



ICLR
International Conference On
Learning Representations

S4M:S4 for multivariate time series forecasting with Missing values

Addressing the challenge of missing observation in time series forecasting

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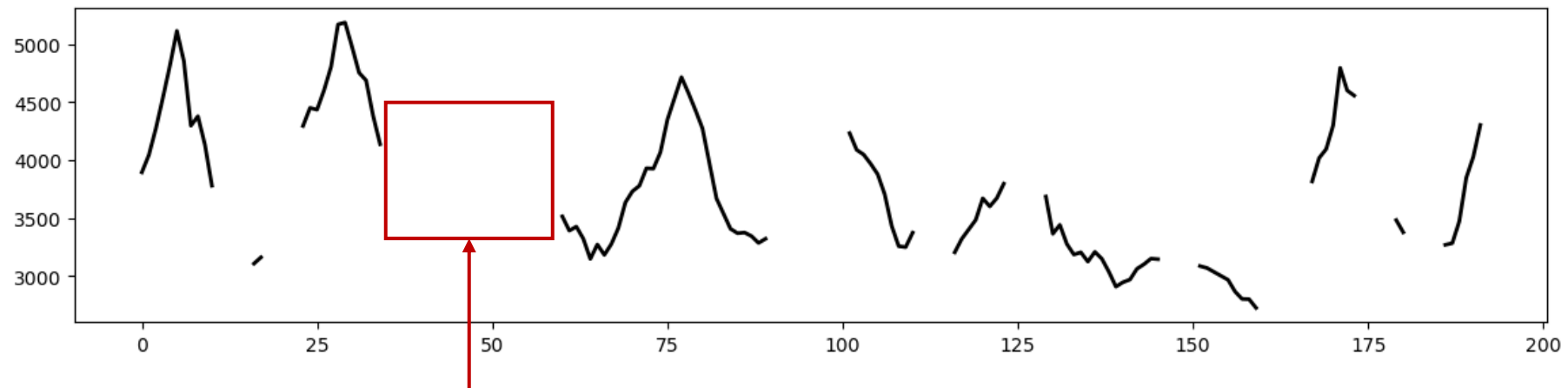
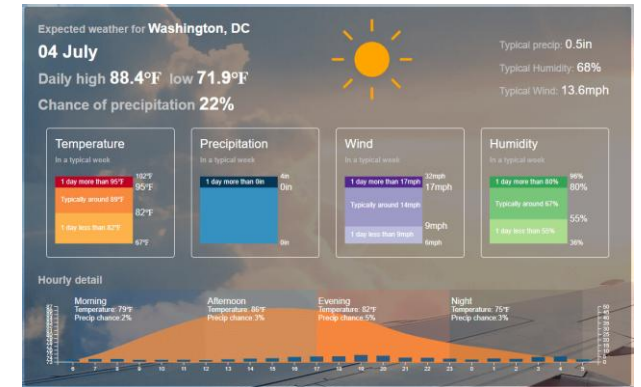
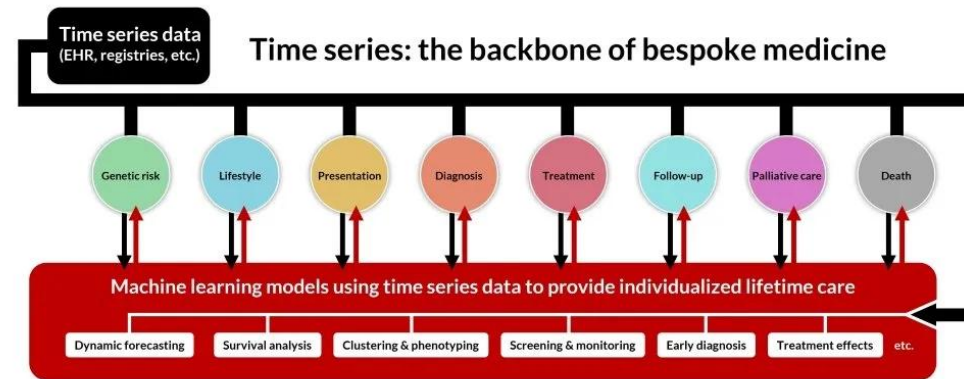
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Background

