

Rethinking Time Series Forecasting with LLMs via Nearest Neighbor Contrastive Learning

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Abstract

Adapting Large Language Models (LLMs) that are extensively trained on abundant text data, and customizing the input prompt to enable time series forecasting has received considerable attention. While recent work has shown great potential for adapting the learned prior of LLMs, the formulation of the prompt to finetune LLMs remains challenging as prompt should be aligned with time series data. Additionally, current approaches do not effectively leverage word token embeddings which embody the rich representation space learned by LLMs. This emphasizes the need for a robust approach to formulate the prompt which utilizes the word token embeddings while effectively representing the characteristics of the time series. To address these challenges, we propose NNCL-TLLM: Nearest Neighbor Contrastive Learning for Time series forecasting via LLMs. First, we generate time series compatible text prototypes such that each text prototype represents both word token embeddings in its neighborhood and time series characteristics via end-to-end finetuning. Next, we draw inspiration from Nearest Neighbor Contrastive Learning to formulate the prompt while obtaining the top- k nearest neighbor time series compatible text prototypes. We then fine-tune the layer normalization and positional embeddings of the LLM, keeping the other layers intact, reducing the trainable parameters and decreasing the computational cost. Our comprehensive experiments demonstrate that NNCL-TLLM outperforms in few-shot forecasting while achieving competitive or superior performance over the state-of-the-art methods in long-term and short-term forecasting tasks.

Introduction

Time series forecasting is a pivotal analytical task with applications across various domains including retail, finance, healthcare, meteorology, energy, and transportation (Fildes, Ma, and Kolassa 2022; Huber and Stuckenschmidt 2020; Stirling et al. 2021; Hong et al. 2020; Perera et al. 2024) where accurate predictions are crucial for decision making and strategic planning. Classical time series forecasting techniques such as autoregressive integrated moving average (ARIMA), exponential smoothing and Theta (Brockwell and Davis 2002; Makridakis, Spiliotis, and Assimakopoulos 2018) have been frequently used for such predictive analytics. With the rapid advent of deep learning, deep neural networks (DNNs) have become main contributors to time series forecasting. DNNs such as Recurrent Neural Networks

(RNNs), Long Short-Term Memory networks (LSTMs) and more recently transformer-based architectures have shown significant promise in time series forecasting (Benidis et al. 2022). However, a model designed for a specific time series dataset is not typically generalizable for other datasets due to the domain-variant characteristics (Jiang et al. 2024).

Large foundation models have captured significant interest in several fields such as natural language processing (Touvron et al. 2023; Radford et al. 2019; Raffel et al. 2020) and computer vision (Kirillov et al. 2023; He et al. 2022; Caron et al. 2021). However, developing a general-purpose foundation model for time series analysis presents unique challenges. Time series data comes from different domains: healthcare, finance, transportation, *etc* and is inherently non-stationary, with underlying statistical properties that vary over time. This variability necessitates frequent retraining of foundation models to maintain their effectiveness (Jiang et al. 2024). Additionally, the scarcity of large, high-quality datasets to train foundation models in the time series domain poses a significant problem. Therefore, recent work focuses on leveraging Large Language Models (LLMs) for time series forecasting that capitalizes on the transfer learning capabilities of LLMs (Jiang et al. 2024; Jin et al. 2024). LLMs are trained on abundant text data, as such are well-known to have a robust capability to recognize patterns in sequences (Mirchandani et al. 2023). However, adapting LLMs for time series forecasting introduces two significant challenges. First, since LLMs are trained on data from the modality of text, adapting the learned prior of the LLMs for a new modality of time series is required. Second, time series data is continuous in nature in contrast to discrete text data (Jin et al. 2023). Recent work has proposed distinct approaches to address these challenges including unique tokenization methods to generate time series tokens (Gruver et al. 2024), template-based techniques to create sentences from time series data for sentence-to-sentence processing (Xue and Salim 2023), reprogramming methods to align time series data with text (Jin et al. 2023; Sun et al. 2023), and finetuning LLMs using carefully formulated prompts as input (Cao et al. 2023; Zhou et al. 2023; Pan et al. 2024). Latest approaches demonstrate the importance of effective prompting which aligns with both time series and text data when finetuning the LLMs (Cao et al. 2023; Pan et al. 2024). This enables the LLMs to leverage time series specific infor-

mation. During prompt formulation, the word token embeddings of the LLM are utilized to generate text prototype embeddings. Current methods use different techniques to obtain the text prototype embeddings including linear probing (Jin et al. 2023; Pan et al. 2024) and using a fixed set of text prototype embeddings (Sun et al. 2023). However, formulating the prompt with time series compatible text prototypes remains challenging. These text prototypes should leverage the word token embeddings which embody the rich representation space learned by LLMs while effectively representing the time series characteristics. In addition, a robust representation learning approach can be significant for few-shot forecasting as time series compatible text prototypes needs to be optimized with only a few training samples (He et al. 2022). Furthermore, most of the existing methods employ time series decomposition techniques (e.g. additive seasonal-trend decomposition) to learn time series embeddings (Pan et al. 2024; Cao et al. 2023). However, decomposition may not be ideal for time series with more complex non-stationary patterns, which are more common in real-world applications (Wen et al. 2019).

In this work, we propose **Nearest Neighbor Contrastive Learning for Time series forecasting via LLMs (NNCL-TLLM)** to harness the power of LLMs for time series forecasting while addressing the aforementioned limitations. Drawing inspiration from nearest neighbor contrastive learning (NNCL) in the field of computer vision (Dwivedi et al. 2021), NNCL-TLLM introduces an approach to formulate prompts which better represent the time series characteristics without using customized techniques such as time series decomposition to learn time series embeddings. Since there cannot be an explicit mapping between word tokens in LLM and time series, our method introduces a technique to generate time series compatible text prototypes using the word token embeddings of the LLM and a customized optimization objective through NNCL. The layer normalization and positional embeddings of the LLM are finetuned, keeping the other layers intact to preserve the learned prior of the LLMs while reducing the trainable parameters and decreasing the computational cost. We demonstrate that our method achieves superior performance in few-shot forecasting showing the ability to perform in data-scarce settings and competitive performance in long-term and short-term forecasting. The main contributions of our work are summarized as follows:

1. We propose an NNCL based approach to formulate prompts which better represent the time series characteristics by jointly aligning text and time series.
2. We introduce a technique to generate time series compatible text prototypes by leveraging the word token embeddings of the LLM while optimizing through NNCL.
3. We demonstrate the advantage of the above two contributions by obtaining competitive performance over multiple benchmark datasets.

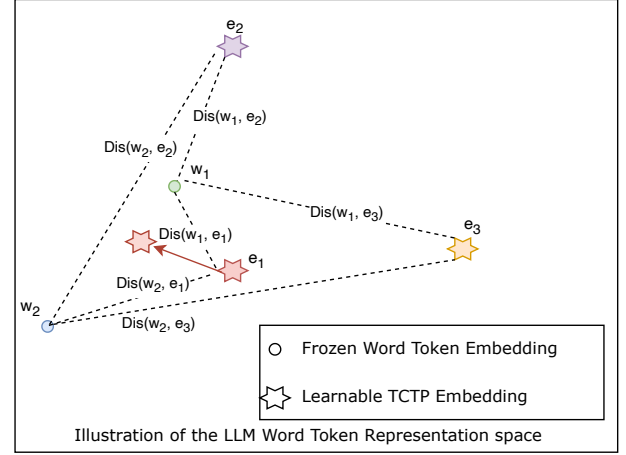


Figure 1: Overview of the proposed neighborhood aware time series compatible text prototype (TCTP) learning. The TCTPs are learned such that, each TCTP is a representative of the word token embeddings in its neighborhood. The learning process minimizes the distance between each word token embedding and its nearest TCTP embedding. The TCTP embedding e_1 moves to reduce the distance between its neighborhood word token embeddings: w_1 and w_2 . The text prototypes become time series compatible via end-to-end finetuning of the framework.

Related Work

Time Series Forecasting

Time series forecasting methods range from classical time series models, machine learning models to DNN based methods. Within the classical models, Autoregressive integrated moving average (ARIMA) models followed by seasonal ARIMA (SARIMA) models, vector autoregressive and exponential smoothing have been developed (Makridakis, Spiliotis, and Assimakopoulos 2018). On the other hand, deep learning based models encompass a variety of architectures including RNN models (Lai et al. 2018; Smyl 2020), temporal convolutional network (TCN) models (Sen, Yu, and Dhillon 2019; Wu et al. 2022), transformer models (Nie et al. 2022; Wu et al. 2021; Wang et al. 2024b; Zhang and Yan 2023; Zhou et al. 2022, 2021; Liu et al. 2023, 2022), multi-layer perceptron (MLP) models (Das et al. 2023; Zeng et al. 2023; Oreshkin et al. 2019; Challu et al. 2023; Chen et al. 2023) and graph neural network models (Yu, Yin, and Zhu 2017; Wu et al. 2020). However, these models are often domain and task-specific, making it challenging to generalize them across different tasks and datasets (Jiang et al. 2024).

LLMs for Time Series Forecasting

Recent advancements in LLMs such as LLaMa (Touvron et al. 2023), GPT-2 (Radford et al. 2019), and T5 (Rafael et al. 2020) have sparked a growing interest in integrating LLMs into various downstream tasks across different modalities, including time series (Jiang et al. 2024; Jin et al. 2024), video (Ataallah et al. 2024) and tabular data

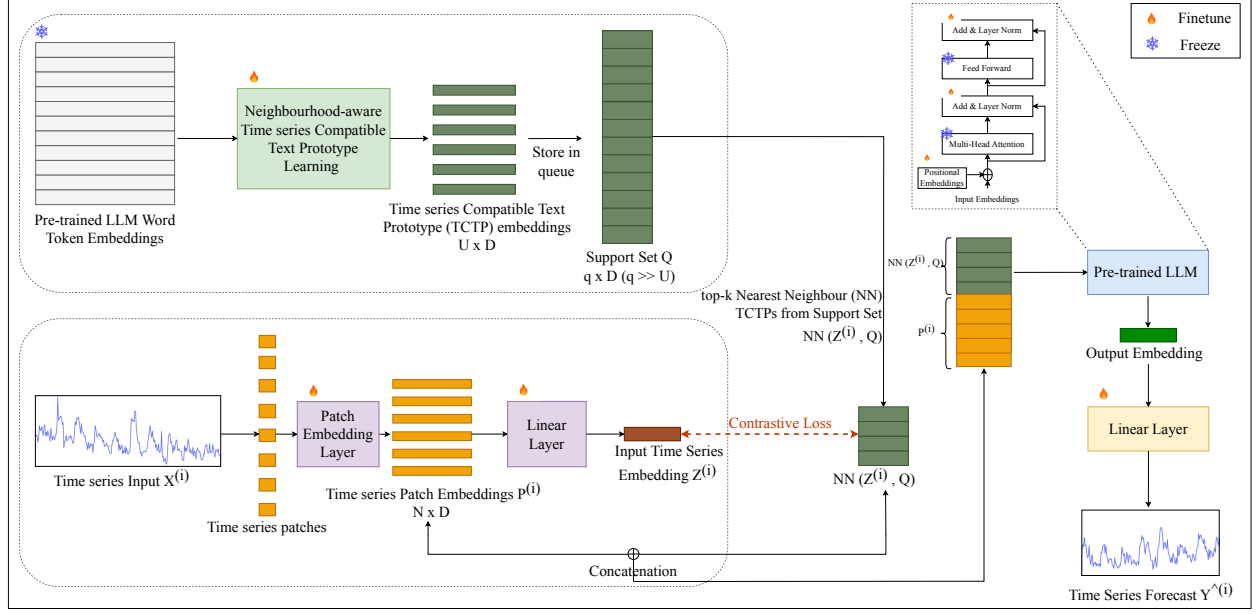


Figure 2: Illustration of NNCL-TLLM architecture. Given the univariate time series input we obtain the time series embedding $Z^{(i)}$ using a patch embedding layer and a linear layer. LLM word token embeddings are used to generate neighborhood aware time series compatible text prototypes (TCTPs). We use NNCL by inserting the TCTPs into a support set at the end of each training step. The top- k nearest neighbor TCTPs from the support set is obtained and we compute the contrastive loss; (L_{NNCL}) between the time series embedding and the top- k nearest neighbor TCTPs. Finally, we formulate the prompt to finetune the LLM by concatenating the time series patch embeddings and top- k nearest neighbor TCTPs from the support set.

