Harnessing Emerging Knowledge and Extensibility Techniques for Stationarity and Normalization in Multi-Agent Time Series Forecasting

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ABSTRACT

This study introduces a novel multi-agent approach designed to optimize time series forecasting through an efficient normalization framework. The proposed architecture leverages the knowledge-emerging and extensibility properties, enabling an adaptive and scalable forecasting performance. The system is evaluated using the Hiroshima human mobility dataset. It consists of two key components: (1) a stationarity verification module employing the Augmented Dickey-Fuller (ADF) test and (2) a dynamic normalization module that selects the optimal technique based on ADF statistics and p-values. Five normalization methods—MaxAbs, MinMax, Log, Z-Score, and Sigmoid are analyzed to determine the most effective approach for different time series characteristics. Additionally, knowledge-emerging techniques, specifically the J48 decision tree algorithm, are integrated to enhance the system's predictive efficiency. Experimental results demonstrate the effectiveness of the proposed multi-agent architecture in improving the accuracy and adaptability of time series forecasting.

Keywords-time series; stationary testing; normalization; multi-agent architecture

I. INTRODUCTION

Time series forecasting is a critical tool across various domains, enabling the prediction of future data points based on historical patterns. Given that time series data is one of the most complex types of datasets, due to its temporal dependencies, noise, and often non-stationary nature, mastering its analysis requires both advanced techniques and deep domain expertise. This technique is widely applied in fields, such as finance, healthcare, and environmental studies, where understanding the temporal dynamics is essential [1]. The effectiveness of time series forecasting hinges on the choice of models and methodologies, which can range from traditional statistical models to advanced machine learning techniques. ARIMA, ARIMAX, SARIMA [2], and LSTM [3] are among the most widely used techniques for time series forecasting. Despite the apparent simplicity of time series forecasting, it often involves complex and challenging preprocessing steps, such as missing value imputation [4], outlier detection and correction [5], normalization, and stationarity testing. The interconnected nature of these tasks makes multi-agent techniques a promising approach. Building upon previous research on missing value imputation, outlier detection, and correction, this study explores a multi-agent approach to stationarity testing and normalization within the context of time series forecasting.

II. LITERATURE REVIEW

Time series forecasting relies heavily on the concept of stationarity, which refers to a time series whose statistical properties, such as mean and variance, remain constant over time [6]. Various statistical tests are employed to ensure that a time series is stationary. One of the primary methods for testing stationarity is the ADF test, which evaluates the null hypothesis that a unit root is present in the time series, indicating non-stationarity [7]. The ADF test is widely used due to its effectiveness in identifying unit roots. Additionally, the Dickey-Fuller Generalized Least Squares (DF-GLS) test, an enhancement of the ADF test, offers improved power in detecting stationarity [8]. This test is particularly useful when dealing with time series that may exhibit long memory or fractional integration, which can complicate the analysis of stationarity. The combination of these tests allows researchers to robustly assess the stationarity of their data, leading to more reliable forecasting models. In practice, the visual assessment of stationarity can also be beneficial. By plotting the time series and inspecting it for trends and seasonality, analysts can gain preliminary insights into the stationarity of the data. However, visual methods should be supplemented with formal statistical tests to confirm the findings. If a time series is found to be non-stationary, differencing is a common technique used to transform it into a stationary series. This method calculates the differences between consecutive observations, effectively removing trends and seasonality.

In summary, testing for stationarity in time series forecasting is essential for ensuring the validity of predictive models. Employing a combination of statistical tests, such as ADF, KPSS, and DF-GLS, along with visual assessments and differencing techniques, provides a comprehensive framework for analyzing time series data [9]. This multifaceted approach enhances the robustness of the forecasting efforts, ultimately leading to more accurate predictions.

Normalization in time series forecasting is a crucial preprocessing step that enhances the accuracy and reliability of predictive models by ensuring data consistency and reducing anomalies. This process involves scaling data to a common range, which helps in improving the model performance, especially in deep learning applications. The following sections explore various aspects of normalization techniques and their impact on time series forecasting, as discussed in the provided research papers.

A. Traditional and Alternative Normalization Methods

Traditional normalization methods, such as Min-Max and Z-Score, are widely employed to scale data without distorting the value ranges. Authors in [10] introduced the MMAD-based Z-Score normalization, which offers robustness against outliers compared to Min-Max normalization [10]. Authors in [11] discussed a time-symmetric self-normalization approach that provides a unified inference procedure and potentially narrower confidence intervals, enhancing the reliability of time series forecasts.

