DLP final project

Topic: Revision of Time Series Forecasting

Motivation

- Traditional transformer-based models have already achieve precise result on time-series forecasting

- The prediction of financial datasets still face some challenges
  - Complexity and noise
  - Efficient markey hypothesis
  - Uncertainity event

Models	**iTransformer (Ours)**		RLinear (2023)		PatchTST (2023)	
Metric	MSE	MAE	MSE	MAE	MSE	MAE
ECL	**0.178**	**0.270**	0.219	0.298	0.205	0.290
ETT (Avg)	0.383	0.399	**0.380**	**0.392**	0.381	0.397
Exchange	0.360	**0.403**	0.378	0.417	0.367	0.404
Traffic	**0.428**	**0.282**	0.626	0.378	0.481	0.304
Weather	**0.258**	**0.278**	0.272	0.291	0.259	0.281
Solar-Energy	**0.233**	**0.262**	0.369	0.356	0.270	0.307
PEMS (Avg)	**0.119**	**0.218**	0.514	0.482	0.217	0.305

Related Work

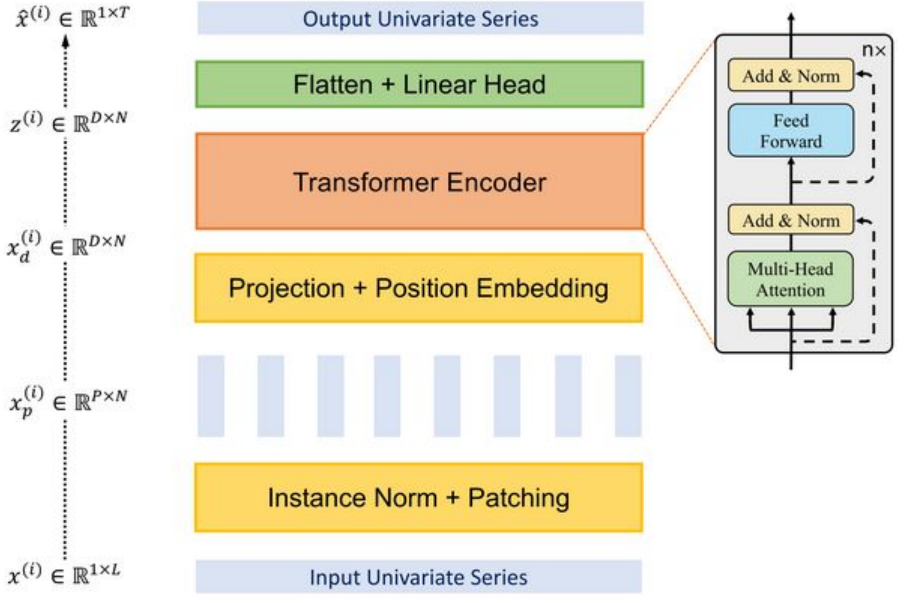
PatchTST (ICLR, 2023)

Pros

- extract local semantic information
- longer look back window

Cons

- Δ channel-independence



(b) Transformer Backbone (Supervised)

