TIME SERIES FOUNDATION MODELS: BENCHMARKING CHALLENGES AND REQUIREMENTS

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ABSTRACT

Time Series Foundation Models (TSFMs) represent a new paradigm for time series forecasting, offering zero-shot forecasting capabilities without the need for domain-specific pre-training or fine-tuning. However, as with Large Language Models (LLMs), evaluating TSFMs is tricky, as with ever more extensive training sets, it becomes more and more challenging to ensure the integrity of benchmarking data. Our investigation of existing TSFM evaluation highlights multiple challenges, ranging from the representativeness of the benchmark datasets, over the lack of spatiotemporal evaluation, to risks of information leakage due to overlapping and obscure datasets, and the memorization of global patterns caused by external shocks like economic crises or pandemics. Our findings reveal widespread confusion regarding data partitions, risking inflated performance estimates and incorrect transfer of global knowledge to local time series. We argue for the development of robust evaluation methodologies to prevent pitfalls already observed in LLM and classical time series benchmarking, and call upon the research community to design new, principled approaches, such as evaluations on truly out-of-sample future data, to safeguard the integrity of TSFM assessment.

1 Introduction

Time Series Foundation Models (TSFMs) are an emerging class of time series forecasting models inspired by the architecture and training procedures of foundation models in natural language processing, especially Large Language Models (LLMs). Prominent examples of TSFMs include Chronos (Ansari et al., 2024), TimesFM (Das et al., 2024), Moirai/Moirai-MoE (Woo et al., 2024; Liu et al., 2024b), MOMENT (Goswami et al., 2024) and Time-MoE (Shi et al., 2024). In contrast to traditional time series forecasting models, which need to be trained from scratch on the time series that should be forecasted, TSFMs use transfer learning. That is, they are pre-trained on massive amounts of generic and/or domain-specific time series and are, thus, able to produce zero-shot forecasts.

However, pre-training TSFMs on massive amounts of time series data, typically scraped from publicly accessible online repositories, introduces challenges similar to those observed in LLM evaluation. The practice of training LLMs on much of the Internet has led to an LLM "evaluation crisis" (Liao & Xiao, 2023), describing a situation in which most benchmark data has already been exposed to an LLM during pre-training. Combining such test set contamination (Mirzadeh et al., 2024; Ravaut et al., 2024; Li et al., 2024a) with memorization effects (Chang et al., 2024) can result in overly-optimistic estimates of a model's predictive performance and complicate the fair comparison of models through common benchmarks. Furthermore, as with LLMs (Chang et al., 2024), cross-validation in TSFMs is omitted due to its exhaustive resource requirements with large foundation models (Das et al., 2024; Gruver et al., 2024), and the diversity and generalizability of benchmarking datasets can be questioned (Aksu et al., 2024).

As the awareness about evaluation challenges in TSFMs is growing, researchers have begun to propose mitigation strategies, such as held-out-driven benchmarks (Aksu et al., 2024) and clean train-test splits within benchmarks (Qiu et al., 2024) that include more diverse and generalizing test sets Aksu et al. (2024). Especially when comparing TSFMs against each other, current approaches face limitations in defining an information-leakage-free test set for all investigated models (Aksu et al., 2024). This challenge is even more pronounced for larger models developed based on scaling laws,

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as their increased capacity may amplify the memorization effect, leading to a greater impact of test set contamination (see Section 2).

In this article, we discuss the evaluation challenges arising from current practices of training and evaluating TSFMs and propose requirements that a TSFM benchmark should fulfill. Empirically, our position is supported by an analysis of the lineage of the training and test sets of 15 prominent TSFMs and a further investigation of existing TSFM benchmarks². In addition, we provide a theoretical derivation of the phenomenon of global pattern memorization, which is specific to TSFMs and, to the best of our knowledge, has not been formally introduced before.

First, while we did not identify cases of information leakage *within* any of the underlying studies, our analysis highlights the increasing confusion with regards to a clear separation between training and test sets, one of the fundamental principles of time series forecasting and machine learning, and outlines possible adverse effects. Concretely, we found that one model's training set is another model's test set. This confusion, which is further exacerbated through the practice of remixing and renaming of datasets, stems from an ever-growing size of datasets, combined with non-transparent documentation about which exact data points have been used for training and testing, and complicates the fair benchmarking *between* TSFMs. We will show that this is not just a danger, but is actually already happening, using two examples where information leakage occurs in benchmarks 3.1.

Second, we highlight a more subtle instance of information leakage, particularly in time series forecasting, namely the memorization of global patterns. Global external shocks like the COVID-19 pandemic or global economic crises can profoundly impact numerous aspects of our economies and societies and, hence, are reflected in many diverse time series. A TSFM trained and evaluated on time series that are disjunct but stem from the same period and are both impacted by such an external shock can still profit from memorizing these patterns.

In addition to the issue of information leakage, we point out that current TSFM evaluation methods are not fully consistent with previous approaches in time series forecasting. In Section 3.3 and 3.4 we show that TSFMs typically do not implement best practices such as time series cross-validation or choosing representative time series for a domain.

This article argues that in the age of TSFMs a new benchmarking methodology is required to prevent a repetition of the LLM evaluation crisis and calls for new proposals that fulfill the requirements developed in this paper.

2 Foundation Models in Time Series

A foundation model is "any model that is trained on broad data (generally using self-supervision at scale) that can be adapted (e.g., fine-tuned) to a wide range of downstream tasks" (Bommasani et al., 2021). The term is primarily associated with Transformer-based LLMs, especially decoder-only models like the ChatGPT or Llama families of models (OpenAI, 2023; Grattafiori et al., 2024). The success of foundation models can be attributed to scaling laws (Kaplan et al., 2020), that is, increasing training data, model parameters, and computational resources significantly improves the model's performance.

LLMs have demonstrated remarkable zero-shot learning capabilities across diverse benchmarks (Liang et al., 2022). However, concerns have been raised that these models might just memorize publicly available questions and answers of well-known benchmarks (Chang et al., 2024). Memorization (Carlini et al., 2022) is closely related to test set contamination, describing the situation where exact or highly similar samples from a test set are leaked to the LLM's pre-training data (Li et al., 2024a). This contamination is a side-effect of the vast size and incomprehensible nature of today's pre-training datasets, such as Common Crawl³ or The Pile⁴ (Li et al., 2024a; Singh et al., 2024). Despite efforts to improve dataset curation in recent LLMs (Grattafiori et al., 2024), evidence shows that test set contamination remains prevalent in various forms inflating generalization performance (Mirzadeh et al., 2024; Ravaut et al., 2024; Li et al., 2024a).

Like generative LLMs, time series forecasting models are trained to autoregressively predict the next value(s) given a sequential series of past data points. Hence, it is not surprising, that researchers started to adapt decoder-only Transformers for time series forecasting. Some of these models encoded numerical time series values as natural language tokens (Gruver et al., 2024; Xue & Salim, 2024), others have developed novel tokenization techniques for numerical data, such as TimeGPT-1 (Garza et al., 2024) and Chronos (Ansari et al., 2024). Like LLMs, decoder-only Transformers for time series forecasting can be pre-trained on generic time series and adapted or fine-tuned to domain-specific time series optionally. At this, they seem to leverage the same scaling laws as LLMs (Edwards et al., 2024),

²TSFM benchmarks that existed in the beginning of 2025.

³https://commoncrawl.org/

⁴https://pile.eleuther.ai/

leading to *Time Series Foundation Models* able to zero or few-shot forecast time series of different frequencies and domains adapting to diverse lengths of input context and forecasting horizons (Das et al., 2024; Liang et al., 2024).

Traditional statistical or machine-learning-based time series forecasting models have to be trained on the time series that should be forecasted. These local models exhibit only limited generalization capabilities, that is, they can only predict values that are independent and identically distributed (i.i.d.) to their training data. Combined with the common practice to use time-based train/test splits when evaluating time series models (Hyndman & Athanasopoulos, 2021), this property of local models protects them from information leakage. TSFMs, in contrast, are often evaluated on

Model Name	AUTHOR	YEAR
Тіме-МоЕ	SHI ET AL. (2024)	2025
CHRONOS	Ansari et al. (2024)	2024
LAG-LLAMA	RASUL ET AL. (2024)	2024
Moirai	WOO ET AL. (2024)	2024
Moirai-MoE	LIU ET AL. (2024B)	2024
MOMENT	GOSWAMI ET AL. (2024)	2024
TIMER	LIU ET AL. (2024C)	2024
TIMESFM	DAS ET AL. (2024)	2024
TIME-LLM	JIN ET AL. (2024)	2024
TTM	EKAMBARAM ET AL. (2024)	2024
UNITIME	LIU ET AL. (2024A)	2024
VISIONTS	CHEN ET AL. (2024)	2024
FORECASTPFN	DOOLEY ET AL. (2023)	2023
GPT4TS	ZHOU ET AL. (2023)	2023
LLMTIME	GRUVER ET AL. (2024)	2023
TIMEGPT-1	GARZA ET AL. (2024)	2023

Table 1: Summary of models, citations, and release years.

zero-shot or few-shot forecasting tasks using held-out datasets, similar to LLM evaluation (Ansari et al., 2024; Liu et al., 2024b; Woo et al., 2024). Notably, the terms "zero-shot" and analogously "few-shot" need to be distinguished between LLMs and TSFMs: while LLMs adapt to *different tasks* without any example in zero-shot learning (Brown et al., 2020), TSFMs usually *forecast* zero-shot by adapting to different input lengths, frequencies, horizons and domains (Ansari et al., 2024; Das et al., 2024; Woo et al., 2024).

The specialized practices of pre-training and zero-shot forecasting in TSFMs introduce novel challenges while simultaneously amplifying existing difficulties in the evaluation of time series models, as discussed in the following sections.

3 Challenges of Evaluating Time Series Foundation Models

3.1 Challenge: Test Set Contamination Through Multi-Purpose Use of Datasets

In order to empirically study whether test set contamination is a problem in existing TSFM evaluations, we tried to track the lineage of the various datasets used for training and evaluating the TSFM listed in Table 1. Specifically, we distinguish between three types of data usages: *pre-training* datasets, *train/test* datasets, and *zero-shot* datasets.

