A Survey of Time Series Foundation Models: Generalizing Time Series Representation with Large Language Model

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Time series data are ubiquitous across various domains, making time series analysis critically important. Traditional time series models are task-specific, featuring singular functionality and limited generalization capacity. Recently, large language foundation models have unveiled their remarkable capabilities for cross-task transferability, zero-shot/few-shot learning, and decision-making explainability. This success has sparked interest in the exploration of foundation models to solve multiple time series challenges simultaneously. There are two main research lines, namely **pre-training foundation models from scratch for time series** and **adapting large language foundation models for time series**. They both contribute to the development of a unified model that is highly generalizable, versatile, and comprehensible for time series analysis. This survey offers a 3E analytical framework for comprehensive examination of related research. Specifically, we examine existing works from three dimensions, namely **Effectiveness**, **Efficiency** and **Explainability**. In each dimension, we focus on discussing how related works devise tailored solution by considering unique challenges in the realm of time series. Furthermore, we provide a domain taxonomy to help followers keep up with the domain-specific advancements. In addition, we introduce extensive resources to facilitate the field's development, including datasets, open-source, time series libraries. A GitHub repository is also maintained for resource updates (https://github.com/start2020/Awesome-TimeSeries-LLM-FM).

1 INTRODUCTION

Time series data refers to a sequence of data points recorded at successive time intervals. Time series analysis has a longstanding research history closely tied to the real-world applications [51]. The earliest time series mining can be traced back to ancient Egypt, where observations of the Nile River's fluctuations were analyzed to guide agricultural production [35]. In the early days, research on time series focused on areas such as business and economic activities [57], meteorology and population statistics where the collected data was relatively small in simple structure (e.g., univariate sequence). At that time, statistics was the dominant methodology, leading to the development of various classical models including ARIMA, ARCH [50] and Markov transition model [64]. However, the advent of large-scale industrial systems, spanning sectors such as transportation [216], healthcare [101], Internet of Things (IoT) [59] and E-commerce [8], has led to the generation of vast and intricate time series data. Beyond time series data, some systems also generate data in varied modalities including text [82], images [150], and graphs [98]. The data explosion has fueled the emergence of novel time series applications with increasingly sophisticated patterns. Examples include traffic congestion detection [7],

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electrocardiograms (ECGs) classification [74], e-commerce sales demand prediction [17]. Statistical methods fall short in managing such massive and heterogeneous datasets, and the reliance on pre-defined pattern assumptions restricts their utility in tackling those applications with dynamic and complex patterns.

Over the past few decades, machine learning and deep learning have made remarkable strides across various domains, notably in computer vision (CV) and natural language processing (NLP) [196]. Unlike statistical methods, these approaches can handle larger, more diverse datasets in a more automated manner, requiring less human effort and expertise. These technologies have introduced sophisticated architectures capable of detecting more intricate patterns, sparking significant interest of time series community [79, 106, 125, 160]. Consequently, a diverse array of effective architectures tailored for time series modeling have emerged with different backbones, including RNNs [108], CNNs [29, 109, 207], GNNs [28, 32], Transformers [182], Diffusion model [107].

Although these powerful architectures have propelled time series analysis to a new level, there are still unsolved challenges in this field.

- The first challenge is about **knowledge transferability** [149]. Time series often exhibit seasonality (regular fluctuations at specific intervals) [56] and trends (long-term direction of the data) [132]. Alongside with these identifiable patterns, time series data also manifests a degree of randomness or noise, often attributed to unknown factors or patterns. These characteristics can differ greatly across various domains or even within the same domain over time, due to distribution shifts [88], making it challenging to transfer model or time series representations learned from one specific task to others. For instance, time series models [188] trained on stock market data learn patterns influenced by highly volatile factors like economic indicators, investor sentiment. While climate models [131] focus on long-term patterns, seasonal cycles, governed by physical laws rather than human behavior. Owing to the fundamentally distinct data nature, the knowledge transferability between different domains remains challenging.
- The second is related to **data sparseness**. In many traditional time series scenarios [49, 157], the data is gathered daily, monthly, or annually (e.g., economic indicators [18]), resulting in inherently sparse datasets. Alternatively, acquiring and annotating data may have privacy restrictions. For example, classifying electrocardiograms (ECGs) [136] necessitates clinical diagnoses but they are expensive and the data availability is constrained by patient privacy. This data scarcity hampers the effective training of deep learning models. Indeed, in most cases, the available datasets are still not enough for learning high-quality models [110].
- The third is about the **multimodal learning** [16]. In the context of multimodal time series analysis, leveraging the complementary insights across different modalities can enhance explainability and boost model performance. For example, in stock movement prediction, news and comments from social media can directly affect trading activities and integrating them into models can result in more precise forecasts [170, 189]. However, aligning multimodal data collected at various frequencies or intervals to accurately reflect temporal relationships between different modality is challenging. Moreover, different modalities may require distinct techniques to capture information effectively and integrating these information seamlessly into a cohesive model can be complex.
- Finally, explainability is also highly needed [210]. Detailed explanations of how models generate predictions or
 identify patterns can significantly enhance the utility and acceptability of time series. One case is that if a utility
 company uses an energy demand forecasting model [77] to plan electricity generation or set prices, it needs to
 justify these decisions to regulators and consumers, showing that the model decisions are based on reasonable

and understandable factors. However, most of the existing time series models are black-box in nature and lack of explanation about the model behavior or prediction.



Fig. 1. Foundation models have been employed across various tasks and domains in the context of time series analysis. They have two classes, namely foundation models pre-trained from scratch for time series and adapted large language foundation models (i.e. LLM) for time series. Currently, researches focus on improving the generalization capability of these models by effectively integrating time series properties or fusing multi-modality data. The explainability and efficiency are also concerned topics in this field.

Some efforts have been made to tackle the aforementioned challenges, like transfer learning for time series [78, 120, 177, 193], time series data augmentation [181], multimodal time series analysis [26, 42] and explainable artificial intelligence for time series [143]. However, these works mostly concentrate on individual challenges. The time series community anticipates a multifaceted model capable of addressing multiple challenges simultaneously. An ideal model would possess robust generalization abilities for unseen time series tasks during training and those with scarce data. Additionally, it should also demonstrate the capability to integrate data from different modalities seamlessly and provide understandable explanations for its decision-making processes.

Over the past few years, to facilitate knowledge transfer, a novel learning paradigm that combines transfer learning and self-supervision has emerged, namely pre-training and fine-tuning paradigm [65]. It first pre-trains a model on a source domain with broad data and then fine-tunes it on the target task relevant to the source domain [39]. BERT [41] is a language model pre-trained on a large-scale corpora. Researchers find that it can be adapted to a wide range of downstream NLP tasks and largely raise their performance bar. This study has inspired a large number of follow-up works in both NLP [97, 138, 212] and CV [14, 137]. Such class of models is termed foundation model (FM) [22]. They demonstrate strong generalization capabilities on various downstream tasks. When NLP researchers scale up foundation models by increasing data or model size, they observe that these larger foundation models acquire surprising abilities which are not present in smaller counterparts. Such unexpected capacities are termed emergent abilities [179], including in-context learning [24], instruction following [69], chain-of-thought (CoT) [128]. They shift the language foundation models from a transferable NLP task solver to a general-purpose task solver across domains, now widely known as large language models (LLMs). The development of LLMs has been rapid and vigorous, giving rise to many powerful LLMs, like GPT series [24, 138].

Inspired by the remarkable success of large language foundation models in NLP, time series community is increasingly interested in the potential of foundation models for time-series analysis [25, 82, 112]. One research line is to pre-train a foundation model from scratch with time series data, mirroring language foundation models. Pioneering efforts, such as TimesFM [36] and TimeGPT [58], have initiated the pre-training of foundation models in time series domain. However, data in time series field is relatively small in scale compared to the vast corpus available in NLP, making it challenging to produce foundation models with emergent abilities as LLM. Additionally, foundation models pre-trained on time series

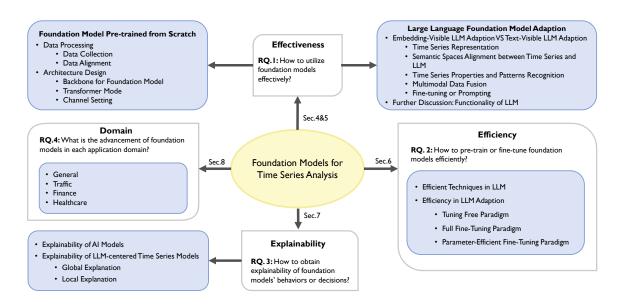


Fig. 2. Four research questions and their corresponding contents and sections.

data lack the language generation capabilities, hindering their ability to generate human-readable explanations. Attracted by the strong generalization ability of large language foundation models in various downstream tasks, another research line focuses on adapting large language foundation models (namely LLM) for time series tasks. Large language foundation models' strengths in cross-task generalization, zero-shot/few-shot learning, and reasoning can address challenges such as knowledge transfer, data scarcity and explainability in the context of time-series analysis. Broadly speaking, there are two adaption paradigms of LLM towards time series tasks, namely embedding-visible LLM adaption and text-visible LLM adaption [113, 190, 192]. They are different in LLM utilization, using fine-tuning for prompting strategy to adapt LLM towards time series task. They both face challenges including temporal and LLM space alignment, time series properties and patterns recognition, multimodal data fusion. Although these two research lines explore foundation models pre-trained on datasets with different structures (i.e. time series or text corpus), they all contribute to a ultimate goal, that is to solve multiple time series challenges in a unified and comprehensible architecture with powerful generalization capacity.

This survey provides an in-depth analysis on the advancement of foundation models for time series. The review is guided by four research questions in Figure 2, covering three analytical dimensions (i.e. effectiveness, efficiency, explainability) and one taxonomy (i.e. domain taxonomy). (1) How to adapt foundation models effectively in the context of time series analysis? We classify the related works into two research lines: pre-training foundation models from scratch for time series and adapting large language foundation models (namely LLMs) for time series. For the first line, we discuss effectiveness through two key phases: data collection and alignment, architectural design. Regarding the second line, we identify two adaption paradigms, i.e. embedding visible LLM adaption and textual visible LLM adaption. Under each adaption paradigm, we discuss the LLM utilization, time series extraction and multi-modal data fusion. The time series extraction includes challenges like obtaining appropriate time series representation, aligning temporal space and LLM space, identifying time series properties and patterns. Additionally, we examine diverse roles of LLMs that

	Effectiveness						Explainability		Domain
	Foundation Model Pre-trained from Scratch	LLM Adaption for Time Series				Efficient	Local	Global	Specific or
Survey	for Time Series	Adaption to Time Series Characteristics Multimod		Multimodal	Tuning	Explanation		General	
[84]	Х	/	/	X	/	Х	Х	Х	Specific
[83]	✓	1	/	Х	1	Х	Х	Х	Both
[154]	Х	1	/	1	Х	Х	Х	Х	General
[81]	Х	✓	/	✓	✓	✓	Х	Х	Both
[205]	✓	1	/	X	1	Х	X	Х	Both
Ours	✓	1	/	1	1	/	1	1	Both

Table 1. Comparative overview of related surveys, spanning four aspects: Effectiveness, Efficiency, Explainability, and Domain.

further increase the effectiveness of LLM adaption. (2) How to pre-train or fine-tune foundation models efficiently for time series tasks? Given that this area is emerging, current efficient techniques are adapted from NLP. Therefore, we first provide a brief overview of cutting-edge NLP efficient methods that are transferable to this context. We then discuss the efficiency under different tuning paradigms and summarize efficient methods already in use. (3) How to obtain explainability of foundation models' behaviors or decisions in time series applications? The practical deployment of models necessitates explainability. We start by exploring the concept of explainability in AI, highlighting both global and local explanations. We then proceed to review and distill the advancements in explainability within existing research. (4) What is the advancement of foundation models in each time series application domain? To answer this question, we introduce a domain taxonomy. This taxonomy allows us to compare the objectives, contributions, and limitations of existing studies within each domain. Furthermore, we offer a wealth of resources, such as code, benchmark datasets, time series libraries, and tools for accelerating LLMs, to support future research endeavors. Figure 4 provides a comprehensive overview of works based on the four research questions.

Paper Organization The remainder of the survey is arranged as follows: Section 2 introduces relevant survey on foundation models and time series analysis, directing readers to more studies in each area. Section 3 equips readers with basic knowledge on foundation models and time series tasks. Section 4 delves into the critical phases of pre-training foundation models for time series. Section 5 examines LLM adaption towards time series tasks. Section 6 discusses efficiency of model fine-tuning and inference. Section 7 summarizes research on explaining model behavior or decisions. Section 8 introduces the advancement within each domain. Lastly, Section 9 provides resources including benchmark datasets, code, and time series libraries and LLM tools.

2 RELATED SURVEYS

In recent years, traditional algorithms for time series analysis have undergone significant development and have been thoroughly reviewed in the literature [20, 63]. Furthermore, studies by [120, 129] have delved into the methodologies of pre-training and universal representation in this field. Recent trends in time series research have increasingly shifted towards leveraging Large Language Models (LLMs), motivated by their demonstrated versatility and transferability across various domains. [81] summarizes the general pipeline for LLM-based time series analysis and highlights the key techniques for existing methods (i.e., direct query, prompt design, fine-tuning). [205] explores strategies for transferring and distilling knowledge from LLMs to numerical time series analysis. Various methodologies (i.e., direct prompting, time series quantization, alignment) are detailed in this survey. [154] analyzes the applications of LLMs to time-series forecasting and anomaly detection. [83] comprehensively reviews large models tailored for analyzing time series and spatiotemporal data. [84] explore and debate possible directions towards LLM-centric time series analysis where LLMs

play roles of augmenters, predictors, or agents. While these surveys have investigated the application of Large Language Models in the domain of time series analysis, they have not systematically summarized large models for time series —not only the LLMs but also the foundational time series models trained from scratch. This survey aims to address this gap by providing a comprehensive review. Furthermore, we extend beyond merely summarizing existing literature by analyzing the explainability and efficiency of LLM-based time series models. More detailed comparisons of this survey with related work are shown in Table 1. Our goal is to provide answers to the previously outlined research questions and suggest future research directions.

3 PRELIMINARY

3.1 Foundation Models

Foundation models are built on the pre-training and fine-tuning paradigm. A large amount of data is involved in model pre-training, whose target is to train a general model that could be fine-tuned easily in various downstream applications and tasks. The development of foundation models has driven the advancement of AI algorithms in terms of homogenization and emergence [22, 179]. In detail, foundation models accelerate the consolidation of methodologies and have demonstrated great potential in learning feature representations automatically and implicitly.

Unlike LLMs, which mainly focus on natural language related data, foundation models have been widely developed in many different domains, for example, computer vision [46, 67, 89], natural language processing [5, 41, 97, 163], and graph learning [33, 72, 158, 187, 217]. Given that data exhibits multiple modalities in the real world, numerous discussions have emerged on how to develop multimodal foundation models. For example, CLIP [137] learns joint visual and textual representations. DALL-E [140] focuses on efficient image generation conditioned on open-ended text descriptions/prompts. VALL-E [169] shows the in-context learning capabilities for text to speech synthesis. However, how to incorporate time series data as one of the inputs for multimodal foundation models remains a topic worth discussing.

3.2 Time Series Analysis

Time series data, regarding the number of channels, could be divided into univariate time series and multivariate time series. For a T-length univariate time series sample $X = \{x_t\}_{t \in \{1, \dots T\}} \in \mathbb{R}^T$, x_t is the temporal signal collected at timestamp t. A multivariate time series sample with N(N > 1) channels $X = \{x_t\}_{t \in \{1, \dots T\}} \in \mathbb{R}^{N \times T}$ consisted of an ordered set of N-dimensional vectors, where each record x_t is the signal at a specific timestamp t. For simplicity, we discuss the multivariate time series in the remaining sections. The univariate time series could be treated in a similar way.

To tackle different channels of multivariate time series, there are two popular strategies [112]: channel-mixing and channel-independence. For the channel-mixing strategy, the time series model will first project multiple channels into the hidden space for channel fusion. For channel-independence, the model will process different channels individually, which indicates that all the channels share the same model. Compared with channel-mixing, whose projector depends on the number of multivariate time series channels, channel-independence configuration could easily handle the time series with varying channels. In this vein, channel-independence is adopted widely for time series analysis with domain transfer or model pre-training.

In general, the mainstream time series analysis tasks include time series classification, time series forecasting, time series imputation, and time series anomaly detection (as shown in Fig. 3).

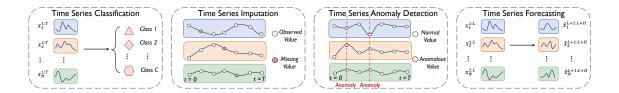


Fig. 3. Illustration for typical time series analysis tasks: Time series classification, imputation, anomaly detection, and forecasting

3.2.1 Time series classification. Given a multivariate time series data X, the time series classification model $f: \mathbb{R}^{N \times T} \to \mathbb{R}^{C}$ aims to distinguish the time series data of C different categories by

$$I^c = f(X),$$

and return the class index I^c .

3.2.2 Time series imputation. The goal of time series imputation is to recover the value of missing observations precisely. To describe the data missingness of time series X, we denote $M \in \{0, 1\}^{N \times T}$ as the mask matrix, where $X_{i,j}$ can be observed only if $M_{i,j} = 1$.

Given the observed time series data X^* , mask matrix M, the imputation algorithm aims to recover the missingness of data matrix by

$$\hat{X} = f\left(X^{\star}\right),\,$$

where $X_{i,j}^{\star} = \begin{cases} \text{NA,} & \text{if } M_{i,j} = 0 \\ X_{i,j}, & \text{otherwise} \end{cases}$, NA represents a missing value, and $f: (\mathbb{R} \cup \{\text{NA}\})^{N \times T} \to \mathbb{R}^{N \times T}$ denotes a learnable imputation function.

3.2.3 Time series anomaly detection. At timestamp t, the anomaly detection model is developed to find out whether there exist anomalies in the past time series subsequence. Given a multivariate time series subsequence $\{x_{t-w+1},...,x_t\}$ with window size w, the multivariate time series anomaly detection model $f: \mathbb{R}^{N \times W} \to \{0,1\}$ aims to return an anomaly indicator $I_t^t \in \{0,1\}$ by

$$I_t^a = f(\{x_{t-w+1}, ..., x_t\}),$$

where there is indeed an anomaly in subsequence if $I_t^a = 1$, the subsequence has no anomaly otherwise.

3.2.4 Time series forecasting. Time series forecasting aims at predicting the future value with horizon H based on the input time series with lookback window L. Given the input time series data $X_L = \{x_1, ..., x_L\}$, the forecasting model provide the predicted value for future H timestamps by

$$\{\hat{x}_{L+1},...,\hat{x}_{L+H}\}=f(X_L),$$

where $f: \mathbb{R}^{N \times L} \to \mathbb{R}^{N \times H}$ is a learnable forecasting function. Meanwhile, considering the length of the forecasting horizon, the task could be further divided into long-term/short-term time series forecasting. Based on the quantity of training data, few-shot/zero-shot forecasting pipeline could also be established.