Multivariate time series forecasting are ubiquitous

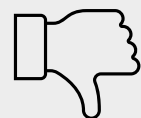


Consecutive missing: sensor failures, data collection issues, or external disruption

Existing work

Transformer-based

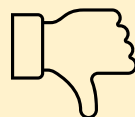
Autoformer (Wu et al., 2021)
iTransformer (Liu et al., 2023)
CARD (Xue et al., 2023)



Not designed for
missing data

Two step: Impute then forecast

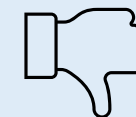
SAITS (Du et al., 2023)



Accumulated errors
Imputation in high-D

RNN-based

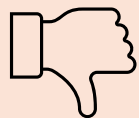
GRU-D (Che et al., 2018)
BRITS (Cao et al., 2018)



Long training time
Poor performance

ODE-based

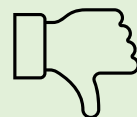
Neural ODE (Chen et al., 2018)
GraFITi (Yalavarthi et al., 2024)
CRUs (Schirmer et al., 2022)



Expensive computation

Graph model-based

BiTGraph (Chen et al., 2023)



High memory

Our method

Low memory
Low computation
Good performance

Motivation for our design

Q: Impute then forecast lead to accumulated errors

S: End-to-end

Q: Imputation in high-dim. is difficult

S: Imputation in lower-dim latent space

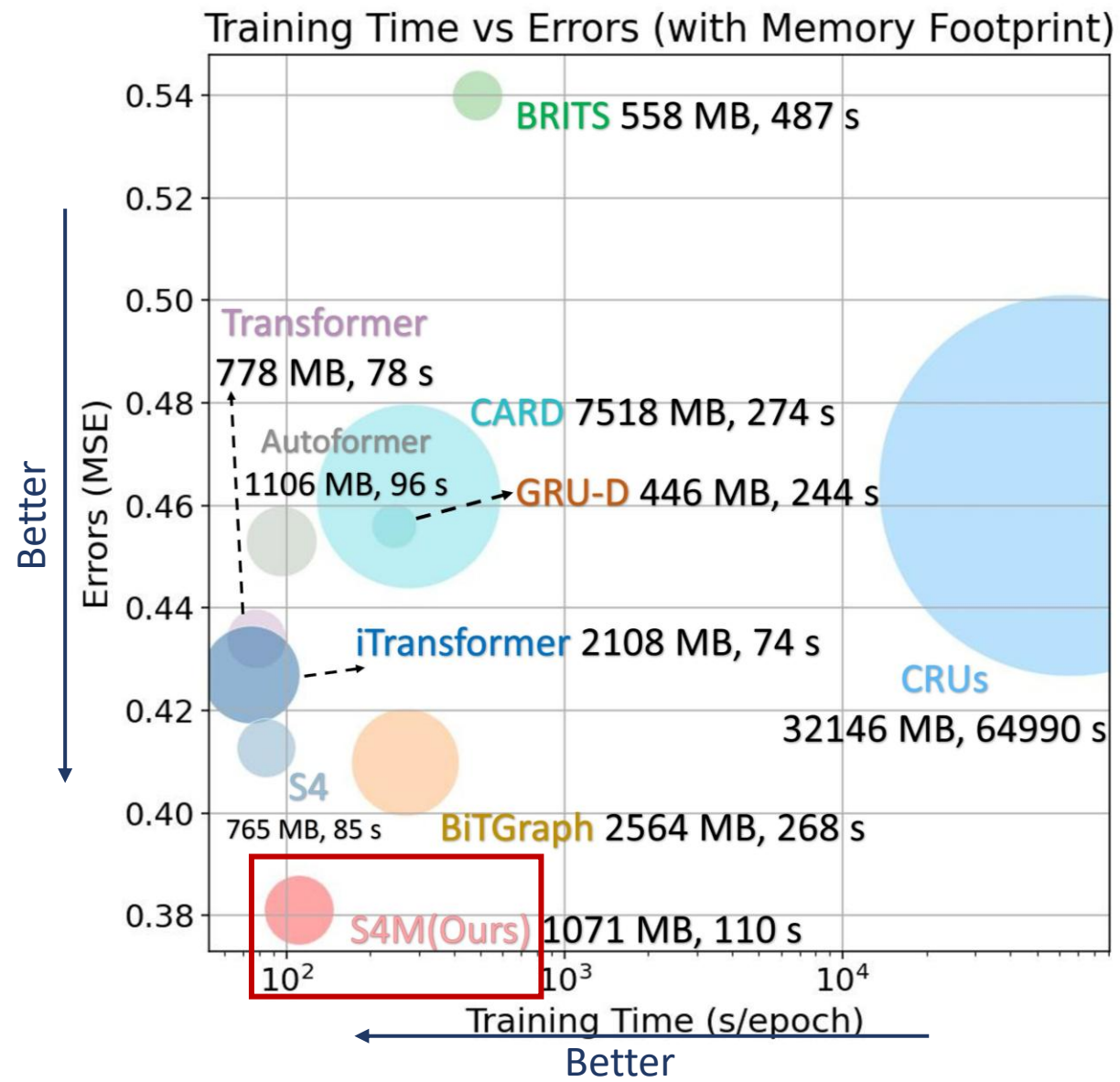
Q: Limited historical patterns for reference

