Are Language Models Actually Useful for Time Series Forecasting?

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Abstract

Large language models (LLMs) are being applied to time series forecasting. But are language models actually useful for time series? In a series of ablation studies on three recent and popular LLM-based time series forecasting methods, we find that removing the LLM component or replacing it with a basic attention layer does not degrade forecasting performance—in most cases, the results even improve! We also find that despite their significant computational cost, pretrained LLMs do no better than models trained from scratch, do not represent the sequential dependencies in time series, and do not assist in few-shot settings. Additionally, we explore time series encoders and find that patching and attention structures perform similarly to LLM-based forecasters.[1]

1 Introduction

Time series analysis is a critical problem across many domains, including disease propagation forecasting [8], retail sales analysis [3], healthcare [26, 17] and finance [31]. A great deal of recent work in time series analysis (constituting repositories with more than 1200 total stars on GitHub) has focused on adapting pretrained large language models (LLMs) to classify, forecast, and detect anomalies in time series [15, 50, 22, 4, 5, 32, 14, 44, 16]. These papers posit that language models, being advanced models for sequential dependencies in text, may generalize to the sequential dependencies in time series data. This hypothesis is unsurprising given language models are now pervasive in machine learning research. However, direct connections between language modeling and time series forecasting remain largely undefined. So to what extent is language modeling *really* beneficial for traditional time series tasks?

Our claim is simple but profound: **popular LLM-based time series forecasters perform the same or worse than basic LLM-free ablations, yet require orders of magnitude more compute**. Derived from extensive ablations, this reveals a worrying trend in contemporary time series forecasting literature. Our goal is not to imply that language models will never be useful for time series. In fact, recent works point to many exciting and promising ways that language and time series interact, like time series reasoning [25, 7, 45, 42, 37], social understanding [6] and financial reasoning [36, 20]. Rather, we aim to highlight surprising findings that existing methods do very little to use the innate reasoning power of pretrained language models on established time series tasks.

We substantiate our claim by performing three ablations of three popular and recent LLM-based forecasting methods [50, 15, 22] using eight standard benchmark datasets from reference methods

[1]All resources needed to reproduce our work are available: https://github.com/BennyTMT/LLMsForTimeSeries

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and another five datasets from MONASH [13]. First, we successfully reproduce results from the original publications. Then, we show that replacing language models with simple attention layers, basic transformer blocks, randomly-initialized language models, and *even removing the language model entirely*, yields comparable or better performance. The same performance was observed on another five datasets that were not studied by the reference methods.

Next, we compare the training and inference speed of these methods against their ablations, showing that these simpler methods reduce training and inference time by up to three orders of magnitude while maintaining comparable performance. Then, to investigate the source of LLM forecaster's performance, we further explore time series encoders. We find that a simple linear model with an encoder composed of patching and attention can achieve forecasting performance similar to that of LLMs. Next, we test whether the sequence modeling capabilities of LLMs transfer to time series by shuffling input time series and find no appreciable change in performance. Finally, we show that LLMs do not even help forecasting in few-shot settings with 10% of the training data. We discuss the implications of our findings and suggest that time series methods that use large language models are better left to multimodal applications [4, 12, 38] that require textual reasoning.

The key contributions we make in this paper are as follows:

- We propose three straightforward ablation methods for methods that pass time series into LLMs for forecasting. We then ablate three top-tier methods on thirteen standard datasets and find that LLMs fail to convincingly improve time series forecasting. However, they significantly increase computational costs in both training and inference.
- We study the impact of an LLM's pretraining by re-initializing their weights prior to forecasting. We find that this has no impact on forecasting performance. Additionally, in shuffling input time series, we find no evidence the LLMs successfully transfer sequence modeling abilities from text to time series and no indication they help in few-shot settings.
- We find a very simple model, with patching and attention as encoder, can achieve performance similar to LLMs. This suggests a massive gap between the benefits LLMs pose and the time series forecasting problem, despite a rapid rush to adopt LLMs.

2 Related Work

Here, we summarize the key works relevant to LLM-based time series models. They can be broadly classified into three sections: (i) time series forecasting using LLMs; (ii) encoders in LLM time series models; and (iii) smaller and efficient neural models for time-series.

Time Series Forecasting Using LLMs. Recently, with the development of Large Language Models (LLMs) [10, 29, 34] and their demonstrated multi-modal capabilities, more researchers have successfully applied LLMs to time series forecasting tasks [14, 16, 5, 4]. Chang *et al.,* [5] used finetuning the transformer module and positional encoding in GPT-2 to align pre-trained LLMs with time series data for forecasting tasks. Zhou et al. [50] proposed a similar finetuning method, named "OneFitsAll", for time series forecasting with GPT-2. Additionally, Jin et al. [15] introduced a reprogramming method to align LLM's Word Embedding with time series embeddings, showing good representation of time series data on LLaMA [34]. Similarly, CALF [22] and TEST [32] adapted word embeddings to enable LLMs to forecast time series data effectively. In addition to time-series forecasting models, Liu et al. [23] show that these models can be extended to classifying health-time series, such as heart-rate and daily-footsteps. These models have also been shown to outperform supervised neural models in few-shot settings.

Encoders in LLM Time Series Models. In order for an LLM to learn from text it must first be discretized and encoded as word tokens which are $1 \times d$ vectors [10, 29, 34]. Similarly, LLM-based methods for time series learn discrete time series tokens. One method is to segment the time series into overlapping patches, which effectively shortens the time series while retaining its features [15, 50, 5, 4, 28, 27, 11]. Other methods decompose time series into trend, seasonal components, and residual components [4, 28]. Lastly, Liu et al. [22] feed the multivariate time series using a Transformer to enable different channels to learn the dynamics of other channels. These embedding procedures are followed by a linear neural network layer that projects the time series encoding to the same dimensions used by the pre-trained LLM.

Dataset	ETTh1 & ETTh2	ETTm1 & ETTm2	Traffic	Electricity	Weather	Illness
Channels	7	7	862	321	21	7
Sampling-Rate	1 Hour	15 Min.	1 Hour	1 Hour	10 Min.	1 Week
Timesteps	17,420	69,680	17,544	26,304	52,696	966

Table 1: Statistics for all datasets used in reference methods [50, 22, 15].

Method	Base Model	Learnable LM Parameters	Positional Embeddings	Align Word Embeddings	Multimodal
OneFitsAll [50]	GPT-2	Add&Norm	Fine-Tune	○	○
Time-LLM [15]	LLaMA	None	Freeze	●	●
CALF [22]	GPT-2	LoRA	Fine-Tune	●	○

Table 2: Three popular methods for time series forecasting with Large Language Models.

Small and Efficient Neural Forecasters. In addition to LLMs, there has been a large body of research on smaller yet efficient frameworks that outperform their bulky counterparts in time series forecasting [19, 47, 33, 24, 2]. For example, Zeng et al. [46] present DLinear, an incredibly simple model that combines decomposition techniques and achieves better forecasting performance than state-of-the-art transformer-based time series architectures at the time, such as Informer [48], FEDformer [49], and Autoformer [40]. Furthermore, Xu et al. [43] introduces a lightweight model with only 10k parameters, which captures both amplitude and phase information in the time-series to outperform transformer-based models.

3 Experimental Setup

We use three state-of-the-art methods for time series forecasting and propose three ablation methods for LLMs: (i) "**w/o LLM**"; (ii) "**LLM2Attn**"; (iii) and "**LLM2Trsf**". To evaluate the effectiveness of LLMs in time series forecasting, we test these methods on eight standard datasets.

3.1 Reference Methods for Language Models and Time Series

We experiment with three recent methods for time series forecasting using LLMs. All models were published between December 2023 and May 2024 and are popular, with their GitHub repositories collectively amassing 1,245 stars. These methods are summarized in Table 2, and use either GPT-2 [29] or LLaMA [34] as base models, with different alignment and fine-tuning strategies.

- **OneFitsAll [50]**: OneFitsAll, sometimes called GPT4TS, applies instance norm and patching to the input time series and then feeds it into a linear layer to obtain a input representation for the language model. The multi-head attention and feed forward layers of the language model are frozen while the positional embeddings and layer norm are optimized during training. A final linear layer is used to transform the language model's final hidden states into a prediction.
- **Time-LLM [15]**: In Time-LLM the input time series is tokenized via patching and aligned with a low-dimensional representation of word embeddings using multi-head attention. The outputs of this alignment, combined with the embeddings of descriptive statistical features, are passed to a frozen pre-trained language model. The output representations of the language model are then flattened and passed through a linear layer to obtain a forecast.
- **CALF [22]**: CALF embeds the input time series by treating each channel as a token. One half of the architecture is a "textual branch" which uses cross attention to align the time series representation with a low dimensional representation of the language model's word embeddings. This representation is then passed through a pretrained, frozen language model to obtain a "textual prediction". Simultaneously, a "temporal" branch learns a low-rank adapter for a pretrained language model based on the input time series to produce a "temporal prediction" which is used for inference. The model includes additional loss terms that enforce similarity between these representations.

Reproducibility Note. While experimenting with each model, we tried to replicate the conditions of their original papers. We used the original hyper-parameters, runtime environments, and code, including model architectures, training loops, and data-loaders. To ensure a fair comparison, we have included error metrics from the original papers alongside our results wherever possible.

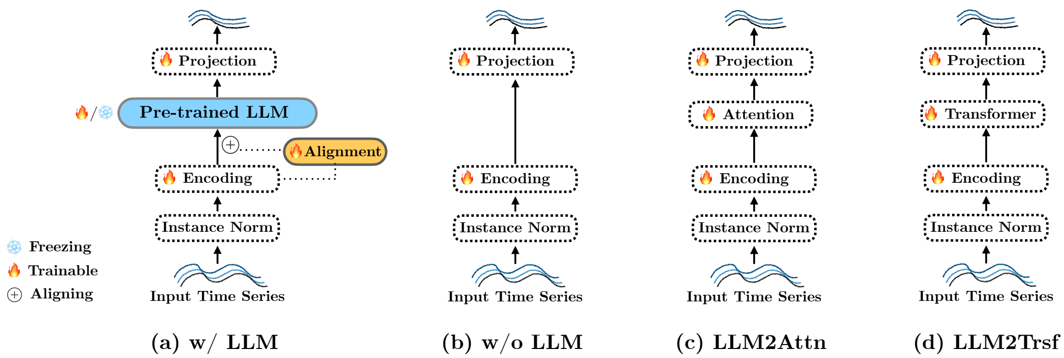

Figure 1: Overview of all LLM ablation methods. Figure (a) represents time series forecasting using an LLM as the base model. In some works, the LLM components are frozen [15, 14], while in others, they undergo fine-tuning [50, 22, 4]. Figure (b) shows the model with the LLM components removed, retaining only the remaining structure. Figure (c) replaces the LLM components with a single-layer self-attention mechanism. Figure (d) replaces the LLM components with a simple Transformer.

3.2 Proposed Ablations

To isolate the influence of the LLM in an LLM-based forecaster, we propose three ablations: removing the LLM component or replacing it with a simple block. Specifically, for each of the three methods we make the following three modifications:

- **w/o LLM** (Figure 1 (b)). We remove the language model entirely, instead passing the input tokens directly to the reference method's final layer.
- **LLM2Attn** (Figure 1 (c)). We replace the language model with a single randomly-initialized multi-head attention layer.
- **LLM2Trsf** (Figure 1 (d)). We replace the language model with a single randomly-initialized transformer block.

In the above ablations, we keep left parts of the forecasters unchanged (trainable). For example, as shown in Figure 1 (a), after removing the LLM, the input encodings are passed directly to the output projection. Alternatively, as shown in Figure 1 (b) or (c), after replacing the LLM with attention or a transformer, they are trained along with the remaining structure of the original method.

3.3 Datasets and Evaluation Metrics

Benchmark Datasets. We evaluate on the following real-world datasets: (1) **ETT** [21]: encompasses seven factors related to electricity transformers across four subsets: ETTh1 and ETTh2, which have hourly recordings, and ETTm1 and ETTm2, which have recordings every 15 minutes; (2) **Illness** [40]: includes the weekly recorded influenza illness among patients from the Centers for Disease Control, which describes the ratio of patients seen with influenza-like illness to the total number of patients; (3) **Weather** [40]: local climate data from 1,600 U.S. locations, between 2010 and 2013, and each data point consists of 11 climate features; (4) **Traffic** [40]: is an hourly dataset from California transportation department, and consists of road occupancy rates measured on San Francisco Bay area freeways; (5) **Electricity** [35]: contains the hourly electricity consumption of 321 customers from 2012 to 2014. The train-val-test split for ETT datasets is 60%-20%-20%, and for Illness, Weather, and Electricity datasets is 70%-10%-20% respectively. The statistics for all datasets is given in Table 1. We highlight that these datasets, with the same splits and size, have been extensively used to evaluate time-series forecasting ability of LLM-based and other neural models for time-series data [48, 50, 4, 15, 5, 46, 40, 49]. (6) **Exchange Rate** [18]: collected between 1990 and 2016, it contains daily exchange rates for the currencies of eight countries (Australia, British, Canada, Switzerland, China, Japan, New Zealand and Singapore). (7) **Covid Deaths** [13]: contains daily statistics of COVID-19 deaths in 266 countries and states between January and August 2020. (8) **Taxi (30 min)** [1]: contains taxi rides from 1,214 locations in New York City between January 2015 and January 2016. The data is collected every 30 minutes, with an average of 1,478 samples. (9) **NN5 (Daily)** [13]: contains daily cash withdrawal data from 111 ATMs in the UK, with each ATM having

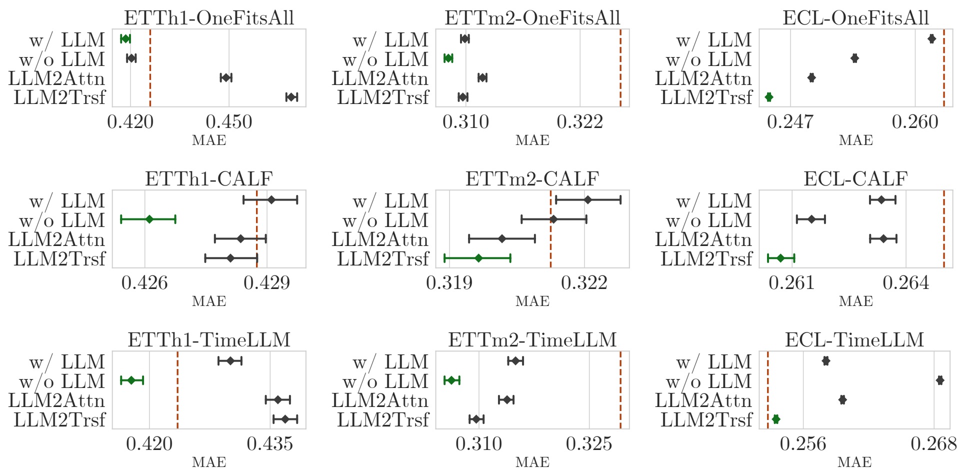

Figure 2: In the above examples, only OneFitsAll "w/ LLM" performs better than the ablation methods on ETTh1, but there is substantial overlap in bootstraped confidence intervals. The figures show the comparison of OneFitsAll, CALF, and Time-LLM using LLMs and ablations (*i.e.*, **w/o LLM**, **LLM2Attn**, and **LLM2Trsf**) on ETTh1, ETTm2, and Electricity, and the vertical dashed lines represent the results from the original work. Others Figures for MSE and other datasets are available in Figure 5 and Figure 6 in the Appendix.

791 data points. (10) **FRED-MD** [13]: contains 107 monthly macroeconomic indices released by the Federal Reserve Bank since 01/01/1959. It was extracted from the FRED-MD database.

Evaluation Metrics and Setup. We report the results in terms of mean absolute error (MAE) and mean squared error (MSE) between predicted and true values of the time-series. Mathematically, given a test-set with $\mathcal{D}$ elements, $\text{MAE} = \frac{1}{|\mathcal{D}|}\sum_{t_i \in \mathcal{D}}[|c_i - \widehat{c}_i|]$ and $\text{MSE} = \frac{1}{|\mathcal{D}|}\sum_{t_i \in \mathcal{D}}(c_i - \widehat{c}_i)^2$, where c_i and $\widehat{c}_i$ denote the true value and predicted value at the i-th index of the time-series respectively.