(Hegselmann et al. 2023). Among these applications, leveraging the learned prior of LLMs for time series forecasting has emerged as a significant focus. One of the first methods, Promptcast (Xue and Salim 2023), converted numerical time series data into sentences and finetuned LLMs using a large-scale prompt-based dataset. Despite its effectiveness, this approach was annotation-intensive as it required to generate corresponding sentences for time series. In response, the LLMLTime method (Gruver et al. 2024) introduced a new tokenization technique to accurately process time series data with respect to LLMs, thereby reducing annotation burden. Another approach (Zhou et al. 2023), partitioned the time series into patches following the PatchTST framework (Nie et al. 2022) and finetuned LLMs using sequences of time series patches. Meanwhile, methods such as Time-LLM (Jin et al. 2023) and TEST (Sun et al. 2023) focused on reprogramming and aligning time series representations with text to make the input comprehensible to LLMs without the need for extensive fine-tuning. Time-LLM employed cross-attention mechanisms, whereas the TEST method utilized contrastive learning techniques. Recent work such as TEMPO (Cao et al. 2023) and S^2 IP-LLM (Pan et al. 2024) demonstrated that effective prompting with text prototypes obtained from word token embeddings via linear probing has a positive impact on adapting LLMs for time series forecasting. Specifically, the S^2 IP-LLM method employed cosine similarity to identify the most similar text prototypes

derived from a linear layer and incorporated this similarity measure into the overall optimization objective. This emphasizes the importance of a robust approach to formulate the input prompt to finetune the LLMs while effectively aligning time series and text. To learn time series embeddings, TEMPO and S^2 IP-LLM frameworks use a time series decomposition method: seasonal-trend decomposition using Loess (STL) (Cleveland et al. 1990). However, STL decomposition often struggles to accurately extract the seasonal component when there are shifts and fluctuations in seasonality (Wen et al. 2019; Trull, García-Díaz, and Peiró-Signes 2022; Phungtua-eng and Yamamoto 2024).

In contrast to these methods, we draw inspiration from NNCL (Dwivedi et al. 2021) to formulate the input prompt and finetune the layer normalization and positional embeddings of the LLMs. With the utilization of NNCL, we ensure that the prompt aligns with both word tokens and time series embeddings. To the best of our knowledge, we are the first to adopt NNCL to harness the power of LLMs for time series forecasting. Utilizing neighborhood information to learn more effective representations is shown to be useful in the fields such as continual learning (Malepathirana, Senanayake, and Halgamuge 2023). Drawing inspiration from this, we propose to learn neighborhood aware time series compatible text prototypes using the word token embeddings of LLM while optimizing through the introduced NNCL approach to enable better time series compatibility.

Method

This section outlines the proposed NNCL-TLLM method which is depicted in Fig. 2. First, we partition the multivariate time series into univariate time series and process them independently following a channel independence strategy. Utilization of channel independence allows the learning of time series embeddings without sharing information among different channels which can be useful in multivariate time series with different behaviors related to each channel (Nie et al. 2022). The univariate time series is divided into overlapping patches and a mapping function is used to obtain the embedding of the univariate time series. Then we utilize a custom mapping function which leverages neighborhood information to learn the time series compatible text prototypes from the word token embeddings of the LLM. We formulate the input prompt using the NNCL concept (Dwivedi et al. 2021) by aligning the time series and text. Since the self-attention and feed forward layers of the LLMs encapsulate most of the knowledge learned during pre-training (Zhou et al. 2023; Zhao et al. 2023), we only finetune the layer normalization and positional embeddings of the LLM using the formulated prompt to adapt the LLM for time series forecasting while maintaining the learned prior of the LLM.

Problem Definition

We define the time series forecasting problem as follows: Let $X \in \mathbb{R}^{M \times T}$ be the input multivariate time series of historical observations where M is the number of variables or channels and T is the time steps. Since X consists of M channels, $X^{(i)} \in \mathbb{R}^{1 \times T}$ represents the univariate time series corresponding to channel i . Given $X^{(i)}$, our objective is to predict the data points for H future time steps as denoted by $\hat{Y}^{(i)} \in \mathbb{R}^{1 \times H}$ while minimizing the error between the prediction $\hat{Y}^{(i)}$ and the ground truth $Y^{(i)} \in \mathbb{R}^{1 \times H}$.

Time Series Representation Learning

The input multivariate time series X is partitioned into M univariate time series; $X^{(i)}$ which only contains data points from one channel (i). Afterwards, each univariate time series is processed independently. The input time series $X^{(i)}$ is normalized using reversible instance normalization (RevIN) (Kim et al. 2021) to avoid the effects of temporal distribution shift. The concept of time series patching is adopted to obtain the time series embeddings as it allows to capture relevant information from the time series with a long look-back window while minimizing computational costs (Nie et al. 2022). The normalized time series $X^{(i)}$ is divided into overlapping patches where the length of a patch is C and the stride is S . After the patching operation, the total number of patches created is defined by $N = \lceil (T - C) / S \rceil + 1$. A 1-Dimensional (1D) convolution layer is utilized to obtain the time series patch embeddings as $P^{(i)} \in \mathbb{R}^{N \times D}$, where the dimension of the embedding is denoted by $N \times D$. The patch embeddings are finally fed into a simple linear layer to generate the embedding of the input univariate time series; $Z^{(i)} \in \mathbb{R}^{1 \times D}$.

Neighborhood aware Time series Compatible Text Prototype Learning

Word token embeddings in the LLM are denoted as $W \in \mathbb{R}^{V \times D}$, where V is the size of the vocabulary. Since the vocabulary of LLMs contains approximately 50000 word tokens (Radford et al. 2019), directly utilizing the word token embeddings to formulate the prompt is computationally intensive (Jin et al. 2023; Pan et al. 2024; Cao et al. 2023; Sun et al. 2023). As there can not be an explicit mapping between the time series and word tokens, we propose a new concept called: time series compatible text prototypes (TCTPs) which are text prototypes that represent time series characteristics and may not make sense from a natural language perspective. While a linear layer can learn linear relationships with an adequate amount of data, a more sophisticated approach is required to learn TCTPs in few-shot learning scenarios where only a limited amount of data is available for optimization. To this end, we propose to find neighborhood aware TCTPs, such that each TCTP is a representative of the word token embeddings in its neighborhood in the embedding space as illustrated in Fig. 1. These TCTPs become time series compatible through the end-to-end finetuning of the entire framework with NNCL.

The TCTP embeddings; $E \in \mathbb{R}^{U \times D}$, where U ($U \ll V$) is the number of learned TCTPs, are learnable vectors which are randomly initialized at first. During training, these TCTPs are dynamically adjusted based on the word token distribution in the embedding space. The distance between each word token embedding; w and each learnable TCTP embedding e is measured using Euclidean distance as:

$$Dis(w, e) = \|w - e\|_2 \quad (1)$$

The optimization objective is to minimize the distance between each word token embedding and its nearest TCTP embedding. Each word token embedding w is assigned to the nearest TCTP embedding e^* , where e^* is determined by Eq. 2.

$$e^* = e \text{ where } \operatorname{argmin}(Dis(w, e)) \quad (2)$$

Mean squared error (MSE) loss between the word token embeddings and their nearest TCTP embeddings is calculated as \mathcal{L}_{proto} using Eq. 3.

$$\mathcal{L}_{proto} = \frac{1}{V} \sum_{i=1}^V \|w_i - e_i^*\|_2^2 \quad (3)$$

Prompt Formulation via Nearest Neighbor Contrastive Learning

Neighborhood aware TCTPs are learned so as to be compatible with time series through NNCL. Thus, the prompts formulated using the TCTPs become aligned with both time series and text. Formulation of such prompts has shown significant promise in adapting LLMs for time series forecasting (Pan et al. 2024; Cao et al. 2023). Therefore, inspired by the idea of NNCL in the domain of computer vision (Dwivedi et al. 2021), we propose to adopt NNCL to formulate the input prompt utilizing TCTPs to finetune the LLM. Contrastive learning is built upon the idea of learning a representation space in which positive pairs (e.g. augmentations

