

# xLSTM-Mixer: Multivariate Time Series Forecasting by Mixing via Scalar Memories

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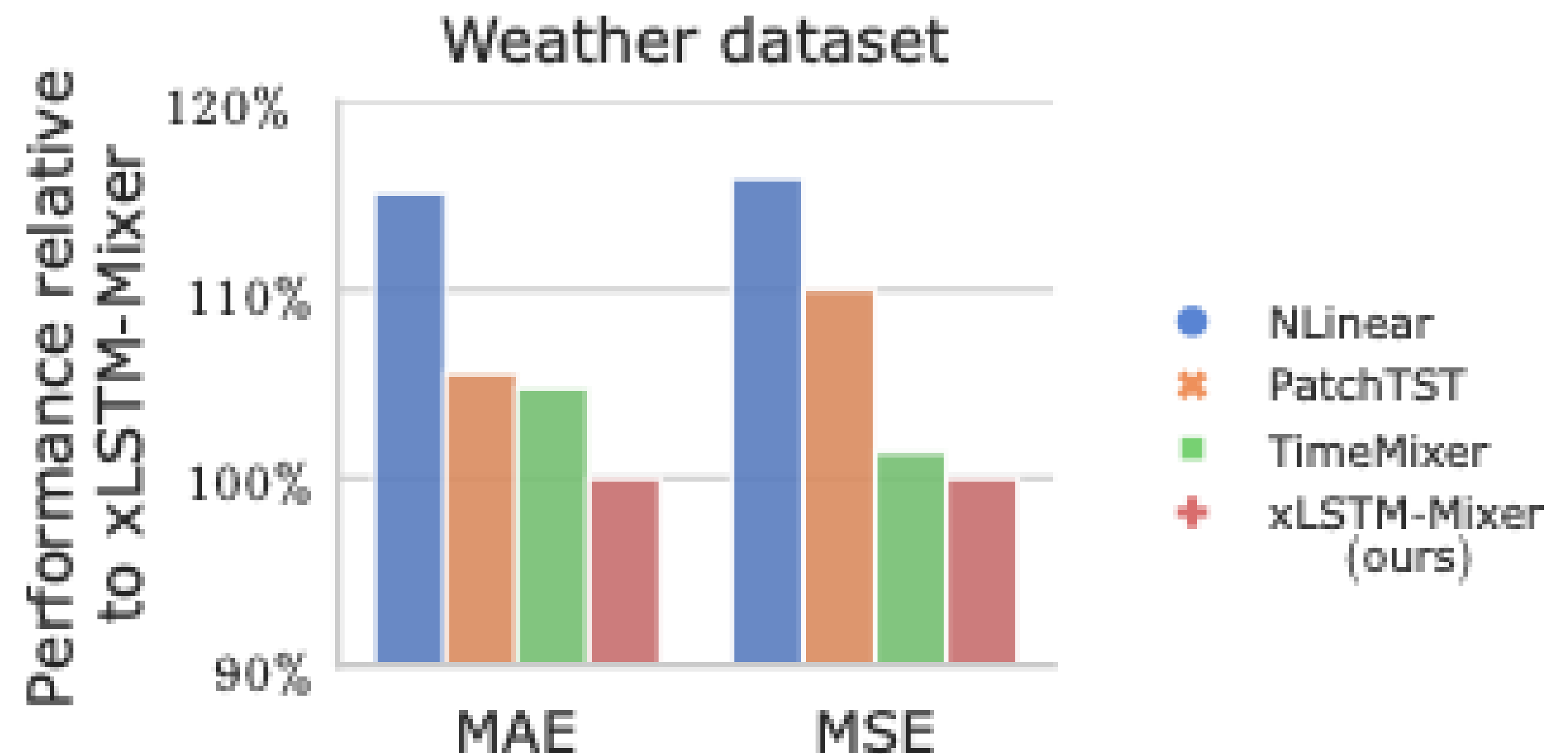


