LAMPER: LANGUAGE MODEL AND PROMPT ENGINEERING FOR ZERO-SHOT TIME SERIES CLASSIFICATION

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ABSTRACT

This study constructs the LanguAge Model with Prompt EngineeRing (LAMPER) framework, designed to systematically evaluate the adaptability of pre-trained language models (PLMs) in accommodating diverse prompts and their integration in zero-shot time series (TS) classification. We deploy LAMPER in experimental assessments using 128 univariate TS datasets sourced from the UCR archive. Our findings indicate that the feature representation capacity of LAMPER is influenced by the maximum input token threshold imposed by PLMs.

1 INTRODUCTION

The exploration of time series (TS)-based tasks constitutes a research-intensive domain with significant implications with wide-ranging implications in diverse professional fields, including healthcare, finance, and energy (Zhang et al., 2022; Zheng et al., 2023; Santoro et al., 2023). Within the realms of natural language processing (NLP), the dynamic landscape witnesses the rapid evolution of pre-trained language models (PLMs) and prompt engineering (Min et al., 2023; Wei et al., 2022). These advancements underscore their commendable capacity to adeptly execute an extensive array of tasks, particularly under few-shot or even zero-shot conditions (Brown et al., 2020; Webson & Pavlick, 2022). In stark contrast, various TS-based tasks necessitate substantial domain expertise and bespoke model design, thereby constraining both model performance and generalization capabilities. Recent efforts have seen the application of PLMs and prompt engineering to diverse TS tasks, encompassing forecasting, restoration, and anomaly detection (Dang et al., 2021; Hu et al., 2023; Jin et al., 2023). However, the effectiveness of amalgamating PLMs and prompt engineering for the realization of zero-shot learning in the realm of TS remains uncharted territory. In response, this study introduces LanguAge Models with Prompt EngineeRing (LAMPER) for exploring the latent potential of PLMs in feature representation for TS data, with a specific focus on achieving zero-shot TS classification through the strategic utilization of diverse prompts and their fusion.

2 METHOD

The overall pipeline of LAMPER is illustrated in Figure 1. The process begins with the design of three prompts: the Simple Description Prompt (SDP), Detailed Description Prompt (DDP), and Feature Prompt (FP), whose formats are detailed in Appendix A. These prompts are strategically crafted to harness the strengths of both prompts and PLM to effectively represent features of TS data. To accommodate the maximum token input limit for the PLM, we overcome this challenge by slicing the TS into multiple sub-sequences and constructing corresponding sub-prompts. Following encoding with the PLM, we obtain multiple embeddings. The final embedding, serving as the feature representation of the TS, is acquired through a pooling method. Here, we deploy two PLMs with different length token constraints, namely the longformer (Beltagy et al., 2020) with 4096 maximum token length and the BERT (Devlin et al., 2019) with 512 maximum token length. The features for the FP are obtained from the feature extraction algorithm of the Tsfresh (Christ et al., 2018) module.

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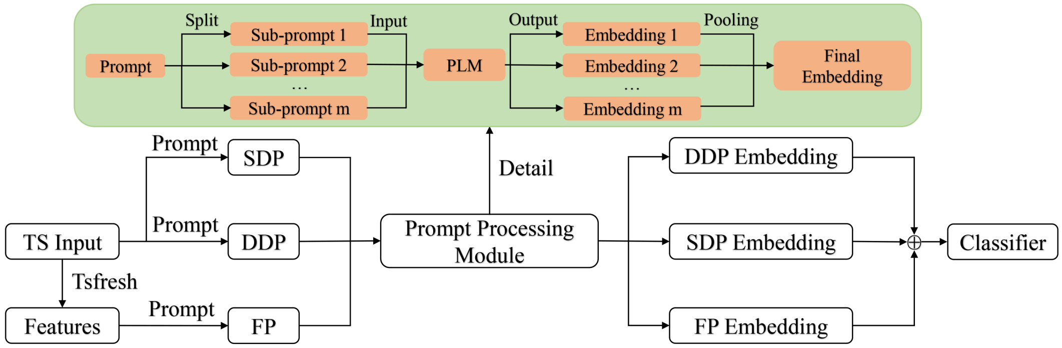

Figure 1: Overall pipeline of LAMPER for zero-shot time series classification.

