TEST: Text Prototype Aligned Embedding to Activate LLM's Ability for Time Series

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Abstract

This work summarizes two strategies for completing timeseries (TS) tasks using today's language model (LLM): LLMfor-TS, design and train a fundamental large model for TS data; TS-for-LLM, enable the pre-trained LLM to handle TS data. Considering the insufficient data accumulation, limited resources, and semantic context requirements, this work focuses on TS-for-LLM methods, where we aim to activate LLM's ability for TS data by designing a TS embedding method suitable for LLM. The proposed method is named TEST. It first tokenizes TS, builds an encoder to embed them by instancewise, feature-wise, and text-prototype-aligned contrast, and then creates prompts to make LLM more open to embeddings, and finally implements TS tasks. Experiments are carried out on TS classification and forecasting tasks using 8 LLMs with different structures and sizes. Although its results cannot significantly outperform the current SOTA models customized for TS tasks, by treating LLM as the pattern machine, it can endow LLM's ability to process TS data without compromising the language ability. This paper is intended to serve as a foundational work that will inspire further research.

Introduction

Implementing Time Series (TS) based tasks, such as medical, industrial, and meteorological, is a research-intensive field. The relevant models evolved from statistical models to RNNs, CNNs, and Transformers. Nowadays, we see a fast growth and remarkable performances of Large-scale pre-trained Language Models (LLM) in NLP and CV fields.

Consequently, it seems sense to ask whether it is possible to integrate TS with LLMs. However, according to experiments, most LLMs have not made significant progress with relation to abstract time series. In this work, we envision two ways to achieve the paradigm of TS+LLM:

- LLM-for-TS. Towards TS data, design and pre-train a fundamental large model from scratch, then fine turn the model accordingly for the various downstream tasks.
- TS-for-LLM. Based on the existing LLMs, enable them to handle TS data and tasks. Instead of creating a new LLM, design some mechanisms to customize TS for LLMs.

We acknowledge that the first way is the most fundamental solution because pre-training is the crucial step of instilling

knowledge to the model. And the second way is actually challenging to break beyond the model's original capabilities. However, in this work, we still focus on the second way due to the following three considerations:

Data. LLM-for-TS necessitates the large accumulative data. Since TS is more professional and involves privacy, it is harder to obtain in huge amounts as compared to text or image data, especially in non-industrial positions; TS-for-LLM can use relatively small dataset as its objective is solely to assist the existing LLM in inferring TS.

Model. LLM-for-TS focuses on vertical industries. Because of the major disparities in TS across domains, various large models targeting medical TS, industrial TS, and etc must be built and trained from the start; TS-for-LLM needs little or even no training. By utilizing plug-in modules, it makes the utilization more general and convenient.

Usage. LLM-for-TS is appropriate for instances involving specialists; TS-for-LLM maintains the LLM's textual capabilities while providing rich complementing semantics, being easily accessible, and being user-friendly.

Based on the pre-trained LLM, the most natural approach is treating TS as text data. For example, a possible dialogue is: [Q] Diagnose if a patient has sepsis through the following mean arterial pressure sequence in mm Hg: 88, 95, 78, 65, 52, 30. [A] Yes. However, TS is often multivariate while text is univariate. For example, excepting mean arterial pressure, dozens of vital signs and laboratory values, such as heart rate, lactic acid, and etc, need to be included when diagnosing sepsis. LLM that processes univariate text will transform a multivariate TS into multiple univariate sequences and input them one by one. However, this will lead to three drawbacks. First, different prompts, order, and connection statements will produce different results; Second, a long input sequence likely to make LLM inefficient and hard to remember the previous univariate TS; Third, the crucial aspects of multivariate dependency in TS will be ignored.

Thus, in this work, we tokenize TS, design a model to embed TS tokens, and replace the embedding layer of the LLM. In this way, the core is to create embeddings that can be understood by LLMs.

TS embedding can provide identities by including typical, associated, and dependant attributes, as well as reveal the underlying mechanics of the relevant systems. High-quality

embedding are critical for downstream tasks, where they can be employed as the computational phenotype that the deep learning model can understand. For instance, sepsis diagnosis models can use the vital signs embedding of ICU patients.

To make the embedding understandable by language models. Most multimodal approaches use alignment. For example, SOTA methods align text embedding and image embedding through text descriptions of the image. However, when compared to other data modalities, TS lacks visual cues and has an annotation bottleneck caused by its complex characteristics. Only a few specific TS, such as ECG, have text descriptions in each segment, where the image-text matching route could be implemented. But in most cases, it's not feasible.