| Method | | NNCL-TLLM | | S^2 IP-LLM | | Time-LLM | | OFA | | PatchTST | | iTransformer | | DLinear | |
|-------------------|-----|--------------|--------------|--------------|--------------|--------------|--------------|-------|--------------|--------------|--------------|--------------|-------|--------------|-------|
| Metric | | MSE | MAE | MSE | MAE | MSE | MAE | MSE | MAE | MSE | MAE | MSE | MAE | MSE | MAE |
| ETTh ₁ | 96 | 0.364 | 0.394 | 0.366 | 0.396 | 0.383 | 0.410 | 0.379 | 0.402 | 0.379 | 0.407 | 0.395 | 0.420 | 0.367 | 0.396 |
| | 192 | 0.395 | 0.415 | <u>0.401</u> | <u>0.420</u> | 0.419 | 0.435 | 0.415 | 0.424 | 0.428 | 0.442 | 0.427 | 0.441 | 0.401 | 0.419 |
| | 336 | <u>0.419</u> | 0.430 | 0.412 | 0.431 | <u>0.426</u> | 0.440 | 0.435 | 0.440 | 0.465 | 0.465 | 0.445 | 0.457 | 0.434 | 0.449 |
| | 720 | <u>0.429</u> | 0.453 | 0.440 | 0.458 | 0.428 | 0.456 | 0.441 | 0.459 | 0.504 | 0.500 | 0.537 | 0.530 | 0.472 | 0.493 |
| | Avg | 0.402 | 0.423 | <u>0.406</u> | <u>0.427</u> | 0.414 | <u>0.435</u> | 0.418 | 0.431 | 0.444 | 0.453 | 0.451 | 0.462 | 0.418 | 0.439 |
| ETTh ₂ | 96 | 0.273 | 0.338 | 0.278 | 0.340 | 0.297 | 0.357 | 0.289 | 0.347 | 0.296 | 0.353 | 0.304 | 0.360 | 0.301 | 0.367 |
| | 192 | 0.333 | 0.377 | <u>0.346</u> | <u>0.385</u> | 0.349 | 0.390 | 0.358 | 0.392 | 0.382 | 0.404 | 0.377 | 0.403 | 0.394 | 0.427 |
| | 336 | 0.360 | 0.401 | <u>0.367</u> | <u>0.406</u> | 0.373 | 0.408 | 0.383 | 0.414 | 0.402 | 0.425 | 0.405 | 0.429 | 0.506 | 0.495 |
| | 720 | 0.397 | 0.434 | <u>0.400</u> | <u>0.436</u> | <u>0.400</u> | <u>0.436</u> | 0.438 | 0.456 | 0.444 | 0.465 | 0.443 | 0.464 | 0.805 | 0.635 |
| | Avg | 0.341 | 0.388 | <u>0.347</u> | <u>0.391</u> | 0.355 | 0.398 | 0.367 | 0.402 | 0.381 | 0.411 | 0.382 | 0.414 | 0.502 | 0.481 |
| ETTh ₁ | 96 | 0.285 | 0.343 | 0.288 | 0.346 | 0.291 | 0.346 | 0.296 | 0.353 | 0.303 | 0.351 | 0.312 | 0.366 | 0.304 | 0.348 |
| | 192 | <u>0.324</u> | 0.365 | 0.323 | 0.365 | 0.336 | 0.373 | 0.335 | 0.373 | 0.341 | 0.376 | 0.347 | 0.385 | 0.336 | 0.367 |
| | 336 | <u>0.360</u> | 0.386 | 0.359 | 0.390 | 0.362 | 0.390 | 0.369 | 0.394 | 0.377 | 0.401 | 0.379 | 0.404 | 0.368 | 0.387 |
| | 720 | 0.411 | 0.416 | 0.403 | 0.418 | 0.410 | 0.421 | 0.418 | 0.424 | 0.431 | 0.436 | 0.441 | 0.442 | 0.421 | 0.418 |
| | Avg | <u>0.345</u> | 0.378 | 0.343 | <u>0.379</u> | 0.349 | 0.382 | 0.355 | 0.386 | 0.363 | 0.391 | 0.370 | 0.399 | 0.357 | 0.389 |
| ETTh ₂ | 96 | 0.169 | <u>0.260</u> | 0.165 | 0.257 | 0.184 | 0.275 | 0.170 | 0.264 | 0.173 | 0.262 | 0.179 | 0.271 | <u>0.168</u> | 0.263 |
| | 192 | 0.227 | 0.298 | 0.222 | 0.299 | 0.238 | 0.310 | 0.231 | 0.306 | 0.231 | 0.300 | 0.242 | 0.313 | 0.229 | 0.310 |
| | 336 | 0.274 | 0.330 | <u>0.277</u> | 0.330 | 0.286 | 0.340 | 0.280 | <u>0.339</u> | 0.292 | 0.345 | 0.288 | 0.344 | 0.289 | 0.352 |
| | 720 | 0.353 | 0.381 | <u>0.363</u> | 0.390 | 0.379 | 0.403 | 0.373 | 0.402 | 0.371 | 0.394 | 0.378 | 0.397 | 0.416 | 0.437 |
| | Avg | 0.256 | 0.317 | <u>0.257</u> | <u>0.319</u> | 0.271 | 0.332 | 0.265 | 0.328 | 0.267 | 0.325 | 0.272 | 0.331 | 0.275 | 0.340 |
| Weather | 96 | 0.146 | 0.198 | 0.145 | 0.195 | 0.158 | 0.210 | 0.162 | 0.212 | 0.149 | 0.198 | 0.253 | 0.304 | 0.176 | 0.237 |
| | 192 | 0.190 | <u>0.241</u> | 0.190 | 0.235 | 0.197 | 0.245 | 0.204 | 0.248 | <u>0.194</u> | <u>0.241</u> | 0.280 | 0.319 | 0.220 | 0.282 |
| | 336 | 0.243 | 0.281 | 0.243 | 0.280 | 0.248 | 0.285 | 0.254 | 0.286 | <u>0.245</u> | 0.282 | 0.321 | 0.344 | 0.265 | 0.319 |
| | 720 | 0.323 | 0.338 | 0.312 | 0.326 | 0.319 | <u>0.334</u> | 0.326 | 0.337 | <u>0.314</u> | <u>0.334</u> | 0.364 | 0.374 | 0.333 | 0.362 |
| | Avg | 0.226 | 0.265 | 0.222 | 0.259 | 0.230 | 0.268 | 0.237 | 0.270 | <u>0.225</u> | <u>0.264</u> | 0.304 | 0.335 | 0.248 | 0.300 |
| Traffic | 96 | 0.371 | 0.274 | 0.379 | 0.274 | 0.380 | 0.277 | 0.388 | 0.282 | 0.360 | 0.249 | 0.367 | 0.288 | 0.410 | 0.282 |
| | 192 | 0.390 | 0.287 | 0.397 | <u>0.282</u> | 0.399 | 0.288 | 0.407 | 0.290 | <u>0.379</u> | 0.256 | 0.378 | 0.293 | 0.423 | 0.287 |
| | 336 | 0.403 | 0.296 | 0.407 | 0.289 | 0.408 | 0.290 | 0.412 | 0.294 | <u>0.392</u> | 0.264 | 0.389 | 0.294 | 0.436 | 0.296 |
| | 720 | 0.441 | 0.315 | 0.440 | <u>0.301</u> | 0.445 | 0.308 | 0.450 | 0.312 | <u>0.432</u> | 0.286 | 0.401 | 0.304 | 0.466 | 0.315 |
| | Avg | 0.401 | 0.293 | 0.405 | <u>0.286</u> | 0.408 | 0.290 | 0.414 | 0.294 | <u>0.390</u> | 0.263 | 0.389 | 0.295 | 0.433 | 0.295 |
| ECL | 96 | 0.142 | 0.253 | <u>0.135</u> | <u>0.230</u> | 0.137 | 0.237 | 0.139 | 0.238 | 0.129 | 0.222 | 0.147 | 0.248 | 0.140 | 0.237 |
| | 192 | 0.155 | 0.257 | 0.149 | <u>0.247</u> | 0.150 | 0.249 | 0.153 | 0.251 | 0.157 | 0.240 | 0.165 | 0.267 | 0.153 | 0.249 |
| | 336 | 0.173 | 0.288 | <u>0.167</u> | <u>0.266</u> | 0.168 | 0.266 | 0.169 | 0.266 | 0.163 | 0.259 | 0.178 | 0.279 | 0.169 | 0.267 |
| | 720 | 0.216 | 0.316 | <u>0.200</u> | 0.287 | 0.203 | 0.293 | 0.206 | 0.297 | 0.197 | 0.290 | 0.322 | 0.398 | 0.203 | 0.301 |
| | Avg | 0.172 | 0.279 | 0.161 | <u>0.257</u> | <u>0.164</u> | 0.261 | 0.167 | 0.263 | 0.161 | 0.252 | 0.203 | 0.298 | 0.166 | 0.263 |

Table 1: Long term forecasting results for four prediction horizons; [96, 192, 336, 720] and the average MSE and MAE values across the four horizons. Lower values indicate better performance. Bold: the best, Underline: the second best. GPT-2 (Radford et al. 2019) is used as the backbone in all the LLM based methods. NNCL-TLLM achieves best results in 21 out of 35 cases. More results comparing with additional methods are in the Appendix.

of the same time series) are pulled closer while the negative samples (e.g. other time series in the batch) are pushed apart (Chen et al. 2020). A variant of the InfoNCE loss (i.e. contrastive loss) (Chen et al. 2020), which is commonly employed in contrastive learning methods is utilized as the loss function (Dwivedi et al. 2021).

The TCTPs learned via neighborhood aware time series compatible text prototype learning; E are used to populate a support set of TCTPs. By formulating this support set that has a large enough capacity, we aim to approximate and represent the full TCTP data distribution in the embedding space which can also be useful for few-shot learning. Positive pairs are formed by utilizing the nearest neighbors of the time series embedding $Z^{(i)}$ in the support set; Q and the loss function is defined as Eq. 4. The contrastive loss: L_{NNCL} is used to align the TCTP with the time series, ensuring that the

TCTPs are representative of the time series characteristics.

$$\mathcal{L}_{\text{NNCL}} = -\log \frac{\exp(\text{NN}(Z^{(i)}, Q) \cdot Z^{(i)} / \tau)}{\sum_{b=1}^B \exp(\text{NN}(Z^{(i)}, Q) \cdot Z_b^{(i)} / \tau)} \quad (4)$$

In Eq. 4, $\text{NN}(Z^{(i)}, Q)$ is the operator to obtain the top- k nearest neighbor TCTPs from the support set as denoted by Eq. 5 and τ and B represent the softmax temperature and batch size respectively. Each embedding is l_2 normalized.

$$\text{NN}(Z^{(i)}, Q) = \underset{Q^{(j)} \in Q}{\text{argmin}} \left\| Z^{(i)} - Q^{(j)} \right\|_2 \quad (5)$$

Support Set. We design our support set as a first in first out (FIFO) queue; $Q \in \mathbb{R}^{q \times D}$, where q ($q \gg U$) is the length of the queue and D is the size of the TCTP embeddings. After each training step, we update the support set by inserting the current batch of TCTP embeddings to the end of the queue and removing the oldest batch of embeddings.

| Metric | Method | | | | | | | |
|--------|---------------|-----------------------|----------|--------|----------|--------------|---------|--------|
| | NNCL-TLLM | S ² IP-LLM | Time-LLM | OFA | PatchTST | iTransformer | DLinear | N-HiTS |
| SMAPE | 11.947 | <u>12.021</u> | 12.494 | 12.690 | 12.059 | 12.142 | 13.639 | 12.035 |
| MASE | 1.595 | <u>1.612</u> | 1.731 | 1.808 | 1.623 | 1.631 | 2.095 | 1.625 |
| OWA | <u>0.858</u> | 0.857 | 0.913 | 0.940 | 0.869 | 0.874 | 1.051 | 0.869 |

Table 2: Short term forecasting results on M4 dataset. The weighted average values of SMAPE, MASE and OWA are reported from different sampling intervals. Lower values indicate better performance. Bold: the best, Underline: the second best. GPT-2 (Radford et al. 2019) is used as the backbone in all the LLM based methods. Full results are provided in Appendix.

LLM finetuning and Output projection

The prompt which is used as the input to the LLM is formulated by concatenating the two representations including the time series patch embeddings; $P^{(i)}$ and top- k set of nearest neighbor TCTPs from the support set; NN ($Z^{(i)}, Q$) as denoted by *prompt*.

$$prompt = [P^{(i)}; \text{NN}(Z^{(i)}, Q)] \quad (6)$$

Utilization of this information-rich embedding as the input prompt to finetune the LLM ensures that the LLM has not only the temporal context from time series embedding but also the corresponding time series compatible textual representations via top- k set of nearest neighbor TCTP embeddings from the support set.

We follow a finetuning strategy (Zhou et al. 2023) where only the layer normalization and positional embeddings in the LLM are finetuned while keeping the multi-head attention and feed-forward layers intact. Finetuning of the LLM can enable the capability to forecast the time series with the help of the formulated input prompt while preserving the prior it has learned during extensive training.

Output prediction of the LLM is flattened and then followed by a linear layer to get the final forecast; $\hat{Y}^{(i)}$. We compute the MSE loss between the forecast $\hat{Y}^{(i)}$ and the ground truth $Y^{(i)}$ using Eq. 7.

$$\mathcal{L}_{\text{forecast}} = \frac{1}{B} \sum_{b=1}^B \left\| \hat{Y}_b^{(i)} - Y_b^{(i)} \right\|_2^2 \quad (7)$$

Training

Overall Optimization Objective. The total loss used in our framework is shown in Eq. 8, where λ (> 0) is the weight which controls the contribution of the components in the loss. This loss function is proposed considering all the components in NNCL-TLLM. This ensures that the learned embedding space and the formulated prompt implicitly align across the two modalities: text and time series, while optimally leveraging the rich representation space learned by the LLMs to generate TCTPs via end-to-end finetuning.

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{forecast}} + \lambda(\mathcal{L}_{\text{NNCL}} + \mathcal{L}_{\text{proto}}) \quad (8)$$

Experiments

We conduct comprehensive experiments with widely used public datasets that cover distinct domains including energy, electricity, transportation, meteorology, finance and

economics. Results are presented in terms of long-term forecasting, short-term forecasting and few-shot forecasting.

Implementation Details. We use GPT-2 (Radford et al. 2019) as the backbone of the LLM in our framework in the experiments. The concrete details of the implementation of NNCL-TLLM framework can be found in Appendix.

Baselines. We compare our NNCL-TLLM method with state-of-the-art (SOTA) methods in time series forecasting and the results of the baseline methods are cited from (Pan et al. 2024). The baseline methods encompass LLM-based time series models; S²IP-LLM (Pan et al. 2024), Time-LLM (Jin et al. 2023) and OFA (Zhou et al. 2023) and transformer-based models; PatchTST (Nie et al. 2022), iTransformer (Liu et al. 2023), Informer (Zhou et al. 2021), Autoformer (Wu et al. 2021), FEDformer (Zhou et al. 2022) and Non-stationary Transformer (Liu et al. 2022). To maintain the consistency of the results, we perform comparisons considering a TCN-based model; TimesNet (Wu et al. 2022) and a MLP-based model; DLinear (Zeng et al. 2023). In our comparative analysis of short-term forecasting results, we additionally compare with N-HiTS (Challu et al. 2023).

Long-Term Forecasting

Setup. We evaluate the long-term forecasting performance of our framework considering the datasets; ETTh₁, ETTh₂, ETTm₁, ETTm₂, Electricity (ECL), Traffic and Weather (Zhou et al. 2021). Additional explanations of the datasets are provided in Appendix. In all the experiments, the input time series length is set to 512 historical observations. In line with the previous works, we report the performance in terms of Mean Squared Error (MSE) and Mean Absolute Error (MAE) which are discussed in detail in Appendix. The evaluation is conducted across four forecasting horizons; [96, 192, 336, 720] and finally the average MSE and MAE values across these four horizons are computed.

