KUMA: A Novel Framework with Koopman Separation and Efficient Multilevel Extraction in Time Series Forecasting

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Abstract

Time Series Forecasting plays a crucial role in a wide range of real-world applications and has become increasingly complex with the growth of multivariate dimensions and extended historical observations → **Deep Forecasting Model**.

Three Challenges:

1. High computational complexity (**HCC**). $\mathcal{O}(L^2 d)$ and $\mathcal{O}(L^2)$.
2. Inefficient token utilization (**ITU**). *Redundancy* and *Scarcity*.
3. Temporal distribution shift (**TDS**). *Dynamic patterns*.

Inspirations:

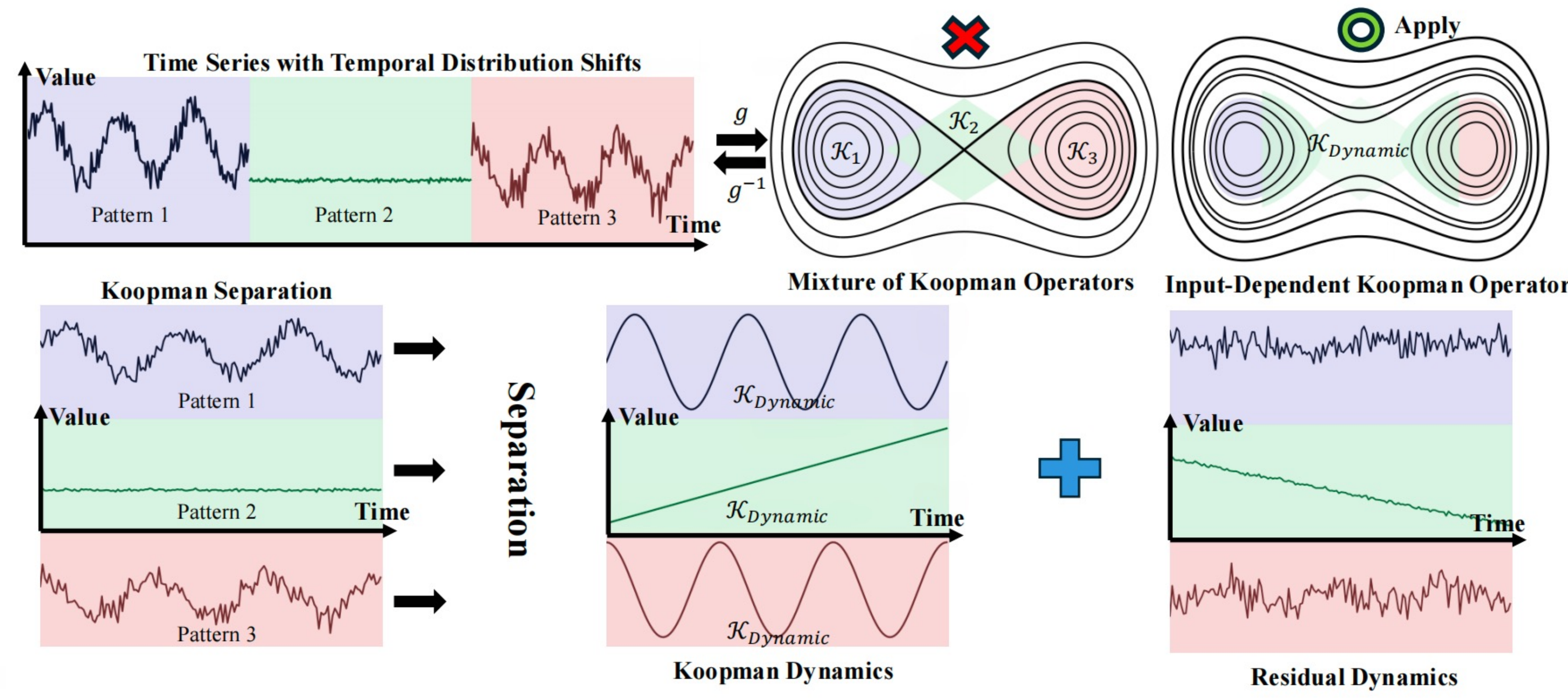
1. Mamba-Inspired Linear Attention → ***Concise***.
2. **Multilevel** Encoder-Decoder Structure wit **Skip Connection**.
3. Koopman Theory → ***Mixture of Koopman Operators***.