3.3 Time Series Properties

3.3.1 Temporal Dependency. Time series data, gathered at various timestamps, inherently exhibits temporal dependencies. Past observations serve as indicators for predicting future values. Consequently, time series analysis models typically necessitate a subsequence of the time series as input to effectively discern these latent temporal relationships [40, 96, 105, 198, 199, 204].

For instance, in various practical contexts, time series data exhibit characteristics like nonstationarity and seasonality. Nonstationarity refers to the statistical properties of the series, such as its distribution, evolve over time. This variability introduces complexity to forecasting since past trends may not persist, given changes in the data's generative process [114–116, 148].

Seasonality, another key aspect of temporal dependency, involves consistent and predictable fluctuations occurring at regular intervals—daily, weekly, monthly, or yearly. Identifying and understanding seasonality enhances the modeling process by allowing for the incorporation of these cyclic patterns and some timestamp information into predictions, thereby improving the comprehension and analysis of the data [25, 183, 185, 204].

- 3.3.2 Spatial Dependency. For multivariate time series data, individual time series could represent different entities of complex systems. The inter-series relationship, referred to as spatial dependency, is vital for holistic system modeling. On the one hand, certain variables within a multivariate time series might fall short of providing ample information for model construction. On the other hand, effective modeling of spatial dependency is crucial to uncover the concealed patterns within the time series data [147, 172, 194, 203].
- 3.3.3 Semantics Diversity. Unlike image and text data, where consistent semantics can often be found across different domains (with each word or visual patch representing similar meanings in various sentences or images), time series data lacks this uniformity. Identical subsequences or shapelets in time series datasets can represent entirely different concepts depending on the context. This variability complicates the process of learning representations and transferring models in time series analysis, presenting unique challenges to accurately interpret and utilize the data [164].

4 PRE-TRAINING FOUNDATION MODELS FROM SCRATCH FOR TIME SERIES

Model	Parameter Size	Transformer Mode	Channel Setting	Task Type	Pre-trained Dataset	Data Size
ForecastPFN [45]	-	Encoder-only	Uni.	Fore.	Synthetic Data	-
TimeGPT [58] - Encoder-decoder		Uni.	Fore.	-	100 B time points	
TimesFM [36] 225M		Decoder-only	Uni.	Fore.	Google Trends [2] Wiki Pageviews [4] Synthetic Data	101B time points
Lag-Llama [141]	-	Decoder-only	Uni.	Fore.	Monash [159]	0.3B time points
TimeCLR [195]	-	Encoder-only	Uni.	Class.	UCR [38]	-
GTT [54]	57M	Encoder-only	Multi.	Fore.	-	2.4B time points

Table 2. A comparable analysis of general purposes foundation models. The channel setting has two types, i.e. univariate (Univ.) and multivariate (Mult.). "Fore." and "Class." mean forecasting and classification tasks, respectively.

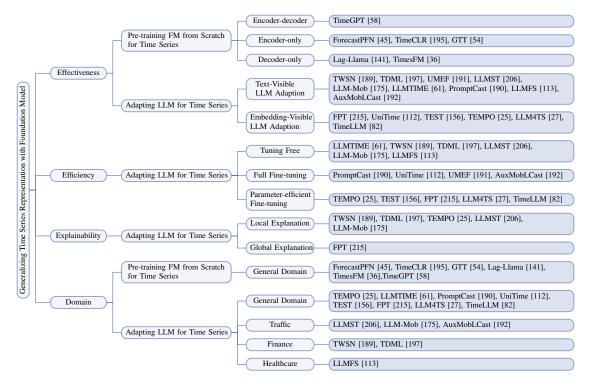


Fig. 4. A taxonomy of investigated works under four research themes, namely effectiveness, efficiency, explainability and domain. FM refers to Foundation Model.

The term "foundation model" was coined in [22] to describe a broad category of models initially trained on large and diverse datasets, subsequently adapted for various downstream tasks through methods such as fine-tuning. Originating from deep learning, incorporating self-supervision and transfer learning, foundation models are not entirely new. As these models grow in scale, they demonstrate impressive zero-shot and few-shot learning capabilities for a range of new tasks, alongside unexpected emergent abilities, such as chain-of-thought reasoning, frequently surpassing task-specific models. This success is notably evident in NLP and CV. On the other hand, many traditional time series scenarios often grapple with data limitations, struggling to accumulate enough data to train complex models effectively. This drawback has led to growing anticipation within the time series community for a foundational model akin to large language models, expected to excel in zero-shot/few-shot learning with limited time series data.

Compared to the exponential growth of foundation models in NLP and CV, the foundation model pre-trained on time series data has been comparatively limited. This limitation is primarily attributed to the relatively modest scale of available time series datasets. However, there have been some pioneering efforts recently, including ForecastPFN [45], TimeGPT [58], Lag-Llama [141], GTT [54], TimeCLR [195], TimesFM [36]. We provide a comprehensive comparison of the current foundation models in Table 2. In this section, we examine the crucial stages in pre-training a foundation model that influences its effectiveness, including data processing and architecture design.

4.1 Data Processing

4.1.1 Data Collection. The remarkable generalization capability of Large Language Models (LLMs) stems from their pre-training on large-scale and high-quality textual corpora. Similarly, for time series analysis, access to extensive and high-quality data is essential for pre-training an effective foundation model. We review the data collection practices of existing studies, focusing on aspects such as data split, data source and scale, data augmentation, and data quality.

Data Split. In constructing a foundation model with standardized protocols, datasets for pre-training are divided into training and validation sets. During the fine-tuning phase, the model is exposed to target datasets not seen during pre-training, with each dataset being further split into training, validation, and test sets.

Data Source and Scale. Among the existing foundation models for time series forecasting, Lag-Llama [141] is pre-trained mainly on the Monash time series repository with 305,443 individual time series. The unseen M4 Weekly and traffic datasets are reserved as test sets. GTT [54] collects a repository from both internal and public sources, consisting of 180,000 time series with a total of 2.4 billion time points. It generates about 200M high-quality training samples and 24M validation samples for pre-training data. Following PatchTST [133], GTT [54] uses 8 popular datasets as the target datasets. To build a large pre-training corpus, TimesFM [36] mainly chooses three data sources, i.e., Google trends, Wiki Pageview statistics, and synthetic time series with approximately 101B data points. They utilize three common archives as target datasets, namely Darts [70], Monash [159], and Informer datasets [213]. TimeGPT [58] claims that it has built up the largest time series repository with over 100 billion data points from public sources. However, it does not public its repository and reveal the data details. TimeCLR [195] builds a foundation model for time series classification with the UCR [38] archive. A pre-training set is created by randomly sampling 50% of each dataset in UCR but the label information is not available. The fine-tuning set is the remainder of each UCR dataset with a mutually exclusive 3:1:1 ratio as training/validation/test sets.

Data Augmentation. To enlarge the pre-training datasets, various data augmentation techniques are utilized in the existing works. Lag-Llama [141] employs Freq-Mix and Freq-Mask [30] to generate more training samples to prevent overfitting. TimeCLR [195] adopts the data augmentation techniques (e.g., jittering, time warping, cropping) to generate more data, enabling the model to be invariant to warping, different noise types, and so on. It also utilizes a single augmentation function to generate positive pairs for contrastive learning. Instead of utilizing real-world data, ForecastPFN [45] is pre-trained on purely synthetic data distribution. It assumes that the real-world datasets are derived from a prior distribution of time series.

Data Quality. Data quality is essential for ensuring the effectiveness of models. Poor-quality pre-training data has been shown to impair the performance of Large Language Models [94]. Challenges such as missing values, noise, and outliers are common in time series data. For example, UCR archive contains series with missing values [38]. To remove the diverse outliers that might cause exploding gradients, ForecastPFN [45] first masks out the missing value and then clips all 3-sigma outliers. Similarly, GTT eliminates data points normalized beyond a value of 9 to remove extreme outliers [54].

In summary, the time series data used in current studies are predominantly public, with the exception of GTT's internal sources. For more information on these public datasets, please refer to section 9. When it comes to data volume, TimeGPT has assembled the largest repository of time series data to date, though it remains unavailable for public access.

4.1.2 Data Alignment. Different from a specific model trained on one dataset, the foundation model is pre-trained on multiple datasets from diverse domains. These datasets are different in data scale, numerical magnitude, channel number, input and output length. It is essential to align and balance these datasets to ensure the generalizability of model.

Unlike modalities such as images, audio and text, a unique challenge in handling time series data lies in the variability of value ranges across datasets. Standard scaling methods, such as Z-score normalization and min-max scaling, are often ineffective because the absolute range differs greatly across datasets. GTT [54] normalizes each time series sample on a channel-wise basis while Lag-Llama [141] uses the scaling heuristic from DeepAR [146] for normalization within each univariate input window. These sample-specific normalization techniques greatly improve the convenience of model usage during inference.

To address the variation in channel numbers across datasets, most studies convert multichannel data into single-channel inputs. But GTT [54] is the only work to build a multivariate foundation model by setting the channel count to 32 and using zero-padding for datasets with fewer than 32 channels. As for the context length, GTT [54] fixes it to 1024 and uses zero-masking to create samples of varied lengths within the training dataset.

Given the significant variance in dataset sizes, it is crucial to adopt a balanced approach to guarantee that the model learns patterns from a wide range of datasets instead of overfitting specific ones. TimesFM [36] employs variable context lengths for datasets of different granularities (e.g., weekly, monthly) to achieve data balance across all levels of granularity.

In summary, critical measures for model alignment include value scaling, handling variable input and output lengths, managing multichannel data, and implementing balanced sampling. These strategies are essential for stabilizing the training process and preventing performance degradation.

4.2 Architecture Design

In this subsection, we delve into the factors that shape the effective architecture of foundation models, covering aspects like the choice of backbone models, transformer variants, and strategies for input tokenization. First, we summarize how existing works choose their backbone models. Interestingly, all the works ultimately select transformers as the backbone model but with different variants. We then discuss the pros and cons of these variants for time series analysis. Given that transformers are designed for token-like inputs, the discussion will extend to how current studies handle channel settings of time series data.

4.2.1 Backbone for Foundation Model. A deep learning model can serve as the basis for a foundation model, provided that its size can be scaled up. Scaling is indeed crucial for developing remarkably successful LLMs [34, 87]. Due to transformer architecture's outstanding capacity for parallelization, it allows scaling to a massive number of parameters, making it the preferred backbone for LLMs.

In the context of time series analysis, TimeCLR [195] compares several backbone models, including GRU, LSTM, ResNet, and transformer, and finds that the transformer outperforms the alternatives. TimesFM [36] suggests that the transformer's adaptability to varying context lengths makes it suitable for processing time series data of diverse lengths. It also replaces the transformer with different architectures, namely PatchTST and N-BEATS, and finds that the transformer has a better or similar performance than its counterparts in most benchmark datasets. Lag-Llama [141] holds that the attention mechanism can extract the diverse past events and predict the potential future distributions correctly, which is suitable for probabilistic time series forecasting. Ultimately, all the existing foundation models choose transformers as their backbone models. The key differences among these transformer-based foundation models lie in the transformer mode, input tokenization, and predictive objects. We will continue the discussion and comparisons in the following. Note that additional potential architectures have been suggested in [129], including Transformer++ and State-Space Models [119].

4.2.2 Transformer Mode. The first transformer [165] encompasses two stacks of blocks as the encoder and decoder. Each block is composed of multiple layers with the multi-head self-attention mechanism. The encoder embeds the input sequence into latent representations, and then the decoder processes them to generate the output sequence. It has two modes, namely, the encode-only and the decoder-only transformer. At the early stage, the encoder-only LLMs are more popular, and the most representative one is BERT [41]. Since the introduction of GPT-3, decoder-only LLMs have seen a significant rise in popularity, e.g., GPT series [138], LLaMA [163], OPT [202], PaLM [34], Bloom [184]. The encoder-decoder LLM includes BART [97] and T5 [139], Flan-T5 [86]. Experiments show that the decoder-only mode has better performance in zero-shot and few-shot learning than other architectures [173]. GPT-3 [24] serves as the most convincing proof of being an effective few-shot learner. Also, the scaling law has been widely observed in decoder-only LLMs to improve the performance substantially, while efforts to investigate the large-scale encoder-decoder models are still lacking.

These modes differ in properties and suitability for time series tasks. The encoder-only architecture handles the entire input sequence at once and predicts based on the understanding of the full context. It is ideal for tasks that require interpreting the whole input data (such as classification, sentiment analysis [37], or named entity recognition [48]). TimeCLR [195] builds an encoder-only foundation model for time series classification. Although the encoder-only model lacks auto-regressive nature, GTT [54] and ForecastPFN [45] still develop encoder-only foundation models for time series forecasting. GTT [54] clarifies that it adopts the encoder-only mode for ensuring the normalization of predicted values within the entire context window, while the decoder-only mode can not assure this due to its causal attention mechanism. The decoder-only models generate tokens autoregressively, where each output token is generated based on all the previous tokens. It is suitable for sequential generation tasks, such as text generation, machine translation, or summarization. TimesFM [36] and Lag-Llama [141] choose decoder-only architecture for time series forecasting. The encoder-decoder mode is more complex in architecture than its counterparts. But its distinct separation of input processing and output generation phases gives it a competitive edge in tasks where the relationship between input and output is complicated. TimeGPT [58] chooses encoder-decoder mode perhaps because it needs to extract varied and intricate patterns from over 100 billion data points.

4.2.3 Channel Setting. Another issue relevant to the architecture design of time series foundation models is the channel setting, specifically channel-independence and channel-mixing. Channel-independence refers to accept univariate sequence input while channel-mixing involves the utilization of multivariate sequence input. These different channel settings result in varied tokenization approaches for time sequences and necessitate distinct model designs.

Channel-Independence. Designing univariate foundational models is simpler than multivariate models because the channel numbers of multivariate data may differ across datasets [141]. Moreover, since multivariate series can be converted into univariate series, most researches prefer the channel-independence setting for model design. To construct a univariate transformer-based foundation model, the initial step involves converting the univariate input sequence into a vector sequence, similar to the token sequence. There are different techniques to achieve this goal. Inspired by the success of time series patching strategy in PatchTST [133], TimesFM [36] cuts the univariate sequence into patches. By aggregating adjacent time steps to form a single patch, the patching strategy can extract local temporal information of the input sequence. Lag-Llama [141] argues that the overlapping patch strategy may mix causality, as each patch vector includes values from both preceding and subsequent vectors. To address this, they recommend tailoring vectorization to the time series data's frequency, constructing lag vectors by applying lag operations to capture features at various time intervals—quarterly, monthly, weekly, daily, and hourly. In this way, each lag vector contains values from only the

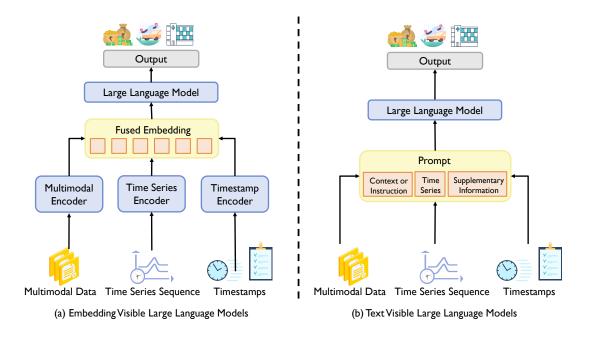


Fig. 5. There are two LLM adaption paradigms for time series: (a) Embedding visible LLM adaption, which repurposes LLM to fit time series task with redesigning LLM to perceive time series embedding directly. (b) Text visible LLM adaption, which adapt time series task to fit LLM with formulating time series input-output in a sentence-to-sentence manner.

previous vectors. TimeCLR [195] utilizes 1-D convolution to vectorize the univariate sequence into a 2D embedding. ForecastPFN [45] constructs a token to include the time value and its temporal attributes, like year, month, and day.

Channel-Mixing. The decomposition of multivariate sequences into multiple univariate sequences may overlook the relationships and interactions between different channels/variables. GTT [54] builds a multivariate foundation model for time series forecasting. They reshape the channel variables into the batch size to get a univariate sequence and slice it into patches. During the inference stage, the model can accept varying channel numbers since the channel variable has been fused into the batch size.

5 ADAPTING LARGE LANGUAGE MODELS FOR TIME SERIES

After pre-training, LLMs acquire general abilities for various downstream tasks, sparking increased interest in their application to time series analysis. Effectiveness, efficiency, and explainability are all concerned topics for LLM adaption toward time series. This section will concentrate on examining the effectiveness of adapting LLMs to time series, with subsequent sections dedicated to efficiency and explainability.

In NLP, "pre-train and fine-tune" paradigm used to be prevalent since 2017. This paradigm adapts LLM to downstream tasks by reprogramming pre-trained LLM via objective engineering [110]. However, since 2021, "pre-train, prompt, and predict" paradigm has gained prominence [110] for the rapid expansion of Large Language Models (LLMs). This paradigm adapts downstream tasks to LLM by reformulating their input-output in sentence-to-sentence manner to activate LLM's capacities, minicing NLP tasks. Inspired by these two paradigms, we classify LLM adaption in the context of time series analysis into two categories, namely **embedding-visible LLM adaption** and **textual-visible LLM adaption**.

These two paradigms mainly differ in input-output manner, LLM utilization and the way to extract time series information or multi-modal data fusion. There is a general comparison of these two adaption paradigms in Figure 5.

The two paradigms above have contains an implicit assumption that LLM is utilized as a forecaster to solve time series problem. However, the functionality of LLMs extends beyond forecasting; they also serve as enhancers, data generators and explainers. These roles greatly expand LLMs' versatility across various applications.

In this section, we first introduce some key concepts of LLM adaptation to facilitate understanding. Then we analyze each paradigm from multiple critical stages, including time series extraction (namely time series representation, semantic spaces alignment between time series and LLM, time series properties and patterns recognition), multi-modal data fusion and LLM utilization through fine-tuning or prompting. Finally, we discuss various roles of LLMs beyond forecaster in solving time series problems.

5.1 Terminology

Here, we introduce two learning paradigms and some classical fine-tuning and prompting techniques to equip readers with essential concepts for understanding this section.

5.1.1 Zero-Shot and Few-Shot Learning. Both zero-shot and few-shot learning are promising learning paradigms, which mimic human reasoning to quickly learn new tasks from past experiences with few or even no samples. They can alleviate the heavy reliance on current AI methods for large-scale data. Zero-shot learning, first proposed in CV [92, 134], requires models to perform tasks unseen during training [174]. Few-shot learning introduced earlier [53], focuses on learning and generalization from a limited number of examples [176].