Self-supervised contrastive learning can avoid the annotation bottleneck through designing pretext tasks by utilizing intrinsic information instead of relying on pre-defined prior knowledge. Contrastive learning employs the instance discrimination pretext task to bring similar pairs closer while pushing dissimilar pairs apart in the embedding space. Currently, efforts have been made to implement instance-level contrast, temporal-level contrast, and prototype-level contrast, with promising results. These methods evaluate the effectiveness of TS' embedding through follow-up classification, prediction, or clustering models, such as SVM. However, these simple and newly-trained models are considerably different from the complex and pre-trained LLM. The representation vector generated by unconstrained contrastive learning is likely to deviate greatly from the LLM's cognitive embedding space.

To address this issue, we propose an embedding method for TimE Series tokens to align the Text embedding space of LLM (TEST). On the basis of comparative learning, TEST uses orthogonal text embedding vectors as prototypes to constrain the TS' embedding space, and highlights patterns by identifying feature-wise prototypes to activate LLM's ability of pattern machine. The contributions of this work are:

- Summarize two TS+LLM paradigms, LLM-for-TS and TS-for-LLM, with potential implementation ways.
- Propose TEST to achieve TS-for-LLM. TEST can produce the similarity-based, instance-wise, feature-wise, and text-prototype-aligned embedding for TS tokens.
- Experiments on TS classification and forecasting tasks shows TEST can activate LLM's TS capability. It can elevate the random and unsatisfactory results produced by original LLM to the baseline.

As the name of TEST implies, although TS-for-LLM cannot significantly outperform current SOTA models that are customized for TS tasks, it is a forward-looking test that we hope will lay the groundwork for future research. And it does, in fact, give the LLM new capabilities and reflect its qualities as a pattern machine.

Related Work

TS+LLM. There are three existing practices.

PromptCast (Xue and Salim 2023) and Health Learner (Liu et al. 2023) regard TS as the text sequence. They input univariate numerical TS to LLM directly and design prompts

to implement TS tasks. Obviously, they are limited by the three dilemmas summarized in Introduction section. METS (Li et al. 2023) aligns the clinical reports text and ECG signals. It satisfies ECG-text multimodal conditions, but cannot be generalized to most TS data without segment annotation.

TS embedding. We utilize the idea of contrastive learning.

It is a special form of self-supervised learning with instance discrimination as the pretext task. Most approaches focus on instance-level contrast that treats instances (full-length TS, TS segment, etc) independently and regards augmented views of the anchor as positives and the remaining views as negatives (Chen et al. 2020).

In TS contrastive learning, considering the inherent temporal dependency, researchers have explored the feasibility of distinguishing contextual information at a fine-grained temporal level (Meng et al. 2023). The selection of instances includes both inter- and intra-series (Woo et al. 2022; Zheng et al. 2023). Such idea of temporal-level contrast (Franceschi, Dieuleveut, and Jaggi 2019) offers us a basic modeling approach to embed TS tokens.

However, the direct contrast cannot bridge TS embedding and the LLM's comprehensible space. In our setting, we prefer to freeze the pre-trained LLM, and let the embedding to compromise. That is, we use the text token embedding in LLM to limit and guide the TS token embedding.

We notice that the essence of LLM is actually general pattern machines (Mirchandani et al. 2023). Thus, regardless of whether the combination of token list has semantics that can be understood by humans, we forcefully align the pattern of TS token and the pattern of text token. That is, a TS token list can be approximately expressed by a sentence without semantic information. But our goal is to obtain a pattern sequence that can be understood by LLM.

Inspired by the prototype-level contrast (Caron et al. 2020), which goes beyond the independence assumption and exploits latent cluster information present within samples. We can select some text embeddings as basic prototypes to lead the learning. However, in addition to the alignment, we still need to consider issues of prototype selection, differentiation (Meng et al. 2023), uniformity (Wang and Isola 2020), stability (Huang et al. 2023) and etc.

Methods

Overview

To achieve TS FOR LLM, Our approach has two key steps:

- Figure 1: Tokenize TS and train an encoder to embed TS tokens with contrastive learning.
- Figure 2: Create prompts to make LLM more open to embeddings and implement TS tasks.

TS Token Augmentation and Encoding

Definition 1 (Token Embedding of Time Series) A multivariate time series $x = \{x_t^d\}_{t=1,d=1}^{T,D}$ has D variables and T time points. It can be segmented to a list of K nonoverlapping subsequences $s = \{s_k\}_{k=1}^{K}$ by a segmentation function $\mathcal{F}_s : x \to s$, where the length of $s_k = x_{t_i:t_j}$ is arbitrary, $1 \le t_i < t_j \le T$. We call s as the token list of