# Why Another Time Series Model?

# Why Forecasting is hard

*Recurrent models to the rescue?*

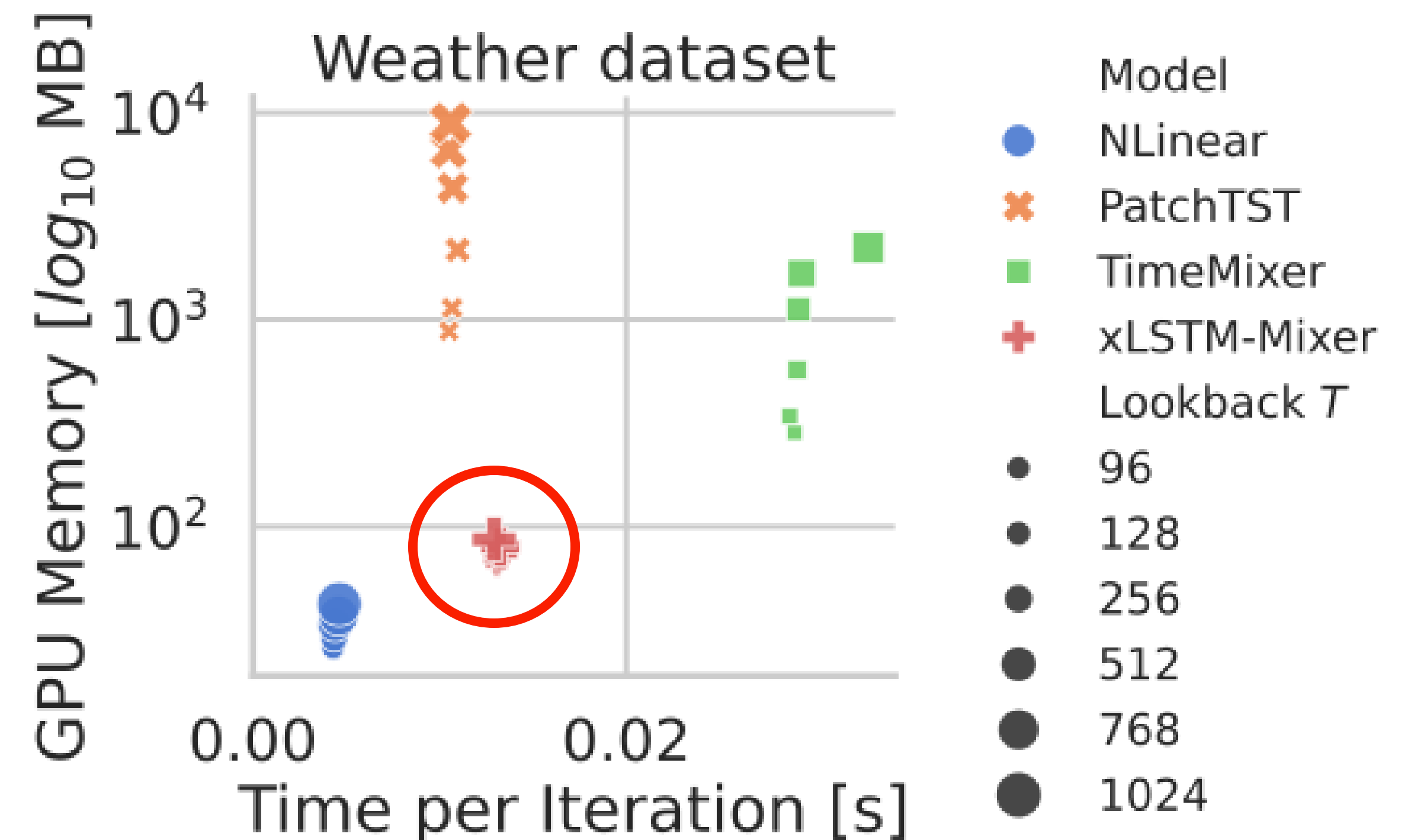
- Long-horizon, multivariate forecasting is still hard.
- Transformers are accurate but memory-heavy.
- Also MLPs don't scale well.
- We need SOTA models that run under tight compute.