3 Experiments

Dataset and Experimental setting. Our study leverages a corpus of 128 univariate datasets sourced from the UCR archive (Dau et al., 2019) to achieve the training and evaluation of LAMPER. LAMPER employs the 'bert-base-uncased' and 'longformer-base-4096' PLMs[1] to extract features from prompts. Additionally, we configure the Tsfresh to extract 11 features from TS, including sum, median, mean, length, standard deviation, variance, root mean square, maximum, absolute maximum, and minimum value. The final phase involves the training of a SVM classifier with the RBF kernel.

Results. Table 1 delineates the outcomes obtained by employing SVM with the raw TS input, various prompts, and integration of multiple prompts (details available in appendix D). Confronted with the observed inadequacy in the zero-shot classification endeavor, we meticulously scrutinize the performance of LAMPER across various datasets. Our deduction suggests that PLMs possess a constraint in grasping the nuances of TS data, despite a marginal enhancement in performance attributable to detailed prompts. Simultaneously, we posit that the imposition of a maximum token input constraint by PLMs results in the inadvertent loss of crucial contextual information embedded within the TS data, with the Longformer model therefore outperforming BERT. The Critical Sifference (CD) diagram (Demšar, 2006) for Nemenyi tests on 128 datasets is presented in Appendix B and the ablation experiments results pertaining to the prompts fusion are delineated in Appendix C.

Method	Metrics	SDP	DDP	FP	Fusion	TS (Benchmark)
BERT	Average Accuracy	45.02%	48.60%	41.54%	49.39%	79.99%
	Average Rank	8.79	8.77	10.15	7.65	2.06
Longformer	Average Accuracy	47.50%	49.75%	48.68%	51.47%	79.99%
	Average Rank	8.72	8.62	8.26	7.29	2.06

Table 1: Zero-shot classification results of various prompts based on SVM.

4 Discussion and Conclusion

This paper delves into an investigation into the impact of various prompts and their integration on enhancing the performance of PLMs in zero-shot TS classification tasks. Despite their adeptness in diverse zero-shot tasks within NLP, our endeavors to implement zero-shot TS classification through collaborative prompt engineering and PLMs did not yield the anticipated outcomes. In general, our experimental findings yield insightful observations: (i) The constraints imposed by the maximum input length of PLMs necessitate the segmentation of TS data, resulting in a loss of contextual information when fed into PLMs. This compromise adversely affects the feature representation of TS data, with a discernible performance decline in PLMs as the length of the TS increases in most cases. Notably, the introduction of a well-designed TS encoder proves instrumental in ameliorating PLMs' performance in zero-shot TS tasks (Sun et al., 2023; Liu et al., 2023). (ii) Our results underscore the influence of diverse prompts on zero-shot classification outcomes, emphasizing that the

[1] https://huggingface.co/bert-base-uncased, https://huggingface.co/allenai/longformer-base-4096

integration of multiple prompts does not uniformly confer improvements to the model. Subsequent investigations should focus on the construction of varied prompt types, such as sentiment analysis and mask filling derived from PLMs, alongside the development of a multi-prompts fusion model. These avenues hold promise for augmenting the adaptive capabilities of PLMs in handling TS data.

ACKNOWLEDGEMENTS

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URM STATEMENT

The authors acknowledge that all key authors of this work meet the URM criteria of ICLR 2024 Tiny Papers Track.

REPRODUCIBILITY STATEMENT

The source code for this work will be available at https://github.com/dodoxxb/lamper.

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A Prompts' format

Prompt	Format
SDP	Raw values of time series
DDP	*The length of time series is [**length of time series**]. The original time series is splited into [**number of sub-series**] sub-series, whose length is [**length of sub-series**]. The specific value of the [**index of sub-series**] sub-series are [**sub-series data**] in order.*
FP	***[num of features]** features of the time series are extracted via tsfresh, the feature of **[feature name]** is **[feature value]**, ... , the feature of **[feature name]** is **[feature value]**.*

Table 2: The format of various prompts used in this study.