B. Challenges and Considerations

While normalization is beneficial, it can sometimes alter the inherent structure of the original data, leading to a potential loss of information. This concern is addressed by comparing models built on transformed versus original data, with the findings generally favoring the normalized data for improved accuracy [12]. The choice of the normalization technique can depend on the specific characteristics of the dataset and the forecasting task. For instance, authors in [13] emphasized the need for optimal input variable disposition in ANN models to enhance the forecasting accuracy, which may involve selecting appropriate normalization methods.

In Conclusion, normalization is vital in time series forecasting, significantly improving the model accuracy and reliability. However, choosing the appropriate normalization technique is essential based on the data characteristics and the specific forecasting task. While adaptive and traditional methods have advantages, the ultimate goal is to enhance the model's ability to learn from the data effectively. Despite the benefits, researchers must remain cautious of the potential data structure alterations and select normalization strategies that best preserve the integrity of the original data.

C. Multi-Agent Systems in Time Series Forecasting

Stationary testing and normalization are essential in time series forecasting to improve forecasting. Selecting the best technique for the given dataset is essential. Multi-agent systems have emerged as a powerful approach in time series forecasting, particularly in handling non-stationary data and normalization processes.

The study primarily discusses the development and application of multi-agent forecasting using Dynamic, Multiply-Sectioned Bayesian Networks (DMSBNs) and compares their performance with that of Dynamic Bayesian Networks (DBNs) [14]. In financial time series, multi-agent systems can adapt to non-stationary data by employing a system of adaptive forecasting agents that evolve and compete, leading to more accurate predictions than the single prediction algorithms [15]. The current paper introduces a system of several adaptive forecasting agents, instead of relying on a single prediction rule. These agents are designed to evolve and compete, allowing for a more dynamic and responsive forecasting system. A collective approach makes the final decision on the most successful agents at present. AgentFormer, a novel transformer model, integrates both the temporal and social dimensions of multi-agent interactions, allowing for more accurate trajectory predictions by preserving the agent identities and modeling latent intents [16]. Multiple employed strategies have collectively enabled the model to effectively handle the challenges posed by non-stationary environments in multi-agent trajectory forecasting. By considering both the temporal and social dimensions and incorporating stochastic elements, the model is better equipped to adapt to the changes and uncertainties in agent interactions. However, this has not been proved [16].

Stationary testing is crucial in time series forecasting to ensure that the data's statistical properties do not change over time. Multi-agent systems can handle non-stationary processes by employing distributed computational schemes with diverse predictive algorithms, significantly improving the forecast quality [17]. Normalization, a preprocessing step, is essential for managing data from different sources. The currency data aggregation shows that multi-agent systems can automate this process, enhancing the forecasting performance by learning accurate behavior patterns [18].

While multi-agent systems offer significant advantages in time series forecasting, challenges remain in their implementation. The complexity of the agent interactions and the need for advanced communication technologies can limit their effectiveness. Additionally, integrating multi-agent systems with existing forecasting models requires careful consideration to ensure compatibility and optimal performance. Despite these challenges, the potential of multi-agent systems in improving the forecasting accuracy and adaptability makes them a valuable tool in various domains.

Time series forecasting requires a comprehensive stationary testing mechanism and correcting the non-stationary time series using proper normalization techniques that will be suited for a given dataset.

III. METHODOLOGY

This research develops an extensible and adaptable multi-agent architecture to cover all aspects of time series forecasting, such as missing value imputation, outlier detection, outlier correction, stationary testing, and normalization. Missing value imputation [19], outlier detection [20], and outlier corrections [21] were studied in previous works, while this research covers the stationary testing and normalization techniques. Even though, stationary testing and normalization are two different components of time series forecasting, considering the fact that both of these components are related, it was decided to introduce a single multi-agent model for stationary testing and normalization.

To verify the scalability of the proposed multi-agent model, the human mobility dataset of Hiroshima, Japan [22], similarly to prior studies was also used in the present work [19, 20]. The specific dataset is not publicly available and was obtained under a commercial license. The former includes a session ID of the user for a given day, time components (year, month, date, hour, minute), and latitude/longitude coordinates. A sample record is shown in the Table I.