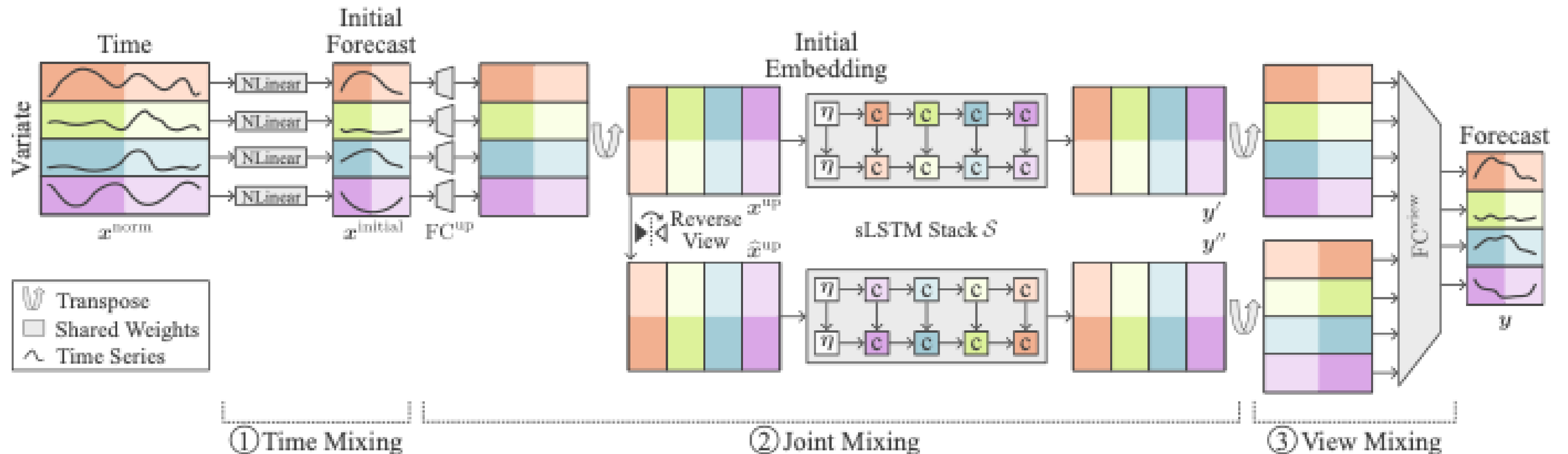
# Efficiency

## *Why xLSTMs here?*

- xLSTMs [1] use **scalar memories** and gating → strong sequence modeling without quadratic attention.
- **Very low GPU memory and competitive iteration time.**
- Fits edge / constrained deployments.



