	1.183	0.871	1.220	0.895	1.124	0.837	1.190	0.872	1.192	0.893	1.270	0.911	1.131	0.865	1.110	0.841	1.092	0.839
	MM-TSFLib	1.044	0.810	1.030	0.806	1.002	0.772	1.104	0.837	1.011	0.797	1.179	0.871	1.053	0.827	1.001	0.792	0.998	0.783
	TaTS (ours)	1.028	0.804	1.004	0.798	0.938	0.755	0.931	0.759	0.926	0.760	0.945	0.772	0.980	0.789	0.930	0.756	0.920	0.753
	Promotion	1.5%	0.7%	2.5%	1.0%	6.4%	2.2%	15.7%	9.3%	8.4%	4.6%	19.8%	11.4%	6.9%	4.6%	7.1%	4.5%	7.8%	3.8%
Economy	Uni-modal	0.014	0.096	0.017	0.105	0.758	0.828	0.058	0.192	0.042	0.166	0.025	0.129	0.071	0.207	1.325	1.110	0.584	0.711
	MM-TSFLib	0.011	0.086	0.014	0.096	0.250	0.458	0.058	0.192	0.035	0.153	0.026	0.129	0.058	0.192	0.432	0.618	0.213	0.416
	TaTS (ours)	0.008	0.077	0.009	0.079	0.219	0.419	0.021	0.117	0.015	0.101	0.009	0.080	0.024	0.121	0.299	0.512	0.079	0.232
	Promotion	27.3%	10.5%	35.7%	17.7%	12.4%	8.5%	63.8%	39.1%	57.1%	34.0%	64.0%	38.0%	58.6%	37.0%	30.8%	17.2%	62.9%	44.2%
Energy	Uni-modal	0.269	0.375	0.269	0.376	0.293	0.406	0.291	0.396	0.240	0.351	0.278	0.385	0.319	0.428	0.309	0.425	0.297	0.405
	MM-TSFLib	0.267	0.378	0.272	0.379	0.291	0.407	0.289	0.395	0.238	0.354	0.279	0.385	0.320	0.428	0.301	0.413	0.293	0.405
	TaTS (ours)	0.265	0.376	0.258	0.371	0.279	0.394	0.283	0.388	0.237	0.355	0.271	0.379	0.314	0.430	0.284	0.396	0.279	0.395
	Promotion	0.7%	-0.3%	4.1%	1.3%	4.1%	3.0%	2.1%	1.8%	0.4%	-1.1%	2.5%	1.6%	1.6%	-0.5%	5.6%	4.1%	4.8%	2.5%
Environment	Uni-modal	0.441	0.494	0.552	0.537	0.551	0.581	0.558	0.591	0.503	0.549	0.577	0.543	0.599	0.598	0.459	0.512	0.460	0.511
	MM-TSFLib	0.421	0.478	0.459	0.501	0.427	0.488	0.429	0.502	0.423	0.486	0.478	0.490	0.452	0.502	0.424	0.480	0.425	0.481
	TaTS (ours)	0.267	0.369	0.273	0.371	0.284	0.403	0.298	0.428	0.275	0.378	0.272	0.371	0.285	0.387	0.285	0.406	0.276	0.397
	Promotion	36.6%	22.8%	40.5%	25.9%	33.5%	17.4%	30.5%	14.7%	35.0%	22.2%	43.1%	24.3%	36.9%	22.9%	32.8%	15.4%	35.1%	17.5%
Health	Uni-modal	1.587	0.817	1.652	0.855	1.535	0.827	1.737	0.848	1.486	0.909	1.982	1.005	1.962	1.039	1.278	0.773	1.378	0.776
	MM-TSFLib	1.446	0.816	1.347	0.797	1.273	0.744	1.541	0.800	1.252	0.792	1.675	0.949	1.494	0.887	1.215	0.740	1.218	0.748
	TaTS (ours)	1.315	0.744	1.283	0.753	1.226	0.728	1.412	0.787	1.244	0.791	1.421	0.838	1.409	0.861	1.183	0.752	1.142	0.718
	Promotion	9.1%	8.8%	4.8%	5.5%	3.7%	2.2%	8.4%	1.6%	0.6%	0.1%	15.2%	11.7%	5.7%	2.9%	2.6%	-1.6%	6.2%	4.0%
Security	Uni-modal	115.94	5.660	112.85	5.371	126.96	6.277	109.11	4.711	114.48	5.158	115.55	5.487	115.27	5.118	131.78	6.623	131.35	6.582
	MM-TSFLib	116.34	5.532	112.84	5.369	125.72	6.183	108.03	4.712	113.73	5.107	109.19	4.897	111.44	4.973	128.95	6.415	128.47	6.378
	TaTS (ours)	112.05	5.151	109.69	5.019	125.16	6.148	107.92	4.676	107.37	4.718	107.85	4.736	108.49	4.787	126.66	6.276	124.58	6.134
	Promotion	3.4%	6.9%	2.8%	6.5%	0.4%	0.6%	0.1%	0.7%	5.6%	7.6%	1.2%	3.3%	2.7%	3.7%	1.8%	2.2%	3.0%	3.8%
Social Good	Uni-modal	1.212	0.483	1.097	0.495	0.865	0.467	1.151	0.712	0.979	0.476	1.261	0.654	1.278	0.701	0.870	0.504	0.910	0.484
	MM-TSFLib	1.197	0.520	1.073	0.515	0.837	0.398	1.083	0.673	0.962	0.462	1.236	0.626	1.229	0.670	0.839	0.457	0.856	0.461
	TaTS (ours)	0.987	0.452	0.972	0.465	0.779	0.412	1.006	0.622	0.888	0.430	1.104	0.626	1.195	0.666	0.810	0.459	0.807	0.419
	Promotion	17.5%	6.4%	9.4%	6.1%	6.9%	-3.5%	7.1%	7.6%	7.7%	6.9%	10.7%	0.0%	2.8%	0.6%	3.5%	-0.4%	5.7%	9.1%
Traffic	Uni-modal	0.213	0.238	0.188	0.242	0.214	0.376	0.230	0.359	0.205	0.264	0.215	0.314	0.212	0.298	0.202	0.355	0.209	0.346
	MM-TSFLib	0.199	0.347	0.178	0.230	0.188	0.334	0.209	0.330	0.193	0.238	0.207	0.300	0.212	0.272	0.172	0.299	0.171	0.295
	TaTS (ours)	0.187	0.217	0.172	0.209	0.168	0.286	0.188	0.300	0.173	0.212	0.176	0.248	0.177	0.229	0.164	0.281	0.164	0.274
	Promotion	6.0%	8.8%	3.4%	9.1%	10.6%	14.4%	10.0%	9.1%	10.4%	10.9%	15.0%	17.3%	16.5%	15.8%	4.7%	6.0%	4.1%	7.1%

Time Series Imputation. We also conduct Time Series Imputation task in Appendix F.5. Our TaTS framework effectively achieving notable improvements over baseline methods.

Further Empirical Analysis. We conduct hyperparameter sensitivity, ablation with different text encoders, ablation on corrupted datasets, computational overhead and performance gain. Due to space limitations, the details are provided in Appendix F.2. Overall, our findings demonstrate that TaTS remains robust across diverse configurations

TaTS Benefits from Better Alignment (i.e., lower TT-Wasserstein). We compute the average forecasting improvement of TaTS compared to numerical-only modeling, as well as the ratio of TT-Wasserstein between original and shuffled Time-MMD datasets. The results, shown in Table 7 in Appendix, reveal that, within the same sampling frequency, lower TT-Wasserstein original-shuffled ratios tend to correlate with larger performance gains from TaTS.

Comparison with Various Baselines. We compare our TaTS with covariate-based methods N-BEATS [26] and N-HiTS [3], convolution-based TCN [1], and the recent multimodal time series foundation model ChatTime [35]. The results are shown in Table 2. The results show that covariate-based and convolution-based models perform comparably or worse than iTransformer, and consistently underperform compared to our TaTS.

Table 2: TaTS compared several baselines.

Dataset	Climate		Security		Traffic	
Methods	MSE	MAE	MSE	MAE	MSE	MAE
iTransformer [2024]	1.127	<u>0.843</u>	<u>113.57</u>	<u>5.698</u>	<u>0.203</u>	<u>0.228</u>
N-BEATS [2020]	1.123	0.894	131.91	6.866	0.352	0.409
N-HiTS [2022]	<u>1.114</u>	0.881	135.41	6.896	0.295	0.372
TCN [2018]	1.137	0.875	129.61	6.801	0.779	0.775
ChatTime [2025]	1.507	1.007	130.75	6.854	0.369	0.435
iTransformer + TaTS **(ours)**	**1.020**	**0.797**	**107.11**	**4.856**	**0.174**	**0.218**

5 Conclusion

We identify *Chronological Textual Resonance*, where text embeddings exhibit periodic patterns similar to their paired time series. To leverage this insight, we propose a plug-and-play framework that transforms text representations into auxiliary variables. Extensive experiments demonstrate the state-of-the-art performance of our approach.

References

[1] Shaojie Bai, J. Zico Kolter, and Vladlen Koltun. An empirical evaluation of generic convolutional and recurrent networks for sequence modeling. *CoRR*, abs/1803.01271, 2018. URL http://arxiv.org/abs/1803.01271. 4

[2] Defu Cao, Furong Jia, Sercan Ö. Arik, Tomas Pfister, Yixiang Zheng, Wen Ye, and Yan Liu. TEMPO: prompt-based generative pre-trained transformer for time series forecasting. In *The Twelfth International Conference on Learning Representations, ICLR 2024, Vienna, Austria, May 7-11, 2024*. OpenReview.net, 2024. URL https://openreview.net/forum?id=YH5w12OUuU. 16

[3] Cristian Challu, Kin G. Olivares, Boris N. Oreshkin, Federico Garza, Max Mergenthaler, and Artur Dubrawski. N-hits: Neural hierarchical interpolation for time series forecasting. *CoRR*, abs/2201.12886, 2022. URL https://arxiv.org/abs/2201.12886. 4

[4] Shari De Baets and Nigel Harvey. Incorporating external factors into time series forecasts. In *Judgment in Predictive Analytics*, pages 265–287. Springer, 2023. 1

[5] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: pre-training of deep bidirectional transformers for language understanding. In Jill Burstein, Christy Doran, and Thamar Solorio, editors, *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2019, Minneapolis, MN, USA, June 2-7, 2019, Volume 1 (Long and Short Papers)*, pages 4171–4186. Association for Computational Linguistics, 2019. doi: 10.18653/V1/N19-1423. URL https://doi.org/10.18653/v1/n19-1423. 23

[6] Saeede Anbaee Farimani, Majid Vafaei Jahan, Amin Milani Fard, and Gholamreza Haffari. Leveraging latent economic concepts and sentiments in the news for market prediction. In *8th IEEE International Conference on Data Science and Advanced Analytics, DSAA 2021, Porto, Portugal, October 6-9, 2021*, pages 1–10. IEEE, 2021. doi: 10.1109/DSAA53316.2021.9564122. URL https://doi.org/10.1109/DSAA53316.2021.9564122. 16

[7] Dongqi Fu, Yada Zhu, Hanghang Tong, Kommy Weldemariam, Onkar Bhardwaj, and Jingrui He. Generating fine-grained causality in climate time series data for forecasting and anomaly detection. *CoRR*, abs/2408.04254, 2024. doi: 10.48550/ARXIV.2408.04254. URL https://doi.org/10.48550/arXiv.2408.04254. 1

[8] Sebastian Gerard, Yu Zhao, and Josephine Sullivan. Wildfirespreadts: A dataset of multi-modal time series for wildfire spread prediction. In Alice Oh, Tristan Naumann, Amir Globerson, Kate Saenko, Moritz Hardt, and Sergey Levine, editors, *Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 - 16, 2023*, 2023. URL http://papers.nips.cc/paper_files/paper/2023/hash/ebd545176bdaa9cd5d45954947bd74b7-Abstract-Datasets_and_Benchmarks.html. 16

[9] Nate Gruver, Marc Finzi, Shikai Qiu, and Andrew Gordon Wilson. Large language models are zero-shot time series forecasters. In Alice Oh, Tristan Naumann, Amir Globerson, Kate Saenko, Moritz Hardt, and Sergey Levine, editors, *Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 - 16, 2023*, 2023. URL http://papers.nips.cc/paper_files/paper/2023/hash/3eb7ca52e8207697361b2c0fb3926511-Abstract-Conference.html. 16

[10] Lei Huang, Weijiang Yu, Weitao Ma, Weihong Zhong, Zhangyin Feng, Haotian Wang, Qianglong Chen, Weihua Peng, Xiaocheng Feng, Bing Qin, and Ting Liu. A survey on hallucination in large language models: Principles, taxonomy, challenges, and open questions. *CoRR*, abs/2311.05232, 2023. doi: 10.48550/ARXIV.2311.05232. URL https://doi.org/10.48550/arXiv.2311.05232. 16

[11] Minyoung Huh, Brian Cheung, Tongzhou Wang, and Phillip Isola. Position: The platonic representation hypothesis. In *Forty-first International Conference on Machine Learning, ICML 2024, Vienna, Austria, July 21-27, 2024*. OpenReview.net, 2024. URL https://openreview.net/forum?id=BH8TYy0r6u. 1, 2

[12] Ming Jin, Shiyu Wang, Lintao Ma, Zhixuan Chu, James Y. Zhang, Xiaoming Shi, Pin-Yu Chen, Yuxuan Liang, Yuan-Fang Li, Shirui Pan, and Qingsong Wen. Time-llm: Time series forecasting by reprogramming large language models. In *The Twelfth International Conference on Learning Representations, ICLR 2024, Vienna, Austria, May 7-11, 2024*. OpenReview.net, 2024. URL https://openreview.net/forum?id=Unb5CVPtae. 16

[13] Leonid V Kantorovich. Mathematical methods of organizing and planning production. *Management science*, 6(4):366–422, 1960. 2

[14] Kai Kim, Howard Tsai, Rajat Sen, Abhimanyu Das, Zihao Zhou, Abhishek Tanpure, Mathew Luo, and Rose Yu. Multi-modal forecaster: Jointly predicting time series and textual data. *CoRR*, abs/2411.06735, 2024. doi: 10.48550/ARXIV.2411.06735. URL https://doi.org/10.48550/arXiv.2411.06735. 17

[15] Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In Yoshua Bengio and Yann LeCun, editors, *3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings*, 2015. URL http://arxiv.org/abs/1412.6980. 20

[16] Leander Kotzur, Peter Markewitz, Martin Robinius, and Detlef Stolten. Impact of different time series aggregation methods on optimal energy system design. *CoRR*, abs/1708.00420, 2017. URL http://arxiv.org/abs/1708.00420. 1

[17] Kwabena A Kyei and Albert Antwi. Internal and external factors of future returns in the banking business: Time series analysis of interrelationship. *Journal of Economics and Behavioral Studies*, 9(1 (J)):82–89, 2017. 1

[18] Li Li, Xiaonan Su, Yi Zhang, Yuetong Lin, and Zhiheng Li. Trend modeling for traffic time series analysis: An integrated study. *IEEE Trans. Intell. Transp. Syst.*, 16(6):3430–3439, 2015. doi: 10.1109/TITS.2015.2457240. URL https://doi.org/10.1109/TITS.2015.2457240. 1

[19] Desheng Liu and Shanshan Cai. A spatial-temporal modeling approach to reconstructing land-cover change trajectories from multi-temporal satellite imagery. *Annals of the Association of American Geographers*, 102(6):1329–1347, 2012. 16

[20] Haoxin Liu, Shangqing Xu, Zhiyuan Zhao, Lingkai Kong, Harshavardhan Kamarthi, Aditya B. Sasanur, Megha Sharma, Jiaming Cui, Qingsong Wen, Chao Zhang, and B. Aditya Prakash. Time-mmd: A new multi-domain multimodal dataset for time series analysis. *CoRR*, abs/2406.08627, 2024. doi: 10.48550/ARXIV.2406.08627. URL https://doi.org/10.48550/arXiv.2406.08627. 2, 3, 16, 19, 23

[21] Nelson F. Liu, Kevin Lin, John Hewitt, Ashwin Paranjape, Michele Bevilacqua, Fabio Petroni, and Percy Liang. Lost in the middle: How language models use long contexts. *Trans. Assoc. Comput. Linguistics*, 12:157–173, 2024. doi: 10.1162/TACL_A_00638. URL https://doi.org/10.1162/tacl_a_00638. 16

[22] Yong Liu, Tengge Hu, Haoran Zhang, Haixu Wu, Shiyu Wang, Lintao Ma, and Mingsheng Long. itransformer: Inverted transformers are effective for time series forecasting. In *The Twelfth International Conference on Learning Representations, ICLR 2024, Vienna, Austria, May 7-11, 2024*. OpenReview.net, 2024. URL https://openreview.net/forum?id=JePfAI8fah. 1, 3, 4, 16, 20, 25, 26, 27

[23] Björn Lütjens, Brandon Leshchinskiy, Océane Boulais, Farrukh Chishtie, Natalia Díaz Rodríguez, Margaux Masson-Forsythe, Ana Mata-Payerro, Christian Requena-Mesa, Aruna Sankaranarayanan, Aaron Piña, Yarin Gal, Chedy Raïssi, Alexander Lavin, and Dava Newman. Generating physically-consistent satellite imagery for climate visualizations. *IEEE Trans. Geosci. Remote. Sens.*, 62:1–11, 2024. doi: 10.1109/TGRS.2024.3493763. URL https://doi.org/10.1109/TGRS.2024.3493763. 16

[24] Yuqi Nie, Nam H. Nguyen, Phanwadee Sinthong, and Jayant Kalagnanam. A time series is worth 64 words: Long-term forecasting with transformers. In *The Eleventh International Conference on Learning Representations, ICLR 2023, Kigali, Rwanda, May 1-5, 2023*. OpenReview.net, 2023. URL https://openreview.net/forum?id=Jbdc0vTOcol. 3, 4, 16, 25, 26, 27, 34

[25] Henri J Nussbaumer. *The fast Fourier transform*. Springer, 1982. 2, 13

[26] Boris N. Oreshkin, Dmitri Carpov, Nicolas Chapados, and Yoshua Bengio. N-BEATS: neural basis expansion analysis for interpretable time series forecasting. In *8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020*. OpenReview.net, 2020. URL https://openreview.net/forum?id=r1ecqn4YwB. 4

[27] Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9, 2019. 3, 23

[28] Anish Rai, Salam Rabindrajit Luwang, Md Nurujjaman, Chittaranjan Hens, Pratyay Kuila, and Kanish Debnath. Detection and forecasting of extreme events in stock price triggered by fundamental, technical, and external factors. *Chaos, Solitons & Fractals*, 173:113716, 2023. 1

[29] Filipe Rodrigues, Ioulia Markou, and Francisco C. Pereira. Combining time-series and textual data for taxi demand prediction in event areas: A deep learning approach. *Inf. Fusion*, 49: 120–129, 2019. doi: 10.1016/J.INFFUS.2018.07.007. URL https://doi.org/10.1016/j.inffus.2018.07.007. 16

[30] Omer Berat Sezer, Mehmet Ugur Gudelek, and Ahmet Murat Özbayoglu. Financial time series forecasting with deep learning : A systematic literature review: 2005-2019. *Appl. Soft Comput.*, 90:106181, 2020. doi: 10.1016/J.ASOC.2020.106181. URL https://doi.org/10.1016/j.asoc.2020.106181. 1

[31] Ian Naismith Sneddon. *Fourier transforms*. Courier Corporation, 1995. 2, 13

[32] Mingtian Tan, Mike A. Merrill, Vinayak Gupta, Tim Althoff, and Thomas Hartvigsen. Are language models actually useful for time series forecasting? *CoRR*, abs/2406.16964, 2024. doi: 10.48550/ARXIV.2406.16964. URL https://doi.org/10.48550/arXiv.2406.16964. 16

[33] Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, Dan Bikel, Lukas Blecher, Cristian Canton-Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel Kloumann, Artem Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, Ranjan Subramanian, Xiaoqing Ellen Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu, Zheng Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurélien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom. Llama 2: Open foundation and fine-tuned chat models. *CoRR*, abs/2307.09288, 2023. doi: 10.48550/ARXIV.2307.09288. URL https://doi.org/10.48550/arXiv.2307.09288. 23