4 Results

In this section, we provide the details of our comprehensive evaluation of all baseline LLM models for time-series forecasting. Specifically, we ask the following research questions. **(RQ1)** Do pretrained language models contribute to forecasting performance? **(RQ2)** Are LLM-based methods worth the computational cost? **(RQ3)** Does language model pretraining help performance on forecasting tasks? **(RQ4)** Do LLMs represent sequential dependencies in time series? **(RQ5)** Do LLMs help with few-shot learning? **(RQ6)** Where does the performance come from?

4.1 Do pretrained language models contribute to forecasting performance? (RQ1)

Our results show that pretrained LLMs **are not useful for time series forecasting tasks yet**. Overall, as shown in Table 3, across 13 datasets and two metrics, ablations out perform Time-LLM methods in $26/26$ cases, CALF in $22/26$ cases, and OneFitsAll in $19/26$ cases. We averaged results over different predicting lengths, as in [50, 15, 22]. Across all prediction lengths (thirteen datasets and four prediction lengths) ablations outperformed Time-LLM, CALF, and OneFitsAll in $35/40$, $31/40$, and $29/40$ cases as measured by MAE, respectively. To ensure a fair comparison, we also report results from each method's original paper alongside our replication. For specific results refer to Appendix E.1. To better evaluate the effectiveness of LLMs and ablation methods, we include 95% bootstrapped confidence intervals for each task. In tasks where LLMs performed better, such as OneFitsAll with ETTh1, shown in Figure 2, there is still substantial overlap in the confidence intervals with the ablation method "**w/o LLM**" in MAE. Other datasets results and MSE metrics are shown in Figure 5 and Figure 6 in the Appendix. To summarize, our results on the evaluation above, it is hard to conclude that LLMs are effective in time series forecasting.

4.2 Are LLM-based methods worth the computational cost? (RQ2)

In the previous section, we showed that LLMs do not meaningfully improve performance on time series forecasting tasks. Here, we evaluate the computational intensity of these methods with their

Time-LLM [15]	Model → Dataset ↓	Time-LLM MAE	Time-LLM MSE	w/o LLM MAE	w/o LLM MSE	LLM2Attn MAE	LLM2Attn MSE	LLM2Trsf MAE	LLM2Trsf MSE	From Original Paper MAE	From Original Paper MSE
	ETTh1	0.432	0.417	**0.419**	**0.405**	0.437	0.422	0.439	0.429	0.423	0.408
	ETTh2	0.396	0.360	**0.383**	**0.345**	0.389	0.353	0.394	0.359	0.383	0.334
	ETTm1	0.377	0.356	**0.371**	**0.350**	0.376	0.356	0.377	0.359	0.371	0.329
	ETTm2	0.315	0.260	**0.307**	**0.252**	0.314	0.259	0.310	0.253	0.329	0.250
	Illness	0.894	2.017	0.924	1.956	0.849	**1.789**	**0.837**	1.795	0.801	1.435
	Weather	0.270	0.243	0.272	0.243	0.254	**0.224**	**0.254**	0.226	0.257	0.225
	Traffic	0.281	0.421	0.295	0.428	0.276	0.416	**0.275**	**0.416**	0.263	0.387
	Electricity	0.259	0.164	0.269	0.171	0.260	0.167	**0.254**	**0.161**	0.252	0.158
	Exchange Rate	0.448	0.422	**0.413**	**0.384**	0.432	0.403	0.442	0.422	-	-
	Covid Deaths	0.089	0.189	0.080	0.198	0.058	0.086	**0.054**	**0.079**	-	-
	Taxi (30 Min)	0.277	0.163	0.286	0.176	0.269	0.157	**0.255**	**0.141**	-	-
	NN5 (Daily)	0.432	0.402	0.425	0.379	0.411	0.364	**0.401**	**0.347**	-	-
	FRED-MD	0.0004	5e-7	**0.0002**	**3e-7**	0.0046	2.53e-5	0.0008	2.6e-6	-	-
	# Wins	**0**		**12**		**2**		**12**		-	
	#Parameters	6651.82M		0.55M		0.55M		0.66M		-	

CALF [22]	Model → Dataset ↓	CALF MAE	CALF MSE	w/o LLM MAE	w/o LLM MSE	LLM2Attn MAE	LLM2Attn MSE	LLM2Trsf MAE	LLM2Trsf MSE	From Original Paper MAE	From Original Paper MSE
	ETTh1	0.431	0.431	**0.428**	0.436	0.430	**0.428**	0.430	0.430	0.428	0.432
	ETTh2	0.383	0.351	0.383	0.352	**0.382**	**0.349**	0.383	0.350	0.382	0.349
	ETTm1	0.391	0.396	0.390	0.397	0.390	0.396	**0.390**	**0.394**	0.390	0.395
	ETTm2	0.323	0.283	0.322	0.282	0.321	**0.281**	**0.320**	0.281	0.321	0.281
	Illness	0.869	1.699	0.861	1.639	0.892	1.748	**0.860**	**1.630**	-	-
	Weather	**0.273**	**0.251**	0.277	0.257	0.279	0.258	0.277	0.255	0.274	0.250
	Traffic	0.284	0.443	0.278	0.439	0.275	0.430	**0.271**	**0.426**	0.281	0.439
	Electricity	0.266	0.175	0.262	0.174	0.264	0.175	**0.261**	**0.172**	0.265	0.175
	Exchange Rate	0.417	0.388	0.409	**0.367**	0.417	0.389	**0.409**	0.367	-	-
	Covid Deaths	0.084	0.163	**0.066**	0.115	0.131	0.431	0.066	**0.106**	-	-
	Taxi (30 Min)	**0.258**	**0.142**	0.264	0.147	0.267	0.150	0.267	0.150	-	-
	NN5 (Daily)	0.403	0.362	**0.386**	**0.336**	0.463	0.445	0.415	0.381	-	-
	FRED-MD	0.0012	2.9e-6	**0.0011**	**2.7e-6**	0.0015	4.9e-6	0.0017	4.5e-6	-	-
	# Wins	**4**		**7**		**4**		**11**		-	
	#Parameters	180.25M		8.17M		10.5M		13.68M		-	

OneFitsAll [50]	Model → Dataset ↓	OneFitsAll MAE	OneFitsAll MSE	w/o LLM MAE	w/o LLM MSE	LLM2Attn MAE	LLM2Attn MSE	LLM2Trsf MAE	LLM2Trsf MSE	From Original Paper MAE	From Original Paper MSE
	ETTh1	**0.420**	0.417	0.422	**0.417**	0.452	0.465	0.474	0.525	0.426	0.427
	ETTh2	**0.388**	**0.353**	0.389	0.356	0.402	0.375	0.397	0.367	0.394	0.354
	ETTm1	0.377	0.362	**0.374**	**0.358**	0.379	0.369	0.379	0.369	0.383	0.351
	ETTm2	0.310	**0.253**	**0.309**	0.255	0.312	0.256	0.310	0.254	0.326	0.266
	Illness	0.852	1.871	0.924	1.960	**0.829**	**1.763**	0.850	1.830	0.903	1.925
	Weather	**0.254**	0.226	0.272	0.245	0.256	**0.226**	0.256	0.228	0.270	0.236
	Traffic	0.273	0.420	0.273	0.439	0.266	0.415	**0.256**	**0.409**	0.294	0.414
	Electricity	0.262	0.169	0.254	0.165	0.250	0.162	**0.245**	**0.157**	0.263	0.166
	Exchange Rate	0.378	0.357	**0.361**	**0.323**	0.376	0.350	0.393	0.387	-	-
	Covid Deaths	0.057	0.075	**0.050**	**0.073**	0.058	0.103	0.078	0.162	-	-
	Taxi (30 Min)	**0.252**	**0.138**	0.259	0.143	0.259	0.145	0.257	0.140	-	-
	NN5 (Daily)	0.438	0.438	0.422	**0.385**	0.423	0.390	**0.420**	0.386	-	-
	FRED-MD	0.0006	1.2e-6	**0.0002**	**4e-7**	0.0006	1.5e-6	0.0012	2.4e-6	-	-
	# Wins	**7**		**11**		**3**		**5**		-	
	#Parameters	91.36M		9.38M		10.71M		13.54M		-	

Table 3: Forecasting performance of all models – Time-LLM, CALF, and OneFitsAll and results from our ablations. All results are averaged across different prediction lengths, though full results are available in Appendix E.1. Results in **Red** denote the best-performing model. # Wins refers to the number of times the method performed best, and # Params is the number of model parameters. "-" means the dataset is not included in the original paper.

nominal performance in mind. The language models in our reference methods use hundreds of millions and sometimes billions of parameters to perform time series forecasting. Even when the parameters of the language models are frozen they still contribute to substantial overhead during training and inference. For instance, Time-LLM has 6642 M parameters and takes 3003 minutes to train on the Weather dataset whereas ablation methods have only 0.245 M parameters and take 2.17 minutes on average. Information about training other methods on ETTh1 and Weather datasets are shown in Table 4. In the case of inference time, we divide by the maximum batch size to give an estimate of inference time per example. Time-LLM, OneFitsAll, and CALF take, on average, **28.2**,

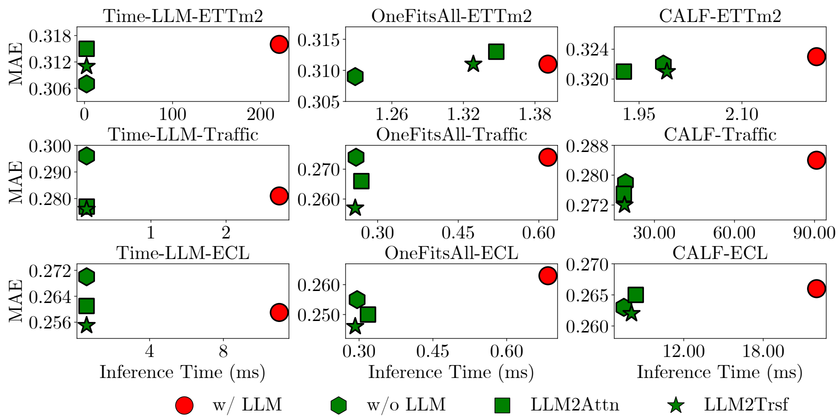

Figure 3: Ablation methods consume less time for inference while providing better forecasting performance. The figure above shows the inference time and prediction accuracy of Time-LLM, OneFitsAll, and CALF on ETTm2, Traffic, and Electricity datasets, averaged across prediction lengths. For more datasets and MSE metrics refer to Figure 7 and Figure 8 in the Appendix.

	Method	Time-LLM (LLaMA)		OneFitsAll (GPT-2)		CALF (GPT-2)	
		# Param (M)	Time (min)	# Param (M)	Time (min)	# Param (M)	Time (min)
ETTh1	**w/ LLM**	6652	181	85	7.36	180	3.28
	w/o LLM	0.198	0.99	3	0.27	8	0.35
	LLM2Attn	0.202	1.41	5	0.70	10	0.37
	LLM2Trsf	0.336	0.84	8	0.64	13	0.40
Weather	**w/ LLM**	6642	3003	86	152	180	12
	w/o LLM	0.198	1.91	4	16	8	2.32
	LLM2Attn	0.202	2.22	7	21	10	2.14
	LLM2Trsf	0.336	2.38	10	24	13	1.89

Table 4: In time series tasks, LLM (LLaMA and GPT-2) significantly increases training time. The table shows the number of model parameters (in millions) and total training time (in minutes) for three methods predicting over a length of 96 on ETTh1 and Weather data. Compared with original method "**w/ LLM**" are "**w/o LLM**", "**LLM2Attn**" and "**LLM2Trsf**".

2.3, and **1.2** times longer than the modified models. Examples can be seen in Figure 3, where the green marks (ablation methods) are typically below the red one (LLM) and are positioned towards the left of the axis, indicating a lower computational costs and better forecasting performance. Other datasets and MSE metric refer to Figure 7 and Figure 8 in Appendix. In conclusion, the computational intensity of LLMs in time series forecasting tasks does not result in a corresponding performance improvement.

4.3 Does language model pretraining help performance on forecasting tasks? (RQ3)

Our evaluation in this section indicates that **pretraining with language datasets is unnecessary for time series forecasting.** To test whether the knowledge learned during pretraining meaningfully improves forecasting performance we experimented with different combinations of pretraining and finetuning CALF's [22] language model on time series.

- **Pretrain + Finetune (Pre+FT)**. This is the original method, wherein a pretrained language model is finetuned on time series data. In the case of CALF, the base language model is frozen and low rank adapters (LoRA) are learned.
- **Random Initialization + Finetune (woPre+FT)**. Does the textual knowledge from pretraining aid time series forecasting? In this method we randomly initialize the weights of the language model (thereby erasing any effect of pretraining) and train the LLM from scratch.
- **Pretrain + No Finetuning (Pre+woFT)**. How much does finetuning on time series improve prediction performance? For this baseline we again leave the language model frozen and forgo

Methods	Pre+FT (GPT-2)		woPre+FT		Pre+woFT		woPre+woFT	
	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE
ETTh1	0.4312	**0.4313**	0.4284	0.4362	**0.4267**	0.4342	0.4365	0.4474
ETTh2	0.3838	0.3510	0.3839	**0.3508**	**0.3830**	0.3514	0.3872	0.3554
ETTm1	0.3910	0.3963	0.3933	0.4013	**0.3898**	**0.3954**	0.3949	0.4028
ETTm2	0.3230	0.2831	**0.3221**	0.2852	0.3221	**0.2827**	0.3224	0.2829
Illness	0.8691	1.6996	**0.8523**	**1.6146**	0.8742	1.6640	0.8663	1.6381
Weather	**0.2737**	**0.2510**	0.2760	0.2520	0.2771	0.2535	0.2776	0.2582
Traffic	0.2844	0.4438	**0.2771**	**0.4409**	0.2820	0.4446	0.2863	0.4483
Electricity	0.2660	0.1758	**0.2597**	**0.1669**	0.2635	0.1730	0.2663	0.1784
# Wins:	**3**		**8**		**5**		**0**	

Table 5: Randomly initializing LLM parameters and training from scratch (woPre) achieved better results than using a pretrained (Pre) model. “woFT” and “FT” refer to whether the LLM parameters are frozen or trainable.

Dataset	**ETTh1**				**Illness**			
Input Ablation	Sf-all.	Sf-half.	Ex-half	Masking	Sf-all.	Sf-half.	Ex-half	Masking
Time-LLM	51.8%	5.6%	79.6%	32.5%	99.0%	33.6%	34.9%	64.6%
w/o LLM	56.0%	4.5%	89.7%	39.5%	76.5%	20.9%	18.4%	53.0%
LLM2Attn	53.8%	3.3%	92.2%	33.8%	72.7%	20.4%	13.1%	44.6%
LLM2Trsf	50.3%	3.4%	89.2%	34.8%	74.5%	23.0%	14.3%	49.3%
OneFitsAll	62.1%	6.1%	16.6%	31.3%	86.2%	30.9%	36.7%	77.5%
w/o LLM	58.6%	6.1%	19.2%	36.1%	68.9%	13.0%	17.3%	43.5%
LLM2Attn	68.5%	9.0%	15.0%	34.4%	108.3%	39.8%	44.2%	74.2%
LLM2Trsf	58.0%	7.8%	12.6%	30.2%	90.8%	27.4%	40.3%	60.6%
CALF	50.5%	9.6%	5.6%	8.5%	113.0%	47.4%	24.4%	22.9%
w/o LLM	56.2%	12.1%	6.1%	10.4%	118.0%	50.4%	45.8%	28.9%
LLM2Attn	51.9%	10.8%	5.8%	7.3%	87.3%	42.4%	35.1%	25.8%
LLM2Trsf	50.3%	8.5%	5.5%	7.0%	102.6%	56.2%	32.6%	26.0%

Table 6: For the input shuffling/masking experiments on ETTh1 (predict length is 96) and Illness (predict length is 24), the impact of shuffling the input on the degradation of time series forecasting performance does not change significantly before and after model modifications. Results of other predict lengths refer to table 21 in Appendix.

learning LoRAs. Results from this model are therefore indicative of the base language model’s performance without additional guidance on processing time series.