TABLE I. RECORD SAMPLE FOR THE DATASET

Session ID	ffff49b7b4e318506ba1c4c
Year	2020
Month	10
Day	16
Hour	21
Minute	41
Latitude	34.44408
Longitude	132.45720

A mobile dataset, comprising 112,318,484 data points collected in Hiroshima, Japan, between December 2019 and November 2020, was utilized for this research. Figure 1 illustrates the human distribution in the Hiroshima map.

Before executing the stationary testing sub-system, human mobility data were converted to time series for multiple locations, as outlined in Table II, and missing values detection and imputations were carried out. Furthermore, outlier detection and outlier corrections were performed. The proposed message space multi-agent model consists of a coordination agent, which is responsible for the coordination of sub agents.

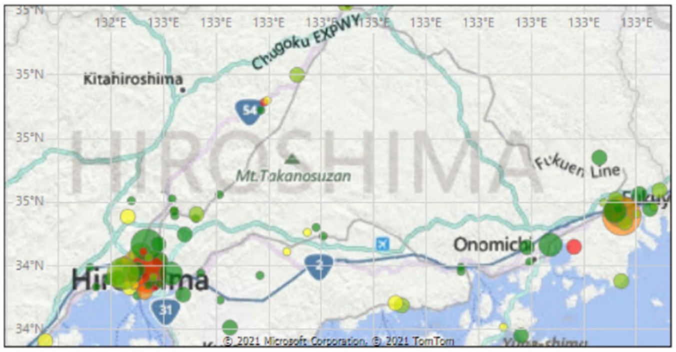

Fig. 1. Hiroshima mobility dataset on a map.

TABLE II. LOCATIONS IN HIROSHIMA

ID	Type	Location
1	Site	Hiroshima Botanical Garden
2	Site	Hiroshima MOCA
3	Local Gov.	Hiroshima Prefectural Office
4	Local Gov.	Hiroshima City Hall
5	Local Gov.	Hiroshima Station
6	Intersection	Kamiyacho, Hiroshima
7	Intersection	Hachobori, Hiroshima
8	Site	Hiroshima Castle
9	Site	Bomb Site
10	Site	Ballpark

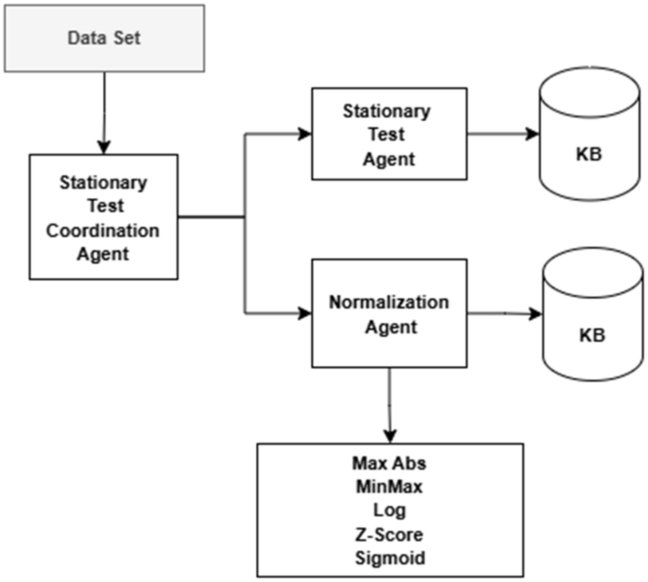

Fig. 2. Proposed multi-agent architecture for stationary testing and normalization.

A Stationary test agent is used in the proposed architecture to perform the Stationary testing. ADF is deployed for stationary testing. However, this can be extended to Dickey-Fuller (DF), Auto Correlation Function (ACF), while Partial Auto Correlation Function can also be used. Considering the popularity of ADF, the current agent is limited to ADF.

If the time series is non-stationary, a normalization agent will be executed. The normalization agent is an extensible agent that is currently capable of performing the MaxAbs, MinMax [23], Log [24], Z-Score, and Sigmoid normalization techniques. However, this subagent is not limited to the above techniques as it can be extended. Figure 2 shows the multi-agent architecture for the stationary testing and normalization for time series forecasting.

IV. IMPLEMENTATION

The mobility data from ten locations in Hiroshima City were transformed into time series. A human was considered present at a given location if their mobile data fell within a 200-m radius. To ensure temporal consistency, the data, which were aggregated hourly, were deduplicated by consolidating records based on session IDs, with each entry representing a unique hourly observation. After these preprocessing techniques, the dataset is ready for time series forecasting. Figure 3 portrays the number of visitors for the Hiroshima city hall.