[34] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. In Isabelle Guyon, Ulrike von Luxburg, Samy Bengio, Hanna M. Wallach, Rob Fergus, S. V. N. Vishwanathan, and Roman Garnett, editors, *Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA*, pages 5998–6008, 2017. URL https://proceedings.neurips.cc/paper/2017/hash/3f5ee243547dee91fbd053c1c4a845aa-Abstract.html. 3, 4, 31, 32, 33

[35] Chengsen Wang, Qi Qi, Jingyu Wang, Haifeng Sun, Zirui Zhuang, Jinming Wu, Lei Zhang, and Jianxin Liao. Chattime: A unified multimodal time series foundation model bridging numerical and textual data. In Toby Walsh, Julie Shah, and Zico Kolter, editors, *AAAI-25, Sponsored by the Association for the Advancement of Artificial Intelligence, February 25 - March 4, 2025, Philadelphia, PA, USA*, pages 12694–12702. AAAI Press, 2025. doi: 10.1609/AAAI.V39I12.33384. URL https://doi.org/10.1609/aaai.v39i12.33384. 4, 17

[36] Xindi Wang, Mahsa Salmani, Parsa Omidi, Xiangyu Ren, Mehdi Rezagholizadeh, and Armaghan Eshaghi. Beyond the limits: A survey of techniques to extend the context length in large language models. In *Proceedings of the Thirty-Third International Joint Conference on Artificial Intelligence, IJCAI 2024, Jeju, South Korea, August 3-9, 2024*, pages 8299–8307. ijcai.org, 2024. URL https://www.ijcai.org/proceedings/2024/917. 16

[37] Yuxuan Wang, Haixu Wu, Jiaxiang Dong, Yong Liu, Mingsheng Long, and Jianmin Wang. Deep time series models: A comprehensive survey and benchmark. 2024. 1

[38] Yuxuan Wang, Haixu Wu, Jiaxiang Dong, Guo Qin, Haoran Zhang, Yong Liu, Yunzhong Qiu, Jianmin Wang, and Mingsheng Long. Timexer: Empowering transformers for time series forecasting with exogenous variables. *arXiv preprint arXiv:2402.19072*, 2024. 1

[39] Andrew Robert Williams, Arjun Ashok, Étienne Marcotte, Valentina Zantedeschi, Jithendaraa Subramanian, Roland Riachi, James Requeima, Alexandre Lacoste, Irina Rish, Nicolas Chapados, and Alexandre Drouin. Context is key: A benchmark for forecasting with essential textual information. *CoRR*, abs/2410.18959, 2024. doi: 10.48550/ARXIV.2410.18959. URL https://doi.org/10.48550/arXiv.2410.18959. 17

[40] Haixu Wu, Jiehui Xu, Jianmin Wang, and Mingsheng Long. Autoformer: Decomposition transformers with auto-correlation for long-term series forecasting. In Marc'Aurelio Ranzato, Alina Beygelzimer, Yann N. Dauphin, Percy Liang, and Jennifer Wortman Vaughan, editors, *Advances in Neural Information Processing Systems 34: Annual Conference on Neural Information Processing Systems 2021, NeurIPS 2021, December 6-14, 2021, virtual*, pages 22419–22430, 2021. URL https://proceedings.neurips.cc/paper/2021/hash/bcc0d400288793e8bdcd7c19a8ac0c2b-Abstract.html. 3, 4, 16, 31, 32, 33

[41] Haixu Wu, Tengge Hu, Yong Liu, Hang Zhou, Jianmin Wang, and Mingsheng Long. Timesnet: Temporal 2d-variation modeling for general time series analysis. In *The Eleventh International Conference on Learning Representations, ICLR 2023, Kigali, Rwanda, May 1-5, 2023*. OpenReview.net, 2023. URL https://openreview.net/forum?id=ju_Uqw384Oq. 20

[42] Haixu Wu, Tengge Hu, Yong Liu, Hang Zhou, Jianmin Wang, and Mingsheng Long. Timesnet: Temporal 2d-variation modeling for general time series analysis. In *International Conference on Learning Representations*, 2023. 1

[43] Zhe Xie, Zeyan Li, Xiao He, Longlong Xu, Xidao Wen, Tieying Zhang, Jianjun Chen, Rui Shi, and Dan Pei. Chatts: Aligning time series with llms via synthetic data for enhanced understanding and reasoning. *CoRR*, abs/2412.03104, 2024. doi: 10.48550/ARXIV.2412.03104. URL https://doi.org/10.48550/arXiv.2412.03104. 17

[44] Yumo Xu and Shay B. Cohen. Stock movement prediction from tweets and historical prices. In Iryna Gurevych and Yusuke Miyao, editors, *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics, ACL 2018, Melbourne, Australia, July 15-20, 2018, Volume 1: Long Papers*, pages 1970–1979. Association for Computational Linguistics, 2018. doi: 10.18653/V1/P18-1183. URL https://aclanthology.org/P18-1183/. 16

[45] Hao Xue and Flora D. Salim. Promptcast: A new prompt-based learning paradigm for time series forecasting. *IEEE Trans. Knowl. Data Eng.*, 36(11):6851–6864, 2024. doi: 10.1109/TKDE.2023.3342137. URL https://doi.org/10.1109/TKDE.2023.3342137. 16

[46] Kun Yi, Qi Zhang, Wei Fan, Shoujin Wang, Pengyang Wang, Hui He, Ning An, Defu Lian, Longbing Cao, and Zhendong Niu. Frequency-domain mlps are more effective learners in time series forecasting. *Advances in Neural Information Processing Systems*, 36, 2024. 1

[47] Ailing Zeng, Muxi Chen, Lei Zhang, and Qiang Xu. Are transformers effective for time series forecasting? In Brian Williams, Yiling Chen, and Jennifer Neville, editors, *Thirty-Seventh AAAI Conference on Artificial Intelligence, AAAI 2023, Thirty-Fifth Conference on Innovative Applications of Artificial Intelligence, IAAI 2023, Thirteenth Symposium on Educational Advances in Artificial Intelligence, EAAI 2023, Washington, DC, USA, February 7-14, 2023*, pages 11121–11128. AAAI Press, 2023. doi: 10.1609/AAAI.V37I9.26317. URL https://doi.org/10.1609/aaai.v37i9.26317. 3, 4, 16, 28, 29, 30, 34

[48] Weiqi Zhang, Jiexia Ye, Ziyue Li, Jia Li, and Fugee Tsung. Dualtime: A dual-adapter multimodal language model for time series representation. *CoRR*, abs/2406.06620, 2024. doi: 10.48550/ARXIV.2406.06620. URL https://doi.org/10.48550/arXiv.2406.06620. 17

[49] Xi Zhang, Yuan Pu, Yuki Kawamura, Andrew Loza, Yoshua Bengio, Dennis L. Shung, and Alexander Tong. Trajectory flow matching with applications to clinical time series modeling. *CoRR*, abs/2410.21154, 2024. doi: 10.48550/ARXIV.2410.21154. URL https://doi.org/10.48550/arXiv.2410.21154. 1

[50] Xiyuan Zhang, Ranak Roy Chowdhury, Rajesh K. Gupta, and Jingbo Shang. Large language models for time series: A survey. In *Proceedings of the Thirty-Third International Joint Conference on Artificial Intelligence, IJCAI 2024, Jeju, South Korea, August 3-9, 2024*, pages 8335–8343. ijcai.org, 2024. URL https://www.ijcai.org/proceedings/2024/921. 16

[51] Yunhao Zhang and Junchi Yan. Crossformer: Transformer utilizing cross-dimension dependency for multivariate time series forecasting. In *The Eleventh International Conference on Learning Representations, ICLR 2023, Kigali, Rwanda, May 1-5, 2023*. OpenReview.net, 2023. URL https://openreview.net/forum?id=vSVLM2j9eie. 1, 3, 4, 16, 25, 26, 27

[52] Dawei Zhou, Lecheng Zheng, Yada Zhu, Jianbo Li, and Jingrui He. Domain adaptive multimodality neural attention network for financial forecasting. In Yennun Huang, Irwin King, Tie-Yan Liu, and Maarten van Steen, editors, *WWW '20: The Web Conference 2020, Taipei, Taiwan, April 20-24, 2020*, pages 2230–2240. ACM / IW3C2, 2020. doi: 10.1145/3366423.3380288. URL https://doi.org/10.1145/3366423.3380288. 16

[53] Haoyi Zhou, Shanghang Zhang, Jieqi Peng, Shuai Zhang, Jianxin Li, Hui Xiong, and Wancai Zhang. Informer: Beyond efficient transformer for long sequence time-series forecasting. In *Thirty-Fifth AAAI Conference on Artificial Intelligence, AAAI 2021, Thirty-Third Conference on Innovative Applications of Artificial Intelligence, IAAI 2021, The Eleventh Symposium on Educational Advances in Artificial Intelligence, EAAI 2021, Virtual Event, February 2-9, 2021*, pages 11106–11115. AAAI Press, 2021. doi: 10.1609/AAAI.V35I12.17325. URL https://doi.org/10.1609/aaai.v35i12.17325. 1, 3, 4, 16, 31, 32, 33

[54] Tian Zhou, Ziqing Ma, Xue Wang, Qingsong Wen, Liang Sun, Tao Yao, Wotao Yin, and Rong Jin. Film: Frequency improved legendre memory model for long-term time series forecasting. In Sanmi Koyejo, S. Mohamed, A. Agarwal, Danielle Belgrave, K. Cho, and A. Oh, editors, *Advances in Neural Information Processing Systems 35: Annual Conference on Neural Information Processing Systems 2022, NeurIPS 2022, New Orleans, LA, USA, November 28 - December 9, 2022*, 2022. URL http://papers.nips.cc/paper_files/paper/2022/hash/524ef58c2bd075775861234266e5e020-Abstract-Conference.html. 3, 4, 16, 28, 29, 30, 34

[55] Tian Zhou, Ziqing Ma, Qingsong Wen, Xue Wang, Liang Sun, and Rong Jin. Fedformer: Frequency enhanced decomposed transformer for long-term series forecasting. In Kamalika Chaudhuri, Stefanie Jegelka, Le Song, Csaba Szepesvári, Gang Niu, and Sivan Sabato, editors, *International Conference on Machine Learning, ICML 2022, 17-23 July 2022, Baltimore, Maryland, USA*, volume 162 of *Proceedings of Machine Learning Research*, pages 27268–27286. PMLR, 2022. URL https://proceedings.mlr.press/v162/zhou22g.html. 3, 4, 16, 28, 29, 30

Appendix

Roadmap. In this appendix, we provide a detailed overview of our methodology and experimental setup. Appendix A outlines the complete process of frequency analysis for both time series and paired texts. Appendix B discusses of preprints that are related to this work. Appendix D illustrates the TaTS algorithms for time series forecasting and imputation. Appendix E includes details on datasets, hyperparameters, evaluation metrics, and additional implementation specifics. Due to space constraints in the main text, Appendix F presents the full experimental results, including comprehensive forecasting and imputation outcomes, hyperparameter and ablation studies, efficiency evaluations, and visualizations. The table of contents is provided below for reference.

Table of Contents

A Detailed Frequency Analysis Process of Time Series with Paired Texts

Here, we provide a detailed explanation of the frequency analysis process for both the time series and their paired texts. In Proposition A.1 and A.2, we simplify the proof by analyzing each periodic component individually as a single cosine. This is without loss of generality, as the operations involved are linear. Therefore, the conclusions naturally extend to signals composed of multiple periodic components through linear superposition.

Proposition A.1. *The computation of lag similarity preserves the original periodicities of the data.*

Proof. Let $\mathbf{S} = \{s_t\}_{t=1}^{T}$ represent the paired texts or data sequence, where each s_t corresponds to a time step t. Define the lag similarity at lag k as:

$$\text{LagSim}(k) = \frac{1}{T-k} \sum_{t=1}^{T-k} \text{sim}(s_t, s_{t+k}), \tag{6}$$

where $\text{sim}(\cdot, \cdot)$ is a similarity measure (e.g., cosine similarity).

Now, consider the periodic component of the data sequence $\mathbf{S}$, which can be represented as:

$$s_t = A \cos\left(\frac{2\pi t}{P} + \phi\right), \tag{7}$$

where A is the amplitude, P is the period, and ϕ is the phase.

For two points separated by lag k, the similarity $\text{sim}(s_t, s_{t+k})$ depends on the relative difference between their phases:

$$s_{t+k} = A \cos\left(\frac{2\pi(t+k)}{P} + \phi\right) = A \cos\left(\frac{2\pi t}{P} + \frac{2\pi k}{P} + \phi\right). \tag{8}$$

The lag similarity is then computed as:

$$\text{LagSim}(k) = \frac{1}{T-k} \sum_{t=1}^{T-k} \text{sim}\left(A \cos\left(\frac{2\pi t}{P} + \phi\right), A \cos\left(\frac{2\pi t}{P} + \frac{2\pi k}{P} + \phi\right)\right). \tag{9}$$

Since the cosine function is periodic with period P, the similarity $\text{sim}(s_t, s_{t+k})$ also inherits this periodicity. Therefore, the overall lag similarity $\text{LagSim}(k)$ retains the periodicities of the original sequence $\mathbf{S}$.

Thus, the computation of lag similarity preserves the original periodicities of the data. $\square$

Proposition A.2. *The stabilization of a data sequence using first-order differentiation preserves its original periodicities.*

Proof. Let $\mathbf{S} = \{s_t\}_{t=1}^{T}$ represent a data sequence, where s_t is the value at time step t. The first-order differentiation of the sequence is defined as:

$$\Delta s_t = s_{t+1} - s_t, \quad t = 1, 2, \ldots, T-1. \tag{10}$$

Suppose the sequence $\mathbf{S}$ exhibits periodic behavior with period P and can be represented as:

$$s_t = A \cos\left(\frac{2\pi t}{P} + \phi\right), \tag{11}$$

where A is the amplitude, P is the period, and ϕ is the phase.

The first-order difference of s_t is:

$$\Delta s_t = s_{t+1} - s_t = A \cos\left(\frac{2\pi(t+1)}{P} + \phi\right) - A \cos\left(\frac{2\pi t}{P} + \phi\right). \tag{12}$$

Using the trigonometric identity for the difference of cosines:

$$\cos(x+y) - \cos(x) = -2 \sin\left(\frac{y}{2}\right) \sin\left(x + \frac{y}{2}\right), \tag{13}$$

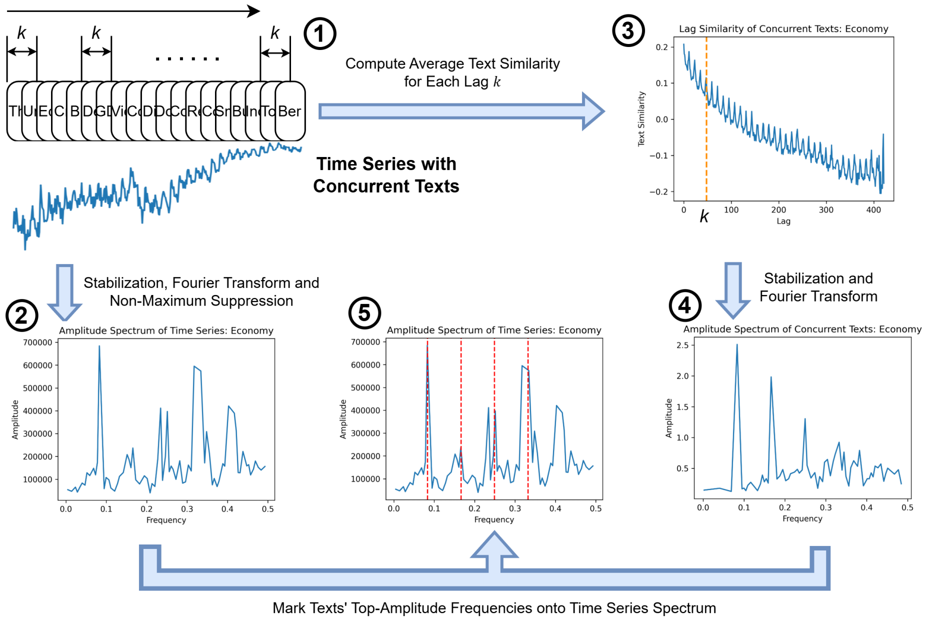


Figure 4: Illustration of the frequency analysis process for time series with paired texts in the Economy dataset. Step ①: Compute the average text similarity for each lag k. Step ②: Stabilize the time series using first-order differentiation, apply Fourier Transform, and perform Non-Maximum Suppression (NMS) to obtain the amplitude spectrum. Step ③: Visualize the lag similarity of paired texts. Step ④: Stabilize the paired texts, compute the Fourier Transform, and visualize the amplitude spectrum. Step ⑤: Overlay the top-l (here l=4) frequencies of paired texts onto the time series amplitude spectrum to highlight shared periodic patterns. All the data transformation operations in this process are periodicity-preserving according to Proposition A.1 and Proposition A.2.

we set $x = \frac{2\pi t}{P} + \phi$ and $y = \frac{2\pi}{P}$, giving:

$$\Delta s_t = -2A \sin\left(\frac{\pi}{P}\right) \sin\left(\frac{2\pi t}{P} + \phi + \frac{\pi}{P}\right). \tag{14}$$

The first term, $\sin\left(\frac{\pi}{P}\right)$, is a constant dependent on the period P. The second term, $\sin\left(\frac{2\pi t}{P} + \phi + \frac{\pi}{P}\right)$, retains the periodicity of P, as it is a sinusoidal function with the same frequency as the original sequence.

Thus, the first-order difference Δs_t preserves the periodicity P of the original data sequence. $\square$

The overall process of frequency analysis for the time series $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N\} \in \mathbb{R}^{T\times N}$ and paired texts $\mathbf{S} = \{s_1, s_2, \ldots, s_T\}$ in the Economy dataset $\mathcal{D}_{\text{Economy}} = \{\mathbf{X}, \mathbf{S}\}$ is illustrated in Figure 4. In this process, starting from the original dataset (subfigure ①), the time series and paired texts are analyzed independently. **For the time series $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N\}$, we perform standard frequency analysis**, stabilizing the data through first-order differentiation.

$$\Delta \mathbf{X}_t = \mathbf{X}_{t+1} - \mathbf{X}_t, \quad \text{for } t = 1, 2, \ldots, T-1, \tag{15}$$

where $\Delta \mathbf{X}_t$ represents the first-order difference of the time series. This step removes long-term trends and ensures that the data is stationary, allowing for a more accurate analysis of its frequency components.

Then, we compute the Fourier Transform [25, 31] of $\Delta \mathbf{X}$ to analyze its frequency components. The Fourier Transform of $\Delta \mathbf{X}$ is defined as:

$$\mathcal{F}_{\Delta \mathbf{X}}(f) = \sum_{t=1}^{T-1} \Delta \mathbf{X}_t e^{-i2\pi f t}, \tag{16}$$

where f represents the frequency, $\Delta \mathbf{X}_t$ is the first-order difference of the time series at time t, and i is the imaginary unit. The resulting $\mathcal{F}_{\Delta \mathbf{X}}(f)$ provides the amplitude and phase information of each frequency component present in the time series.

The magnitude spectrum, which represents the amplitude of each frequency component, is computed as:

$$|\mathcal{F}_{\Delta \mathbf{X}}(f)| = \sqrt{\mathrm{Re}(\mathcal{F}_{\Delta \mathbf{X}}(f))^2 + \mathrm{Im}(\mathcal{F}_{\Delta \mathbf{X}}(f))^2}, \tag{17}$$

where $\mathrm{Re}(\mathcal{F}_{\Delta \mathbf{X}}(f))$ and $\mathrm{Im}(\mathcal{F}_{\Delta \mathbf{X}}(f))$ are the real and imaginary parts of $\mathcal{F}_{\Delta \mathbf{X}}(f)$, respectively.

