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Times2D: A Time-Frequency Method for Time Series Forecasting

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Abstract : Time series data consist of successive data points collected over a period of time. Accurate prediction of future values is essential for informed decision-making in several real-world applications, including electricity load demand forecasting, lifetime estimation of industrial machinery, traffic planning, weather prediction, and the stock market. Due to their critical relevance and wide application, there has been considerable interest in time series forecasting in recent years. However, the proliferation of sensors and IoT devices, real-time monitoring systems, and high-frequency trading data introduce significant intricate temporal variations, rapid changes, noise, and non-linearities, making time series forecasting more challenging. Classical methods such as Autoregressive integrated moving average (ARIMA) and Exponential Smoothing aim to extract pre-defined temporal variations, such as trends and seasonality. While these methods are effective for capturing well-defined seasonal patterns and trends, they often struggle with more complex, non-linear patterns present in real-world time series data. In recent years, deep learning has made significant contributions to time series forecasting. Recurrent Neural Networks (RNNs) and their variants, such as Long short-term memory (LSTMs) and Gated Recurrent Units (GRUs), have been widely adopted for modeling sequential data. However, they often suffer from the locality, making it difficult to capture local trends and rapid fluctuations. Convolutional Neural Networks (CNNs), particularly Temporal Convolutional Networks (TCNs), leverage convolutional layers to capture temporal dependencies by applying convolutional filters along the temporal dimension. Despite their advantages, TCNs struggle with capturing relationships between distant time points due to the locality of one-dimensional convolution kernels. Transformers have revolutionized time series forecasting with their powerful attention mechanisms, effectively capturing long-term dependencies and relationships between distant time points. However, the attention mechanism may struggle to discern dependencies directly from scattered time points due to intricate temporal patterns. Lastly, Multi-Layer Perceptrons (MLPs) have also been employed, with models like N-BEATS and LightTS demonstrating success. Despite this, MLPs often face high volatility and computational complexity challenges in long-horizon forecasting. To address intricate temporal variations in time series data, this study introduces Times2D, a novel framework that parallelly integrates 2D spectrogram and derivative heatmap techniques. The spectrogram focuses on the frequency domain, capturing periodicity, while the derivative patterns emphasize the time domain, highlighting sharp fluctuations and turning points. This 2D transformation enables the utilization of powerful computer vision techniques to capture various intricate temporal variations. To evaluate the performance of Times2D, extensive experiments were conducted on standard time series datasets and compared with various state-of-the-art algorithms, including DLinear (2023), TimesNet (2023), Non-stationary Transformer (2022), PatchTST (2023), N-HiTS (2023), Crossformer (2023), MICN (2023), LightTS (2022), FEDformer (2022), FiLM (2022), SCINet (2022a), Autoformer (2021), and Informer (2021) under the same modeling conditions. The initial results demonstrated that Times2D achieves consistent state-of-the-art performance in both short-term and long-term forecasting tasks. Furthermore, the generality of the Times2D framework allows it to be applied to various tasks such as time series imputation, clustering, classification, and anomaly detection, offering potential benefits in any domain that involves sequential data analysis.

Keywords : derivative patterns, spectrogram, time series forecasting, times2D, 2D representation
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