Pre-training datasets are utilized exclusively for foundational training to teach typical time series patterns (e.g., trends, seasonality) to a model. Here, the entire time series is usually used for training, and no evaluation is conducted on these datasets. Train/test datasets, also called in-domain or in-distribution datasets, fit a model to time series from a specific domain (e.g., finance, energy, transportation). Following the traditional time series forecasting methodology, these datasets are typically split at a particular time point into training and test sets (Hyndman & Athanasopoulos, 2021; Kapoor & Narayanan, 2023). The training data is included in the model's training corpus during pre-training or subsequent task-specific adaptation/fine-tuning. The test data is used to evaluate the model's performance within the given domain. When benchmarking multiple models in a specific domain, all models should use the same datasets with the same train-test splits in order to ensure a fair comparison. Zero-shot datasets (held-out datasets) are entirely excluded from the pre-training and task-specific fine-tuning process and used for inference only. Unlike LLM zero-shot datasets with diverse tasks, TSFM datasets often share frequencies and domains with pre-training data, primarily evaluating frequency and domain generalization. However, in zero-shot evaluation, the TSFMs make forecasts, typically in a rolling manner, taking a limited context of historical values as inputs and producing output for future time steps (Aksu et al., 2024). Ideally, all TSFMs would be benchmarked on the same zero-shot datasets.

Our lineage analysis, visualized in Figure 1, reveals that each TSFM uses a different combination of pre-training, train/test, and zero-shot datasets.

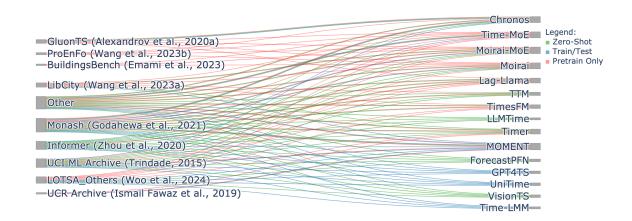


Figure 1: Lineage of dataset collections (left) used for training and evaluating recent Time Series Foundation Models (right). Typically, a collection contains multiple different datasets. Lines indicate cases where at least one dataset of a collection was used for pre-training, train/test, or zero-shot evaluation.

While we did not find a TSFM that used the same set for different purposes, we still argue that this multi-purpose use of datasets is a problem. For example, suppose Model A uses a dataset for pre-training, and Model B uses the same dataset for evaluation. In that case, it becomes impossible to evaluate these models against each other on that dataset fairly.

A notable case for the multi-purpose use of datasets is the subset *Australian Electricity Demand* from the Monash dataset collection (Godahewa et al., 2021), which is used for pre-training (e.g., Lag-Llama, Timer), train/test evaluation (e.g., Moirai), and zero-shot forecasting (e.g., Chronos, TimesFM). This multi-purpose use makes the dataset practically useless for benchmarking between models (e.g., it cannot be used to compare Chronos to Lag-Llama).

Another interesting case is the Informer collection (Zhou et al., 2021), which is primarily used for zero-shot evaluations (indicated by green connections in Figure 1). However, some individual time series of the Informer collection, such as ETTh1, ETTh2, and ETTm1, have also been used for pre-training (e.g., in LagLlama) or train/test evaluation (e.g., in UniTime). Again, this means that LagLlama or UniTime cannot be benchmarked against any other model using the Informer collection. Note that it is not easy to exactly determine which datasets a model has been trained on. It requires careful reading of the original paper and sometimes even analyzing published source code. Doing this for a dozen or more models in a benchmarking study requires substantial effort.

No dataset has been universally used across all TSFMs for train/test or zero-shot evaluation (see Table 2 and Table 3). Considering all investigated datasets, only 7% have never been used for pre-training or train/test fine-tuning, making them the only suitable candidates for genuine zero-shot model benchmarking.

Renaming datasets is another issue we encountered during our analysis. For example, the Monash dataset "Elecdemand" is a scaled subset (1/1000) of the "Australian Electricity Demand" dataset. Normalization practices could introduce unintended information leakage if these datasets are treated as separate. Similarly, the dataset "ElectricityLoadDiagrams20112014" appears under various names, such as "Electricity" in the Autoformer and Monash collections (Godahewa et al., 2021; Wu et al., 2022) and "ECL" in the Informer (Zhou et al., 2021) collection. Dataset collections sometimes also contain the same variables but different observations. For instance, the car ride shares dataset is included in both the Monash and GluonTS collections. Although both repositories cite the same GitHub source⁵, a close examination reveals that they represent different time series of distinct For-Hire Vehicles.

The empirical analysis using the Moirai TSFM by Aksu et al. (2024) demonstrates the effects of information leakage between training and test sets on the predictive performance of TSFMs. The authors prepared a new pre-training and held-out evaluation dataset without any overlap and trained the Moirai architecture on it. A different Moirai model from a previous publication was taken which pre-training dataset contained 0.1% data of the newly defined held-out evaluation dataset leading to a deliberate small portion of information-leakage. They then compared the performance of the models with different numbers of parameters and different forecasting horizons. The models trained on the training set with information leakage achieved an average MAPE between 7.6 and 59 percentage points lower than the

⁵https://github.com/fivethirtyeight/uber-tlc-foil-response

same architecture trained on leakage-free training data (see Appendix B.2 for detailed results). These results vividly demonstrate the significant impact that *test set contamination* has on the performance of TSFMs. Larger model sizes especially seem prone to this, suggesting that bigger models tend to memorize rather than generalize. Another example of the information leakage effect is observable in a recently proposed TSFM benchmark. The benchmark creators, due to the TSFMs' incomprehensible datasets, unintentionally included three evaluation datasets as test sets that had already been used in the pretraining of TimesFM, UniTS, and TTM (Li et al., 2024b). Based on an analysis of the benchmark results, this leads to an advantage of 47% - 184% lower mean squared error (MSE) rate compared to best models not pre-trained on the leaking datasets. The advantage of the best TSFM on non-leaked datasets is only between 0.3% and 14%. Of course, the effect should be evaluated using comparisons on the same datasets, but the performance benefit through information leakage appears to align with findings from the Moirai leakage example. This highlights the difficulties for benchmarking *between* TSFMs.

3.2 Challenge: Memorization of Global Patterns

Direct overlap between observations of the training and test sets is not the only cause for information leakage. A more subtle case of information leakage can happen due to indirect dependencies between data points in the training and test sets (Kapoor & Narayanan, 2023). Typically, these indirect dependencies stem from confounding bias, that is, an external factor independently associated with observations in both datasets. In the context of time series forecasting, global events or crises like COVID-19 or the European energy crisis, caused by Russia's invasion of Ukraine, can influence a large number of time series from different domains.

A key strength of TSFMs is learning patterns and transferring a suitable pattern to an unseen time series. But when a TSFM is trained on data including such global events or crises, information may inadvertently carry over to forecasts on test set time series from the same period and affected by the same external factors. This introduces a problematic dependency between the training and test data, violating the assumption of independence that is crucial for robust evaluation. As a result, the model gains access to information during training that is usually inaccessible in a real-world scenario at the time of prediction, leading to inflated performance metrics. The time component and the actual information inside a time series plays a new role for globally trained models such as TSFMs.

Global Pattern Memorization

(TSFM A learns global pattern (COVID-19) from pre-training data and memorizes it for other time series in zero-shot forecast)

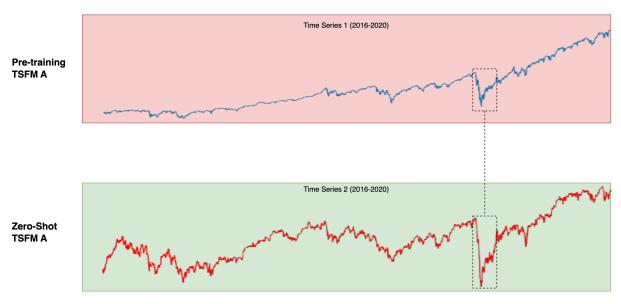


Figure 2: Global pattern memorization of TSFM A when trained on time series 1 and zero-shot forecasting time series 2.

3.3 Challenge: Evaluation Dimensions

The typical evaluation in time series forecasting is performed across the time dimension to assess a model's capabilities over time (Hyndman & Athanasopoulos, 2021), particularly its performance across different seasonal patterns (Figure 3,

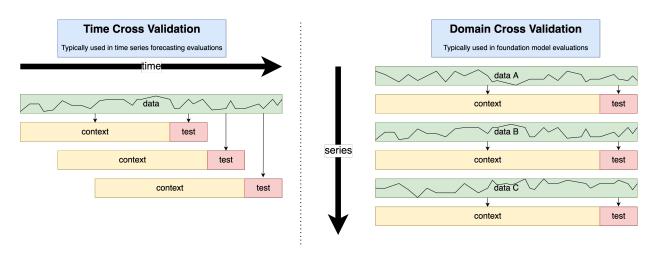


Figure 3: Evaluation strategies along the time or the domain dimension.

left side). Using time-series cross-validation, one can verify whether a model provides reliable forecasts, for example during winter and summer. It should be emphasized that a rolling evaluation does not necessarily require retraining the model for each rolling interval. One can just as well use a fixed training dataset and then roll inference over the various test sets (Hewamalage et al., 2023), making it a suitable evaluation strategy for TSFMs.

Interestingly, current TSFMs seem to evaluate only using a single time split per series (Figure 3, right side) without performing time series cross-validation, usually to reduce resource utilization or costs (Das et al., 2024; Gruver et al., 2024). Results are then often reported based on a single prediction per time series (Ansari et al., 2024; Das et al., 2024; Shi et al., 2024). They demonstrate foundation model capabilities as the models are evaluated against multiple time series from different domains (see Section 2). But we have not found any TSFM for which a combined time and domain cross-validation is explicitly conducted (Figure 4), even though this approach would easily increase the number of predictions and ultimately lead to a more meaningful evaluation.

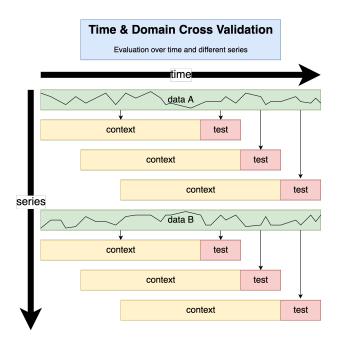


Figure 4: Evaluation along time and domain dimension.

3.4 Challenge: Domain Representative Time Series

Foundation models in particular aim to be generalizable across different domains. Still, there is no systematic derivation of why domains such as energy, transportation, weather, or web trends in particular should be predicted. A particularly illustrative example is the ETT dataset (Zhou et al., 2021), which is used in many TSFMs as a zero-shot benchmark (see Section 3.1). However, this dataset is based on two years of measurements from just two transformers in China. The exact location of these transformers within China is not specified, and only very general information about their origin is provided. Moreover, while the dataset indeed captures some noteworthy characteristics, such as both short- and long-term seasonal patterns, it still consists of only two specific time-series use cases among an uncountable variety of possible temporal dynamics observed in real-world applications. It is therefore unclear to what extent results obtained on ETT can be considered generalizable, whether to transformers deployed in other regions such as Africa, America, Europe, or even to a third transformer within China. Accordingly, it remains questionable whether the dataset allows for any broader conclusions about the overall capability of models in a special domain (Hewamalage et al., 2023).