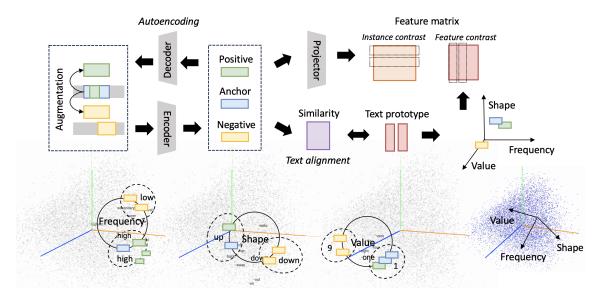


Figure 1: Text-prototype-aligned Time Series Embedding by Instance-aware and Feature-aware Contrastive Learning

time series x. Further, each token can be embeded to a M-dimensional representation space by an embedding function $\mathcal{F}_e: s_k \in \mathbb{R}^{D \times T} \to e_k \in \mathbb{R}^M$. Finally, the token embedding list of x is $e = \{e_k\}_{k=1}^K = \mathcal{F}_e(s) = \mathcal{F}_e(\mathcal{F}_s(x))$.

Fist, we tokenize TS $s = \mathcal{F}_s(x)$. In TS representation learning, the segmentation function \mathcal{F}_s usually is the sliding window (Yue et al. 2022). We use random lengths and steps to segment TS and get many tokens s.

Then, we define a TS token s as the anchor instance. For positives s^+ , we define two acquisition sources. The first is the overlapping instance, using instances which have the same subsequence as s. The second is the augmented instance, producing two views from augmentations family $s^{weak} \sim \mathcal{T}_{weak}, s^{strong} \sim \mathcal{T}_{strong}$. In detail, to get the weak augmented view x_{weak} , we use the jitter-and-scale strategy, adding random variations to the signal and scale up its magnitude. To get the strong augmented view s_{strong} , we use the permutation-and-jitter strategy, splitting the sequence into a random number of segments and randomly shuffling them. For negatives s^- , we use instances which do not have the same subsequence as s.

After getting anchor-positive-negative, we built a neural network as the encoder to embed instance into vector $e = \mathcal{F}_e(s)$. The encoder \mathcal{F}_e must can extract relevant information from TS, needs to be time- and memory-efficient, both for training and testing, and has to allow variable-length inputs. Thus, inspired by (Franceschi, Dieuleveut, and Jaggi 2019), we use exponentially dilated causal convolution network to handle TS. We build each layer of the network as a combination of causal convolutions, weight normalizations, activation and residual connections. Each layer is given an exponentially increasing dilation parameter.

We also trained a decoder f_d by using the auto-encoding loss $\mathcal{L}_{ae} = \frac{1}{N} \sum_{i=1}^{N} \text{sim}(s, f_d(e))$ to ensure the representativeness of the embedding and subsequent verification. Because our primary goal is to retrieve the encoder, this decoder

can likewise be unbuilt without harming the future process.

Instance-wise and Feature-wise Contrast

The basic instance-wise contrastive learning treat each instance independently and design the instance discrimination pretext task to keep similar instances close and dissimilar instances far away.

We treats augmented views of the same instance as the unique positive pair, and all remaining ones within the B size minibatch as negative pairs. Specifically, we apply the MoCo (He et al. 2020) variant of contrastive learning which makes use of a momentum encoder to obtain representations of the positive pair, and a dynamic dictionary with a queue to obtain negative pairs. Given a TS token instance and B negative samples, the instance-wise contrastive loss is shown in Equation 1. Where given a instance embedding e, we apply select a random time step t for the contrastive loss and construct a projection head f_p , which is a one-layer MLP to obtain $f_p(e)$. $e^{+/-}$ is the positive/negative of the corresponding instance from the momentum encoder. $\sigma(e, e^{+/-})$ is used to calculate the similarity between two projected vectors, $f_p(e)$ and $f_p(e^{+/-})$, through a similarity function sim like cosine similarity. τ_I is the instance-level temperature parameter.

$$\mathcal{L}_{ins} = -\log \frac{\exp(\sigma_{ins}(e, e^{+}))}{\exp(\sigma_{ins}(e, e^{+})) + \sum_{i=1}^{B} \exp(\sigma_{ins}(e, e_{i}^{-}))}$$
$$\sigma_{ins}(e, e^{+/-}) = \frac{\sin(f_{p}(e), f_{p}(e^{+/-}))}{\tau_{I}}$$
(1)

However, instance-wise contrastive learning tends to treat semantically similar samples as negatives (Caron et al. 2020). To address this limitation, we propose feature-wise contrast to break the independence between instances.

As shown in Figure 1, after embedding, a feature matrix $\mathbb{R}^{B \times M}$ is formed by the representation vectors of instances

in a minibatch. Where each row is an embedding of a instance, thus rows could be regarded as soft labels of instances which are used in Equation 1. In addition to rows, columns of feature matrix also have semantic information. (Li et al. 2021) proposed that the columns could be further regarded as cluster representations, motivated by the observation of label as representation when the dimensionality of representations during projection matches the number of clusters. But such cluster-wise methods require prior knowledge to pre-specify the number of clusters, which is non-trivial for the unlabeled TS data in this work.