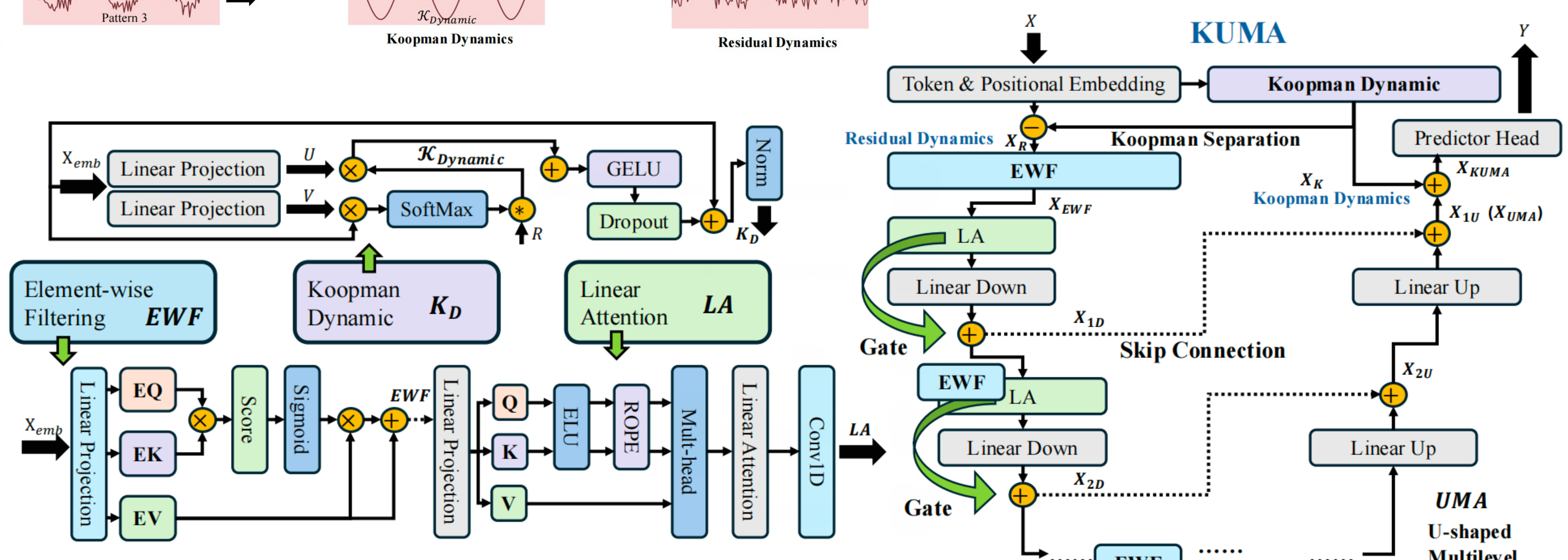
Methodology

Specific Designs

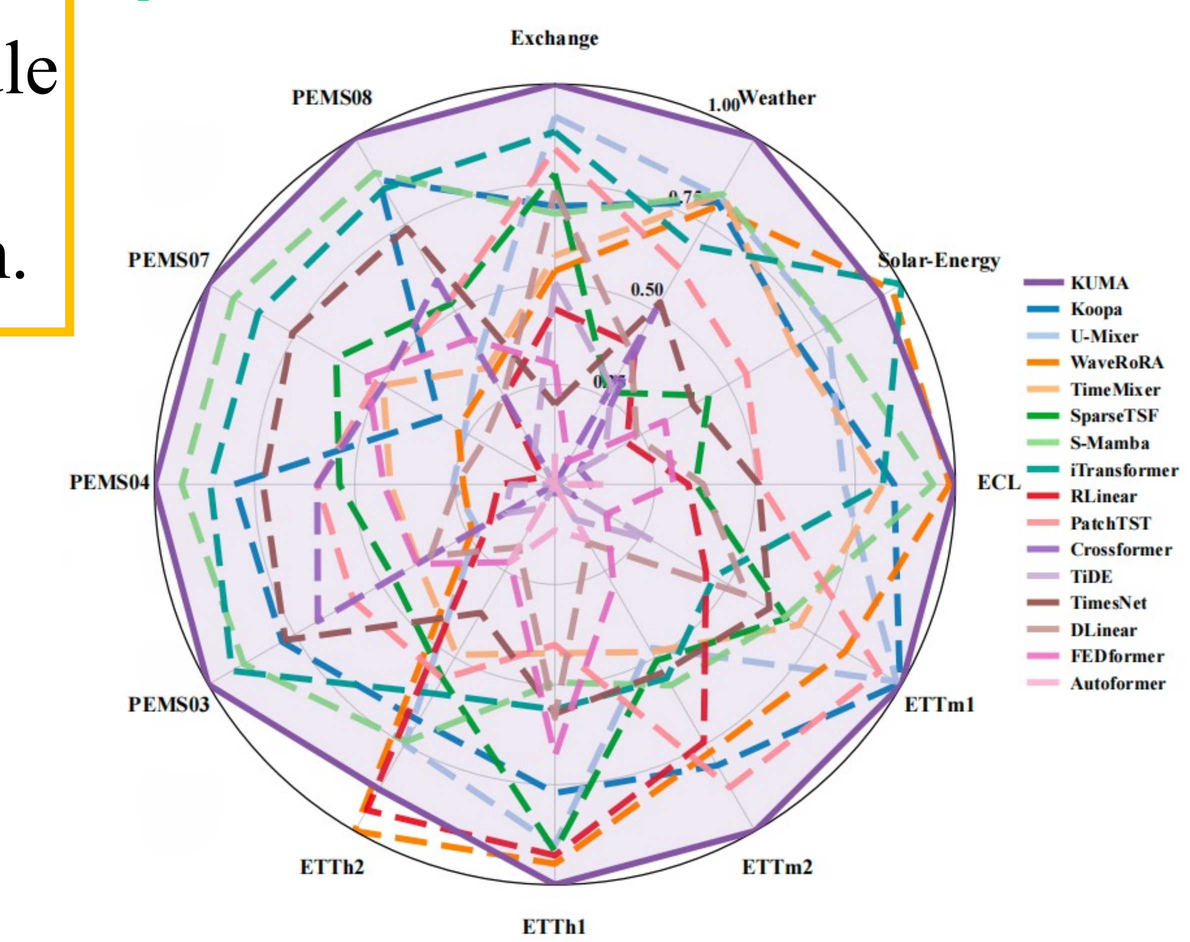
Separate and **TDS** → Koopman Dynamic Module (**K**DM): Koopman Dynamics and Residual Dynamics.