4 Current Benchmarking Approaches

One could argue that existing best practices for model training and testing are sufficient to mitigate risks such as test set contamination and global pattern memorization. But are these strategies still adequate in the age of TSFMs, or must they be adapted, combined, or restructured?

Existing strategies can be broadly categorized into benchmarking strategies and research best practices. As the dominant logic of time series benchmarking (Hyndman & Athanasopoulos, 2021), *time-based train/test splits*, including those in the Monash dataset collection (Godahewa et al., 2021) and TFB (Qiu et al., 2024), prevent leakage within a single TSFM. However, it is still unsuitable for fair benchmarking, as teams may choose different training and testing sets (see Section 2). Moreover, such predefined train/test splits typically do not use a global split point across all series in a collection, which would protect against information leakage through memorizing global patterns. For example, the Monash collection series uses varying start and end points, preventing the possibility of a global time-based split across all included time series (see Appendix 7).

In terms of foundation models, *held-out datasets* like GIFT-Eval (Aksu et al., 2024) focus on creating curated pretraining and test datasets without any overlap to prevent test set contamination. This approach enables a robust zero-shot forecasting evaluation, which is critical to TSFMs. However, the held-out dataset approach only applies to TSFMs developed in the future, as past models cannot be benchmarked reliably due to potential data contamination caused by overlap between their pre-training data and the held-out dataset. Furthermore, in case researchers want to include more data into pre-training than provided in a collection like GIFT-Eval, it requires careful checks for potential test set contamination in zero-shot forecasting. Lastly, global patterns like events or crises can still affect both the training and held-out test sets of such collection as long as no global time-based split is enforced.

Combining held-out datasets, global time-based train/test splits and *retraining* and benchmarking all TSFMs on a standard pre-training and test set would prevent information leakage and enable fair benchmarking. Yet, retraining all model architectures used in a benchmark is obviously very resource-intensive and prone to implementation errors. In addition, forcing all models to use the same data for pre-training mitigates the advantages of the scaling laws (Edwards et al., 2024).

Using anonymized real-world benchmarking test datasets (e.g., masking or scaling them) can also help to address information leakage concerns. Anonymizing real-world time series would help prevent the simple recall of original data points in case they have been included in a model's pre-training set (Der et al., 2023). However, pre-processing techniques like scaling, feature engineering, and tokenization, which are usually implemented in a TSFM architecture, could potentially reverse such anonymization efforts, leading to the original or a very similar time series. Hence, the effectiveness of this approach is questionable and would require sophisticated anonymization techniques that preserve statistical properties while preventing direct recalling of data points.

Competition-based splits, like in the M-competitions (Makridakis et al., 2022), require forecasts on unpublished time-splits of known series. Such competitions start by publishing the training set while the test set remains private. Forecasts are registered during the competition, usually organized via Kaggle⁶ and metrics are calculated using the private test set. Although these approaches prevent test set contamination by registering forecasts based on time-based splits, they do not ensure a rigorous held-out dataset split for zero-shot forecasting. Furthermore, the hidden test set usually contains static, past data for evaluation throughout the competition. Besides enabling TSFMs to benefit from global pattern memorization, organizing such competitions requires substantial resources for administration, leading to

⁶https://www.kaggle.com/competitions/m5-forecasting-accuracy/overview

long waiting periods between competitions. In a more innovative way, the recent M6 competition employed a strategy of using real-world live data from 100 financial assets and registering predictions into the real future (Makridakis et al., 2024). The main task was not forecasting but ranking the assets according to their future values. Still, it was a closed competition in a predefined time frame where long waiting period persists for results as with previous competitions which can be a hurdle in the fast developments of TSFMs.

In contrast, *synthetic* data for testing promises an unlimited amount of truly novel and so far unknown data. In fact, for pre-training, synthetic data has already been used successfully (Dooley et al., 2023). Yet, the external validity of solely using synthetic data for testing remains questionable, as synthetic data generation itself needs to be evaluated (Yuezhang et al., 2021).

Research best practices such as *pre-registration for predictive modeling* provide indirect mechanisms to mitigate risks of test set contamination due to multi-purpose use of datasets or global pattern memorization. Pre-registration for predictive modeling has been proposed as a rigorous research method originating from the experimental sciences (e.g., medicine, psychology) (Hofman et al., 2023). This method requires an ex-ante documentation and publication of the whole predictive modeling process before model training, including all planned data collection and preparation as well as modeling and evaluation activities. *Model cards* can complement this ex-post, by providing all information on data, training, and benchmarking to other researchers in one document (Mitchell et al., 2019). While these best research practices have the potential to prevent cherry picking of training and test sets and evaluation metrics and provide deeper insights into the models, they cannot mitigate the risks stemming from multi-purpose use of datasets and memorization of global patterns.

Lastly, the *academic review process* ensures proper data splits and detects any information leakage. While the peer review process has proven its ability to spot methodological issues, relying solely on this approach may not comprehensively prevent unintentional benchmark contamination (Li et al., 2024b). Furthermore, reviewers indeed cannot assess the validity of all models included in a benchmarking study. Hence, as witnessed in LLM evaluation research, academic review processes may oversee test set contaminations (see Section 2).

In sum, while pre-defined distinctions between training, test, and zero-shot sets improve evaluation integrity, they hinder comparability with prior models and mitigate scaling laws. Adhering to best practices may help identify test set contamination, but cannot entirely prevent it, especially in the presence of global pattern memorization. Given the rapid evolution of TSFMs, waiting long periods between competitions is increasingly impractical and risks stagnating meaningful progress, while anonymization of data cannot fully mitigate TSFM benchmarking challenges.

5 TSFM Benchmark Requirements

The essence of time series forecasting is to predict the *future*. Paradoxically, using data from the *past* to evaluate their ability to do so is standard practice as we have seen in previous Section 4. Before the advent of TSFMs, this paradox was not a serious issue, as traditional time series models have to be trained on past values of the same time series they are expected to continue. The only pitfall to avoid is adhering to the correct ordering of training and test observations. Yet, as we have outlined in Section 2, the possibility of pre-training TSFMs on vast collections of time series from different domains and using them without training on the target time series introduces new risks of information leakage, possibly resulting in test set contamination and memorization of global patterns. Now there are a variety of ways (Section 4) to test and compare TSFM, but in our opinion none of them fully solves the problems identified (Section 2).

Instead of only pointing out which benchmarking methodologies are not suitable for TSFMs, we want to be proactive and develop guidelines how a TSFM benchmark *should* be designed. Based on the advantages and disadvantages of the current benchmarking approaches (Section 4) combined with our analysis (Section 2), we propose the following requirements for a time series foundation model benchmark methodology:

- 1. **Prevention of Information Leakage.** The benchmark must guarantee that no portion of test data is present within any model's training corpus.
- Unambiguous Data Splits and Transparency. It should employ clear and standardized protocols for dividing data into training and test sets.
- 3. **Time- and Domain Dimension Evaluation.** It should apply cross-validation across both time and domain dimensions, verifying model consistency across seasonal periods (e.g., summer/winter) and across diverse datasets or domains to ensure generalization and robustness.
- 4. **Retrospective and Prospective Evaluation.** The methodology should not be limited to models developed after the introduction of the benchmark, but must also be applicable to existing models and future models as the field evolves.

- 5. **Flexibility in Pre-Training Data.** Researchers should not face artificial restrictions on the amount, provenance, or specificity of pre-training data.
- 6. **Mitigation of Global Pattern Memorization.** Mechanisms must be in place such as global temporal cut-off points to reduce the risk of models exploiting global patterns.
- 7. **Scalability and Sustainability.** The framework should remain practical for long-term community use, avoiding excessive computational, infrastructural, or administrative requirements.
- 8. **Real-World Representativeness.** Evaluation data should reflect the diversity of time series in relevant real-world domains and frequencies.
- 9. **Support for Zero-Shot and Fine-Tuned Evaluation.** The protocol should enable assessment of models in both zero-shot and fine-tuned settings.
- Inclusivity and Accessibility. Participation should be open to both academic and industry teams, including those using open-source or closed-source models.
- 11. **Robustness Against Gaming and Overfitting.** Safeguards must be implemented to prevent exploitation of the test data, such as rotating test series, or anonymizing series during evaluation.

Now, one could argue that these are wishful requirements for a benchmark, but that they are unrealistic to fulfill all and compromises must be made. We would like to challenge precisely this and encourage the community to look for solutions that cover as wide a range of requirements as possible.

For example, a benchmark based entirely on constantly generated synthetic data could meet more than half of the 11 requirements. While there has been impressive progress in mimicking real-world data (Narasimhan et al., 2024), a question arises: as the generation process becomes more similar to actual historical data, does the risk of information leakage or memorizing global patterns increase? On the other hand, if the generation process is more independent of past data, we once again encounter the issue of lacking real-world relevance. Additionally, such synthetic data may be vulnerable to gaming if someone can reverse-engineer the data generation process. Nevertheless, it is worth considering this approach further.

To more comprehensively address the spectrum of requirements, a conceptual shift in how TSFM benchmarks are designed might be necessary. Imagine a framework built around a continuously advancing global temporal split. In such a system, TSFMs would be tasked with forecasting actual future events, with evaluations performed retrospectively as real-world data becomes available. This dynamic approach, where the "test set" is always the yet-unseen future, inherently addresses critical issues like information leakage from test set contamination or rote memorization. This evaluation seems especially applicable for time-series forecasting, which is uniquely concerned with future prediction unlike typical NLP or computer vision tasks.

Furthermore, since the test data would not exist during model training, restrictions on training data could be completely lifted, facilitating the evaluation of a broader range of models, including closed-source TSFMs. Still, this paradigm introduces new complexities. For instance, distinguishing purely zero-shot forecasts from fine-tuned forecasts could be difficult and leading to nonfulfillment of requirement 9. Here it might require complementary ideas. To further promote transparency regarding training data, the adoption of model cards could be encouraged as a best practice, though community acceptance, as seen with LLMs, might present a hurdle.

Undoubtedly, operationalizing such a benchmark would present significant implementation challenges, likely necessitating a dedicated platform. However, we posit that pursuing this line of thinking offers a promising avenue to resolve many of the current impasses in TSFM evaluation. We therefore call upon the research community to collaboratively explore and develop these concepts further, shaping a more robust and reliable future for time series forecasting benchmarks.