The zero-shot learning ability of LLMs was discovered in GPT-1 and further developed in GPT-2 [138], albeit with moderate success. To address this issue, GPT-3 [24] shifted focus towards few-shot learning. With its massive scale and extensive pre-training data, GPT-3 demonstrates impressive few-shot performance in diverse NLP tasks without specific fine-tuning. Subsequently, GPT-4 elevates the capabilities of zero-shot/few-shot learning to a new level. Inspired by this success, the time series community has also begun to explore and evaluate the zero-shot/few-shot performance of LLMs in time series analysis.

- 5.1.2 In-Context Learning. In-context learning (ICL), introduced by GPT-3, is a widely used prompt method in LLM applications. It combines task descriptions, test instances, and demonstrations in natural language, allowing LLMs (particularly GPT series) to execute tasks using only the provided context without further fine-tuning or training. ICL exemplifies zero-shot/few-shot learning in LLMs. In essence, it leverages the model's existing knowledge and capabilities to perform new tasks by carefully crafting prompts [44]. Several works have demonstrated that the effectiveness of ICL heavily relies on the instruction design and demonstration designs (i.e. demonstration selection, order, and format) [130, 211]. In addition, [24] indicates that a model's in-context learning capabilities improve with increasing model size [24].
- 5.1.3 Chain-of-Thought. Chain-of-thought (CoT) is an advanced prompt strategy to enable the LLMs to solve complex reasoning tasks (e.g. arithmetic reasoning [128], symbolic reasoning [180]). CoT can be adopted with in-context learning under both few-shot and zero-shot settings. Few-shot CoT, introduced in [180], incorporates intermediate reasoning steps into ICL prompt, transforming each demonstration from <input, output> to <input, CoT, output> [209]. Zero-shot CoT, proposed in [90], adds the phrase "Let's think step by step" to the end of ICL prompt. CoT significantly improves

Model	Domain	Task Type	LLM Adaption	Time Series Properties
TWSN [189]	Finance	Class.	Text-Visible	Multivariate Dependency
TDML [197]	Finance	Class.	Text-Visible	Cross-sequence Dependency
LLMST [206]	Transportation	Anom.	Text-Visible	Cross-sequence Dependency
LLM-Mob [175]	Transportation	Fore.	Text-Visible	Temporal Patterns
AuxMobLCast [192]	Transportation	Fore.	Text-Visible	Temporal Patterns
LLMFS [113]	Healthcare	Class.	Text-Visible	-
LLMTIME [61]	General	Fore.	Text-Visible	-
PromptCast [190]	General	Fore.	Text-Visible	-
FPT [215]	General	Fore.	Embedding-Visible	-
TEMPO [25]	General	Fore.	Embedding-Visible	Temporal Patterns
UniTime [112]	General	Fore.	Embedding-Visible	-
TEST [156]	General	Fore./Class.	Embedding-Visible	Multivariate Dependency
LLM4TS [27]	General	Fore.	Embedding-Visible	-
TimeLLM [82]	General	Fore.	Embedding-Visible	-
UMEF [191]	Other	Fore.	Text-Visible	-

Table 3. LLM Adaption for Time Series Analysis. There are three kinds of task, i.e., Forecasting (Fore.), Classification (Class.), and Anomaly Detection (Anom.)

large-scale models' performance, marking an emergent capability while being less effective for smaller models. Moreover, CoT boosts model explainability by detailing the reasoning process, helping users comprehend the model decision.

5.1.4 Instruction Tuning. Instruction tuning is an approach to fine-tune pre-trained language models by performing tasks described by instructions [118, 178]. It is a combination of the pretrain–finetune and prompting paradigms [110]. This method enhances LLM's instruction-following ability through supervised fine-tuning, boosting zero-shot performance on unseen tasks. Typically, an instruction-based prompt in the zero-shot setting includes a task description (i.e., instruction) and an input-output pair, while in the few-shot setting, it also incorporates additional exemplars [209]. In addition, [178] concludes that the design of instruction, model scale, and variety of datasets influence the effectiveness of instruction tuning.

In summary, both instruction tuning and in-context learning utilize natural language to format the task. However, instruction tuning involves fine-tuning LLMs for adaptation while ICL simply prompts LLMs for utilization [209].

5.2 Embedding-Visible LLM Adaption

The embedding-visible LLM adaption utilizes traditional "pre-train and fine-tune" paradigm to redesign LLM and fine-tune it towards downstream time series tasks. Under this paradigm, LLM is redesigned to perceive time series embedding directly instead of the traditional textual input.

5.2.1 Vectorized Time Series Representation. The first step to utilize LLM in the context of time series analysis is to transform time series input into representations that can be perceived by LLM. LLMs are based on transformer and require vector sequence as input. In NLP tasks, each word (also called token) has its own vector embedding and sentence composed of multiple words is a vector sequence to be fed into LLM. Under the embedding-visible LLM adaption, time series input is transformed to vectorized time series representation and the LLM is also redesigned to perceive the time series embedding directly.

Inspired by the success of the patching strategy in transformer-based models [133], many works slice the univariate time series into patches and feed them into LLM as tokens [25, 27, 82, 215]. Each single patch is a sub-sequence of a time series, and it can retain meaningful local semantic information. The patch length is fixed for any input length which can broaden the input scope. As for the multivariate time series, many works decompose them into multiple univariate time series and then adopt the patching tokenization technique. One reason to support channel independence setting is that every channel acts differently, and combining them all could reduce overall performance. However, TEST [156] vectorizes time series data under channel-mixing settings with the argument that the cross-variable dependency should not be neglected.

5.2.2 Semantic Spaces Alignment between Time Series and LLM. After transformation, time series can be represented as vector sequence to be fed into LLM. However, these representations are likely to deviate a lot from the LLM's cognitive embedding space as there is modality gap between temporal space and natural language space.

For those transform time series into temporal embedding sequence, they first need to consider the dimension alignment. For example, GPT-2 of different sizes has a unique text space with different embedding dimensions [138]. To align these two dimension space and enable LLM to understand the time series embedding, existing research works usually redesign the input embedding layer and fine-tuning it on downstream time series datasets. The new embedding layer projects time series tokens to the required dimension of the specific LLMs [25, 27, 215]. Besides the modification of the input layer, some works explore the mapping of time series features to the corresponding linguistic elements within LLMs. Time-LLM [82] considers that a frozen LLM without fine-tuning can not directly comprehend patch embedding. They propose to reprogram the embedding with text prototypes to align the source and target modalities. Specifically, they utilize a small collection of pre-trained word embedding to learn connecting language cues (e.g. "short up", "long steady") for characterizing each patch and fuse them by trainable multi-head attention layers. TEST [156] also adopts a frozen LLM as backbone and utilizes the text prototypes to constrain the embedding space of time series based on contrastive learning.

5.2.3 Time Series Properties and Patterns Recognition. Besides filling the semantic gap of temporal modality and natural language modality, another issue is to identify time series unique characteristics. Time series data fundamentally differs from natural language in patterns and properties, posing challenges in applying LLMs to the time series tasks. Time series unique characteristics include multivariate and cross-sequence dependencies, distribution shifts, and complex temporal patterns such as seasonality, trends, and randomness. These elements are crucial for time series modeling.

While transformer-based architectures have reached SOTA performance in certain time series tasks, largely due to their capacity for modeling long-range dependencies via self-attention, they often fail to account for the unique properties of time series data. For instance, TEMPO [25] highlights that transformers cannot inherently detect trends and seasonality. Some recent findings demonstrate that time series transformers do not match the robustness of their counterparts in CV and may even be outperformed by linear models in specific benchmarks [198]. Furthermore, LLMs are not intrinsically

equipped with the knowledge and reasoning capacities to identify time series properties and patterns during their pretraining phase. From this perspective, it is worth our attention to consider these intrinsic characteristics when activating LLMs for time series analysis.

Temporal Patterns. TEMPO [25] decomposes each univariate sequence into trend, seasonal, and residual components. They prove that such decomposition significantly simplifies the prediction of LLMs by identifying abnormal observations of seasonality or trends. In addition, they design a learnable prompt pool to encode shared temporal patterns across different time periods. The decomposed components are normalized, patched, and embedded individually and then concatenated with the retrieved prompts before being fed into a GPT module. In the experiments, they design variant models to validate the effectiveness of the decomposition method and prompt pool.

AuxMobLCast [192] observes that the POI category is associated closely with passenger patterns in human mobility forecasting. They integrate an auxiliary POI classification module into the encoder-decoder architecture to help it better identify different visiting patterns correlated with different POI categories. The ablation study shows that the auxiliary module achieves a substantial improvement with BERT encoder.

Multivariate Dependency. Many time series data are multivariate, e.g., stock prices dataset and ECG dataset, while the text is univariate. Many studies adapt LLMs towards time series partition multivariate time series into multiple univariate sequences and process them individually [112, 215]. However, TEST [156] argues that these channel-independence works overlook the multivariate dependency in time series. Indeed, variables of time series can be highly correlated or have causal relationships, and such inter-dependencies are beneficial for modeling. TEST perceives multivariate time sequence as input and slices it into tokens at random lengths, which are then fed into an encoder to produce temporal embedding.

Timestamp Information. Many studies have validated the benefits of incorporating the timestamp information in transformer-based models [182, 186, 213, 214], especially in those scenarios with explicit temporal patterns, e.g. disease forecasting, traffic flow forecasting. LLM4TS [27] designates the initial timestamp to each time series patch. They encode each time attribute and fuse them into one temporal embedding, which is then summed with token and positional embedding to produce the final embedding.

Distribution Shift. FPT [215] and TEMPO [25] incorporate a normalization block to normalize the univariate input sequence with reverse instance norm (RevIN [88]) before patching to mitigate the distribution shift and further facilitate knowledge transfer. LLM4TS [27] considers that trainable affine transformation of RevIN is not suitable for autoregressive models like GPT-2. They adopt standard instance normalization in the supervised fine-tuning stage.

5.2.4 Multi-modal Data Fusion. Multi-modal learning has been a well-established topic, especially in NLP and CV, such as visual question answering [99], image-text generation [140, 201], and audio-text generation [169]. Time series analysis also encounters multi-modal scenarios. For instance, financial datasets can be enriched with textual news and reports. Medical datasets may include relevant textual or image-based supplementary information. Time series data is inherently numeric and abstract, and similar temporal segments could have varying meanings in different contexts, posing significant challenges in semantic mining and knowledge transfer. Supplementing time series data with other multi-modal information (e.g. textual descriptions) can assist the model in learning complex temporal patterns, enhancing the representation ability, generalization ability, and explainability for time series analysis.

Recently, inspired by the success of multi-modal LLMs in jointly leveraging multiple knowledge bases, some works utilize the advanced pre-trained LLMs to design multi-modal models for time series analysis. They can be divided into two groups based on the granularity of multi-modal signals.

Sample-Level Multi-modal Fusion One research line utilizes multi-modal signals to enrich details and complement internal knowledge to time series samples. To be specific, the granularity of such signals is usually sample-level. METS [100] feeds the ECG signals and its paired clinical report into a multi-modal comparative learning framework. The report is processed by a large, pre-trained medical language model, namely ClinicalBert, to guide the training of the ECG encoder. In other words, ClinicalBert, acting like a medical expert, summarizes the prior diagnostic knowledge from the ECG report text and distills it into the ECG encoder to enrich the information of the ECG signal. TEMPO [25] incorporates contextual information like quarterly news and reports for predicting quarterly financial indicators with temporal embedding. They also train a soft prompt to extract the summary information.

Task-Level Multi-modal Fusion Another research line leverages multi-modal knowledge to improve the model's generalization ability and facilitate knowledge transfer across datasets. Typically, such knowledge pertains to the task level or domain level. UniTime [112] argues that there is domain confusion when training a model on datasets from various domains. Since the temporal patterns or distributions in different domains might show significant differences, the model may have difficulties in discerning and generalizing different datasets. They provide domain instructions to help the model identify the data source and adopt the prediction strategy correspondingly. The domain instructions are hand-crafted in sentence descriptions to contain domain knowledge, which goes through a tokenizer and an encoder, and finally fused with the temporal embedding. To enhance model's understanding of time series concepts, Time-LLM [82] proposes Prompt-as-Prefix, a technique to augment time series representation with a prompt containing domain knowledge, task instruction, and data statistics. The prompt is fed into a frozen LLM and then added at the top of the temporal embedding, facilitating reasoning and pattern recognition of LLM.

5.2.5 Fine-tuning. Fine-tuning a pre-trained Large Language Model (LLM) is crucial for harnessing its potential for specific downstream tasks. In embedding-visible LLM adaption, the input/output layers and the objective function of the LLM are reconfigured to suit the target task. This process involves updating all or partial LLM parameters using thousands of supervised training samples. Once fine-tuned, the model typically demonstrates enhanced performance on the target tasks.

Among the time series works we investigate, UniTime [112] adopts the traditional fine-tune strategy on GPT-2 to learn a unified model for cross-domain time series forecasting and finds that the fully tuning yields the best performance compared with baselines. However, updating all the parameters may disrupt the internal knowledge of LLMs obtained from pre-training stage. The catastrophic forgetting may occur, where LLM loses its previous capacities. Another drawback is the requirement of large training datasets and heavy computational resources. For downstream tasks with small datasets, fully fine-tuning LLM may have unstable performance or over-fit.

To alleviate these defects, some works leverage efficient tuning, aiming to reduce the number of trainable parameters while retaining a good performance as possible. FPT [215], TEMPO [25] and LLM4TS [27] all freeze the majority of the LLM parameters and only update the minority ones in general time series forecasting. This method can retain the major knowledge and capacities of LLM and require less data for training. TEST [156] and TimeLLM [82] further freeze all the parameters of LLMs and add learnable "soft prompt" parameters to the input for fine-tuning LLMs to forecast time series. For those works that utilize a frozen LLM, they need to align the time series embedding to the textual space of LLM to make it understand time series representations. To further enhance the reasoning capacities of LLM on time series data, some works also re-purpose LLM by explicitly identifying the temporal patterns [25] or incorporating supplementary information from other modalities [82]. The details will be discussed later in subsections ?? and 5.2.4.

5.3 Text-Visible LLM Adaption

The text-visible LLM adaption follows the "pre-train, prompt, and predict" paradigm to redesign time series tasks and utilize prompting techniques to activate the LLM capacities. Under this paradigm, the input-output pair of time series tasks is reformulated into textual prompts.

- 5.3.1 Textual Time Series Representation. Under the text-visible LLM adaption, numerical time series data is transformed into a string so that they can be seamlessly integrated into prompt as natural language inputs [81]. Previous works that utilize LLMs to infer directly on downstream tasks without any fine-tuning always format the task in a sentence-to-sentence manner. Numerical values are transferred and described as natural language sentences and integrated into the prompt along with other contextual information. Some works fine-tune LLMs towards specific downstream tasks and formulate tasks in natural language, for instance, AuxMobLCast [192] for human mobility forecasting, LLMFS [113] for health tasks, PromptCast [190] for weather, energy consumption, and customer flow forecasting.
- 5.3.2 Semantic Spaces Alignment between Time Series and LLM. For those transform time series into sentence, LLM tokenizes the strings into words to comprehend them. However, [152] points out that tokenization methods of LLMs are originally designed for words instead of numerical values. They may separate the consecutive values into several tokens and disregard the temporal meaning, which can significantly complicate arithmetic [111]. For example, GPT-3 [24] tokenizer slices the number 42235630 into [422, 35, 630] tokens while LLaMA [163] tokenizes the number into individual digits by default [61]. LLMTIME [61] proposes to carefully pre-process time series before they are tokenized, for example, adding space technique for GPT series. [152] proposes that prompt tuning could be a potential solution to bridge the gap between numerical data and text. Prompt tuning involves adding a trainable embedding to the input, which can be optimized to incorporate knowledge and aim at guiding the LLM to comprehend time series information that may not be present in the original pre-trained LLM.
- 5.3.3 Time Series Properties and Patterns Recognition. Different from time series characteristics extraction under embedding-visible LLM adaption, text-visible LLMs identify time series unique properties and patterns by integrating relevant information into prompt.

Temporal Patterns. LLM-Mob [175] argues that it is difficult for LLMs to capture useful information from complex raw stays directly for human mobility prediction. They propose to decompose the mobility data into historical sequence and context sequence to help LLMs better understand the underlying long-term and short-term mobility patterns of passengers, which are later utilized to form the prompt.

AuxMobLCast [192] observes that the POI category is associated closely with passenger patterns in human mobility forecasting. They integrate an auxiliary POI classification module into the encoder-decoder architecture to help it better identify different visiting patterns correlated with different POI categories. The ablation study shows that the auxiliary module achieves a substantial improvement with BERT encoder.

Cross-sequence Dependency. To solve the cross-sequence dependency challenge in stock movement forecasting, To address the challenge of cross-sequence dependencies in stock movement forecasting, TDML [197] offers numerous examples from stocks similar to the target stock when creating in-context learning prompts. This approach illustrates that LLMs can effectively incorporate cross-sequence information from related stocks. LLMST [206] puts all the trajectories in a single prompt to observe whether the model can consider the interaction between different trajectories for human mobility detection. They conclude that the presentation of all the trajectories in a single prompt may result in better performance.

Multivariate Dependency. TWSN [189] leverages multiple historical stock features like open, close, high, and low prices for stock movement prediction. They transform these multivariate price features into a tabular format string and integrate it into the textual prompt.

Timestamp Information. UMEF [191] incorporates the timestamp into a pre-defined template prompt for energy consumption prediction, namely "The electric load at {*Time*} is {*Usage*}." LLM-Mob [175] considers the time information of the target stays in the prompt for human mobility prediction. They also guide LLMs towards analytical thinking by incorporating facts into the prompt that highlight how people's mobility patterns vary according to different times and days. AuxMobLCast [192] also integrates the date information in its mobility prompting. It finds performance reduction when removing the temporal date information from the prompt. They explain that the timestamp is beneficial for the LLMs to capture the temporal patterns from the numerical tokens.

- 5.3.4 Multi-modal Data Fusion. Compared to the embedding-visible LLM setting, there is relatively less research on multi-modal learning in the text-visible LLM setting. As to sample level multi-modal data fusion, TWSN [189] analyzes ChatGPT's capabilities for stock movement prediction by constructing a multi-modal prompt to combine historical stock price features with tweets from the same days. When it comes to task-level multi-modal data fusion, the task-level information can be added into the prompt as supplementary information to augment the model performance.
- 5.3.5 Prompting. Motivated by LLMs' powerful generalization across NLP tasks, many works utilize prompting to activate LLM's capacities on downstream time series tasks. They integrate time series input into textual prompts to guide a pre-trained LLM to generate desired output in natural language. It can be divided into tuning free prompting and fine-tuning based prompting. The former directly evaluates LLM performance on time series tasks under zero-shot/few-shot settings without fine-tuning while the latter fine-tunes the LLM model and update all or some of its parameters. We summarize each branch and discuss its pros and cons.
- (1) **Tuning Free Prompting** This branch relies only on prompts to utilize the internal knowledge of LLM without any parameter update, and prompt engineering is pivotal to improving model performance. Some prompts are designed as instruction, and the instruction following capacity also influences the model performance [200].

