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Peer Review

Review of: "LLM-ABBA: Understanding Time Series via Symbolic Approximation"

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The manuscript introduces LLM-ABBA, which integrates the Adaptive Brownian Bridge-Based Symbolic Aggregation (ABBA) technique with Large Language Models (LLMs) to enhance time series analysis. By converting time series data into symbolic representations, LLM-ABBA enables LLMs to process and interpret temporal patterns effectively. The study demonstrates the efficacy of this approach across various tasks, including classification, regression, and prediction, achieving state-of-the-art (SOTA) performance on benchmarks such as the UCR archive and Time Series Extrinsic Regression (TSER) datasets. The authors use a fixed-polygonal chain trick to mitigate cumulative errors during the transition from symbolic to numerical data, thereby improving predictive accuracy.

The paper presents a novel fusion of symbolic time series representation with LLMs, addressing the challenge of aligning time series data with LLM architectures. This integration leverages the strengths of both methodologies to enhance performance in time series tasks. The authors conduct extensive experiments, comparing LLM-ABBA to recent SOTA methods across multiple benchmarks, including the UCR archive and medical time series classification tasks. The results indicate that LLM-ABBA matches and often surpasses existing methods in accuracy and robustness. The introduction of the fixed-polygonal chain trick is a significant advancement. This technique reduces cumulative errors by addressing the issue of drift during symbol-to-numeric transitions, thereby enhancing the reliability of predictions. The framework's design suggests potential for seamless extension to various time series tasks beyond those tested, indicating its versatility and adaptability in different domains. The manuscript introduces the fixed-polygonal chain trick within the LLM-ABBA framework to mitigate cumulative errors during the transition from symbolic to numerical representations in time series analysis. This technique has significantly improved results in various datasets, particularly in the UCR

 doi.org/10.32388/M70Z49

archive and medical time series classification tasks. For instance, in the UCR archive, which encompasses diverse time series data, the application of the fixed-polygonal chain trick has enhanced predictive accuracy by reducing drift during prediction tasks.

The paper would benefit from a more detailed discussion on mechanisms to manage out-of-vocabulary tokens or rare patterns in time series data. This is particularly relevant in complex datasets, such as EEG signals, where high variability can impact accuracy. An analysis of the computational complexity and scalability of LLM-ABBA would be valuable. Understanding the method's performance in real-time applications and latency considerations is crucial for practical deployment. Including ablation studies to dissect the contributions of different components within the LLM-ABBA framework would provide deeper insights into which elements are most critical for its success. For example, assessing the impact of the symbolic approximation process on the model's performance can help determine its effectiveness in capturing essential time series features, and investigating how aligning the embedding space of LLMs with the hidden information of time series affects overall performance can provide insights into the integration efficacy.

This manuscript offers a compelling and innovative approach to enhancing time series analysis by integrating symbolic representation and LLMs. The study's strengths are evident in its novel methodology, comprehensive evaluations, and practical contributions. I recommend this paper for publication, subject to minor revisions.

Specific Questions for the Authors:

Can the proposed method be extended to real-time applications, and what are the latency considerations?

How does the choice of symbol granularity influence the performance of LLM-ABBA?

What mechanisms are in place to handle out-of-vocabulary tokens or rare patterns in time series data?

I look forward to the authors' responses and revisions.

Declarations

Potential competing interests: No potential competing interests to declare.