Lightweight and **ITU** → **U**-shaped **M**ultilevel **A**ttention.





The Entire Architecture of KUMA,KDM, UMA, EWF and LA.



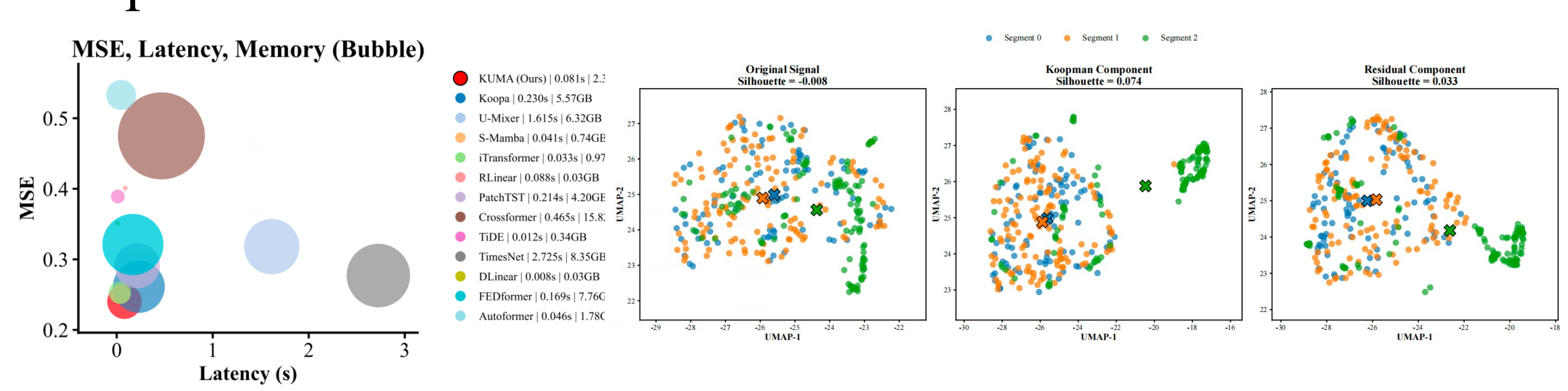
Experiments

Datasets: ETTm1, ETTm2, ETTh1, ETTh2, Exchange, Weather, Solar Energy, PEMS03, PEMS04, PEMS07, PEMS08.

Baselines: Koopa, U-Mixer, WaveRoRA, TimeMixer, SparseTSF, S-Mamba, iTransformer, RLinear, PatchTST, Crossformer, TiDE, TimesNet, DLinear, FEDformer, Autoformer.

Experiments:

- Accuracy Performance (MSE and MAE) → **Radar Chart**.
- Robustness: 5% Random Noise → **Scatter Plots**.
- Robustness: Seeds → **Line Chart** and **Confidence Intervals**.
- Lightweight: **Latency** and **Memory Occupation**.
- Separation: **UMAP** and **Silhouette Score**.



Visualizations