- **Random Initialization + No Finetuning (woPre+woFT)**. This baseline is effectively a random projection from the input time series to a forecasting prediction and serves as a baseline comparison with the other methods.

Overall, as shown in Table 5, across 8 datasets using MAE and MSE metrics, the "Pretraining + Finetune" method performed the best 3 times, while "Random Initialization + Finetune" achieved this 8 times. This indicates that language knowledge offers very limited help for forecasting. However, "Pretrain + No Finetuning" and the baseline "Random Initialization + No Finetuning" performed the best 5 times and 0 times, respectively, suggesting that Language knowledge does not contribute meaningfully during the finetuning process. Detailed results refer to Table 20 in Appendix.

In summary, textual knowledge from pretraining provides very limited aids for time series forecasting.

4.4 Do LLMs represent sequential dependencies in time series? (RQ4)

Most time series forecasting methods that use LLMs finetune the positional encoding to help understand the position of time steps in the sequence [4, 50, 22, 5, 32]. We would expect a time series model with good positional representations to show a significant drop in predictive performance when the input is shuffled [46]. We applied three types of shuffling to the time series: shuffling the entire sequence randomly ("sf-all"), shuffling only the first half of the sequence ("sf-half"), and swapping the first and second halves of the sequence ("ex-half"). As shown in Table 6, **LLM-based methods were no more vulnerable to input shuffling than their ablations.** This implies that LLMs do not have unique capabilities for representing sequential dependencies in time series.

Model	LLaMA		w/o LLM		LLM2Attn		LLM2Trsf	
	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE
ETTh1	**0.522**	**0.555**	0.543	0.621	0.547	0.611	0.566	0.656
ETTh2	**0.394**	**0.371**	0.432	0.407	0.437	0.416	0.433	0.412
ETTm1	0.426	0.404	**0.403**	**0.393**	0.428	0.440	0.438	0.457
ETTm2	0.323	0.277	**0.319**	**0.269**	0.355	0.316	0.351	0.311
Weather	0.273	**0.234**	**0.271**	0.241	0.275	0.241	0.271	0.239
Traffic	0.306	**0.429**	0.303	0.431	0.302	0.432	**0.298**	0.432
Electricity	**0.270**	**0.175**	0.275	**0.175**	0.273	0.179	0.274	0.181
# Wins:	8		7		0		1	

Table 7: In few-shot scenarios (10% dataset), LLaMA (Time-LLM) performs similarly to the ablation methods. LLaMA and "**w/o LLM**" each outperformed the other 8 times. Note that the results of Time-LLM is from the original paper [15].

Model	GPT-2		w/o LLM		LLM2Attn		LLM2Trsf	
	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE
ETTh1	0.543	0.649	**0.542**	**0.642**	0.545	0.646	0.544	0.643
ETTh2	0.433	0.434	**0.429**	**0.427**	0.433	0.431	0.432	0.434
ETTm1	0.500	0.574	**0.499**	**0.572**	0.503	0.581	0.507	0.586
ETTm2	0.339	0.304	**0.338**	**0.303**	0.340	0.305	0.340	0.305
Weather	**0.286**	**0.263**	0.287	0.265	0.293	0.270	0.286	0.264
Traffic	0.369	0.571	0.337	0.517	0.341	0.518	**0.333**	**0.510**
Electricity	0.301	0.220	**0.287**	**0.205**	0.292	0.208	0.290	0.206
# Wins:	2		10		0		2	

Table 8: In few-shot scenarios (10% dataset), Ablation methods perform much better than GPT-2 (CALF). Without LLMs, 12 out of 14 cases showed better performance.

4.5 Do LLMs help with few-shot learning in forecasting? (RQ5)

In this section, our evaluation demonstrates that LLMs are still **not meaningfully useful in few-shot learning scenarios.**

While our results indicate that LLMs are not useful for time series forecasting, it is nonetheless possible that knowledge encoded in pretrained weights could help performance in few-shot settings where data are scarce. To evaluate whether this is the case we trained models and their ablations on 10% of each dataset. Specifically, we evaluated LLaMA in Time-LLM methods. The results for LLaMA, shown in Table 7, compared LLaMA with completely removing the LLM (**w/o LLM**). There was no difference, with each performing better in 8 cases. We conducted similar experiments with CALF, a GPT-2-based method. Our results in Table 8 indicate that our ablations can perform better than LLMs in few-shot scenarios.

4.6 Where does the performance come from? (RQ6)

In this section, we evaluate common encoding techniques used in LLM time series models. We find that combining **patching with one-layer attention is a simple and effective choice.**

In subsection 3.2, we found that simple ablations of LLM-based methods did not decrease performance. To understand why such simple methods work so well we selected some popular techniques used for encoding in LLM time series tasks, such as patching [50, 15, 5, 32, 22, 11], decomposition [4, 28]. A basic transformer block also can be used to aid in encoding [22].

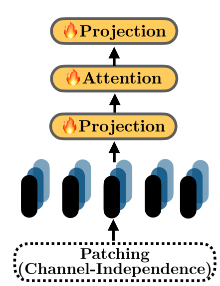

Figure 4: PAttn Model.

The specific results, shown in Table 18 in the Appendix, indicate that a structure combining patching and attention, named "PAttn", performs better than most other encoding methods on small datasets (with time stamps less than 1 million) and is even comparable to LLM methods. Its detailed structure, as shown in Figure 4, involves applying "instance norm" to the time series, followed by patching and projection. Then, one-layer attention enables feature learning between patches. For larger datasets, such as Traffic (~15 million) and Electricity (~8 million), a model named "LTrsf," using the encoder from CALF [22], performs better. In those methods, finally, time series embedding will be projected with a single linear layer to forecast. Details of other encoders is in Appendix subsection D.3.

Overall, patching plays a crucial role in encoding. Additionally, basic Attention and Transformer blocks also effectively aid in encoding.

5 Conclusion

In this paper we showed that despite the recent popularity of LLMs in time series forecasting they do not appear to meaningfully improve performance. We experimented with simple ablations, showing that they maintain or improve the performance of the LLM-based counterparts while requiring considerably less compute. Once more, our goal is not to suggest that LLMs have no place in time series analysis. To do so would likely prove to be a shortsighted claim. Rather, we suggest that the community should dedicate more focus to the exciting tasks could be unlocked by LLMs at the interface of time series and language such as time series reasoning [25, 7, 45, 37], or social understanding [6].

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Are Language Models Actually Useful for Time Series Forecasting? (Appendix)

A Limitations

Here, we discuss the limitations of our paper.

1. We evaluate the ability of LLMs using time-series forecasting. However, to get a better picture of how LLMs can work with time-series, this ability should be evaluated across other downstream tasks as well, such as time-series classification and question-answering.
2. Our evaluation is limited to only time-series datasets, *i.e.*, sequences with even time-intervals. However, there also exists a large fraction of data in the form of non-uniform series, such as payment records, online purchases, etc. Understanding the ability of LLMs in forecasting non-uniform sequences is also necessary to verify our claim on the usefulness of LLMs for time-series data.

B Broader Societal Impact

One of the major impacts our study will have is on the influx of models that use LLMs for modeling time-series. Our results will help researchers to not simply follow the trend of using LLMs in all applications, but to check their usability in detail. Specifically, these findings will help them determine if the LLM component is necessary and if the computational costs are reasonable for the specific setting. In addition to the research community, our findings on the better performance of smaller and simpler models will help develop scalable models that are easy to understand, interpret, and can be deployed cheaply in real-world applications. While we agree that a majority of our results are experimental and limited to selected datasets, we feel that these results will also help researchers narrow down their search space for better models in time-series forecasting, and not simply neglect the simpler models.

C License

All our contributions will be released under the MIT License.

D Additional Experimental Details

D.1 System Configuration

We train and evaluate each reference method and each architecture modification using the same device. For Time-LLM [15], applying LlaMA-7B [34], we use NVIDIA A100 GPU with 80GB memory. For other methods [50, 22], applying GPT-2 [29], we use NVIDIA RTX A6000 GPU with 48GB memory. Though an analysis of memory footprint is beyond scope of this research, we note that training the baselines in the absence of LLM can be done within smaller GPUs as well.

D.2 Baseline Hyper-Parameter Details

When reproducing the reference methods, we used the original repository's hyper-parameters and model structures. In the ablation study, due to the smaller model parameters, we adjusted the learning rate or increased the batch size in some cases. All other training details remained identical with the reference methods. The specific training details and hyper-parameters are provided in the code and run scripts of the repository[2]. Note that the training process and hyper-parameters for the simple methods can also be accessed via this link.

D.3 Details of Encoder Exploration and Simple Methods

To investigate the source of LLM method performance, we conducted further research on encoders. We used various encoders to encode time series data, followed by a linear layer to project the time

[2]https://github.com/BennyTMT/LLMsForTimeSeries

series embeddings to the forecast. The encoder structure combining patching and attention is shown in Figure 4. The key difference between PAttn and PatchTST [27] is the absence of position embedding and the Feed Forward in PatchTST [27], or, more specifically, replacing the Transformer Encoder with a simple single-layer Attention structure. It could be a simple yet effective method to help evaluate the trade-off between cost and performance for newly proposed methods.

In addition, we propose three different neural models (i) "LTrsf": which performs better on larger datasets, uses CALF 's [22] encoder without cross-modal attention. This could be a potential source of CALF 's performance; (ii) "D-LTrsf"; and (iii) "D-PAttn": both of them decompose the time series into three sub-sequences and forecast each using the above two methods respectively, and then linearly combine the results for the final forecast. Across our results in Table 18, we note that even simpler models significantly outperform LLM-based time-series models. In detail, the LLM-based models, all combined we able to appear 33 times as the best and the second-best performer. However, "PAttn" was outperforming them by appearing 34 times as the best and the second-best performer. In addition, the comparison between "PAttn", "LTrsf" and other state-of-the-art methods is shown in Table 19.

E Additional Experiments

Here we present the results of additional experiments that also highlight the ability of LLMs in modeling time-series data.

E.1 Confidence Intervals for Forecasting

Since LLMs and deep learning models in general are probabilistic in nature, their predictions can vary across different runs and different random initializations. Thus, we report the confidence intervals (CIs) for all MAE and MSE predictions made by our baseline models. We report the CIs for MAE prediction by Time-LLM, CALF, OneFitsAll in Tables 9, 11, and 13, for MSE predictions in Tables 10, 12, and 14, respectively. Across all results, we note that the range of variation is quite small, and these intervals do not affect our observations. To illustrate the subtle differences more clearly, we present the visualized results in Figure 5 and Figure 6.

Confidence Intervals for other Datasets. To evaluate the generality of the ablations in the paper, we introduce five additional datasets that have not been studied by the reference methods [50, 15, 22]. The above datasets are used in many time series forecasting studies [30, 9, 39, 1, 46]. The prediction lengths for the "Exchange Rate" are "96, 192, 336, 720", as in [46, 18]. The prediction lengths for the other four datasets are 30, 48, 56, and 12, respectively, following the settings in Chronos [1]. As shown in Tables 15, 16, and 17, the forecasting performance on the five new datasets, using the three methods [50, 15, 22] we referenced, still demonstrates that language models are unnecessary for forecasting tasks.

E.2 Complete Results

Here we provide the results for all methods and datasets that we were unable to add to the main paper.

Inference Times. All results regarding "inference time" and forecast performance are shown in Figure 7 and Figure 8 respectively.

Randomized Parameters and Random-Shuffling of Inputs. The results of the randomized parameters are shown in Table 20. The remaining results for shuffled input are shown in Table 21,22,23 and 24.

Models		Time-LLM		**w/o LLM**		**LLM2Attn**		**LLM2Trsf**		From Paper
Dataset	Window	MAE	CI	MAE	CI	MAE	CI	MAE	CI	
ETTh1	96	0.402	(0.399,0.405)	0.385	(0.383,0.388)	0.400	(0.397,0.402)	0.402	(0.399,0.405)	0.392
	192	0.421	(0.418,0.424)	0.412	(0.409,0.415)	0.423	(0.420,0.426)	0.426	(0.424,0.429)	0.418
	336	0.438	(0.435,0.440)	0.431	(0.428,0.433)	0.475	(0.472,0.478)	0.449	(0.447,0.453)	0.427
	720	0.468	(0.465,0.470)	0.452	(0.450,0.455)	0.452	(0.449,0.455)	0.480	(0.477,0.483)	0.457
ETTh2	96	0.346	(0.343,0.350)	0.331	(0.328,0.334)	0.338	(0.334,0.342)	0.346	(0.342,0.350)	0.328
	192	0.391	(0.387,0.396)	0.374	(0.369,0.378)	0.384	(0.381,0.389)	0.390	(0.386,0.393)	0.375
	336	0.414	(0.410,0.418)	0.407	(0.402,0.410)	0.406	(0.402,0.410)	0.404	(0.400,0.408)	0.409
	720	0.434	(0.429,0.437)	0.424	(0.421,0.428)	0.430	(0.426,0.434)	0.437	(0.434,0.441)	0.420
ETTm1	96	0.341	(0.340,0.342)	0.337	(0.336,0.338)	0.333	(0.332,0.335)	0.336	(0.335,0.338)	0.334
	192	0.369	(0.368,0.371)	0.360	(0.359,0.361)	0.366	(0.364,0.367)	0.366	(0.365,0.368)	0.358
	336	0.379	(0.378,0.381)	0.379	(0.378,0.381)	0.386	(0.385,0.387)	0.386	(0.385,0.388)	0.384
	720	0.419	(0.418,0.420)	0.410	(0.409,0.411)	0.422	(0.421,0.423)	0.419	(0.418,0.421)	0.411
ETTm2	96	0.248	(0.247,0.250)	0.246	(0.245,0.248)	0.249	(0.248,0.251)	0.249	(0.248,0.251)	0.253
	192	0.304	(0.303,0.306)	0.285	(0.283,0.287)	0.293	(0.291,0.295)	0.294	(0.292,0.295)	0.293
	336	0.329	(0.328,0.331)	0.321	(0.319,0.323)	0.333	(0.331,0.335)	0.323	(0.321,0.325)	0.392
	720	0.382	(0.380,0.385)	0.377	(0.375,0.379)	0.384	(0.382,0.387)	0.377	(0.376,0.380)	0.379
Illness	24	0.807	(0.772,0.841)	0.913	(0.879,0.950)	0.848	(0.812,0.884)	0.837	(0.805,0.870)	0.727
	36	0.833	(0.804,0.861)	0.902	(0.878,0.931)	0.846	(0.813,0.882)	0.846	(0.816,0.872)	0.814
	48	1.012	(0.986,1.041)	0.932	(0.907,0.958)	0.828	(0.805,0.847)	0.805	(0.785,0.842)	0.807
	60	0.925	(0.898,0.953)	0.949	(0.920,0.979)	0.873	(0.846,0.905)	0.862	(0.836,0.893)	0.857
Weather	96	0.199	(0.198,0.200)	0.213	(0.212,0.214)	0.189	(0.188,0.190)	0.189	(0.188,0.190)	0.201
	192	0.261	(0.260,0.262)	0.252	(0.251,0.253)	0.231	(0.230,0.232)	0.229	(0.229,0.230)	0.234
	336	0.279	(0.278,0.280)	0.288	(0.286,0.289)	0.272	(0.270,0.273)	0.273	(0.271,0.274)	0.279
	720	0.342	(0.341,0.343)	0.337	(0.336,0.338)	0.327	(0.326,0.328)	0.327	(0.326,0.329)	0.316
Traffic	96	0.267	(0.267,0.267)	0.287	(0.287,0.287)	0.266	(0.266,0.266)	0.269	(0.269,0.269)	0.248
	192	0.271	(0.270,0.271)	0.290	(0.290,0.290)	0.270	(0.270,0.271)	0.272	(0.272,0.272)	0.247
	336	0.296	(0.296,0.297)	0.294	(0.294,0.294)	0.278	(0.278,0.278)	0.269	(0.269,0.269)	0.271
	720	0.291	(0.291,0.292)	0.312	(0.312,0.312)	0.294	(0.293,0.294)	0.294	(0.294,0.294)	0.288
Electricity	96	0.233	(0.233,0.233)	0.246	(0.246,0.246)	0.234	(0.233,0.234)	0.229	(0.229,0.230)	0.224
	192	0.247	(0.247,0.247)	0.257	(0.257,0.257)	0.250	(0.249,0.250)	0.242	(0.241,0.242)	0.241
	336	0.267	(0.266,0.267)	0.273	(0.273,0.274)	0.263	(0.263,0.264)	0.257	(0.257,0.258)	0.248
	720	0.290	(0.290,0.290)	0.302	(0.302,0.302)	0.296	(0.296,0.296)	0.290	(0.290,0.290)	0.298
#Wins		5		13		6		8		-

Table 9: Confidence Intervals for MAE predictions of Time-LLM. The best performing model in highlighted in Red color text. #Wins refers to the total number of times the method performed best.