Thus, we propose to regard the columns as the soft labels of features and perform discrimination between groups of similar feature. Here we obtain two kind of positive feature matrix and a negative feature matrix $\mathbf{m}^{weak+}, \mathbf{m}^{strong+}, \mathbf{m}^{-}$ of a anchor instance, where $\mathbf{m}^{+/-} = \mathcal{F}_e(\mathbf{e}^{+/-}), \mathbf{m}^{+/-} \in \mathbb{R}^{B \times M}, \mathbf{e}^{+/-} = \{e_i\}_{i=1}^B$. We narrow the gap between same columns of two positive feature matrix $\mathbf{m}^{weak+}, \mathbf{m}^{strong+}$ as shown in the first term of Equation 2, and magnify the gap between between that of positive feature matrix \mathbf{m}^+ and negative feature matrix \mathbf{m}^- as shown in the second term. We mark the columns in the matrix as $m \in \mathbf{m}^T$.

$$\mathcal{L}_{fea} = -\underbrace{\sum_{m_i \in \mathbf{m}^{\mathsf{T}}, i=1}^{M} \sigma_{fea}(m_i^{weak+}, m_i^{strong+})}_{\text{Feature alignment}} + \underbrace{\sum_{m_i \in \mathbf{m}^{\mathsf{T}}, i=1}^{M} \sigma_{fea}(m_i^+, m_i^-)}_{\text{Feature difference}}$$

$$\Rightarrow -\sum_{i=1}^{M} \underbrace{\log \frac{\exp(\frac{\operatorname{sim}(m_i^{s+}, m_i^{w+})}{\tau_F})}{\sum_{j=1}^{M} [\exp(\frac{\operatorname{sim}(m_i^{s+}, m_j^{w+})}{\tau_F}) + \exp(\frac{\operatorname{sim}(m_i^{s+}, m_j^{-})}{\tau_F})]}_{\text{Feature category uniformity}}$$
(2)

As shown in Equation 2, the feature-wise contrast mainly align and differentiate the same feature column among the positive and negative. However, due to the dominance of similarity, this may cause the representation space to shrink within a small area. We find that ensuring differences between features can better address this issue. That is, we add contrastive learning between different feature columns as shown in the modified Equation 2. It ensures that each feature column of positives m_i^{w+} , m_i^{s+} are similar while expanding the differences between different feature columns m_i^+ , m_j^+ , m_j^- , where τ_F is the feature-level temperature parameter to increase the difference and control the negative sample discrimination. Note that the form of our feature contrast loss is similar to that of infoNCE (He et al. 2020).

More importantly, the injection of feature column differences can also greatly assist in subsequent implementation of text-prototype-aligned contrast. Because that contrast will apply the selected text token embedding to the feature columns, like coordinate axes.

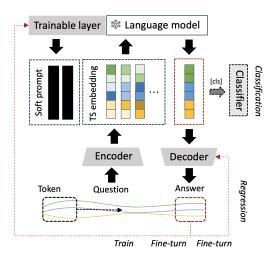


Figure 2: Framework of LLM for TS Tasks

Text-prototype-aligned Contrast

To make the LLM understand the TS embedding, we align it to the text representation space.

The pre-trained LLM has its own text token embedding. For example, small, medium, big GPT-2 embed text tokens from word dictionary in to representation spaces with 768, 1024, and 1280 dimensions, respectively (Radford et al. 2019). Naively, as shown in the first term of Equation 3, we can align these two types of embedding vectors of TS token e and text token tp using the similarity estimation forcefully. For example, although TS tokens lack text annotation, we can place their embedding near typical text descriptions of TS, such as value, shape, and frequency, as shown in Figure 1. In this fashion, it is intuitively expected that various TS tokens can represent various descriptive terms such as small, big, up, down, stable, fluctuating, and so on. Naturally, the example above is based on the closest neighbor principle because the embedding space of a text token is discrete, akin to a vector table, but that of our TS token is continuous.

$$\mathcal{L}_{text} = -\underbrace{\sin(tp, e)}_{\text{Text alignment}} + \underbrace{\mathcal{L}_{fea}(e \cdot tp, e^{+} \cdot tp, e^{-} \cdot tp)}_{\text{Text contrast}}$$

However, of course, the actual outcomes will not match what we expect because we are not providing the supervised label or the ground truth. For example, the embedding of a subsequence with an upward trend may be very close to that of a decline text, or even that of a text that does not describe the trend. But it is irrelevant whether semantics can be understood by us. As usual, the fact is that humans cannot comprehend the model's perceptual mode. Recently, researchers proved that LLMs are pattern machines (Mirchandani et al. 2023). Thus, in this work, we achieve "TS \rightarrow token list \rightarrow embedding list \rightarrow text pattern list" to activate LLM's ability for TS tasks. For example, through simple prompts, the LLM can recognize the differences between patterns of different classes, so as to realize the TS classification task.