By analyzing $|\mathcal{F}_{\Delta \mathbf{X}}(f)|$, we identify the dominant frequencies in the time series, which reveal its periodic patterns. To further highlight the dominant frequencies, we apply Non-Maximum Suppression (NMS) to the magnitude spectrum $|\mathcal{F}_{\Delta \mathbf{X}}(f)|$. NMS ensures that only the most prominent frequencies are retained while suppressing nearby less significant frequencies. The NMS operation is defined as follows:

$$\mathcal{N}(f) = \begin{cases} |\mathcal{F}_{\Delta \mathbf{X}}(f)|, & \text{if } |\mathcal{F}_{\Delta \mathbf{X}}(f)| > |\mathcal{F}_{\Delta \mathbf{X}}(f')| \, \forall f' \in \mathcal{N}(f), \\ 0, & \text{otherwise,} \end{cases} \tag{18}$$

where $\mathcal{N}(f)$ represents a local neighborhood around the frequency f. The operation compares the magnitude of $|\mathcal{F}_{\Delta \mathbf{X}}(f)|$ with those of neighboring frequencies and retains only the largest value within the neighborhood. Frequencies that do not satisfy the condition are set to zero.

After applying NMS, the remaining frequencies represent the dominant periodic components of the time series, making it easier to identify significant periodic patterns. This process eliminates noise and reduces the influence of minor frequency components, enhancing the interpretability of the spectrum. The final visualization of the amplitude spectrum of the time series is shown in Figure 4, subfigure ②.

For the paired texts $\mathbf{S} = \{s_1, s_2, \dots, s_T\}$, we first embed each s_t using the text encoder $\mathcal{H}_{\text{text}}$:

$$\mathbf{e}_t = \mathcal{H}_{\text{text}}(s_t; \theta_{\text{text}}) \in \mathbb{R}^{d_{\text{text}}}, \tag{19}$$

where θ_{text} represents the parameters of the text encoder, and $\mathbf{e}_t$ is the resulting text embedding at timestamp t.

Since the text embeddings are typically close in the embedding space, leading to similar cosine similarity values, we normalize the embeddings by centering them around their mean to improve numerical stability and enhance sensitivity to differences. Specifically, we compute the mean embedding:

$$\mathbf{e}_{\text{mean}} = \frac{1}{T} \sum_{t=1}^{T} \mathbf{e}_t, \tag{20}$$

and shift all embeddings by subtracting the mean:

$$\mathbf{e}'_t = \mathbf{e}_t - \mathbf{e}_{\text{mean}}, \tag{21}$$

where $\mathbf{e}'_t$ represents the centered (shifted) embeddings.

Next, we compute the average text similarity for each lag $k \in \{1, T-1\}$ as:

$$\mathrm{Sim}(k) = \frac{1}{T-k} \sum_{t=1}^{T-k} \mathrm{sim}(\mathbf{e}'_t, \mathbf{e}'_{t+k}), \tag{22}$$

where $\mathrm{sim}(\mathbf{e}'_t, \mathbf{e}'_{t+k})$ denotes the similarity measure (e.g., cosine similarity) between the centered embeddings at time t and $t+k$, defined as:

$$\mathrm{sim}(\mathbf{e}'_t, \mathbf{e}'_{t+k}) = \frac{\mathbf{e}'_t \cdot \mathbf{e}'_{t+k}}{\|\mathbf{e}'_t\| \|\mathbf{e}'_{t+k}\|}. \tag{23}$$

We visualize the lag similarity of paired texts, $\mathrm{Sim}(k)$, in Figure 4, subfigure ③. Subsequently, we stabilize the data by applying first-order differentiation and perform a Fourier Transform, following a similar process as previously described for the time series frequency analysis. The final visualization of the amplitude spectrum of the paired texts is presented in Figure 4, subfigure ④.

Then, we compute the frequencies with the top-l amplitudes from the lag similarity $\text{Sim}(k)$. We apply the Fourier Transform to $\text{Sim}(k)$:

$$\mathcal{F}_{\text{text}}(f) = \sum_{t=1}^{T-1} \text{Sim}(k)\, e^{-i2\pi f t}, \tag{24}$$

where f is the frequency, and $\mathcal{F}_{\text{text}}(f)$ represents the complex Fourier coefficients corresponding to each frequency f.

Next, we compute the amplitude spectrum as:

$$|\mathcal{F}_{\text{text}}(f)| = \sqrt{\text{Re}(\mathcal{F}_{\text{text}}(f))^2 + \text{Im}(\mathcal{F}_{\text{text}}(f))^2}, \tag{25}$$

where $\text{Re}(\mathcal{F}_{\text{text}}(f))$ and $\text{Im}(\mathcal{F}_{\text{text}}(f))$ are the real and imaginary parts of $\mathcal{F}_{\text{text}}(f)$, respectively.

We then identify the top-l dominant frequencies by selecting the l frequencies corresponding to the largest amplitudes:

$$\mathcal{F}_{\text{top}} = \{f_i \mid |\mathcal{F}_{\text{text}}(f_i)| \text{ is among the top-}l \text{ largest amplitudes}\}. \tag{26}$$

These top-l frequencies represent the most significant periodic components of the paired texts, revealing their dominant temporal patterns. we overlay the top-l (in the Economy dataset l=4) frequencies of the paired texts onto the amplitude spectrum of the time series, as illustrated in Figure 4, subfigure ⑤.

We also visualize the frequency analysis process in the Social Good dataset and Traffic dataset respectively in Figure 5 and Figure 6.

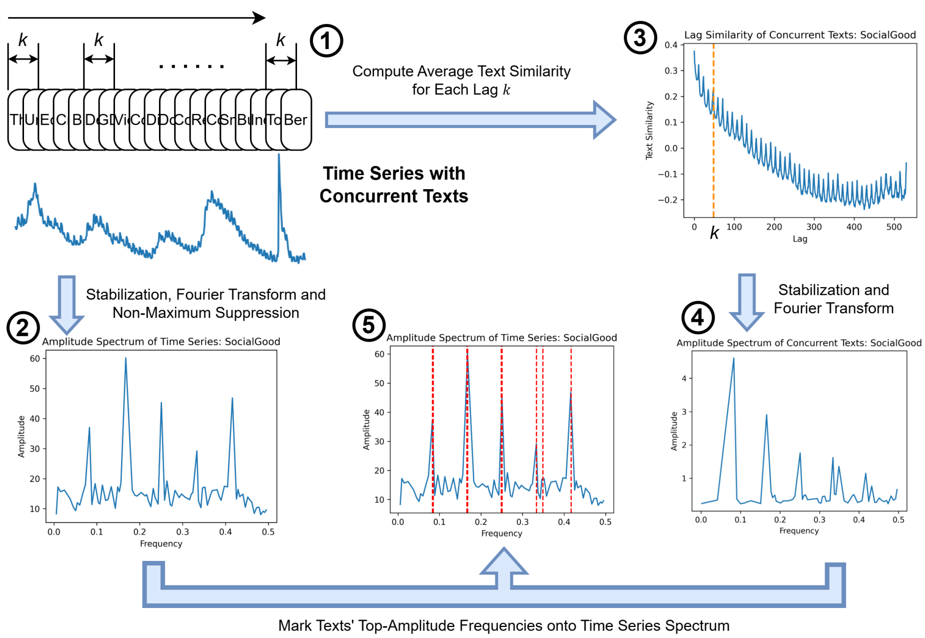


Figure 5: Illustration of the frequency analysis process for time series with paired texts in the Social Good dataset. In Step ⑤, we overlay the top-9 frequencies of paired texts onto the time series amplitude spectrum.

B Further Discussion

C Related Work

Numerical-only Time Series Modeling. Recently, various deep learning models have been developed for time series analysis, which can be broadly categorized into three categories. (1) **Patch-based**

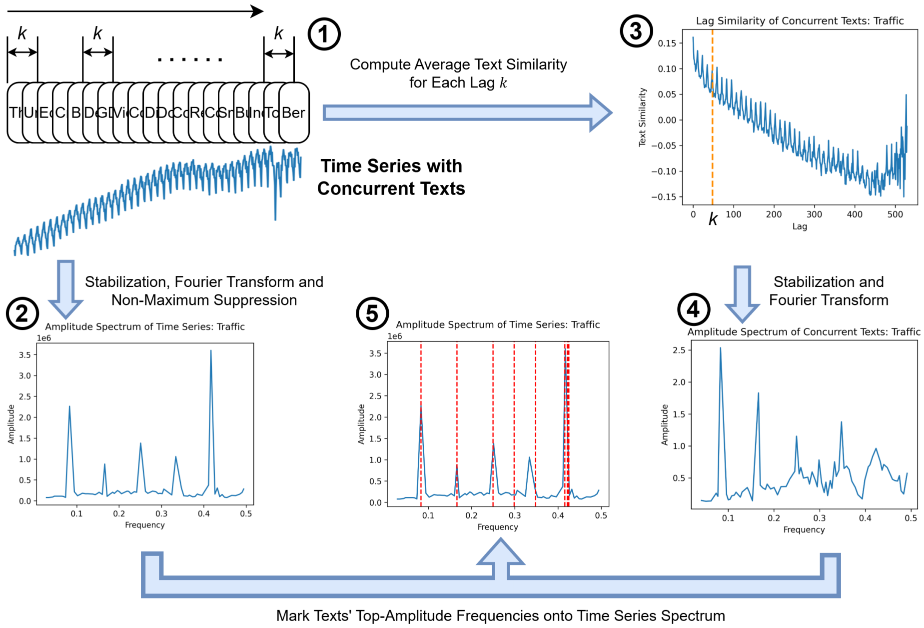


Figure 6: Illustration of the frequency analysis process for time series with paired texts in the Traffic dataset. In Step ⑤, we overlay the top-7 frequencies of paired texts onto the time series amplitude spectrum.

models. PatchTST [24] segments time series into subseries-level patches to capture dependencies, while Crossformer [51] employs a two-stage attention mechanism to model both cross-time and cross-variable dependencies efficiently. Autoformer [40] introduces decomposition blocks to separate seasonal and trend-cyclical components. (2) **Global representation models.** iTransformer [22] utilizes attention over global series representations to capture multivariate correlations. Informer [53] reduces self-attention complexity using ProbSparse self-attention for improved efficiency. Dlinear [47] demonstrates that simple linear regression in the raw space can perform competitively on MTS tasks. (3) **Frequency-aware models.** FEDformer [55] represents series through randomly selected Fourier components, while FiLM [54] enhances representations with frequency-based layers to reduce noise and accelerate training. In this work, our proposed TaTS is compatible with all of the models listed above.

Time Series with other data sources. In the financial domain, several early works have explored integrating time series with textual data, albeit not in a timestamp-aligned manner, or often leveraging general machine learning models rather than time series-specific architectures. For example, StockNet [44] uses a VAE-like model for chaotic stock-text data, while [29] fuses time series with a single event-related document. BoEC [6] applies a bag-of-economic-concepts approach, and Dandelion [52] leverages multimodal attention for feature aggregation from multiple text sources. Some works also explored time series with vision information [19, 8, 23] for spatio-temporal analysis. Recently, Time-MMD [20] constructs a dataset of time series paired with parallel text, covering multiple domains, which we used in our main experiments.

Large Language Models on Time Series. The rapid advancement of Large Language Models (LLMs) has inspired a new line of research that transforms time series into natural language representations, enabling LLMs to perform downstream tasks [50]. While these approaches demonstrate strong generalization capabilities due to the power of LLMs [9, 2, 12, 45], they also inherit limitations such as hallucination [10] and context length constraints [36, 21]. Notably, a recent work [32] suggests that replacing complex LLM architectures with basic attention layers does not necessarily degrade the performance.

In Appendix B, we also discuss available preprints that are related to this research.

C.1 Concurrent Works

We discuss concurrent preprints available online that relate to this research, providing a more comprehensive understanding of existing works and ongoing efforts to integrate texts into time series modeling.

[39] introduces a benchmark (CiK) for time-series forecasting that integrates both numerical data and textual context. While both [39] and our work emphasize the integration of textual context into time series forecasting, the textual contexts in [39] are descriptions regarding the time series itself, but in our work, we do not have such a constraint.

[14] develops a hybrid forecaster that jointly predicts both time series and textual data by projecting time series to the language space and fine-tuning the pre-trained LLM. Their assumption is that though LLMs are originally for language but not for time series, they can be fine-tuned to adapt to time series.

[48] introduces a dual-adapter model for time series and textual data, but their data format is similar to [35], where the whole time series is paired with one text.

[43] proposes a novel multimodal LLM framework (TS-MLLM) that treats time series as a modality akin to images. But they are using synthetic generation and focus on NLP tasks rather than time series forecasting.

C.2 Limitations

This work focuses on revealing and quantifying Chronological Textual Resonance (CTR) and designing the TaTS framework to leverage it. However, several limitations remain. First, we do not thoroughly investigate the data construction processes that may induce CTR, such as biases introduced during text collection or the choice of contextual information. Understanding how these factors affect CTR would provide deeper insights into the robustness and generalizability of our approach. Second, we do not analyze how text embeddings are utilized at the neural level within the TaTS framework. A more detailed study on how the model learns temporal patterns from paired texts could inform improvements in architecture design. Third, the effectiveness of TaTS is influenced by the quality and relevance of paired texts. While we study cases where texts are randomly shuffled, real-world texts could have different patterns, and the model's performance may degrade. Future work could explore methods to assess and enhance text quality or develop more robust models to handle noisy input. Lastly, while TaTS demonstrates strong empirical performance across benchmark datasets, its generalization to other types of multimodal time series or domains with fundamentally different patterns remains untested, for example, time series with paired images or audio. We leave these investigations and improvements for future work.

C.3 Ethical Impact Statement

Our work is solely focused on the technical challenge of multimodal time series and does not involve any elements that could pose ethical risks.

D Algorithms

Algorithm 1: Texts as Time Series for Forecasting Task

Input: Time series with concurrent texts embeddings
$\mathcal{D} = \{\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N\}, \mathbf{E} = \{e_1, e_2, \ldots, e_T\}\}$ in the input training dataset; prediction length H.

Output: TaTS model parameters $\Theta = \{\theta_{\text{forecast}}, \theta_{\text{MLP}}\}$.

Prepare training samples of sequence length L and prediction length H as:

$$\{\mathbf{X}^{(i)} = \mathbf{X}_{l_i+1:l_i+L}, \mathbf{E}^{(i)} = \mathbf{X}_{l_i+1:l_i+L}, \mathbf{Y}^{(i)} = \mathbf{X}_{l_i+L+1:l_i+L+H}\}_{i=1}^{n}$$

Initialize time series model $\mathcal{F}(\cdot; \theta_{\text{forecast}})$; projector MLP$(\cdot; \theta_{\text{MLP}})$ for dimensionality reduction.

while *not converged* **do**
  for *each training sample* $\{\mathbf{X}^{(i)}, \mathbf{E}^{(i)}, \mathbf{Y}^{(i)}\}$ **do**
    Map $\mathbf{E}^{(i)}$ to $\mathbf{Z}^{(i)}$: $\mathbf{Z}^{(i)}[j] = \text{MLP}(\mathbf{E}^{(i)}[j]; \theta_{\text{MLP}})$
    Compute $\mathbf{U} = [\mathbf{X}^{(i)}; (\mathbf{Z}^{(i)})^{\intercal}]_{\text{dim=1}}$ as shown in Eq. (3).
    Forecast: $\widehat{\mathbf{X}}^{(i)} = \mathcal{F}(\mathbf{U}; \theta_{\text{forecast}})[: N]$
    Optimize: $\arg\min_{\Theta=\{\theta_{\text{forecast}}, \theta_{\text{MLP}}\}} \mathcal{L}_{\text{forecast}}(\mathbf{X}^{(i)}, \widehat{\mathbf{X}}^{(i)})$ as shown in Eq. (5)

return TaTS model parameters $\Theta = \{\theta_{\text{forecast}}, \theta_{\text{MLP}}\}$

Algorithm 2: Texts as Time Series for Imputation Task

Input: Time series with concurrent text embeddings
$\mathcal{D} = \{\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N\}, \mathbf{E} = \{e_1, e_2, \ldots, e_T\}\}$ in the input training dataset; binary mask $\mathbf{M} \in \{0, 1\}^{T \times N}$.

Output: TaTS model parameters $\Theta = \{\theta_{\text{impute}}, \theta_{\text{MLP}}\}$.

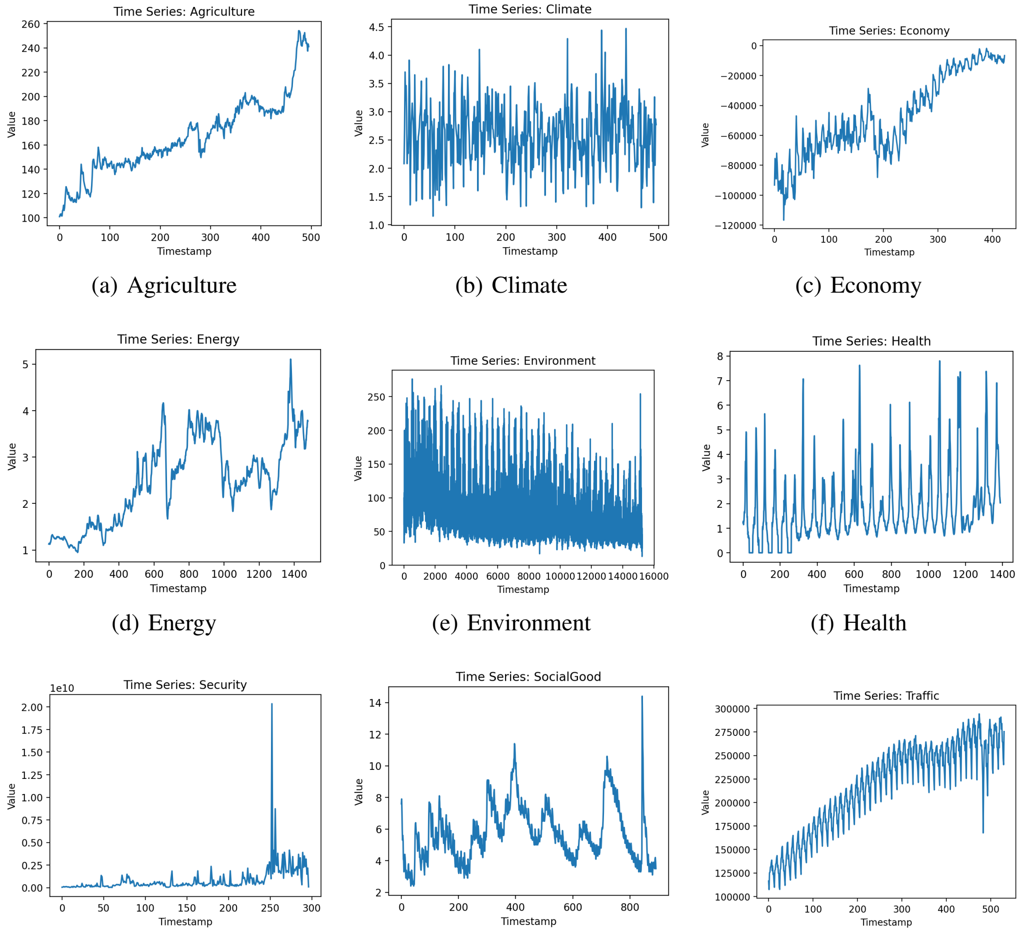
Prepare training samples with observed entries:

$$\{\mathbf{X}^{(i)} = \mathbf{X}_{l_i+1:l_i+L}, \mathbf{E}^{(i)} = \mathbf{E}_{l_i+1:l_i+L}, \mathbf{M}^{(i)} = \mathbf{M}_{l_i+1:l_i+L}\}_{i=1}^{n}$$

Initialize time series imputation model $\mathcal{G}(\cdot; \theta_{\text{impute}})$; projector MLP$(\cdot; \theta_{\text{MLP}})$ for dimensionality reduction.

while *not converged* **do**
  for *each training sample* $\{\mathbf{X}^{(i)}, \mathbf{E}^{(i)}, \mathbf{M}^{(i)}\}$ **do**
    Map $\mathbf{E}^{(i)}$ to $\mathbf{Z}^{(i)}$: $\mathbf{Z}^{(i)}[j] = \text{MLP}(\mathbf{E}^{(i)}[j]; \theta_{\text{MLP}})$
    Construct the augmented input: $\mathbf{U} = [(\mathbf{X}^{(i)} \odot \mathbf{M}^{(i)}); (\mathbf{Z}^{(i)})^{\intercal}]_{\text{dim=1}}$
    Impute missing values: $\widehat{\mathbf{X}}^{\text{Imputed}(i)} = \mathcal{G}(\mathbf{U}; \theta_{\text{impute}})$
    Optimize: $\arg\min_{\Theta=\{\theta_{\text{impute}}, \theta_{\text{MLP}}\}} \mathcal{L}_{\text{impute}}(\mathbf{X}^{(i)}, \widehat{\mathbf{X}}^{\text{Imputed}(i)})$

return TaTS model parameters $\Theta = \{\theta_{\text{impute}}, \theta_{\text{MLP}}\}$



(a) Agriculture (b) Climate (c) Economy

(d) Energy (e) Environment (f) Health

(g) Security (h) Social Good (i) Traffic

Figure 7: Visualization of the numerical data in each multimodal time series dataset.