Models		Time-LLM		**w/o LLM**		**LLM2Attn**		**LLM2Trsf**		From Paper
Dataset	Window	MSE	CI	MSE	CI	MSE	CI	MSE	CI	
ETTh1	96	0.376	(0.371,0.382)	0.360	(0.355,0.364)	0.377	(0.371,0.383)	0.382	(0.375,0.387)	0.362
	192	0.407	(0.401,0.412)	0.401	(0.397,0.406)	0.408	(0.403,0.414)	0.416	(0.411,0.422)	0.398
	336	0.430	(0.423,0.437)	0.431	(0.425,0.437)	0.477	(0.470,0.482)	0.441	(0.437,0.446)	0.430
	720	0.457	(0.450,0.463)	0.429	(0.422,0.434)	0.429	(0.423,0.434)	0.479	(0.473,0.484)	0.442
ETTh2	96	0.286	(0.282,0.295)	0.271	(0.264,0.278)	0.281	(0.276,0.288)	0.292	(0.284,0.297)	0.268
	192	0.361	(0.354,0.367)	0.342	(0.336,0.349)	0.355	(0.346,0.363)	0.360	(0.354,0.367)	0.329
	336	0.390	(0.384,0.396)	0.379	(0.373,0.384)	0.384	(0.377,0.393)	0.379	(0.371,0.385)	0.368
	720	0.405	(0.397,0.410)	0.389	(0.382,0.396)	0.395	(0.390,0.400)	0.405	(0.397,0.412)	0.372
ETTm1	96	0.291	(0.288,0.293)	0.292	(0.289,0.295)	0.289	(0.286,0.292)	0.292	(0.289,0.295)	0.272
	192	0.341	(0.339,0.344)	0.331	(0.328,0.334)	0.336	(0.334,0.340)	0.341	(0.338,0.344)	0.310
	336	0.359	(0.356,0.362)	0.362	(0.359,0.364)	0.373	(0.368,0.376)	0.374	(0.370,0.377)	0.352
	720	0.433	(0.431,0.436)	0.417	(0.414,0.419)	0.429	(0.425,0.432)	0.429	(0.426,0.433)	0.383
ETTm2	96	0.162	(0.160,0.164)	0.161	(0.159,0.163)	0.163	(0.160,0.165)	0.165	(0.163,0.167)	0.161
	192	0.235	(0.232,0.239)	0.217	(0.214,0.220)	0.223	(0.221,0.227)	0.222	(0.219,0.225)	0.219
	336	0.280	(0.276,0.282)	0.272	(0.268,0.275)	0.284	(0.281,0.287)	0.270	(0.266,0.273)	0.271
	720	0.366	(0.362,0.370)	0.359	(0.356,0.362)	0.367	(0.363,0.371)	0.355	(0.352,0.359)	0.352
Illness	24	1.792	(1.651,1.954)	2.034	(1.872,2.225)	1.860	(1.691,2.059)	1.923	(1.755,2.073)	1.285
	36	1.833	(1.701,2.009)	1.923	(1.753,2.056)	1.805	(1.657,1.967)	1.816	(1.707,1.961)	1.404
	48	2.269	(2.153,2.379)	1.916	(1.804,2.024)	1.716	(1.601,1.844)	1.655	(1.552,1.760)	1.523
	60	2.177	(2.064,2.308)	1.953	(1.844,2.076)	1.777	(1.680,1.874)	1.789	(1.637,1.916)	1.531
Weather	96	0.155	(0.153,0.157)	0.171	(0.168,0.173)	0.147	(0.144,0.149)	0.147	(0.145,0.150)	0.147
	192	0.223	(0.221,0.225)	0.214	(0.212,0.217)	0.191	(0.189,0.193)	0.191	(0.189,0.194)	0.189
	336	0.251	(0.249,0.254)	0.260	(0.258,0.262)	0.242	(0.240,0.245)	0.246	(0.243,0.248)	0.262
	720	0.345	(0.343,0.348)	0.328	(0.325,0.331)	0.319	(0.317,0.322)	0.323	(0.321,0.326)	0.304
Traffic	96	0.392	(0.390,0.394)	0.409	(0.407,0.411)	0.395	(0.393,0.397)	0.395	(0.393,0.397)	0.362
	192	0.409	(0.407,0.411)	0.417	(0.415,0.420)	0.405	(0.403,0.407)	0.407	(0.405,0.409)	0.374
	336	0.434	(0.432,0.436)	0.426	(0.424,0.428)	0.416	(0.414,0.418)	0.412	(0.410,0.415)	0.385
	720	0.451	(0.450,0.454)	0.461	(0.459,0.463)	0.450	(0.448,0.452)	0.451	(0.448,0.453)	0.430
Electricity	96	0.137	(0.137,0.138)	0.143	(0.143,0.143)	0.138	(0.137,0.138)	0.133	(0.133,0.134)	0.131
	192	0.152	(0.151,0.152)	0.157	(0.157,0.158)	0.154	(0.154,0.155)	0.148	(0.148,0.149)	0.152
	336	0.169	(0.169,0.169)	0.174	(0.173,0.174)	0.169	(0.169,0.170)	0.164	(0.164,0.165)	0.160
	720	0.200	(0.199,0.200)	0.211	(0.210,0.211)	0.209	(0.208,0.209)	0.201	(0.201,0.202)	0.192
1^{st}**count**		5		11		10		7		-

Table 10: Confidence Intervals for MSE predictions of Time-LLM. The best performing model in highlighted in Red color text. #Wins refers to the total number of times the method performed best.

Models		CALF		**w/o LLM**		**LLM2Attn**		**LLM2Trsf**		From Paper
Dataset	Window	MAE	CI	MAE	CI	MAE	CI	MAE	CI	
ETTh1	96	0.393	(0.391,0.394)	0.391	(0.390,0.392)	0.391	(0.389,0.392)	0.393	(0.392,0.395)	0.389
	192	0.426	(0.424,0.427)	0.419	(0.418,0.420)	0.424	(0.423,0.425)	0.423	(0.422,0.425)	0.423
	336	0.440	(0.439,0.441)	0.437	(0.436,0.438)	0.441	(0.440,0.442)	0.439	(0.438,0.440)	0.436
	720	0.466	(0.465,0.467)	0.467	(0.465,0.467)	0.467	(0.466,0.467)	0.465	(0.464,0.466)	0.467
ETTh2	96	0.336	(0.333,0.339)	0.332	(0.329,0.335)	0.333	(0.331,0.336)	0.333	(0.331,0.336)	0.331
	192	0.378	(0.376,0.381)	0.378	(0.376,0.381)	0.379	(0.376,0.382)	0.379	(0.376,0.382)	0.380
	336	0.394	(0.391,0.396)	0.394	(0.391,0.398)	0.393	(0.390,0.396)	0.394	(0.391,0.398)	0.394
	720	0.428	(0.425,0.430)	0.428	(0.426,0.430)	0.427	(0.424,0.430)	0.427	(0.425,0.429)	0.426
ETTm1	96	0.350	(0.349,0.352)	0.348	(0.346,0.350)	0.348	(0.347,0.349)	0.348	(0.347,0.349)	0.349
	192	0.376	(0.375,0.376)	0.374	(0.374,0.375)	0.376	(0.375,0.377)	0.374	(0.373,0.375)	0.375
	336	0.401	(0.400,0.402)	0.399	(0.398,0.400)	0.401	(0.400,0.401)	0.399	(0.398,0.400)	0.399
	720	0.438	(0.437,0.439)	0.442	(0.441,0.443)	0.439	(0.438,0.439)	0.439	(0.438,0.440)	0.438
ETTm2	96	0.255	(0.255,0.256)	0.256	(0.255,0.257)	0.253	(0.252,0.254)	0.252	(0.251,0.253)	0.256
	192	0.300	(0.299,0.302)	0.299	(0.297,0.300)	0.297	(0.295,0.298)	0.297	(0.296,0.298)	0.297
	336	0.341	(0.340,0.343)	0.340	(0.338,0.341)	0.339	(0.338,0.341)	0.339	(0.338,0.341)	0.339
	720	0.395	(0.394,0.397)	0.395	(0.394,0.397)	0.395	(0.394,0.397)	0.395	(0.393,0.396)	0.393
Illness	24	0.788	(0.742,0.841)	0.800	(0.740,0.852)	0.806	(0.757,0.845)	0.792	(0.745,0.832)	0.000
	36	0.837	(0.798,0.872)	0.802	(0.771,0.830)	0.892	(0.849,0.943)	0.928	(0.895,0.974)	0.000
	48	0.890	(0.842,0.937)	0.888	(0.849,0.933)	0.897	(0.868,0.938)	0.859	(0.816,0.907)	0.000
	60	0.962	(0.917,0.999)	0.955	(0.917,0.997)	0.975	(0.937,1.022)	0.861	(0.832,0.904)	0.000
Weather	96	0.207	(0.206,0.207)	0.212	(0.212,0.213)	0.217	(0.216,0.217)	0.211	(0.210,0.211)	0.204
	192	0.251	(0.250,0.252)	0.256	(0.255,0.257)	0.257	(0.256,0.258)	0.255	(0.254,0.255)	0.250
	336	0.292	(0.291,0.293)	0.296	(0.295,0.297)	0.298	(0.297,0.299)	0.296	(0.295,0.297)	0.291
	720	0.345	(0.344,0.347)	0.347	(0.346,0.349)	0.347	(0.345,0.348)	0.347	(0.346,0.349)	0.352
Traffic	96	0.274	(0.272,0.275)	0.267	(0.266,0.268)	0.265	(0.264,0.266)	0.258	(0.257,0.260)	0.268
	192	0.276	(0.275,0.277)	0.271	(0.270,0.273)	0.268	(0.267,0.269)	0.265	(0.265,0.267)	0.278
	336	0.286	(0.285,0.287)	0.278	(0.277,0.279)	0.275	(0.274,0.276)	0.272	(0.271,0.273)	0.281
	720	0.301	(0.300,0.302)	0.297	(0.296,0.298)	0.293	(0.292,0.294)	0.291	(0.290,0.291)	0.300
Electricity	96	0.240	(0.239,0.240)	0.238	(0.238,0.239)	0.238	(0.238,0.239)	0.236	(0.235,0.236)	0.238
	192	0.254	(0.253,0.254)	0.250	(0.249,0.251)	0.251	(0.250,0.252)	0.248	(0.248,0.249)	0.252
	336	0.270	(0.270,0.271)	0.265	(0.265,0.266)	0.266	(0.266,0.267)	0.264	(0.263,0.264)	0.267
	720	0.300	(0.300,0.301)	0.297	(0.296,0.297)	0.302	(0.302,0.303)	0.299	(0.299,0.300)	0.303
#Wins		7		9		4		12		-

Table 11: Confidence Intervals for MAE predictions of CALF. The best performing model in highlighted in Red color text. #Wins refers to the total number of times the method performed best.

Models		CALF		**w/o LLM**		**LLM2Attn**		**LLM2Trsf**		From Paper
Dataset	Window	MSE	CI	MSE	CI	MSE	CI	MSE	CI	
ETTh1	96	0.370	(0.366,0.373)	0.375	(0.372,0.378)	0.368	(0.364,0.371)	0.371	(0.368,0.374)	0.369
	192	0.429	(0.426,0.433)	0.427	(0.424,0.430)	0.425	(0.422,0.428)	0.428	(0.424,0.431)	0.427
	336	0.451	(0.448,0.454)	0.457	(0.454,0.460)	0.448	(0.446,0.452)	0.449	(0.446,0.451)	0.456
	720	0.476	(0.474,0.478)	0.488	(0.486,0.491)	0.471	(0.470,0.473)	0.475	(0.474,0.478)	0.479
ETTh2	96	0.284	(0.279,0.289)	0.282	(0.277,0.286)	0.282	(0.278,0.286)	0.282	(0.278,0.286)	0.279
	192	0.353	(0.347,0.359)	0.354	(0.349,0.359)	0.354	(0.348,0.359)	0.353	(0.349,0.358)	0.353
	336	0.361	(0.356,0.365)	0.366	(0.362,0.371)	0.360	(0.356,0.364)	0.363	(0.359,0.367)	0.362
	720	0.406	(0.403,0.409)	0.408	(0.404,0.412)	0.404	(0.400,0.408)	0.404	(0.400,0.408)	0.404
ETTm1	96	0.323	(0.319,0.329)	0.323	(0.320,0.325)	0.320	(0.318,0.323)	0.321	(0.319,0.324)	0.323
	192	0.375	(0.374,0.377)	0.374	(0.371,0.376)	0.375	(0.373,0.377)	0.372	(0.370,0.374)	0.374
	336	0.411	(0.409,0.413)	0.409	(0.407,0.411)	0.411	(0.410,0.414)	0.408	(0.406,0.410)	0.409
	720	0.476	(0.474,0.478)	0.484	(0.482,0.485)	0.477	(0.476,0.479)	0.478	(0.476,0.480)	0.477
ETTm2	96	0.177	(0.175,0.179)	0.178	(0.176,0.180)	0.176	(0.174,0.178)	0.175	(0.173,0.176)	0.178
	192	0.245	(0.243,0.246)	0.244	(0.241,0.246)	0.241	(0.239,0.243)	0.242	(0.240,0.245)	0.242
	336	0.309	(0.306,0.311)	0.308	(0.305,0.310)	0.306	(0.304,0.309)	0.308	(0.305,0.310)	0.307
	720	0.402	(0.400,0.405)	0.401	(0.397,0.404)	0.401	(0.398,0.404)	0.401	(0.398,0.404)	0.397
Illness	24	1.460	(1.297,1.672)	1.544	(1.342,1.719)	1.573	(1.382,1.758)	1.450	(1.267,1.625)	-
	36	1.573	(1.441,1.705)	1.437	(1.307,1.533)	1.699	(1.540,1.868)	1.780	(1.610,1.960)	-
	48	1.784	(1.630,1.937)	1.710	(1.500,1.883)	1.716	(1.602,1.854)	1.639	(1.528,1.821)	-
	60	1.982	(1.786,2.128)	1.867	(1.720,2.025)	2.004	(1.837,2.186)	1.652	(1.522,1.832)	-
Weather	96	0.168	(0.166,0.169)	0.176	(0.175,0.177)	0.178	(0.177,0.180)	0.173	(0.172,0.175)	0.164
	192	0.216	(0.214,0.218)	0.224	(0.223,0.226)	0.225	(0.223,0.226)	0.221	(0.220,0.223)	0.214
	336	0.271	(0.269,0.273)	0.277	(0.275,0.279)	0.279	(0.277,0.280)	0.276	(0.274,0.278)	0.269
	720	0.350	(0.347,0.353)	0.352	(0.350,0.355)	0.352	(0.349,0.354)	0.353	(0.350,0.355)	0.355
Traffic	96	0.416	(0.413,0.419)	0.410	(0.407,0.413)	0.402	(0.399,0.404)	0.396	(0.393,0.399)	0.407
	192	0.430	(0.429,0.433)	0.428	(0.425,0.431)	0.419	(0.416,0.421)	0.416	(0.414,0.418)	0.430
	336	0.451	(0.449,0.453)	0.443	(0.441,0.445)	0.435	(0.433,0.437)	0.431	(0.429,0.432)	0.444
	720	0.478	(0.476,0.480)	0.476	(0.474,0.479)	0.467	(0.465,0.469)	0.463	(0.461,0.465)	0.477
Electricity	96	0.147	(0.146,0.148)	0.149	(0.148,0.151)	0.148	(0.146,0.149)	0.145	(0.144,0.147)	0.145
	192	0.163	(0.162,0.164)	0.162	(0.161,0.163)	0.161	(0.160,0.162)	0.159	(0.158,0.160)	0.161
	336	0.178	(0.178,0.179)	0.175	(0.175,0.176)	0.175	(0.174,0.176)	0.172	(0.171,0.173)	0.175
	720	0.215	(0.214,0.215)	0.212	(0.211,0.213)	0.217	(0.217,0.218)	0.213	(0.213,0.214)	0.222
#Wins		6		4		9		13		-

Table 12: Confidence Intervals for MSE predictions of CALF. The best performing model in highlighted in Red color text. #Wins refers to the total number of times the method performed best. Note that '-' means the dataset has not been included in the original paper.