TDML [197] designs an instruction-based prompt to experiment with GPT-4 in both zero-shot and few-shot inference. The prompt's structure is optimized empirically by splitting the instruction into two parts placed at the start and end of the prompt. They also augment the prompt with the zero-shot CoT technique by pretending, "Can you reason step by step before finalizing the output?" Surprisingly, they found that a zero-shot CoT prompt can improve model performance notably.

TWSN [189] evaluates the strengths and limitations of ChatGPT in multi-modal stock price prediction with instruction prompt in zero-shot inference. Unlike TDML, TWSN adds tweet information to its prompt. However, the experiments show that ChatGPT underperforms the state-of-the-art methods. Besides vanilla prompting, they also experiment with the CoT enhanced prompt. They conclude that even the CoT technique can improve the model performance to some extent but it is still worse than other specialized approaches.

LLMF [113] tests the zero-shot performance of PaLM-24B on four arithmetic health problems. They also construct an ICL prompt with three demonstrations to evaluate the few-shot model performance. The findings indicate that PaLM is not capable of zero-shot inferences and struggles to numerical tasks, perhaps due to the inadequate representation of the target health tasks in the PaLM training set. The 3-shot performance is slightly better than zero-shot performance on most tasks, but PaLM is unable to generate output for about 50% of test data in two health tasks under the 3-shot setting.

LLMST [206] constructs different prompts to evaluate the effectiveness of several LLMs (i.e. GPT-3.5, GPT-4 and Claude-2) for human mobility anomaly detection. They form the prompt by incorporating trajectory sequence along with task instruction. They then supplement the prompt with indicative clues about potential anomalies to test their effectiveness. Their conclusion is that LLM demonstrates reasonable performance on detecting anomaly mobility behavior. They also prepend "Give your analysis" in the prompt to improve the transparency of model decisions.

LLM-Mob [175] leverages the textual understanding and reasoning capabilities of GPT-3.5 for human mobility data analysis by carefully designed prompt engineering. They first manually decompose the raw mobility data into two separated sequences and incorporate them with particular instructions in the prompt to enable LLM better identify mobility patterns. They also give clear instructions and provide prior knowledge to inform LLM of the activity patterns. They believe that these operations can guide the model to think logically and serve as CoT function.

LLMFS [113] examines the current LLM's performance on health tasks under zero-shot and few-shot in-context learning. They demonstrate that the PaLM with 24 billion parameters can digest time-series health data under few-shot learning setting and make meaningful inferences. But the performance falls significantly in zero-shot ICL, which proves that LLM struggles with arithmetic tasks without any contextual information.

All the works above require careful design of the context-inclusive prompts, which integrate numerical time sequence with supplementary contextual information (e.g., task descriptions). However, LLMTIME [61] shows that LLM can be directly utilized as a zero-shot forecaster with a numerical-only prompt, which purely contains the numerical data without any additional textual information. They argue that careful pre-processing of the time sequence is the key to fitting the tokenization strategy of LLM, influencing LLM to learn from meaningful patterns within the tokenized sequences.

(2) Fine-tuning based Prompting The tuning free prompting is inflexible for it can only leverage the inherent knowledge of LLM which might be limited for specific time series downstream task. Some works combine traditional fine-tuning and prompting to update parameters of LLM to make it more suitable for time series tasks.

PromptCast [190] is the first to adopt instruction tuning for general time series forecasting. They design a zero-shot instruction-based prompt in a question-answer format for three forecasting tasks, i.e., weather temperature, energy consumption forecasting, and customer flow forecasting. The prompt has a template that contains a context part providing historical time series sequence and timestamps, a question part for queries about the future steps, and an answer part providing ground truth to respond to the question. UMEF [191] adopts the instructionless tuning for energy consumption forecasting. A template is pre-defined to convert energy consumption data into descriptive sentences, like "The electric load at {Time} is {Usage}." They evaluate the effectiveness of three LLMs, i.e., BART, Bigbird, and Pegasus, for energy load forecasting. The experiments demonstrate that LLM outperforms traditional numerical forecasting in energy consumption prediction. AuxMobLCast [192] also utilizes instructionless tuning for human mobility forecasting. They design a mobility prompt to combine the mobility data, timestamp, and POI information in the input sentence and integrate the target visitors' number in the answer sentence. They fine-tune a LLM-based encoder-decoder architecture. The encoder (e.g., BERT) extracted interaction between mobility data and other clues to produce prompting embedding for the decoder. GPT-2 is utilized as the decoder for final prediction. They also design different prompts to find out the most effective combination of the input elements. LLMFS [113] designs a question-answer based prompt for various health tasks. Different from the above works updating all the parameters of LLM, LLMFS freezes the whole LLM and adds a soft learnable prompt embedding as a prefix for each downstream task to enable LLM to comprehend time series data from different tasks.

In summary, the key contribution of studies utilizing prompting lies in their intricate prompt designs tailored to specific time series scenarios. To enhance prompt effectiveness, some studies integrate additional information, such as time series

Model Predictor		Enhancer	Data Generator	Explainer	
TEMPO [25]	GPT2	-	GPT4	No	
PromptCast [190]	10 LLMs	-	-	No	
LLMTIME [61]	GPT3/LLaMA2-70B	-	-	No	
TEST [156]	GPT2/BERT/ChatGLM/LLaMa2	-	-	No	
FPT [215]	GPT2	-	-	No	
LLM4TS [27]	GPT2	-	-	No	
TimeLLM [82]	LLaMA-7B	LLaMA	-	No	
UniTime [112]	GPT2	-	-	No	
CIGN [31]	-	-	ChatGPT	No	
LLMFS [113]	PaLM	-	-	No	
METS [100]	-	ClinicalBert	-	No	
UMEF [191]	BART/Bigbird/Pegasu	-	-	No	
AuxMobLCast [192]	GPT2	-	-	No	
TWSN [189]	ChatGPT	-	-	CoT	
TDML [197]	GPT4/LLaMA-13B	-	GPT4	СоТ	
LLMST [206]	GPT3.5/GPT4/Claude2	-	-	Yes	
LLM-Mob [175]	GPT3.5	-	-	Yes	

Table 4. Functionality and backbones of LLMs in investigated works.

characteristics [175], alternative data modalities [189], and expert knowledge [206]. Techniques like chain-of-thought (CoT) have been applied in several works [175, 189, 197, 206], showing promise in boosting model performance.

5.4 Further Discussion: Functionality of LLMs

Most research utilizes LLM as a core module for prediction in the context of time series analysis. However, the functionality of LLM extends beyond predictor. It varies from processing other modality data, producing raw data for specific tasks, and providing a reasoning process or explanation for their predictions. The diverse applications of LLMs enhance solutions for time series tasks and unlock their potential from multiple perspectives. In this section, we discuss the diverse roles of LLMs in current research (as shown in Table 4).

- 5.4.1 Predictor. Specifically, if an LLM mainly takes the representations of temporal data as input and produces the output, it is treated as a predictor. All the works analyzed in subsection 5 adopt LLM as a predictor, i.e., the core module for time series tasks. The differences among these works lie in the tunability of LLM, the time series tokenization, the prompting techniques, and some enhanced model designs for different time series tasks. More details have been introduced in the previous subsections.
- 5.4.2 Enhancer. If an LLM is in charge of extracting high-level information only from other modality data without time series data and assisting the core module to predict, we identify it as an enhancer. As analyzed in subsection 5.2.4, the multi-modal signal can be classified into sample-level and task-level, providing supplementary information in different granularities to enrich the representation of time series data.

METS [100] utilizes ClinicalBert to process ECG-paired medical reports for ECG classification. TWSN [189] adopts ChatGPT to incorporate stock-level tweets with daily stock price for stock movement prediction. TEMPO [25] provides quarterly news and reports for forecasting quarterly financial indicators by feeding it into GPT2. TimeLLM [82] and UniTime [112] leverage domain knowledge described in sentences to help LLMs identify sources of time series data, facilitating the recognition of different temporal patterns in different domains.

Note that all the multi-modal signals in the existing works are textual information currently, like reports, news, and domain knowledge in short sentences. Different from the predictor LLMs, the enhancer LLMs are usually frozen and do not require training or fine-tuning. Furthermore, the enhancer may consist of a specialized LLM, such as ClinicalBert, or a general LLM, such as GPT2. Intuitively, a specialized LLM is a better choice for domain-specific information extraction if it is available.

5.4.3 Data Generator. Drawing inspiration from the vast knowledge possessed by LLMs and their robust capabilities in language generation and contextual understanding, some studies employ LLMs to generate additional data needed to complement the input.

CIGN [31] considers that ChatGPT has learned massive information about financial entities (e.g., stocks, companies, events) during training, and it is an ideal tool to extract the inter-dependencies among stock equities. They feed financial news headlines into ChatGPT to produce affected company sets. Then, they construct a graph of these companies. The company graph is then utilized as model input for stock movement prediction. TDML [197] utilizes GPT-4 to produce company descriptions and general positive/negative factors for each stock. This textual information is utilized with stock prices for prediction. They also use GPT-4 to extract a condensed summary and keywords from crawled news articles of each stock, which is utilized as the ground truth to evaluate the quality of the explanations generated by GPT-4. TEMPO [25] adopts ChatGPT to collect news and reports for each company in a specified duration and these data will be treated as contextual information for financial indicator prediction.

In summary, large language models (LLMs) are able to generate the desired data through a well-designed prompt. They can also be utilized to preprocess or refine the raw data. Generating data with LLMs can be more efficient and cost-effective than some traditional methods of data collection or annotation. Furthermore, the LLMs utilized as data generators in existing studies are high-quality and advanced models, such as ChatGPT, all of which are employed to generate textual information in the finance domain. However, it is worth noting that the data generated by LLMs is not always reliable or accurate for the hallucination challenge.

5.4.4 Explainer. If an LLM generates an explanation for its output, it is regarded as an explainer. The explainability of model behavior or prediction is important in time series analysis, especially in those high-stakes scenarios.

While LLMs are often considered black boxes with limited explainability, their proficiency in text generation allows them to serve as natural explainers, generating human-readable explanations for their decisions. Furthermore, augmented with prompting techniques like Chain-of-Thoughts (CoT), LLMs can reveal their reasoning process step by step and provide detailed explanations for the predictions.

LLMST [206] utilizes ChatGPT to support anomalous human mobility detection. LLM-Mob [175] also explores the explainability of how GPT-3.5 predicts human mobility. TWSN [189] designs a CoT enhanced prompt to enable ChatGPT to provide cogent explanations for results. TDML [197] also investigates the GPT-4's potential for explainable stock price forecasting. More details about model explainability can be found in Section 7.

6 EFFICIENCY

In deep learning, efficiency [126] refers to the effectiveness of computational resources utilization. It involves multiple aspects, e.g. computation time, processor utilization (CPU or GPU), memory requirements, and energy consumption. Both pre-trained time series foundation models and LLM-centered models for time series have exhibited powerful generalization ability, surpassing many task-specific models. However, these advanced capabilities are accompanied by intensive resource consumption. For example, when using a large language model (such as GPT-3) for time series data, the training and inference processes can be very time-consuming due to the complexity and large number of parameters of the model. This may lead to the need to consider efficiency issues when using large language models for time series analysis in real-time applications. Given that time series foundation models are still in the early stages of development, the efficient methods employed in time series domain are derived from NLP. we first summarize the efficiency techniques for LLMs that can be transferred to time series analysis, followed by efficiency discussion on existing works with different tuning paradigms.

6.1 Efficient Techniques in Large Language Models

large language models (LLMs) have expansive parameter size (e.g.billions or trillions), leading to significant computational and memory demand [167]. Efficiency is increasingly crucial for large language models (LLMs) and can be improved through the entire lifecycle of LLM, including input handling, architecture design, model compression, pre-training, fine-tuning, and inference [167].

Since fine-tuning the whole LLM for downstream tasks is inefficient as it always updates all the LLM parameters, requiring huge computation resources. Many works utilize **parameter-efficient fine-tuning (PEFT)** (also named **light-weight fine-tuning**). PEFT solves the infeasibility and impracticality of fully fine-tuning LLM. It freezes the majority of LLM parameters and only trains a small set of parameters which might be a subset of existing model parameters or newly added parameters [104]. We introduce some popular PEFT techniques that have been applied or can be potentially applied in LLM-centered time series research, including adapters, prompt tuning, prefix-tuning, Low-Rank Adaptation (LoRA).

Adapters. The idea of adapters was initially proposed in CV [142] and then adapted to NLP [73]. It injects small-scale neural networks after attention and feedforward neural network (FNN) layers in the transformer. Adapters might have only less than 4% of the model parameters but they show competitive performance to full fine-tuning [73]. There are various adapters, like SparseAdapter [68], MAM Adapter [66], Parallel Adapter [66].

Prompt Tuning. Unlike the adapters that add extra FFN layers, prompt tuning [95] wraps a trainable tensor to the model input embedding, commonly referred as "soft prompt". Prompt tuning becomes more effective with larger model size, and its efficiency improvement accelerates at a rate faster than the growth of model size [155].

Prefix-Tuning. To directly optimize the soft prompt in prompt tuning is observed to be unstable in [103]. Different from prompt tuning prepending soft prompt to the input layer, prefix-tuning [103] adds a trainable vector (namely prefix token) to each intermediate layer. It is shown to have a close performance to full fine-tuning by only updating 0.1% parameters of BART [103].

Low-Rank Adaptation (LoRA). Inspired by the idea of Intrinsic SAID [6] to adopt low-rank fine-tuning, LoRA [75] decomposes the weight matrix of LLMs into a product of two low-rank matrices. During the fine-tuning process, the original matrix is frozen while the two low-rank matrices are updated. Although LoRA is effective, it necessitates updating the low-rank matrices for all layers of the LLMs in every iteration. Note that While LoRA is a reparameterization-based method, the remainder are additive methods [43].

6.2 Efficiency in LLM Adaption

In this subsection, we discuss the efficiency issues when adapting LLM towards time series analysis. We first provide a tuning paradigm taxonomy for existing works based on the updated parameter amount of their LLM-centered architectures. The taxonomy has three branches, i.e. tuning free paradigm without any updated parameters, fully fine-tuning paradigm which updating all the parameters of LLM backbone and parameter-efficient fine-tuning which updating only a small set of model parameters.

6.2.1 Tuning Free Paradigm. In the development of LLM-centered time series solutions, the most efficient strategy is to directly call API interfaces [61, 175, 206], without any updating of model parameters, i.e. tuning free paradigm. For instance, TWSN [189] and TDML [197] explore the zero-shot inference of ChatGPT/GPT-4 in multimodal stock movement prediction. No parameter is updated under this strategy. This approach does not alter the model's structure. Instead, it heavily depends on the inherent pattern recognition and reasoning capabilities of LLMs, along with prompt engineering, to enhance model performance. However, recent research shows that this strategy may lead to poorer performance of the model on some tasks. For instance, TDML [197] observes that LLM underperforms not only SOTA methods but also some traditional methods like linear regression. In addition, it is also expensive to call ChatGPT API for a large amount of input.

6.2.2 Full Fine-Tuning Paradigm. Due to the inferior performance of tuning free paradigm, some works choose to fine-tune LLM to adapt it for downstream time series tasks. A fully fine-tuning strategy usually redesigns the input layer to encode time series data and the output layer to adapt to downstream tasks. This strategy can better guide LLMs to perform on a specific time series task, like AuxMobLCast for human mobility prediction [192], UniTime [112] and TEMPO [25] for general forecasting. However, it is usually computationally intensive and requires a longer training time, as it involves updating all the parameters of a large language model.

6.2.3 Parameter-Efficient Fine-Tuning Paradigm. To strike a good balance between effectiveness and efficiency, more works adopt a parameter-efficient fine-tuning (PEFT) strategy.

FPT [215] retains a significant portion of the pre-trained knowledge by freezing the major parameters of GPT-2, specifically the self-attention and feedforward layers. It redesigns the input layer and retrains it with the positional embedding layers and normalization layers on varied time series datasets to activate LLM's capacity for downstream tasks. Similar to FPT [215], TEMPO [25] also freezes and updates the same layers in the GPT block. Furthermore, it utilizes LoRA [75] within the multi-head attention block for model compression, thereby facilitating efficient adaptation to diverse time series distributions. Drawing inspiration from supervised fine-tuning in the chatbot domain, LLM4TS [27] introduces a dual-phase fine-tuning approach. The initial phase employs techniques similar to those used in TEMPO [25], such as partial freezing and LoRA. The distinction lies in the subsequent phase, which allocates the first half of the epochs to linear probing and the remainder to comprehensive fine-tuning.

All the works above only freeze the majority of LLM parameters and leave the remainder tunable. To further alleviate the challenges of insufficient data and limited computational resources, some works choose to employ a completely frozen LLM [82, 113, 156] and introduce a small number of new parameters for fine-tuning. TEST [156] designs a soft prompt (i.e., trainable task-specific embedding vectors) concatenated with time series embedding to instruct LLM on subsequent time series tasks efficiently. TimeLLM [82] reprograms the input layer by aligning the trainable patch embedding with text prototypes. LLMFS [113] attaches a soft learnable embedding as a prefix to each sample in the prompt to make LLM comprehend the domain knowledge in time series data.

In conclusion, LoRA has been utilized in TEMPO [25] and LLM4TS [27]. Similarly, prompt tuning is employed in TEST [156], TimeLLM [82], LLMFS [113]. However, specific strategies for efficient architecture design and model compression have yet to be explored in LLM-centered time series analysis.

7 EXPLAINABILITY

Explainability or explainability refers to how well humans can understand the behaviors or predictions of a model, which has always been an important problem for both AI and time series communities [143]. Making the model transparent and explainable can enable users to understand, appropriately trust and effectively manage the model deployment in real-world scenarios [47]. In some contexts where the competent model performance can meet most requirements (e.g. text generation), the lack of explainability might not be a major issue. However, for those critical decision-making domains where user trust, safety, fairness, and privacy are of utmost importance, like automatic driving, healthcare and finance [23], the absence of explainability will hamper the practical model applications. In fact, the benefits of explainability extend far to knowledge discovery [47], model debugging [47], and solving disagreements between AI systems and human experts [55].

In this section, we aim to clarify what to explain and how to explain in the context of large model based time series analysis. Although the complexity of large models greatly exceeds general AI methods, they are essentially black-box AI models. The explanatory methods and principles applicable to other AI models can be adapted to these large models. Therefore, we start with a brief introduction to the research background in AI explainability. We then proceed to summarize and analyze the contributions of existing research in enhancing the explainability of large models for time series analysis.

7.1 Explainability of Al Models

While certain models, such as decision trees, inherently offer explainability due to their straightforward structures, most models, especially those within deep learning, are black-box in nature, obscuring their inner working mechanism from users [210]. To address this challenge, the field of Explainable AI (XAI) [11] focuses on developing methods that make the internal mechanisms or outcomes of deep learning models comprehensible to humans. Research in XAI can be broadly categorized into two approaches: local and global explanations [47]. Local explanations [135] aim to clarify the reasoning behind the model's decision for a specific instance, seeking to reveal the causal relationships between a given input and its outcome. In contrast, global explanations [76] strive to shed light on the model's overall internal mechanisms, examining its structure and parameters across all instances. The explanation techniques can be also divided into ante-hoc and post-hoc methods [143]. Ante-hoc method [145, 171] directly incorporates the explainability of the model structure while the post-hoc method [62] focuses on explaining the model behaviors without changing its underlying structure.