Thus, the choice of text prototype can be relaxed, not necessarily the description related to TS data. In this work,

to make the two embedding spaces match better, inspired by unsupervised alignment for multilingual word embeddings (Alaux et al. 2019), we map TS embedding to the pivot text embedding. In detail, first, we guarantee that the range of the two spaces is roughly the same through the similarity constraint of the vector, maximizing the cosine similarity between TS vector and text prototype vector, as shown in the first term of Equation 3; Second, we use the text prototypes as the coordinate axis to map the TS embedding, making the representation values in text coordinate axes of similar instance similar, as shown in the second term of Equation 3.

The modeling function of the text prototype tp is realized by the feature-wise contrastive learning described in the previous section. The feature matrix \mathbf{m} is no longer obtained through the projector used in instance-wise contrast, but through the prototype mapping, $e \cdot tp \to \mathbf{m}$.

Learnable Prompt Embedding

Even when the TS has been described using an embedded representation that LLM can understand, the LLM still has to be instructed on how to do subsequent TS tasks.

Nowadays, the hard prompt methods, such as template engineering and chain-of-thought, are intuitive, easy to understand and can produce good results. However, their contexts are coherent in human's semantics. But as we mentioned, a TS embedding list has no human's semantics, it is more about a pattern sequence.

Thus, to create a more consistent prompt pattern, we train a soft prompt make LLM be easier to understand the input (Lester, Al-Rfou, and Constant 2021). These soft prompts are the task-specific embedding vectors, learning through the loss from LLM's output and task ground truth, as shown in Equation 4. The soft prompts can be initialized from the uniform distribution randomly, or the text embedding of the downstream task' labels, or the most common words from the vocab $pe_{init} \sim \mathcal{N}(e_{random/task/desc}, \sigma)$.

$$\mathcal{L}_{promp} = L_{reg/cls}(\text{concat}(pe, e)) \tag{4}$$

But at the same time, we also believe that the supervised fine-tuning approach might offer a better way to improve the TS task accuracy. However, the main reason we gave it up is that, in addition to the high cost of training, the LLM can no longer guarantee its ability to understand human semantic texts after fine-tuning. This is because the semantics of the TS embeddings in line with humans.

We prove that the trained soft prompt not only can protect the LLM's semantic understanding ability by freezing it, but also can achieve a similar effect to supervised fine-tuning method: Consider a conditional generation task where the input x is a context and the output y is a sequence of tokens. Assume an autoregression LLM $p_{\phi}(y|x)$ with parameter ϕ , z = [x;y]. The inference of a pre-trained LLM is computing h_i as a function of z_i and the past activations in its left context, $Y = \mathcal{LM}_{\phi}(z_i, h_i)$. The past h_i in the soft prompt turning with prompt pe_{θ} is Equation 5. The fine turning from LLM to TS-LLM is Equation 6. Its transformation shows that the soft prompt tuning is approximately equivalent to the fine tuning.

$$h_i = \begin{cases} pe_{\theta}[i,:], & \text{if } i \in pe_{\text{idx}} \\ \mathcal{L}\mathcal{M}_{\phi}(z_i, h_i), & \text{otherwise} \end{cases}$$
 (5)

Algorithm 1: TEST Training Method

```
1: for e in epochs do
2: \theta_{f_e} = \theta_{f_e} - \eta \nabla_{\theta_{f_e}} (\mathcal{L}_{ins} + \mathcal{L}_{text}) > \text{UPDATE ENCODER}
3: \|\theta_{f_d} = \theta_{f_d} - \eta \nabla_{\theta_{f_d}} \mathcal{L}_{ae} > \text{UPDATE DECODER}
4: \theta_{f_p} = \theta_{f_p} - \eta \nabla_{\theta_{f_p}} \mathcal{L}_{ins} > \text{UPDATE PROJECTOR}
5: end for
6: for e in epochs do
7: pe = pe - \eta \nabla_{\theta_{pe}} \mathcal{L}_{promp} > \text{UPDATE PROMPT}
8: \|\theta_{f_d} = \theta_{f_d} - \eta' \nabla_{\theta_{f_d}} \mathcal{L}_{reg} > \text{FINETUNE DECODER}
9: \|\theta_{f_c} = \theta_{f_c} - \eta \nabla_{\theta_{f_c}} \mathcal{L}_{cls} > \text{UPDATE CLASSIFER}
10: end for
```

$$\max_{\phi} p_{\phi}(y'|x) = \max_{\phi} \sum_{i \in Y_{idx}} \log p_{\phi}(z'_{i}|h_{< i})$$

$$= \sum_{i \in Y_{idx}} \log p_{\phi+\Delta}(z_{i} + \delta z_{i}|h_{< i})$$

$$\approx \sum_{i \in Y_{idx}} \log p_{\phi}(z_{i}|h_{< i}) \cdot \sum_{i \in pe_{idx}} \log p_{\Delta}(\delta z_{i}|h_{< i})$$

$$= \sum_{i \in Y_{idx}} \log p_{\phi}(z_{i}| \underbrace{\mathcal{F}_{e}(s)}_{\text{Text-TS alignment}})$$
Frozen LLM
$$\cdot \underbrace{\sum_{i \in pe_{idx}} \log p_{\Delta}(\delta z_{i}|h_{< i})}_{\text{Prompt } pe_{\theta}}$$
(6)