Dataset	Models Window	OneFitsAll MAE	OneFitsAll CI	**w/o LLM** MAE	**w/o LLM** CI	**LLM2Attn** MAE	**LLM2Attn** CI	**LLM2Trsf** MAE	**LLM2Trsf** CI	From Paper
ETTh1	96	0.389	(0.387,0.391)	0.390	(0.387,0.392)	0.406	(0.404,0.409)	0.412	(0.408,0.414)	0.397
	192	0.413	(0.411,0.416)	0.416	(0.413,0.418)	0.441	(0.438,0.443)	0.455	(0.452,0.458)	0.418
	336	0.431	(0.428,0.433)	0.430	(0.428,0.432)	0.461	(0.458,0.464)	0.460	(0.457,0.462)	0.433
	720	0.449	(0.446,0.451)	0.454	(0.451,0.457)	0.501	(0.498,0.504)	0.570	(0.566,0.575)	0.456
ETTh2	96	0.335	(0.333,0.336)	0.337	(0.335,0.338)	0.351	(0.349,0.353)	0.348	(0.346,0.350)	0.342
	192	0.380	(0.378,0.381)	0.382	(0.380,0.383)	0.395	(0.393,0.396)	0.391	(0.389,0.392)	0.389
	336	0.405	(0.403,0.406)	0.410	(0.407,0.411)	0.416	(0.414,0.418)	0.414	(0.413,0.416)	0.407
	720	0.436	(0.435,0.438)	0.430	(0.428,0.432)	0.448	(0.446,0.450)	0.439	(0.437,0.441)	0.441
ETTm1	96	0.340	(0.339,0.340)	0.342	(0.341,0.342)	0.337	(0.336,0.338)	0.339	(0.338,0.340)	0.346
	192	0.368	(0.367,0.368)	0.363	(0.362,0.363)	0.366	(0.366,0.367)	0.369	(0.369,0.370)	0.372
	336	0.386	(0.386,0.387)	0.381	(0.381,0.382)	0.389	(0.389,0.390)	0.387	(0.386,0.387)	0.394
	720	0.416	(0.415,0.416)	0.413	(0.412,0.413)	0.427	(0.426,0.428)	0.421	(0.420,0.422)	0.421
ETTm2	96	0.249	(0.248,0.250)	0.248	(0.247,0.248)	0.251	(0.251,0.252)	0.250	(0.249,0.250)	0.262
	192	0.291	(0.291,0.292)	0.286	(0.286,0.287)	0.291	(0.290,0.292)	0.288	(0.287,0.289)	0.301
	336	0.327	(0.326,0.328)	0.323	(0.322,0.324)	0.327	(0.326,0.327)	0.323	(0.322,0.324)	0.341
	720	0.376	(0.375,0.377)	0.380	(0.379,0.381)	0.382	(0.381,0.383)	0.382	(0.381,0.383)	0.401
Illness	24	0.823	(0.806,0.841)	0.930	(0.914,0.945)	0.807	(0.788,0.824)	0.846	(0.830,0.865)	0.881
	36	0.854	(0.840,0.868)	0.913	(0.901,0.926)	0.816	(0.799,0.830)	0.848	(0.833,0.864)	0.892
	48	0.855	(0.840,0.866)	0.911	(0.897,0.923)	0.846	(0.828,0.860)	0.848	(0.837,0.860)	0.884
	60	0.877	(0.867,0.889)	0.942	(0.932,0.957)	0.850	(0.836,0.863)	0.861	(0.850,0.876)	0.957
Weather	96	0.188	(0.188,0.189)	0.212	(0.212,0.213)	0.193	(0.192,0.193)	0.188	(0.187,0.188)	0.212
	192	0.230	(0.230,0.231)	0.251	(0.251,0.252)	0.231	(0.230,0.232)	0.233	(0.232,0.234)	0.248
	336	0.273	(0.272,0.273)	0.289	(0.288,0.290)	0.273	(0.273,0.274)	0.275	(0.274,0.275)	0.286
	720	0.328	(0.328,0.329)	0.339	(0.339,0.340)	0.328	(0.327,0.328)	0.328	(0.328,0.329)	0.337
Traffic	96	0.264	(0.263,0.264)	0.264	(0.264,0.264)	0.257	(0.257,0.257)	0.252	(0.252,0.252)	0.282
	192	0.268	(0.268,0.268)	0.271	(0.271,0.271)	0.260	(0.260,0.261)	0.246	(0.245,0.246)	0.290
	336	0.273	(0.273,0.273)	0.271	(0.270,0.271)	0.264	(0.264,0.265)	0.255	(0.254,0.255)	0.294
	720	0.291	(0.291,0.291)	0.289	(0.289,0.289)	0.284	(0.284,0.284)	0.274	(0.274,0.274)	0.312
Electricity	96	0.239	(0.238,0.239)	0.230	(0.229,0.230)	0.224	(0.224,0.224)	0.218	(0.218,0.218)	0.238
	192	0.253	(0.252,0.253)	0.242	(0.242,0.242)	0.238	(0.238,0.238)	0.233	(0.233,0.233)	0.251
	336	0.266	(0.266,0.267)	0.258	(0.258,0.258)	0.254	(0.254,0.254)	0.250	(0.250,0.250)	0.266
	720	0.293	(0.293,0.294)	0.290	(0.290,0.290)	0.285	(0.285,0.285)	0.283	(0.283,0.283)	0.297
#Wins		9		8		6		9		-

Table 13: Confidence Intervals for MAE predictions of OneFitsAll. The best performing model in highlighted in Red color text. #Wins refers to the total number of times the method performed best.

Dataset	Models Window	OneFitsAll MSE	OneFitsAll CI	**w/o LLM** MSE	**w/o LLM** CI	**LLM2Attn** MSE	**LLM2Attn** CI	**LLM2Trsf** MSE	**LLM2Trsf** CI	From Paper
ETTh1	96	0.370	(0.365,0.375)	0.371	(0.366,0.376)	0.403	(0.397,0.409)	0.397	(0.391,0.403)	0.376
	192	0.412	(0.406,0.417)	0.416	(0.410,0.420)	0.454	(0.448,0.461)	0.482	(0.476,0.489)	0.416
	336	0.448	(0.443,0.454)	0.441	(0.434,0.446)	0.483	(0.475,0.490)	0.480	(0.475,0.487)	0.442
	720	0.441	(0.436,0.447)	0.442	(0.437,0.448)	0.522	(0.515,0.527)	0.743	(0.732,0.752)	0.477
ETTh2	96	0.280	(0.278,0.283)	0.284	(0.282,0.287)	0.304	(0.301,0.307)	0.298	(0.295,0.301)	0.285
	192	0.348	(0.346,0.352)	0.355	(0.352,0.357)	0.370	(0.367,0.375)	0.363	(0.360,0.366)	0.354
	336	0.380	(0.377,0.383)	0.388	(0.384,0.390)	0.399	(0.396,0.401)	0.392	(0.389,0.395)	0.373
	720	0.406	(0.403,0.409)	0.400	(0.398,0.403)	0.431	(0.428,0.433)	0.419	(0.416,0.422)	0.406
ETTm1	96	0.300	(0.298,0.301)	0.301	(0.300,0.303)	0.299	(0.297,0.300)	0.304	(0.303,0.306)	0.292
	192	0.343	(0.342,0.344)	0.338	(0.337,0.339)	0.349	(0.348,0.351)	0.356	(0.355,0.358)	0.332
	336	0.376	(0.374,0.377)	0.369	(0.368,0.370)	0.383	(0.382,0.385)	0.379	(0.378,0.381)	0.366
	720	0.431	(0.430,0.433)	0.425	(0.424,0.427)	0.447	(0.446,0.449)	0.438	(0.437,0.440)	0.417
ETTm2	96	0.163	(0.162,0.164)	0.163	(0.162,0.164)	0.165	(0.164,0.166)	0.164	(0.163,0.165)	0.173
	192	0.222	(0.220,0.223)	0.221	(0.219,0.222)	0.223	(0.221,0.224)	0.219	(0.218,0.220)	0.229
	336	0.273	(0.272,0.275)	0.275	(0.273,0.276)	0.275	(0.273,0.276)	0.272	(0.270,0.273)	0.286
	720	0.357	(0.355,0.359)	0.364	(0.363,0.366)	0.362	(0.360,0.364)	0.362	(0.360,0.363)	0.378
Illness	24	1.869	(1.780,1.950)	2.119	(2.022,2.215)	1.799	(1.711,1.887)	1.929	(1.868,2.020)	2.063
	36	1.853	(1.791,1.925)	1.929	(1.857,1.997)	1.727	(1.660,1.800)	1.801	(1.741,1.859)	1.868
	48	1.886	(1.828,1.942)	1.883	(1.827,1.932)	1.804	(1.744,1.866)	1.807	(1.749,1.869)	1.790
	60	1.877	(1.827,1.937)	1.911	(1.861,1.953)	1.724	(1.672,1.776)	1.784	(1.736,1.841)	1.979
Weather	96	0.148	(0.147,0.150)	0.173	(0.172,0.175)	0.150	(0.149,0.152)	0.149	(0.148,0.150)	0.162
	192	0.192	(0.191,0.194)	0.216	(0.215,0.218)	0.192	(0.191,0.194)	0.196	(0.194,0.197)	0.204
	336	0.246	(0.244,0.247)	0.263	(0.261,0.264)	0.244	(0.243,0.246)	0.247	(0.246,0.248)	0.254
	720	0.320	(0.318,0.321)	0.330	(0.329,0.332)	0.318	(0.316,0.319)	0.322	(0.321,0.324)	0.326
Traffic	96	0.396	(0.393,0.398)	0.422	(0.419,0.424)	0.393	(0.391,0.395)	0.391	(0.389,0.393)	0.388
	192	0.412	(0.410,0.414)	0.430	(0.428,0.432)	0.406	(0.404,0.408)	0.395	(0.393,0.397)	0.407
	336	0.421	(0.419,0.423)	0.437	(0.435,0.439)	0.413	(0.412,0.416)	0.406	(0.405,0.408)	0.412
	720	0.455	(0.453,0.457)	0.470	(0.468,0.472)	0.451	(0.449,0.453)	0.444	(0.442,0.446)	0.450
Electricity	96	0.141	(0.141,0.142)	0.137	(0.136,0.137)	0.133	(0.133,0.134)	0.128	(0.128,0.129)	0.139
	192	0.158	(0.157,0.158)	0.151	(0.151,0.152)	0.149	(0.149,0.150)	0.145	(0.145,0.146)	0.153
	336	0.172	(0.172,0.172)	0.167	(0.167,0.168)	0.165	(0.164,0.165)	0.160	(0.160,0.161)	0.169
	720	0.207	(0.207,0.208)	0.206	(0.205,0.206)	0.201	(0.201,0.202)	0.196	(0.195,0.196)	0.206
#Wins		10		5		7		10		-

Table 14: Confidence Intervals for MSE predictions of OneFitsAll. The best performing model in highlighted in Red color text. #Wins refers to the total number of times the method performed best.

Dataset	Models / Window	Time-LLM MAE	CI	**w/o LLM** MAE	CI	**LLM2Attn** MAE	CI	**LLM2Trsf** MAE	CI
Exchange Rate	96	0.251	(0.248,0.255)	0.209	(0.206,0.212)	0.213	(0.210,0.217)	0.239	(0.237,0.242)
	192	0.344	(0.340,0.349)	0.305	(0.301,0.309)	0.330	(0.325,0.334)	0.331	(0.326,0.336)
	336	0.451	(0.446,0.456)	0.423	(0.417,0.428)	0.471	(0.465,0.477)	0.453	(0.447,0.458)
	720	0.771	(0.761,0.782)	0.719	(0.709,0.727)	0.762	(0.752,0.771)	0.762	(0.753,0.771)
Covid Deaths	30	0.090	(0.018,0.193)	0.080	(0.015,0.178)	0.059	(0.007,0.125)	0.055	(0.008,0.113)
Taxi (30 Min)	48	0.275	(0.270,0.280)	0.286	(0.280,0.292)	0.269	(0.265,0.275)	0.256	(0.251,0.261)
NN5 (Daily)	56	0.432	(0.358,0.500)	0.425	(0.360,0.498)	0.411	(0.341,0.484)	0.401	(0.327,0.465)
FRED-MD	12	6.0e-04	(5.2e-04,7.9e-04)	2.0e-04	(1.4e-04,2.7e-04)	4.7e-03	(4.5e-03,4.8e-03)	9.0e-04	(6.7e-04,1.1e-03)
#Wins		0		5		0		3	
Dataset	**Models / Window**	**Time-LLM MSE**	**CI**	**w/o LLM MSE**	**CI**	**LLM2Attn MSE**	**CI**	**LLM2Trsf MSE**	**CI**
Exchange Rate	96	0.123	(0.120,0.127)	0.090	(0.087,0.093)	0.090	(0.087,0.093)	0.110	(0.107,0.113)
	192	0.224	(0.217,0.230)	0.185	(0.180,0.190)	0.211	(0.206,0.217)	0.211	(0.206,0.216)
	336	0.377	(0.369,0.387)	0.341	(0.332,0.348)	0.407	(0.398,0.418)	0.384	(0.376,0.392)
	720	1.018	(0.997,1.041)	0.922	(0.896,0.943)	1.022	(1.007,1.043)	0.996	(0.975,1.023)
Covid Deaths	30	0.194	(0.000,0.467)	0.199	(0.004,0.462)	0.087	(0.009,0.196)	0.082	(0.002,0.183)
Taxi (30 Min)	48	0.161	(0.154,0.169)	0.177	(0.168,0.188)	0.157	(0.149,0.164)	0.141	(0.134,0.148)
NN5 (Daily)	56	0.404	(0.273,0.548)	0.379	(0.271,0.525)	0.365	(0.233,0.539)	0.347	(0.234,0.474)
FRED-MD	12	1.4e-06	(7.5e-07,2.2e-06)	2.8e-07	(8.0e-08,5.6e-07)	2.5e-05	(2.4e-05,2.7e-05)	2.6e-06	(1.7e-06,3.7e-06)
#Wins		0		5		0		3	

Table 15: Confidence Intervals for MAE and MSE predictions of Time-LLM. The best performing model in highlighted in Red color text. #Wins refers to the total number of times the method performed best. The ablation results in the table above are from datasets that have not been studied by the reference methods [50, 15, 22].