Results. Comparison with the SOTA methods for long-term forecasting is shown in Table 1. Our NNCL-TLLM method outperforms SOTA methods for several datasets including ETTh₁, ETTh₂, ETTm₁ and ETTm₂, while performing competitively for other datasets. It is also evident that the LLM-based time series analysis methods perform better than the other transformer based and non-transformer based methods benefiting from the strong learned prior of the LLMs. Note that, our NNCL-TLLM method achieves better performance without using any specialized technique including STL decomposition (Pan et al. 2024) to learn time

| Method | NNCL-TLLM | S^2 IP-LLM | Time-LLM | OFA | PatchTST | iTransformer | DLinear |
|-------------------|---------------------------|---------------------------|---------------------------|---------------------------|--------------------|--------------|--------------------|
| Metric | MSE MAE | MSE MAE | MSE MAE | MSE MAE | MSE MAE | MSE MAE | MSE MAE |
| ETTh ₁ | 0.563 0.503 | 0.593 0.529 | 0.785 0.553 | <u>0.590</u> <u>0.525</u> | 0.633 0.542 | 0.910 0.860 | 0.691 0.600 |
| ETTh ₂ | 0.379 0.415 | 0.419 0.439 | 0.424 0.441 | <u>0.397</u> <u>0.421</u> | 0.415 0.431 | 0.489 0.483 | 0.605 0.538 |
| ETTh ₁ | <u>0.432</u> <u>0.432</u> | 0.455 0.435 | 0.487 0.461 | 0.464 0.441 | 0.501 0.466 | 0.728 0.565 | 0.411 0.429 |
| ETTh ₂ | 0.270 0.323 | <u>0.284</u> <u>0.332</u> | 0.305 0.344 | 0.293 0.335 | 0.296 0.343 | 0.336 0.373 | 0.316 0.368 |
| Weather | 0.242 0.281 | 0.233 0.272 | <u>0.237</u> <u>0.275</u> | 0.238 <u>0.275</u> | 0.242 0.279 | 0.308 0.338 | 0.241 0.283 |
| Traffic | 0.434 0.319 | 0.427 <u>0.307</u> | <u>0.429</u> <u>0.307</u> | 0.440 0.310 | 0.430 0.305 | 0.495 0.361 | 0.447 0.313 |
| ECL | 0.186 0.288 | 0.175 <u>0.271</u> | 0.177 0.273 | <u>0.176</u> 0.269 | 0.180 0.273 | 0.196 0.293 | 0.180 0.280 |

Table 3: Few-shot forecasting results with 10% of the training data. The average MSE and MAE values across the four prediction horizons; $H \in [96, 192, 336, 720]$ are reported. Lower values indicate better performance. Bold: the best, Underline: the second best. NNCL-TLLM achieves best results in 3 out of 7 cases. Full results are in Appendix.

| Method | NNCL-TLLM | S^2 IP-LLM | Time-LLM | OFA | PatchTST | iTransformer | DLinear |
|-------------------|---------------------------|---------------------------|--------------------|---------------------------|--------------------|--------------|---------------------------|
| Metric | MSE MAE | MSE MAE | MSE MAE | MSE MAE | MSE MAE | MSE MAE | MSE MAE |
| ETTh ₁ | <u>0.671</u> 0.532 | 0.650 <u>0.550</u> | 0.891 0.627 | 0.681 0.560 | 0.694 0.569 | 1.070 0.710 | 0.750 0.611 |
| ETTh ₂ | 0.370 0.406 | <u>0.380</u> <u>0.413</u> | 0.581 0.519 | 0.400 0.433 | 0.827 0.615 | 0.488 0.475 | 0.694 0.577 |
| ETTh ₁ | <u>0.447</u> <u>0.444</u> | 0.455 0.446 | 0.524 0.479 | 0.472 0.450 | 0.526 0.476 | 0.784 0.596 | 0.400 0.417 |
| ETTh ₂ | 0.289 0.335 | <u>0.296</u> <u>0.342</u> | 0.325 0.361 | 0.308 0.346 | 0.314 0.352 | 0.356 0.388 | 0.399 0.426 |
| Weather | 0.260 0.303 | 0.260 0.297 | 0.264 <u>0.301</u> | <u>0.263</u> <u>0.301</u> | 0.269 0.303 | 0.309 0.339 | <u>0.263</u> 0.308 |
| Traffic | 0.418 0.309 | <u>0.420</u> <u>0.299</u> | 0.423 0.302 | 0.434 0.305 | 0.418 0.296 | 0.450 0.324 | 0.450 0.317 |
| ECL | 0.192 0.295 | 0.179 <u>0.275</u> | 0.181 0.279 | 0.178 0.273 | 0.181 0.277 | 0.201 0.296 | 0.176 <u>0.275</u> |

Table 4: Few-shot forecasting results with 5% of the training data. The average MSE and MAE values across the four prediction horizons; $H \in [96, 192, 336, 720]$ are reported. Lower values indicate better performance. Bold: the best, Underline: the second best. NNCL-TLLM achieves best results in 5 out of 7 cases. Full results are in Appendix.

series embeddings. We report the performance comparing with several additional methods in Appendix.

Short-Term Forecasting

Setup. The M4 dataset is selected as the benchmark for short-term forecasting (Makridakis, Spiliotis, and Assimakopoulos 2018). Additional details about the M4 dataset is provided in Appendix. The prediction horizons range from 6 to 48 and the input time series lengths are set to be twice the prediction horizons. The evaluation metrics include symmetric mean absolute percentage error (SMAPE), mean absolute scaled error (MASE), and overall weighted average (OWA). Further details related to the evaluation metrics can be found in Appendix.

Results. As illustrated in Table 2, NNCL-TLLM outperforms the SOTA methods in terms of SMAPE and MASE metrics. A more detailed comparison is presented in the Appendix. In addition, NNCL-TLLM surpasses the non-transformer based method, N-HiTS (Challu et al. 2023).

Few-Shot Forecasting

Setup. LLMs often excel at few-shot downstream tasks where only a limited amount of data is available for training, owing to their strong prior learned via extensive train-

ing with abundant data. We conduct long-term forecasting experiments in few-shot settings where only 10% and 5% of data is available for finetuning.

Results. As summarized in Table 3, NNCL-TLLM exhibits better performance with relation to the 10% few-shot forecasting setting. For multiple datasets including ETTh₁, ETTh₂ and ETTh₂, our method indicates up to 5% reduction in MSE highlighting the effectiveness of NNCL-TLLM. We also achieve competitive or superior performance for 5% few-shot forecasting as shown in Table 4. The results exemplifies the ability of NNCL-TLLM to be effective in time series forecasting even in data scarce settings harnessing the strong prior learned by the LLMs via effectively formulating the prompt using NNCL and neighborhood aware time series compatible text prototype learning.

Conclusion

This paper proposes NNCL-TLLM, a new approach for adapting LLMs for time series forecasting by effectively formulating the prompt using nearest neighbor contrastive learning. We demonstrate that time series compatible text prototypes can be learned via NNCL. A limitation that needs to be addressed is incorporating the channel dependencies of multivariate time series.

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Appendices

A. Experimental Details

A.1. Datasets Description

The experiments are conducted on different datasets which encompasses distinct domains such as energy, electricity, transportation, meteorology, finance and economics. The statistics of the datasets are presented in Table 5. Long-term forecasting performance was evaluated on seven benchmark datasets including Electricity Transformer Temperature (ETT), Weather, Traffic and Electricity (ECL) (Zhou et al. 2021). We evaluate short-term forecasting performance on M4 dataset (Makridakis, Spiliotis, and Assimakopoulos 2018). ETT datasets consist of electricity power load information and the oil temperature of electrical transformers which were collected for two years, from two different locations in China. Based on the sampling rate ETT datasets are categorized into ETTh1, ETTh2, ETTm1 and ETTm2. ETTh1 and ETTh2 have a sampling rate of 1 hour while ETTm1 and ETTm2 have a sampling rate of 15 minutes. The weather dataset comprises of one year of data obtained from 21 meteorological stations in Germany with a sampling rate of 10 minutes. The traffic dataset consists of occupancy rate data from 862 freeway sensors across California, collected at hourly sampling rate. The ECL dataset includes electricity consumption data collected from 321 customers and the measurements are taken every one hour. The M4 dataset has 100 000 time series from diverse domains, frequently used in business, economic and financial forecasting. The time series in M4 dataset is divided into six datasets each with different sampling rates ranging from hourly to yearly.

A.2. Evaluation Metrics

We use mean square error (MSE) and mean absolute error (MAE) to evaluate the performance of the model in terms of long-term forecasting. To evaluate the short-term forecasting performance on the M4 benchmark dataset, we utilize symmetric mean absolute percentage error (SMAPE), mean absolute scaled error (MASE) and overall weighted average (OWA) (Oreshkin et al. 2019). The OWA metric was specifically introduced for the evaluation of short-term forecasting performance on M4 dataset. The calculations of the men-

tioned metrics are presented as follows:

$$\begin{aligned} \text{MSE} &= \frac{1}{H} \sum_{h=1}^T (\mathbf{Y}_h - \hat{\mathbf{Y}}_h)^2 \\ \text{MAE} &= \frac{1}{H} \sum_{h=1}^H |\mathbf{Y}_h - \hat{\mathbf{Y}}_h| \\ \text{SMAPE} &= \frac{200}{H} \sum_{h=1}^H \frac{|\mathbf{Y}_h - \hat{\mathbf{Y}}_h|}{|\mathbf{Y}_h| + |\hat{\mathbf{Y}}_h|} \\ \text{MAPE} &= \frac{100}{H} \sum_{h=1}^H \frac{|\mathbf{Y}_h - \hat{\mathbf{Y}}_h|}{|\mathbf{Y}_h|} \\ \text{MASE} &= \frac{1}{H} \sum_{h=1}^H \frac{|\mathbf{Y}_h - \hat{\mathbf{Y}}_h|}{\frac{1}{H-s} \sum_{j=s+1}^H |\mathbf{Y}_j - \mathbf{Y}_{j-s}|} \\ \text{OWA} &= \frac{1}{2} \left[\frac{\text{SMAPE}}{\text{SMAPE}_{\text{Naive2}}} + \frac{\text{MASE}}{\text{MASE}_{\text{Naive2}}} \right] \end{aligned}$$

where s is the periodicity of the time series and H is the prediction interval or the prediction horizon. The h^{th} ground truth time series and prediction forecast are denoted as \mathbf{Y}_h and $\hat{\mathbf{Y}}_h$ respectively where $h \in \{1, \dots, H\}$.

A.3. Implementation Details

We utilize GPT2 model (Radford et al. 2019) as the backbone of the pre-trained LLM in our framework while enabling the first 6 hidden layers. The model was implemented using Pytorch (Paszke et al. 2019) and 80GB Nvidia A100 GPUs for training. The experiments are repeated three times and the average results are computed. The configurations used in our framework are presented in Table 6. We conducted experiments using varying values for number of neighborhood aware time series compatible text prototypes (TCTPs) as [1000, 5000, 8000] and the size of the support set was adjusted accordingly as [x10, x20, x50, x70, x100] times the number of TCTPs. The top-k nearest neighbor TCTP value was set to 8 for all the experiments. The input time series length was fixed as 512 for long-term forecasting tasks. The prediction horizons range from 6 to 48 and the input time series lengths are set to be twice the prediction horizons for short-term forecasting. The dimension of the embeddings were set to 768 to be consistent with the size of the word token embedding in pre-trained LLM.