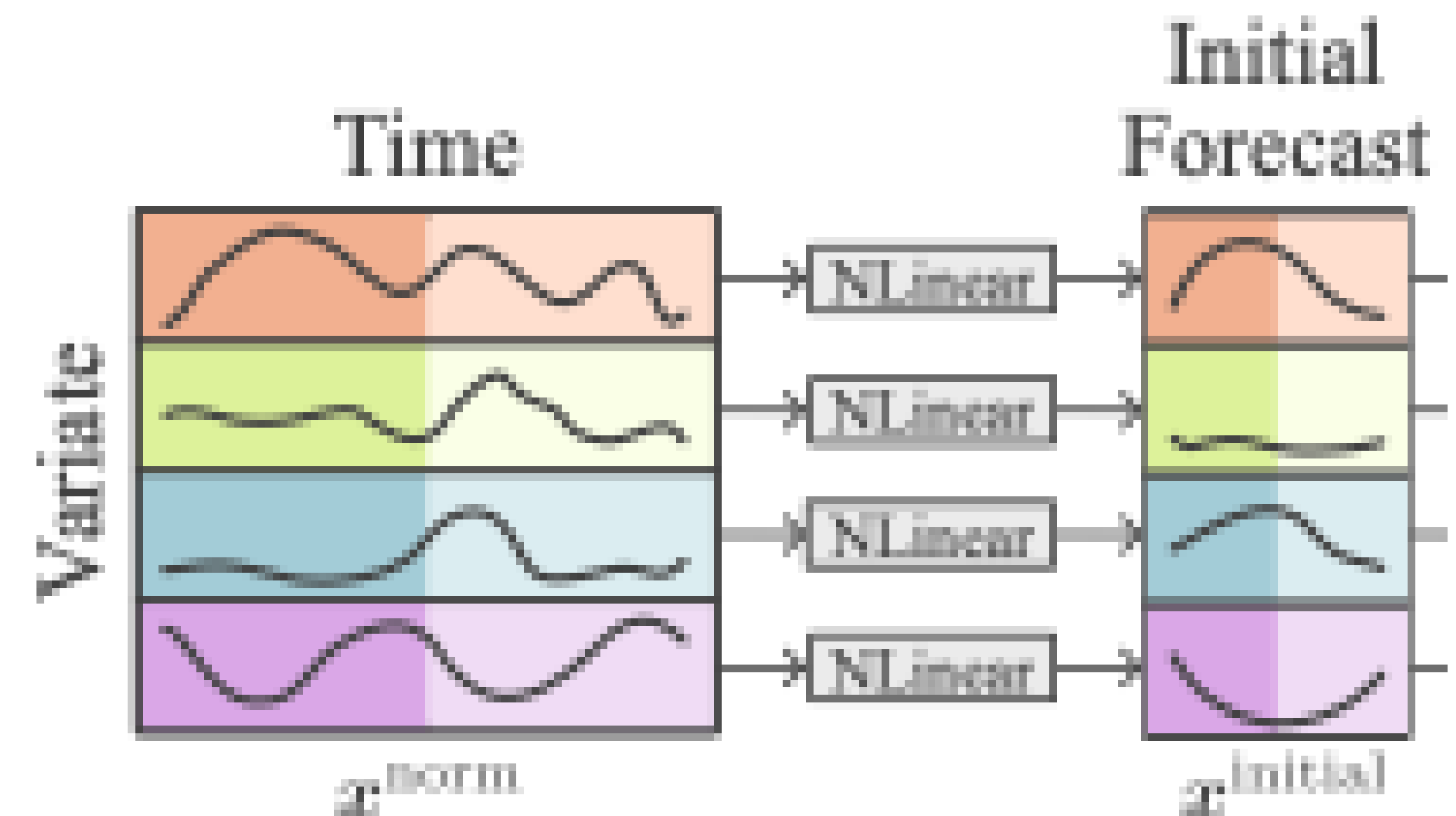
# The Mixing Process



# The Mixing Process

## Time Mixing

- Start with a **shared linear forecast [2]** (cheap, channel-independent).