The Equation 6 also suggests that the projection space of TS tokens should preferably cover the complete set of embedding space of text token. That is, we need to choose such text prototypes with semantics and more importantly, a wide coverage. Thus, we take the top k principal components of the representation space of LLM's first embedding layer as the text prototypes.

Training TEST

The core of TEST is to train an encoder f_e and a soft prompt pe. As described in Algorithm 1, they relay on two processes: f_e is trained by contrastive learning, where it is self-supervised by the contrast of features projected by f_p and the contrast of features aligned by text prototype. f_d is trained for forecasting task; pe is trained by the output of LLM, where it is supervised by the class label or true value. For classification task, LLM's head f_c needs to be trained. For forecasting tasks, f_d needs to be fine tuned.

The process of using LLM to inferring TS is shown in Figure 2. In this framework, the text data is input into the embedding layer of LLM, while the prompts and TS embeddings skip this layer. For the downstream tasks, TS classification task needs an additional head on the top of LLM f_c , like implementing the sentiment classification task in NLP; TS forecasting task needs a decoder f_d trained along with the encoder. We annotate these optional plugins in the algorithm.

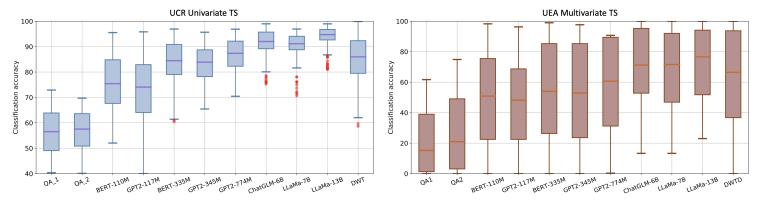


Figure 3: Classification Accuracy of Methods on 128 UCR Univariate TS Datasets and 30 UEA Multivariate TS Datasets

Experiments

In this section, we implement TS classification and forecasting tasks on UCR, UAE, and TSER dataset archives to evaluate TEST and other baselines.

Implementation Details

The encoder model is a causal TCN. We choose for each considered dataset archive a single set of hyperparameters regardless of the downstream task. A fully connected layer is first used to project each time step from the dimensionality of the multivariate TS to the hidden channel with size of 64. Then, there are 10 layers of convolution blocks. Each convolution block is a sequence of GELU, DilatedCony, BatchNorm, GELU, DilatedCony, with skip connections across each block. The DilatedConys have dilation of 2i in each layer i of convolution block, wherer all have kernel size of 3 and input/output channel size of 64. A final convolution block is used to map the hidden channels to the output channel which size is same as the LLM's embedding size.

Each encoder and soft prompt are trained using the Adam optimizer on 10 NVIDIA Tesla V100-SXM2 GPU with CUDA 11.3, unless stated otherwise.

The used LLMs includes Bert (Devlin et al. 2018), GPT2 (Radford et al. 2019), ChatGLM (Du et al. 2022), and LLaMa2 (Touvron et al. 2023) from Hugging Face¹, as listed in Table 1. TS tokens' embedding size is same as that of text token in LLM.

Model	Model size	Embedding dimension
Bert	110M, 335M	748, 1024
GPT2	117M, 345M, 774M	768, 1024, 1280
ChatGLM	6B	4096
LLaMa	7B, 13B	4096

Table 1: The used Language Model

¹Hugging Face: https://huggingface.co

Bert: https://huggingface.co/bert-base-uncased;

GPT2: https://huggingface.co/gpt2;

ChatGLM: https://huggingface.co/THUDM/chatglm2-6b; LLaMa: https://huggingface.co/meta-llama/Llama-2-7b.

Classification

We present accuracy scores for all 128 kinds of varied univariate time series datasets of the new iteration of the UCR archive (Dau et al. 2019), which is a standard set for TS classification tasks. To complement our evaluation on the UCR archive which exclusively contains univariate series, we evaluate our method on multivariate series. This can be done by simply changing the number of input filters of the first convolutional layer of the proposed encoder. We test our method on all 30 kinds of varied multivariate time series datasets of the newly released UEA archive (Bagnall et al. 2018), which is also a standard set for TS classification tasks.