7.2 Explainability of LLM-centered Time Series Models

Here we delve into the explainability of time series analysis with LLM, involving both local and global explanation.

7.2.1 Global Explanation. The global explanation refers to understanding what LLMs have learned and how they can effectively interpret numerical time series. On one hand, LLM lacks of built-in explainability, and its internal mechanisms are still unclear [208], posing challenges to explain its adaption to time series. On the other hand, the current modification of LLM structure towards time series data concerns about performance improvement instead of explainability. Fortunately, there is one work providing explanation on the adaption of LLMs to time series anlaysis. FPT [215] proves

that the behaviors of the self-attention module in LLMs is similar to principle component analysis (PCA). It can perform task-agnostic operations as a general computation calculator on time series tasks.

7.2.2 Local Explanation. Compared with other black-box deep learning models, LLMs can generate reasonable natural language explanations for its output guided by the chain-of-thought prompt. Several studies have examined LLM's ability to produce local explanations.

When activating LLMs for detecting anomalous human mobility, LLMST [206] prompts GPT-3.5 and GPT-4 to provide supporting analysis for their detections by including an instruction in the prompt: "Give your analysis...". They find that LLMs are capable of providing persuasive explanation for their decisions. Mob [175] also structures its prompts to request explanations, using an instruction "Please organize your answer around the key reason (a concise explanation supporting your prediction)." They argue that this approach not only improves the explainability of the results but also enhances the model's reasoning capabilities.

Explainable predictions also play a vital role in numerous financial applications, enhancing decision-making by ensuring reliability and transparency. In stock movement prediction, TWSN [189] utilizes a chain of thought enhanced zero-shot prompt to enable ChatGPT to deliver coherent explanations for its predictions. Guiding by the zero-shot CoT "explain your predictions step by step"," ChatGPT can provide detailed insights into its stock movement forecasts. However, it's noted that ChatGPT's explanations are constrained by its concentration on a narrow range of input factors, whereas the stock market's dynamics are much more intricate. TDML [197] also explores the potential of LLM for explainable stock price forecasting. They prompt GPT-4 to predict the summary and keywords for the following week, which subsequently serve as explanations for the predicted stock returns during that period. Additionally, they experiment with the CoT technique by appending an instruction at the end of the prompt: "Can you provide step-by-step reasoning before finalizing the output?" They found that this method enhances GPT-4's ability to generate detailed and coherent reasoning steps, leading to improved model performance in most experiments.

All these works above utilize GPT-3.5 and GPT-4 to generate explanations. No work has yet used smaller LLMs like GPT-2 [138] for explanation generation, possibly because their language generation and reasoning capabilities are still lacking. For those embedding-visible LLMs, the CoT prompt can not be utilized to generate an explanation in natural language. TEMPO [25] is the first to introduce a post-hoc method for local explanation of an embedding-visible LLM (GPT-2), namely. They propose to build a generalized additive model to measure the contributions of different components (i.e. trend, season, and residual) based on GPT's output.

8 DOMAIN TAXONOMY

Time series analysis has a broad spectrum of applications across various domains. This section provides a domain taxonomy to classify research into general, traffic, healthcare, finance, and other domain. By examining the motivations, contributions, and limitations of studies within each domain, we intend to provide a clear road map of the advancement of foundation models in each domain.

8.1 General Domain

While specialized methods still dominate in time series analysis, general-purpose models like ChatGPT and CLIP [137] have achieved considerable success in a wide range of downstream NLP and CV tasks. These universal task solvers markedly diminish the need for extensive data collection, intensive model design, and trivial task-specific training, thus greatly attracting attention from time series community.

(1) Foundation Model Pre-trained for Time Series. To develop a universal model for time series analysis, one research line focuses on pre-training a foundational model with time series data which serves as a domain-agnostic solver. ForecastPFN [45] is the first transformer-based network trained purely on synthetic time series data for zero-shot forecasting. TimeGPT [58] is the largest transformer-based foundation model pre-trained on more than 100B data points. Lag-Llama [141] is a decoder-only foundation model trained on Monash repository for univariate probabilistic time-series forecasting. GTT [54] is an encoder-only foundation model pre-trained on 200M samples for zero-shot multivariate time series forecasting. TimesFM [36] is a patched-decoder pre-trained on Google Trends for univariate time series forecasting. All these foundation models have a certain degree of zero-shot capacity on unseen tasks. However, due to the lack of large-scale time series data, they are still limited in emergent abilities compared with LLMs.

(2) LLM Adaption for Time Series. Another research line concentrates on customizing LLMs for time series tasks. FPT [215] utilizes parameter-efficient fine-tuning on GPT-2 and evalutes it on all major types of time series tasks including forecasting, classification and anomaly detection. They also offer a theoretical rationale for the successful application of LLMs to time series data. They contribute such success to the self-attention module behaviors of LLM similar to principle component analysis (PCA). LLM4TS [27] employs a lightweight, two-stage fine-tuning approach for GPT-2, drawing inspiration from the methods used in supervised fine-tuning within chatbot applications. The initial stage involves autoregressive supervised fine-tuning to acquaint the LLM with the general patterns of time series forecasting. The second stage implements a downstream fine-tuning to guide LLM towards specific application. Different from fine-tuning an embedding-visible LLM in [27, 215], PromptCast [190] is the first to fully fine-tune a text-visible LLM with carefully designed prompt.

TimeLLM [82] and TEST [156] consider that the successful transferability of LLM for time-series forecasting lies in effectively aligning modalities of time series data and text. They both focus on reprogramming the input layer of frozen LLM. More specifically, TimeLLM [82] reprograms the input time series with text prototypes to directly bootstrap LLM for understanding time series. It also adds a prompt as prefix of input to enhance the LLM's adaptability to downstream tasks. TEST [156] utilizes contrastive learning to produce similarity-based, instance-wise, feature-wise, and text-prototype-aligned embeddings as input for LLM to understand. A soft prompt is then designed to instruct LLM on subsequent time series tasks. Furthermore, LLMTIME [61] finds that LLM under frozen setting can show impressive performance with purely numerical sequence input after carefully pre-processing. This success is attributed to the LLM's affinity for simple or repetitive sequences, aligning well with the inherent structure of time series data. The study also reveals that the method of number tokenization in LLMs significantly impacts their forecasting effectiveness.

UniTime [112] identifies the challenges to learn a unified model for cross-domain time series forecasting while handling varying domain-dependent characteristics of time series data, e.g. different temporal patterns or distributions, diverse convergence rates. They utilize GPT-2 as the backbone to align time series data and domain instruction to solve the domain confusion. In addition, they adopt masking to mitigate the domain convergence speed imbalance. TEMPO [25] focuses on activating GPT-2 to fully capture the temporal pattern evolution and interrelated dynamics of time series data. They first model specific time series patterns by trend, seasonality, and residual decomposition and then encode more universal temporal patterns from historical data in a shared prompt pool. These inputs enable more effective fine-tuning of LLM towards time series modeling.

8.2 Finance

The textual and time series data are two major modalities in the financial realm. Large language models have demonstrated great potential in financial text mining, e.g. pre-trained financial foundation models, financial sentiment analysis [93],

financial text mining [117], investment portfolio selection [144]. However, their application in financial time series data remains in the early stages of development.

The stock movement prediction is one of the multimodal financial applications that relied on historical prices along with textual information, where some researchers tried to unlock LLMs' capacities from different perspectives. CIGN [31] contributes ChatGPT's success to its extensive knowledge of entities (e.g. companies, events, individuals) and their relationships. They offer financial news headlines to ChatGPT to generate relationships among the listed companies of DOW 30, which are subsequently utilized to construct company graphs for stock movement prediction. They argue that such automatically latent relationship extraction may be more efficient than handcrafted features.

TWSN [189] provides historical stock prices and tweets data to ChatGPT to test its zero-shot learning capacities in stock movement prediction. They find that ChatGPT shows inferior performance compared with both deep learning and traditional linear regression. They also observe its limitations of explainability and stability. Compared with TWSN [189], Yu et al. [197] draw a nearly opposite conclusion about LLM's performance. They focus on NASDAQ-100 stocks with price time series and utilize GPT-4 to produce company metadata and preprocess financial news as supplementary input. They test GPT-4 under zero-shot, few-shot with/without chain-of-thought (CoT) settings and find it outperforms the widely applied classic ARMA-GARCH model. They also find that CoT can enhance LLM's performance and provide human-readable reasoning over input. Moreover, they fine-tune LLaMA to demonstrate the feasibility of open source LLMs for this task.

8.3 Traffic

Time series sequences are the primary data type for numerous traffic-related applications, including traffic flow prediction and human trajectory detection. While some applications also utilize tabular data, textual information is rarely encountered in traffic-related tasks. The current works exploring LLMs' potential in traffic field concentrated on human mobility forecasting or detection. In Mob, [175] implements an in-context learning process to harness the textual understanding and reasoning capabilities of GPT-3.5 for human mobility data analysis. They decompose the raw stay sequence into historical stays and context stays and integrate them into instruction based prompt to help LLM understand the short-term and long-term dependencies in human movement. LLMST [206] also employ GPT-3.5 and GPT-4 to detect anomalous behaviors from mobility data. They develop various prompts to evaluate the impact of specific indicators of anomalies and the interactions among distinct trajectories. AuxMobLCast [192] also designs different prompts to find out the most effective combination of mobility data, timestamp, and POI information. But different from the frozen LLM configuration in [175, 206], AuxMobLCast [192] is the first work to fine-tune a LLM based encoder-decoder architecture. The encoder (e.g. BERT) extracted interaction between mobility data and other clues to produce prompting embedding for decoder. GPT-2 is utilized as the decoder for final prediction. They also integrate an auxiliary POI classification module in the architecture to provide LLM with traveling pattern information for better volume prediction.

8.4 Healthcare

Some applications in the health domain can collect time series data from wearable and medical sensor recordings, like activity recognition and disease diagnosis. LLMF [113] examines the current LLM's performance on health tasks with a limited number of training examples. They demonstrated that the PaLM with 24 billion parameters can digest time-series health data under few-shot learning setting and make meaningful inferences. METS [100] is the first work to use LLM as an enhancer for ECG multimodal self-supervised learning. Specifically, they utilized a large clinical language model, named ClinicalBert, to analyze the ECG reports and direct the training of the ECG encoder via contrastive learning. During

the inference phase, they expanded the ECG labels into medical diagnostic sentences and input these into ClinicalBert to acquire embeddings for ECG classification.

8.5 Other Domains

Motivated by the LLM's ability to learn rich representations of textual data, UMEF [191] formulates the energy load forecasting in a sentence-to-sentence form. A template is pre-defined to convert energy consumption data into descriptive sentences, like "The electric load at {*Time*} is {*Usage*}". LLM is then fully fine-tuned using prompting and an autoregressive prediction mechanism focused on the hourly energy consumption of buildings. The experiments demonstrate that LLM outperforms traditional numerical forecasting in energy consumption prediction.

9 RESOURCES

In this section, we introduce the common time series datasets and archives utilized in investigated works. We also provide some practical time series libraries for the baselines comparison of time series analysis. Moreover, we introduce some LLM deployment resources to the fine-tuning of LLM towards time series or the pre-training of time series foundation models.

9.1 Datasets

Time series analysis is a fundamental problem studied in various fields and the research popularity of real-world applications largely depends on the accessible time series datasets. In addition, some datasets not only include time series data but also other data modalities, enabling the implementation of multimodal learning. Except for those task-specific datasets, there are some time series archives encompassing multiple datasets cross-application and cross-domain for general time series analysis. In the following, we briefly introduce several widely used datasets and archives to reveal information about data size, sampling frequency, features, processing tools, download links, and more.

9.1.1 Stock Datasets. The stock dataset typically comprises time series data representing market information for each stock, sampled at a daily frequency. This includes various price metrics (open, close, high, low), daily ask and bid prices, and trading volume. A stock dataset usually contains multiple chosen stocks and the commonly used ones include NASDAQ100 [197] and the Dow Industrial Average 30 Companies (DOW 30) [31]. As for obtaining datasets, we can get them from public channels, such as obtaining NASDAQ-100 from yfinance package. We can also obtain them from non-public channels, such as accessing Dow30 from CRSP databases [31].

In addition, some stock datasets may also include data from other modalities, mostly text data. These textual data associated with the stocks includes news headlines [31], company profile data [197], tweets [189]. However, most of these data are not public. Some research works utilize LLMs to be data generator, providing a new approach to accessing textual data. For example, [197] utilizes GPT-4 to generate company descriptions, and general positive/negative factors.

9.1.2 ECG Datasets. The electrocardiogram (ECG) is the most popular diagnostic tool to assist in the clinical diagnosis of heart diseases and computational ECG analysis has been studied for over 60 years [121]. The ECG dataset contains recordings of ECG signals capturing the electrical activity of the heart over a specific period from individuals. There are many publicly available databases containing ECG datasets with different recording settings, like duration, leads, and sampling frequency [127]. Usually, ECG datasets with 12 or 15 leads are obtained from the standard resting ECG monitor, while those with a few leads are produced by the Holter monitor. The recording duration usually ranges from 6s to 30 min and the sampling frequencies of each recording generally vary from 250HZ to 1000HZ. The majority

of available ECG datasets can be accessed through public repositories such as PhysioNet, Figshare, Zenodo, and IEEE Data Port [127]. In recent years, there has been a notable increase in the publication of large-scale arrhythmia datasets, like PTB-XL [166], MIMIC-III [85].

Some ECG datasets also have textual data as complementary descriptions of the ECG signals. Each recording in PTB-XL [166] is paired with the corresponding ECG reports. The reports are generated by the machine and only describe the ECG without final diagnosis. These time series texts can be utilized for multimodal learning akin to image-text pairs in CLIP [137].

- 9.1.3 ETT Datasets. ETT (Electricity Transformer Temperature) dataset was first introduced by [213] for long sequence time-series forecasting in 2021. It is a collection of time series data closely related to the temperature of electricity transformers, serving as a crucial indicator for long-term electric power deployment. This dataset was gathered between July 2016 and July 2018 from two distinct counties in China. ETT involves four subsets with different temporal granularity, ETTm1 and ETTm2 are recorded at 15-minute intervals, while ETTh1 and ETTh2 are recorded hourly. Each data point comprises the target variable "oil temperature" and six power load features. ETT is very popular in the works we investigate [25, 82, 112, 215].
- 9.1.4 Other Popular Benchmarks. There are three widely used benchmarks in the works for general time series analysis. (1) Weather: It is recorded every 10 minutes for the whole year in 2020 in Germany. It is used for meteorologic monitoring and contains 52696 instances with 21 meteorological features, such as air temperature, humidity, etc. (2) Traffic: It contains the occupation rate of the freeway system across the State of California. It is recorded hourly with 17544 length and each record has 862 variables. (3) Electricity: ECL (Electricity Consuming Load) consists of the hourly power consumption of 321 clients from 2012 to 2014 and it has 26304 instances.
- 9.1.5 General Archives. To pre-train a foundation model for time series or to test the generalization ability of LLMs on various time series tasks, we need various time series datasets from different applications and domains. There are several popular benchmarking archives that have motivated the development of SOTA time series algorithms, including UCR [38], UEA [15], TSER [159], M4 [123], Monash [60], UCI [12].

Time Series Classification: Time series classification has greatly benefited from the University of California Riverside (UCR) and University of East Anglia (UEA) time series archives. UCR archive was first introduced in 2002 with 16 datasets, then grew to 85 datasets in 2015, and finally expanded to 128 datasets in 2018. The latest UCR archive contains a wide range of problems, including variable length series, but it still only contains univariate time series. To remedy this defect, also in 2018, UEA researchers released the first official multivariate time series classification archive encompassing 30 datasets of equal length with no missing values. Furthermore, TSER was released in 2020 as the first time series extrinsic regression archive containing 19 multi-dimensional time series datasets.

Time Series Forecasting: M-competition series [122, 123] is the most popular one with the latest version M5 [124] in 2020. Others well-known competitions include NN3 and NN5 [19], CIF 2016 [153], Wikipedia web traffic [168], and Rossmann sales competitions. The M4 benchmark includes a collection of 100,000 time series data from diverse fields typically encountered in business, finance, and economic forecasting. Among these competitions, there was a paradigm shift from single-series to cross-series learning in competition models. The previous archives with mostly unrelated single time series are of limited use to evaluate the cross-series learning models. The Monash forecasting archive was proposed in 2021 for multivariate time series forecasting and the latest version contains 30 publicly available datasets with over 400,000 individual time series. The University of California Irvine (UCI) repository currently contains 507 datasets from

various domains and is the most well-known benchmark archive in general machine learning. It also contains multiple time series datasets for both forecasting and classification.

While these archives have made notable contributions to the advancement of general time series mining, their utility for pre-training foundation model is still hindered by the sample sizes and generality. The time series community still lacks large-scale, generic datasets comparable to ImageNet, which are crucial for facilitating research on large models.

9.2 Time series Libraries

Library	Institute	Release Time	Channel Setting	Task Type	Model Type
Prophet [162]	Facebook	2017	Uni.	Fore.	Statistical
HyperTS	Polytechnic University of Catalonia	2019	Mult.	Fore., Class.	Statistical, Deep learning
GluonTS [9, 10]	Amazon	2019	Multi.	Fore., Anom.	Deep learning
Tslearn [161]	University of Rennes	2020	Uni.	Fore., Class., Clust.	Machine learning
GreyKite [71]	LinkedIn	2020	Uni.	Fore., Anom.	Statistical, Deep learning
Kats [80]	Facebook	2021	Multi.	Fore., Anom.	Statistical, Deep learning
Merlion [21]	Salesforce	2021	Multi.	Fore., Anom.	Statistical, Ensemble
Darts [70]	Unit8 Sa	2022	Multi.	Fore., Anom.	Statistical, Ensemble, Deep Learning

Table 5. Time Series Libraries. The task type includes time series forecasting (Fore.), classification (Class.), anomaly detection (Anom.), and cluster (Clust.). The channel setting "Uni." and "Multi." refer to univariate and multivariate time series respectively.

There exist numerous code libraries for time series analysis, and among the earliest, Prophet [162] stands out as a relatively simple yet mature tool, primarily designed for univariate time series forecasting. Due to its compact size and established functionality, it has become one of the essential models integrated into subsequent time series analysis toolkits. Merlion [21] is positioned for applications in time series forecasting and anomaly detection, offering support for both univariate and multivariate time series. The models primarily encompass statistical and machine learning methodologies. One of its significant highlights is the capability for automated time series modeling as well as ensemble modeling across multiple models. Darts [70] is also a comprehensive library for time series analysis, particularly geared towards addressing tasks in time series forecasting. It distinguishes itself through its extensive array of models, with a notable strength being the support for a variety of cutting-edge deep learning models such as Transformers and Temporal Convolutional Networks (TCNs), which have emerged as prominent architectures in sequence modeling. Table 5 provides detailed comparison of various useful time series libraries.