B CD diagram of LAMPER with SVM

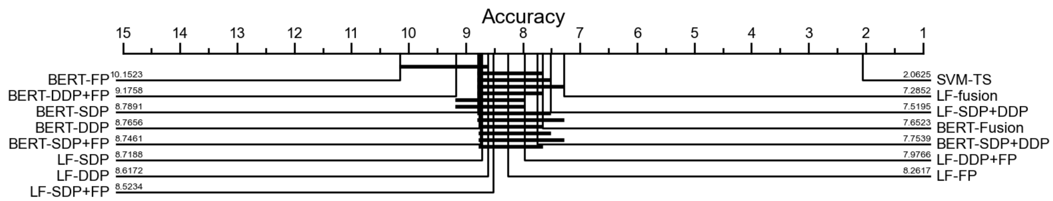

Figure 2: CD diagram of LAMPER with SVM on zero-shot time series classification tasks with a confidence level of 95%, where classifiers that are not connected by a bold line are significantly different in average ranks.

C Ablation experiment

Method	Metrics	SDP+DDP	SDP+FP	DDP+FP	Fusion
BERT	Average Accuracy	49.73%	45.13%	45.49%	49.39%
	Average Rank	7.75	8.75	9.18	7.65
Longformer	Average Accuracy	51.12%	47.88%	50.96%	51.47%
	Average Rank	7.52	8.52	7.98	7.29

Table 3: Ablation experiment results of prompts fusion.

D 128 univariate datasets of UCR archive and experimental results

Table 4: Description of 128 univariate datasets of UCR archive and detailed results of PLMs

	BERT				Longformer				
Length	SVM-SDP	SVM-DDP	SVM-FP	SVM-Fusion	SVM-SDP	SVM-DDP	SVM-FP	SVM-Fusion	SVM-TS
1460	34.0%	60.0%	29.0%	47.0%	70.0%	72.0%	65.0%	79.0%	58.0%
176	3.8%	3.8%	3.8%	3.8%	3.8%	3.8%	3.8%	3.8%	9.2%
Vary	27.3%	68.7%	21.0%	36.3%	32.3%	72.3%	34.0%	51.3%	66.3%
Vary	30.7%	69.3%	21.3%	39.0%	26.0%	70.3%	41.7%	49.3%	67.3%
Vary	26.3%	62.3%	17.3%	23.7%	36.0%	67.7%	40.3%	57.0%	54.0%
251	63.9%	36.1%	52.8%	63.9%	66.7%	36.1%	77.8%	72.2%	75.0%
470	53.3%	73.3%	53.3%	60.0%	46.7%	70.0%	50.0%	83.3%	50.0%
512	60.0%	70.0%	65.0%	75.0%	65.0%	95.0%	75.0%	100.0%	100.0%
512	70.0%	55.0%	65.0%	80.0%	80.0%	70.0%	70.0%	90.0%	90.0%
128	76.7%	80.0%	60.0%	73.3%	86.7%	73.3%	73.3%	73.3%	80.0%
577	28.3%	28.3%	28.3%	28.3%	28.3%	28.3%	28.3%	28.3%	55.0%
128	40.0%	40.0%	40.0%	40.0%	40.0%	40.0%	40.0%	40.0%	96.7%
24	70.0%	70.0%	55.0%	80.0%	80.0%	75.0%	70.0%	80.0%	80.0%
166	56.1%	56.1%	56.1%	56.1%	56.1%	56.1%	56.1%	56.1%	58.0%
1639	32.5%	32.5%	32.5%	32.5%	32.5%	32.5%	32.5%	32.5%	100.0%
286	57.1%	82.1%	71.4%	75.0%	71.4%	75.0%	89.3%	82.1%	96.4%
720	62.0%	55.6%	56.0%	70.4%	59.2%	55.6%	70.0%	60.0%	90.4%
300	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	87.9%
300	10.5%	9.7%	13.6%	12.6%	10.3%	10.3%	12.8%	10.3%	80.8%
300	10.5%	10.5%	10.5%	10.5%	10.5%	10.5%	10.5%	10.5%	85.6%
46	22.9%	70.9%	6.5%	28.6%	35.7%	75.9%	18.2%	54.2%	71.8%
345	37.5%	37.5%	37.5%	37.5%	37.5%	37.5%	37.5%	37.5%	37.5%
80	67.5%	64.8%	64.3%	65.8%	64.3%	64.3%	64.3%	64.3%	80.8%
80	63.0%	63.0%	63.0%	63.0%	63.0%	63.0%	63.0%	63.0%	71.5%
80	70.8%	53.3%	53.3%	53.3%	53.3%	53.3%	53.3%	53.3%	76.8%
288	16.7%	39.7%	21.8%	30.8%	28.2%	39.7%	39.7%	32.1%	69.2%
288	60.0%	75.0%	70.0%	75.0%	55.0%	65.0%	85.0%	80.0%	100.0%
288	55.0%	95.0%	55.0%	95.0%	95.0%	100.0%	90.0%	100.0%	100.0%
512	82.0%	82.0%	82.0%	82.0%	82.0%	82.0%	82.0%	82.0%	92.9%
96	69.0%	69.0%	69.0%	69.0%	69.0%	69.0%	69.0%	69.0%	87.0%
140	75.4%	58.4%	58.4%	72.2%	58.4%	58.4%	58.4%	58.4%	95.0%
136	60.9%	60.9%	60.9%	60.9%	60.9%	60.9%	60.9%	60.9%	82.6%
96	53.5%	32.9%	27.0%	51.6%	45.5%	30.5%	27.0%	44.5%	84.7%
1250	26.8%	10.5%	13.0%	20.4%	13.8%	9.9%	14.9%	13.5%	71.0%
1250	17.4%	8.6%	13.0%	14.6%	12.7%	8.6%	12.4%	12.7%	51.1%
1751	31.2%	27.2%	30.6%	33.7%	36.5%	29.2%	30.8%	34.5%	33.1%