S: Prototype bank to store rich representations

Q: High memory, computation

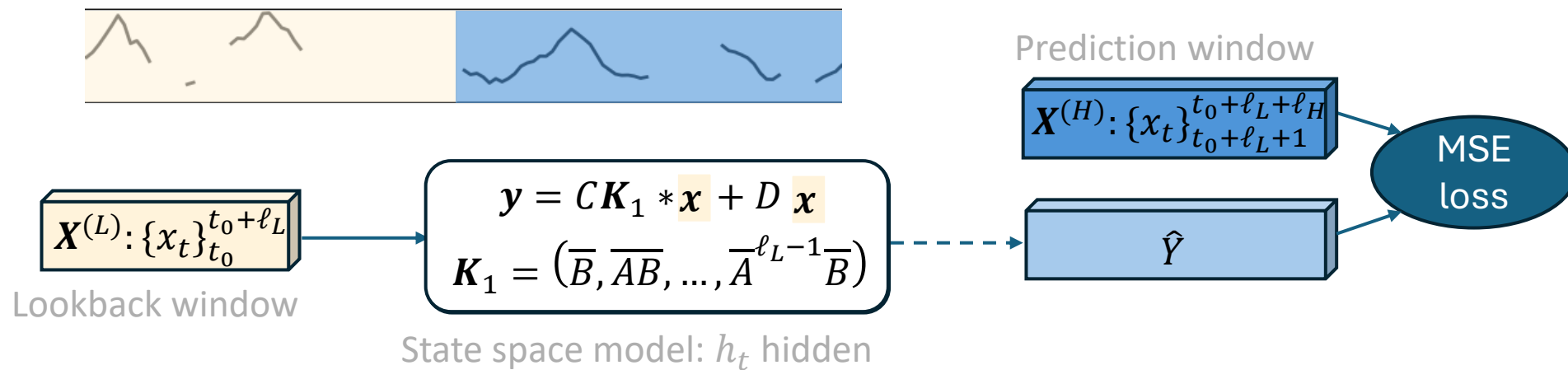
S: S4 (Structured State Space Sequence) model

- High accuracy
- High computational efficiency
- Specialized kernel structure extendable to multiple input streams