9.3 LLM Tools

The frameworks used for training and deploying large language models are diverse (as shown in Table 6). Nvidia's Megatron [151] framework specifically optimizes tensor operations and inference in GPU architecture, using technologies such as FasterTransformer and TensorRTLLM to improve performance. ColossalAI [102], developed by HPC-AI Tech, focuses on addressing the challenges of large-scale distributed training by providing scalable, efficient, and universal solutions, integrating various deep learning components to improve training efficiency. Meta's FairScale [52] extends PyTorch's high-performance features for large-scale training, emphasizing availability, modularity, and efficiency, and

Framework/Library	Developer	Key Features
Megatron [151] Nvidia		Optimizes tensor operations and inference on GPUs; employs Faster- Transformer and TensorRT-LLM for performance enhancement.
ColossalAI [102] HPC-AI Tech		Facilitates large-scale distributed training with scalability, efficiency, and deep learning component integration.
FairScale [52] Meta		Enhances PyTorch for large-scale, high-performance training with usability and efficiency; supports FSDP.
Pax [13] Google		Scalable JAX-based framework for distributed training, integrating with JAX ecosystem for diverse model training.
vLLM [91]	-	Achieves superior throughput with continuous batching and PagedAttention for efficient inference.
DeepSpeed-MII [1] Microsoft		Offers load balancing and quantized inference across machines, supporting a variety of model libraries.
Text-generation-inference [3] HuggingFace		Deployment framework for text generation with server load monitoring, flash attention, and support for HuggingFace models.

Table 6. LLM Deployment Resources

provides features such as fully shared data parallelism for optimizing training in resource-constrained environments. Google's Pax [13] utilizes the JAX ecosystem to provide a scalable and efficient distributed training framework for training large-scale models in different patterns. vLLM [91] significantly outperforms traditional transformers in terms of throughput, introducing continuous batch processing and PagedAttention to achieve efficient inference. Microsoft's DeepSpeed MII [1] provides load balancing and model quantification across multiple machines, supporting a wide range of model libraries. HuggingFace's text generation inference [3] framework supports advanced deployment features tailored for text generation, including server load monitoring and flash attention.

10 CONCLUSION

In this survey, we investigate foundation models for time series analysis, including foundation model pre-trained from scratch with time series data and large language foundation models repurposed for time series tasks. We provide a 3E analytical framework to summarize related research from three critical dimensions, i.e. effectiveness, efficiency, and explainability. We discuss how to solve the time series challenges when applying foundation models for time series tasks. We provide a domain taxonomy for tracking advancements in each domain. This survey aims to equip followers with a holistic conceptual framework for foundation models in time series field, fostering a deeper understanding and inspiring innovation for future research.

REFERENCES

- [1] 2023. DeepSpeed-MII. https://github.com/microsoft/DeepSpeed-MII
- [2] 2023. Google Trends. https://trends.google.com
- [3] 2023. text-generation-inference. https://github.com/huggingface/text-generation-inference
- [4] 2023. Wiki Pageviews. https://en.wikipedia.org/wiki/Wikipedia:Pageview_statistics
- [5] Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. 2023. Gpt-4 technical report. arXiv preprint arXiv:2303.08774 (2023).

[6] Armen Aghajanyan, Sonal Gupta, and Luke Zettlemoyer. 2021. Intrinsic Dimensionality Explains the Effectiveness of Language Model Fine-Tuning. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing. 7319–7328.

- [7] Mahmuda Akhtar and Sara Moridpour. 2021. A review of traffic congestion prediction using artificial intelligence. *Journal of Advanced Transportation* 2021 (2021). 1–18.
- [8] Shahriar Akter and Samuel Fosso Wamba. 2016. Big data analytics in E-commerce: a systematic review and agenda for future research. Electronic Markets 26 (2016), 173–194.
- [9] A. Alexandrov, K. Benidis, M. Bohlke-Schneider, V. Flunkert, J. Gasthaus, T. Januschowski, D. C. Maddix, S. Rangapuram, D. Salinas, J. Schulz, L. Stella, A. C. Türkmen, and Y. Wang. 2019. GluonTS: Probabilistic Time Series Modeling in Python. arXiv preprint arXiv:1906.05264 (2019).
- [10] Alexander Alexandrov, Konstantinos Benidis, Michael Bohlke-Schneider, Valentin Flunkert, Jan Gasthaus, Tim Januschowski, Danielle C. Maddix, Syama Rangapuram, David Salinas, Jasper Schulz, Lorenzo Stella, Ali Caner Türkmen, and Yuyang Wang. 2020. GluonTS: Probabilistic and Neural Time Series Modeling in Python. *Journal of Machine Learning Research* 21, 116 (2020), 1–6. http://jmlr.org/papers/v21/19-820.html
- [11] Alejandro Barredo Arrieta, Natalia Díaz-Rodríguez, Javier Del Ser, Adrien Bennetot, Siham Tabik, Alberto Barbado, Salvador García, Sergio Gil-López, Daniel Molina, Richard Benjamins, et al. 2020. Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information fusion* 58 (2020), 82–115.
- [12] Arthur Asuncion. 2007. UCI Machine Learning Repository. (Jan 2007).
- [13] Pax Authors. 2023. Pax: A Jax-based Machine Learning Framework for Large Scale Models. https://github.com/google/paxml. https://github.com/google/paxml GitHub repository.
- [14] Muhammad Awais, Muzammal Naseer, Salman Khan, RaoMuhammad Anwer, Hisham Cholakkal, Mubarak Shah, Ming-Hsuan Yang, and FahadShahbaz Khan. 2023. Foundational Models Defining a New Era in Vision: A Survey and Outlook. (Jul 2023).
- [15] AnthonyJ. Bagnall, SonHoang Dau, Jason Lines, Michael Flynn, James Large, Aaron Bostrom, Paul Southam, and Eamonn Keogh. 2018. The UEA multivariate time series classification archive, 2018. arXiv: Learning (Oct 2018).
- [16] Tadas Baltrušaitis, Chaitanya Ahuja, and Louis-Philippe Morency. 2018. Multimodal machine learning: A survey and taxonomy. IEEE transactions on pattern analysis and machine intelligence 41, 2 (2018), 423–443.
- [17] Kasun Bandara, Peibei Shi, Christoph Bergmeir, Hansika Hewamalage, Quoc Tran, and Brian Seaman. 2019. Sales demand forecast in e-commerce using a long short-term memory neural network methodology. In Neural Information Processing: 26th International Conference, ICONIP 2019, Sydney, NSW, Australia, December 12–15, 2019, Proceedings, Part III 26. Springer, 462–474.
- [18] Mahabub Basha, Karthik Reddy, Samiya Mubeen, K Hari Hara Raju, and V Jalaja. 2023. Does the Performance of Banking Sector Promote Economic Growth? A Time Series Analysis. *International Journal of Professional Business Review: Int. J. Prof. Bus. Rev.* 8, 6 (2023), 7.
- [19] Souhaib Ben Taieb, Gianluca Bontempi, Amir F. Atiya, and Antti Sorjamaa. 2012. A review and comparison of strategies for multi-step ahead time series forecasting based on the NN5 forecasting competition. Expert Systems with Applications (Jun 2012), 7067–7083.
- [20] Konstantinos Benidis, Syama Sundar Rangapuram, Valentin Flunkert, Yuyang Wang, Danielle Maddix, Caner Turkmen, Jan Gasthaus, Michael Bohlke-Schneider, David Salinas, Lorenzo Stella, et al. 2022. Deep learning for time series forecasting: Tutorial and literature survey. Comput. Surveys 55, 6 (2022), 1–36.
- [21] Aadyot Bhatnagar, Paul Kassianik, Chenghao Liu, Tian Lan, Wenzhuo Yang, Rowan Cassius, Doyen Sahoo, Devansh Arpit, Sri Subramanian, Gerald Woo, Amrita Saha, Arun Kumar Jagota, Gokulakrishnan Gopalakrishnan, Manpreet Singh, K C Krithika, Sukumar Maddineni, Daeki Cho, Bo Zong, Yingbo Zhou, Caiming Xiong, Silvio Savarese, Steven Hoi, and Huan Wang. 2021. Merlion: A Machine Learning Library for Time Series. (2021). arXiv:2109.09265 [cs.LG]
- [22] Rishi Bommasani and et.al Hudson. 2021. On the Opportunities and Risks of Foundation Models. Cornell University (Aug 2021).
- [23] Philippe Bracke, Anupam Datta, Carsten Jung, and Shayak Sen. 2019. Machine learning explainability in finance: an application to default risk analysis. (2019).
- [24] T.B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, and Dhariwal. 2020. Language Models are Few-Shot Learners. arXiv: Computation and Language, arXiv: Computation and Language (May 2020).
- [25] Defu Cao, Furong Jia, Sercan O Arik, Tomas Pfister, Yixiang Zheng, Wen Ye, and Yan Liu. [n. d.]. TEMPO: PROMPT-BASED GENERATIVE PRE-TRAINED TRANSFORMER FOR TIME SERIES FORECASTING. ([n. d.]).
- [26] Stanislas Chambon, Mathieu N. Galtier, Pierrick J. Arnal, Gilles Wainrib, and Alexandre Gramfort. 2018. A deep learning architecture for temporal sleep stage classification using multivariate and multimodal time series. IEEE Transactions on Neural Systems and Rehabilitation Engineering (Apr 2018), 758–769. https://doi.org/10.1109/tnsre.2018.2813138
- [27] Ching Chang, Wen-Chih Peng, and Tien-Fu Chen. 2023. LLM4TS: Two-Stage Fine-Tuning for Time-Series Forecasting with Pre-Trained LLMs. In arXiv:2308.08469.
- [28] Hongjie Chen and Hoda Eldardiry. 2023. Graph Time-series Modeling in Deep Learning: A Survey. ACM Transactions on Knowledge Discovery from Data (2023).
- [29] Jou-Fan Chen, Wei-Lun Chen, Chun-Ping Huang, Szu-Hao Huang, and An-Pin Chen. 2016. Financial time-series data analysis using deep convolutional neural networks. In 2016 7th International conference on cloud computing and big data (CCBD). IEEE, 87–92.
- [30] Muxi Chen, Zhijian Xu, Ailing Zeng, and Qiang Xu. 2023. FrAug: Frequency Domain Augmentation for Time Series Forecasting. (Feb 2023).

- [31] Zihan Chen, Lei Nico Zheng, Cheng Lu, Jialu Yuan, and Di Zhu. 2023. ChatGPT Informed Graph Neural Network for Stock Movement Prediction. SSRN Electronic Journal (2023).
- [32] Dawei Cheng, Fangzhou Yang, Sheng Xiang, and Jin Liu. 2022. Financial time series forecasting with multi-modality graph neural network. *Pattern Recognition* 121 (2022), 108218.
- [33] Jiashun Cheng, Man Li, Jia Li, and Fugee Tsung. 2023. Wiener Graph Deconvolutional Network Improves Graph Self-Supervised Learning. In AAAI, 7131–7139.
- [34] Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, et al. 2023. Palm: Scaling language modeling with pathways. *Journal of Machine Learning Research* 24, 240 (2023), 1–113
- [35] D Conway and M Hulme. 1993. Recent fluctuations in precipitation and runoff over the Nile sub-basins and their impact on main Nile discharge. Climatic change 25, 2 (1993), 127–151.
- [36] Abhimanyu Das, Weihao Kong, Rajat Sen, and Yichen Zhou. 2023. A Decoder-Only Foundation Model for Time-Series Forecasting. In arXiv:2310.10688.
- [37] Ringki Das and Thoudam Doren Singh. 2023. Multimodal sentiment analysis: a survey of methods, trends, and challenges. Comput. Surveys 55, 13s (2023), 1–38.
- [38] Hoang Anh Dau, Anthony Bagnall, Kaveh Kamgar, Chin-Chia Michael Yeh, Yan Zhu, Shaghayegh Gharghabi, Chotirat Ann Ratanamahatana, and Eamonn Keogh. 2019. The UCR time series archive. IEEE/CAA Journal of Automatica Sinica (Nov 2019), 1293–1305.
- [39] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. 2009. ImageNet: A large-scale hierarchical image database. In 2009 IEEE Conference on Computer Vision and Pattern Recognition.
- [40] Leyan Deng, Defu Lian, Zhenya Huang, and Enhong Chen. 2022. Graph convolutional adversarial networks for spatiotemporal anomaly detection. IEEE Transactions on Neural Networks and Learning Systems 33, 6 (2022), 2416–2428.
- [41] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In *Proceedings of the 2019 Conference of the North*. https://doi.org/10.18653/v1/n19-1423
- [42] Chaoyue Ding, Shiliang Sun, and Jing Zhao. 2023. MST-GAT: A multimodal spatial–temporal graph attention network for time series anomaly detection. *Information Fusion* 89 (2023), 527–536.
- [43] Ning Ding, Yujia Qin, Guang Yang, Fuchao Wei, Zonghan Yang, Yusheng Su, Shengding Hu, Yulin Chen, Chi-Min Chan, Weize Chen, et al. 2022. Delta tuning: A comprehensive study of parameter efficient methods for pre-trained language models. arXiv preprint arXiv:2203.06904 (2022).
- [44] Qingxiu Dong, Lei Li, Damai Dai, Ce Zheng, Zhiyong Wu, Baobao Chang, Xu Sun, Jingjing Xu, and Zhifang Sui. 2022. A survey for in-context learning. arXiv preprint arXiv:2301.00234 (2022).
- [45] Samuel Dooley, Gurnoor Singh Khurana, Chirag Mohapatra, Siddartha V Naidu, and Colin White. 2024. Forecastpfn: Synthetically-trained zero-shot forecasting. Advances in Neural Information Processing Systems 36 (2024).
- [46] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. 2020. An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale. In *International Conference on Learning Representations*.
- [47] Mengnan Du, Ninghao Liu, and Xia Hu. 2019. Techniques for interpretable machine learning. Commun. ACM 63, 1 (2019), 68-77.
- [48] Maud Ehrmann, Ahmed Hamdi, Elvys Linhares Pontes, Matteo Romanello, and Antoine Doucet. 2023. Named entity recognition and classification in historical documents: A survey. *Comput. Surveys* 56, 2 (2023), 1–47.
- [49] Vijay Ekambaram, Kushagra Manglik, Sumanta Mukherjee, Surya Shravan Kumar Sajja, Satyam Dwivedi, and Vikas Raykar. 2020. Attention based multi-modal new product sales time-series forecasting. In Proceedings of the 26th ACM SIGKDD international conference on knowledge discovery & data mining. 3110–3118.
- [50] Robert F Engle. 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica: Journal of the econometric society (1982), 987–1007.
- [51] Philippe Esling and Carlos Agon. 2012. Time-series data mining. ACM Computing Surveys (CSUR) 45, 1 (2012), 1-34.
- [52] FairScale authors. 2021. FairScale: A general purpose modular PyTorch library for high performance and large scale training. https://github.com/facebookresearch/fairscale.
- [53] Li Fei-Fei, R. Fergus, and P. Perona. 2006. One-shot learning of object categories. IEEE Transactions on Pattern Analysis and Machine Intelligence (Apr 2006), 594–611. https://doi.org/10.1109/tpami.2006.79
- [54] Cheng Feng, Long Huang, and Denis Krompass. 2024. Only the Curve Shape Matters: Training Foundation Models for Zero-Shot Multivariate Time Series Forecasting through Next Curve Shape Prediction. arXiv preprint arXiv:2402.07570 (2024).
- [55] Juliana Jansen Ferreira and Mateus de Souza Monteiro. 2020. Do ML Experts Discuss Explainability for AI Systems? A discussion case in the industry for a domain-specific solution. arXiv preprint arXiv:2002.12450 (2020).
- [56] David F Findley, Demetra P Lytras, and Tucker S McElroy. 2017. Detecting seasonality in seasonally adjusted monthly time series. Statistics 3 (2017).
- [57] Murray Frank and Thanasis Stengos. 1988. Chaotic dynamics in economic time-series. Journal of Economic Surveys 2, 2 (1988), 103–133.
- [58] Azul Garza and Max Mergenthaler-Canseco. 2023. TimeGPT-1. arXiv preprint arXiv:2310.03589 (2023).

[59] Mouzhi Ge, Hind Bangui, and Barbora Buhnova. 2018. Big data for internet of things: a survey. Future generation computer systems 87 (2018), 601–614.