131	26.4%	71.3%	16.6%	31.1%	26.8%	75.2%	30.4%	42.3%	98.8%
350	50.0%	37.5%	37.5%	54.2%	54.2%	37.5%	66.7%	50.0%	95.8%
131	16.5%	16.5%	16.5%	16.5%	16.5%	16.5%	16.5%	16.5%	96.0%
270	11.6%	11.6%	11.6%	11.6%	11.6%	11.6%	11.6%	11.6%	77.1%
463	25.7%	17.7%	16.6%	19.4%	25.1%	18.9%	22.9%	25.7%	53.1%
500	51.3%	51.3%	51.3%	51.3%	51.3%	51.3%	51.3%	51.3%	94.0%
500	51.6%	51.1%	51.2%	51.2%	51.2%	51.2%	51.2%	51.2%	95.9%
301	70.7%	59.3%	71.3%	70.7%	67.3%	55.3%	79.3%	84.7%	78.0%
301	85.7%	67.9%	78.6%	89.3%	71.4%	71.4%	100.0%	96.4%	85.7%
201	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
Vary	35.6%	6.7%	23.1%	47.1%	34.1%	8.2%	30.3%	36.5%	68.3%
Vary	41.3%	7.2%	14.4%	31.3%	45.2%	7.2%	24.0%	51.4%	54.8%
Vary	30.3%	9.6%	15.9%	35.1%	14.4%	9.6%	29.8%	14.9%	40.4%
Vary	30.3%	18.9%	18.9%	18.9%	18.9%	18.9%	18.9%	18.9%	100.0%
Vary	31.5%	17.8%	17.8%	17.8%	17.8%	17.8%	17.8%	17.8%	97.9%
150	52.0%	52.0%	52.0%	52.0%	52.0%	52.0%	52.0%	52.0%	88.0%
150	50.4%	72.6%	50.4%	51.1%	50.4%	50.4%	50.4%	50.4%	90.4%
150	52.6%	52.6%	52.6%	52.6%	52.6%	52.6%	52.6%	52.6%	97.0%
150	88.2%	52.2%	52.2%	66.2%	52.2%	52.2%	52.2%	52.2%	100.0%
431	52.3%	52.3%	52.3%	52.3%	52.3%	52.3%	52.3%	52.3%	90.8%
2709	63.8%	63.8%	63.8%	63.8%	63.8%	63.8%	63.8%	63.8%	86.4%
1092	23.2%	23.2%	23.2%	23.2%	23.2%	23.2%	23.2%	23.2%	57.4%
512	60.9%	60.9%	60.9%	60.9%	60.9%	60.9%	60.9%	60.9%	60.9%
2000	67.5%	57.5%	55.0%	92.5%	82.5%	67.5%	55.0%	95.0%	100.0%
1882	23.0%	19.0%	25.0%	24.0%	27.0%	22.0%	29.0%	27.0%	43.0%
601	100.0%	48.4%	83.9%	83.9%	48.4%	48.4%	48.4%	48.4%	100.0%
601	52.9%	47.1%	47.1%	47.1%	47.1%	47.1%	47.1%	47.1%	100.0%
256	13.2%	15.0%	16.8%	35.0%	31.4%	15.0%	48.2%	35.9%	74.5%