Table 3: Overview of the numerical data in the experimental datasets [20]. Our experiments utilize 9 datasets spanning multiple domains. “Prediction Length" refers to the number of future time points to be forecasted, with each dataset including four distinct prediction settings. refers to the number of variables (or variates) in each dataset.

Dataset Name/Domain	Prediction Length	Dimension	Frequency	Number of Samples	Timespan
Agriculture	{6, 8, 10, 12}	1	Monthly	496	1983 - Present
Climate	{6, 8, 10, 12}	5	Monthly	496	1983 - Present
Economy	{6, 8, 10, 12}	3	Monthly	423	1989 - Present
Energy	{12, 24, 36, 48}	9	Weekly	1479	1996 - Present
Environment	{48, 96, 192, 336}	4	Daily	11102	1982 - 2023
Health	{12, 24, 36, 48}	11	Weekly	1389	1997 - Present
Security	{6, 8, 10, 12}	1	Monthly	297	1999 - Present
Social Good	{6, 8, 10, 12}	1	Monthly	900	1950 - Present
Traffic	{6, 8, 10, 12}	1	Monthly	531	1980 - Present

E Experiment Details

E.1 Dataset Statistics and Details

Table 3 provides a summary of the statistics for the publicly available real-world datasets. Additionally, we visualize the numerical data for each multimodal time series dataset in Figure 7. For further details, please refer to the original work that introduced these datasets and benchmarks [20].

Table 4: Default hyperparameters for the TaTS framework

Hyperparameter	Description	Value or Choices
batch_size	The batch size for training	32
criterion	The criterion for calculating loss	Mean Square Error (MSE)
learning_rate	The learning rate for the optimizer	{0.0001, 0.00005, 0.00001}
seq_len	Input sequence length	24
label_len	Start token length for prediction	12
prior_weight	Weight for prior combination	{0, 0.1, 0.2, 0.3, 0.5}
train_epochs	Number of training epochs	50
patience	Early stopping patience	20
text_emb	Dimension of text embeddings	{6, 12, 24}
learning_rate2	Learning rate for MLP layers	{0.005, 0.01, 0.02, 0.05}
pool_type	Pooling type for embeddings	“avg"
init_method	Initialization method for combined weights	“normal"
dropout	dropout	0.1
use_norm	whether to use normalize	True

E.2 Hyperparameters

We use Adam optimizer [15] when training the neural networks. The default choices of hyperparameters in our code are provided in Table 4. For LLM-based text encoders, we initialize them using the default configurations provided by Hugging Face[1]. Consistent with existing works [41, 22], we apply instance normalization to standardize the time series data within each dataset.

E.3 Metrics

Throughout this paper, we use the following metrics to evaluate performance:

MSE (Mean Squared Error): Measures the average squared difference between the predicted and actual values. It penalizes larger errors more heavily, making it sensitive to outliers.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2, \tag{27}$$

where y_i and $\hat{y}_i$ denote the ground truth and predicted values, respectively, and n is the number of data points.

MAE (Mean Absolute Error): Represents the average absolute difference between the predicted and actual values, providing a more interpretable measure of average error magnitude.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right|. \tag{28}$$

RMSE (Root Mean Squared Error): The square root of MSE, which provides an error measure in the same units as the original data. It is more sensitive to large deviations than MAE.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}. \tag{29}$$

MAPE (Mean Absolute Percentage Error): Expresses errors as a percentage of the actual values, offering a scale-independent metric that facilitates comparisons across datasets.

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100. \tag{30}$$

[1] https://huggingface.co/

MSPE (Mean Squared Percentage Error): Similar to MAPE but squares the percentage error, penalizing larger percentage deviations more heavily.

$$\mathrm{MSPE} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i - \hat{y}_i}{y_i}\right)^2. \tag{31}$$

These metrics collectively provide a comprehensive evaluation of model performance, capturing both absolute and relative errors as well as their sensitivity to outliers. For all metrics, **lower values indicate better performance**.

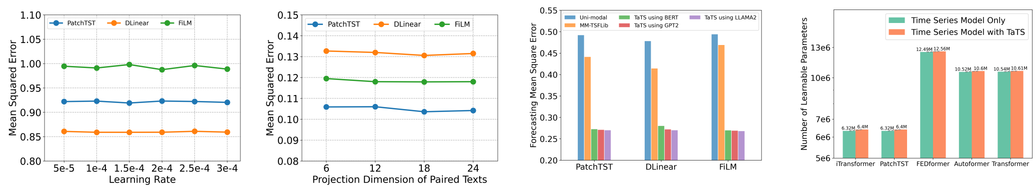
E.4 Implementation Details

E.4.1 Code and Reproducibility

The code for the experiments is included in the supplementary material, accompanied by a comprehensive README file. We provide detailed commands, scripts, and instructions to facilitate running the code. Additionally, the datasets used in the experiments are provided in the supplementary material as CSV files.

E.4.2 Hardware and Environment

We conducted all experiments on an Ubuntu 22.04 machine equipped with an Intel(R) Xeon(R) Gold 6240R CPU @ 2.40GHz, 1.5TB of RAM, and a 32GB NVIDIA V100 GPU. The CUDA version used was 12.4. All algorithms were implemented in Python (version 3.11.11). To run our code, users must install several commonly used libraries, including pandas, scikit-learn, patool, tqdm, sktime, matplotlib, transformers, and others. Detailed installation instructions can be found in the README file within the code directory. We have optimized our code to ensure efficiency. Our tests confirmed that the CPU memory usage remains below 16 GB, while the GPU memory usage is under 20 GB. Additionally, the execution time for a single experiment is less than 10 minutes on our machine.



(a) (b) (c) (d)

Figure 8: Further analysis of our TaTS framework. (a) Learning rate sensitivity: TaTS maintains stable performance across different learning rates (full results in Appendix F.6). (b) Text Projection Dimension sensitivity: TaTS remains robust across varying d_{mapped} (full results in Appendix F.7). (c) Varying text encoder: TaTS consistently outperforms baselines across different text encoders (full results in Appendix F.8). (d) Efficiency: TaTS introduces only a minor parameter increase ($\sim 1\%$) but significantly improves the performance according to Table 1.

F Full Experiment Results

F.1 Why should we leverage CTR?

Table 5: Performance on time series forecasting task. Leveraging periodicity with a single-dimension feature can significantly reduce the prediction error.

Method	Economy		Social Good		Traffic	
	MSE(↓)	**MAE(↓)**	**MSE(↓)**	**MAE(↓)**	**MSE(↓)**	**MAE(↓)**
Uniformly Random $(+)$	5.673	2.356	2.059	1.230	1.207	0.995
Uniformly Random $(\pm)$	11.535	2.879	8.860	2.404	3.794	1.618
Normally Random	9.284	2.878	2.926	1.374	3.163	1.511
Exponentially Random	4.521	1.960	3.724	1.564	1.141	0.911
Using 1D Text only	**1.995**	**1.404**	**1.315**	**0.853**	**0.714**	**0.797**

Parallel text provides complementary information and expert knowledge that can significantly enhance the understanding of time series data. To demonstrate the benefits of utilizing periodicity in the text modality, we present an illustrative example in the univariate forecasting task, where the goal is to use $\mathbf{X}_{1:T} = \{\mathbf{x}_1\} \in \mathbb{R}^{T\times 1}$ to predict the next H values, $\widehat{\mathbf{X}}_{T+1:T+H}$. We first concatenate the text embeddings to form $\mathbf{E} = [e_1; e_2; \ldots; e_T]_{\text{dim=1}} \in \mathbb{R}^{d_{\text{text}}\times T}$, then replace $\mathbf{x}_1$ with only the first dimension of the text embeddings to leverage very partial text periodicity, $\mathbf{x}_1' = (\mathbf{E}[1,:])^\intercal \in \mathbb{R}^{T\times 1}$. In other words, we rely solely on a single evolving dimension of the paired text features to forecast future time series values.

As shown in Table 5, leveraging just the periodicity of a single text feature significantly outperforms random time series forecasting. The random baselines mean that the forecasts are purely random according to several different distributions. These random baselines use the training data as well, for example, normally random computes the mean and standard deviation of a normal distribution to forecast the time series. These results highlight that even partial periodicity from the text modality contributes valuable insights for improving forecasting accuracy.

F.2 Further Experimental Analysis

Hyperparameter Sensitivity. We perform hyperparameter studies to evaluate the impact of (i) the learning rate and (ii) d_{mapped}, the dimension to which high-dimensional text embeddings are projected by the MLP, as defined in Equation 2. The results are presented in Figure 8, subfigures (a) and (b), with full results available in Appendix F.6 and Appendix F.7. The findings indicate that TaTS maintains robust performance across different choices of the learning rate and the text projection dimension d_{mapped}.

Table 7: TT-Wasserstein measure of Time-MMD [20] datasets and their random shuffle.

Dataset	Monthly Sampled Agriculture	Climate	Economy	Security	Social Good	Traffic	Weekly Sampled Energy	Health	Daily Sampled Environment
Ratio of Original to Shuffled TT-Wasserstein (%)	26.8	72.4	22.3	91.5	38.2	34.6	97.1	85.6	83.6
Avg. Improvement of TaTS over uni-modal (%)	20.70	18.03	64.80	4.05	10.99	16.78	3.62	19.51	36.00

Ablation with Different Text Encoders in TaTS. While GPT-2 was used as the primary text encoder in our main experiments to demonstrate the effectiveness of TaTS, we further evaluate the performance of TaTS with different text encoders, including BERT [5], GPT-2 [27], and LLaMA2 [33]. We utilize the official implementations available on Hugging Face and present the results in Figure 8, with full results provided in Appendix F.8. The results show that TaTS remains robust across different text encoders and consistently outperforms both the uni-modal and MM-TSFLib baselines. Notably, as the size of the language models used in TaTS increases from 110M (BERT) to 1.5B (GPT-2) and further to 7B (LLaMA2), we observe a slight improvement in performance. Investigating the relationship between the text encoder size and TaTS's effectiveness remains an open direction for future research.

Ablation on Corrupted Datasets. To validate that the performance gains stem from useful textual cues, we conducted corruption experiments where the textual information was randomly shuffled across timestamps. All other settings are unchanged, and the results are in Table 6. The results demonstrate that when textual alignment is destroyed, the model's performance drops significantly to matching or even being worse than the uni-modal baseline. This is expected, as randomly shuffled text acts as noise rather than a meaningful signal.

Table 6: Ablation study of TaTS on text-shuffled datasets.

Dataset	Climate		Security		Traffic	
Methods	MSE	MAE	MSE	MAE	MSE	MAE
iTransformer + TaTS + original data	1.020	0.797	107.11	4.856	0.174	0.218
iTransformer + TaTS + corrupted data	1.147	0.831	116.48	5.714	0.208	0.270
iTransformer + uni-modal + original data	1.127	0.843	113.57	5.698	0.203	0.228

Computational Overhead vs. Performance Gain. We also evaluate the efficiency of our proposed TaTS by measuring the training time per epoch and the total number of model parameters. Figure 8 (d) presents the total number of parameters for the best-performing models in our forecasting experiments. TaTS introduces only a lightweight three-layer MLP to project high-dimensional text embeddings into a lower-dimensional space, adding a minimal number of parameters compared to the original time series models. As a result, the overall parameter count increases by only about 1%.

Due to the inclusion of augmented time series with auxiliary variables from paired texts, the training time per epoch increases slightly, as shown in Figure 9, with average performance of each framework indicated by cross markers. Full results for all datasets are provided in Appendix F.9. However, this marginal efficiency trade-off ($\sim 1\%$ in terms of number of learnable parameters and $\sim 8\%$ in terms of training time) leads to significant improvements ($\sim 14\%$) in forecasting performance, demonstrating the effectiveness of TaTS in enhancing time series modeling with paired texts.

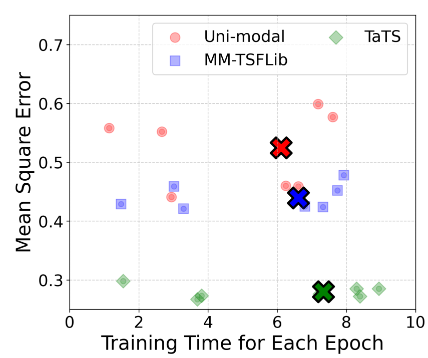


Figure 9: Efficiency comparison on Environment dataset. While TaTS incurs a slight increase in training time due to the augmentation of auxiliary variables, it significantly enhances forecasting accuracy. Full results in Appendix F.9.

F.3 Full Forecasting Performance Comparison Visualization

To provide a comprehensive comparison of different frameworks for modeling time series with paired texts, we visualize the forecasting performance using radar plots in Figure F.3. Each subfigure corresponds to a dataset, with each axis representing a different time series model. The axes are inverted, where values closer to the center indicate worse performance, and larger areas signify better results. The results demonstrate that TaTS consistently outperforms both baselines across all datasets while maintaining compatibility with various time series models.

(a) Agriculture (b) Climate (c) Economy

(d) Energy (e) Environment (f) Health

(g) Security (h) Social Good (i) Traffic

Figure 10: Comparison of different frameworks for modeling time series with paired texts. Our TaTS achieves the best performance across all datasets and is compatible with various existing time series models.

F.4 Full Forecasting Results

Due to space limitations, we provide the full results of the time series forecasting task on paired time series and text in the appendix. We conduct extensive experiments across 9 datasets using 9 existing time series models, evaluating various prediction lengths as detailed in Table 3. The complete results are presented from Table 8 to Table 16. Overall, TaTS consistently achieves the best performance across all datasets, time series models, and prediction lengths. The averaged results across all prediction lengths are summarized in the main text (Table 1). For better readability, we also visualize the performance of different frameworks using radar plots, as detailed in Appendix F.3 and Figure 10.

Table 8: Full forecasting results for the Agriculture, Climate, and Economy datasets using iTransformer, PatchTST, and Crossformer as time series models. Compared to numerical-only unimodal modeling and MM-TSFLib, our TaTS framework seamlessly enhances existing time series models to effectively handle time series with concurrent texts. Avg: the average results across all prediction lengths.

Models			iTransformer [2024]					PatchTST [2023]					Crossformer [2023]				
Method			MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE
Agriculture	Uni-modal	6	0.077	0.200	0.274	0.090	0.014	0.074	0.197	0.269	0.090	0.014	0.222	0.331	0.412	0.136	0.031
		8	0.104	0.228	0.315	0.100	0.017	0.104	0.234	0.317	0.104	0.018	0.304	0.406	0.496	0.168	0.044
		10	0.142	0.273	0.372	0.119	0.024	0.136	0.262	0.357	0.112	0.021	0.357	0.435	0.530	0.176	0.049
		12	0.167	0.301	0.400	0.128	0.026	0.168	0.294	0.396	0.124	0.025	0.409	0.451	0.582	0.181	0.054
		Avg	0.122	0.251	0.340	0.109	0.020	0.120	0.247	0.335	0.107	0.020	0.323	0.406	0.505	0.165	0.044
	MM-TSFLib	6	0.070	0.189	0.261	0.085	0.013	0.071	0.183	0.261	0.082	0.012	0.146	0.259	0.331	0.106	0.020
		8	0.091	0.212	0.296	0.093	0.016	0.093	0.212	0.296	0.093	0.015	0.171	0.278	0.354	0.112	0.022
		10	0.130	0.248	0.346	0.105	0.019	0.126	0.251	0.344	0.108	0.020	0.252	0.344	0.428	0.136	0.032
		12	0.158	0.272	0.377	0.112	0.022	0.168	0.288	0.391	0.119	0.024	0.304	0.372	0.471	0.144	0.036
		Avg	0.112	0.230	0.320	0.099	0.018	0.114	0.233	0.323	0.100	0.018	0.218	0.313	0.396	0.124	0.027
	TaTS (ours)	6	0.067	0.184	0.256	0.083	0.012	0.066	0.171	0.247	0.076	0.011	0.148	0.264	0.332	0.108	0.020
		8	0.094	0.210	0.297	0.091	0.015	0.096	0.217	0.300	0.094	0.016	0.197	0.298	0.374	0.119	0.026
		10	0.122	0.251	0.341	0.109	0.020	0.126	0.260	0.349	0.113	0.021	0.216	0.315	0.397	0.124	0.028
		12	0.153	0.271	0.374	0.112	0.022	0.166	0.292	0.394	0.123	0.025	0.289	0.371	0.466	0.145	0.036
		Avg	0.109	0.229	0.317	0.099	0.017	0.114	0.235	0.323	0.101	0.018	0.212	0.312	0.392	0.124	0.027
Climate	Uni-modal	6	1.127	0.843	1.052	2.549	50.662	1.259	0.915	1.122	3.168	105.890	1.159	0.852	1.076	3.036	148.840
		8	1.191	0.876	1.088	3.208	134.908	1.208	0.878	1.099	2.778	64.950	1.104	0.829	1.051	2.600	123.988
		10	1.215	0.885	1.100	3.169	123.266	1.218	0.894	1.103	2.746	55.831	1.127	0.829	1.057	3.246	193.108
		12	1.199	0.879	1.091	2.752	65.916	1.197	0.891	1.092	3.177	115.617	1.105	0.837	1.047	3.322	194.844
		Avg	1.183	0.871	1.083	2.920	93.688	1.220	0.895	1.104	2.967	85.572	1.124	0.837	1.058	3.051	165.195
	MM-TSFLib	6	1.031	0.787	1.013	2.298	38.389	1.003	0.800	1.001	2.652	57.709	0.995	0.758	0.996	2.393	51.345
		8	1.039	0.809	1.017	2.598	49.903	1.012	0.790	1.005	2.387	42.258	1.016	0.773	1.007	2.824	107.865
		10	1.049	0.817	1.020	2.547	55.014	1.036	0.813	1.016	2.293	28.894	0.999	0.779	0.997	2.740	95.790
		12	1.057	0.828	1.025	2.894	87.976	1.071	0.822	1.032	2.965	95.248	0.997	0.777	0.994	2.240	43.968
		Avg	1.044	0.810	1.019	2.584	57.821	1.030	0.806	1.014	2.574	56.027	1.002	0.772	0.998	2.549	74.742
	TaTS (ours)	6	1.020	0.797	1.007	2.563	56.209	0.976	0.782	0.987	2.318	33.843	0.924	0.747	0.961	1.895	20.405
		8	1.025	0.797	1.011	2.391	38.756	0.995	0.803	0.997	2.574	57.639	0.923	0.757	0.961	2.318	51.592
		10	1.033	0.808	1.014	2.647	77.697	1.022	0.796	1.007	2.657	76.287	0.963	0.764	0.979	2.439	59.881
		12	1.033	0.812	1.013	2.607	58.107	1.022	0.810	1.009	2.436	42.471	0.943	0.754	0.967	2.220	40.186
		Avg	1.028	0.804	1.011	2.552	57.692	1.004	0.798	1.000	2.496	52.560	0.938	0.755	0.967	2.218	43.016
Economy	Uni-modal	6	0.015	0.099	0.124	0.035	0.002	0.017	0.104	0.129	0.036	0.002	0.659	0.749	0.806	0.257	0.076
		8	0.014	0.098	0.120	0.034	0.002	0.016	0.104	0.128	0.036	0.002	0.661	0.767	0.808	0.263	0.076
		10	0.014	0.094	0.119	0.033	0.002	0.017	0.104	0.130	0.036	0.002	0.836	0.884	0.911	0.303	0.097
		12	0.013	0.091	0.112	0.032	0.002	0.018	0.109	0.135	0.037	0.002	0.875	0.912	0.932	0.313	0.101
		Avg	0.014	0.096	0.119	0.034	0.002	0.017	0.105	0.131	0.036	0.002	0.758	0.828	0.864	0.284	0.087
	MM-TSFLib	6	0.011	0.081	0.103	0.028	0.001	0.014	0.094	0.118	0.033	0.002	0.209	0.420	0.450	0.143	0.024
		8	0.011	0.085	0.106	0.029	0.001	0.015	0.099	0.123	0.034	0.002	0.214	0.424	0.456	0.145	0.024
		10	0.012	0.090	0.110	0.031	0.001	0.013	0.091	0.115	0.031	0.002	0.277	0.463	0.522	0.158	0.032
		12	0.012	0.090	0.110	0.031	0.001	0.016	0.099	0.124	0.034	0.002	0.299	0.526	0.540	0.180	0.034
		Avg	0.011	0.086	0.107	0.030	0.001	0.014	0.096	0.120	0.033	0.002	0.250	0.458	0.492	0.156	0.029
	TaTS (ours)	6	0.008	0.077	0.090	0.027	0.001	0.009	0.080	0.097	0.028	0.001	0.140	0.312	0.367	0.106	0.016
		8	0.008	0.077	0.090	0.027	0.001	0.008	0.078	0.091	0.027	0.001	0.212	0.426	0.454	0.145	0.024
		10	0.009	0.079	0.093	0.027	0.001	0.009	0.079	0.092	0.027	0.001	0.302	0.510	0.544	0.174	0.034
		12	0.008	0.076	0.091	0.026	0.001	0.009	0.080	0.096	0.028	0.001	0.222	0.428	0.466	0.145	0.025
		Avg	0.008	0.077	0.091	0.027	0.001	0.009	0.079	0.094	0.028	0.001	0.219	0.419	0.458	0.142	0.025

Table 9: Full forecasting results for the Energy, Environment, and Health datasets using iTransformer, PatchTST, and Crossformer as time series models. Compared to numerical-only unimodal modeling and MM-TSFLib, our TaTS framework seamlessly enhances existing time series models to effectively handle time series with concurrent texts. Avg: the average results across all prediction lengths.