6 Conclusion

Remarkably, TSFMs appear to follow a development trajectory similar to that of LLMs in terms of both data and model size. Scaling laws seem to apply to TSFMs, and there are notable similarities in the evaluation challenges they face, particularly concerning potential information leakage. We highlight key evaluation challenges that arise from the emergence of TSFMs. By investigating the data lineage of 15 prominent TSFMs and reflecting the common TSFM training and evaluation strategy, we identified two significant sources of information leakage: test set contamination through multi-purpose use of datasets and memorization of global patterns induced by external events or crises. Furthermore, we question the current evaluation strategy that considers only the domain dimension while disregarding the temporal dimension, as well as the selection of time series used to represent a domain.

Current benchmark approaches from time-series or machine learning do not mitigate all information leakage risks. Based on our investigations and existing methodologies, we propose requirements for a benchmark in the age of TSFMs. We would like to encourage the community to develop new ideas which can fulfill the requirements like benchmarking on real future data. Besides the development of a benchmark methodology, we see several directions for future research that could also reinterpret our current results. The effect size of test set contamination (when a test dataset was present in the pretraining corpus) has only been proven to be significant in isolated cases so far. The magnitude of global pattern memorization is also largely unknown and is likely to vary depending on the domain, type of global event, and other factors. Carefully designed training regimes for TSFMs will be required to properly quantify these effects.

Ultimately, we believe that the criteria we have established lay the foundation for robust, fair, and information-leakage-free benchmarking. This is essential for preventing an evaluation crisis for TSFMs akin to what has been observed with LLMs.

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A Time Series Foundation Model Analysis

A.1 Overlap in test data usage

Table 2: Comparison of train/test evaluations of selected different models ordered by the total number of overlaps. For full results see Section C.

DATASET	CHRONOS	Moirai	MOMENT	TIME-LMM
ELECTRICITY (H)	T/T	-	T/T	T/T
TRAFFIC HOURLY (H)	-	T/T	T/T	T/T
ETT1 (H)	-	-	T/T	T/T
WEATHER (AUSTRALIA) (D)	-	T/T	-	T/T
M4 MONTHLY (M)	T/T	T/T	-	-
M4 HOURLY (H)	T/T	T/T	-	-
M4 Daily (D)	T/T	T/T	-	-
M4 WEEKLY (W-SUN)	T/T	T/T	-	-
ETT1 (15T)	-	-	T/T	T/T
ETT2 (15T)	-	-	T/T	T/T
ETT2 (H)	-	-	T/T	T/T
CDC FLUVIEW ILINET (W)	-	-	T/T	T/T

Table 3: Comparison of zero-shot evaluations of selected different models ordered by the total number of overlaps. Only datasets with 5 or more overlaps are shown. Models which have not included any of the shown datasets into their train/test evaluation are not displayed. For full results see Section C.

Dataset	CHRONOS	Moirai	Moirai-MoE	LAG-LLAMA	LLMTIME
JENA WEATHER (10T)	-	ZS	ZS	-	ZS
ETT2 (15T)	ZS	ZS	-	ZS	-
ELECTRICITY (H)	-	ZS	ZS	-	ZS
ETT2 (H)	ZS	ZS	-	-	-
ETT1 (H)	ZS	ZS	-	-	-
ETT1 (15T)	ZS	ZS	-	-	-
TRAFFIC HOURLY (H)	ZS	-	-	-	ZS

A.2 Data Analysis

Additional visualizations based on the analysis of Time Series Foundation Models training and evaluation data.

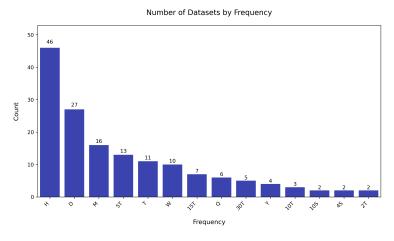


Figure 5: Most common frequencies in investigated datasets.

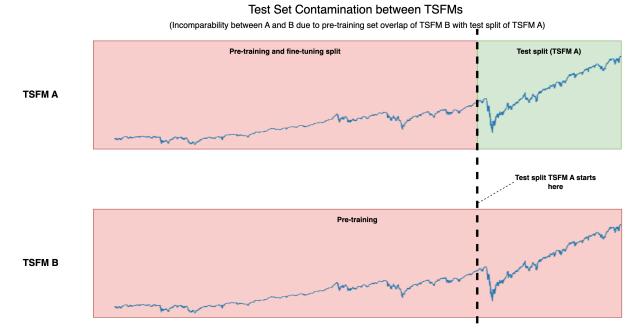


Figure 6: Test set contaminations when comparing TSFM A with TSFM B with overlapping pre-training and test sets on the test set of TSFM A.

B Leakage Investigations

B.1 Potential global pattern leakage in dataset collections

It may be theoretically possible that existing model evaluation results have already been influenced by global pattern leakage. We analyse the overlapping time frames in the Monash Dataset ⁷ as can be seen in Figure 7. Test datasets shouldn't lie in the same time period as other training datasets. As an example, the proposed Australian Electricity Demand test time frame (April 2015) lays in the same period as the training period of the "Weather (Australia)" training set (1900-2021). The Moirai and Moirai-MoE models use both datasets for train/test forecasts, meaning if their are any global patterns in the weather data which could influence the Australian Electricity Demand data, this would be a kind of information leakage. Similarly, the Oikolab Weather dataset ranges from 2010 January to 2021 May, which is weather data located in Melbourne. The test set of the dataset Pedestrian Count (also Melbourne) is located at the end of April 2020. This test period lays within the training data of the Oikolab Weather, which could be a greater potential global pattern information leakage than in previous example. Both datasets are included as well in the train/test datasets of Moirai and Moirai-MoE.

Moreover, LagLlama uses the *Beijing Multi-Site Air Quality* dataset from 12 districts in Beijing from 2013 to 2017 as a pre-training dataset and simultaneously uses the *Beijing PM2.5* air quality dataset from the Beijing airport between 2010 and 2013.

B.2 Leakage in Moirai Model

The investigated data includes 9 datasets on short horizons, four datasets each on medium (10x short horizon) and long horizons (15x short horizon). We filtered the results to 4 datasets where data is available for all horizons to reasonably compare the metrics and model sizes, as shown in Figure 8. On short horizons, both models perform better with increasing model size while *Moirai Leakage* has on average 7.6% points lower MAPE score. At medium horizons, the leakage-free *Moirai*_L generally underperforms compared to other model sizes, exhibiting an average performance deficit of 32% points compared to the *Moirai Leakage*_L model. On long horizons, all models perform significantly worse. However, *Moirai Leakage* achieves an average MAPE score that is 29% points lower than the leakage-free *Moirai*. Across all horizons, the biggest difference is between *Moirai*_L and *Moirai Leakage*_L, similar to typical LLM memorization behavior, when large models better memorize pre-train data than smaller models.

⁷https://huggingface.co/datasets/Monash-University/monash_tsf

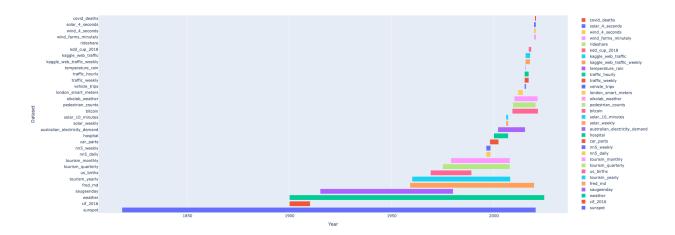


Figure 7: Date range of datasets within Monash dataset collection. Note that the "cif_2016" dataset was originally delivered without a timestamp and the start year was defined as 1900. No data cleaning was done.

Table 4: Information leakage in TSFM comparing Moirai with (MoiLeak) and without (Moi) information leakage during training phase for different model sizes. Metric is MAPE. Based on experiments by Aksu et al. (2024).

		Horizon	SHORT		MEDIUM		Long	
DATASET	FREQUENCY	MODEL SIZE	Moirai Leakage	Moirai	Moirai Leakage	Moirai	Moirai Leakage	Moirai
		S	0.84	0.87	0.75	0.77	0.70	0.75
LOOP_SEATTLE	5T	В	0.67	0.84	0.42	0.83	0.50	0.78
		L	0.66	0.83	0.33	0.85	0.46	0.81
		S	1.22	1.19	0.73	0.70	0.70	0.71
LOOP_SEATTLE	H	В	0.96	1.08	0.54	0.65	0.49	0.59
		L	0.84	0.89	0.53	0.71	0.47	1.18
		S	0.73	0.70	0.70	0.71	0.71	0.91
M_DENSE	H	В	0.54	0.65	0.49	0.59	0.53	0.61
		L	0.53	0.71	0.47	1.18	0.49	1.69
		S	0.95	1.11	0.65	0.60	2.12	2.30
SZ_TAXI	15T	В	0.90	0.84	0.71	0.64	2.16	2.42
		L	0.78	0.82	0.71	0.60	2.14	2.24

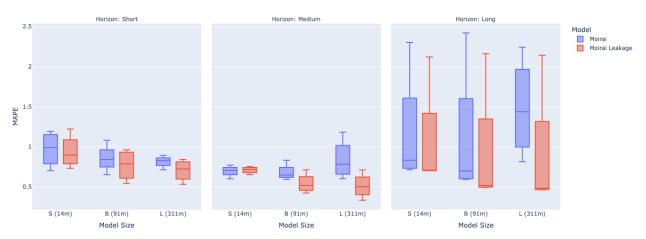


Figure 8: Comparing the model Moirai once with information leakage (Moirai Leakage), where the model was exposed to the test data during pre-training and the same model trained without information leakage (Moirai). Short, Medium and Long forecasting horizons were investigated. Model sizes are S (small), B (base) and L (large) and compared by the MAPE metric (the lower the better). Based on experiments by Aksu et al. (2024).

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C TSFM Data Lineage

Table 5: Analysis of datasets used by investigated TSFMs with Pre-training (P), train-test splits (T/T) and test (T).