Dataset	Models / Window	CALF MAE	CI	**w/o LLM** MAE	CI	**LLM2Attn** MAE	CI	**LLM2Trsf** MAE	CI
Exchange Rate	96	0.203	(0.200,0.206)	0.207	(0.204,0.211)	0.206	(0.203,0.209)	0.207	(0.204,0.210)
	192	0.306	(0.300,0.312)	0.305	(0.300,0.311)	0.305	(0.298,0.309)	0.305	(0.298,0.309)
	336	0.427	(0.420,0.435)	0.426	(0.419,0.436)	0.427	(0.418,0.435)	0.415	(0.406,0.424)
	720	0.732	(0.721,0.745)	0.697	(0.687,0.710)	0.731	(0.716,0.750)	0.708	(0.695,0.723)
Covid Deaths	30	0.084	(0.025,0.174)	0.066	(0.012,0.144)	0.131	(0.027,0.274)	0.066	(0.014,0.151)
Taxi (30 Min)	48	0.258	(0.254,0.263)	0.264	(0.259,0.268)	0.267	(0.262,0.271)	0.267	(0.263,0.272)
NN5 (Daily)	56	0.403	(0.348,0.471)	0.386	(0.325,0.432)	0.433	(0.367,0.504)	0.431	(0.357,0.495)
FRED-MD	12	1.3e-03	(1.2e-03,1.4e-03)	1.2e-03	(1.0e-03,1.3e-03)	1.6e-03	(1.4e-03,1.7e-03)	1.7e-03	(1.6e-03,1.9e-03)
#Wins		2		4		1		1	
Dataset	**Models / Window**	**CALF MSE**	**CI**	**w/o LLM MSE**	**CI**	**LLM2Attn MSE**	**CI**	**LLM2Trsf MSE**	**CI**
Exchange Rate	96	0.083	(0.080,0.085)	0.086	(0.084,0.089)	0.086	(0.084,0.089)	0.087	(0.085,0.090)
	192	0.186	(0.180,0.193)	0.183	(0.177,0.188)	0.182	(0.177,0.189)	0.181	(0.175,0.186)
	336	0.350	(0.339,0.361)	0.345	(0.335,0.360)	0.345	(0.332,0.356)	0.324	(0.310,0.337)
	720	0.935	(0.906,0.965)	0.854	(0.833,0.877)	0.943	(0.911,0.978)	0.878	(0.856,0.900)
Covid Deaths	30	0.163	(0.005,0.373)	0.115	(0.003,0.287)	0.431	(0.010,1.046)	0.106	(0.008,0.207)
Taxi (30 Min)	48	0.142	(0.134,0.152)	0.147	(0.140,0.158)	0.150	(0.143,0.157)	0.150	(0.142,0.158)
NN5 (Daily)	56	0.362	(0.275,0.522)	0.336	(0.236,0.451)	0.405	(0.277,0.618)	0.399	(0.272,0.585)
FRED-MD	12	2.9e-06	(2.0e-06,4.5e-06)	2.7e-06	(2.0e-06,3.3e-06)	4.9e-06	(3.4e-06,6.8e-06)	4.5e-06	(3.7e-06,5.4e-06)
#Wins		2		3		0		3	

Table 16: Confidence Intervals for MAE and MSE predictions of CALF. The best performing model in highlighted in Red color text. #Wins refers to the total number of times the method performed best. The ablation results in the table above are from datasets that have not been studied by the reference methods [50, 15, 22].

Dataset	Window	OneFitsAll MAE	OneFitsAll CI	**w/o LLM** MAE	**w/o LLM** CI	**LLM2Attn** MAE	**LLM2Attn** CI	**LLM2Trsf** MAE	**LLM2Trsf** CI
Exchange Rate	96	0.218	(0.215,0.221)	0.204	(0.202,0.207)	0.215	(0.213,0.218)	0.224	(0.221,0.226)
	192	0.307	(0.303,0.311)	0.308	(0.304,0.312)	0.339	(0.334,0.344)	0.343	(0.340,0.347)
	336	0.461	(0.455,0.467)	0.452	(0.446,0.457)	0.469	(0.463,0.477)	0.434	(0.430,0.440)
	720	0.767	(0.756,0.777)	0.727	(0.716,0.736)	0.735	(0.722,0.747)	0.781	(0.771,0.790)
Covid Deaths	30	0.057	(0.019,0.122)	0.050	(0.004,0.100)	0.058	(0.019,0.114)	0.078	(0.015,0.175)
Taxi (30 Min)	48	0.260	(0.256,0.267)	0.265	(0.259,0.271)	0.264	(0.258,0.272)	0.263	(0.256,0.268)
NN5 (Daily)	56	0.438	(0.364,0.517)	0.422	(0.352,0.497)	0.423	(0.363,0.480)	0.420	(0.354,0.487)
FRED-MD	12	6.7e-04	(5.6e-04,7.7e-04)	2.5e-04	(1.9e-04,3.3e-04)	6.1e-04	(4.9e-04,7.1e-04)	1.2e-03	(1.2e-03,1.3e-03)
#Wins		2		4		0		2	
Dataset	Window	OneFitsAll MSE	OneFitsAll CI	**w/o LLM** MSE	**w/o LLM** CI	**LLM2Attn** MSE	**LLM2Attn** CI	**LLM2Trsf** MSE	**LLM2Trsf** CI
Exchange Rate	96	0.096	(0.093,0.098)	0.086	(0.084,0.089)	0.092	(0.090,0.095)	0.103	(0.100,0.106)
	192	0.182	(0.177,0.186)	0.189	(0.184,0.194)	0.232	(0.224,0.239)	0.228	(0.221,0.233)
	336	0.402	(0.393,0.414)	0.392	(0.382,0.401)	0.462	(0.444,0.481)	0.359	(0.351,0.368)
	720	1.055	(1.028,1.084)	0.932	(0.909,0.951)	0.985	(0.958,1.010)	1.113	(1.090,1.146)
Covid Deaths	30	0.075	(0.004,0.161)	0.073	(0.002,0.175)	0.103	(0.003,0.265)	0.162	(0.009,0.435)
Taxi (30 Min)	48	0.148	(0.139,0.158)	0.150	(0.141,0.159)	0.150	(0.143,0.159)	0.149	(0.141,0.158)
NN5 (Daily)	56	0.438	(0.309,0.555)	0.385	(0.252,0.508)	0.390	(0.262,0.542)	0.385	(0.254,0.515)
FRED-MD	12	1.2e-06	(7.4e-07,1.9e-06)	3.8e-07	(1.0e-07,7.6e-07)	1.5e-06	(8.4e-07,2.2e-06)	2.4e-06	(2.1e-06,3.0e-06)
#Wins		2		5		0		1	

Table 17: Confidence Intervals for MAE and MSE predictions of OneFitsAll. The best performing model in highlighted in Red color text. #Wins refers to the total number of times the method performed best.

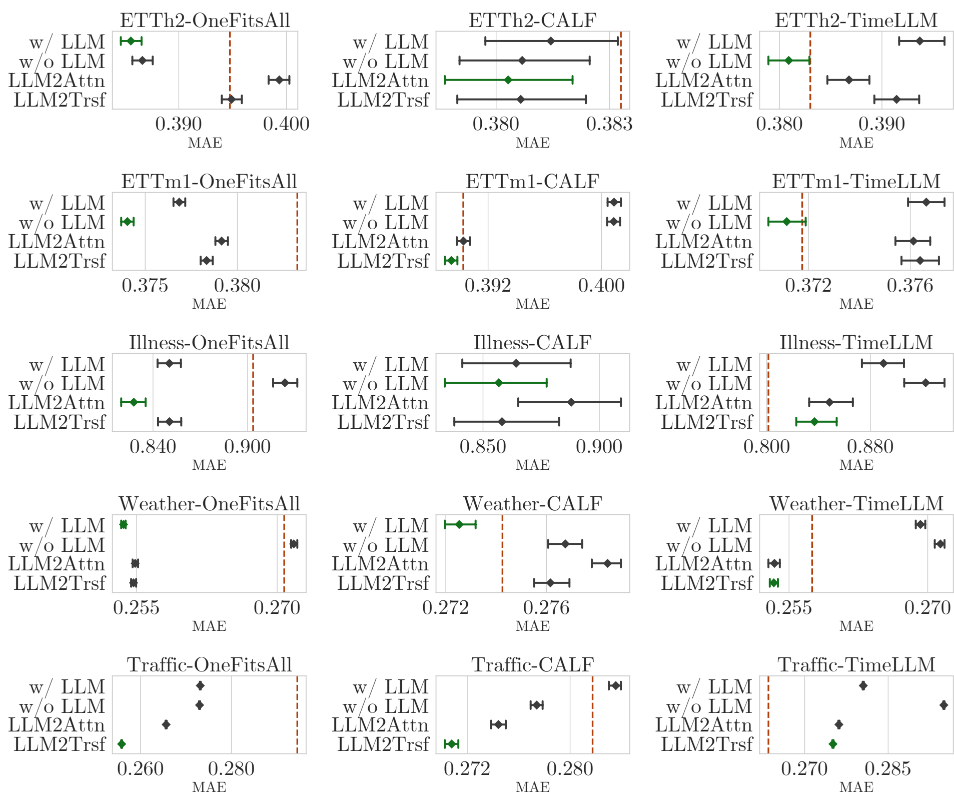


Figure 5: Ablation studies indicate that when different methods remove the LLM ("**w/o LLM**") or replace it with a single-layer attention ("**LLM2Attn**") or Transformer ("**LLM2Trsf**"), the performance on time series forecasting tasks with MAE metric does not decline and even improves, compared with original methods, such as "GPT-2" or "LLaMA". The vertical dashed line in the figures represents the results from the original paper. Above figures are from 'ETTh2', 'ETTm1', 'Illness', 'Weather', and 'Traffic' datasets.

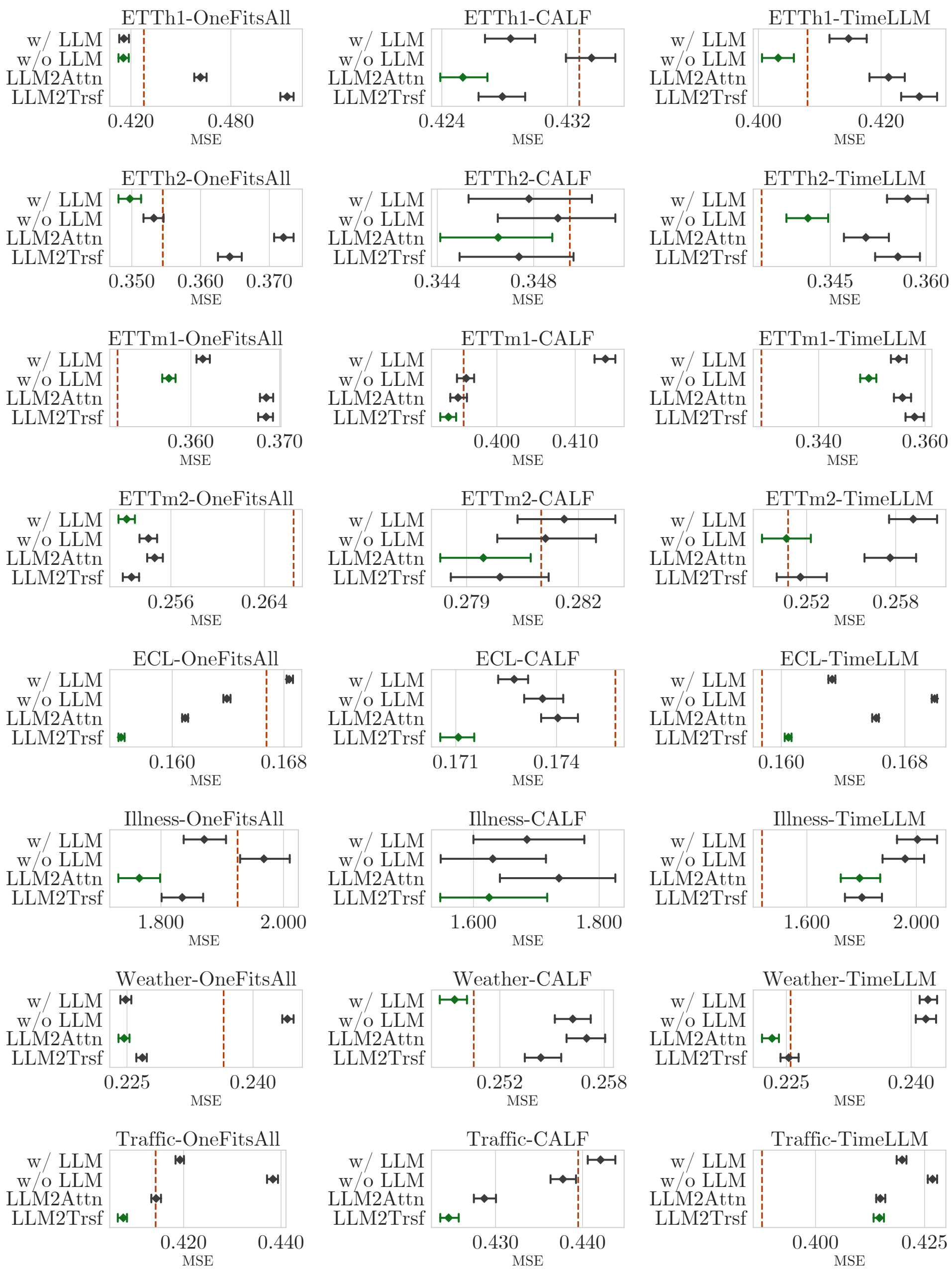


Figure 6: Ablation studies indicate that when different methods remove the LLM ("**w/o LLM**") or replace it with a single-layer attention ("**LLM2Attn**") or Transformer ("**LLM2Trsf**"), the performance on time series forecasting tasks with MSE metric does not decline and even improves, compared with original methods, such as "GPT-2" or "LLaMA". The vertical dashed line in the figures represents the results from the original paper.