Models			iTransformer [2024]					PatchTST [2023]					Crossformer [2023]				
Method			MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE
Energy	Uni-modal	12	0.112	0.231	0.305	0.940	10.877	0.105	0.229	0.301	1.120	40.016	0.138	0.262	0.338	1.121	31.808
		24	0.222	0.352	0.438	1.626	35.711	0.241	0.363	0.458	1.507	41.679	0.281	0.399	0.482	1.619	46.008
		36	0.306	0.409	0.511	1.767	58.611	0.304	0.408	0.512	1.782	60.280	0.331	0.443	0.541	3.296	229.673
		48	0.435	0.509	0.617	2.454	95.250	0.427	0.502	0.610	2.405	91.255	0.422	0.521	0.626	4.574	347.533
		Avg	0.269	0.375	0.468	1.697	50.112	0.269	0.376	0.470	1.704	58.307	0.293	0.406	0.497	2.652	163.756
	MM-TSFLib	12	0.107	0.228	0.300	0.999	17.267	0.115	0.242	0.311	1.357	30.739	0.126	0.251	0.326	1.141	30.653
		24	0.223	0.354	0.443	1.692	45.580	0.236	0.361	0.453	1.506	35.353	0.268	0.389	0.477	1.875	69.289
		36	0.313	0.424	0.520	1.916	63.383	0.311	0.413	0.518	1.885	64.280	0.338	0.454	0.553	2.956	202.647
		48	0.423	0.507	0.615	2.494	101.822	0.426	0.501	0.610	2.404	95.489	0.433	0.534	0.637	4.716	415.767
		Avg	0.267	0.378	0.469	1.775	57.013	0.272	0.379	0.473	1.788	56.465	0.291	0.407	0.498	2.672	179.589
	TaTS (ours)	12	0.106	0.234	0.302	1.116	30.716	0.106	0.234	0.300	1.024	17.615	0.127	0.254	0.326	1.053	18.277
		24	0.226	0.355	0.439	1.555	34.060	0.206	0.336	0.417	1.491	35.509	0.253	0.376	0.462	1.823	62.566
		36	0.306	0.411	0.512	1.790	57.729	0.305	0.412	0.506	1.781	57.481	0.312	0.431	0.524	2.602	144.944
		48	0.421	0.502	0.612	2.370	91.346	0.416	0.501	0.607	2.427	93.658	0.425	0.516	0.619	3.314	183.016
		Avg	0.265	0.376	0.466	1.708	53.463	0.258	0.371	0.457	1.681	51.066	0.279	0.394	0.483	2.198	102.201
Environment	Uni-modal	48	0.415	0.473	0.604	2.218	214.087	0.492	0.500	0.644	2.315	238.477	0.495	0.509	0.651	2.275	235.830
		96	0.439	0.493	0.630	2.338	250.510	0.541	0.538	0.693	2.390	256.244	0.562	0.585	0.712	1.880	130.832
		192	0.454	0.506	0.661	2.462	259.311	0.581	0.556	0.741	2.727	356.251	0.567	0.607	0.739	1.659	90.234
		336	0.455	0.505	0.671	2.446	276.348	0.593	0.553	0.763	2.898	424.764	0.582	0.621	0.761	1.656	80.409
		Avg	0.441	0.494	0.641	2.366	250.064	0.552	0.537	0.710	2.583	318.934	0.551	0.581	0.716	1.867	134.326
	MM-TSFLib	48	0.413	0.470	0.600	2.187	211.597	0.441	0.489	0.621	1.954	159.971	0.421	0.472	0.604	1.982	161.068
		96	0.420	0.478	0.616	2.233	213.865	0.461	0.495	0.643	2.063	177.553	0.425	0.485	0.617	1.839	128.131
		192	0.423	0.482	0.636	2.320	225.635	0.462	0.508	0.664	2.203	214.665	0.427	0.495	0.638	1.830	125.150
		336	0.429	0.483	0.651	2.308	236.965	0.472	0.513	0.683	2.210	220.009	0.434	0.500	0.656	1.867	128.536
		Avg	0.421	0.478	0.626	2.262	222.016	0.459	0.501	0.653	2.107	193.049	0.427	0.488	0.629	1.879	135.721
	TaTS (ours)	48	0.268	0.370	0.480	1.140	21.157	0.271	0.377	0.483	1.115	19.355	0.274	0.373	0.485	1.152	20.952
		96	0.267	0.370	0.488	1.123	20.955	0.279	0.376	0.498	1.176	21.868	0.284	0.391	0.505	1.127	18.484
		192	0.272	0.366	0.508	1.215	23.115	0.272	0.366	0.508	1.215	23.342	0.283	0.415	0.523	1.039	14.150
		336	0.261	0.369	0.508	1.174	22.437	0.269	0.366	0.516	1.222	23.081	0.294	0.431	0.541	1.031	12.734
		Avg	0.267	0.369	0.496	1.163	21.916	0.273	0.371	0.501	1.182	21.912	0.284	0.403	0.513	1.087	16.580
Health	Uni-modal	12	1.171	0.674	0.967	2.596	149.272	1.267	0.735	0.999	3.651	262.953	1.453	0.809	1.086	2.699	145.979
		24	1.594	0.807	1.169	2.832	136.133	1.681	0.846	1.167	3.371	160.263	1.537	0.825	1.153	2.744	100.232
		36	1.742	0.862	1.253	2.893	118.496	1.819	0.918	1.281	3.751	243.238	1.565	0.831	1.173	2.687	108.731
		48	1.840	0.923	1.313	3.263	153.559	1.842	0.921	1.310	3.192	152.876	1.586	0.841	1.208	2.730	165.914
		Avg	1.587	0.817	1.175	2.896	139.365	1.652	0.855	1.189	3.491	204.832	1.535	0.827	1.155	2.715	130.214
	MM-TSFLib	12	0.987	0.696	0.928	3.334	190.818	1.029	0.710	0.945	3.400	182.961	1.017	0.664	0.933	2.796	171.177
		24	1.388	0.787	1.113	3.457	169.217	1.288	0.769	1.053	3.207	129.039	1.318	0.747	1.072	2.917	161.566
		36	1.672	0.877	1.216	3.674	176.904	1.460	0.831	1.152	3.492	168.807	1.357	0.775	1.113	3.210	192.422
		48	1.737	0.902	1.270	3.531	155.800	1.612	0.878	1.231	3.317	127.827	1.399	0.788	1.146	2.821	149.248
		Avg	1.446	0.816	1.132	3.499	173.185	1.347	0.797	1.095	3.354	152.159	1.273	0.744	1.066	2.936	168.603
	TaTS (ours)	12	0.939	0.649	0.892	2.764	138.387	0.990	0.659	0.912	2.721	151.988	0.974	0.661	0.911	2.838	163.149
		24	1.251	0.712	1.032	2.744	112.080	1.288	0.764	1.050	3.364	155.937	1.254	0.741	1.062	3.104	170.871
		36	1.489	0.781	1.147	2.885	112.555	1.397	0.780	1.122	2.638	93.114	1.306	0.741	1.083	2.805	152.713
		48	1.581	0.834	1.215	2.909	107.995	1.456	0.808	1.165	2.623	88.216	1.369	0.770	1.136	2.770	144.765
		Avg	1.315	0.744	1.071	2.825	117.754	1.283	0.753	1.062	2.837	122.314	1.226	0.728	1.048	2.879	157.874

Table 10: Full forecasting results for the Security, Social Good, and Traffic datasets using iTransformer, PatchTST, and Crossformer as time series models. Compared to numerical-only unimodal modeling and MM-TSFLib, our TaTS framework seamlessly enhances existing time series models to effectively handle time series with concurrent texts. Avg: the average results across all prediction lengths.

Models			iTransformer [2024]					PatchTST [2023]					Crossformer [2023]				
Method			MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE
Security	Uni-modal	6	113.573	5.698	10.657	6.008	1020.167	108.795	5.119	10.430	4.255	549.239	124.972	6.077	11.179	2.435	113.813
		8	115.878	5.743	10.765	5.977	1035.504	113.534	5.524	10.655	3.681	424.901	126.513	6.237	11.248	1.909	67.155
		10	116.950	5.615	10.814	3.109	332.477	114.820	5.484	10.715	2.523	185.108	127.701	6.346	11.300	1.678	70.642
		12	117.396	5.585	10.835	2.645	262.692	114.253	5.357	10.689	1.951	117.032	128.686	6.449	11.344	1.484	35.512
		Avg	115.949	5.660	10.768	4.435	662.710	112.850	5.371	10.622	3.103	319.070	126.968	6.277	11.268	1.877	71.781
	MM-TSFLib	6	115.170	5.403	10.732	4.284	482.301	109.240	5.189	10.452	4.386	560.668	123.515	5.958	11.114	2.771	175.140
		8	116.158	5.544	10.778	5.742	985.203	113.248	5.445	10.642	3.237	322.665	124.714	6.100	11.168	2.169	126.854
		10	117.340	5.633	10.832	3.090	320.102	114.109	5.442	10.682	2.500	196.618	127.701	6.346	11.300	1.678	70.642
		12	116.694	5.548	10.803	2.560	243.369	114.764	5.398	10.713	2.136	165.771	126.985	6.327	11.269	1.510	42.745
		Avg	116.341	5.532	10.786	3.919	507.744	112.840	5.369	10.622	3.065	311.430	125.729	6.183	11.213	2.032	103.845
	TaTS (ours)	6	107.113	4.856	10.350	3.600	320.907	106.160	4.696	10.303	3.316	282.430	122.887	5.915	11.085	2.831	191.546
		8	112.560	5.204	10.609	3.258	345.121	108.803	5.052	10.431	3.082	312.449	124.302	6.067	11.149	2.656	178.725
		10	113.789	5.227	10.667	2.488	204.306	111.110	5.090	10.541	2.423	205.196	126.203	6.258	11.234	1.720	60.667
		12	114.754	5.318	10.712	2.057	140.148	112.699	5.237	10.616	2.185	171.929	127.263	6.352	11.281	1.433	36.934
		Avg	112.054	5.151	10.584	2.851	252.621	109.693	5.019	10.473	2.752	243.001	125.164	6.148	11.187	2.160	116.968
Social Good	Uni-modal	6	1.129	0.438	0.741	1.395	72.570	1.047	0.443	0.749	1.420	70.855	0.791	0.431	0.681	1.320	39.179
		8	1.133	0.466	0.770	1.448	67.692	1.102	0.458	0.741	1.502	68.611	0.832	0.414	0.668	0.917	13.263
		10	1.275	0.496	0.808	1.718	112.603	1.089	0.469	0.749	1.568	75.225	0.916	0.463	0.728	0.709	6.748
		12	1.313	0.534	0.841	2.052	159.814	1.148	0.610	0.866	2.185	94.833	0.921	0.559	0.766	1.682	54.438
		Avg	1.212	0.483	0.790	1.653	103.170	1.097	0.495	0.776	1.669	77.381	0.865	0.467	0.711	1.157	28.407
	MM-TSFLib	6	1.061	0.451	0.752	1.399	60.240	1.023	0.442	0.741	1.333	62.404	0.753	0.350	0.604	0.753	8.426
		8	1.175	0.498	0.789	1.390	59.283	1.111	0.533	0.807	1.295	34.722	0.814	0.357	0.618	0.576	5.614
		10	1.253	0.561	0.863	1.627	66.938	1.049	0.520	0.799	1.504	54.694	0.866	0.492	0.726	1.127	10.642
		12	1.298	0.570	0.872	1.710	72.310	1.110	0.566	0.840	1.632	50.501	0.917	0.395	0.650	0.693	3.899
		Avg	1.197	0.520	0.819	1.531	64.693	1.073	0.515	0.797	1.441	50.580	0.837	0.398	0.649	0.787	7.145
	TaTS (ours)	6	0.942	0.398	0.677	1.221	49.723	0.923	0.436	0.722	1.153	18.695	0.711	0.407	0.631	0.749	6.772
		8	0.967	0.433	0.713	1.430	50.480	0.900	0.461	0.713	1.279	22.919	0.748	0.453	0.646	0.963	7.987
		10	0.994	0.463	0.740	1.538	54.466	0.996	0.461	0.728	1.348	42.272	0.800	0.373	0.615	0.724	5.977
		12	1.045	0.514	0.780	1.753	61.884	1.069	0.501	0.770	1.549	60.142	0.857	0.415	0.663	0.827	7.195
		Avg	0.987	0.452	0.728	1.486	54.138	0.972	0.465	0.733	1.332	36.007	0.779	0.412	0.639	0.816	6.983
Traffic	Uni-modal	6	0.203	0.228	0.393	0.216	0.307	0.182	0.252	0.377	0.285	0.513	0.227	0.394	0.472	0.340	0.388
		8	0.209	0.236	0.399	0.224	0.321	0.167	0.226	0.348	0.255	0.450	0.216	0.382	0.458	0.324	0.333
		10	0.211	0.243	0.398	0.229	0.321	0.178	0.242	0.362	0.270	0.464	0.202	0.363	0.441	0.313	0.327
		12	0.231	0.246	0.392	0.281	0.532	0.226	0.250	0.393	0.300	0.580	0.212	0.365	0.450	0.337	0.399
		Avg	0.213	0.238	0.395	0.238	0.370	0.188	0.242	0.370	0.278	0.502	0.214	0.376	0.455	0.329	0.362
	MM-TSFLib	6	0.187	0.338	0.422	0.292	0.324	0.165	0.229	0.353	0.248	0.391	0.184	0.335	0.418	0.307	0.371
		8	0.197	0.355	0.433	0.297	0.303	0.163	0.218	0.346	0.237	0.373	0.183	0.331	0.416	0.305	0.367
		10	0.190	0.338	0.422	0.285	0.283	0.174	0.235	0.357	0.252	0.402	0.184	0.331	0.416	0.303	0.363
		12	0.222	0.358	0.459	0.333	0.410	0.211	0.237	0.378	0.281	0.524	0.200	0.340	0.431	0.329	0.427
		Avg	0.199	0.347	0.434	0.302	0.330	0.178	0.230	0.359	0.255	0.422	0.188	0.334	0.420	0.311	0.382
	TaTS (ours)	6	0.174	0.218	0.351	0.227	0.348	0.155	0.204	0.334	0.225	0.359	0.159	0.275	0.372	0.273	0.392
		8	0.177	0.213	0.357	0.215	0.319	0.162	0.210	0.334	0.235	0.389	0.166	0.294	0.385	0.279	0.369
		10	0.186	0.225	0.366	0.223	0.324	0.167	0.214	0.340	0.233	0.368	0.163	0.285	0.378	0.277	0.386
		12	0.213	0.212	0.361	0.241	0.451	0.204	0.209	0.356	0.249	0.468	0.184	0.291	0.395	0.296	0.428
		Avg	0.187	0.217	0.359	0.227	0.361	0.172	0.209	0.341	0.235	0.396	0.168	0.286	0.383	0.281	0.394

Table 11: Full forecasting results for the Agriculture, Climate, and Economy datasets using DLinear, FEDformer, and FiLM as time series models. Compared to numerical-only unimodal modeling and MM-TSFLib, our TaTS framework seamlessly enhances existing time series models to effectively handle time series with concurrent texts. Avg: the average results across all prediction lengths.