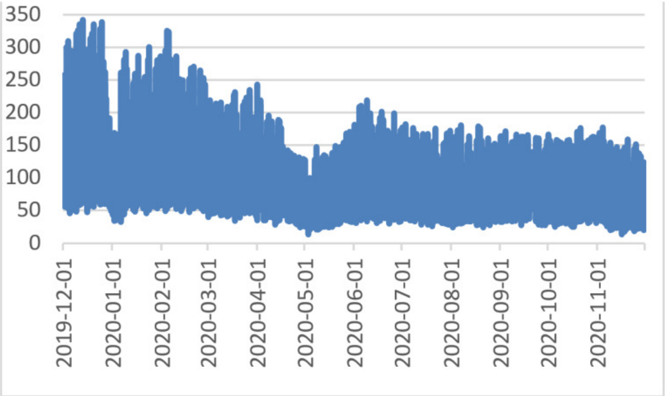

Fig. 3. Human mobile data for Hiroshima city hall.

The observed decline in human mobility during mid-2020 was a direct consequence of the COVID-19 pandemic, which prompted widespread restrictions, including lockdowns and reduced public activity. Upon acquiring the time series data, the missing values were identified and imputed to ensure continuity, as uninterrupted temporal data are essential for a robust time series forecasting. Following imputation, the outlier detection and correction procedures were implemented. Detailed methodologies for these preprocessing steps were analyzed in [19, 20].

Once the data are converted through time series, the stationary and normalization multi-agent model will detect whether the given dataset is stationary, as can be seen in Table III. This is handled by the stationary test sub agent. As demonstrated in Table III, Kamiyacho Hiroshima is the only non-stationary location per the ADF statistics. This location data should be normalized by the normalization agent while other locations are ready for forecasting.

Once the stationary testing is completed, the non-stationary time series should be converted to the stationary time series by the normalization of multi-agent sub-components. After the multiple normalization techniques were applied, stationary testing was performed again by executing the stationary test agent. Table IV presents the normalization values for each technique for the Kamiyacho Hiroshima location.

TABLE III. STATIONARY TESTING FOR THE LOCATIONS

Location	**ADF statistics**	**p-value**	**Stationary**
Ballpark	-5.563215	0.000002	Yes
BombSite	-3.496749	0.008071	Yes
Hachobori Hiroshima	-4.047772	0.001180	Yes
Hiroshima Botanical Garden	-10.99756	0.000000	Yes
Hiroshima Castle	-6.469651	0.000000	Yes
Hiroshima City Hall	-6.097020	0.000000	Yes
Hiroshima MOCA	-4.941027	0.000029	Yes
Hiroshima Prefectural Office	-3.498652	0.008022	Yes
Hiroshima Station	-3.257844	0.016871	Yes
Kamiyacho Hiroshima	-2.727592	0.069384	No

TABLE IV. NORMALIZATION VALUES PER TECHNIQUE

Technique	**ADF statistics**	**p-value**	**Stationary**
Original	-2.727592	0.069384	No
MinMax	-2.727592	0.069384	No
Log	-3.865730	0.002302	Yes
MaxAbs	-2.727592	0.069384	No
Z-Score	-2.727592	0.069384	No
Sigmoid	-9.568754	0.0000000000001	Yes

Log and Sigmoid normalization techniques have converted the human mobility of Kamiyacho Hiroshima location time series into a stationary time series, as displayed in Table IV. Since Sigmoid normalization has the lowest ADF statistics, the Sigmoid normalized time series is selected for forecasting.

If all time series are non-normalized, the lowest ADF statistics time series is applied for another execution of normalization. The pseudocode for the said logic is:

```
1. Initialize a list of time series data.
2. Initialize a variable 'lowest_adf_value' as None.
3. Initialize an empty list `stationary_series` to store
   stationary series and their ADF values.
4. Loop through each time series in the data:
•  Perform the ADF test on the series.
•  Store the ADF value for the current series.
•  If the ADF test result indicates stationarity, add this series
   and its ADF value to 'stationary_series'.
•  If 'lowest_adf_value' is None or the current ADF value is
   lower than 'lowest_adf_value':
     i.  Update 'lowest_adf_value' with the current ADF
         value.
5. After looping through all series:
•  If 'stationary_series' is not empty:
       i.  Find the series with the lowest ADF value in
           'stationary_series'.
       ii. Select this series as the result.
•  Else (no stationary series found):
```

i. Sort the original list of time series by their ADF values in ascending order.

ii. Normalize each time series in this order.