A.4. Baselines

We compare our method with state-of-the-art (SOTA) methods in time series forecasting and the results of the baseline methods are cited from (Pan et al. 2024). The baseline methods encompass LLM-based time series models; S²IP-LLM (Pan et al. 2024), Time-LLM (Jin et al. 2023) and OFA (Zhou et al. 2023), transformer-based models; PatchTST (Nie et al. 2022), iTransformer (Liu et al. 2023), Informer (Zhou et al. 2021), Autoformer (Wu et al. 2021), FEDformer (Zhou et al. 2022), Non-stationary Transformer (Liu et al. 2022), a TCN-based model; TimesNet (Wu et al. 2022) and

| Tasks | Dataset | Dim | Series Length | Dataset Size | Frequency | Domain |
|------------------------|--------------|-----|---------------------|-----------------------|-----------|----------------|
| Long-term Forecasting | ETTh1 | 7 | [96, 192, 336, 720] | (8545, 2881, 2881) | 1 hour | Temperature |
| | ETTh2 | 7 | [96, 192, 336, 720] | (8545, 2881, 2881) | 1 hour | Temperature |
| | ETTm1 | 7 | [96, 192, 336, 720] | (34465, 11521, 11521) | 15 min | Temperature |
| | ETTm2 | 7 | [96, 192, 336, 720] | (34465, 11521, 11521) | 15 min | Temperature |
| | Weather | 21 | [96, 192, 336, 720] | (36792, 5271, 10540) | 10 min | Weather |
| | Traffic | 862 | [96, 192, 336, 720] | (12185, 1757, 3509) | 1 hour | Transportation |
| | ECL | 321 | [96, 192, 336, 720] | (18317, 2633, 5261) | 1 hour | Electricity |
| Short-term Forecasting | M4-Yearly | 1 | 6 | (23000, 0, 23000) | Yearly | Demographic |
| | M4-Quarterly | 1 | 8 | (24000, 0, 24000) | Quarterly | Finance |
| | M4-Monthly | 1 | 18 | (48000, 0, 48000) | Monthly | Industry |
| | M4-Weekly | 1 | 13 | (359, 0, 359) | Weekly | Macro |
| | M4-Daily | 1 | 14 | (4227, 0, 4227) | Daily | Macro |
| | M4-Hourly | 1 | 48 | (414, 0, 414) | Hourly | Other |

Table 5: Statistics of the datasets from (Wu et al. 2022). Dimensions of the datasets are included as Dim which indicates the number of channels in the time series. The dataset size includes the training, validation and testing splits.

MLP-based models; DLinear (Zeng et al. 2023), TiDE (Das et al. 2023) and TimeMixer (Wang et al. 2024a). We have reproduced the results for TiDE and TimeMixer with input time series length as 512, to maintain consistency across the experiments. In our comparative analysis of short-term forecasting results, we additionally compare with two methods: N-HiTS (Challu et al. 2023) and N-BEATS (Oreshkin et al. 2019).

B. Long-Term Forecasting

We present comparisons with additional transformer-based methods including FEDformer (Zhou et al. 2022), Autoformer (Wu et al. 2021), Stationary (Non-Stationary Transformer) (Liu et al. 2022), and non-transformer based methods, TimesNet (Wu et al. 2022), TiDE (Das et al. 2023) and TimeMixer (Wang et al. 2024a) in Table 1. It is observed that NNCL-TLLM outperforms in long-term forecasting in terms of most of the datasets compared to the additional baselines.

C. Short-Term Forecasting

Short-term forecasting results are reported for M4 benchmark dataset. As illustrated in Table 8 and Table 9, NNCL-TLLM outperforms the baseline methods in terms of average SMAPE and MASE metrics. We have divided the results into two tables due to space limitations. The full results are presented in terms of varying sampling rates ranging from yearly to hourly and the averaging across the sampling rates.

C. Few-Shot Forecasting

LLMs often excel at few-shot downstream tasks where only a limited amount of data is available for training, owing to their strong prior learned via extensive training with abundant data. We conduct long-term forecasting experiments in few-shot settings where only 10% and 5% of data is available for finetuning. We report the 10% few-shot forecasting

results in Table 10 and 5% few-shot forecasting results are presented in Table 11. Based on the results, it is evident that NNCL-TLLM perform effectively in time series forecasting even in data scarce settings harnessing the strong prior learned by the LLMs via effectively formulating the prompt using NNCL and neighborhood aware time series compatible text prototype learning.

C. Ablations and Parameter Sensitivity

In Table 12, we show the impact of the components in NNCL-TLLM. The ablations are conducted considering the neighborhood aware time series compatible text prototype learning and formulation of the prompt via NNCL. The experiments were conducted using the ETTh1 dataset for [96, 192] prediction horizons. Additionally, the results using ETTh1 dataset in 10% few-shot forecasting setting is reported. We present the results by only incorporating one component at a time and final results are obtained by combining both the components together. The results demonstrate that combination of both components enables to adapt the LLMs for time series forecasting effectively which can be highlighted in few-shot forecasting.

We performed qualitative analysis of the learned neighborhood aware time series compatible text prototypes in our method by visualizing them in the 2-dimensional space before and after the training process. The Fig. 3 UMAP visualizations of the TCTP embeddings reveal a clear distinction in the distribution patterns before and after optimization. After optimization, it displays well-defined clusters. This demonstrates that the neighborhood aware TCTPs are learned such that each TCTP is a representative of the word token embeddings in its neighborhood.

The Fig. 4 illustrates the performance of NNCL-TLLM in terms of MSE loss with varying parameter values of NNCL-TLLM including the number of time series compatible text prototypes, number of nearest neighbor time series compat-

| Tasks | Dataset | Input Length | Batch Size | Initial LR | Number of TCTPs |
|------------------------|---------|--------------|------------|------------|-----------------|
| Long-term Forecasting | ETTh1 | 512 | 16 | 10^{-3} | 1000 |
| | ETTh2 | 512 | 8 | 10^{-4} | 1000 |
| | ETTm1 | 512 | 16 | 10^{-4} | 5000 |
| | ETTm2 | 512 | 16 | 10^{-4} | 5000 |
| | Weather | 512 | 8 | 10^{-2} | 8000 |
| | Traffic | 512 | 8 | 10^{-2} | 8000 |
| | ECL | 512 | 8 | 10^{-2} | 8000 |
| Short-term Forecasting | M4 | 2 x H | 16 | 10^{-3} | 1000 |

Table 6: Configurations of the framework. Input length specifies the number of historical time steps used as the input to the model. Initial LR indicates the initial learning rate. H denotes the prediction horizons for the short-term forecasting.

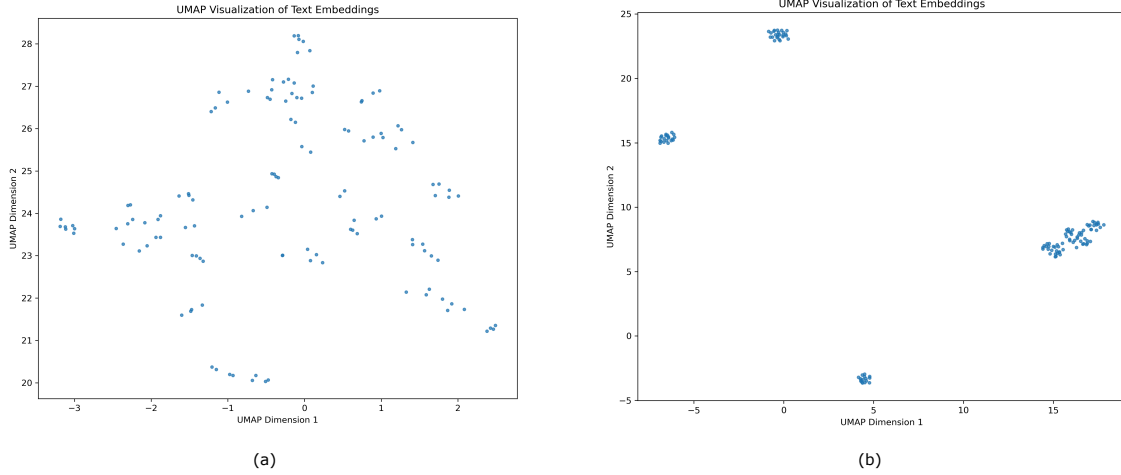


Figure 3: Illustration of the UMAP visualizations of neighborhood aware TCTP embeddings in 2-dimensional space before (a) and after (b) optimization.

ible text prototypes to formulate the prompt and the weight of the custom loss component.

D. Computational efficiency Analysis

We conducted experiments by randomly initializing the GPT-2 backbone, excluding the use of pre-trained weights. These experiments underscore the critical role of leveraging the learned prior in LLMs for effective time series forecasting. Additionally, we evaluated the computational costs associated with NNCL-TLLM, which involves fine-tuning only the layer normalization and positional embeddings, compared to training the entire LLM backbone from scratch. The analysis, summarized in Table 13 and Table 14, demonstrates that our method not only achieves superior performance but also significantly reduces the number of trainable parameters.

In addition, we compared the performance using Llama-2 (Touvron et al. 2023) as the backbone for ETTh1 and ETTm2 datasets. The number of trainable parameters, time taken per training iteration and inference time per sample

are also specified with respect to using GPT-2 and Llama-2 as the backbones of our method. According to Table 13 and 14, it is evident that the superior performance can be achieved while reducing the computational cost through GPT-2. Therefore, we opted to use GPT-2 as the LLM backbone of our method for all the experiments.