- [60] Rakshitha Wathsadini Godahewa, Christoph Bergmeir, Geoffrey I Webb, Rob Hyndman, and Pablo Montero-Manso. 2021. Monash Time Series Forecasting Archive. In Thirty-fifth Conference on Neural Information Processine Systems Datasets and Benchmarks Track (Round 2).
- [61] Nate Gruver, Marc Finzi, Shikai Qiu, and Andrew Gordon Wilson. 2023. Large Language Models Are Zero-Shot Time Series Forecasters. ArXiv abs/2310.07820 (2023). https://api.semanticscholar.org/CorpusID:263908782
- [62] Riccardo Guidotti, Anna Monreale, Salvatore Ruggieri, Franco Turini, Fosca Giannotti, and Dino Pedreschi. 2018. A survey of methods for explaining black box models. ACM computing surveys (CSUR) 51, 5 (2018), 1–42.
- [63] Yannik Hahn, Tristan Langer, Richard Meyes, and Tobias Meisen. 2023. Time Series Dataset Survey for Forecasting with Deep Learning. *Forecasting* 5, 1 (2023), 315–335.
- [64] James D Hamilton. 1989. A new approach to the economic analysis of nonstationary time series and the business cycle. Econometrica: Journal of the econometric society (1989), 357–384.
- [65] Xu Han, Zhengyan Zhang, Ning Ding, Yuxian Gu, Xiao Liu, Yuqi Huo, Jiezhong Qiu, Yuan Yao, Ao Zhang, Liang Zhang, et al. 2021. Pre-trained models: Past, present and future. AI Open 2 (2021), 225–250.
- [66] Junxian He, Chunting Zhou, Xuezhe Ma, Taylor Berg-Kirkpatrick, and Graham Neubig. 2021. Towards a unified view of parameter-efficient transfer learning. arXiv preprint arXiv:2110.04366 (2021).
- [67] Kaiming He, Xinlei Chen, Saining Xie, Yanghao Li, Piotr Dollár, and Ross Girshick. 2022. Masked autoencoders are scalable vision learners. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 16000–16009.
- [68] Shwai He, Liang Ding, Daize Dong, Miao Zhang, and Dacheng Tao. 2022. Sparseadapter: An easy approach for improving the parameter-efficiency of adapters. arXiv preprint arXiv:2210.04284 (2022).
- [69] Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. 2020. Measuring Massive Multitask Language Understanding. In International Conference on Learning Representations.
- [70] Julien Herzen and Francesco LĤssig et.al. 2022. Darts: User-Friendly Modern Machine Learning for Time Series. Journal of Machine Learning Research 23, 124 (2022), 1–6. http://jmlr.org/papers/v23/21-1177.html
- [71] Reza Hosseini, Albert Chen, Kaixu Yang, Sayan Patra, Yi Su, Saad Eddin Al Orjany, Sishi Tang, and Parvez Ahammad. 2022. Greykite: Deploying Flexible Forecasting at Scale at LinkedIn. In Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining (Washington DC, USA) (KDD '22). Association for Computing Machinery, New York, NY, USA, 3007–3017. https://doi.org/10.1145/3534678. 3539165
- [72] Zhenyu Hou, Xiao Liu, Yukuo Cen, Yuxiao Dong, Hongxia Yang, Chunjie Wang, and Jie Tang. 2022. Graphmae: Self-supervised masked graph autoencoders. In Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining. 594–604.
- [73] Neil Houlsby, Andrei Giurgiu, Stanislaw Jastrzebski, Bruna Morrone, Quentin De Laroussilhe, Andrea Gesmundo, Mona Attariyan, and Sylvain Gelly. 2019. Parameter-efficient transfer learning for NLP. In *International Conference on Machine Learning*. PMLR, 2790–2799.
- [74] Essam H Houssein, Moataz Kilany, and Aboul Ella Hassanien. 2017. ECG signals classification: a review. International Journal of Intelligent Engineering Informatics 5, 4 (2017), 376–396.
- [75] Edward J Hu, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, Weizhu Chen, et al. 2021. LoRA: Low-Rank Adaptation of Large Language Models. In *International Conference on Learning Representations*.
- [76] Mark Ibrahim, Melissa Louie, Ceena Modarres, and John Paisley. 2019. Global explanations of neural networks: Mapping the landscape of predictions. In Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society. 279–287.
- [77] MA Islam, Hang Seng Che, M Hasanuzzaman, and NA Rahim. 2020. Energy demand forecasting. In Energy for sustainable development. Elsevier, 105–123.
- [78] Hassan Ismail Fawaz, Germain Forestier, Jonathan Weber, Lhassane Idoumghar, and Pierre-Alain Muller. 2018. Transfer learning for time series classification. In 2018 IEEE International Conference on Big Data (Big Data). https://doi.org/10.1109/bigdata.2018.8621990
- [79] Hassan Ismail Fawaz, Germain Forestier, Jonathan Weber, Lhassane Idoumghar, and Pierre-Alain Muller. 2019. Deep learning for time series classification: a review. Data mining and knowledge discovery 33, 4 (2019), 917–963.
- [80] Xiaodong Jiang, Sudeep Srivastava, and et.al Chatterjee. 2022. Kats. https://github.com/facebookresearch/Kats
- [81] Yushan Jiang, Zijie Pan, Xikun Zhang, Sahil Garg, Anderson Schneider, Yuriy Nevmyvaka, and Dongjin Song. 2024. Empowering Time Series Analysis with Large Language Models: A Survey. arXiv preprint arXiv:2402.03182 (2024).
- [82] Ming Jin, Shiyu Wang, Lintao Ma, Zhixuan Chu, James Y. Zhang, Xiao Long Shi, Pin-Yu Chen, Yuxuan Liang, Yuan-Fang Li, Shirui Pan, and Qingsong Wen. 2023. Time-LLM: Time Series Forecasting by Reprogramming Large Language Models. ArXiv abs/2310.01728 (2023).
- [83] Ming Jin, Qingsong Wen, Yuxuan Liang, Chaoli Zhang, Siqiao Xue, Xue Wang, James Zhang, Yi Wang, Haifeng Chen, Xiaoli Li, et al. 2023. Large models for time series and spatio-temporal data: A survey and outlook. arXiv preprint arXiv:2310.10196 (2023).
- [84] Ming Jin, Yifan Zhang, Wei Chen, Kexin Zhang, Yuxuan Liang, Bin Yang, Jindong Wang, Shirui Pan, and Qingsong Wen. 2024. Position Paper: What Can Large Language Models Tell Us about Time Series Analysis. arXiv preprint arXiv:2402.02713 (2024).
- [85] Alistair E.W. Johnson, Tom J. Pollard, Lu Shen, Li-wei H. Lehman, Mengling Feng, Mohammad Ghassemi, Benjamin Moody, Peter Szolovits, Leo Anthony Celi, and Roger G. Mark. 2016. MIMIC-III, a freely accessible critical care database. Scientific Data (May 2016).

- [86] Kamal Raj Kanakarajan and Malaikannan Sankarasubbu. 2023. Saama AI Research at SemEval-2023 Task 7: Exploring the Capabilities of Flan-T5 for Multi-evidence Natural Language Inference in Clinical Trial Data. In Proceedings of the 17th International Workshop on Semantic Evaluation (SemEval-2023). 995–1003.
- [87] Jared Kaplan, McCandlish Sam, Henighan Tom, T.B. Brown, Chess Benjamin, Rewon Child, Scott Gray, Alec Radford, Jeffrey Wu, and Dario Amodei. 2020. Scaling Laws for Neural Language Models. arXiv: Learning, arXiv: Learning (Jan 2020).
- [88] Taesung Kim, Jinhee Kim, Yunwon Tae, Cheonbok Park, Jang-Ho Choi, and Jaegul Choo. 2021. Reversible instance normalization for accurate time-series forecasting against distribution shift. In *International Conference on Learning Representations*.
- [89] Alexander Kirillov, Eric Mintun, Nikhila Ravi, Hanzi Mao, Chloe Rolland, Laura Gustafson, Tete Xiao, Spencer Whitehead, Alexander C Berg, Wan-Yen Lo, et al. 2023. Segment anything. arXiv preprint arXiv:2304.02643 (2023).
- [90] Takeshi Kojima, Shixiang Shane Gu, Machel Reid, Yutaka Matsuo, and Yusuke Iwasawa. 2022. Large language models are zero-shot reasoners. Advances in neural information processing systems 35 (2022), 22199–22213.
- [91] Woosuk Kwon, Zhuohan Li, Siyuan Zhuang, Ying Sheng, Lianmin Zheng, Cody Hao Yu, Joseph E. Gonzalez, Hao Zhang, and Ion Stoica. 2023. Efficient Memory Management for Large Language Model Serving with PagedAttention. In *Proceedings of the ACM SIGOPS 29th Symposium on Operating Systems Principles*.
- [92] Christoph H. Lampert, Hannes Nickisch, and Stefan Harmeling. 2009. Learning to detect unseen object classes by between-class attribute transfer. In 2009 IEEE Conference on Computer Vision and Pattern Recognition.
- [93] Yinyu Lan, Yanru Wu, Wang Xu, Weiqiang Feng, and Youhao Zhang. 2023. Chinese Fine-Grained Financial Sentiment Analysis with Large Language Models. arXiv preprint arXiv:2306.14096 (2023).
- [94] Katherine Lee, Daphne Ippolito, Andrew Nystrom, Chiyuan Zhang, Douglas Eck, Chris Callison-Burch, and Nicholas Carlini. 2022. Deduplicating Training Data Makes Language Models Better. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*.
- [95] Brian Lester, Rami Al-Rfou, and Noah Constant. 2021. The power of scale for parameter-efficient prompt tuning. arXiv preprint arXiv:2104.08691 (2021).
- [96] Kin Kwan Leung, Clayton Rooke, Jonathan Smith, Saba Zuberi, and Maksims Volkovs. 2023. Temporal Dependencies in Feature Importance for Time Series Prediction. In *The Eleventh International Conference on Learning Representations*. https://openreview.net/forum?id=C0q9oBc3n4
- [97] Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer.
 2020. BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation, Translation, and Comprehension.. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics. https://doi.org/10.18653/v1/2020.acl-main.703
- [98] Jia Li, Zhichao Han, Hong Cheng, Jiao Su, Pengyun Wang, Jianfeng Zhang, and Lujia Pan. 2019. Predicting path failure in time-evolving graphs. In Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining. 1279–1289.
- [99] Junnan Li, Dongxu Li, Silvio Savarese, and Steven Hoi. 2023. Blip-2: Bootstrapping language-image pre-training with frozen image encoders and large language models. arXiv preprint arXiv:2301.12597 (2023).
- [100] Jun Li, Che Liu, Sibo Cheng, Rossella Arcucci, and Shenda Hong. 2023. Frozen Language Model Helps ECG Zero-Shot Learning. In arXiv:2303.12311.
- [101] Jia Li, Yu Rong, Helen Meng, Zhihui Lu, Timothy Kwok, and Hong Cheng. 2018. TATC: predicting Alzheimer's disease with actigraphy data. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. 509–518.
- [102] Shenggui Li, Hongxin Liu, Zhengda Bian, Jiarui Fang, Haichen Huang, Yuliang Liu, Boxiang Wang, and Yang You. 2023. Colossal-ai: A unified deep learning system for large-scale parallel training. In Proceedings of the 52nd International Conference on Parallel Processing. 766–775.
- [103] Xiang Lisa Li and Percy Liang. 2021. Prefix-tuning: Optimizing continuous prompts for generation. arXiv preprint arXiv:2101.00190 (2021).
- [104] Vladislav Lialin, Vijeta Deshpande, and Anna Rumshisky. 2023. Scaling down to scale up: A guide to parameter-efficient fine-tuning. arXiv preprint arXiv:2303.15647 (2023).
- [105] Zhiyu Liang, Jianfeng Zhang, Chen Liang, Hongzhi Wang, Zheng Liang, and Lujia Pan. 2023. A Shapelet-based Framework for Unsupervised Multivariate Time Series Representation Learning. Proceedings of the VLDB Endowment 17, 3 (2023), 386–399.
- [106] Bryan Lim and Stefan Zohren. 2021. Time-series forecasting with deep learning: a survey. Philosophical Transactions of the Royal Society A 379, 2194 (2021). 20200209.
- [107] Lequan Lin, Zhengkun Li, Ruikun Li, Xuliang Li, and Junbin Gao. 2023. Diffusion models for time-series applications: a survey. Frontiers of Information Technology & Electronic Engineering (2023), 1–23.
- [108] Benjamin Lindemann, Timo Müller, Hannes Vietz, Nasser Jazdi, and Michael Weyrich. 2021. A survey on long short-term memory networks for time series prediction. *Procedia CIRP* (Jan 2021), 650–655. https://doi.org/10.1016/j.procir.2021.03.088
- [109] Chien-Liang Liu, W. Hsaio, and Yao-Chung Tu. 2019. Time Series Classification With Multivariate Convolutional Neural Network. IEEE Transactions on Industrial Electronics 66 (2019), 4788–4797. https://api.semanticscholar.org/CorpusID:59601646
- [110] Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. 2023. Pre-train, Prompt, and Predict: A Systematic Survey of Prompting Methods in Natural Language Processing. Comput. Surveys (Sep 2023), 1–35. https://doi.org/10.1145/3560815
- [111] Tiedong Liu and Bryan Kian Hsiang Low. [n. d.]. Goat: Fine-tuned LLaMA Outperforms GPT-4 on Arithmetic Tasks, May 2023. *URL http://arxiv.org/abs/2305.14201* ([n. d.]).

[112] Xu Liu, Junfeng Hu, Yuan Li, Shizhe Diao, Yuxuan Liang, Bryan Hooi, and Roger Zimmermann. 2023. UniTime: A Language-Empowered Unified Model for Cross-Domain Time Series Forecasting. In arXiv:2310.09751.

- [113] Xin Liu, Daniel McDuff, Geza Kovacs, Isaac Galatzer-Levy, Jacob Sunshine, Jiening Zhan, Ming-Zher Poh, Shun Liao, Paolo Di Achille, and Shwetak Patel. 2023. Large Language Models Are Few-Shot Health Learners. In arXiv:2305.15525.
- [114] Yong Liu, Chenyu Li, Jianmin Wang, and Mingsheng Long. 2023. Koopa: Learning Non-stationary Time Series Dynamics with Koopman Predictors. In *Thirty-seventh Conference on Neural Information Processing Systems*. https://openreview.net/forum?id=A4zzxu82a7
- [115] Yong Liu, Haixu Wu, Jianmin Wang, and Mingsheng Long. 2022. Non-stationary transformers: Exploring the stationarity in time series forecasting. Advances in Neural Information Processing Systems 35 (2022), 9881–9893.
- [116] Zhiding Liu, Mingyue Cheng, Zhi Li, Zhenya Huang, Qi Liu, Yanhu Xie, and Enhong Chen. 2024. Adaptive normalization for non-stationary time series forecasting: A temporal slice perspective. Advances in Neural Information Processing Systems 36 (2024).
- [117] Zhuang Liu, Degen Huang, Kaiyu Huang, Zhuang Li, and Jun Zhao. 2021. Finbert: A pre-trained financial language representation model for financial text mining. In *Proceedings of the twenty-ninth international conference on international joint conferences on artificial intelligence*. 4513–4519.
- [118] Renze Lou, Kai Zhang, and Wenpeng Yin. 2023. Is prompt all you need? no. A comprehensive and broader view of instruction learning. arXiv preprint arXiv:2303.10475 (2023).
- [119] Chris Lu, Yannick Schroecker, Albert Gu, Emilio Parisotto, Jakob Foerster, Satinder Singh, and Feryal Behbahani. 2024. Structured state space models for in-context reinforcement learning. Advances in Neural Information Processing Systems 36 (2024).
- [120] Qianli Ma, Zhen Liu, Zhenjing Zheng, Ziyang Huang, Siying Zhu, Zhongzhong Yu, and James T Kwok. 2023. A Survey on Time-Series Pre-Trained Models. arXiv preprint arXiv:2305.10716 (2023).
- [121] Peter W. Macfarlane and Julie Kennedy. 2021. Automated ECG Interpretation—A Brief History from High Expectations to Deepest Networks. Hearts (Sep 2021), 433–448.
- [122] S. Makridakis, A. Andersen, R. Carbone, R. Fildes, M. Hibon, R. Lewandowski, J. Newton, E. Parzen, and R. Winkler. 1982. The accuracy of extrapolation (time series) methods: Results of a forecasting competition. *Journal of Forecasting* (Apr 1982), 111–153.
- [123] Spyros Makridakis, Evangelos Spiliotis, and Vassilios Assimakopoulos. 2018. The M4 Competition: Results, findings, conclusion and way forward. International Journal of Forecasting 34, 4 (Oct 2018), 802–808.
- [124] Spyros Makridakis, Evangelos Spiliotis, and Vassilios Assimakopoulos. 2022. M5 accuracy competition: Results, findings, and conclusions. International Journal of Forecasting (Oct 2022), 1346–1364.
- [125] Ricardo P Masini, Marcelo C Medeiros, and Eduardo F Mendes. 2023. Machine learning advances for time series forecasting. *Journal of economic surveys* 37, 1 (2023), 76–111.
- [126] Gaurav Menghani. 2023. Efficient deep learning: A survey on making deep learning models smaller, faster, and better. Comput. Surveys 55, 12 (2023), 1–37.
- [127] Elena Merdjanovska and Aleksandra Rashkovska. 2023. A framework for comparative study of databases and computational methods for arrhythmia detection from single-lead ECG. Scientific Reports (Jul 2023).
- [128] Shen-Yun Miao, Chao-Chun Liang, and Keh-Yih Su. 2021. A diverse corpus for evaluating and developing English math word problem solvers. arXiv preprint arXiv:2106.15772 (2021).
- [129] John A Miller, Mohammed Aldosari, Farah Saeed, Habib Barna, Subas Rana, IBudak Arpinar, Ninghao Liu, and NasidHabib Barna. 2024. A Survey of Deep Learning and Foundation Models for Time Series Forecasting. arXiv preprint arXiv:2401.13912 (2024).
- [130] Sewon Min, Xinxi Lyu, Ari Holtzman, Mikel Artetxe, Mike Lewis, Hannaneh Hajishirzi, and Luke Zettlemoyer. 2022. Rethinking the Role of Demonstrations: What Makes In-Context Learning Work?. In Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing. 11048–11064.
- [131] Manfred Mudelsee. 2010. Climate time series analysis. Atmospheric and 397 (2010).
- [132] Manfred Mudelsee. 2019. Trend analysis of climate time series: A review of methods. Earth-science reviews 190 (2019), 310–322.
- [133] Yuqi Nie, Nam H Nguyen, Phanwadee Sinthong, and Jayant Kalagnanam. 2022. A Time Series is Worth 64 Words: Long-term Forecasting with Transformers. In The Eleventh International Conference on Learning Representations.
- [134] Mark Palatucci, Dean Pomerleau, Geoffrey E Hinton, and Tom M Mitchell. 2009. Zero-shot learning with semantic output codes. Advances in neural information processing systems 22 (2009).
- [135] Gregory Plumb, Denali Molitor, and Ameet S Talwalkar. 2018. Model agnostic supervised local explanations. Advances in neural information processing systems 31 (2018).
- [136] Boris Pyakillya, Natasha Kazachenko, and Nikolay Mikhailovsky. 2017. Deep learning for ECG classification. In *Journal of physics: conference series*, Vol. 913. IOP Publishing, 012004.
- [137] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. 2021. Learning transferable visual models from natural language supervision. In *International conference on machine learning*. PMLR, 8748–8763.
- [138] Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. 2019. Language models are unsupervised multitask learners. *OpenAI blog* 1, 8 (2019), 9.