Models			DLinear [2023]					FEDformer [2022]					FiLM [2022]				
	Method		MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE
Agriculture	Uni-modal	6	0.170	0.312	0.395	0.135	0.028	0.091	0.239	0.301	0.110	0.019	0.088	0.207	0.290	0.092	0.015
		8	0.195	0.340	0.423	0.145	0.031	0.127	0.281	0.355	0.127	0.024	0.115	0.230	0.318	0.097	0.017
		10	0.218	0.355	0.448	0.150	0.034	0.154	0.313	0.392	0.142	0.030	0.151	0.255	0.351	0.103	0.020
		12	0.308	0.407	0.514	0.165	0.041	0.180	0.313	0.415	0.134	0.028	0.200	0.333	0.433	0.140	0.030
		Avg	0.223	0.354	0.445	0.149	0.034	0.138	0.286	0.366	0.128	0.025	0.139	0.256	0.348	0.108	0.021
	MM-TSFLib	6	0.166	0.314	0.396	0.137	0.028	0.079	0.219	0.280	0.102	0.016	0.089	0.208	0.291	0.092	0.015
		8	0.193	0.342	0.425	0.148	0.032	0.112	0.269	0.335	0.125	0.024	0.112	0.225	0.314	0.095	0.016
		10	0.214	0.358	0.450	0.153	0.035	0.153	0.292	0.387	0.128	0.026	0.156	0.262	0.357	0.106	0.020
		12	0.300	0.408	0.514	0.167	0.042	0.180	0.319	0.416	0.137	0.028	0.204	0.338	0.437	0.142	0.031
		Avg	0.218	0.355	0.446	0.151	0.034	0.131	0.275	0.354	0.123	0.024	0.140	0.258	0.350	0.109	0.021
	TaTS (ours)	6	0.164	0.311	0.392	0.136	0.028	0.082	0.222	0.286	0.102	0.016	0.087	0.205	0.289	0.091	0.015
		8	0.192	0.343	0.425	0.148	0.032	0.111	0.256	0.330	0.115	0.020	0.110	0.223	0.312	0.094	0.016
		10	0.215	0.358	0.451	0.152	0.035	0.147	0.288	0.377	0.126	0.025	0.146	0.249	0.345	0.100	0.019
		12	0.287	0.392	0.496	0.159	0.038	0.183	0.339	0.418	0.145	0.029	0.196	0.328	0.429	0.138	0.029
		Avg	0.214	0.351	0.441	0.149	0.033	0.131	0.276	0.353	0.122	0.023	0.135	0.251	0.344	0.106	0.020
Climate	Uni-modal	6	1.158	0.866	1.076	3.462	204.312	1.206	0.909	1.098	4.551	394.050	1.277	0.912	1.129	4.953	410.091
		8	1.191	0.874	1.091	3.400	190.434	1.175	0.897	1.084	3.680	176.984	1.158	0.862	1.076	3.282	162.026
		10	1.225	0.882	1.107	3.392	185.912	1.199	0.893	1.095	3.215	134.937	1.160	0.857	1.077	2.152	48.217
		12	1.185	0.868	1.089	2.856	126.200	1.190	0.875	1.091	2.883	99.696	1.487	1.012	1.219	3.993	164.875
		Avg	1.190	0.872	1.091	3.277	176.715	1.192	0.893	1.092	3.582	201.417	1.270	0.911	1.125	3.595	196.302
	MM-TSFLib	6	1.074	0.822	1.036	2.997	154.862	1.012	0.795	1.006	2.492	59.880	1.165	0.869	1.079	3.798	270.733
		8	1.108	0.844	1.053	3.117	160.555	1.003	0.787	1.001	2.265	34.593	1.173	0.867	1.083	3.599	191.009
		10	1.123	0.844	1.059	3.233	167.366	1.011	0.810	1.004	2.133	24.604	1.134	0.843	1.065	1.946	31.959
		12	1.112	0.838	1.054	2.815	116.283	1.019	0.795	1.007	2.321	40.325	1.245	0.904	1.116	3.641	223.644
		Avg	1.104	0.837	1.050	3.040	149.767	1.011	0.797	1.004	2.303	39.851	1.179	0.871	1.086	3.246	179.336
	TaTS (ours)	6	0.905	0.749	0.951	2.025	36.745	0.893	0.748	0.945	1.806	13.948	0.912	0.758	0.955	2.598	82.597
		8	0.926	0.756	0.962	2.018	37.680	0.937	0.771	0.968	1.893	16.622	0.917	0.751	0.957	1.939	26.990
		10	0.943	0.764	0.971	1.989	34.385	0.924	0.751	0.960	1.756	14.796	0.947	0.759	0.972	1.597	10.958
		12	0.950	0.766	0.973	1.938	30.964	0.952	0.770	0.974	1.921	21.544	1.005	0.821	1.003	2.686	68.310
		Avg	0.931	0.759	0.964	1.992	34.944	0.926	0.760	0.962	1.844	16.727	0.945	0.772	0.972	2.205	47.214
Economy	Uni-modal	6	0.056	0.189	0.236	0.065	0.006	0.042	0.168	0.203	0.058	0.005	0.021	0.115	0.146	0.039	0.002
		8	0.056	0.191	0.237	0.066	0.006	0.039	0.162	0.197	0.056	0.005	0.028	0.132	0.168	0.045	0.003
		10	0.047	0.173	0.216	0.060	0.006	0.036	0.153	0.188	0.053	0.004	0.026	0.134	0.162	0.045	0.003
		12	0.075	0.216	0.272	0.074	0.009	0.053	0.183	0.225	0.063	0.006	0.027	0.133	0.163	0.046	0.003
		Avg	0.058	0.192	0.240	0.066	0.007	0.042	0.166	0.203	0.058	0.005	0.025	0.129	0.160	0.044	0.003
	MM-TSFLib	6	0.059	0.200	0.243	0.070	0.007	0.035	0.153	0.188	0.053	0.004	0.018	0.104	0.133	0.036	0.002
		8	0.062	0.194	0.248	0.068	0.007	0.043	0.170	0.206	0.059	0.005	0.031	0.138	0.177	0.047	0.003
		10	0.064	0.195	0.253	0.068	0.008	0.040	0.160	0.200	0.056	0.005	0.026	0.133	0.160	0.045	0.003
		12	0.049	0.180	0.221	0.062	0.006	0.024	0.129	0.157	0.045	0.003	0.029	0.140	0.170	0.048	0.003
		Avg	0.058	0.192	0.241	0.067	0.007	0.035	0.153	0.188	0.053	0.004	0.026	0.129	0.160	0.044	0.003
	TaTS (ours)	6	0.020	0.115	0.141	0.040	0.002	0.012	0.093	0.111	0.033	0.002	0.009	0.080	0.096	0.028	0.001
		8	0.020	0.115	0.142	0.040	0.002	0.014	0.099	0.120	0.034	0.002	0.009	0.079	0.096	0.028	0.001
		10	0.019	0.112	0.137	0.039	0.002	0.016	0.106	0.126	0.037	0.002	0.009	0.079	0.096	0.027	0.001
		12	0.025	0.127	0.157	0.044	0.003	0.017	0.107	0.129	0.037	0.002	0.009	0.081	0.096	0.028	0.001
		Avg	0.021	0.117	0.144	0.041	0.002	0.015	0.101	0.121	0.035	0.002	0.009	0.080	0.096	0.028	0.001

Table 12: Full forecasting results for the Energy, Environment, and Health datasets using DLinear, FEDformer, and FiLM as time series models. Compared to numerical-only unimodal modeling and MM-TSFLib, our TaTS framework seamlessly enhances existing time series models to effectively handle time series with concurrent texts. Avg: the average results across all prediction lengths.

Models			DLinear [2023]					FEDformer [2022]					FiLM [2022]				
Method			MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE
Energy	Uni-modal	12	0.136	0.264	0.335	0.947	10.373	0.095	0.212	0.281	0.895	9.380	0.118	0.245	0.314	1.208	25.502
		24	0.261	0.385	0.467	1.453	33.690	0.170	0.303	0.385	1.573	47.676	0.221	0.347	0.433	1.414	29.039
		36	0.335	0.437	0.528	1.780	56.178	0.249	0.373	0.475	2.165	133.305	0.335	0.434	0.533	1.852	60.033
		48	0.431	0.498	0.603	2.294	83.886	0.445	0.514	0.643	4.141	340.071	0.437	0.512	0.620	2.414	89.205
		Avg	0.291	0.396	0.483	1.619	46.032	0.240	0.351	0.446	2.194	132.608	0.278	0.385	0.475	1.722	50.945
	MM-TSFLib	12	0.133	0.262	0.332	0.950	10.725	0.098	0.227	0.289	1.083	15.260	0.119	0.247	0.315	1.202	24.419
		24	0.256	0.380	0.461	1.428	32.596	0.172	0.300	0.388	1.425	47.727	0.224	0.349	0.436	1.415	28.417
		36	0.340	0.442	0.533	1.803	56.982	0.252	0.376	0.477	2.120	124.465	0.332	0.431	0.531	1.839	59.454
		48	0.428	0.496	0.601	2.287	83.443	0.430	0.511	0.611	2.775	146.406	0.440	0.514	0.623	2.416	89.684
		Avg	0.289	0.395	0.482	1.617	45.936	0.238	0.354	0.441	1.851	83.465	0.279	0.385	0.476	1.718	50.493
	TaTS (ours)	12	0.132	0.260	0.330	0.954	11.225	0.090	0.210	0.275	0.880	12.877	0.118	0.245	0.314	1.202	25.174
		24	0.236	0.359	0.441	1.359	29.647	0.172	0.305	0.387	1.375	44.042	0.222	0.347	0.434	1.410	28.640
		36	0.340	0.442	0.533	1.805	57.123	0.250	0.372	0.472	2.412	152.144	0.311	0.414	0.514	1.773	55.535
		48	0.425	0.493	0.597	2.285	84.710	0.435	0.531	0.631	3.501	222.058	0.434	0.510	0.618	2.399	88.602
		Avg	0.283	0.388	0.475	1.601	45.676	0.237	0.355	0.441	2.042	107.780	0.271	0.379	0.470	1.696	49.488
Environment	Uni-modal	48	0.478	0.531	0.646	1.791	119.315	0.505	0.543	0.671	1.932	128.444	0.494	0.502	0.644	2.323	241.494
		96	0.562	0.608	0.724	1.539	68.485	0.465	0.524	0.657	2.440	237.225	0.581	0.546	0.707	2.639	314.062
		192	0.592	0.608	0.748	1.938	132.178	0.510	0.556	0.702	2.656	297.619	0.612	0.559	0.759	3.081	461.654
		336	0.600	0.618	0.768	1.938	134.420	0.531	0.573	0.725	2.528	300.421	0.621	0.566	0.779	2.989	440.819
		Avg	0.558	0.591	0.722	1.801	113.600	0.503	0.549	0.689	2.389	240.927	0.577	0.543	0.722	2.758	364.507
	MM-TSFLib	48	0.414	0.474	0.598	1.888	142.797	0.413	0.468	0.599	1.867	128.047	0.469	0.484	0.652	2.046	177.399
		96	0.420	0.489	0.615	1.743	112.990	0.413	0.479	0.613	1.998	138.883	0.476	0.493	0.662	1.987	173.914
		192	0.439	0.521	0.650	1.659	92.080	0.423	0.489	0.635	2.205	197.315	0.477	0.486	0.674	2.135	218.811
		336	0.444	0.526	0.664	1.680	95.029	0.445	0.507	0.665	1.850	125.600	0.490	0.497	0.696	2.233	243.544
		Avg	0.429	0.502	0.632	1.742	110.724	0.423	0.486	0.628	1.980	147.461	0.478	0.490	0.671	2.100	203.417
	TaTS (ours)	48	0.272	0.385	0.486	1.083	17.610	0.272	0.369	0.484	1.172	21.826	0.269	0.373	0.481	1.124	19.765
		96	0.301	0.427	0.528	1.034	13.731	0.271	0.371	0.495	1.143	22.305	0.279	0.377	0.499	1.180	21.986
		192	0.306	0.443	0.544	1.007	11.494	0.277	0.379	0.501	1.145	22.438	0.271	0.367	0.507	1.202	22.318
		336	0.313	0.456	0.557	0.996	10.408	0.278	0.393	0.524	1.137	18.379	0.267	0.366	0.514	1.210	22.394
		Avg	0.298	0.428	0.529	1.030	13.311	0.275	0.378	0.501	1.149	21.237	0.272	0.371	0.500	1.179	21.616
Health	Uni-modal	12	1.595	0.808	1.113	2.599	252.012	1.051	0.756	0.975	4.069	371.454	1.900	1.008	1.278	6.208	1054.818
		24	1.778	0.835	1.170	2.742	312.129	1.493	0.933	1.176	4.818	434.785	1.946	0.973	1.287	4.194	322.873
		36	1.759	0.850	1.241	2.738	263.854	1.661	0.980	1.252	5.182	426.708	2.029	1.013	1.352	4.495	346.381
		48	1.818	0.899	1.299	2.964	278.936	1.737	0.969	1.285	4.775	392.270	2.054	1.026	1.379	4.356	305.131
		Avg	1.737	0.848	1.206	2.761	276.733	1.486	0.909	1.172	4.711	406.304	1.982	1.005	1.324	4.813	507.301
	MM-TSFLib	12	1.403	0.763	1.061	2.065	64.534	0.978	0.685	0.930	3.371	273.283	1.406	0.915	1.141	4.787	421.324
		24	1.544	0.782	1.114	2.167	68.258	1.272	0.804	1.073	3.538	212.521	1.730	0.975	1.257	4.258	251.992
		36	1.600	0.824	1.185	2.264	56.729	1.344	0.828	1.121	3.768	222.549	1.769	0.944	1.267	3.785	205.906
		48	1.617	0.830	1.222	2.368	87.198	1.416	0.852	1.163	3.913	243.392	1.793	0.960	1.286	3.626	178.720
		Avg	1.541	0.800	1.145	2.216	69.180	1.252	0.792	1.072	3.647	237.936	1.675	0.949	1.238	4.114	264.486
	TaTS (ours)	12	1.273	0.742	1.027	2.702	159.975	0.966	0.671	0.925	3.309	294.367	1.211	0.794	1.035	3.570	236.037
		24	1.421	0.788	1.090	3.221	254.155	1.264	0.823	1.080	4.068	289.731	1.414	0.827	1.107	3.160	130.456
		36	1.449	0.787	1.133	2.812	148.843	1.320	0.801	1.110	3.885	280.248	1.497	0.851	1.165	3.274	133.041
		48	1.505	0.832	1.183	2.990	186.495	1.426	0.868	1.164	4.140	264.871	1.562	0.878	1.209	3.225	121.440
		Avg	1.412	0.787	1.108	2.931	187.367	1.244	0.791	1.070	3.851	282.304	1.421	0.838	1.129	3.307	155.243

Table 13: Full forecasting results for the Security, Social Good, and Traffic datasets using DLinear, FEDformer, and FiLM as time series models. Compared to numerical-only unimodal modeling and MM-TSFLib, our TaTS framework seamlessly enhances existing time series models to effectively handle time series with concurrent texts. Avg: the average results across all prediction lengths.

Models			DLinear [2023]					FEDformer [2022]					FiLM [2022]				
Method			MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE
Security	Uni-modal	6	107.046	4.531	10.346	3.489	324.650	112.106	4.830	10.588	4.456	571.690	115.130	5.587	10.730	5.029	637.394
		8	107.700	4.649	10.378	2.992	295.719	113.897	5.200	10.672	3.223	355.929	112.097	5.034	10.588	3.228	336.503
		10	109.360	4.759	10.458	2.449	216.866	117.484	5.467	10.839	2.563	216.459	112.267	4.901	10.596	2.310	188.201
		12	112.343	4.904	10.599	1.980	149.507	114.452	5.135	10.698	2.697	329.415	122.711	6.425	11.077	3.554	437.883
		Avg	109.112	4.711	10.445	2.728	246.685	114.485	5.158	10.699	3.235	368.373	115.551	5.487	10.748	3.530	399.995
	MM-TSFLib	6	106.121	4.545	10.301	3.788	386.715	109.854	4.690	10.481	4.252	541.638	105.809	4.755	10.286	4.286	525.309
		8	107.445	4.670	10.366	3.101	319.555	114.833	5.233	10.716	3.119	330.374	108.045	4.638	10.394	2.727	249.934
		10	108.713	4.758	10.427	2.613	251.113	115.261	5.294	10.736	2.563	233.233	111.391	4.843	10.554	1.953	137.888
		12	109.848	4.876	10.481	2.373	227.133	115.001	5.211	10.724	2.558	291.461	111.541	5.354	10.561	3.023	363.599
		Avg	108.032	4.712	10.394	2.969	296.129	113.737	5.107	10.664	3.123	349.177	109.197	4.897	10.449	2.997	319.183
	TaTS (ours)	6	106.015	4.516	10.296	3.850	404.799	106.015	4.532	10.296	4.542	597.429	105.482	4.511	10.270	4.024	451.366
		8	107.477	4.623	10.367	3.050	312.447	107.678	4.618	10.377	3.303	371.986	107.657	4.792	10.376	3.150	310.920
		10	108.505	4.728	10.417	2.632	260.096	107.301	4.885	10.359	3.138	375.009	109.886	4.771	10.483	2.338	193.865
		12	109.717	4.836	10.475	2.336	224.134	108.506	4.837	10.417	2.738	331.710	108.375	4.870	10.410	2.549	267.339
		Avg	107.928	4.676	10.389	2.967	300.369	107.375	4.718	10.362	3.430	419.034	107.850	4.736	10.385	3.015	305.873
Social Good	Uni-modal	6	1.018	0.627	0.859	1.503	19.120	0.821	0.386	0.649	1.086	28.066	1.123	0.604	0.878	2.432	149.647
		8	1.137	0.702	0.929	1.607	19.248	0.929	0.451	0.726	1.061	17.701	1.116	0.542	0.841	2.275	128.188
		10	1.210	0.755	0.972	1.732	21.287	1.059	0.478	0.784	1.469	52.985	1.154	0.601	0.882	1.823	42.492
		12	1.238	0.763	0.982	1.705	20.522	1.105	0.588	0.846	1.876	76.675	1.653	0.869	1.125	2.998	140.138
		Avg	1.151	0.712	0.935	1.637	20.044	0.979	0.476	0.751	1.373	43.857	1.261	0.654	0.931	2.382	115.116
	MM-TSFLib	6	0.946	0.583	0.810	1.481	21.957	0.816	0.395	0.667	1.182	33.446	1.070	0.529	0.824	2.269	159.103
		8	1.095	0.678	0.904	1.596	20.076	0.910	0.438	0.717	1.010	15.845	1.120	0.584	0.869	2.138	83.150
		10	1.128	0.709	0.924	1.713	22.953	1.032	0.456	0.757	1.395	53.857	1.128	0.539	0.839	2.235	120.886
		12	1.164	0.724	0.940	1.655	20.260	1.091	0.560	0.838	1.737	71.467	1.624	0.852	1.111	3.005	149.026
		Avg	1.083	0.673	0.894	1.611	21.312	0.962	0.462	0.745	1.331	43.654	1.236	0.626	0.911	2.412	128.041
	TaTS (ours)	6	0.859	0.516	0.740	1.453	29.534	0.746	0.365	0.620	0.983	23.097	0.992	0.588	0.834	1.623	30.115
		8	0.963	0.592	0.812	1.582	29.073	0.880	0.448	0.701	1.221	34.945	1.001	0.550	0.806	1.609	28.399
		10	1.118	0.703	0.917	1.711	23.312	0.944	0.453	0.720	1.138	28.381	1.065	0.583	0.837	1.447	17.661
		12	1.085	0.676	0.888	1.657	24.350	0.983	0.453	0.718	1.315	51.258	1.358	0.782	1.025	1.920	27.141
		Avg	1.006	0.622	0.839	1.601	26.567	0.888	0.430	0.690	1.164	34.420	1.104	0.626	0.876	1.650	25.829
Traffic	Uni-modal	6	0.221	0.358	0.461	0.357	0.549	0.202	0.294	0.416	0.285	0.377	0.202	0.302	0.426	0.346	0.682
		8	0.220	0.357	0.458	0.355	0.552	0.184	0.234	0.364	0.259	0.461	0.203	0.332	0.436	0.341	0.564
		10	0.217	0.347	0.451	0.358	0.601	0.198	0.251	0.386	0.271	0.474	0.203	0.340	0.438	0.323	0.447
		12	0.261	0.374	0.499	0.395	0.663	0.237	0.275	0.410	0.315	0.600	0.250	0.280	0.426	0.347	0.719
		Avg	0.230	0.359	0.467	0.366	0.591	0.205	0.264	0.394	0.283	0.478	0.215	0.314	0.431	0.339	0.603
	MM-TSFLib	6	0.204	0.332	0.439	0.321	0.465	0.180	0.245	0.372	0.258	0.408	0.197	0.294	0.419	0.339	0.664
		8	0.202	0.335	0.435	0.320	0.448	0.178	0.225	0.352	0.253	0.458	0.195	0.322	0.427	0.332	0.540
		10	0.205	0.325	0.435	0.320	0.478	0.184	0.234	0.364	0.258	0.446	0.195	0.328	0.428	0.312	0.424
		12	0.225	0.329	0.451	0.351	0.602	0.228	0.247	0.388	0.292	0.570	0.240	0.258	0.403	0.315	0.631
		Avg	0.209	0.330	0.440	0.328	0.498	0.193	0.238	0.369	0.265	0.471	0.207	0.300	0.419	0.325	0.565
	TaTS (ours)	6	0.184	0.312	0.412	0.301	0.435	0.159	0.208	0.329	0.228	0.355	0.157	0.228	0.351	0.254	0.426
		8	0.185	0.302	0.409	0.308	0.500	0.159	0.209	0.329	0.230	0.368	0.162	0.260	0.370	0.266	0.401
		10	0.184	0.297	0.403	0.309	0.524	0.160	0.206	0.323	0.229	0.370	0.169	0.269	0.380	0.262	0.358
		12	0.199	0.291	0.413	0.309	0.489	0.213	0.224	0.368	0.269	0.518	0.215	0.236	0.383	0.298	0.612
		Avg	0.188	0.300	0.409	0.307	0.487	0.173	0.212	0.337	0.239	0.403	0.176	0.248	0.371	0.270	0.449

Table 14: Full forecasting results for the Agriculture, Climate, and Economy datasets using Autoformer, Informer, and Transformer as time series models. Compared to numerical-only unimodal modeling and MM-TSFLib, our TaTS framework seamlessly enhances existing time series models to effectively handle time series with concurrent texts. Avg: the average results across all prediction lengths.