We compare our method to LLM QA methods using or not using prompts (Xue and Salim 2023; Liu et al. 2023), and TS classification baselines DWT, DWTD (Bagnall et al. 2018).

Two QA templates are: 1) [Q] Classify the given [domain] sequence as either [class label] or [class label]: [numerical sequence]. [A]; 2) [Q] Classify the sequence with average of [numerical value], variance of [numerical value], and sampling rate of [numerical value] as either [class label] or [class label]. [A]. Meanwhile, we treat the multivariate TS as a series of univariate series and fill them into the QA template sequentially.

We do not compare our method with other well-designed deep-learning-based methods. Because we don't want to make LLM a model that targets TS in particular. We aim to maintain its original language abilities while enhancing its performance on TS tasks from the previously almost impossible to comparable to the accepted baseline, e.i. DWT for UCR and DWTD for UEA.

Accuracy The classification results of all methods are shown in Figure 3. Their accuracy scores on 128 UCR datasets and 30 UEA datasets are represented by box plots with medians and quartiles, respectively. From the results, we conclude that:

TEST makes the classification accuracy of LLM increase significantly. LLM's original classification performances are demonstrated through two QA results: It has low accuracy and almost guesses the classification labels at random, especially for multivariate TS. After using TEST, GPT2-117M, which has the lowest accuracy among all models, can im-

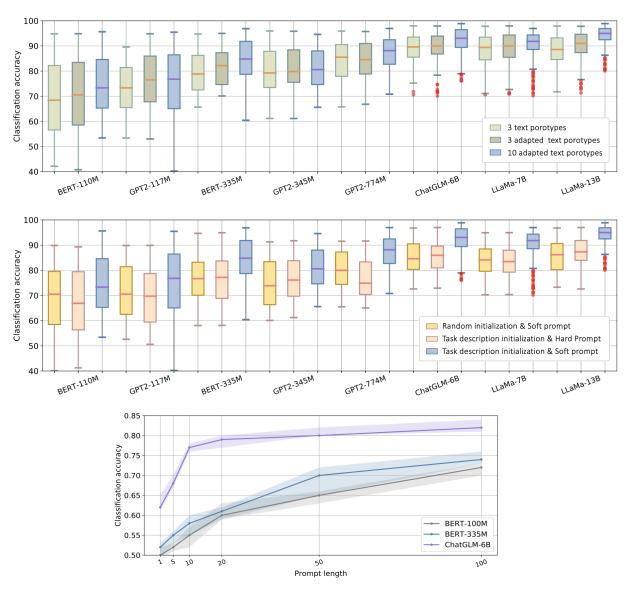


Figure 4: Classification Accuracy With Different Text Prototypes and Prompts

prove accuracy by at least 18% for univariate TS and 25% for multivariate TS.

TEST makes most LLMs comparable to, if not better than, the baseline. When the size reaches about 200M, the accuracy can exceed DWT; When the size reaches about 700M, the accuracy can exceed DWTD.

The model's structure and size will have an impact on the results. The classification accuracy is increasing as the model size grows. Under the same size, the encoder-based model Bert and ChatGLM, is better than the decoder-based generation model GPT2 and LLaMa. This is also consistent with encoder's practice of preferring classification tasks (Du et al. 2022).

Ablation study on text prototypes Different text prototypes will lead to different results. We set three groups of text prototypes: 1) 3 text prototypes of embeddings of text

value, shape, and frequency; 2) 3 adaptive text prototypes of roughly orthogonal embeddings from principal component analysis. 3) 10 adaptive text prototypes. As shown in Figure 4 top, choosing a prototype group that more accurately represents the entire text embedding space of LLM can improve the overall classification performance. This is also suggested by Equation 6. Meanwhile, the performance of the first prototype group which we provided in the previous example in Figure 1 is comparable to that of the second prototype group, it is because that these three embedding vectors are roughly orthogonal coincidentally.

Ablation study on prompts Different kinds of prompts will lead to different results. Our method trains a soft prompt to make LLM be easier to understand the input. To demonstrate its effectiveness, we compare it with hard prompt: Classify the given [domain] sequence as either [class label] or