24	50.7%	50.7%	50.7%	50.7%	50.7%	50.7%	50.7%	50.7%	98.5%
720	43.2%	59.7%	42.9%	43.2%	57.1%	62.7%	56.5%	64.5%	90.7%
637	66.7%	66.7%	66.7%	66.7%	66.7%	66.7%	66.7%	66.7%	85.0%
319	27.1%	27.1%	27.1%	27.1%	27.1%	27.1%	27.1%	27.1%	88.6%
1024	20.0%	20.0%	20.0%	20.0%	20.0%	20.0%	20.0%	20.0%	72.7%
448	45.0%	43.3%	40.0%	43.3%	50.0%	65.0%	71.7%	73.3%	96.7%
99	53.3%	53.3%	53.3%	53.3%	53.3%	53.3%	53.3%	53.3%	64.6%
24	35.3%	65.8%	18.9%	50.0%	41.5%	63.7%	26.0%	52.7%	84.6%
80	67.3%	62.8%	59.3%	60.0%	59.3%	59.3%	59.3%	59.3%	77.3%
80	64.7%	64.7%	64.7%	64.7%	64.7%	64.7%	64.7%	64.7%	64.7%
80	60.4%	40.1%	40.1%	40.1%	40.1%	40.1%	40.1%	40.1%	61.2%
1024	28.4%	73.4%	38.4%	52.6%	47.2%	72.6%	37.2%	52.4%	91.4%
1024	37.0%	58.0%	37.0%	68.0%	55.0%	74.0%	58.0%	67.0%	93.0%
84	60.0%	60.0%	75.0%	90.0%	60.0%	60.0%	70.0%	65.0%	95.0%
750	3.4%	3.1%	5.3%	3.1%	3.1%	3.1%	3.1%	3.1%	66.0%
750	3.1%	3.1%	5.1%	3.1%	3.1%	3.1%	3.1%	3.1%	70.4%
570	43.3%	43.3%	43.3%	43.3%	43.3%	43.3%	43.3%	43.3%	43.3%
427	26.5%	26.5%	26.5%	26.5%	26.5%	26.5%	26.5%	26.5%	85.5%
80	65.1%	65.1%	65.1%	65.1%	65.1%	65.1%	65.1%	65.1%	67.1%
1024	11.2%	11.2%	11.2%	11.2%	11.2%	11.2%	11.2%	11.2%	78.0%
Vary	56.0%	70.0%	30.0%	54.0%	76.0%	86.0%	68.0%	92.0%	94.0%
2000	39.4%	71.2%	56.7%	79.8%	91.3%	85.6%	98.1%	97.1%	43.3%
2000	41.3%	76.9%	47.1%	58.7%	79.8%	86.5%	95.2%	85.6%	93.3%
2000	37.5%	55.8%	38.5%	66.3%	80.8%	79.8%	92.3%	86.5%	90.4%
Vary	16.9%	31.3%	28.7%	30.9%	16.4%	16.4%	16.4%	16.4%	30.5%
144	19.0%	19.0%	19.0%	19.0%	19.0%	19.0%	19.0%	19.0%	99.0%
144	79.4%	60.0%	67.8%	82.8%	70.0%	56.1%	78.9%	75.0%	100.0%
80	73.0%	74.3%	47.3%	73.3%	47.3%	47.3%	47.3%	47.3%	74.8%