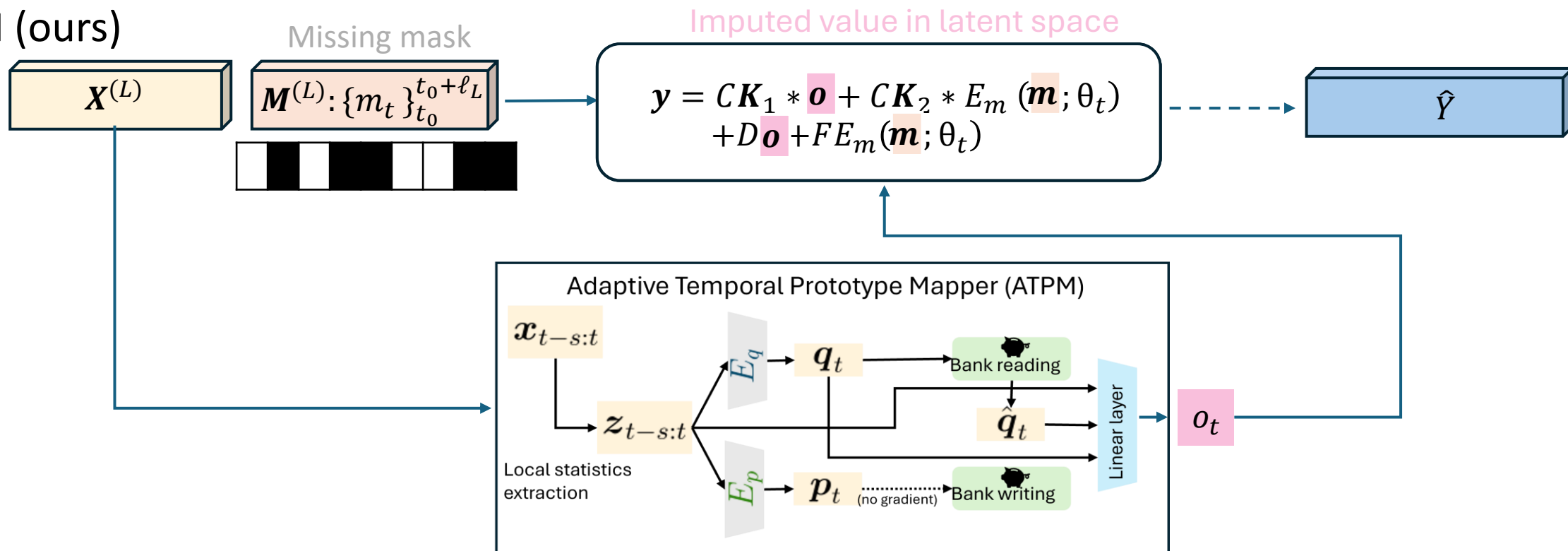


Method overview

Original S4



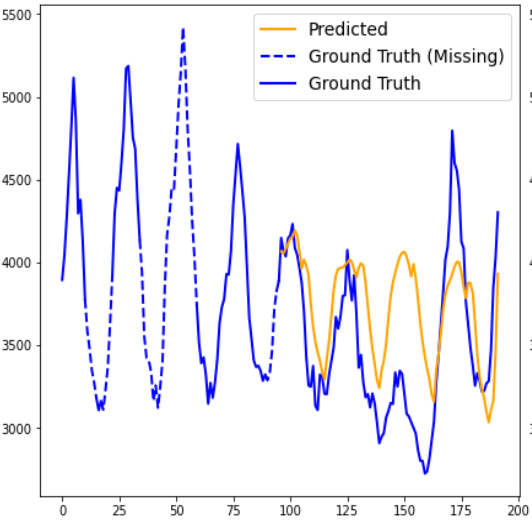
S4M (ours)