Models			Autoformer [2021]					Informer [2021]					Transformer [2017]				
Method			MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE
Agriculture	Uni-modal	6	0.109	0.255	0.329	0.116	0.022	0.451	0.557	0.626	0.240	0.071	0.229	0.326	0.420	0.133	0.032
		8	0.135	0.278	0.366	0.126	0.026	0.569	0.633	0.702	0.270	0.087	0.328	0.432	0.502	0.177	0.045
		10	0.173	0.311	0.413	0.138	0.031	0.618	0.633	0.724	0.263	0.088	0.358	0.422	0.510	0.166	0.045
		12	0.213	0.345	0.457	0.149	0.036	0.756	0.698	0.789	0.284	0.101	0.500	0.555	0.633	0.224	0.064
		Avg	0.158	0.297	0.391	0.132	0.029	0.599	0.630	0.710	0.264	0.087	0.354	0.434	0.516	0.175	0.046
	MM-TSFLib	6	0.095	0.221	0.306	0.100	0.018	0.218	0.352	0.422	0.148	0.032	0.197	0.319	0.392	0.133	0.029
		8	0.143	0.278	0.372	0.122	0.025	0.306	0.429	0.496	0.179	0.044	0.205	0.303	0.384	0.121	0.027
		10	0.176	0.311	0.416	0.137	0.031	0.301	0.398	0.480	0.160	0.040	0.215	0.332	0.411	0.135	0.030
		12	0.217	0.341	0.453	0.144	0.034	0.428	0.479	0.579	0.190	0.054	0.378	0.453	0.531	0.179	0.048
		Avg	0.158	0.288	0.387	0.126	0.027	0.313	0.414	0.494	0.169	0.042	0.249	0.352	0.429	0.142	0.034
	TaTS (ours)	6	0.076	0.205	0.269	0.092	0.014	0.162	0.265	0.342	0.107	0.022	0.150	0.348	0.387	0.166	0.034
		8	0.101	0.234	0.315	0.105	0.019	0.213	0.311	0.392	0.124	0.028	0.192	0.298	0.374	0.120	0.025
		10	0.138	0.299	0.371	0.134	0.026	0.296	0.388	0.465	0.154	0.038	0.209	0.296	0.384	0.114	0.026
		12	0.186	0.324	0.425	0.141	0.030	0.349	0.426	0.506	0.167	0.044	0.213	0.310	0.401	0.121	0.025
		Avg	0.125	0.266	0.345	0.118	0.022	0.255	0.348	0.426	0.138	0.033	0.191	0.313	0.387	0.130	0.028
Climate	Uni-modal	6	1.116	0.861	1.056	4.456	519.418	1.084	0.829	1.041	1.617	15.451	1.032	0.817	1.016	1.656	13.521
		8	1.117	0.856	1.057	3.329	177.957	1.087	0.829	1.043	2.464	66.852	1.135	0.856	1.065	1.868	22.687
		10	1.170	0.886	1.081	3.059	106.074	1.117	0.849	1.056	2.071	49.757	1.103	0.844	1.049	2.355	81.661
		12	1.123	0.855	1.059	3.364	125.779	1.150	0.859	1.071	2.557	94.732	1.100	0.841	1.048	1.663	24.078
		Avg	1.131	0.865	1.063	3.552	232.307	1.110	0.841	1.053	2.177	56.698	1.092	0.839	1.044	1.885	35.487
	MM-TSFLib	6	1.021	0.817	1.010	2.871	82.634	1.019	0.811	1.009	2.844	134.946	0.962	0.771	0.981	2.030	23.607
		8	1.039	0.819	1.018	3.018	99.283	0.970	0.772	0.985	2.210	43.152	0.991	0.783	0.995	1.976	22.312
		10	1.074	0.838	1.035	2.783	92.522	1.006	0.794	1.002	2.311	67.013	1.026	0.790	1.010	2.755	87.765
		12	1.078	0.836	1.038	2.731	78.154	1.009	0.791	0.999	2.499	86.993	1.011	0.789	1.000	1.895	27.637
		Avg	1.053	0.827	1.025	2.851	88.148	1.001	0.792	0.999	2.466	83.026	0.998	0.783	0.996	2.164	40.330
	TaTS (ours)	6	0.880	0.741	0.938	2.222	37.958	0.881	0.741	0.939	2.217	57.260	0.859	0.728	0.926	1.970	35.573
		8	0.937	0.768	0.968	2.136	36.109	0.909	0.749	0.953	1.981	29.665	0.913	0.761	0.955	2.524	73.564
		10	1.027	0.817	1.011	2.260	31.311	0.973	0.771	0.983	2.020	27.051	0.976	0.767	0.985	2.179	31.989
		12	1.075	0.831	1.033	2.317	35.133	0.958	0.764	0.974	1.727	15.480	0.930	0.757	0.960	1.871	23.016
		Avg	0.980	0.789	0.987	2.234	35.128	0.930	0.756	0.962	1.986	32.364	0.920	0.753	0.957	2.136	41.035
Economy	Uni-modal	6	0.083	0.222	0.288	0.077	0.010	0.877	0.896	0.930	0.308	0.102	0.276	0.444	0.517	0.150	0.031
		8	0.069	0.210	0.263	0.073	0.008	1.606	1.238	1.260	0.425	0.187	0.676	0.797	0.816	0.274	0.078
		10	0.070	0.209	0.261	0.072	0.008	1.409	1.153	1.179	0.395	0.162	0.601	0.750	0.768	0.257	0.069
		12	0.062	0.186	0.245	0.064	0.007	1.407	1.153	1.183	0.396	0.163	0.781	0.854	0.879	0.293	0.091
		Avg	0.071	0.207	0.264	0.071	0.008	1.325	1.110	1.138	0.381	0.153	0.584	0.711	0.745	0.243	0.067
	MM-TSFLib	6	0.049	0.173	0.221	0.060	0.006	0.293	0.490	0.531	0.167	0.033	0.110	0.285	0.322	0.096	0.012
		8	0.045	0.171	0.211	0.060	0.005	0.445	0.643	0.660	0.220	0.051	0.157	0.359	0.389	0.122	0.018
		10	0.071	0.214	0.267	0.075	0.009	0.471	0.664	0.680	0.227	0.054	0.240	0.450	0.483	0.154	0.028
		12	0.068	0.209	0.260	0.073	0.008	0.518	0.674	0.715	0.231	0.060	0.347	0.569	0.584	0.195	0.040
		Avg	0.058	0.192	0.240	0.067	0.007	0.432	0.618	0.646	0.211	0.049	0.213	0.416	0.445	0.142	0.025
	TaTS (ours)	6	0.021	0.115	0.144	0.040	0.002	0.247	0.472	0.488	0.161	0.028	0.029	0.137	0.169	0.047	0.003
		8	0.023	0.119	0.150	0.041	0.003	0.166	0.369	0.396	0.125	0.018	0.039	0.162	0.192	0.055	0.004
		10	0.024	0.122	0.153	0.042	0.003	0.400	0.610	0.626	0.209	0.046	0.092	0.266	0.299	0.091	0.010
		12	0.026	0.127	0.161	0.044	0.003	0.385	0.596	0.617	0.203	0.044	0.156	0.364	0.389	0.123	0.017
		Avg	0.024	0.121	0.152	0.042	0.003	0.299	0.512	0.532	0.174	0.034	0.079	0.232	0.262	0.079	0.009

Table 15: Full forecasting results for the Energy, Environment, and Health datasets using Autoformer, Informer, and Transformer as time series models. Compared to numerical-only unimodal modeling and MM-TSFLib, our TaTS framework seamlessly enhances existing time series models to effectively handle time series with concurrent texts. Avg: the average results across all prediction lengths.

Models			Autoformer [2021]					Informer [2021]					Transformer [2017]				
Method			MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE
Energy	Uni-modal	12	0.161	0.282	0.362	1.403	24.893	0.165	0.289	0.373	1.491	35.971	0.124	0.247	0.320	1.021	8.908
		24	0.279	0.416	0.509	2.632	158.931	0.248	0.380	0.475	2.916	185.671	0.291	0.403	0.494	1.951	101.566
		36	0.364	0.464	0.564	2.384	93.988	0.368	0.492	0.585	4.022	356.146	0.329	0.435	0.542	3.964	428.707
		48	0.471	0.550	0.664	3.106	149.374	0.457	0.539	0.640	5.613	589.886	0.445	0.537	0.642	3.824	285.963
		Avg	0.319	0.428	0.525	2.381	106.797	0.309	0.425	0.518	3.511	291.918	0.297	0.405	0.500	2.690	206.286
	MM-TSFLib	12	0.164	0.297	0.369	1.720	78.617	0.166	0.291	0.372	1.667	36.449	0.127	0.270	0.334	1.278	11.692
		24	0.275	0.407	0.504	2.177	81.316	0.242	0.362	0.456	3.040	235.920	0.276	0.402	0.491	2.297	115.390
		36	0.362	0.464	0.561	2.176	88.219	0.342	0.467	0.566	3.221	271.106	0.316	0.439	0.530	3.504	272.971
		48	0.477	0.545	0.665	3.100	192.217	0.456	0.530	0.643	5.430	602.773	0.454	0.508	0.641	5.511	748.943
		Avg	0.320	0.428	0.525	2.293	110.092	0.301	0.413	0.509	3.340	286.562	0.293	0.405	0.499	3.147	287.249
	TaTS (ours)	12	0.153	0.291	0.365	1.490	33.553	0.145	0.271	0.347	1.118	11.872	0.126	0.252	0.324	1.036	12.192
		24	0.276	0.404	0.488	2.040	73.651	0.242	0.361	0.463	2.310	184.196	0.265	0.381	0.469	1.706	53.962
		36	0.360	0.467	0.555	2.167	80.434	0.301	0.415	0.514	3.658	379.160	0.301	0.419	0.515	2.804	209.452
		48	0.466	0.559	0.659	3.431	178.191	0.448	0.538	0.644	4.344	378.638	0.423	0.527	0.620	5.149	416.124
		Avg	0.314	0.430	0.517	2.282	91.457	0.284	0.396	0.492	2.857	238.466	0.279	0.395	0.482	2.674	172.933
Environment	Uni-modal	48	0.503	0.544	0.670	1.953	141.941	0.414	0.481	0.602	2.190	216.476	0.412	0.483	0.600	2.190	214.543
		96	0.594	0.605	0.743	2.015	135.052	0.467	0.520	0.644	2.454	290.858	0.458	0.511	0.639	2.608	340.210
		192	0.607	0.601	0.762	2.163	205.175	0.469	0.519	0.644	2.535	305.217	0.492	0.535	0.677	2.711	404.734
		336	0.690	0.643	0.823	2.624	307.413	0.487	0.529	0.693	2.726	355.026	0.479	0.517	0.688	2.824	389.196
		Avg	0.599	0.598	0.749	2.189	197.395	0.459	0.512	0.646	2.476	291.894	0.460	0.511	0.651	2.583	337.171
	MM-TSFLib	48	0.442	0.492	0.626	2.008	164.960	0.419	0.473	0.604	1.997	163.772	0.420	0.471	0.606	2.027	163.407
		96	0.456	0.505	0.645	1.930	154.161	0.426	0.477	0.616	2.074	173.217	0.426	0.485	0.615	2.380	252.997
		192	0.461	0.505	0.663	1.995	181.553	0.425	0.481	0.634	2.410	256.710	0.418	0.479	0.630	2.356	252.249
		336	0.447	0.506	0.666	1.994	172.427	0.427	0.489	0.651	2.283	225.380	0.435	0.487	0.657	2.551	282.514
		Avg	0.452	0.502	0.650	1.982	168.275	0.424	0.480	0.626	2.191	204.770	0.425	0.481	0.627	2.329	237.792
	TaTS (ours)	48	0.274	0.374	0.486	1.159	21.042	0.272	0.377	0.483	1.103	18.922	0.268	0.378	0.481	1.074	17.152
		96	0.286	0.387	0.509	1.183	21.118	0.287	0.401	0.507	1.040	15.636	0.272	0.391	0.496	1.028	15.508
		192	0.291	0.382	0.528	1.272	24.699	0.297	0.426	0.531	1.003	13.899	0.277	0.398	0.512	1.030	16.253
		336	0.288	0.403	0.534	1.122	20.057	0.286	0.419	0.533	0.989	13.846	0.287	0.420	0.534	1.006	15.226
		Avg	0.285	0.387	0.514	1.184	21.729	0.285	0.406	0.513	1.034	15.576	0.276	0.397	0.506	1.035	16.035
Health	Uni-modal	12	1.389	0.895	1.121	4.898	593.771	1.173	0.743	0.990	4.065	593.314	1.143	0.741	0.998	3.233	133.066
		24	2.328	1.191	1.476	6.117	859.160	1.215	0.766	1.042	3.728	389.282	1.480	0.786	1.096	2.435	59.228
		36	1.953	1.005	1.348	4.614	392.542	1.315	0.773	1.101	3.541	390.034	1.450	0.772	1.132	2.766	136.630
		48	2.179	1.064	1.410	4.865	379.673	1.408	0.809	1.137	3.445	337.635	1.439	0.806	1.137	2.834	125.016
		Avg	1.962	1.039	1.339	5.123	556.286	1.278	0.773	1.067	3.695	427.566	1.378	0.776	1.091	2.817	113.485
	MM-TSFLib	12	1.331	0.864	1.112	4.427	504.600	0.997	0.673	0.928	3.024	221.350	0.953	0.686	0.920	3.309	198.713
		24	1.454	0.868	1.138	3.681	181.137	1.209	0.740	1.046	3.372	257.237	1.315	0.762	1.071	2.833	137.728
		36	1.574	0.906	1.216	4.051	234.643	1.282	0.760	1.092	3.111	213.531	1.276	0.763	1.070	2.906	137.944
		48	1.616	0.911	1.235	3.884	201.678	1.371	0.785	1.137	3.146	234.342	1.330	0.780	1.109	2.769	125.761
		Avg	1.494	0.887	1.175	4.011	280.514	1.215	0.740	1.051	3.163	231.615	1.218	0.748	1.042	2.954	150.036
	TaTS (ours)	12	1.320	0.863	1.105	3.769	309.199	0.949	0.658	0.910	3.707	391.895	0.909	0.655	0.862	3.251	292.588
		24	1.467	0.885	1.159	3.485	152.650	1.130	0.736	1.020	3.897	352.680	1.187	0.728	1.030	3.143	192.685
		36	1.368	0.825	1.120	3.962	230.059	1.301	0.779	1.110	3.540	270.359	1.175	0.728	1.048	3.096	193.526
		48	1.483	0.871	1.180	4.108	279.227	1.354	0.833	1.143	3.962	372.090	1.297	0.762	1.113	3.074	185.199
		Avg	1.409	0.861	1.141	3.831	242.784	1.183	0.752	1.046	3.776	346.756	1.142	0.718	1.013	3.141	216.000

Table 16: Full forecasting results for the Security, Social Good, and Traffic datasets using Autoformer, Informer, and Transformer as time series models. Compared to numerical-only unimodal modeling and MM-TSFLib, our TaTS framework seamlessly enhances existing time series models to effectively handle time series with concurrent texts. Avg: the average results across all prediction lengths.

Models			Autoformer [2021]					Informer [2021]					Transformer [2017]				
Method			MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE
Security	Uni-modal	6	115.544	5.268	10.749	2.437	185.108	133.168	6.626	11.540	1.591	19.155	126.925	6.203	11.266	2.547	120.160
		8	113.355	4.967	10.647	2.888	298.107	134.383	6.804	11.592	1.236	6.780	132.905	6.641	11.528	1.209	14.174
		10	114.407	4.984	10.696	2.164	153.069	131.382	6.631	11.462	1.483	26.411	128.820	6.443	11.350	1.539	32.792
		12	117.801	5.253	10.854	2.692	326.651	128.201	6.430	11.323	1.408	26.498	136.753	7.039	11.694	1.168	4.854
		Avg	115.277	5.118	10.736	2.545	240.734	131.784	6.623	11.479	1.429	19.711	131.351	6.582	11.460	1.616	42.995
	MM-TSFLib	6	108.841	4.861	10.433	3.004	246.068	127.216	6.197	11.279	2.326	99.099	127.277	6.233	11.282	2.592	135.752
		8	113.693	5.031	10.663	2.799	265.988	128.914	6.402	11.354	1.660	40.618	126.589	6.227	11.251	2.010	84.511
		10	112.545	5.098	10.609	1.885	120.031	128.775	6.434	11.348	1.532	38.764	127.986	6.368	11.313	1.520	32.213
		12	110.699	4.902	10.521	2.177	199.450	130.907	6.626	11.441	1.443	33.523	132.033	6.685	11.491	1.217	11.881
		Avg	111.445	4.973	10.556	2.466	207.884	128.953	6.415	11.356	1.740	53.001	128.471	6.378	11.334	1.835	66.089
	TaTS (ours)	6	107.430	4.658	10.365	4.255	528.013	127.814	6.269	11.306	2.263	110.185	122.803	5.927	11.082	2.966	185.980
		8	107.108	4.750	10.349	3.531	455.878	125.990	6.217	11.225	2.390	135.504	123.882	6.057	11.130	2.505	151.979
		10	110.061	4.891	10.491	3.615	562.774	125.737	6.248	11.213	2.231	134.082	125.666	6.262	11.210	2.232	128.702
		12	109.361	4.847	10.458	3.060	457.480	127.103	6.369	11.274	1.885	86.102	125.971	6.290	11.224	1.899	90.926
		Avg	108.490	4.787	10.416	3.615	501.036	126.661	6.276	11.255	2.192	116.468	124.581	6.134	11.162	2.401	139.397
Social Good	Uni-modal	6	1.234	0.684	0.973	1.910	69.347	0.773	0.425	0.668	0.872	13.761	0.848	0.427	0.684	1.208	27.858
		8	1.236	0.664	0.956	1.998	80.017	0.871	0.449	0.708	0.933	11.089	0.877	0.460	0.719	1.520	56.020
		10	1.332	0.708	1.026	2.116	93.499	0.910	0.498	0.755	0.905	6.360	0.976	0.541	0.783	1.725	63.227
		12	1.312	0.749	1.046	2.231	75.925	0.926	0.644	0.818	1.028	7.619	0.938	0.508	0.750	1.389	28.551
		Avg	1.278	0.701	1.000	2.064	79.697	0.870	0.504	0.737	0.934	9.707	0.910	0.484	0.734	1.460	43.914
	MM-TSFLib	6	1.200	0.664	0.954	1.890	66.499	0.772	0.414	0.666	0.726	8.039	0.784	0.422	0.673	0.938	18.507
		8	1.175	0.589	0.891	1.935	84.135	0.829	0.405	0.673	0.746	6.869	0.845	0.426	0.669	1.056	19.505
		10	1.268	0.689	1.002	1.756	44.172	0.876	0.466	0.724	0.855	6.248	0.913	0.486	0.731	1.252	25.176
		12	1.272	0.739	1.032	2.048	56.789	0.879	0.541	0.765	0.888	7.772	0.882	0.510	0.744	1.021	13.844
		Avg	1.229	0.670	0.970	1.907	62.899	0.839	0.457	0.707	0.804	7.232	0.856	0.461	0.704	1.067	19.258
	TaTS (ours)	6	1.057	0.564	0.877	1.451	33.099	0.724	0.448	0.660	0.765	7.156	0.740	0.375	0.616	0.700	3.824
		8	1.184	0.686	0.954	1.476	20.587	0.788	0.463	0.696	0.890	8.039	0.805	0.393	0.632	0.828	11.467
		10	1.278	0.714	0.986	1.578	21.226	0.828	0.468	0.691	0.880	8.487	0.842	0.485	0.700	1.062	11.719
		12	1.261	0.699	0.979	1.544	21.227	0.899	0.455	0.698	0.785	4.917	0.842	0.424	0.650	0.777	5.973
		Avg	1.195	0.666	0.949	1.512	24.035	0.810	0.459	0.686	0.830	7.150	0.807	0.419	0.649	0.842	8.246
Traffic	Uni-modal	6	0.201	0.295	0.416	0.316	0.542	0.197	0.352	0.434	0.303	0.328	0.203	0.344	0.438	0.299	0.307
		8	0.205	0.296	0.419	0.299	0.440	0.202	0.358	0.440	0.320	0.369	0.224	0.364	0.460	0.302	0.285
		10	0.200	0.297	0.413	0.310	0.479	0.196	0.351	0.430	0.296	0.314	0.209	0.353	0.445	0.298	0.295
		12	0.241	0.303	0.448	0.350	0.653	0.213	0.358	0.448	0.326	0.397	0.200	0.323	0.426	0.316	0.416
		Avg	0.212	0.298	0.424	0.319	0.528	0.202	0.355	0.438	0.311	0.352	0.209	0.346	0.442	0.304	0.326
	MM-TSFLib	6	0.195	0.248	0.390	0.247	0.360	0.166	0.297	0.387	0.285	0.391	0.164	0.291	0.384	0.271	0.340
		8	0.204	0.274	0.401	0.277	0.404	0.169	0.306	0.393	0.285	0.372	0.172	0.305	0.395	0.274	0.318
		10	0.207	0.274	0.409	0.268	0.407	0.169	0.305	0.391	0.282	0.358	0.169	0.297	0.391	0.283	0.393
		12	0.241	0.292	0.420	0.343	0.795	0.183	0.290	0.392	0.292	0.414	0.181	0.288	0.392	0.287	0.389
		Avg	0.212	0.272	0.405	0.284	0.492	0.172	0.299	0.391	0.286	0.384	0.171	0.295	0.390	0.279	0.360
	TaTS (ours)	6	0.161	0.225	0.356	0.253	0.440	0.159	0.282	0.375	0.266	0.337	0.159	0.274	0.373	0.269	0.384
		8	0.167	0.237	0.353	0.258	0.416	0.161	0.289	0.378	0.270	0.340	0.156	0.268	0.367	0.266	0.386
		10	0.163	0.214	0.339	0.250	0.477	0.157	0.276	0.368	0.274	0.399	0.157	0.270	0.367	0.267	0.383
		12	0.217	0.242	0.379	0.293	0.575	0.181	0.279	0.387	0.289	0.429	0.183	0.285	0.391	0.292	0.423
		Avg	0.177	0.229	0.357	0.264	0.477	0.164	0.281	0.377	0.275	0.376	0.164	0.274	0.374	0.274	0.394