Dataset	Source	Domain	Frequency	Chrones	TimecEM	Moirei	Moirai-MaF	Time-CPT	ForecastPFN	MOMENT	Lag-Harre	CPTATS	Timer	7SicionTS	TTM	I I MTime	Time-I MM	UniTime	Time-Mo
Jena Weather	Autoformer (Wu et al., 2021)	Nature	10T	Chronos	Timesrivi	ZS	ZS ZS	Time-GFT	Forecastrin	T/T	Lag-Liama	T/T		ZSISIOII I S	ZS		Time-LNIM	UniTime	T/T
Jena Weather	Autoformer (Wu et al., 2021)	Nature	H			Z.O	Z.o			1/1		1/1	Lo	2.3	Z.o	Z.o			1/1
Jena Weather	Autoformer (Wu et al., 2021)	Nature	D						ZS										
BizITObs - Application	AutoMixer (Palaskar et al., 2021)	Web/CloudOps		1					Z.o						ZS				-
BizITObs - Application	AutoMixer (Palaskar et al., 2024) AutoMixer (Palaskar et al., 2024)	Web/CloudOps					ZS								Z.o				
BizITObs - L2C	AutoMixer (Palaskar et al., 2024)	Web/CloudOps					Z.3	-											-
BizITObs - L2C	AutoMixer (Palaskar et al., 2024) AutoMixer (Palaskar et al., 2024)	Web/CloudOps						-											-
BDG-2 Bear	BuildingsBench (Emami et al., 2023)	Energy	H			D	D										1		D
BDG-2 Fox	BuildingsBench (Emami et al., 2023)	Energy	H			P	P D												P.
BDG-2 Pox BDG-2 Panther	BuildingsBench (Emami et al., 2023)	Energy	H			P	D												D
BDG-2 Pantilei	BuildingsBench (Emami et al., 2023)	Energy	H			P	D D	-											D
Borealis	BuildingsBench (Emami et al., 2023)	Energy	H			P	D D												D D
Buildings900K	BuildingsBench (Emami et al., 2023)	Energy	H			P	P												P
IDEAL	BuildingsBench (Emain et al., 2023)	Energy	H			P	P	-											D D
Low Carbon London	BuildingsBench (Emami et al., 2023)	Energy	H			P	P												г
Sceaux	BuildingsBench (Emami et al., 2023) BuildingsBench (Emami et al., 2023)	Energy	Н			P	P												D
SMART	BuildingsBench (Emami et al., 2023) BuildingsBench (Emami et al., 2023)					P	-												P
CMIP6		Energy	H			P	P												P
ERA5	ClimateLearn (Nguyen et al., 2023)	Climate	6H			P	P						- N						P
	ClimateLearn (Nguyen et al., 2023)		H			P	P						P						
Alibaba Cluster Trace 2018	CloudOpsTSF (Woo et al., 2023)		5T			P	P												P
Azure vM Traces 2017	CloudOpsTSF (Woo et al., 2023)	CloudOps	5T			P	P												P
Borg Cluster Data 2011	CloudOpsTSF (Woo et al., 2023)	CloudOps	5T		70	P	P									70			P
Air Passengers	Darts Dataset (Herzen et al., 2021)	Econ/Fin	M		ZS											ZS			
Aus Beer	Darts Dataset (Herzen et al., 2021)	Econ/Fin	Q		ZS											ZS			
Gas Rate CO2	Darts Dataset (Herzen et al., 2021)	Econ/Fin	Y		ZS											ZS			
Monthly Milk	Darts Dataset (Herzen et al., 2021)	Econ/Fin	M		ZS											ZS			
Wine	Darts Dataset (Herzen et al., 2021)	Sales	M		ZS											ZS			
Wooly	Darts Dataset (Herzen et al., 2021)	Econ/Fin	Q		ZS											ZS			
Heart Rate	Darts Dataset (Herzen et al., 2021)	Nature	0.5S		ZS											ZS			
Sunspots	Darts Dataset (Herzen et al., 2021)	Nature	M													ZS			
Bitbrains	Fast Storage Grid Workloads Archive (Shen et al., 2015)		5T																
Bitbrains	Fast Storage Grid Workloads Archive (Shen et al., 2015)		H																
Bitbrains	Fast Storage Grid Workloads Archive (Shen et al., 2015)		5T																
Bitbrains	Fast Storage Grid Workloads Archive (Shen et al., 2015)	Web/CloudOps	Н																
FRED	FRED (Oreshkin et al., 2021)	Econ/Fin	D							P									
FRED	FRED (Oreshkin et al., 2021)	Econ/Fin	Y							P									
FRED	FRED (Oreshkin et al., 2021)	Econ/Fin	W							P									
FRED	FRED (Oreshkin et al., 2021)	Econ/Fin	M							P									
FRED	FRED (Oreshkin et al., 2021)	Econ/Fin	0							P									
M5	GluonTS (Alexandrov et al., 2020a)	Sales	D	ZS		P	P												P
Taxi	GluonTS (Alexandrov et al., 2020a)	Transport	30T	T/T		P	P												P
Taxi	GluonTS (Alexandrov et al., 2020a)	Transport	Н	P															P
Uber TLC Daily	GluonTS (Alexandrov et al., 2020a)	Transport	D	T/T		P	P												P
Uber TLC Hourly	GluonTS (Alexandrov et al., 2020a)	Transport	H	T/T		P	P				P								P
Wiki-Rolling	GluonTS (Alexandrov et al., 2020a)	Web	D	-,-			-				-								P
Trends hourly	Google Trends	Web	H		P														
Trends weekly	Google Trends	Web	W		P			1											1
Trends monthly	Google Trends	Web	D	l	P			t	I			-							
Requests	Huawei Cloud (Joosen et al., 2023)	CloudOps	T		· -			1			ZS						1		1
Function Delay	Huawei Cloud (Joosen et al., 2023)	CloudOps	T								P								
Platform Delay	Huawei Cloud (Joosen et al., 2023)	CloudOps	T								ZS								
CPU Usage	Huawei Cloud (Joosen et al., 2023)	CloudOps	Ť								P								
Memory Usage	Huawei Cloud (Joosen et al., 2023)	CloudOps	Ť								P								
CPU Limit	Huawei Cloud (Joosen et al., 2023)	CloudOps	Ť								P								
Memory Limit	Huawei Cloud (Joosen et al., 2023) Huawei Cloud (Joosen et al., 2023)	CloudOps	T								D								
Instances	Huawei Cloud (Joosen et al., 2023) Huawei Cloud (Joosen et al., 2023)	CloudOps	T								P								
ETT1	Informer (Zhou et al., 2020)		1 15T	ZS		ZS				T/T	P	T/T	ZS	70	ZS		T/T	T/T	T/T
ETT1		Energy						+		T/T	P	T/T		ZS				T/T	
ETTI	Informer (Zhou et al., 2020)	Energy	H	ZS		ZS	70	1	70	T/T	r	T/T	ZS	ZS	ZS		T/T	T/T	T/T
	Informer (Zhou et al., 2020)	Energy	D				ZS	1	ZS										
ETT1	Informer (Zhou et al., 2020)	Energy	W-THU	70		70		1		T.C.	70	TO ATT	70	70	70		TO PE	T.ET	TOTAL
ETT2	Informer (Zhou et al., 2020)	Energy	15T	ZS		ZS		1		T/T	ZS	T/T	ZS	ZS	ZS		T/T	T/T	T/T
ETT2	Informer (Zhou et al., 2020)	Energy	Н	ZS		ZS		1		T/T	P	T/T	ZS	ZS	ZS		T/T	T/T	T/T
ETT2	Informer (Zhou et al., 2020)	Energy	D				ZS		ZS										
ETT2	Informer (Zhou et al., 2020)	Energy	W-THU																
Weather (US)	Informer (Zhou et al., 2020)	Weather	H													ZS			
	Kaggle Competition	Weather	M	P															
Brazilian Cities Temperature																			
Walmart Store Sales	Kaggle Competition	Sales	W			ZS	ZS							ZS					
Walmart Store Sales Istanbul Traffic	Kaggle Competition Kaggle Competition	Transport	Н			ZS	ZS							ZS					
Walmart Store Sales	Kaggle Competition															ZS ZS			