- [139] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *The Journal of Machine Learning Research* 21, 1 (2020), 5485–5551.
- [140] Aditya Ramesh, Mikhail Pavlov, Gabriel Goh, Scott Gray, Chelsea Voss, Alec Radford, Mark Chen, and Ilya Sutskever. 2021. Zero-shot text-to-image generation. In *International Conference on Machine Learning*. PMLR, 8821–8831.
- [141] Kashif Rasul, Arjun Ashok, Andrew Robert Williams, Arian Khorasani, George Adamopoulos, Rishika Bhagwatkar, Marin Biloš, Hena Ghonia, Nadhir Hassen, Anderson Schneider, et al. 2023. Lag-Llama: Towards Foundation Models for Time Series Forecasting. In R0-FoMo: Robustness of Few-shot and Zero-shot Learning in Large Foundation Models.
- [142] Sylvestre-Alvise Rebuffi, Hakan Bilen, and Andrea Vedaldi. 2018. Efficient parametrization of multi-domain deep neural networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 8119–8127.
- [143] Thomas Rojat, Raphael Puget, David Filliat, JavierDel Ser, Rodolphe Gelin, and Natalia Díaz-Rodríguez. 2021. Explainable Artificial Intelligence (XAI) on TimeSeries Data: A Survey. arXiv: Learning, arXiv: Learning (Apr 2021).
- [144] Oleksandr Romanko, Akhilesh Narayan, and Roy H Kwon. 2023. Chatgpt-based investment portfolio selection. In Operations Research Forum, Vol. 4. Springer, 91.
- [145] Cynthia Rudin. 2019. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. Nature machine intelligence 1, 5 (2019), 206–215.
- [146] David Salinas, Valentin Flunkert, Jan Gasthaus, and Tim Januschowski. 2020. DeepAR: Probabilistic Forecasting with Autoregressive Recurrent Networks. *International Journal of Forecasting* (Jul 2020), 1181–1191.
- [147] Zezhi Shao, Zhao Zhang, Fei Wang, and Yongjun Xu. 2022. Pre-training enhanced spatial-temporal graph neural network for multivariate time series forecasting. In *Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*. 1567–1577.
- [148] Li Shen, Yuning Wei, and Yangzhu Wang. 2023. GBT: Two-stage transformer framework for non-stationary time series forecasting. *Neural Networks* 165 (2023), 953–970.
- [149] Yongjie Shi, Xianghua Ying, and Jinfa Yang. 2022. Deep Unsupervised Domain Adaptation with Time Series Sensor Data: A Survey. Sensors (Basel, Switzerland) 22 (2022). https://api.semanticscholar.org/CorpusID:251075217
- [150] Hoo-Chang Shin, Matthew Orton, David J Collins, Simon Doran, and Martin O Leach. 2011. Autoencoder in time-series analysis for unsupervised tissues characterisation in a large unlabelled medical image dataset. In 2011 10th international conference on machine learning and applications and workshops, Vol. 1. IEEE, 259–264.
- [151] Mohammad Shoeybi, Mostofa Patwary, Raul Puri, Patrick LeGresley, Jared Casper, and Bryan Catanzaro. 2019. Megatron-lm: Training multi-billion parameter language models using model parallelism. arXiv preprint arXiv:1909.08053 (2019).
- [152] Dimitris Spathis and Fahim Kawsar. [n. d.]. The First Step Is the Hardest: Pitfalls of Representing and Tokenizing Temporal Data for Large Language Models. ([n. d.]).
- [153] Martin Stepnicka and Michal Burda. 2017. On the results and observations of the time series forecasting competition CIF 2016. In 2017 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE).
- [154] Jing Su, Chufeng Jiang, Xin Jin, Yuxin Qiao, Tingsong Xiao, Hongda Ma, Rong Wei, Zhi Jing, Jiajun Xu, and Junhong Lin. 2024. Large Language Models for Forecasting and Anomaly Detection: A Systematic Literature Review. arXiv preprint arXiv:2402.10350 (2024).
- [155] Yusheng Su, Xiaozhi Wang, Yujia Qin, Chi-Min Chan, Yankai Lin, Zhiyuan Liu, Peng Li, Juanzi Li, Lei Hou, Maosong Sun, et al. 2021. On transferability of prompt tuning for natural language understanding. arXiv preprint arXiv:2111.06719 (2021).
- [156] Chenxi Sun, Yaliang Li, Hongyan Li, and Shenda Hong. 2023. TEST: Text Prototype Aligned Embedding to Activate LLM's Ability for Time Series. In arXiv:2308.08241.
- [157] Hu Sun, Ward Manchester, Zhenbang Jiao, Xiantong Wang, and Yang Chen. 2019. Interpreting LSTM prediction on solar flare eruption with time-series clustering. arXiv preprint arXiv:1912.12360 (2019).
- [158] Xiangguo Sun, Hong Cheng, Jia Li, Bo Liu, and Jihong Guan. 2023. All in One: Multi-Task Prompting for Graph Neural Networks. In Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining. 2120–2131.
- [159] Chang Wei Tan, Christoph Bergmeir, Francois Petitjean, and Geoffrey I Webb. 2020. Monash University, UEA, UCR time series extrinsic regression archive. arXiv preprint arXiv:2006.10996 (2020).
- [160] Yajiao Tang, Zhenyu Song, Yulin Zhu, Huaiyu Yuan, Maozhang Hou, Junkai Ji, Cheng Tang, and Jianqiang Li. 2022. A survey on machine learning models for financial time series forecasting. *Neurocomputing* 512 (2022), 363–380.
- [161] Romain Tavenard, Johann Faouzi, Gilles Vandewiele, Felix Divo, Guillaume Androz, Chester Holtz, Marie Payne, Roman Yurchak, Marc Rußwurm, Kushal Kolar, and Eli Woods. 2020. Tslearn, A Machine Learning Toolkit for Time Series Data. *Journal of Machine Learning Research* 21, 118 (2020), 1–6. http://jmlr.org/papers/v21/20-091.html
- [162] Sean J Taylor and Benjamin Letham. 2018. Forecasting at scale. The American Statistician 72, 1 (2018), 37-45.
- [163] Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. 2023. Llama: Open and efficient foundation language models. arXiv preprint arXiv:2302.13971 (2023).
- [164] Patara Trirat, Yooju Shin, Junhyeok Kang, Youngeun Nam, Jihye Na, Minyoung Bae, Joeun Kim, Byunghyun Kim, and Jae-Gil Lee. 2024. Universal Time-Series Representation Learning: A Survey. arXiv preprint arXiv:2401.03717 (2024).
- [165] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, AidanN. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is All you Need. Neural Information Processing Systems, Neural Information Processing Systems (Jun 2017).

[166] Patrick Wagner, Nils Strodthoff, Ralf-Dieter Bousseljot, Dieter Kreiseler, Fatima I. Lunze, Wojciech Samek, and Tobias Schaeffter. 2020. PTB-XL, a large publicly available electrocardiography dataset. Scientific Data (May 2020).

- [167] Zhongwei Wan, Xin Wang, Che Liu, Samiul Alam, Yu Zheng, Zhongnan Qu, Shen Yan, Yi Zhu, Quanlu Zhang, Mosharaf Chowdhury, et al. 2023.
 Efficient large language models: A survey. arXiv preprint arXiv:2312.03863 1 (2023).
- [168] Bingnan Wang, Dickson K. W. Chiu, and Kevin K. W. Ho. 2022. A Comparison of Deep Learning Models in Time Series Forecasting of Web Traffic Data From Kaggle. 301–319.
- [169] Chengyi Wang, Sanyuan Chen, Yu Wu, Ziqiang Zhang, Long Zhou, Shujie Liu, Zhuo Chen, Yanqing Liu, Huaming Wang, Jinyu Li, et al. 2023.
 Neural codec language models are zero-shot text to speech synthesizers. arXiv preprint arXiv:2301.02111 (2023).
- [170] Heyuan Wang, Tengjiao Wang, and Yi Li. 2020. Incorporating expert-based investment opinion signals in stock prediction: A deep learning framework. In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 34. 971–978.
- [171] Jingyuan Wang, Zhen Peng, Xiaoda Wang, Chao Li, and Junjie Wu. 2020. Deep fuzzy cognitive maps for interpretable multivariate time series prediction. IEEE transactions on fuzzy systems 29, 9 (2020), 2647–2660.
- [172] Luxuan Wang, Lei Bai, Ziyue Li, Rui Zhao, and Fugee Tsung. 2023. Correlated time series self-supervised representation learning via spatiotemporal bootstrapping. In 2023 IEEE 19th International Conference on Automation Science and Engineering (CASE). IEEE, 1–7.
- [173] Thomas Wang, Adam Roberts, Daniel Hesslow, Teven Le Scao, Hyung Won Chung, Iz Beltagy, Julien Launay, and Colin Raffel. 2022. What language model architecture and pretraining objective works best for zero-shot generalization? In *International Conference on Machine Learning*. PMLR, 22964–22984.
- [174] Wei Wang, Vincent W. Zheng, Han Yu, and Chunyan Miao. 2019. A Survey of Zero-Shot Learning: Settings, Methods, and Applications. ACM Trans. Intell. Syst. Technol. 10, 2, Article 13 (jan 2019), 37 pages.
- [175] Xinglei Wang, Meng Fang, Zichao Zeng, and Tao Cheng. 2023. Where would i go next? large language models as human mobility predictors. arXiv preprint arXiv:2308.15197 (2023).
- [176] Yaqing Wang, Quanming Yao, James T. Kwok, and Lionel M. Ni. 2019. Generalizing from a Few Examples: A Survey on Few-Shot Learning. ACM Computing Surveys, ACM Computing Surveys (Apr 2019).
- [177] Manuel Weber, Maximilian Auch, Christoph Doblander, Peter Mandl, and Hans-Arno Jacobsen. 2021. Transfer Learning with Time Series Data: A Systematic Mapping Study. *IEEE Access* (Jan 2021), 165409–165432. https://doi.org/10.1109/access.2021.3134628
- [178] Jason Wei, Maarten Bosma, Vincent Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M Dai, and Quoc V Le. 2021. Finetuned Language Models are Zero-Shot Learners. In *International Conference on Learning Representations*.
- [179] Jason Wei, Yi Tay, Rishi Bommasani, Colin Raffel, Barret Zoph, Sebastian Borgeaud, Dani Yogatama, Maarten Bosma, Denny Zhou, Donald Metzler, et al. 2022. Emergent Abilities of Large Language Models. Transactions on Machine Learning Research (2022).
- [180] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. 2022. Chain-of-thought prompting elicits reasoning in large language models. Advances in Neural Information Processing Systems 35 (2022), 24824–24837.
- [181] Qingsong Wen, Liang Sun, Fan Yang, Xiaomin Song, Jingkun Gao, Xue Wang, and Huan Xu. 2021. Time Series Data Augmentation for Deep Learning: A Survey. In Proceedings of the Thirtieth International Joint Conference on Artificial Intelligence. https://doi.org/10.24963/ijcai.2021/631
- [182] Qingsong Wen, Tian Zhou, Chaoli Zhang, Weiqi Chen, Ziqing Ma, Junchi Yan, and Liang Sun. 2022. Transformers in time series: A survey. arXiv preprint arXiv:2202.07125 (2022).
- [183] Gerald Woo, Chenghao Liu, Doyen Sahoo, Akshat Kumar, and Steven Hoi. 2021. CoST: Contrastive Learning of Disentangled Seasonal-Trend Representations for Time Series Forecasting. In *International Conference on Learning Representations*.
- [184] BigScience Workshop, Teven Le Scao, Angela Fan, Christopher Akiki, Ellie Pavlick, Suzana Ilić, Daniel Hesslow, Roman Castagné, Alexandra Sasha Luccioni, François Yvon, et al. 2022. Bloom: A 176b-parameter open-access multilingual language model. arXiv preprint arXiv:2211.05100 (2022).
- [185] Haixu Wu, Tengge Hu, Yong Liu, Hang Zhou, Jianmin Wang, and Mingsheng Long. 2022. Timesnet: Temporal 2d-variation modeling for general time series analysis. In *The eleventh international conference on learning representations*.
- [186] Haixu Wu, Jiehui Xu, Jianmin Wang, and Mingsheng Long. 2021. Autoformer: Decomposition transformers with auto-correlation for long-term series forecasting. Advances in Neural Information Processing Systems 34 (2021), 22419–22430.
- [187] Jun Xia, Lirong Wu, Jintao Chen, Bozhen Hu, and Stan Z Li. 2022. Simgrace: A simple framework for graph contrastive learning without data augmentation. In Proceedings of the ACM Web Conference 2022. 1070–1079.
- [188] Dejun Xie, Yu Cui, and Yujian Liu. 2023. How does investor sentiment impact stock volatility? New evidence from Shanghai A-shares market. China Finance Review International 13, 1 (2023), 102–120.
- [189] Qianqian Xie, Weiguang Han, Yanzhao Lai, Min Peng, and Jimin Huang. 2023. The Wall Street Neophyte: A Zero-Shot Analysis of ChatGPT Over MultiModal Stock Movement Prediction Challenges. In arXiv:2304.05351.
- [190] Hao Xue and Flora D.Salim. 2022. PromptCast: A New Prompt-Based Learning Paradigm for Time Series Forecasting. IEEE Transactions on Knowledge and Data Engineering (2022). https://api.semanticscholar.org/CorpusID:253254774
- [191] Hao Xue and Flora D. Salim. 2023. Utilizing Language Models for Energy Load Forecasting. In arXiv:2310.17788.
- [192] Hao Xue, Bhanu Prakash Voutharoja, and Flora D. Salim. 2022. Leveraging Language Foundation Models for Human Mobility Forecasting. In Proceedings of the 30th International Conference on Advances in Geographic Information Systems. 1–9.
- [193] Peng Yan, Ahmed Abdulkadir, Paul-Philipp Luley, Matthias Rosenthal, Gerrit A Schatte, Benjamin F Grewe, and Thilo Stadelmann. 2024. A comprehensive survey of deep transfer learning for anomaly detection in industrial time series: Methods, applications, and directions. IEEE Access

(2024).

- [194] Jiexia Ye, Juanjuan Zhao, Kejiang Ye, and Chengzhong Xu. 2022. How to Build a Graph-Based Deep Learning Architecture in Traffic Domain: A Survey. IEEE Transactions on Intelligent Transportation Systems 23, 5 (2022), 3904–3924. https://doi.org/10.1109/TITS.2020.3043250
- [195] Chin-Chia Michael Yeh, Xin Dai, Huiyuan Chen, Yan Zheng, Yujie Fan, Audrey Der, Vivian Lai, Zhongfang Zhuang, Junpeng Wang, Liang Wang, et al. 2023. Toward a foundation model for time series data. In Proceedings of the 32nd ACM International Conference on Information and Knowledge Management. 4400–4404.
- [196] Tom Young, Devamanyu Hazarika, Soujanya Poria, and Erik Cambria. 2018. Recent trends in deep learning based natural language processing. ieee Computational intelligenCe magazine 13, 3 (2018), 55–75.
- [197] Xinli Yu, Zheng Chen, Yuan Ling, Shujing Dong, Zongying Liu, and Yanbin Lu. 2023. Temporal Data Meets LLM Explainable Financial Time Series Forecasting. ArXiv abs/2306.11025 (2023). https://api.semanticscholar.org/CorpusID:259203723
- [198] Ailing Zeng, Muxi Chen, Lei Zhang, and Qiang Xu. 2023. Are transformers effective for time series forecasting? In Proceedings of the AAAI conference on artificial intelligence, Vol. 37. 11121–11128.
- [199] Jiawen Zhang, Shun Zheng, Wei Cao, Jiang Bian, and Jia Li. 2023. Warpformer: A Multi-scale Modeling Approach for Irregular Clinical Time Series. In Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining. 3273–3285.
- [200] Kaiyan Zhang, Jianyu Wang, Ermo Hua, Biqing Qi, Ning Ding, and Bowen Zhou. 2024. CoGenesis: A Framework Collaborating Large and Small Language Models for Secure Context-Aware Instruction Following. arXiv preprint arXiv:2403.03129 (2024).
- [201] Renrui Zhang, Jiaming Han, Aojun Zhou, Xiangfei Hu, Shilin Yan, Pan Lu, Hongsheng Li, Peng Gao, and Yu Qiao. 2023. Llama-adapter: Efficient fine-tuning of language models with zero-init attention. arXiv preprint arXiv:2303.16199 (2023).
- [202] Susan Zhang, Stephen Roller, Naman Goyal, Mikel Artetxe, Moya Chen, Shuohui Chen, Christopher Dewan, Mona Diab, Xian Li, Xi Victoria Lin, et al. 2022. Opt: Open pre-trained transformer language models. arXiv preprint arXiv:2205.01068 (2022).
- [203] Weiqi Zhang, Chen Zhang, and Fugee Tsung. 2022. GRELEN: Multivariate Time Series Anomaly Detection from the Perspective of Graph Relational Learning.. In IJCAI. 2390–2397.
- [204] Weiqi Zhang, Jianfeng Zhang, Jia Li, and Fugee Tsung. 2023. A co-training approach for noisy time series learning. In Proceedings of the 32nd ACM International Conference on Information and Knowledge Management. 3308–3318.
- [205] Xiyuan Zhang, Ranak Roy Chowdhury, Rajesh K. Gupta, and Jingbo Shang. 2024. Large Language Models for Time Series: A Survey. arXiv:2402.01801 [cs.LG]
- [206] Zheng Zhang, Hossein Amiri, Zhenke Liu, Andreas Züfle, and Liang Zhao. 2023. Large Language Models for Spatial Trajectory Patterns Mining. In arXiv:2310.04942.
- [207] Bendong Zhao, Huanzhang Lu, Shangfeng Chen, Junliang Liu, and Dongya Wu. 2017. Convolutional neural networks for time series classification. Journal of Systems Engineering and Electronics 28, 1 (2017), 162–169.
- [208] Haiyan Zhao, Hanjie Chen, Fan Yang, Ninghao Liu, Huiqi Deng, Hengyi Cai, Shuaiqiang Wang, Dawei Yin, and Mengnan Du. 2024. Explainability for large language models: A survey. ACM Transactions on Intelligent Systems and Technology 15, 2 (2024), 1–38.
- [209] Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min, Beichen Zhang, Junjie Zhang, Zican Dong, et al. 2023. A survey of large language models. arXiv preprint arXiv:2303.18223 (2023).
- [210] Ziqi Zhao, Yucheng Shi, Shushan Wu, Fan Yang, Wenzhan Song, and Ninghao Liu. 2023. Interpretation of Time-Series Deep Models: A Survey. arXiv preprint arXiv:2305.14582 (2023).
- [211] Zihao Zhao, Eric Wallace, Shi Feng, Dan Klein, and Sameer Singh. 2021. Calibrate before use: Improving few-shot performance of language models. In International Conference on Machine Learning. PMLR, 12697–12706.
- [212] Ce Zhou, Qian Li, Chen Li, Jun Yu, Yixin Liu, Guangjing Wang, Kai Zhang, Cheng Ji, Qiben Yan, Lifang He, et al. 2023. A comprehensive survey on pretrained foundation models: A history from bert to chatgpt. arXiv preprint arXiv:2302.09419 (2023).
- [213] Haoyi Zhou, Shanghang Zhang, Jieqi Peng, Shuai Zhang, Jianxin Li, Hui Xiong, and Wancai Zhang. 2022. Informer: Beyond Efficient Transformer for Long Sequence Time-Series Forecasting. Proceedings of the AAAI Conference on Artificial Intelligence (Sep 2022), 11106–11115.
- [214] Tian Zhou, Ziqing Ma, Qingsong Wen, Xue Wang, Liang Sun, and Rong Jin. 2022. Fedformer: Frequency enhanced decomposed transformer for long-term series forecasting. In *International Conference on Machine Learning*. PMLR, 27268–27286.
- [215] Tian Zhou, PeiSong Niu, Xue Wang, Liang Sun, and Rong Jin. 2023. One Fits All:Power General Time Series Analysis by Pretrained LM. In arXiv:2302.11939.
- [216] Li Zhu, Fei Richard Yu, Yige Wang, Bin Ning, and Tao Tang. 2018. Big data analytics in intelligent transportation systems: A survey. *IEEE Transactions on Intelligent Transportation Systems* 20, 1 (2018), 383–398.
- [217] Yanqiao Zhu, Yichen Xu, Feng Yu, Qiang Liu, Shu Wu, and Liang Wang. 2021. Graph contrastive learning with adaptive augmentation. In *Proceedings of the Web Conference 2021*. 2069–2080.