| Method | | NNCL-TLLM | | TimesNet | | FEDformer | | Autoformer | | Stationary | | TiDe | | TimeMixer | |
|-------------------|-----|----------------------|----------------------|----------|-------|-----------|-------|------------|-------|------------|-------|---------|-------|-----------|-------|
| Metric | | MSE MAE | | MSE MAE | | MSE MAE | | MSE MAE | | MSE MAE | | MSE MAE | | MSE MAE | |
| ETTh ₁ | 96 | 0.364 ₍₁₎ | 0.394 ₍₁₎ | 0.468 | 0.475 | 0.376 | 0.419 | 0.530 | 0.517 | 0.513 | 0.491 | 0.412 | 0.423 | 0.380 | 0.408 |
| | 192 | 0.395 ₍₁₎ | 0.415 ₍₁₎ | 0.484 | 0.485 | 0.420 | 0.448 | 0.537 | 0.521 | 0.534 | 0.504 | 0.438 | 0.440 | 0.446 | 0.450 |
| | 336 | 0.419 ₍₁₎ | 0.430 ₍₁₎ | 0.536 | 0.516 | 0.459 | 0.465 | 0.596 | 0.583 | 0.588 | 0.535 | 0.441 | 0.439 | 0.421 | 0.443 |
| | 720 | 0.429 ₍₁₎ | 0.453 ₍₁₎ | 0.593 | 0.537 | 0.506 | 0.507 | 0.713 | 0.639 | 0.643 | 0.616 | 0.467 | 0.474 | 0.490 | 0.489 |
| | Avg | 0.402 ₍₁₎ | 0.423 ₍₁₎ | 0.520 | 0.505 | 0.440 | 0.460 | 0.594 | 0.565 | 0.570 | 0.537 | 0.440 | 0.444 | 0.434 | 0.448 |
| ETTh ₂ | 96 | 0.273 ₍₁₎ | 0.338 ₍₁₎ | 0.376 | 0.415 | 0.358 | 0.397 | 0.454 | 0.490 | 0.476 | 0.458 | 0.275 | 0.339 | 0.282 | 0.354 |
| | 192 | 0.333 ₍₁₎ | 0.377 ₍₁₎ | 0.409 | 0.440 | 0.429 | 0.439 | 0.486 | 0.517 | 0.512 | 0.493 | 0.335 | 0.382 | 0.359 | 0.402 |
| | 336 | 0.360 ₍₁₎ | 0.401 ₍₁₎ | 0.425 | 0.455 | 0.496 | 0.487 | 0.493 | 0.533 | 0.552 | 0.551 | 0.362 | 0.406 | 0.376 | 0.414 |
| | 720 | 0.397 ₍₁₎ | 0.434 ₍₁₎ | 0.488 | 0.494 | 0.463 | 0.474 | 0.515 | 0.543 | 0.562 | 0.560 | 0.416 | 0.447 | 0.442 | 0.462 |
| | Avg | 0.341 ₍₁₎ | 0.388 ₍₁₎ | 0.425 | 0.451 | 0.437 | 0.449 | 0.487 | 0.520 | 0.526 | 0.516 | 0.347 | 0.394 | 0.365 | 0.408 |
| ETTm ₁ | 96 | 0.285 ₍₁₎ | 0.343 ₍₁₎ | 0.329 | 0.377 | 0.379 | 0.419 | 0.568 | 0.516 | 0.386 | 0.398 | 0.303 | 0.346 | 0.307 | 0.357 |
| | 192 | 0.324 ₍₁₎ | 0.365 ₍₁₎ | 0.371 | 0.401 | 0.426 | 0.441 | 0.573 | 0.528 | 0.459 | 0.444 | 0.334 | 0.365 | 0.352 | 0.383 |
| | 336 | 0.360 ₍₁₎ | 0.386 ₍₁₎ | 0.417 | 0.428 | 0.445 | 0.459 | 0.587 | 0.534 | 0.495 | 0.464 | 0.366 | 0.384 | 0.412 | 0.419 |
| | 720 | 0.411 ₍₁₎ | 0.416 ₍₁₎ | 0.483 | 0.464 | 0.543 | 0.490 | 0.589 | 0.536 | 0.585 | 0.516 | 0.419 | 0.416 | 0.483 | 0.453 |
| | Avg | 0.345 ₍₁₎ | 0.378 ₍₁₎ | 0.400 | 0.417 | 0.448 | 0.452 | 0.579 | 0.529 | 0.481 | 0.456 | 0.356 | 0.378 | 0.388 | 0.403 |
| ETTm ₂ | 96 | 0.169 ₍₂₎ | 0.260 ₍₂₎ | 0.201 | 0.286 | 0.203 | 0.287 | 0.287 | 0.359 | 0.192 | 0.274 | 0.163 | 0.252 | 0.175 | 0.264 |
| | 192 | 0.227 ₍₂₎ | 0.298 ₍₂₎ | 0.260 | 0.329 | 0.269 | 0.328 | 0.325 | 0.388 | 0.280 | 0.339 | 0.218 | 0.290 | 0.235 | 0.308 |
| | 336 | 0.274 ₍₂₎ | 0.330 ₍₂₎ | 0.331 | 0.376 | 0.325 | 0.366 | 0.498 | 0.491 | 0.334 | 0.361 | 0.271 | 0.325 | 0.277 | 0.332 |
| | 720 | 0.353 ₍₁₎ | 0.381 ₍₁₎ | 0.428 | 0.430 | 0.421 | 0.415 | 0.548 | 0.517 | 0.417 | 0.413 | 0.360 | 0.384 | 0.379 | 0.397 |
| | Avg | 0.256 ₍₂₎ | 0.317 ₍₂₎ | 0.305 | 0.355 | 0.305 | 0.349 | 0.414 | 0.439 | 0.306 | 0.347 | 0.253 | 0.313 | 0.266 | 0.325 |
| Weather | 96 | 0.146 ₍₁₎ | 0.198 ₍₁₎ | 0.172 | 0.220 | 0.217 | 0.296 | 0.266 | 0.336 | 0.173 | 0.223 | 0.169 | 0.225 | 0.149 | 0.202 |
| | 192 | 0.190 ₍₁₎ | 0.241 ₍₁₎ | 0.219 | 0.261 | 0.276 | 0.336 | 0.307 | 0.367 | 0.245 | 0.285 | 0.212 | 0.264 | 0.199 | 0.247 |
| | 336 | 0.243 ₍₁₎ | 0.281 ₍₁₎ | 0.280 | 0.306 | 0.339 | 0.380 | 0.359 | 0.395 | 0.321 | 0.338 | 0.259 | 0.310 | 0.245 | 0.286 |
| | 720 | 0.323 ₍₁₎ | 0.338 ₍₁₎ | 0.365 | 0.359 | 0.403 | 0.428 | 0.419 | 0.428 | 0.414 | 0.410 | 0.319 | 0.356 | 0.316 | 0.334 |
| | Avg | 0.226 ₍₁₎ | 0.265 ₍₁₎ | 0.259 | 0.287 | 0.309 | 0.360 | 0.338 | 0.382 | 0.288 | 0.314 | 0.240 | 0.289 | 0.227 | 0.267 |
| Traffic | 96 | 0.371 ₍₂₎ | 0.274 ₍₂₎ | 0.593 | 0.321 | 0.587 | 0.366 | 0.613 | 0.388 | 0.612 | 0.338 | 0.360 | 0.259 | 0.410 | 0.308 |
| | 192 | 0.390 ₍₂₎ | 0.287 ₍₂₎ | 0.617 | 0.336 | 0.604 | 0.373 | 0.616 | 0.382 | 0.613 | 0.340 | 0.366 | 0.260 | 0.418 | 0.312 |
| | 336 | 0.403 ₍₂₎ | 0.296 ₍₂₎ | 0.629 | 0.336 | 0.621 | 0.383 | 0.622 | 0.337 | 0.618 | 0.328 | 0.376 | 0.262 | 0.420 | 0.305 |
| | 720 | 0.441 ₍₂₎ | 0.315 ₍₂₎ | 0.640 | 0.350 | 0.626 | 0.382 | 0.660 | 0.408 | 0.653 | 0.355 | 0.406 | 0.274 | 0.462 | 0.329 |
| | Avg | 0.401 ₍₂₎ | 0.293 ₍₂₎ | 0.620 | 0.336 | 0.610 | 0.376 | 0.628 | 0.379 | 0.624 | 0.340 | 0.377 | 0.264 | 0.427 | 0.313 |
| ECL | 96 | 0.142 ₍₃₎ | 0.253 ₍₃₎ | 0.168 | 0.272 | 0.193 | 0.308 | 0.201 | 0.317 | 0.169 | 0.273 | 0.135 | 0.232 | 0.132 | 0.228 |
| | 192 | 0.155 ₍₂₎ | 0.257 ₍₃₎ | 0.184 | 0.289 | 0.201 | 0.315 | 0.222 | 0.334 | 0.182 | 0.286 | 0.150 | 0.246 | 0.157 | 0.248 |
| | 336 | 0.173 ₍₂₎ | 0.288 ₍₃₎ | 0.198 | 0.300 | 0.214 | 0.329 | 0.231 | 0.338 | 0.200 | 0.304 | 0.164 | 0.263 | 0.173 | 0.271 |
| | 720 | 0.216 ₍₃₎ | 0.316 ₍₃₎ | 0.220 | 0.320 | 0.246 | 0.355 | 0.254 | 0.361 | 0.222 | 0.321 | 0.199 | 0.297 | 0.205 | 0.297 |
| | Avg | 0.172 ₍₃₎ | 0.279 ₍₃₎ | 0.192 | 0.295 | 0.214 | 0.327 | 0.227 | 0.338 | 0.193 | 0.296 | 0.162 | 0.260 | 0.167 | 0.261 |

Table 7: Additional long term forecasting results for four prediction horizons; [96, 192, 336, 720] and the average MSE and MAE values across the four horizons. Lower values indicate better performance. The ranks which NNCL-TLLM method achieves in terms of the performance are indicated as (.). GPT-2 (Radford et al. 2019) is used as the LLM backbone.

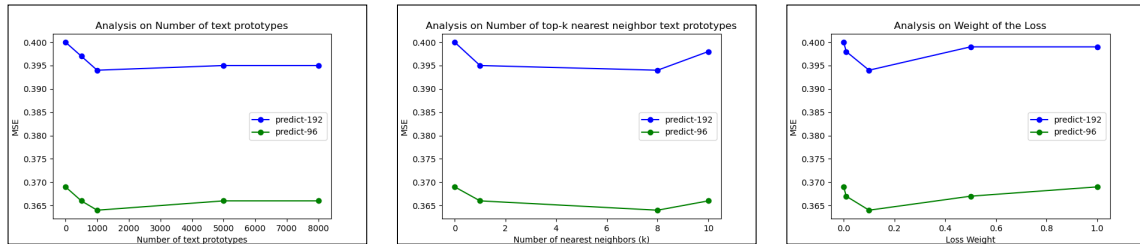


Figure 4: Illustration of the analysis of parameter sensitivity. MSE values are reported for ETTh1 dataset for [96, 192] prediction horizons.

| | Method | NNCL-TLLM | S^2 IP-LLM | Time-LLM | OFA | iTransformer | DLinear | PatchTST | N-HiTS |
|--------|--------|---------------|---------------|----------|--------|--------------|---------|---------------|---------------|
| Year. | SMAPE | 13.479 | 13.413 | 13.75 | 15.11 | 13.652 | 16.965 | 13.477 | <u>13.422</u> |
| | MASE | 3.027 | <u>3.024</u> | 3.055 | 3.565 | 3.095 | 4.283 | 3.019 | 3.056 |
| | OWA | <u>0.793</u> | 0.792 | 0.805 | 0.911 | 0.807 | 1.058 | 0.792 | 0.795 |
| Quart. | SMAPE | 10.134 | 10.352 | 10.671 | 10.597 | 10.353 | 12.145 | 10.38 | <u>10.185</u> |
| | MASE | <u>1.19</u> | 1.228 | 1.276 | 1.253 | 1.209 | 1.520 | 1.233 | 1.18 |
| | OWA | <u>0.894</u> | 0.922 | 0.95 | 0.938 | 0.911 | 1.106 | 0.921 | 0.893 |
| Mon. | SMAPE | 12.87 | 12.995 | 13.416 | 13.258 | 13.079 | 13.514 | <u>12.959</u> | 13.059 |
| | MASE | 0.944 | <u>0.97</u> | 1.045 | 1.003 | 0.974 | 1.037 | <u>0.970</u> | 1.013 |
| | OWA | <u>0.89</u> | 0.91 | 0.957 | 0.931 | 0.911 | 0.956 | <u>0.905</u> | 0.929 |
| Other. | SMAPE | <u>4.744</u> | 4.805 | 4.973 | 6.124 | 4.78 | 6.709 | 4.952 | 4.711 |
| | MASE | <u>3.202</u> | 3.247 | 3.412 | 4.116 | 3.231 | 4.953 | 3.347 | 3.054 |
| | OWA | <u>1.004</u> | 1.017 | 1.053 | 1.259 | 1.012 | 1.487 | 1.049 | 0.977 |
| Avg. | SMAPE | 11.947 | <u>12.021</u> | 12.494 | 12.690 | 12.142 | 13.639 | 12.059 | 12.035 |
| | MASE | 1.595 | <u>1.612</u> | 1.731 | 1.808 | 1.631 | 2.095 | 1.623 | 1.625 |
| | OWA | <u>0.858</u> | 0.857 | 0.913 | 0.94 | 0.874 | 1.051 | 0.869 | 0.869 |

Table 8: Short term forecasting results on M4 dataset. The last three rows include weighted average values of SMAPE, MASE and OWA from different sampling intervals. Lower values indicate better performance. Bold: the best, Underline: the second best. GPT-2 (Radford et al. 2019) is used as the backbone in all the LLM based methods.

| | Method | NNCL-TLLM | N-BEATS | TimesNet | FEDformer | Autoformer | Stationary | ETSformer |
|--------|--------|---------------|---------|----------|-----------|------------|------------|-----------|
| Year. | SMAPE | 13.479 | 13.487 | 15.378 | 14.021 | 13.974 | 14.727 | 18.009 |
| | MASE | 3.027 | 3.036 | 3.554 | 3.036 | 3.134 | 3.078 | 4.487 |
| | OWA | 0.793 | 0.795 | 0.918 | 0.811 | 0.822 | 0.807 | 1.115 |
| Quart. | SMAPE | 10.134 | 10.564 | 10.465 | 11.100 | 11.338 | 10.958 | 13.376 |
| | MASE | 1.19 | 1.252 | 1.227 | 1.35 | 1.365 | 1.325 | 1.906 |
| | OWA | 0.894 | 0.936 | 0.923 | 0.996 | 1.012 | 0.981 | 1.302 |
| Mon. | SMAPE | 12.87 | 13.089 | 13.513 | 14.403 | 13.958 | 13.917 | 14.588 |
| | MASE | 0.944 | 0.996 | 1.039 | 1.147 | 1.103 | 1.097 | 1.368 |
| | OWA | 0.89 | 0.922 | 0.957 | 1.038 | 1.002 | 0.998 | 1.149 |
| Other. | SMAPE | 4.744 | 6.599 | 6.913 | 7.148 | 5.485 | 6.302 | 7.267 |
| | MASE | 3.202 | 4.430 | 4.507 | 4.064 | 3.865 | 4.064 | 5.240 |
| | OWA | 1.004 | 1.393 | 1.438 | 1.304 | 1.187 | 1.304 | 1.591 |
| Avg. | SMAPE | 11.947 | 12.250 | 12.880 | 13.160 | 12.909 | 12.780 | 14.718 |
| | MASE | 1.595 | 1.698 | 1.836 | 1.775 | 1.771 | 1.756 | 2.408 |
| | OWA | 0.858 | 0.896 | 0.955 | 0.949 | 0.939 | 0.930 | 1.172 |

Table 9: Short term forecasting results on M4 dataset comparing with additional methods. The last three rows include weighted average values of SMAPE, MASE and OWA from different sampling intervals. Lower values indicate better performance. Bold: the best, Underline: the second best. GPT-2 (Radford et al. 2019) is used as the backbone in all the LLM based methods.