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Dataset	Source	Domain	Frequency	Chronos	TimesFM	Moirai	Moirai-MoE	Time-GPT	ForecastPFN	MOMENT	Lag-Llama	GPT4TS	Timer	ZSisionTS	TTM	LLMTime	Time-LMM	UniTime	Time-Mo
LargeST	LargeST (Liu et al., 2023a)	Transport	5T		I	P	P												P
Beijing Subway	LibCity (Wang et al., 2023a)	Transport	30T			P	P												P
HZMetro	LibCity (Wang et al., 2023a)	Transport	15T			P	P												P
Loop Seattle	LibCity (Wang et al., 2023a)	Transport	5T			P	P												P
Loop Seattle	LibCity (Wang et al., 2023a)	Transport	Н																
Loop Seattle	LibCity (Wang et al., 2023a)	Transport	D																
Los-Loop	LibCity (Wang et al., 2023a)	Transport	5T			P	P								P				P
M_DENSE	LibCity (Wang et al., 2023a)	Transport	Н																
M DENSE	LibCity (Wang et al., 2023a)	Transport	D				ZS					į							
PEMS Bay	LibCity (Wang et al., 2023a)	Transport	5T			P	P								P				P
PEMS03	LibCity (Wang et al., 2023a)	Transport	5T			P	P						ZS		P				P
PEMS04	LibCity (Wang et al., 2023a)	Transport	5T			P	P						ZS		P				P
PEMS07	LibCity (Wang et al., 2023a)	Transport	5T			P	P						ZS		P				P
PEMS08	LibCity (Wang et al., 2023a)	Transport	5T			P	P			T/T			ZS		P				P
Q-Traffic	LibCity (Wang et al., 2023a)	Transport	15T		P	P	P			-,-					P				P
SHMetro	LibCity (Wang et al., 2023a)	Transport	15T		P	P	P												P
SZ-Taxi	LibCity (Wang et al., 2023a)	Transport	15T		P		•				+				P	+			P
SZ-Taxi	LibCity (Wang et al., 2023a)	Transport	H		-								_		P	+			+•
Rotterdam	LibCity (Wang et al., 2023a)	Transport	2T			P	p				+							_	_
Beijing Air Quality	LOTSA Others (Woo et al., 2024)	Nature	H		+	P	P				P	-	P		_	+		+	P
CDC Fluview ILINet	LOTSA_Others (Woo et al., 2024)	Healthcare	W		+	P	I D		70	T/T	+	T/T	-	ZS	+	+	T/T	T/T	I.
					+	•	P		ZS	1/1	+	1/1	—		+	+			P
CDC Fluview WHO NREVSS	LOTSA_Others (Woo et al., 2024)	Healthcare	W			P	P		1			 '	<u> </u>	ZS			T/T	T/T	I P
China Air Quality	LOTSA_Others (Woo et al., 2024)	Nature	Н			P	P						P						P
Favorita Sales	LOTSA_Others (Woo et al., 2024)	Sales	D		P	P	P					'				1			P
Favorita Transactions	LOTSA_Others (Woo et al., 2024)	Sales	D			P	P												P
GoDaddy	LOTSA_Others (Woo et al., 2024)	Econ/Fin	M			P	P												
KDD Cup 2022	LOTSA_Others (Woo et al., 2024)	Energy	10T			P	P												P
Project Tycho	LOTSA_Others (Woo et al., 2024)	Healthcare	W			P	P												P
Residential Load Power	LOTSA_Others (Woo et al., 2024)	Energy	T			P	P												P
Residential PV Power	LOTSA_Others (Woo et al., 2024)	Energy	T	1	1	P	P					·							P
Restaurant	LOTSA Others (Woo et al., 2024)	Sales	D	1	1				1			г т			T	1		1	P
Solar	LSTNet (Lai et al., 2017)	Energy	10T			-													
Solar	LSTNet (Lai et al., 2017)	Energy	5T	P							_							_	
Solar	LSTNet (Lai et al., 2017)	Energy	H	P		ZS	ZS							ZS	$\overline{}$				
Solar	LSTNet (Lai et al., 2017)	Energy	D	_															
Solar	LSTNet (Lai et al., 2017)	Energy	W-FRI																
Exchange Rate	LSTNet (Lai et al., 2017)	Econ/Fin	D D	ZS					ZS	T/T	ZS					ZS		T/T	p
Hierarchical Sales (M5 Competition)	Mancuso et al. (2020)	Sales	D	LO	+	_			2.3	1/1	2.0					2.3		1/1	P
Hierarchical Sales (M5 Competition)		Sales	W-WED	1	+	+			+		+	├ ──			+	+		+	1
Australian Electricity Demand	Monash (Godahewa et al., 2021)	Energy	30T	ZS	ZS	T/T	T/T		1	D	D		D	ZS	P	ZS			P
	Monash (Godanewa et al., 2021) Monash (Godanewa et al., 2021)		D D	ZS	ZS					P	P		P	ZS	P	ZS			P
Bitcoin		Econ/Fin			ZS	T/T	T/T						P		P	ZS			P
Car Parts	Monash (Godahewa et al., 2021)	Sales	M	770	770	T/T	T/T			P				ZS		70			l'
CIF 2016	Monash (Godahewa et al., 2021)	Econ/Fin	M	ZS	ZS	T/T	T/T			P	4			ZS		ZS			P
COVID Deaths	Monash (Godahewa et al., 2021)	Healthcare	D	ZS	ZS	T/T	T/T			P				ZS		ZS			P
Covid Mobility	Monash (Godahewa et al., 2021)	Transport	D			T/T	T/T												P
Elecdemand	Monash (Godahewa et al., 2021)	Energy	30T			T/T	T/T									4			P
Extended Web Traffic	Monash (Godahewa et al., 2021)	Web	D			T/T	T/T						P		P				P
FRED MD	Monash (Godahewa et al., 2021)	Econ/Fin	M	ZS	ZS	T/T	T/T			P				ZS		ZS			P
Hospital	Monash (Godahewa et al., 2021)	Healthcare	M	ZS	ZS	T/T	T/T			P				ZS		ZS			P
Kaggle Web Traffic Weekly	Monash (Godahewa et al., 2021)	Web	W			P	P			P									P
KDD Cup 2018	Monash (Godahewa et al., 2021)	Nature	Н	T/T		T/T	T/T			P	P		P	ZS	P				P
KDD Cup 2018	Monash (Godahewa et al., 2021)	Nature	D																
London Smart Meters	Monash (Godahewa et al., 2021)	Energy	30T	T/T		P	P			P	P		P		P				P
M1 Monthly	Monash (Godahewa et al., 2021)	Econ/Fin	M	ZS	-	T/T	T/T			P				ZS					P
M1 Quarterly	Monash (Godahewa et al., 2021)	Econ/Fin	0	ZS		P	P P			P		-			_	+			P
M1 Yearly	Monash (Godahewa et al., 2021)	Econ/Fin	Ÿ	ZS		P	P			P		-							P
M3 Monthly	Monash (Godahewa et al., 2021)	Econ/Fin	M	ZS		T/T	T/T			ZS		T/T		ZS				_	P
M3 Other	Monash (Godanewa et al., 2021) Monash (Godanewa et al., 2021)	Econ/Fin Econ/Fin		LO		T/T	T/T			د مع		T/T		ZS					l'
			Q	70			1/1 P			70				2.3				_	D
M3 Quarterly	Monash (Godahewa et al., 2021)	Econ/Fin	Q	ZS		P				ZS	4	T/T				4			P
M3 Yearly	Monash (Godahewa et al., 2021)	Econ/Fin	Y	ZS		P	P			ZS	4	T/T				4			P
M4 Daily	Monash (Godahewa et al., 2021)	Econ/Fin	D	T/T	P	T/T	T/T			P		T/T		ZS					P
M4 Hourly	Monash (Godahewa et al., 2021)	Econ/Fin	Н	T/T	P	T/T	T/T			P		T/T		ZS					P
M4 Monthly	Monash (Godahewa et al., 2021)	Econ/Fin	M	T/T	P	T/T	T/T			ZS		T/T		ZS					P
M4 Quarterly	Monash (Godahewa et al., 2021)	Econ/Fin	Q-DEC	ZS	P	P	P			ZS		T/T							P
	Monash (Godahewa et al., 2021)	Econ/Fin	W-SUN	T/T	P	T/T	T/T					T/T		ZS					P
M4 Weekly		Econ/Fin	A-DEC	ZS	P	P	P			ZS		T/T							P
	Monash (Godahewa et al., 2021)																		
M4 Yearly	Monash (Godahewa et al., 2021) Monash (Godahewa et al., 2021)				ZS	T/T	T/T			P				7.5	P	ZS			P
M4 Weekly M4 Yearly NN5 Daily NN5 Weekly	Monash (Godahewa et al., 2021) Monash (Godahewa et al., 2021) Monash (Godahewa et al., 2021)	Econ/Fin Econ/Fin	D W	ZS ZS	ZS ZS	T/T T/T	T/T T/T			P P				ZS ZS	P	ZS ZS			P

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Dataset	Source	Domain	Frequency		TimesFM			Time-GPT	ForecastPFN	MOMENT		GPT4TS			TTM		Time-LMM	UniTime	Time-MoE
Pedestrian Counts	Monash (Godahewa et al., 2021)	Transport	H	T/T	ZS	T/T	T/T			P	ZS		P	ZS		ZS			P
Rideshare Saugeen	Monash (Godahewa et al., 2021) Monash (Godahewa et al., 2021)	Transport Nature	H D	T/T	ZS	T/T T/T	T/T T/T			P			P	ZS ZS	P	ZS			P
Saugeen	Monash (Godahewa et al., 2021)	Nature	W-THU		2.5	1/1	1/1			Г			г	2.5	г	2.5			Г
Saugeen	Monash (Godahewa et al., 2021)	Nature	M																
Solar Power (Australia)	Monash (Godahewa et al., 2021)	Energy	4S			T/T	T/T			P									P
Solar	Monash (Godahewa et al., 2021)	Energy	W		ZS					P					P	ZS			
Solar	Monash (Godahewa et al., 2021)	Energy	10M							P	P		_		P				
Sunspot Temperature Rain	Monash (Godahewa et al., 2021) Monash (Godahewa et al., 2021)	Nature Nature	D D	T/T	ZS	T/T T/T	T/T T/T			P P	P		P P	ZS ZS	P	ZS			P
Tourism Monthly	Monash (Godahewa et al., 2021)	Econ/Fin	M	ZS	ZS	1/1	1/1			P		T/T	Г	ZS		ZS			P
Tourism Quarterly	Monash (Godahewa et al., 2021)	Econ/Fin	Q	ZS	ZS					P		T/T		ZS		ZS			P
Tourism Yearly	Monash (Godahewa et al., 2021)	Econ/Fin	Ŷ	ZS	ZS	P	P			P		T/T				ZS			P
Traffic Hourly	Monash (Godahewa et al., 2021)	Transport	Н	ZS	P	T/T	T/T			T/T	P	T/T	ZS	ZS	ZS	ZS	T/T		P
Traffic Weekly	Monash (Godahewa et al., 2021)	Transport	W		ZS	T/T	T/T		ZS	P				ZS		ZS			P
US Births	Monash (Godahewa et al., 2021)	Healthcare			ZS	T/T	T/T			P			P	ZS	P	ZS			P
US Births US Births	Monash (Godahewa et al., 2021) Monash (Godahewa et al., 2021)	Healthcare Healthcare														ļ			
Vehicle Trips	Monash (Godahewa et al., 2021)	Transport	D			T/T	T/T			P				ZS					P
Weather (Australia)	Monash (Godahewa et al., 2021)	Climate	D	ZS	ZS	T/T	T/T			P	ZS			ZS	P		T/T	T/T	P
Wind Farms	Monash (Godahewa et al., 2021)	Energy	T			T/T	T/T			P						İ			P
Wind Farms	Monash (Godahewa et al., 2021)	Energy	Н	P											P				
Wind Farms	Monash (Godahewa et al., 2021)	Energy	D	P															
Wind Farms	Monash (Godahewa et al., 2021)	Energy	5T							_	P								
Wind Power	Monash (Godahewa et al., 2021) Monash (Godahewa et al., 2021)	Energy	4S D			T/T	T/T			P			P						
Restaurant Recruit	Other	Web Sales	D							P									
Subseasonal	Other	Climate	D			P	P												P
Subseasonal Precipitation	Other	Climate	D			P	P												P
USHCN	Other	Weather	D	P															
Mexico City Bikes	Other	Transport	Н	P															P
Dominick	Other	Sales	D	ZS						P									P
ERCOT Load Weather (US)	Other Other	Energy Weather	H 10T	ZS	D											ZS			P
Bike Sharing	Other	Transport	H		P										ZS	ZS			
CC Carbon	Other	Energy	2T												ZS	120			
Air Quality	Other	Nature	Н								P								
Beijing PM 2.5	Other	Nature	Н								ZS								
TDBrain	Other	Healthcare	0.002S										P						
SensorData	Other D. F. C. V	IoT	0.02S	ļ		P	P						P			1			 P
BDG-2 Bull BDG-2 Cockatoo	ProEnFo (Wang et al., 2023b) ProEnFo (Wang et al., 2023b)	Energy Energy	H			P	P												P
BDG-2 Cockatoo	ProEnFo (Wang et al., 2023b)	Energy	Н			P P	P												P
Covid19 Energy	ProEnFo (Wang et al., 2023b)	Energy	H			P	P												P
ELF	ProEnFo (Wang et al., 2023b)	Energy	Н			P	P												
GEF12	ProEnFo (Wang et al., 2023b)	Energy	Н			P	P												P
GEF14	ProEnFo (Wang et al., 2023b)	Energy	Н			P	P												P
GEF17	ProEnFo (Wang et al., 2023b)	Energy	H			P	P												D
PDB Spanish	ProEnFo (Wang et al., 2023b) ProEnFo (Wang et al., 2023b)	Energy	H H	p		P	P												P
Australia Rainfall	Tan et al., 2021	Energy Nature	H	Г		г	1"						P						I'
Beijing PM 2.5	Tan et al., 2021	Nature	Н	 									P		1	1			
BenzeneConcentration	Tan et al., 2021	Nature	H										P				1		
IEEEPPG	Tan et al., 2021	Healthcare	0.008S										P		t				
BIDMC32HR	Tan et al., 2021	Healthcare	-										P						
Dodger	TSB-UAD (Paparrizos et al., 2022)	Traffic	-							P									
ECG IOPS	TSB-UAD (Paparrizos et al., 2022)	Healthcare Web	-							P P									
KDD21	TSB-UAD (Paparrizos et al., 2022) TSB-UAD (Paparrizos et al., 2022)	Multiple	-							P									
MGAB	TSB-UAD (Paparrizos et al., 2022)	Synthetic	-							P									
NAB	TSB-UAD (Paparrizos et al., 2022)	Web	-							P									
SensorScope	TSB-UAD (Paparrizos et al., 2022)	Nature	-							P									
YAHOO	TSB-UAD (Paparrizos et al., 2022)	Web	-							P									
NASA-MSL	TSB-UAD (Paparrizos et al., 2022)	Sensor	-							P									
NASA-SMAP	TSB-UAD (Paparrizos et al., 2022)	Sensor	-							P									
Daphnet	TSB-UAD (Paparrizos et al., 2022)	Gait	-							P									
GHL	TSB-UAD (Paparrizos et al., 2022)	Sensor	-							P									