Qualitative result

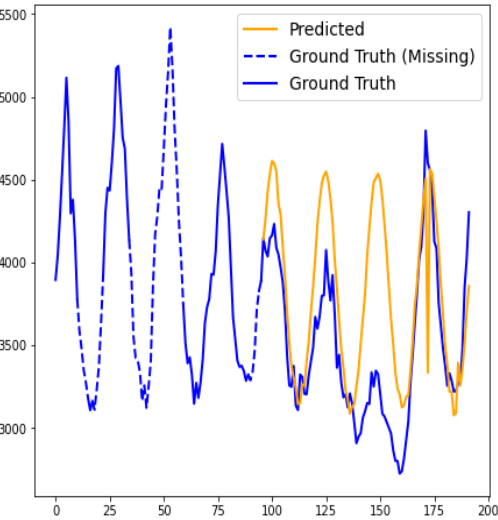
Autoformer

MAE: 0.375



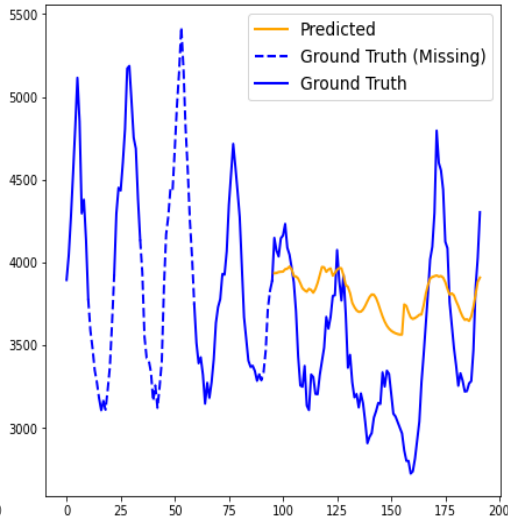
BiTGraph

MAE: 0.397



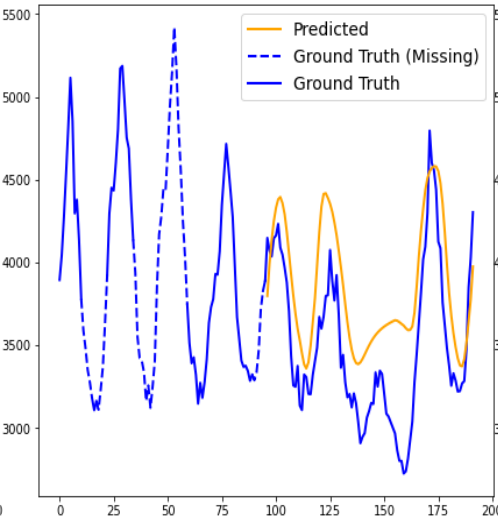
BRITS

MAE: 0.633



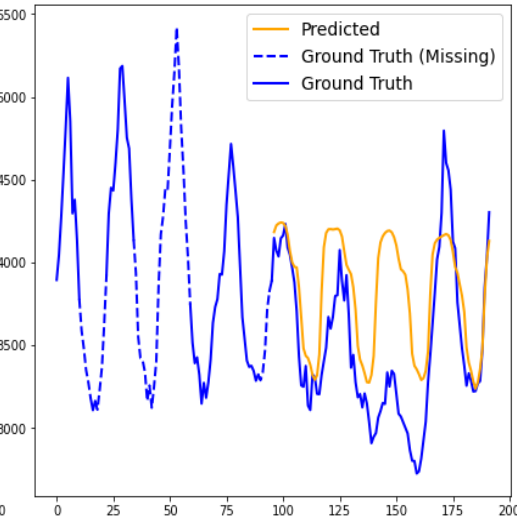
GRU-D

MAE: 0.431



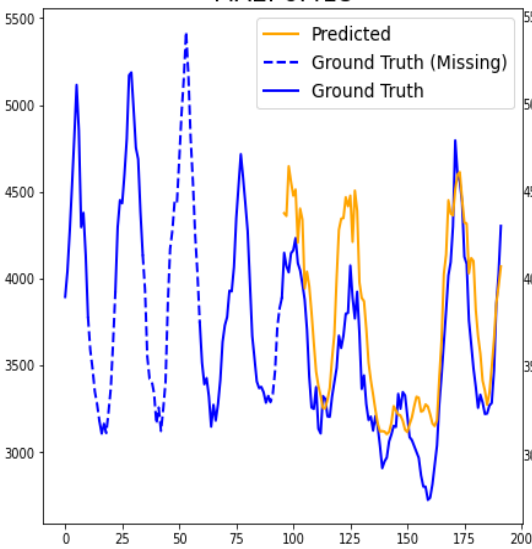
Transformer

MAE: 0.399



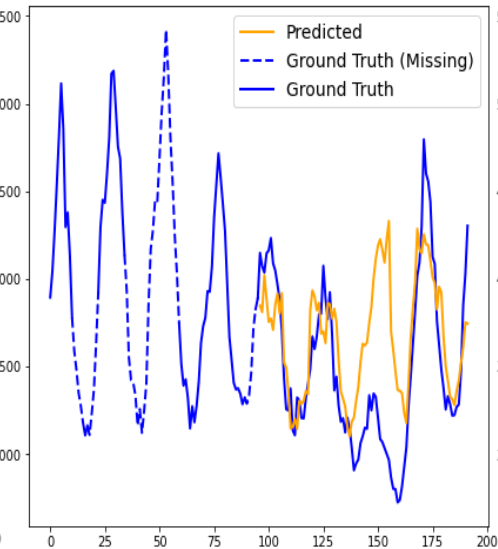
S4 (Ffill)

MAE: 0.418



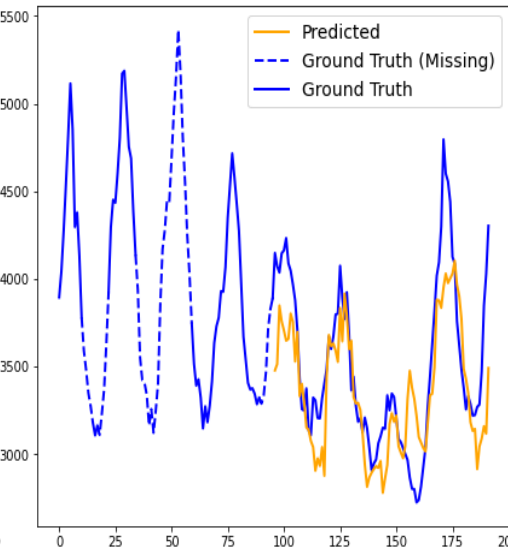
S4 (Mean)

MAE: 0.408



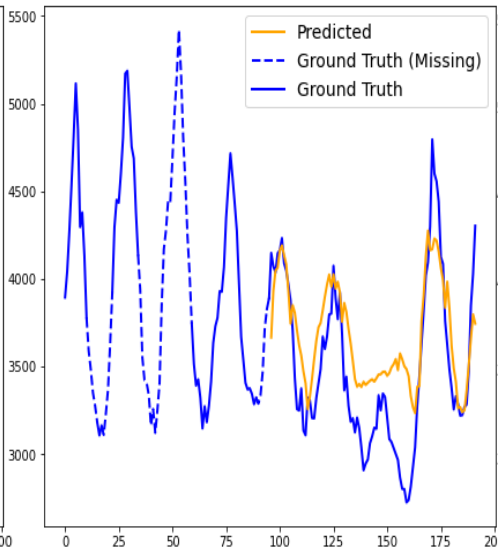
S4 (SAITS)

MAE: 0.432