| Method | | NNCL-TLLM | S^2 IP-LLM | Time-LLM | OFA | iTrans. | DLinear | PatchTST | TimesNet | FEDformer | Autoformer |
|-------------------|-----|--------------------|--------------------|--------------------|--------------------|-------------|--------------------|--------------------|-------------|-------------|-------------|
| Metric | | MSE MAE | MSE MAE | MSE MAE | MSE MAE | MSE MAE | MSE MAE | MSE MAE | MSE MAE | MSE MAE | MSE MAE |
| ETTh ₁ | 96 | 0.428 0.437 | 0.481 0.474 | 0.720 0.533 | <u>0.458 0.456</u> | 0.790 0.586 | 0.492 0.495 | 0.516 0.485 | 0.861 0.628 | 0.512 0.499 | 0.613 0.552 |
| | 192 | 0.510 0.487 | 0.518 0.491 | 0.747 0.545 | <u>0.570 0.516</u> | 0.837 0.609 | 0.565 0.538 | 0.598 0.524 | 0.797 0.593 | 0.624 0.555 | 0.722 0.598 |
| | 336 | 0.579 0.506 | 0.664 0.570 | 0.793 0.551 | <u>0.608 0.535</u> | 0.780 0.575 | 0.721 0.622 | 0.657 0.550 | 0.941 0.648 | 0.691 0.574 | 0.750 0.619 |
| | 720 | <u>0.735 0.582</u> | 0.711 0.584 | 0.880 0.584 | <u>0.725 0.591</u> | 1.234 0.811 | 0.986 0.743 | 0.762 0.610 | 0.877 0.641 | 0.728 0.614 | 0.721 0.616 |
| | Avg | 0.563 0.503 | 0.593 0.529 | 0.785 0.553 | <u>0.590 0.525</u> | 0.910 0.860 | 0.691 0.600 | 0.633 0.542 | 0.869 0.628 | 0.639 0.561 | 0.702 0.596 |
| ETTh ₂ | 96 | 0.283 0.349 | 0.354 0.400 | 0.334 0.381 | <u>0.331 0.374</u> | 0.404 0.435 | 0.357 0.411 | 0.353 0.389 | 0.378 0.409 | 0.382 0.416 | 0.413 0.451 |
| | 192 | 0.362 0.400 | 0.401 0.423 | 0.430 0.438 | <u>0.402 0.411</u> | 0.470 0.474 | 0.569 0.519 | 0.403 0.414 | 0.490 0.467 | 0.478 0.474 | 0.474 0.477 |
| | 336 | 0.396 0.429 | 0.442 0.450 | 0.449 0.458 | <u>0.406 0.433</u> | 0.489 0.485 | 0.671 0.572 | 0.426 0.441 | 0.537 0.494 | 0.504 0.501 | 0.547 0.543 |
| | 720 | <u>0.476 0.482</u> | 0.480 0.486 | 0.485 0.490 | 0.449 0.464 | 0.593 0.538 | 0.824 0.648 | 0.477 0.480 | 0.510 0.491 | 0.499 0.509 | 0.516 0.523 |
| | Avg | 0.379 0.415 | 0.419 0.439 | 0.424 0.441 | <u>0.397 0.421</u> | 0.489 0.483 | 0.605 0.538 | 0.415 0.431 | 0.479 0.465 | 0.466 0.475 | 0.488 0.499 |
| ETTm ₁ | 96 | <u>0.380 0.401</u> | 0.388 <u>0.401</u> | 0.412 0.422 | 0.390 0.404 | 0.709 0.556 | 0.352 0.392 | 0.410 0.419 | 0.583 0.501 | 0.578 0.518 | 0.774 0.614 |
| | 192 | <u>0.403 0.416</u> | 0.422 0.421 | 0.447 0.438 | 0.429 0.423 | 0.717 0.548 | 0.382 0.412 | 0.437 0.434 | 0.630 0.528 | 0.617 0.546 | 0.754 0.592 |
| | 336 | <u>0.439 0.436</u> | 0.456 0.430 | 0.497 0.465 | 0.469 0.439 | 0.735 0.575 | 0.419 0.434 | 0.476 0.454 | 0.725 0.568 | 0.998 0.775 | 0.869 0.677 |
| | 720 | <u>0.504 0.475</u> | 0.554 0.490 | 0.594 0.521 | 0.569 0.498 | 0.752 0.584 | 0.490 0.477 | 0.681 0.556 | 0.769 0.549 | 0.693 0.579 | 0.810 0.630 |
| | Avg | <u>0.432 0.432</u> | 0.455 0.435 | 0.487 0.461 | 0.464 0.441 | 0.728 0.565 | 0.411 0.429 | 0.501 0.466 | 0.677 0.537 | 0.722 0.605 | 0.802 0.628 |
| ETTm ₂ | 96 | 0.183 0.267 | 0.192 0.274 | 0.224 0.296 | <u>0.188 0.269</u> | 0.245 0.322 | 0.213 0.303 | 0.191 0.274 | 0.212 0.285 | 0.291 0.399 | 0.352 0.454 |
| | 192 | 0.235 0.301 | 0.246 0.313 | 0.260 0.317 | <u>0.251 0.309</u> | 0.274 0.338 | 0.278 0.345 | 0.252 0.317 | 0.270 0.323 | 0.307 0.379 | 0.694 0.691 |
| | 336 | 0.283 0.334 | <u>0.301 0.340</u> | 0.312 0.349 | 0.307 0.346 | 0.361 0.394 | 0.338 0.385 | 0.306 0.353 | 0.323 0.353 | 0.543 0.559 | 2.408 1.407 |
| | 720 | 0.379 0.391 | <u>0.400 0.403</u> | 0.424 0.416 | 0.426 0.417 | 0.467 0.442 | 0.436 0.440 | 0.433 0.427 | 0.474 0.449 | 0.712 0.614 | 1.913 1.166 |
| | Avg | 0.270 0.323 | <u>0.284 0.332</u> | 0.305 0.344 | 0.293 0.335 | 0.336 0.373 | 0.316 0.368 | 0.296 0.343 | 0.320 0.353 | 0.463 0.488 | 1.342 0.930 |
| Weather | 96 | 0.158 0.219 | <u>0.159 0.210</u> | 0.160 0.213 | 0.163 0.215 | 0.253 0.307 | 0.171 0.224 | 0.165 0.215 | 0.184 0.230 | 0.188 0.253 | 0.221 0.297 |
| | 192 | 0.207 0.258 | 0.200 0.251 | <u>0.204 0.254</u> | 0.210 0.254 | 0.292 0.328 | 0.215 0.263 | 0.210 0.257 | 0.245 0.283 | 0.250 0.304 | 0.270 0.322 |
| | 336 | 0.272 0.303 | 0.257 0.293 | 0.255 0.291 | <u>0.256 0.292</u> | 0.322 0.346 | 0.258 0.299 | 0.259 0.297 | 0.305 0.321 | 0.312 0.346 | 0.320 0.351 |
| | 720 | 0.331 0.345 | 0.317 0.335 | 0.329 0.345 | <u>0.321 0.339</u> | 0.365 0.374 | <u>0.320 0.346</u> | 0.332 0.346 | 0.381 0.371 | 0.387 0.393 | 0.390 0.396 |
| | Avg | 0.242 0.281 | 0.233 0.272 | <u>0.237 0.275</u> | 0.238 <u>0.275</u> | 0.308 0.338 | <u>0.241 0.283</u> | 0.242 0.279 | 0.279 0.301 | 0.284 0.324 | 0.300 0.342 |
| Traffic | 96 | 0.405 0.305 | 0.403 0.293 | 0.406 0.295 | 0.414 0.297 | 0.448 0.329 | 0.419 0.298 | 0.403 0.289 | 0.719 0.416 | 0.639 0.400 | 0.672 0.405 |
| | 192 | 0.420 0.308 | 0.412 0.295 | 0.416 0.300 | 0.426 0.301 | 0.487 0.360 | 0.434 0.305 | <u>0.415 0.296</u> | 0.748 0.428 | 0.637 0.416 | 0.727 0.424 |
| | 336 | 0.433 0.318 | 0.427 0.316 | 0.430 0.309 | 0.434 0.303 | 0.514 0.372 | 0.449 0.313 | 0.426 0.304 | 0.853 0.471 | 0.655 0.427 | 0.749 0.454 |
| | 720 | 0.479 0.346 | <u>0.469 0.325</u> | 0.467 0.324 | 0.487 0.337 | 0.532 0.383 | 0.484 0.336 | 0.474 0.331 | 1.485 0.825 | 0.722 0.456 | 0.847 0.499 |
| | Avg | 0.434 0.319 | 0.427 0.307 | <u>0.429 0.307</u> | 0.440 0.310 | 0.495 0.361 | 0.447 0.313 | 0.430 0.305 | 0.951 0.535 | 0.663 0.425 | 0.749 0.446 |
| ECL | 96 | 0.146 0.252 | 0.143 0.243 | 0.137 0.240 | <u>0.139 0.237</u> | 0.154 0.257 | 0.150 0.253 | 0.140 0.238 | 0.299 0.373 | 0.231 0.323 | 0.261 0.348 |
| | 192 | 0.165 0.272 | 0.159 0.258 | 0.159 0.258 | 0.156 0.252 | 0.171 0.272 | 0.164 0.264 | 0.160 0.255 | 0.305 0.379 | 0.261 0.356 | 0.338 0.406 |
| | 336 | 0.184 0.287 | 0.170 0.269 | 0.181 0.278 | <u>0.175 0.270</u> | 0.196 0.295 | 0.181 0.282 | 0.180 0.276 | 0.319 0.391 | 0.360 0.445 | 0.410 0.474 |
| | 720 | 0.252 0.342 | <u>0.230 0.315</u> | 0.232 0.317 | <u>0.233 0.317</u> | 0.263 0.348 | 0.223 0.321 | 0.241 0.323 | 0.369 0.426 | 0.530 0.585 | 0.715 0.685 |
| | Avg | 0.186 0.288 | 0.175 0.271 | 0.177 0.273 | <u>0.176 0.269</u> | 0.196 0.293 | 0.180 0.280 | 0.180 0.273 | 0.323 0.392 | 0.346 0.427 | 0.431 0.478 |

Table 10: Few-shot forecasting results with 10% of the training data. Few-shot long-term forecasting results for four prediction horizons; [96, 192, 336, 720] and the average MSE and MAE values across the four prediction horizons are reported. Lower values indicate better performance. Bold: the best, Underline: the second best. GPT-2 (Radford et al. 2019) is used as the LLM backbone.

