**Time Series Analysis Models and Techniques**

Medical data is often represented as time series, such as continuous monitoring of vital signs, ECG signals, or sequences of patient health records. Analyzing such data requires models that can capture temporal dependencies and patterns. ARIMA [1] (Autoregressive Integrated Moving Average) is a fundamental method that models temporal dependencies by combining autoregressive terms, differencing for stationarity, and moving averages. Its seasonal extension, SARIMA [2], is particularly effective for capturing periodic patterns in data with recurring cycles. Another traditional approach is Exponential Smoothing [3], which emphasizes recent observations to adapt quickly to short-term changes. State Space Models [4] offer a flexible framework by decomposing time series into latent state variables and observation equations, allowing for robust modeling of hidden and dynamic processes. These classical models provide strong baselines, especially for linear and stationary time series.

A diagram of a process

AI-generated content may be incorrect.

Figure : Model architecture of Frozen Pretrained Transformer (FPT) [10].

In contrast, deep learning methods have enabled significant advancements in modeling complex and nonlinear temporal patterns in medical data. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are capable of capturing long-term dependencies in sequential data, with LSTMs addressing the vanishing gradient issue common in standard RNNs [5]. Variants such as GRU-D [6] are designed to handle missing values in multivariate clinical time series, improving prediction performance. Convolutional Neural Networks (CNNs), particularly Fully Convolutional Networks (FCNs) [7], have been adapted to time series by treating sequences as one-dimensional signals, enabling effective local pattern recognition. More recently, Transformer-based models have introduced attention mechanisms and parallel processing, leading to improved modeling of both short- and long-range dependencies. Models like TimesNet [8] convert time series into 2D representations to capture intra- and inter-period variations, while attention-based approaches [9] explicitly model variable relationships. Furthermore, Large Language Models (LLMs) are being explored for time series tasks through techniques such as tokenization, text-based prompting, and cross-modal knowledge transfer. The Frozen Pretrained Transformer (FPT) [10] has shown that language models can achieve state-of-the-art performance across various time series applications without modifying their attention mechanisms. As illustrated in Figure 1, pre-trained parameters are transferred directly to time series forecasting through a frozen transformer architecture. In this setup, the self-attention and feedforward layers remain unchanged, while only the embedding layer, normalization layers, and output layer are fine-tuned for the target task. This approach highlights the power of transfer learning and the versatility of language models in temporal domains.

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