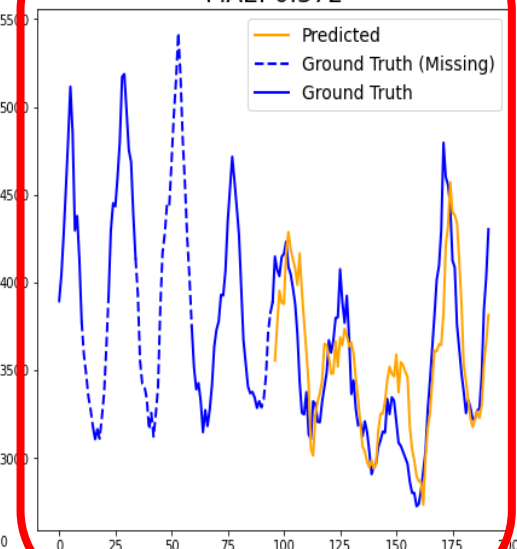
S4 (Decay)

MAE: 0.402



S4M (Ours)

MAE: 0.372



Conclusion

- The **structured state space**(S4) model demonstrates superior forecasting performance with high efficiency, outperforming RNN-based and attention-based models.
- Imputing in a **lower-dimensional latent space**, rather than the original high-dimensional variable space, enhances robustness and accuracy.
- A **prototype bank** that stores rich historical patterns can be highly beneficial for handling missing observations.