80	67.7%	67.7%	67.7%	67.7%	67.7%	67.7%	67.7%	67.7%	67.8%
80	68.8%	45.0%	45.0%	71.3%	45.0%	45.0%	45.0%	45.0%	72.3%
720	44.0%	66.4%	36.8%	53.3%	45.1%	70.9%	42.1%	58.7%	99.2%
2844	55.0%	85.0%	50.0%	85.0%	80.0%	80.0%	95.0%	90.0%	85.0%
720	43.5%	68.3%	37.6%	48.3%	45.9%	61.3%	49.3%	58.1%	82.7%
1500	53.7%	66.0%	53.0%	62.3%	72.7%	52.7%	53.3%	55.0%	94.0%
1500	24.4%	51.6%	21.6%	47.3%	43.3%	75.3%	42.2%	60.2%	66.2%
1500	27.6%	53.1%	28.9%	51.3%	33.6%	66.4%	40.2%	47.8%	83.6%
Vary	52.0%	62.0%	28.0%	56.0%	76.0%	84.0%	72.0%	92.0%	86.0%
500	55.0%	95.0%	65.0%	90.0%	60.0%	75.0%	85.0%	85.0%	100.0%
512	6.3%	66.8%	12.5%	37.3%	32.5%	80.3%	33.0%	43.8%	83.3%
720	46.4%	74.9%	43.2%	59.7%	53.1%	61.6%	55.2%	71.7%	98.4%
15	44.7%	54.0%	40.7%	54.0%	62.0%	73.3%	75.3%	72.0%	98.7%
70	70.0%	70.0%	70.0%	70.0%	70.0%	70.0%	70.0%	70.0%	90.0%
65	59.3%	59.3%	59.3%	59.3%	59.3%	59.3%	59.3%	59.3%	92.6%
1024	57.3%	57.3%	70.0%	78.7%	57.3%	57.3%	57.3%	57.3%	84.8%
235	64.3%	64.3%	64.3%	64.3%	64.3%	64.3%	64.3%	64.3%	64.4%
128	8.4%	8.4%	8.4%	8.4%	8.4%	8.4%	8.4%	8.4%	80.4%
398	32.0%	32.0%	32.0%	32.0%	32.0%	32.0%	32.0%	32.0%	80.0%
60	34.0%	69.7%	21.7%	73.0%	58.0%	78.0%	30.0%	71.7%	100.0%
277	60.0%	50.0%	65.0%	57.5%	60.0%	52.5%	87.5%	62.5%	97.5%
343	55.6%	55.6%	61.1%	72.2%	77.8%	52.8%	83.3%	72.2%	100.0%
275	31.0%	31.0%	33.0%	31.0%	35.0%	31.0%	31.0%	31.0%	69.0%
82	52.2%	52.2%	52.2%	52.2%	52.2%	52.2%	52.2%	52.2%	69.6%
128	27.1%	27.1%	29.0%	27.1%	27.1%	27.1%	27.1%	27.1%	99.6%
150	44.4%	72.2%	50.0%	66.7%	63.9%	75.0%	86.1%	69.4%	72.2%
945	20.4%	14.2%	15.3%	14.2%	14.2%	14.2%	14.2%	14.2%	98.4%
315	16.2%	14.2%	14.2%	14.2%	14.2%	14.2%	14.2%	14.2%	82.6%
315	23.3%	14.2%	18.6%	16.0%	26.9%	14.2%	14.2%	14.2%	78.7%
315	20.9%	14.2%	14.2%	14.8%	26.3%	14.2%	14.2%	14.2%	78.1%
152	90.3%	90.3%	90.3%	90.3%	90.3%	90.3%	90.3%	90.3%	99.8%
234	64.9%	52.6%	52.6%	52.6%	52.6%	52.6%	52.6%	52.6%	52.6%
270	22.5%	22.5%	22.5%	22.5%	22.5%	22.5%	22.5%	22.5%	75.7%
900	42.0%	42.0%	42.0%	42.0%	42.0%	42.0%	42.0%	42.0%	84.5%
900	58.0%	58.0%	58.0%	58.0%	58.0%	58.0%	58.0%	58.0%	90.1%
426	54.3%	54.3%	54.3%	54.3%	54.3%	54.3%	54.3%	54.3%	72.7%