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Dataset	Source	Domain	Frequency	Chronos	TimesFM	Moirai	Moirai-MoE	Time-GPT	ForecastPFN	MOMENT	Lag-Llama	GPT4TS	Timer	ZSisionTS	TTM	LLMTime	Time-LMM	UniTime	Time-MoE
Genesis MITDB	TSB-UAD (Paparrizos et al., 2022) TSB-UAD (Paparrizos et al., 2022)	Sensor Healthcare	-							P								1	
OPP	TSB-UAD (Paparrizos et al., 2022) TSB-UAD (Paparrizos et al., 2022)	Sensor	-							P									
Occupancy	TSB-UAD (Paparrizos et al., 2022)	Sensor	-							P									
SMD	TSB-UAD (Paparrizos et al., 2022)	Web	1							P									+
SZSDB	TSB-UAD (Paparrizos et al., 2022)	Healthcare								P									
Electricity	UCI ML Archive (Trindade, 2015)	Energy	15T	T/T	P					T/T			 						P
Electricity	UCI ML Archive (Trindade, 2015)	Energy	H	T/T	P	ZS	ZS			T/T	P	T/T	ZS	ZS	ZS	ZS	T/T	T/T	+
Electricity	UCI ML Archive (Trindade, 2015)	Energy	D	-7.2	1.	2.0	2.0		ZS	-7.2	•		2.0	2	2.0	2.0	17.1	-/	-
Electricity	UCI ML Archive (Trindade, 2015)	Energy	W-FRI	T/T	-	_			2.0				_						+
Electricity	UCI ML Archive (Trindade, 2015)	Energy	M									T/T							
Electricity	UCI ML Archive (Trindade, 2015)	Energy	W							P									P
SemgHandGenderCh2	UCR Archive (Ismail Fawaz et al., 2019)	Human	-		1					P									_
GestureMidAirD2	UCR Archive (Ismail Fawaz et al., 2019)	Human	-							P									
UWaveGestureLibraryAll	UCR Archive (Ismail Fawaz et al., 2019)	Human	-							T/T									
SelfRegulationSCP1	UCR Archive (Ismail Fawaz et al., 2019)	Healthcare	-							P		i	P					ĺ	1
UWaveGestureLibraryX	UCR Archive (Ismail Fawaz et al., 2019)	Human	-							P									
GesturePebbleZ2	UCR Archive (Ismail Fawaz et al., 2019)	Human	-		İ		İ	İ	İ	P		İ		İ	İ			İ	1
Healthcare5000	UCR Archive (Ismail Fawaz et al., 2019)	Healthcare	-							T/T									
OSULeaf	UCR Archive (Ismail Fawaz et al., 2019)	Nature	-							T/T									
MedicalImages	UCR Archive (Ismail Fawaz et al., 2019)	Healthcare	-							T/T									
Haptics	UCR Archive (Ismail Fawaz et al., 2019)	Human	-							P									
LargeKitchenAppliances	UCR Archive (Ismail Fawaz et al., 2019)	Power	-							P									
Japanesevowels	UCR Archive (Ismail Fawaz et al., 2019)	Audio	-							P									
Worms	UCR Archive (Ismail Fawaz et al., 2019)	Nature	-							P									
Ham	UCR Archive (Ismail Fawaz et al., 2019)	Facilities	-							T/T									
DistalPhalanxTW	UCR Archive (Ismail Fawaz et al., 2019)	Nature	-							P									
	UCR Archive (Ismail Fawaz et al., 2019)	Nature	-							P									
SemgHandMovementCh2	UCR Archive (Ismail Fawaz et al., 2019)	Human	-							P									
RefrigerationDevices	UCR Archive (Ismail Fawaz et al., 2019) UCR Archive (Ismail Fawaz et al., 2019)	Power	-							P									
FreezerRegularTrain PigAirwayPressure	UCR Archive (Ismail Fawaz et al., 2019) UCR Archive (Ismail Fawaz et al., 2019)	Facilities	-							P									1
TwoLeadECG	UCR Archive (Ismail Fawaz et al., 2019)	Nature Healthcare	-							P									
GunPointMaleversusFemale	UCR Archive (Ismail Fawaz et al., 2019)	Human	-		ł			ļ.		P		ļ							
Trace	UCR Archive (Ismail Fawaz et al., 2019)	Power	-							P D									
SmoothSubspace	UCR Archive (Ismail Fawaz et al., 2019)	Generated								D									
MiddlePhalanxTW	UCR Archive (Ismail Fawaz et al., 2019)	Nature								P									
AtrialFibrillation	UCR Archive (Ismail Fawaz et al., 2019)	Healthcare	-							P			P						
SyntheticControl	UCR Archive (Ismail Fawaz et al., 2019)	Generated	-							P									_
ShapesAll	UCR Archive (Ismail Fawaz et al., 2019)	Generated	-							P									
Human	UCR Archive (Ismail Fawaz et al., 2019)	BodyZSerticalSignal	-		İ			İ		P		i			i				1
PLAID	UCR Archive (Ismail Fawaz et al., 2019)	Facilities	-							P									
AllGestureWiimoteX	UCR Archive (Ismail Fawaz et al., 2019)	Human	-		İ		İ	İ	İ	P		i			İ			İ	1
Heartbeat	UCR Archive (Ismail Fawaz et al., 2019)	Healthcare	-							P									
Wafer	UCR Archive (Ismail Fawaz et al., 2019)	Facilities	-							P									
FaceFour	UCR Archive (Ismail Fawaz et al., 2019)	Generated	-							P									
Phoneme	UCR Archive (Ismail Fawaz et al., 2019)	Audio	-							P			P						
InlineSkate	UCR Archive (Ismail Fawaz et al., 2019)	Human	-							P									
CricketX	UCR Archive (Ismail Fawaz et al., 2019)	Human Body	-							P									
SelfRegulationSCP2	UCR Archive (Ismail Fawaz et al., 2019)	Healthcare	-							P			P						
DistalPhalanxOutlineCorrect	UCR Archive (Ismail Fawaz et al., 2019)	Nature	-							P									
ChlorineConcentration	UCR Archive (Ismail Fawaz et al., 2019)	Nature	-							P									
Chinatown	UCR Archive (Ismail Fawaz et al., 2019)	Traffic	-							P									
GestureMidAirD1	UCR Archive (Ismail Fawaz et al., 2019)	Human	-							P									1
	UCR Archive (Ismail Fawaz et al., 2019)	Nature	-							P									+
UMD	UCR Archive (Ismail Fawaz et al., 2019)	Generated	-							P									
Crop	UCR Archive (Ismail Fawaz et al., 2019)	Nature	-							P									
PenDigits GesturePebbleZ1	UCR Archive (Ismail Fawaz et al., 2019) UCR Archive (Ismail Fawaz et al., 2019)	Facilities Human	-							P									1
Handwriting	UCR Archive (Ismail Fawaz et al., 2019) UCR Archive (Ismail Fawaz et al., 2019)	Human Facilities	-							P									
Mallat	UCR Archive (Ismail Fawaz et al., 2019)	Generated	-							P									
ERing	UCR Archive (Ismail Fawaz et al., 2019)	Human								P									
StarLightCurves	UCR Archive (Ismail Fawaz et al., 2019)	Nature	-							P			P						
WordSynonyms	UCR Archive (Ismail Fawaz et al., 2019)	Audio								P			r						
PEMS-SF	UCR Archive (Ismail Fawaz et al., 2019)	Traffic								P									
FaceDetection	UCR Archive (Ismail Fawaz et al., 2019)	Human								P								1	
Computers	UCR Archive (Ismail Fawaz et al., 2019)	Power	-							P									
ArrowHead	UCR Archive (Ismail Fawaz et al., 2019)	Generated	-							P									
Wine	UCR Archive (Ismail Fawaz et al., 2019)	Nature	-							P									
Coffee	UCR Archive (Ismail Fawaz et al., 2019)	Nature	-							P									
		Nature	1 -							P									
Earthquakes	UCR Archive (Ismail Fawaz et al., 2019)																		