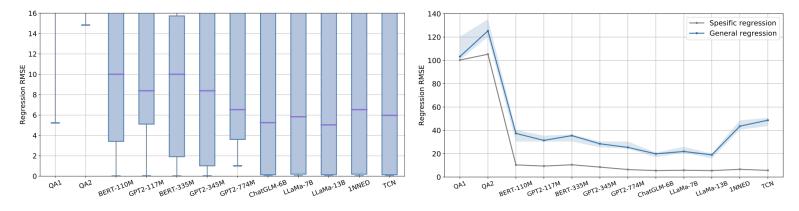


Figure 5: Forecasting Accuracy of Methods on 19 TSER TS Datasets

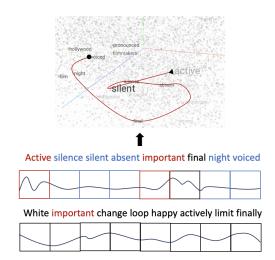


Figure 6: Matching TS Embedding to Words Embedding

[class label]: [TS embedding]. As shown in Figure 4 middle, their accuracy differs by at least 10%. Meanwhile, different initialization of the soft prompt will lead to different results. We set two prompt initialization methods: 1) Random initialization from uniform distribution; 2) Initialization from task description tokens embeddings of Classify the given sequence. As shown in Figure 4 middle, the performance of non random initialization is better than that of random. Besides, different length of prompts will also lead to different results. As shown in Figure 4 bottom, when the model reaches a certain size, a prompt length of 1 can also achieve good results, and a prompt length of 20 can achieve excellent results.

Case study We use nearest neighbor method to find the text that a TS token matches to in the word embedding space of frozen LLM. As shown in the visualization of Figure 6, most words are adjectives and nouns about sentiment. We speculate that by prompting, the model will treat TS classification task as an sentiment classification task. Thus, introducing prompt is like introducing a shortcut for LLM. Besides, the matched words are like a kind of textual Shapelet for TS segmentation, representing TS through a series of

patterns. We suggest that using words to find patterns for TS tasks rather than numbers. Because using numbers may be a sequence reasoning task, and existing LLMs without fine-tuning are not good for math, but they are good at extracting knowledge as a pattern machine.

Forecasting

We present accuracy scores for all 19 kinds of varied time series datasets in TSER archive (Tan et al. 2021).

We compare our method to LLM QA methods using or not using prompts (Xue and Salim 2023; Liu et al. 2023), and TS forecasting baselines 1NNED and TCN (Tan et al. 2021).

Two QA templates are: 1) [Q] Forecast the next value of the given [domain] sequence: [numerical sequence]. [A]; 2) [Q] Forecast the next value of sequence with average of [numerical value], variance of [numerical value], and sampling rate of [numerical value]. [A]. Meanwhile, we treat the multivariate TS as a series of univariate series and fill them into the QA template sequentially.

Accuracy The forecasting results of all methods are shown in Figure 5. Their accuracy scores on 128 UCR datasets and 30 UEA datasets are represented by box plots with medians and quartiles, respectively. TEST makes the forecasting accuracy of LLM increase significantly and comparable to baselines. QA mode of original LLM can not implement forecasting tasks, especially, if TS data is described as mean, frequency, etc. (QA2), the classification task might be partially accomplished, but the forecasting task simply cannot be accomplished.

Generality We fuse 19 datasets into 1 dataset and test the method on this fused dataset. Compared with 1NNED and TCN, LLM-based models have better generality.

Discussion

 The essence of TS-for-LLM is: time series → tokens → TS embeddings ↔ ↔ patterns text/word embedding.

The core is to convert TS into an understandable pattern sequence for LLMs. The semantics of the text corresponding to this sequence may be perplexing to us, but it makes sense to LLM. Especially in classification tasks, TS patterns are

represented by some adjectives, which are the basis for classification tasks of the language model. This also reflects that LLM pays more attention to adjectives with emotions when performing sentiment classification tasks.

• In our method, the primary factors influencing task effectiveness are the size and type of LLM, the selection of text prototypes, and the design of prompts.

The impact of the model type is related to downstream tasks, where the bidirectional structure is beneficial for classification, and the generated structure is beneficial for prediction. A larger model will make the results more accurate. The essence of this phenomenon, we believe, is related to the dataset used to pre-train the LLM. We conjecture that more training data gives the model more opportunities to learn temporal patterns. Based on observation in Figure 5 right, perhaps with more datasets used in pre-training, the selection of prototypes and the design of prompts are no longer as important. In order to determine the reasons for this, we intend to conduct additional experiments in the future to investigate deeper correlations between corpora and time series.

TS-for-LLM may not be as efficient and accurate as training a small task oriented model, but it can enrich the capabilities of large models and explore their mechanisms from other perspectives.

In fact, TS information is more like being located somewhere between text and image information. It denotes both sequence and shape. The abstract meaning of TS makes using classical alignment-based multimodal methods difficult. Our method gives the impression of forcibly aligning operations. We hope that this work inspires future researchers to investigate better fusion methods.

Conclusion

This paper proposes TEST to realize an instance-wise, feature-wise, and text-prototype-aligned embedding method for TS data under the idea of TS-for-LLM. It can activate LLM's ability to achieve TS tasks while maintaining its original language ability. Experiments on classification and forecasting tasks show that using TEST, LLM can archive comparable performance to TS baselines. Future work will test other TS tasks like anomaly detection, research on more alignment methods for TS and text, and even achieve LLM-for-TS by pre-training a TS fundamental large model from scratch.

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