6. Output the selected stationary series (if any) or the normalized series in the order of the lowest ADF values.

Even though the above implementation is limited to six normalization techniques, the proposed multi-agent architecture can be extended to any other normalization technique depending on the need, as extensibility is one of the key features of a multi-agent system. However, in rare cases where neither transformation technique successfully yields a stationary time series, the affected time series may not be suitable for reliable forecasting. Under such circumstances, the non-stationary series must be excluded from further predictive analysis.

V. KNOWLEDGE EMERGING FEATURE

Time series analytics often involves processing large volumes of data, making the execution of the proposed multi-agent model inefficient. A decision tree algorithm is proposed to determine the appropriate normalization technique to address this challenge, as illustrated in Table V. A notable advantage of the multi-agent architecture lies in its capacity to facilitate the emergence of knowledge during dynamic execution.

TABLE V. PARAMETERS FOR KNOWLEDGE EMERGING FEATURE

Data point	Example
Data type	Mobility, temperature
Sub data type	Location type, public places, transportation, offices
Number of records	0 – 1,000, 1,000 – 100,000, more than 100,000
Frequency	Hourly, daily, monthly
Normalization technique	MinMax, Log, MaxAbs, Z-Score, Sigmoid

The classification technique was employed as the knowledge emergence method, with the J48 decision tree algorithm selected for this purpose. The "Normalization Technique" attribute from the dataset presented in Table III was utilized as the classification variable. However, the effectiveness of this knowledge emergence technique mainly depends on the dataset's quality. The performance of the decision tree model was evaluated using an 80/20 train-test split to ensure robust validation. The model demonstrated strong predictive capabilities, achieving an overall accuracy of 85%. Additionally, it attained an average precision score of 82%, indicating its reliability in correctly identifying the positive cases while minimizing the false positives. These results suggest that the decision tree algorithm is well-suited for the given task, effectively balancing accuracy and precision.

Since the proposed time series multi-agent architecture does not consistently execute normalization, the dataset will inherently have fewer instances, potentially impacting the robustness of the classification process.

The above knowledge will be updated with the multi-agent execution. Once the knowledge emerging feature is introduced, the multi-agent architecture will change, as depicted in Figure 4.

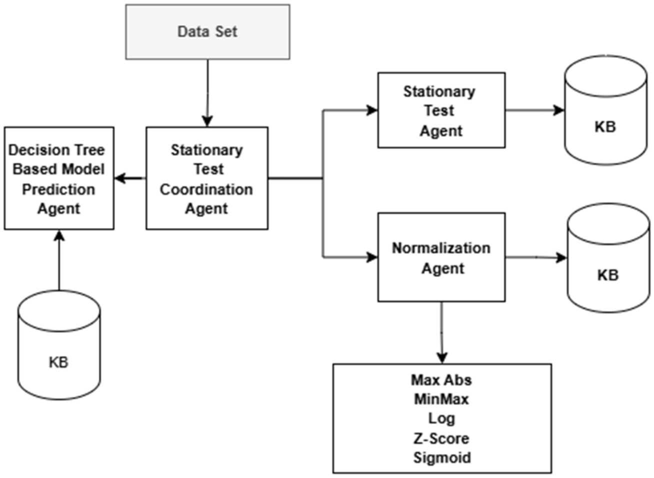

Fig. 4. Updated multi-agent architecture with knowledge base.

VI. CONCLUSION

This research significantly contributes to developing an automated machine learning platform for time series forecasting, focusing on incorporating preprocessing techniques to enhance the forecasting accuracy. It introduces an extensible, knowledge-driven multi-agent framework capable of identifying non-stationary time series and performing normalization as part of the preprocessing workflow. The proposed multi-agent model was tested for real-world Hiroshima mobility data using five normalization techniques: MaxAbs, MinMax, Log, Z-Score, and Sigmoid, after the stationary testing was completed employing ADF. The proposed multi-agent architecture has the knowledge-emerging capability. J48 algorithm was used to determine the best normalization technique before the extensible normalization multi-agent architecture was executed.

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