Methods		CALF [22]		OneFitAll [50]		Time-LLM [15]		D-LTrsf		LTrsf		PAttn		D-PAttn		DLinear		MeanP		Seasonal	
Metric		MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE
ETTh1	96	0.389	0.369	0.397	0.376	0.392	0.362	0.392	0.379	0.390	0.371	0.387	0.383	0.387	0.376	0.399	0.375	0.525	0.753	0.799	1.185
	192	0.423	0.427	0.418	0.416	0.418	0.398	0.421	0.436	0.418	0.428	0.416	0.439	0.415	0.430	0.416	0.405	0.544	0.775	0.788	1.130
	336	0.436	0.456	0.433	0.442	0.427	0.430	0.427	0.447	0.426	0.449	0.419	0.447	0.419	0.440	0.443	0.439	0.548	0.762	0.785	1.099
	720	0.467	0.479	0.456	0.477	0.457	0.442	0.460	0.470	0.465	0.485	0.457	0.474	0.455	0.469	0.490	0.472	0.549	0.720	0.789	1.083
ETTh2	96	0.331	0.279	0.342	0.285	0.328	0.268	0.332	0.281	0.333	0.285	0.327	0.277	0.327	0.276	0.353	0.289	0.378	0.368	1.231	2.777
	192	0.380	0.353	0.389	0.354	0.375	0.329	0.379	0.353	0.376	0.351	0.373	0.345	0.373	0.347	0.418	0.383	0.422	0.444	1.294	2.987
	336	0.394	0.362	0.407	0.373	0.409	0.368	0.382	0.350	0.379	0.346	0.375	0.338	0.376	0.341	0.465	0.448	0.450	0.476	1.313	3.049
	720	0.426	0.404	0.441	0.406	0.420	0.372	0.431	0.411	0.426	0.406	0.425	0.403	0.429	0.408	0.551	0.605	0.456	0.469	1.324	3.073
ETTm1	96	0.349	0.323	0.346	0.292	0.334	0.272	0.347	0.300	0.351	0.300	0.342	0.301	0.346	0.300	0.343	0.299	0.512	0.738	0.752	1.056
	192	0.375	0.374	0.372	0.332	0.358	0.310	0.367	0.335	0.366	0.327	0.366	0.344	0.370	0.343	0.365	0.335	0.518	0.745	0.769	1.075
	336	0.399	0.409	0.394	0.366	0.384	0.352	0.383	0.359	0.386	0.356	0.383	0.369	0.388	0.370	0.386	0.369	0.524	0.752	0.778	1.086
	720	0.438	0.477	0.421	0.417	0.411	0.383	0.414	0.418	0.416	0.421	0.413	0.426	0.418	0.431	0.421	0.425	0.538	0.764	0.782	1.089
ETTm2	96	0.256	0.178	0.262	0.173	0.253	0.161	0.256	0.168	0.258	0.172	0.249	0.164	0.252	0.165	0.260	0.167	0.345	0.312	1.208	2.730
	192	0.297	0.242	0.301	0.229	0.293	0.219	0.294	0.225	0.295	0.226	0.292	0.224	0.291	0.220	0.303	0.224	0.358	0.335	1.285	2.943
	336	0.339	0.307	0.341	0.286	0.392	0.271	0.322	0.268	0.323	0.269	0.319	0.266	0.319	0.263	0.343	0.281	0.376	0.364	1.318	3.036
	720	0.393	0.397	0.401	0.378	0.379	0.352	0.372	0.344	0.372	0.344	0.370	0.345	0.369	0.339	0.421	0.397	0.418	0.433	1.339	3.109
Illness	24	-	-	0.881	2.063	0.727	1.285	0.814	1.602	0.826	1.706	0.800	1.711	0.817	1.685	1.081	2.215	1.393	4.453	1.854	7.099
	36	-	-	0.892	1.868	0.814	1.404	0.895	1.738	0.927	2.300	0.794	1.636	0.853	1.739	0.963	1.963	1.410	4.524	1.897	7.231
	48	-	-	0.884	1.790	0.807	1.523	0.931	1.897	0.992	2.534	0.853	1.767	0.874	1.775	1.024	2.130	1.444	4.819	1.882	7.205
	60	-	-	0.957	1.979	0.857	1.531	0.979	2.049	0.992	2.490	0.829	1.658	0.853	1.695	1.096	2.368	1.492	5.058	1.892	7.096
Weather	96	0.204	0.164	0.212	0.162	0.201	0.147	0.203	0.160	0.204	0.161	0.191	0.151	0.195	0.152	0.237	0.176	0.312	0.297	0.550	0.576
	192	0.250	0.214	0.248	0.204	0.234	0.189	0.242	0.202	0.246	0.205	0.232	0.193	0.236	0.196	0.282	0.220	0.323	0.316	0.577	0.605
	336	0.291	0.269	0.286	0.254	0.279	0.262	0.283	0.253	0.283	0.253	0.273	0.244	0.277	0.247	0.319	0.265	0.341	0.343	0.594	0.625
	720	0.352	0.355	0.337	0.326	0.316	0.304	0.333	0.320	0.332	0.322	0.323	0.311	0.330	0.316	0.362	0.323	0.369	0.384	0.605	0.633
1^{st} and 2^{nd} Wins				**33**				**3**		**2**		**34**		**21**		**3**		**0**		**0**	
Traffic	96	0.268	0.407	0.282	0.388	0.248	0.362	0.264	0.383	0.234	0.357	0.262	0.394	0.262	0.394	0.282	0.410	0.771	1.441	0.884	1.765
	192	0.278	0.430	0.290	0.407	0.247	0.374	0.275	0.399	0.243	0.377	0.265	0.404	0.266	0.404	0.287	0.423	0.774	1.455	0.844	1.628
	336	0.281	0.444	0.294	0.412	0.271	0.385	0.284	0.411	0.250	0.388	0.270	0.413	0.269	0.412	0.296	0.436	0.776	1.469	0.827	1.574
	720	0.300	0.477	0.312	0.450	0.288	0.430	0.309	0.453	0.273	0.428	0.285	0.448	0.289	0.449	0.315	0.466	0.780	1.488	0.816	1.543
Electricity	96	0.238	0.145	0.238	0.139	0.224	0.131	0.226	0.132	0.220	0.130	0.226	0.134	0.227	0.134	0.237	0.140	0.738	0.944	0.891	1.201
	192	0.252	0.161	0.251	0.153	0.241	0.152	0.247	0.154	0.239	0.149	0.239	0.149	0.241	0.149	0.249	0.153	0.742	0.953	0.861	1.107
	336	0.267	0.175	0.266	0.169	0.248	0.160	0.265	0.171	0.254	0.164	0.257	0.166	0.257	0.166	0.267	0.169	0.747	0.966	0.847	1.064
	720	0.303	0.222	0.297	0.206	0.298	0.192	0.299	0.211	0.278	0.193	0.288	0.204	0.289	0.204	0.301	0.203	0.762	0.998	0.838	1.031
1^{st} and 2^{nd} Wins				**11**				**0**		**16**		**4**		**1**		**0**		**0**		**0**	

Table 18: Comparision between simple methods and original results from reference paper [22, 50, 15]. Red: Best performance. Blue Second Best.

		Simple Methods				LLM-Based Methods						Other State-of-the-art Methods											
Methods		LTrsf		PAttn		CALF [22]		OneFitsAll [50]		Time-LLM [15]		DLinear [46]		RLinear [21]		PatchTST [27]		iTransformer [24]		TimesNet [41]		FEDformer [49]	
Metric		MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE
ETTm1	96	0.351	0.300	0.342	0.301	0.349	0.323	0.346	0.292	0.334	0.272	0.343	0.299	0.376	0.355	0.342	0.290	0.368	0.334	0.375	0.338	0.419	0.379
	192	0.366	0.327	0.366	0.344	0.375	0.374	0.372	0.332	0.358	0.310	0.365	0.335	0.392	0.391	0.369	0.332	0.391	0.377	0.387	0.374	0.441	0.426
	336	0.386	0.356	0.383	0.369	0.399	0.409	0.394	0.366	0.384	0.352	0.386	0.369	0.415	0.424	0.392	0.366	0.420	0.426	0.411	0.410	0.459	0.445
	720	0.416	0.421	0.413	0.426	0.438	0.477	0.421	0.417	0.411	0.383	0.421	0.425	0.450	0.487	0.420	0.416	0.459	0.491	0.450	0.478	0.490	0.543
ETTm2	96	0.258	0.172	0.249	0.164	0.256	0.178	0.262	0.173	0.253	0.161	0.260	0.167	0.265	0.182	0.255	0.165	0.264	0.180	0.267	0.187	0.287	0.203
	192	0.295	0.226	0.292	0.224	0.297	0.242	0.301	0.229	0.293	0.219	0.303	0.224	0.304	0.246	0.292	0.220	0.309	0.250	0.309	0.249	0.328	0.269
	336	0.323	0.269	0.319	0.266	0.339	0.307	0.341	0.286	0.392	0.271	0.343	0.281	0.342	0.307	0.329	0.274	0.348	0.311	0.351	0.321	0.366	0.325
	720	0.372	0.344	0.370	0.345	0.393	0.397	0.401	0.378	0.379	0.352	0.421	0.397	0.398	0.407	0.385	0.362	0.407	0.412	0.403	0.408	0.415	0.421
ETTh1	96	0.390	0.371	0.387	0.383	0.389	0.369	0.397	0.376	0.392	0.362	0.399	0.375	0.395	0.386	0.399	0.370	0.405	0.386	0.402	0.384	0.419	0.376
	192	0.418	0.428	0.416	0.439	0.423	0.427	0.418	0.416	0.418	0.398	0.416	0.405	0.424	0.437	0.421	0.413	0.436	0.441	0.429	0.436	0.448	0.420
	336	0.426	0.449	0.419	0.447	0.436	0.456	0.433	0.442	0.427	0.430	0.443	0.439	0.446	0.479	0.436	0.422	0.458	0.487	0.469	0.491	0.465	0.459
	720	0.465	0.485	0.457	0.474	0.467	0.479	0.456	0.477	0.457	0.442	0.490	0.472	0.470	0.481	0.466	0.447	0.491	0.503	0.500	0.521	0.507	0.506
ETTh2	96	0.333	0.285	0.327	0.277	0.331	0.279	0.342	0.285	0.328	0.268	0.353	0.289	0.338	0.288	0.336	0.274	0.349	0.297	0.374	0.340	0.397	0.358
	192	0.376	0.351	0.373	0.345	0.380	0.353	0.389	0.354	0.375	0.329	0.418	0.383	0.390	0.374	0.379	0.339	0.400	0.380	0.414	0.402	0.439	0.429
	336	0.379	0.346	0.375	0.338	0.394	0.362	0.407	0.373	0.409	0.368	0.465	0.448	0.426	0.415	0.380	0.329	0.432	0.428	0.452	0.452	0.487	0.496
	720	0.426	0.406	0.425	0.403	0.426	0.404	0.441	0.406	0.420	0.372	0.551	0.605	0.440	0.420	0.422	0.379	0.445	0.427	0.468	0.462	0.474	0.463
Electricity	96	0.220	0.130	0.226	0.134	0.238	0.145	0.238	0.139	0.224	0.131	0.237	0.140	0.281	0.201	0.222	0.129	0.240	0.148	0.272	0.168	0.308	0.193
	192	0.239	0.149	0.239	0.149	0.252	0.161	0.251	0.153	0.241	0.152	0.249	0.153	0.283	0.201	0.240	0.157	0.253	0.162	0.289	0.184	0.315	0.201
	336	0.254	0.164	0.257	0.166	0.267	0.175	0.266	0.169	0.248	0.160	0.267	0.169	0.298	0.215	0.259	0.163	0.269	0.178	0.300	0.198	0.329	0.214
	720	0.278	0.193	0.288	0.204	0.303	0.222	0.297	0.206	0.298	0.192	0.301	0.203	0.331	0.257	0.290	0.197	0.317	0.225	0.320	0.220	0.355	0.246
Traffic	96	0.234	0.357	0.262	0.394	0.268	0.407	0.282	0.388	0.248	0.362	0.282	0.410	0.389	0.649	0.249	0.360	0.268	0.395	0.321	0.593	0.366	0.587
	192	0.243	0.377	0.265	0.404	0.278	0.430	0.290	0.407	0.247	0.374	0.287	0.423	0.366	0.601	0.256	0.379	0.276	0.417	0.336	0.617	0.373	0.604
	336	0.250	0.388	0.270	0.413	0.281	0.444	0.294	0.412	0.271	0.385	0.296	0.436	0.369	0.609	0.264	0.392	0.283	0.433	0.336	0.629	0.383	0.621
	720	0.273	0.428	0.285	0.448	0.300	0.477	0.312	0.450	0.288	0.430	0.315	0.466	0.387	0.647	0.286	0.432	0.302	0.467	0.350	0.640	0.382	0.626
Weather	96	0.204	0.161	0.191	0.151	0.204	0.164	0.212	0.162	0.201	0.147	0.237	0.176	0.232	0.192	0.198	0.149	0.214	0.174	0.220	0.172	0.296	0.217
	192	0.246	0.205	0.232	0.193	0.250	0.214	0.248	0.204	0.234	0.189	0.282	0.220	0.271	0.240	0.241	0.194	0.254	0.221	0.261	0.219	0.336	0.276
	336	0.283	0.253	0.273	0.244	0.291	0.269	0.286	0.254	0.279	0.262	0.319	0.265	0.307	0.292	0.282	0.245	0.296	0.278	0.306	0.280	0.380	0.339
	720	0.332	0.322	0.323	0.311	0.352	0.355	0.337	0.326	0.316	0.304	0.362	0.323	0.353	0.364	0.334	0.314	0.347	0.358	0.359	0.365	0.428	0.403
1^{st} **Wins**		**11**		**18**		**0**		**1**		**25**		**0**		**0**		**4**		**0**		**0**		**0**	

Table 19: Comparison between simple ablations, LLM-based methods, and non-LLM methods. LLM-based methods slightly outperform non-LLM methods. The non-LLM results are from the LLM-Time and iTransformer papers, which are computed on the same splits. As expected, the main findings in our paper are unchanged: The LLM-based methods are slightly better, but our ablations indicate this isn't due to the LLM. Red: Best performance. Blue: Second Best.

Methods		Pre+FT (GPT2)		woPre+FT		Pre+woFT		woPre+woFT	
Metric		MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE
ETTh1	96	0.3927	0.3695	0.3925	0.3747	0.3920	0.3735	0.3969	0.3798
	192	0.4258	0.4290	0.4185	0.4268	0.4178	0.4243	0.4276	0.4345
	336	0.4404	0.4510	0.4397	0.4627	0.4316	0.4526	0.4413	0.4656
	720	0.4661	0.4757	0.4629	0.4807	0.4654	0.4863	0.4804	0.5099
ETTh2	96	0.3359	0.2841	0.3291	0.2741	0.3340	0.2829	0.3336	0.2831
	192	0.3782	0.3532	0.3780	0.3526	0.3758	0.3510	0.3778	0.3547
	336	0.3937	0.3611	0.3992	0.3697	0.3946	0.3649	0.4006	0.3667
	720	0.4275	0.4057	0.4295	0.4067	0.4277	0.4067	0.4366	0.4172
ETTm1	96	0.3497	0.3228	0.3497	0.3240	0.3483	0.3231	0.3516	0.3243
	192	0.3756	0.3751	0.3783	0.3789	0.3751	0.3750	0.3775	0.3801
	336	0.4009	0.4108	0.3998	0.4092	0.4014	0.4105	0.4050	0.4152
	720	0.4378	0.4765	0.4454	0.4931	0.4343	0.4730	0.4456	0.4916
ETTm2	96	0.2553	0.1771	0.2529	0.1752	0.2544	0.1771	0.2546	0.1768
	192	0.3002	0.2446	0.2986	0.2466	0.2991	0.2451	0.2985	0.2438
	336	0.3413	0.3086	0.3375	0.3064	0.3401	0.3079	0.3397	0.3070
	720	0.3953	0.4023	0.3995	0.4124	0.3947	0.4005	0.3969	0.4038
Illness	24	0.7876	1.4596	0.7862	1.4470	0.8327	1.5333	0.8346	1.5892
	36	0.8373	1.5726	0.8317	1.5531	0.8308	1.5083	0.8438	1.5347
	48	0.8895	1.7839	0.9300	1.8532	0.8931	1.7503	0.9033	1.7689
	60	0.9619	1.9824	0.8612	1.6051	0.9400	1.8644	0.8837	1.6594
Weather	96	0.2065	0.1675	0.2092	0.1678	0.2076	0.1677	0.2112	0.1744
	192	0.2506	0.2159	0.2526	0.2172	0.2555	0.2165	0.2567	0.2247
	336	0.2923	0.2709	0.2967	0.2734	0.2939	0.2714	0.2949	0.2777
	720	0.3454	0.3495	0.3458	0.3494	0.3514	0.3582	0.3476	0.3559
Traffic	96	0.2737	0.4159	0.2622	0.4103	0.2708	0.4158	0.2751	0.4201
	192	0.2764	0.4302	0.2694	0.4287	0.2742	0.4324	0.2776	0.4356
	336	0.2863	0.4507	0.2781	0.4456	0.2817	0.4485	0.2868	0.4530
	720	0.3010	0.4783	0.2986	0.4792	0.3013	0.4817	0.3056	0.4844
Electricity	96	0.2397	0.1469	0.2308	0.1377	0.2382	0.1442	0.2430	0.1530
	192	0.2538	0.1629	0.2506	0.1581	0.2522	0.1605	0.2541	0.1652
	336	0.2701	0.1785	0.2676	0.1733	0.2673	0.1768	0.2699	0.1797
	720	0.3004	0.2148	0.2897	0.1987	0.2964	0.2104	0.2980	0.2156
#Wins		**17**		**28**		**17**		**2**	

Table 20: Pretraining on language datasets is not necessary for time series forecasting tasks. The table shows the performance of using pretraining models versus not using pretraining, as well as the combination of fine-tuning and not fine-tuning LLMs in time series forecasting.