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Dataset	Source		Chronos	TimesFM	Moirai	Moirai-MoE	Time-GPT	ForecastPFN	MOMENT	Lag-Llama	GPT4TS	Timer	ZSisionTS	TTM LLMTime	Time-LMM	UniTime	Time-MoE
Lightning2		Nature -							P								
Beef	UCR Archive (Ismail Fawaz et al., 2019)	Nature -							P								
MiddlePhalanxOutlineCorrect	UCR Archive (Ismail Fawaz et al., 2019)	Nature -							P								
HealthcareFiveDays Yoga	UCR Archive (Ismail Fawaz et al., 2019) UCR Archive (Ismail Fawaz et al., 2019)	Healthcare - Human -							P								
Adiac		Nature -							P								
HandMovementDirection	UCR Archive (Ismail Fawaz et al., 2019)	Human -							P								
MoteStrain	UCR Archive (Ismail Fawaz et al., 2019)	Facilities -							P								
Rock	UCR Archive (Ismail Fawaz et al., 2019)	Nature -							P								
Strawberry	UCR Archive (Ismail Fawaz et al., 2019)	Nature -							P								
InsectWingbeatSound	UCR Archive (Ismail Fawaz et al., 2019) UCR Archive (Ismail Fawaz et al., 2019)	Nature - Traffic -							P								
DodgerLoopWeekend MixedShapesSmallTrain	UCR Archive (Ismail Fawaz et al., 2019) UCR Archive (Ismail Fawaz et al., 2019)	Generated -							P								
EthanolConcentration	UCR Archive (Ismail Fawaz et al., 2019)	Power -							P								
OliveOil	UCR Archive (Ismail Fawaz et al., 2019)	Nature -							P								
Meat	UCR Archive (Ismail Fawaz et al., 2019)	Nature -							P								
MelbournePedestrian	UCR Archive (Ismail Fawaz et al., 2019)	Traffic -							P								
Car	UCR Archive (Ismail Fawaz et al., 2019)	Facilities -							P								
FaceAll	UCR Archive (Ismail Fawaz et al., 2019)	Human -							P								
FacesUCR AllGestureWiimoteY	UCR Archive (Ismail Fawaz et al., 2019) UCR Archive (Ismail Fawaz et al., 2019)								P								
AllGestureWilmote Y NATOPS	UCR Archive (Ismail Fawaz et al., 2019) UCR Archive (Ismail Fawaz et al., 2019)	Human -							P								
SemgHandSubjectCh2	UCR Archive (Ismail Fawaz et al., 2019)	Human -							P								
ShakeGestureWiimoteZ	UCR Archive (Ismail Fawaz et al., 2019)	Human -							P								
Cricket	UCR Archive (Ismail Fawaz et al., 2019)	Human -							P								
BME	UCR Archive (Ismail Fawaz et al., 2019)	Generated -							P								
EigenWorms	UCR Archive (Ismail Fawaz et al., 2019)	Nature -							P			P					
FordB	UCR Archive (Ismail Fawaz et al., 2019)	Facilities -							P								
NonInvasiveFetalHealthcareThorax1	UCR Archive (Ismail Fawaz et al., 2019)	Healthcare -							P								
UWaveGestureLibrary	UCR Archive (Ismail Fawaz et al., 2019)	Human -							P								
CinCHealthcareTorso PigArtPressure	UCR Archive (Ismail Fawaz et al., 2019) UCR Archive (Ismail Fawaz et al., 2019)	Healthcare - Nature -							P			D					
Fish	UCR Archive (Ismail Fawaz et al., 2019)	Nature -							P			г					
SonyAIBORobotSurface2	UCR Archive (Ismail Fawaz et al., 2019)	Facilities -							P								
FiftyWords	UCR Archive (Ismail Fawaz et al., 2019)	Facilities -							P								
MotorImagery	UCR Archive (Ismail Fawaz et al., 2019)	Healthcare -							P			P					
ToeSegmentation1	UCR Archive (Ismail Fawaz et al., 2019)	Human -							P								
PhonemeSpectra	UCR Archive (Ismail Fawaz et al., 2019)	Audio -							P								
FreezerSmallTrain	UCR Archive (Ismail Fawaz et al., 2019)	Facilities -							P								
TwoPatterns	UCR Archive (Ismail Fawaz et al., 2019) UCR Archive (Ismail Fawaz et al., 2019)	Generated -							P								
ShapeletSim Plane	UCR Archive (Ismail Fawaz et al., 2019)	Generated -							P								
GestureMidAirD3	UCR Archive (Ismail Fawaz et al., 2019)	Human -							P								
DiatomSizeReduction	UCR Archive (Ismail Fawaz et al., 2019)	Generated -							P								
Human	UCR Archive (Ismail Fawaz et al., 2019)	BodyHorizontalSignal -							P								
CricketZ		Human -							P								
StandWalkJump	UCR Archive (Ismail Fawaz et al., 2019)	Human -							P								
WormsTwoClass	UCR Archive (Ismail Fawaz et al., 2019)	Human -							P								
Lightning7		Nature -							P								
UWaveGestureLibraryY	UCR Archive (Ismail Fawaz et al., 2019) UCR Archive (Ismail Fawaz et al., 2019)	Human -							P								
GunPointAgeSpan DistalPhalanxOutlineAgeGroup	UCR Archive (Ismail Fawaz et al., 2019)	Nature -							P								
SwedishLeaf	UCR Archive (Ismail Fawaz et al., 2019)	Nature -							P								
LSST	UCR Archive (Ismail Fawaz et al., 2019)	Nature -							P								
CBF	UCR Archive (Ismail Fawaz et al., 2019)	Generated -							P								
BeetleFly		Nature -							P								
Libras	UCR Archive (Ismail Fawaz et al., 2019)	Human -							P								
HouseTwenty	UCR Archive (Ismail Fawaz et al., 2019)	Facilities -							P								
ScreenType InsectEPGSmallTrain	UCR Archive (Ismail Fawaz et al., 2019) UCR Archive (Ismail Fawaz et al., 2019)	Facilities -							P								
AllGestureWiimoteZ	UCR Archive (Ismail Fawaz et al., 2019)	Sensor -							P								
DodgerLoopDay	UCR Archive (Ismail Fawaz et al., 2019)	Sensor -							P								
NonInZSasiZSeFetalHealthcareThorax2	UCR Archive (Ismail Fawaz et al., 2019)	Healthcare -							P								
BasicHuman	UCR Archive (Ismail Fawaz et al., 2019)	Bodys -							P								
GunPointOldversusYoung	UCR Archive (Ismail Fawaz et al., 2019)	Human -							P								
FordA	UCR Archive (Ismail Fawaz et al., 2019)	Sensor -							P								
InsectWingbeat	UCR Archive (Ismail Fawaz et al., 2019)	Nature -							P								
ItalyPowerDemand	UCR Archive (Ismail Fawaz et al., 2019)	Power -							P								
ProximalPhalanxOutlineAgeGroup ACSF1	UCR Archive (Ismail Fawaz et al., 2019) UCR Archive (Ismail Fawaz et al., 2019)	Nature -							P								
GunPoint	UCR Archive (Ismail Fawaz et al., 2019) UCR Archive (Ismail Fawaz et al., 2019)								P								
RacketSports	UCR Archive (Ismail Fawaz et al., 2019)	Human -							P								
SmallKitchenAppliances	UCR Archive (Ismail Fawaz et al., 2019)	Power -							P								
ProximalPhalanxTW	UCR Archive (Ismail Fawaz et al., 2019)								P								
			-														

arXiv Template

Dataset	Source	Domain	Frequency	Chronos	TimesFM	Moirai Moirai-MoE	Time-GPT	ForecastPFN	MOMENT	Lag-Llama	GPT4TS	Timer	ZSisionTS	TTM	LLMTime	Time-LMM	UniTime	Time-MoF
DuckDuckGeese	UCR Archive (Ismail Fawaz et al., 2019)		-		ĺ	i i			P									
PickupGestureWiimoteZ	UCR Archive (Ismail Fawaz et al., 2019)	Human	-						P									
EthanolLevel	UCR Archive (Ismail Fawaz et al., 2019)	Power	-						P	İ	İ	i						
SpokenArabicDigits	UCR Archive (Ismail Fawaz et al., 2019)		-						P									
SonyAIBORobotSurface1	UCR Archive (Ismail Fawaz et al., 2019)		-						P									
HandOutlines	UCR Archive (Ismail Fawaz et al., 2019)		-						P									
PowerCons	UCR Archive (Ismail Fawaz et al., 2019)		-						P									
PhalangesOutlinesCorrect	UCR Archive (Ismail Fawaz et al., 2019)	Nature	-						P									
BirdChicken	UCR Archive (Ismail Fawaz et al., 2019)	Nature	-						P									
ToeSegmentation2	UCR Archive (Ismail Fawaz et al., 2019)	Human	-	İ				İ	P	İ	İ	İ			İ	İ	İ	
PigCVP	UCR Archive (Ismail Fawaz et al., 2019)	Healthcare	-						P			P						
CricketY	UCR Archive (Ismail Fawaz et al., 2019)	Human	-						P									
FingerMovements	UCR Archive (Ismail Fawaz et al., 2019)	Human	-						P									
ElectricDevices	UCR Archive (Ismail Fawaz et al., 2019)	Power	-						P									
InsectEPGRegularTrain	UCR Archive (Ismail Fawaz et al., 2019)	Nature	-						P									
DodgerLoopGame	UCR Archive (Ismail Fawaz et al., 2019)	Traffic	-						P									
Fungi	UCR Archive (Ismail Fawaz et al., 2019)	Nature	-						P									
Symbols	UCR Archive (Ismail Fawaz et al., 2019)	Generated	-						P		İ	i						
MixedShapesRegularTrain	UCR Archive (Ismail Fawaz et al., 2019)		-						P									
ArticularyWordRecognition			-						P									
UWaveGestureLibraryZ	UCR Archive (Ismail Fawaz et al., 2019)	Human	-						P									
Epilepsy	UCR Archive (Ismail Fawaz et al., 2019)	Human	-						P									
Healthcare200	UCR Archive (Ismail Fawaz et al., 2019)	Healthcare	-						P									
Weatherbench (Daily)	Weather Bench	Weather	D	P														P
Weatherbench (Hourly)	Weather Bench	Weather	H	P														P
Weatherbench (Weekly)	Weather Bench	Weather	W	P														P
Wiki hourly	Wikipedia Metrics	Web	H	İ	P					İ								
Wiki daily	Wikipedia Metrics	Web	D	P	P													P
Wiki weekly	Wikipedia Metrics	Web	W		P													
Wiki monthly	Wikipedia Metrics	Web	M		P													
Global Temp	Corrformer (Wu et al., 2023)	Weather	10T															T/T
TSMixup 10M	Chronos (Ansari et al., 2024)	Synthetic	-	İ	İ				İ	İ	İ	İ			i			P
KernelSynth 1M	Chronos (Ansari et al., 2024)	Synthetic	-									İ						P
TaxiBJ	Zhang et al., 2017	Traffic and weather	30T							1	1							ZS