F.5 Imputation Results

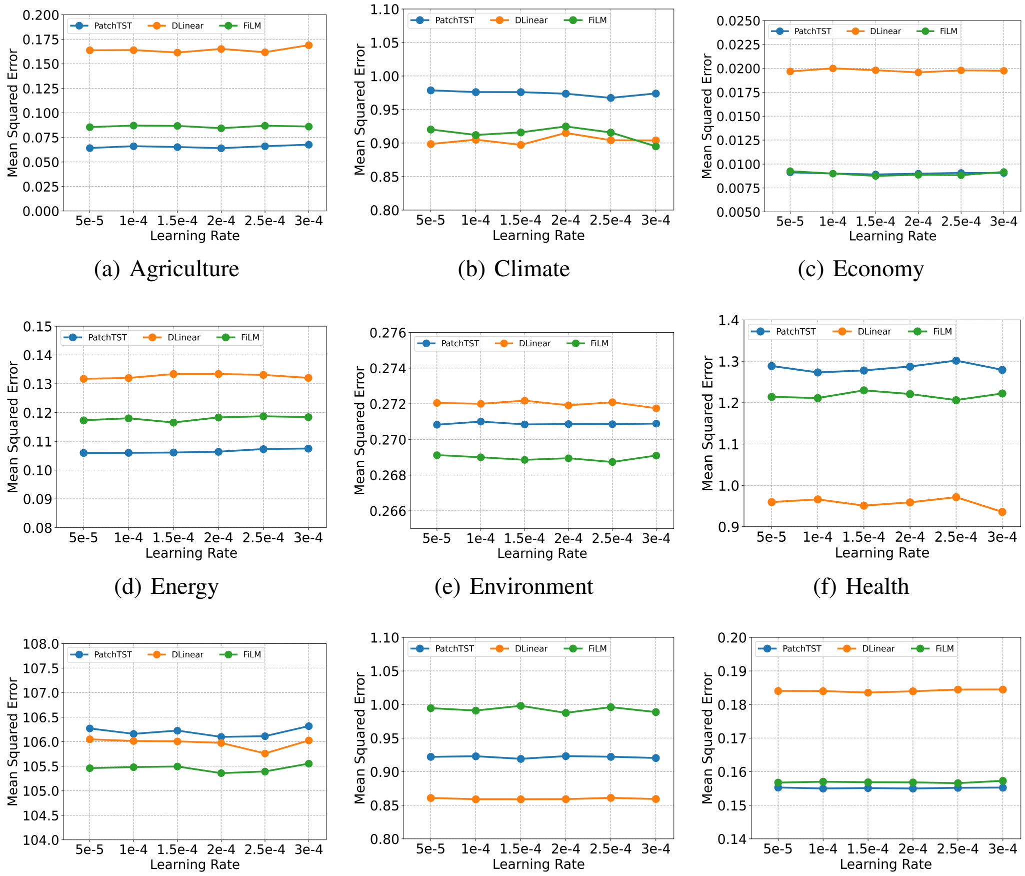
Time Series Imputation. We evaluate the performance of our TaTS framework on the imputation task using the Climate, Economy, and Traffic datasets, each with an imputation length of 24. Since the original MM-TSFLib only supports forecasting tasks, we extend it by applying a similar linear interpolation approach to serve as a baseline. For this evaluation, we select one representative time series model from each category and present the results in Table 17. The results demonstrate that TaTS consistently enhances the imputation capabilities of existing time series models, achieving improvements of up to 30% compared to baseline methods.

From the above results, it is evident that leveraging the text modality provides significant benefits over numerical-only unimodal modeling when paired texts are available. Our proposed TaTS framework effectively captures the temporal properties encoded in paired texts, achieving notable improvements over baseline methods that disregard the positional information inherent in the texts paired with time series.

Table 17: Full imputation results for the Climate, Economy, and Traffic datasets using PatchTST, DLinear and FiLM as time series models. Compared to numerical-only unimodal modeling and MM-TSFLib, our TaTS framework seamlessly enhances existing time series models to effectively handle time series with concurrent texts. Promotion: the improvement of the best baseline.

Models		PatchTST [2023]					DLinear [2023]					FiLM [2022]				
Metric		MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE
Climate	Uni-modal	1.111	0.846	1.052	3.898	442.010	0.969	0.801	0.983	1.881	59.681	1.123	0.829	1.059	2.647	128.421
	MM-TSFLib	1.010	0.821	1.002	2.156	81.983	0.963	0.802	0.980	1.394	18.580	1.130	0.833	1.061	1.949	51.811
	TaTS (ours)	0.878	0.720	0.937	1.573	35.877	0.912	0.757	0.951	1.701	25.242	0.820	0.718	0.902	1.478	30.622
	Promotion	13.1%	12.3%	6.5%	27.0%	56.2%	5.3%	5.5%	3.0%	-22.0%	-35.9%	27.0%	13.4%	14.8%	24.2%	40.9%
Economy	Uni-modal	0.029	0.138	0.170	0.051	0.004	0.057	0.190	0.239	0.068	0.007	0.077	0.209	0.277	0.076	0.010
	MM-TSFLib	0.026	0.137	0.161	0.049	0.003	0.061	0.196	0.247	0.069	0.007	0.075	0.203	0.271	0.072	0.009
	TaTS (ours)	0.017	0.107	0.128	0.038	0.002	0.045	0.171	0.210	0.061	0.006	0.054	0.168	0.232	0.061	0.007
	Promotion	34.6%	21.9%	20.5%	22.4%	33.3%	21.1%	10.0%	12.1%	10.3%	14.3%	28.0%	17.2%	14.4%	15.3%	22.2%
Traffic	Uni-modal	0.210	0.339	0.444	0.358	0.600	0.245	0.417	0.489	0.430	0.720	0.175	0.311	0.409	0.343	0.508
	MM-TSFLib	0.189	0.341	0.428	0.391	0.690	0.179	0.335	0.419	0.362	0.630	0.169	0.288	0.396	0.316	0.545
	TaTS (ours)	0.131	0.248	0.331	0.312	0.647	0.134	0.297	0.352	0.266	0.270	0.137	0.242	0.354	0.281	0.388
	Promotion	30.7%	26.8%	22.7%	12.8%	-7.8%	25.1%	11.3%	16.0%	26.5%	57.1%	18.9%	16.0%	10.6%	11.1%	23.6%

F.6 Full Hyperparameter Study Results of Learning Rate



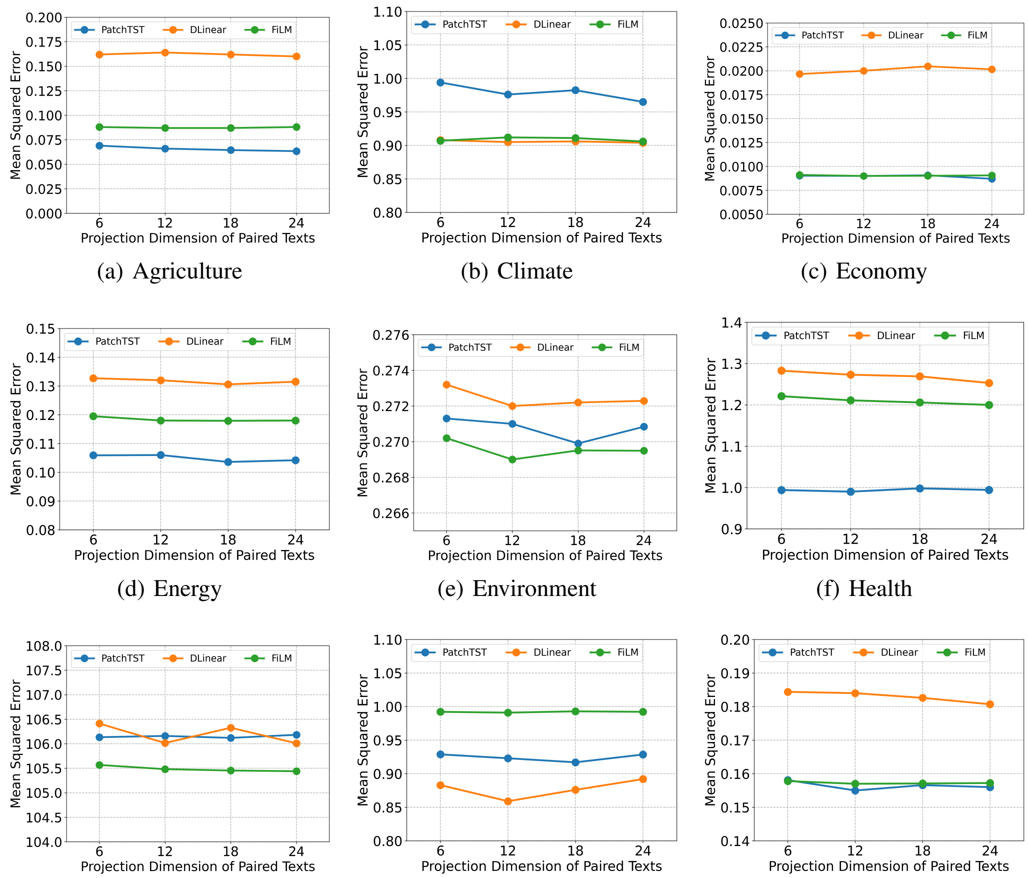
(a) Agriculture (b) Climate (c) Economy

(d) Energy (e) Environment (f) Health

(g) Security (h) Social Good (i) Traffic

Figure 11: Parameter study on the learning rate. We evaluate the impact of varying the learning rate in $\{0.00005, 0.0001, 0.00015, 0.0002, 0.00025, 0.0003\}$ by reporting the mean squared error (MSE) of our TaTS framework across datasets. The results demonstrate that TaTS maintains stable performance across different learning rate choices.

F.7 Full Hyperparameter Study Results of Text Embedding Dimension



(a) Agriculture (b) Climate (c) Economy

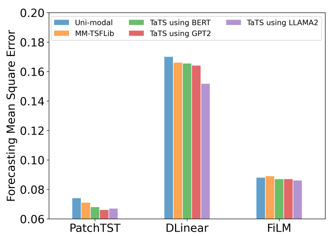
(d) Energy (e) Environment (f) Health

(g) Security (h) Social Good (i) Traffic

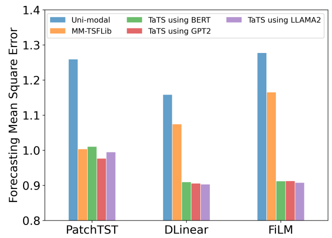
Figure 12: Parameter study on the projection dimension of paired texts. We vary the text projection dimension in $\{6, 12, 18, 24\}$ and report the mean squared error (MSE) of our TaTS framework across datasets. The results indicate that TaTS maintains robust performance across different choices of text projection dimensions.

F.8 Full Ablation Study Results Using Different Text Encoders

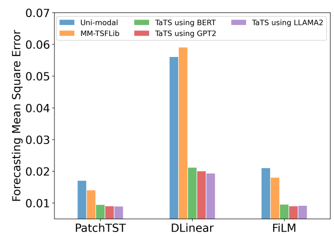
We conduct experiments to evaluate the performance of our TaTS with multiple language encoders. Specifically, we evaluation TaTS with BERT-110M[2], GPT2-1.5B[3] and LLaMA2-7B[4] as the language encoders. The results, presented in Figure 13, demonstrate that TaTS remains robust across different text encoders and consistently outperforms the baselines.



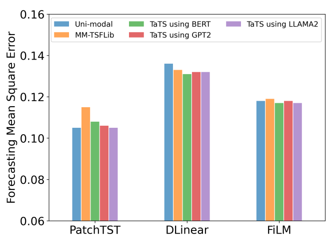
(a) Agriculture



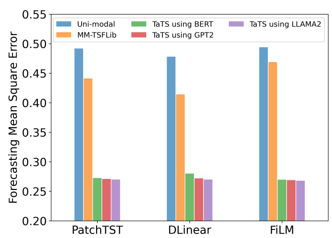
(b) Climate



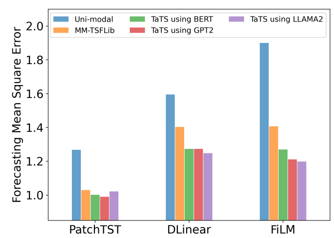
(c) Economy



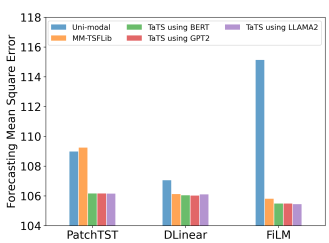
(d) Energy



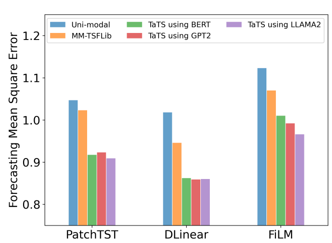
(e) Environment



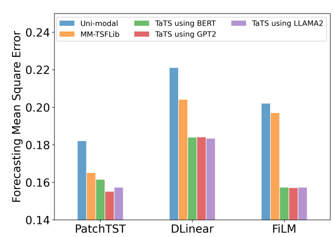
(f) Health



(g) Security



(h) Social Good



(i) Traffic

Figure 13: Performance comparison of different text encoders within the TaTS framework. Specifically, we evaluate BERT-110M, GPT2-1.5B, and LLaMA2-7B across multiple datasets using PatchTST (transformer-based model), DLinear (linear-based model), and FiLM (frequency-based model). The results demonstrate that TaTS maintains relatively stable performance across various models and datasets.

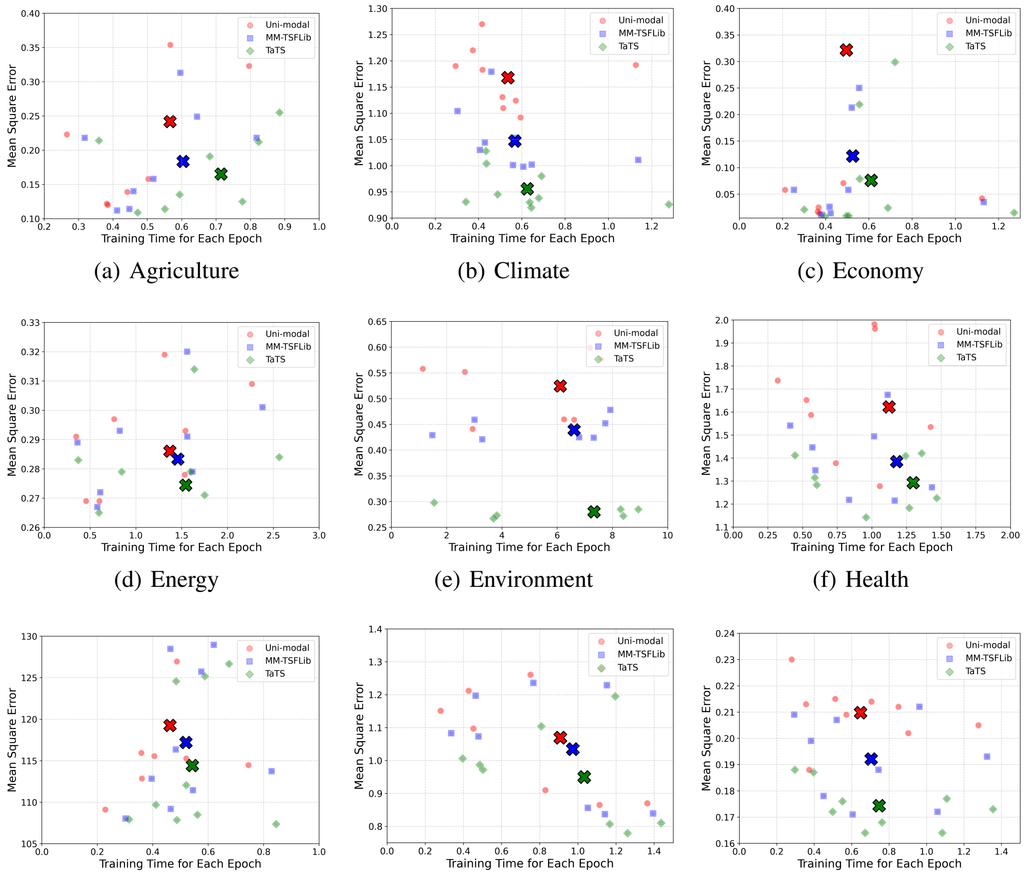
[2]https://huggingface.co/google-bert/bert-base-uncased

[3]https://huggingface.co/openai-community/gpt2

[4]https://huggingface.co/meta-llama/Llama-2-7b

F.9 Full Efficiency Results: Computational Overhead vs. Performance Gain Trade-offs

We conduct experiments to analyze the efficiency of TaTS, with results presented in Figure 14. Each subfigure visualizes the training time per epoch and the forecasting mean squared error (MSE) for different time series models, represented as transparent colored scatter points. The average performance is computed and marked with cross markers: the green cross represents the average performance of TaTS, while the red and blue crosses indicate the average performance of the baseline models. As TaTS introduces a lightweight MLP and augments the original time series with auxiliary variables projected from paired texts, it incurs a slight computational overhead, with an average increase of $\sim 8\%$. Yet this trade-off results in a $\sim 14\%$ average improvement of forecasting MSE.



(a) Agriculture (b) Climate (c) Economy

(d) Energy (e) Environment (f) Health

(g) Security (h) Social Good (i) Traffic

Figure 14: Efficiency and forecasting performance comparison of uni-modal time-series modeling, MM-TSFLib, and our TaTS framework. While TaTS incurs a slight increase in training time due to the augmentation of auxiliary variables projected from paired texts, it significantly enhances forecasting accuracy, achieving a lower MSE.