	Dataset		**ETTh1**				**Illness**			
	Predict Lengths		Sf-all.	Sf-half.	Ex-half	Masking	Sf-all.	Sf-half.	Ex-half	Masking
Time-LLM [15]	96(24)	Time-LLM	51.8%	5.6%	79.6%	32.5%	99.0%	33.6%	34.9%	64.6%
		w/o LLM	56.0%	4.5%	89.7%	39.5%	76.5%	20.9%	18.4%	53.0%
		LLM2Attn	53.8%	3.3%	92.2%	33.8%	72.7%	20.4%	13.1%	44.6%
		LLM2Trsf	50.3%	3.4%	89.2%	34.8%	74.5%	23.0%	14.3%	49.3%
	192(36)	Time-LLM	43.9%	5.9%	72.1%	32.5%	83.9%	43.4%	30.7%	69.9%
		w/o LLM	46.8%	4.3%	77.3%	32.9%	77.0%	24.5%	15.3%	56.6%
		LLM2Attn	45.0%	4.4%	78.0%	30.0%	73.8%	25.7%	11.2%	53.3%
		LLM2Trsf	44.0%	5.5%	77.1%	29.9%	72.1%	27.0%	6.0%	51.3%
	336(48)	Time-LLM	39.1%	5.9%	67.0%	24.7%	51.6%	26.0%	11.2%	48.5%
		w/o LLM	41.7%	3.9%	71.6%	29.9%	73.6%	27.6%	13.6%	52.9%
		LLM2Attn	34.1%	1.2%	69.5%	21.1%	85.1%	38.8%	12.8%	57.5%
		LLM2Trsf	54.9%	3.7%	75.0%	26.3%	85.2%	42.7%	18.6%	63.6%
	720(60)	Time-LLM	72.6%	31.8%	73.3%	32.1%	73.0%	42.4%	27.5%	76.3%
		w/o LLM	39.7%	5.2%	64.3%	29.3%	74.1%	27.7%	14.2%	56.6%
		LLM2Attn	45.5%	6.0%	66.0%	26.0%	66.2%	28.5%	11.9%	51.7%
		LLM2Trsf	53.3%	10.2%	63.7%	27.3%	67.7%	30.7%	7.8%	49.2%
	Dataset		ETTh1				Illness			
	Predict Lengths		Sf-all.	Sf-half.	Ex-half	Masking	Sf-all.	Sf-half.	Ex-half	Masking
CALF [22]	96(24)	CALF	50.5%	9.6%	5.6%	8.5%	113.0%	47.4%	24.4%	22.9%
		w/o LLM	56.2%	12.1%	6.1%	10.4%	118.0%	50.4%	45.8%	28.9%
		LLM2Attn	51.9%	10.8%	5.8%	7.3%	87.3%	42.4%	35.1%	25.8%
		LLM2Trsf	50.3%	8.5%	5.5%	7.0%	102.6%	56.2%	32.6%	26.0%
	192(36)	CALF	41.7%	7.8%	3.3%	3.6%	100.9%	45.7%	12.9%	17.1%
		w/o LLM	50.9%	13.5%	4.5%	6.0%	115.6%	57.0%	28.3%	21.4%
		LLM2Attn	45.8%	9.7%	3.6%	5.0%	78.8%	41.8%	10.1%	19.9%
		LLM2Trsf	42.4%	8.3%	3.4%	4.3%	73.6%	42.5%	7.0%	17.5%
	336(48)	CALF	38.1%	9.0%	1.7%	5.0%	68.9%	43.0%	15.1%	14.9%
		w/o LLM	47.2%	14.5%	2.3%	8.7%	76.3%	49.0%	18.5%	18.1%
		LLM2Attn	39.3%	10.0%	1.7%	5.5%	78.9%	54.2%	22.2%	15.3%
		LLM2Trsf	40.3%	10.0%	1.9%	4.9%	78.9%	52.0%	23.4%	17.7%
	720(60)	CALF	36.5%	10.0%	0.7%	5.5%	63.8%	22.7%	5.4%	15.3%
		w/o LLM	41.0%	10.2%	1.2%	6.2%	69.7%	30.3%	12.1%	19.4%
		LLM2Attn	36.0%	9.9%	0.7%	5.0%	71.7%	29.2%	12.7%	14.2%
		LLM2Trsf	35.2%	9.3%	0.7%	5.1%	90.4%	55.3%	26.4%	21.9%
	Dataset		ETTh1				Illness			
	Predict Lengths		Sf-all.	Sf-half.	Ex-half	Masking	Sf-all.	Sf-half.	Ex-half	Masking
OneFitsAll [50]	96(24)	OneFitsAll	62.1%	6.1%	16.6%	31.3%	86.2%	30.9%	36.7%	77.5%
		w/o LLM	58.6%	6.1%	19.2%	36.1%	68.9%	13.0%	17.3%	43.5%
		LLM2Attn	68.5%	9.0%	15.0%	34.4%	108.3%	39.8%	44.2%	74.2%
		LLM2Trsf	58.0%	7.8%	12.6%	30.2%	90.8%	27.4%	40.3%	60.6%
	192(36)	OneFitsAll	52.7%	8.2%	8.8%	28.5%	52.0%	15.2%	8.5%	44.4%
		w/o LLM	47.5%	6.1%	10.6%	31.8%	76.3%	24.0%	18.0%	47.5%
		LLM2Attn	80.8%	13.4%	6.7%	25.6%	97.8%	42.0%	36.3%	65.0%
		LLM2Trsf	54.7%	12.5%	6.4%	24.1%	82.0%	29.6%	24.4%	63.8%
	336(48)	OneFitsAll	62.1%	6.1%	16.6%	31.3%	79.5%	34.8%	25.1%	74.5%
		w/o LLM	58.6%	6.1%	19.2%	36.1%	78.1%	22.1%	15.7%	49.4%
		LLM2Attn	68.5%	9.0%	15.0%	34.4%	86.4%	45.8%	21.7%	69.8%
		LLM2Trsf	58.0%	7.8%	12.6%	30.2%	89.2%	35.8%	21.6%	66.9%
	720(60)	OneFitsAll	40.1%	8.0%	3.5%	25.4%	53.6%	21.8%	9.9%	44.9%
		w/o LLM	39.4%	7.1%	4.1%	28.2%	74.5%	20.9%	17.1%	45.5%
		LLM2Attn	93.8%	21.9%	1.5%	25.3%	86.0%	41.4%	27.0%	72.8%
		LLM2Trsf	87.2%	20.1%	1.6%	27.1%	92.3%	40.7%	29.3%	76.3%

Table 21: Results for input shuffling/masking for Time-LLM, CALF, and OneFitsAll methods on ETTh1 (predict length are "96, 192, 336 and 720") and Illness (predict length are "24, 36, 48 and 60"), the impact of shuffling the input on the degradation of time series forecasting performance does not change significantly before and after model modifications.

Dataset	**ETTh2**				**Electricity**			
Input Ablation	Sf-all.	Sf-half.	Ex-half	Masking	Sf-all.	Sf-half.	Ex-half	Masking
Time-LLM	27.1%	4.5%	44.6%	99.5%	212.1%	52.2%	323.4%	103.3%
w/o LLM	31.2%	2.9%	52.4%	137.9%	220.9%	47.3%	332.4%	105.5%
LLM2Attn	30.7%	2.9%	46.7%	134.8%	234.7%	58.2%	350.4%	115.3%
LLM2Trsf	24.8%	2.3%	43.4%	115.0%	240.8%	50.8%	362.0%	118.5%
OneFitsAll	33.0%	1.1%	39.7%	112.1%	237.8%	25.2%	382.0%	88.9%
w/o LLM	32.7%	2.8%	38.7%	115.8%	249.7%	43.4%	384.7%	109.2%
LLM2Attn	27.5%	1.0%	36.5%	137.4%	255.2%	49.5%	393.9%	119.2%
LLM2Trsf	29.6%	2.2%	37.2%	130.8%	263.8%	55.1%	406.4%	125.4%
CALF	11.3%	2.0%	9.1%	44.7%	235.1%	108.2%	29.3%	37.6%
w/o LLM	23.1%	4.1%	17.2%	46.9%	239.5%	109.2%	28.6%	39.4%
LLM2Attn	16.7%	3.4%	14.8%	31.7%	237.9%	116.2%	28.9%	42.2%
LLM2Trsf	18.9%	3.0%	15.3%	43.2%	245.6%	107.0%	29.2%	42.3%

Table 22: For the input shuffling/masking experiments on ETTh2 and Electricity, the impact of shuffling the input on the degradation of time series forecasting performance does not change significantly before and after model modifications.

Dataset	**ETTm1**				**ETTm2**			
Input Ablation	Sf-all.	Sf-half.	Ex-half	Masking	Sf-all.	Sf-half.	Ex-half	Masking
Time-LLM	66.6%	10.1%	107.7%	43.5%	47.0%	5.3%	77.7%	202.9%
w/o LLM	68.7%	12.4%	112.0%	52.6%	49.8%	4.7%	78.7%	199.6%
LLM2Attn	73.5%	13.5%	119.3%	50.7%	49.6%	4.7%	75.9%	196.3%
LLM2Trsf	72.0%	27.6%	117.0%	54.2%	46.4%	3.7%	76.5%	191.9%
OneFitsAll	74.4%	8.0%	123.4%	41.8%	48.0%	3.7%	82.9%	172.9%
w/o LLM	66.7%	10.3%	115.1%	45.0%	48.1%	4.4%	81.9%	190.7%
LLM2Attn	73.9%	11.1%	124.8%	51.6%	45.5%	3.3%	77.8%	183.6%
LLM2Trsf	70.1%	8.3%	126.2%	50.5%	48.2%	4.3%	82.0%	182.9%
CALF	64.3%	24.8%	122.3%	13.7%	23.5%	9.1%	47.1%	61.7%
w/o LLM	66.7%	26.0%	123.6%	15.9%	27.1%	11.2%	51.9%	58.1%
LLM2Attn	62.5%	23.4%	122.3%	15.6%	25.2%	8.8%	51.5%	57.3%
LLM2Trsf	61.8%	25.6%	122.6%	13.6%	23.7%	8.2%	51.0%	59.3%

Table 23: For the input shuffling/masking experiments on ETTm1 and ETTm2, the impact of shuffling the input on the degradation of time series forecasting performance does not change significantly before and after model modifications.

Dataset	**Weather**				**Traffic**			
Input Ablation	Sf-all.	Sf-half.	Ex-half	Masking	Sf-all.	Sf-half.	Ex-half	Masking
Time-LLM	65.8%	5.5%	85.9%	85.9%	198.1%	56.6%	309.8%	101.3%
w/o LLM	59.2%	4.7%	78.7%	74.6%	196.8%	70.2%	282.1%	78.3%
LLM2Attn	71.8%	8.5%	91.6%	95.3%	212.3%	82.4%	312.7%	92.2%
LLM2Trsf	71.9%	7.1%	94.9%	103.2%	197.5%	64.6%	307.2%	101.1%
OneFitsAll	71.0%	9.8%	102.1%	97.7%	206.4%	11.7%	369.1%	93.5%
w/o LLM	56.4%	2.3%	81.2%	73.5%	238.4%	67.0%	338.6%	85.9%
LLM2Attn	64.9%	5.4%	90.2%	94.8%	222.6%	57.5%	350.5%	95.1%
LLM2Trsf	77.8%	8.3%	101.9%	111.0%	217.8%	35.9%	361.3%	113.3%
CALF	32.6%	4.2%	54.5%	27.2%	201.7%	105.0%	63.1%	27.2%
w/o LLM	28.1%	5.9%	49.4%	13.6%	217.3%	115.4%	67.2%	29.7%
LLM2Attn	26.0%	6.2%	49.2%	17.1%	226.7%	122.7%	69.4%	30.7%
LLM2Trsf	28.0%	6.4%	54.1%	21.1%	232.8%	120.5%	72.0%	29.6%

Table 24: For the input shuffling/masking experiments on Weather and Traffic, the impact of shuffling the input on the degradation of time series forecasting performance does not change significantly before and after model modifications.

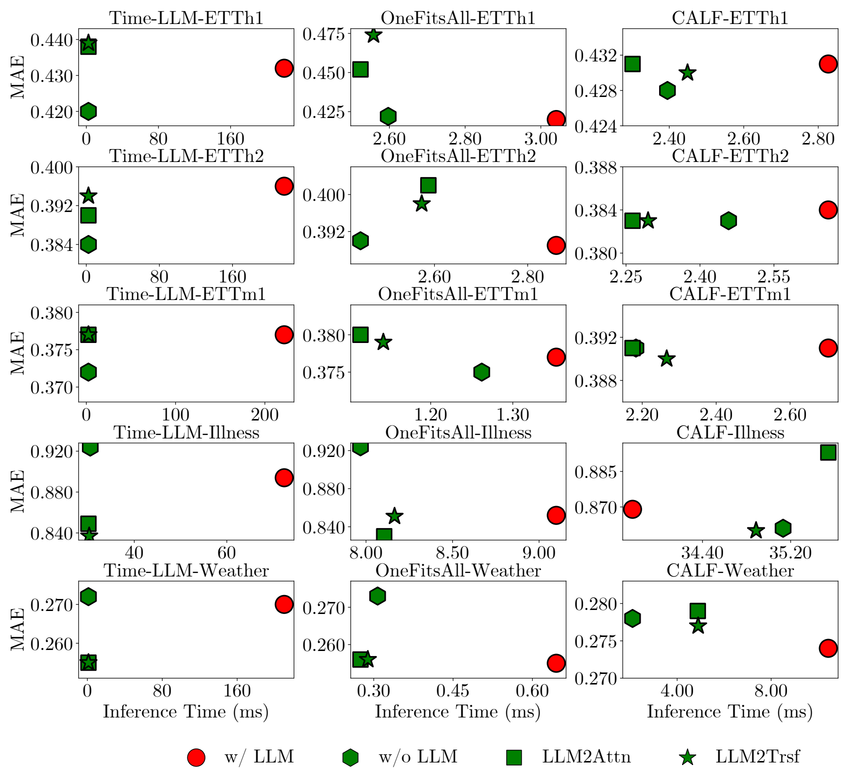
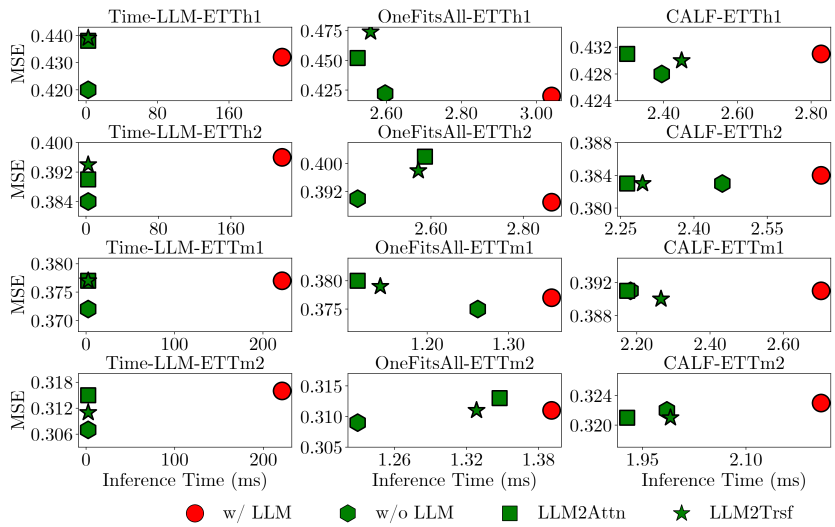
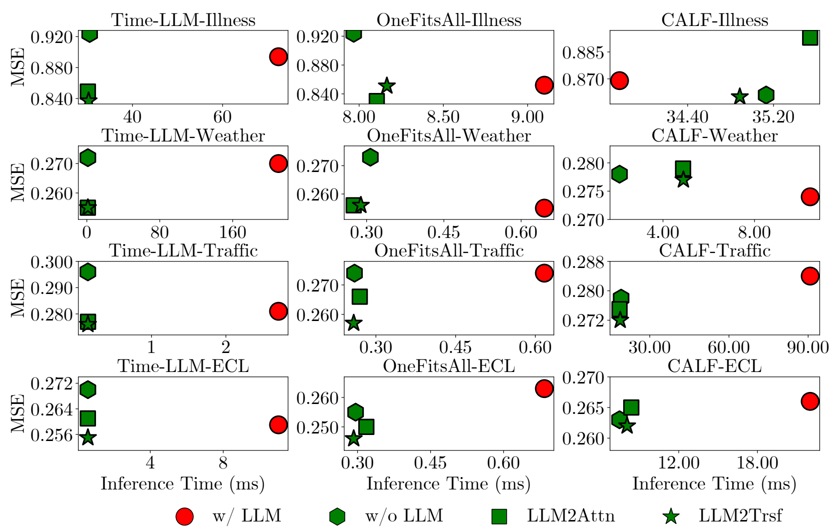


Figure 7: Ablation methods consume less time for inference while providing better forecasting performance in most cases. The figure above shows the inference time and prediction accuracy of Time-LLM, OneFitsAll, and CALF on ETTh1, ETTh2, ETTm1, Illness, and Weather, Traffic datasets, averaged across prediction lengths. Results of other datasets refer to Figure 3.



(a) Inference Time and Performance for ETTh1, ETTh2, ETTm1, and ETTm2.



(b) Inference Time and Performance for Illness, Weather, Traffic, and Electricity.

Figure 8: Ablation methods consume less time for inference while providing better forecasting performance in most cases. The figure above shows the inference time and prediction accuracy of Time-LLM, OneFitsAll, and CALF on all the datasets, averaged across prediction lengths in MSE metric.

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