Related Work

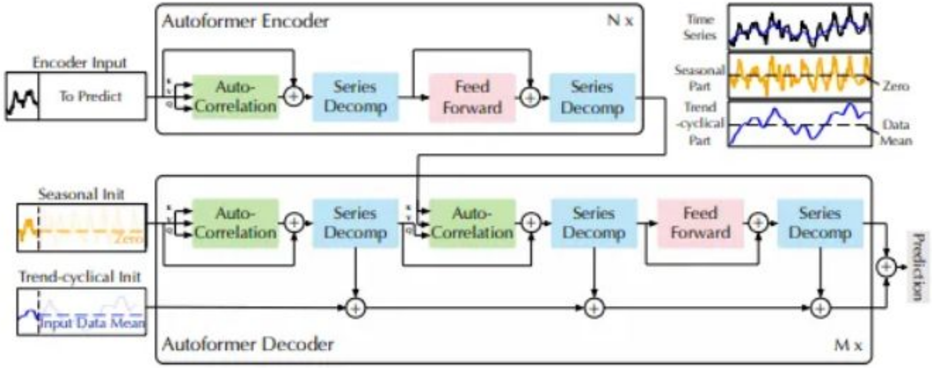
AutoFormer

Pros

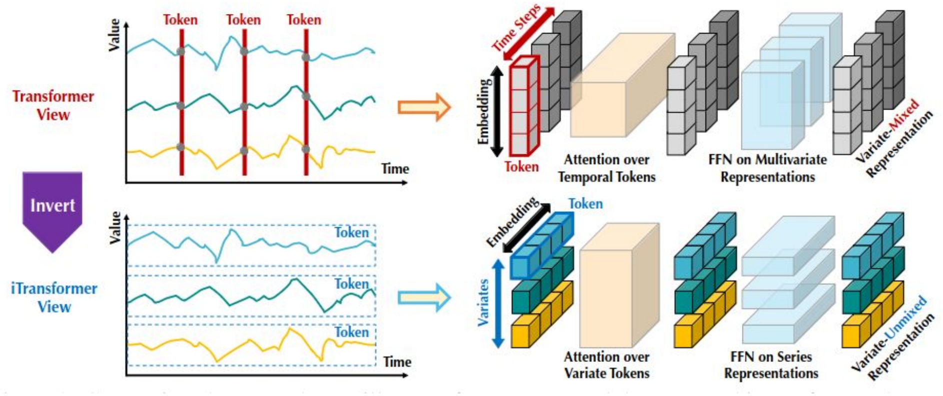
- time series decomposition
- efficient on seasonal datasets

Cons

- process on trend composition



Related Work



iTransformer (ICLR, 2024)

Pros

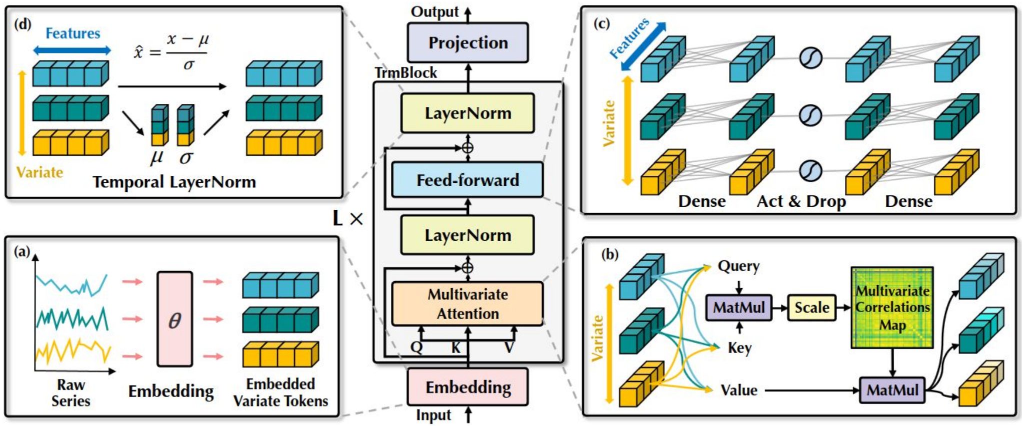
- attention module focus on depicting the multivariate correltations
- on top of linear structure similar to DLinear(AAAI, 2023)

Cons

- embed whole series
- discard temporal information in attention

Characteristics of financial datasets

- Strong seasonal and trend
- Strong time dependent and feature dependent
- Strong noise and volatility



Current Methodology

Based on iTransformer, with

- Series decomposition
- Consider temporal attention with patch
- Some specific models to address

Expected Result

- Well process seasonal and trend information
- Well process different temporal information
- Robustness and denoising ability