| Method | | NNCL-TLLM | S^2 IP-LLM | Time-LLM | OFA | iTrans. | DLinear | PatchTST | TimesNet | FEDformer | Autoformer |
|-------------------|-----|---------------------------|---------------------------|-------------|---------------------------|-------------|---------------------------|---------------------------|-------------|---------------------------|-------------|
| Metric | | MSE MAE | MSE MAE | MSE MAE | MSE MAE | MSE MAE | MSE MAE | MSE MAE | MSE MAE | MSE MAE | MSE MAE |
| ETTh ₁ | 96 | 0.545 0.485 | 0.500 0.493 | 0.732 0.556 | 0.543 0.506 | 0.808 0.610 | 0.547 0.503 | 0.557 0.519 | 0.892 0.625 | 0.593 0.529 | 0.681 0.570 |
| | 192 | 0.667 0.525 | 0.690 <u>0.539</u> | 0.872 0.604 | 0.748 0.580 | 0.928 0.658 | 0.720 0.604 | 0.711 0.570 | 0.940 0.665 | 0.652 0.563 | 0.725 0.602 |
| | 336 | 0.802 0.587 | 0.761 0.620 | 1.071 0.721 | <u>0.754</u> 0.595 | 1.475 0.861 | 0.984 0.727 | 0.816 0.619 | 0.945 0.653 | 0.731 <u>0.594</u> | 0.761 0.624 |
| | 720 | - | - | - | - | - | - | - | - | - | - |
| | Avg | 0.671 0.532 | 0.650 <u>0.550</u> | 0.891 0.627 | 0.681 0.560 | 1.070 0.710 | 0.750 0.611 | 0.694 0.569 | 0.925 0.647 | <u>0.658</u> 0.562 | 0.722 0.598 |
| ETTh ₂ | 96 | 0.351 0.402 | <u>0.363</u> 0.409 | 0.399 0.420 | 0.376 0.421 | 0.397 0.427 | 0.442 0.456 | 0.401 0.421 | 0.409 0.420 | 0.390 0.424 | 0.428 0.468 |
| | 192 | 0.362 0.396 | <u>0.375</u> <u>0.411</u> | 0.487 0.479 | 0.418 0.441 | 0.438 0.445 | 0.617 0.542 | 0.452 0.455 | 0.483 0.464 | 0.457 0.465 | 0.496 0.504 |
| | 336 | 0.396 0.419 | <u>0.403</u> <u>0.421</u> | 0.858 0.660 | 0.408 0.439 | 0.631 0.553 | 1.424 0.849 | 0.464 0.469 | 0.499 0.479 | 0.477 0.483 | 0.486 0.496 |
| | 720 | - | - | - | - | - | - | - | - | - | - |
| | Avg | 0.370 0.406 | <u>0.380</u> <u>0.413</u> | 0.581 0.519 | 0.400 0.433 | 0.488 0.475 | 0.694 0.577 | 0.827 0.615 | 0.439 0.448 | 0.463 0.454 | 0.441 0.457 |
| ETTh ₁ | 96 | 0.371 0.398 | <u>0.357</u> <u>0.390</u> | 0.422 0.424 | 0.386 0.405 | 0.589 0.510 | 0.332 0.374 | 0.399 0.414 | 0.606 0.518 | 0.628 0.544 | 0.726 0.578 |
| | 192 | 0.397 0.413 | 0.432 0.434 | 0.448 0.440 | 0.440 0.438 | 0.703 0.565 | 0.358 0.390 | 0.441 0.436 | 0.681 0.539 | 0.666 0.566 | 0.750 0.591 |
| | 336 | 0.441 0.441 | 0.440 0.442 | 0.519 0.482 | 0.485 0.459 | 0.898 0.641 | 0.402 0.416 | 0.499 0.467 | 0.786 0.597 | 0.807 0.628 | 0.851 0.659 |
| | 720 | 0.580 0.525 | 0.593 0.521 | 0.708 0.573 | <u>0.577</u> 0.499 | 0.948 0.671 | 0.511 0.489 | 0.767 0.587 | 0.796 0.593 | 0.822 0.633 | 0.857 0.655 |
| | Avg | 0.447 0.444 | 0.455 0.446 | 0.524 0.479 | 0.472 0.450 | 0.784 0.596 | 0.400 0.417 | 0.526 0.476 | 0.717 0.561 | 0.730 0.592 | 0.796 0.620 |
| ETTh ₂ | 96 | 0.194 0.275 | <u>0.197</u> 0.278 | 0.225 0.300 | 0.199 0.280 | 0.265 0.339 | 0.236 0.326 | 0.206 0.288 | 0.220 0.299 | 0.229 0.320 | 0.232 0.322 |
| | 192 | 0.247 0.310 | <u>0.254</u> 0.322 | 0.275 0.334 | 0.256 0.316 | 0.310 0.362 | 0.306 0.373 | 0.264 0.324 | 0.311 0.361 | 0.394 0.361 | 0.291 0.357 |
| | 336 | 0.300 0.344 | <u>0.315</u> 0.350 | 0.339 0.371 | 0.318 <u>0.353</u> | 0.373 0.399 | 0.380 0.423 | 0.334 0.367 | 0.338 0.366 | 0.378 0.427 | 0.478 0.517 |
| | 720 | 0.413 0.411 | <u>0.421</u> <u>0.421</u> | 0.464 0.441 | 0.460 0.436 | 0.478 0.454 | 0.674 0.583 | 0.454 0.432 | 0.509 0.465 | 0.523 0.510 | 0.553 0.538 |
| | Avg | 0.289 0.335 | <u>0.296</u> <u>0.342</u> | 0.325 0.361 | 0.308 0.346 | 0.356 0.388 | 0.399 0.426 | 0.314 0.352 | 0.344 0.372 | 0.381 0.404 | 0.388 0.433 |
| Weather | 96 | 0.171 0.239 | <u>0.175</u> <u>0.228</u> | 0.176 0.230 | 0.175 0.230 | 0.264 0.307 | 0.184 0.242 | 0.171 0.224 | 0.207 0.253 | 0.229 0.309 | 0.227 0.299 |
| | 192 | 0.217 0.273 | <u>0.225</u> 0.271 | 0.226 0.275 | 0.227 0.276 | 0.284 0.326 | 0.228 0.283 | 0.230 0.277 | 0.272 0.307 | 0.265 0.317 | 0.278 0.333 |
| | 336 | 0.285 0.321 | <u>0.282</u> 0.321 | 0.292 0.325 | 0.286 0.322 | 0.323 0.349 | 0.279 <u>0.322</u> | 0.294 0.326 | 0.313 0.328 | 0.353 0.392 | 0.351 0.393 |
| | 720 | 0.368 0.380 | 0.361 0.371 | 0.364 0.375 | 0.366 0.379 | 0.366 0.375 | 0.364 0.388 | 0.384 0.387 | 0.400 0.385 | 0.391 0.394 | 0.387 0.389 |
| | Avg | 0.260 0.303 | 0.260 0.297 | 0.264 0.301 | <u>0.263</u> <u>0.301</u> | 0.309 0.339 | <u>0.263</u> 0.308 | 0.269 0.303 | 0.298 0.318 | 0.309 0.353 | 0.310 0.353 |
| Traffic | 96 | 0.399 0.298 | 0.410 0.288 | 0.414 0.293 | 0.419 0.298 | 0.431 0.312 | 0.427 0.304 | 0.404 0.286 | 0.854 0.492 | 0.670 0.421 | 0.795 0.481 |
| | 192 | 0.418 0.307 | 0.416 0.298 | 0.419 0.300 | 0.434 0.305 | 0.456 0.326 | 0.447 0.315 | 0.412 0.294 | 0.894 0.517 | 0.653 0.405 | 0.837 0.503 |
| | 336 | <u>0.437</u> 0.323 | 0.435 <u>0.313</u> | 0.438 0.315 | 0.449 0.313 | 0.465 0.334 | 0.478 0.333 | 0.439 0.310 | 0.853 0.471 | 0.707 0.445 | 0.867 0.523 |
| | 720 | - | - | - | - | - | - | - | - | - | - |
| | Avg | 0.418 0.309 | <u>0.420</u> <u>0.299</u> | 0.423 0.302 | 0.434 0.305 | 0.450 0.324 | 0.450 0.317 | 0.418 0.296 | 0.867 0.493 | 0.676 0.423 | 0.833 0.502 |
| ECL | 96 | 0.150 0.257 | 0.148 0.248 | 0.148 0.248 | 0.143 0.241 | 0.162 0.264 | 0.150 0.251 | 0.145 0.244 | 0.315 0.389 | 0.235 0.322 | 0.297 0.367 |
| | 192 | 0.170 0.277 | 0.159 0.255 | 0.160 0.257 | 0.159 0.255 | 0.180 0.278 | 0.163 0.263 | 0.163 0.260 | 0.318 0.396 | 0.247 0.341 | 0.308 0.375 |
| | 336 | 0.195 0.298 | 0.175 0.271 | 0.183 0.282 | 0.179 0.274 | 0.207 0.305 | 0.175 0.278 | 0.183 0.281 | 0.340 0.415 | 0.267 0.356 | 0.354 0.411 |
| | 720 | 0.256 0.347 | 0.235 0.326 | 0.236 0.329 | <u>0.233</u> <u>0.323</u> | 0.258 0.339 | 0.219 0.311 | 0.233 0.323 | 0.635 0.613 | 0.318 0.394 | 0.426 0.466 |
| | Avg | 0.192 0.295 | 0.179 <u>0.275</u> | 0.181 0.279 | <u>0.178</u> 0.273 | 0.201 0.296 | 0.176 <u>0.275</u> | 0.181 0.277 | 0.402 0.453 | 0.266 0.353 | 0.346 0.404 |

Table 11: Few-shot forecasting results with 5% of the training data. Few-shot long-term forecasting results for four prediction horizons; [96, 192, 336, 720] and the average MSE and MAE values across the four prediction horizons are reported. Lower values indicate better performance. Bold: the best, Underline: the second best. GPT-2 (Radford et al. 2019) is used as the LLM backbone. '-' indicates that 5% data is not sufficient as the training dataset.

| Ablation | ETTh1-96 | ETTh1-192 | ETTh1(10%)-96 | ETTh1(10%)-192 |
|---|--------------|--------------|---------------|----------------|
| Without NNCL and With Neighborhood aware TCTP | 0.370 | 0.399 | 0.441 | 0.556 |
| With NNCL and Without Neighborhood aware TCTP | 0.364 | 0.397 | 0.437 | 0.545 |
| With NNCL and With Neighborhood aware TCTP | 0.364 | 0.395 | 0.428 | 0.510 |

Table 12: Ablation studies on ETTh1 dataset for [96, 192] prediction horizons. Additionally, results for 10% few-shot forecasting on ETTh1 dataset for [96, 192] prediction horizons are included. MSE values are reported. NNCL indicates the formulation of the prompt via nearest neighbor contrastive learning and Neighborhood aware TCTP indicates the neighborhood aware time series compatible text prototype learning.

| Variant | ETTh1 | | | | ETTh2 | | | |
|--------------------------------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| | 96 | 192 | 336 | 720 | 96 | 192 | 336 | 720 |
| GPT-2 (NNCL-TLLM) | 0.364 | 0.395 | 0.419 | 0.429 | 0.169 | 0.227 | 0.274 | 0.353 |
| Llama (32) | 0.395 | 0.424 | 0.446 | 0.463 | 0.182 | 0.238 | 0.284 | 0.364 |
| GPT-2 backbone random initialization | 0.374 | 0.408 | 0.428 | 0.450 | 0.181 | 0.245 | 0.295 | 0.390 |

Table 13: Long term forecasting results for four prediction horizons; [96, 192, 336, 720] for ETTh1 and ETTh2 datasets. MSE values are reported. GPT-2 indicates the NNCL-TLLM method. Llama (32) uses Llama-2 as the backbone with NNCL-TLLM method. GPT-2 backbone random initialization specifies that GPT-2 backbone is trained from scratch without utilizing the pre-trained weights.

| Variant | ETTh1 | | | | ETTh2 | | | |
|---|--------|--------|--------|--------|--------|--------|--------|--------|
| | 96 | 192 | 336 | 720 | 96 | 192 | 336 | 720 |
| Number of trainable parameters (in Millions) | | | | | | | | |
| GPT-2 (NNCL-TLLM) | 6.91 | 12.23 | 20.19 | 41.43 | 9.99 | 15.30 | 23.26 | 44.49 |
| Llama (32) | 32.60 | 60.92 | 103.38 | 216.63 | 48.99 | 77.29 | 119.77 | 233.01 |
| GPT-2 backbone random initialization | 198.29 | 203.59 | 211.56 | 232.79 | 201.36 | 206.67 | 214.63 | 235.87 |
| Training time per iteration (in Seconds) | | | | | | | | |
| GPT-2 (NNCL-TLLM) | 0.088 | 0.088 | 0.091 | 0.085 | 0.094 | 0.057 | 0.059 | 0.053 |
| Llama (32) | 0.312 | 0.304 | 0.309 | 0.318 | 0.324 | 0.317 | 0.320 | 0.333 |
| GPT-2 backbone random initialization | 0.087 | 0.086 | 0.088 | 0.083 | 0.099 | 0.099 | 0.100 | 0.096 |
| Inference time per example (in Milliseconds) | | | | | | | | |
| GPT-2 (NNCL-TLLM) | 0.501 | 0.464 | 0.539 | 0.553 | 0.781 | 0.877 | 0.941 | 0.942 |
| Llama (32) | 8.152 | 7.547 | 7.559 | 7.604 | 8.860 | 8.253 | 8.315 | 8.319 |
| GPT-2 backbone random initialization | 0.400 | 0.404 | 0.471 | 0.484 | 0.693 | 0.700 | 0.751 | 0.766 |

Table 14: Computational efficiency comparison between different variants of LLM finetuning. Total Number of trainable parameters (in Millions), training time per iteration and inference time per example are reported. GPT-2 indicates the NNCL-TLLM method. Llama (32) uses Llama-2 as the backbone with NNCL-TLLM method. GPT-2 backbone random initialization specifies that GPT-2 backbone is trained from scratch without utilizing the pre-trained weights.