SOFTS: EFFICIENT MULTIVARIATE TIME SERIES FORECASTING WITH SERIES-CORE FUSION

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https://github.com/Secilia-Cxy/SOFTS.

INTRODUCTION

Multivariate time series forecasting benefits from modeling inter-channel dependencies, but existing methods either ignore them or suffer from complexity and fragility under distribution shifts. This article proposes a centralized structure that improves robustness and efficiency over distributed approaches like attention and mixers.

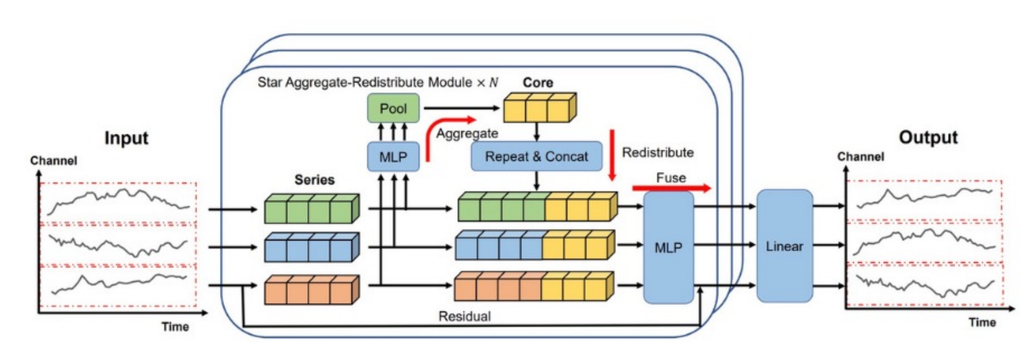
CHALLENGE

- Excessive reliance on inter-channel correlations can lead to limited robustness when handling sequence non-stationarity.
- The use of complex relation modeling techniques, such as attention mechanisms, substantially increases computational complexity and hinders scalability in large-scale applications.

CONTRIBUTION

- SOFTS, a Sequence cOre Fusion-based Time Series predictor, is proposed as a simple MLP-based model achieving state-of-the-art performance with low complexity.
- The STAR (STar Aggregate-Redistribute) module, as the core of SOFTS, uses a centralized structure to aggregate and exchange channel information, reducing complexity and enhancing robustness compared to distributed methods like attention.
- Extensive experiments confirm the effectiveness, scalability, and generalizability of SOFTS and STAR across various attention-based forecasting models.

ARCHITECTURE



Similar to iTransformer, SOFTS employs sequence-level embeddings to extract representations for each channel. However, unlike iTransformer, SOFTS introduces a star-shaped aggregation and redistribution module (STar Aggregate-Redistribute module, or STAR) to capture inter-channel dependencies and facilitate information exchange across sequences. Finally, SOFTS uses a linear layer to predict the future values for each channel individually.

DATASET

The experiments are conducted on a variety of real-world datasets spanning electricity consumption (ECL), traffic flow (Traffic, PEMS03, PEMS04, PEMS07, PEMS08), weather conditions (Weather, ETTh1, ETTh2, ETTm1, ETTm2), and solar energy production (Solar-Energy). Additionally, the M4 Daily Dataset is utilized, comprising 4,227 univariate daily time series across domains such as finance, macroeconomics, demographics, and industry. These datasets collectively provide a diverse and representative benchmark for evaluating time series forecasting models.

RESULTS

Figure 1 reports multivariate forecasting results over various datasets, evaluated using Mean Squared Error (MSE) and Mean Absolute Error (MAE) metrics. For ECL, Traffic, Weather, Solar-Energy, ETTh1, ETTh2, ETTm1, and ETTm2, prediction horizons are set to H∈{96,192,336,720}, while for PEMS03, PEMS04, PEMS07, and PEMS08, horizons are H∈{12,24,48,96}. Datasets such as ECL and Weather exhibit lower errors, whereas Traffic and ETTh1 show comparatively higher errors, particularly at longer horizons. Averaged results (MSE_AVE and MAE_AVE) demonstrate the model’s robust performance across diverse forecasting scenarios.

DATASET	MSE_96	MAE_96	MSE_192	MAE_192	MSE_336	MAE_336	MSE_720	MAE_720	MSE_AVE	MAE_AVE
ECL	0.152	0.239	0.165	0.252	0.183	0.27	0.218	0.3	0.179	0.265
Traffic	0.3901	0.2591	0.4118	0.2687	0.4267	0.2757	0.4602	0.2943	0.4222	0.2744
Weather	0.1736	0.2127	0.2182	0.254	0.2807	0.2988	0.3791	0.3638	0.2629	0.2823
Solar-Energy	0.1957	0.2335	0.2275	0.2567	0.2457	0.2732	0.2462	0.2729	0.2288	0.2591
ETTh1	0.3762	0.3981	4280.0	0.427	0.4811	0.4547	0.5076	0.4922	0.4482	0.443
ETTh2	0.3074	0.3558	0.3775	0.4001	0.4177	0.4301	0.4282	0.4444	0.3827	0.4076
ETTm1	0.3270292	0.3656779	0.3715116	0.3868042	0.4195397	0.4178833	0.4756116	0.4542611	0.398423025	0.406156625
ETTm2	0.1808299	0.2625358	0.2430344	0.3027907	0.3017117	0.3414771	0.4053674	0.4033376	0.28273585	0.3275353
PEMS03	0.0644	0.1654	0.0842	0.1903	0.1223	0.2299	0.1575	0.2646	0.1071	0.2123
PEMS04	0.0841	0.1934	0.096	0.2035	0.1236	0.2341	0.1879	0.2989	0.1229	0.2325
PEMS07	0.0599	0.1566	0.0809	0.1835	0.1058	0.2061	0.1309	0.2319	0.0944	0.1945
PEMS08	0.0772	0.1769	0.1103	0.2105	0.1696	0.2558	0.221	0.2594	0.1445	0.2256

Figure 1: Multivariate forecasting results with prediction horizon $H \in \{96, 192, 336, 720\}$ for ECL, Traffic, Weather, Solar-Energy, ETTh1, ETTh2, ETTm1, and ETTm2, and $H \in \{12, 24, 48, 96\}$ for PEMS03, PEMS04, PEMS07, and PEMS08 datasets, evaluated with MSE and MAE metrics.

DISCUSSION

We reproduced the SOFTS model and found that its performance closely aligns with the original paper in terms of both inference speed and predictive accuracy (MSE/MAE). Quantitative analysis shows that most datasets achieve MSE and MAE deviations within 3%, including ECL, Traffic, and Weather. Slightly larger deviations appear on ETTh1 and ETTm1, with maximum differences around 12%. Overall, the average deviation remains within approximately 5%, confirming the robustness and reproducibility of the SOFTS framework under independent experimental settings.