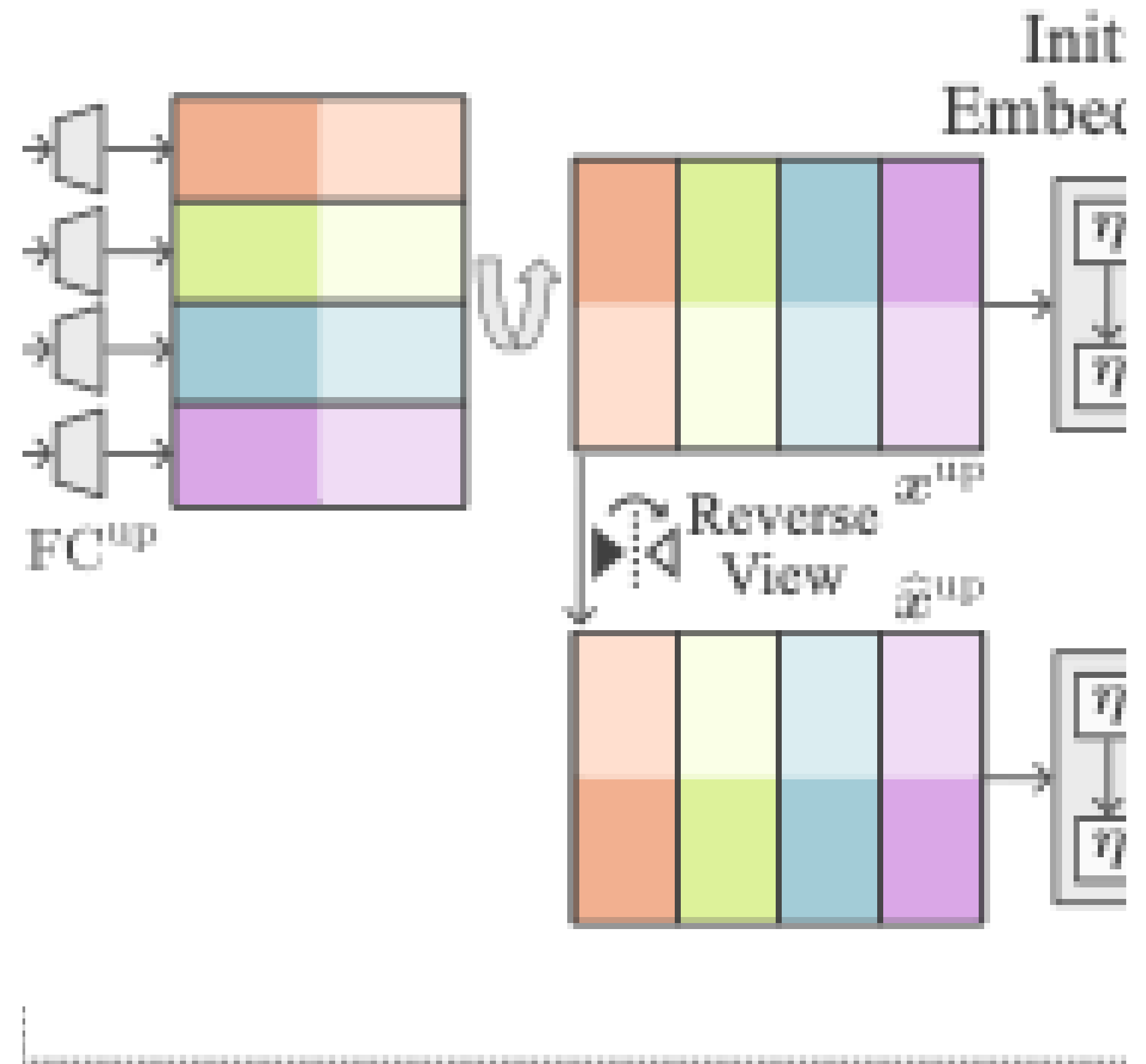


① Time Mixing

# The Mixing Process

## Joint Mixing

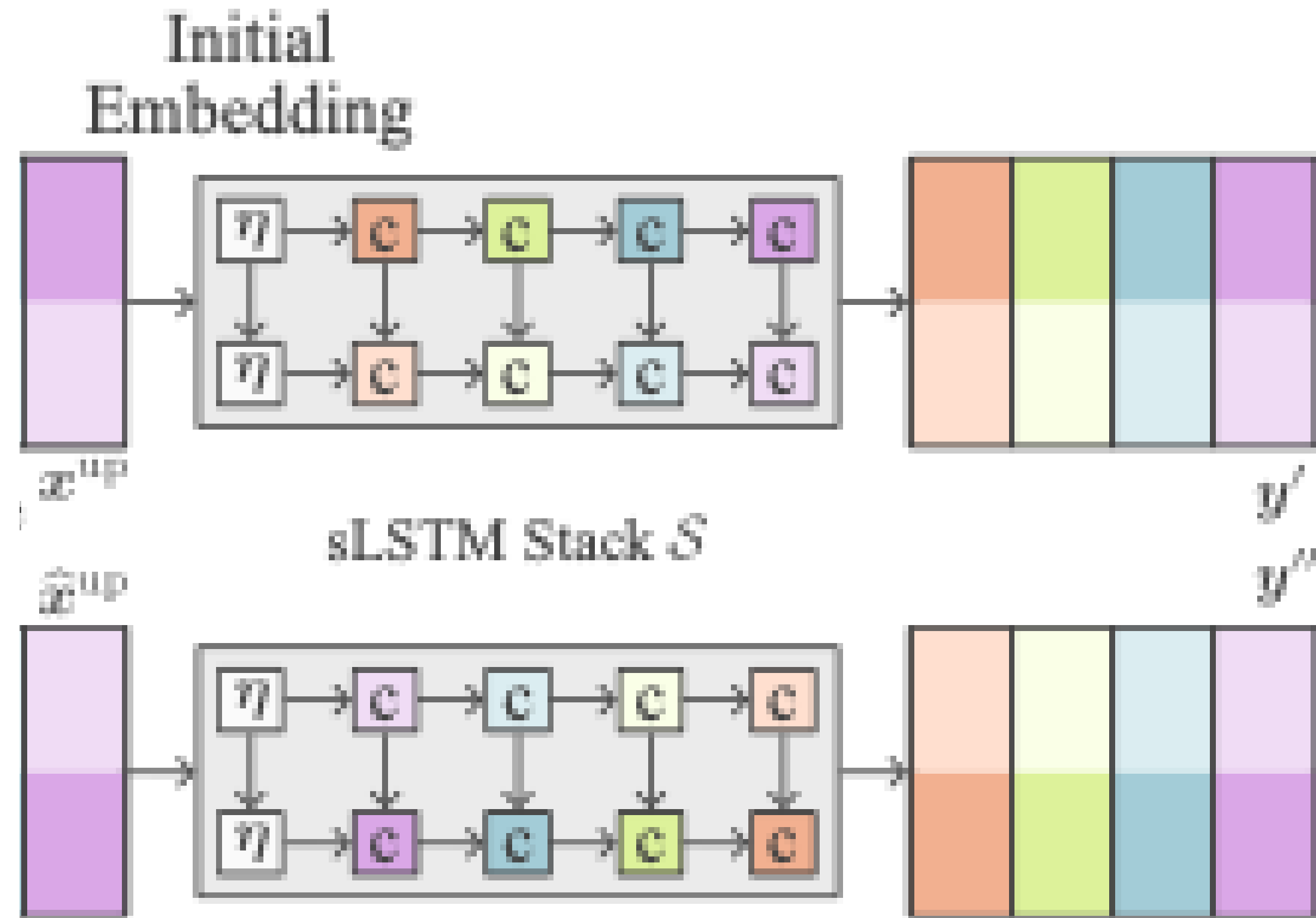
- Start with a **shared linear forecast** (cheap, channel-independent).
- **Two views** (forward + reversed) → **view mixing**.



# The Mixing Process

## Joint Mixing

- Start with a **shared linear forecast** (cheap, channel-independent).
- **Two views** (forward + reversed) → **view mixing** → final forecast.
- **Refine** it with xLSTM block(s) that mix time + variates.



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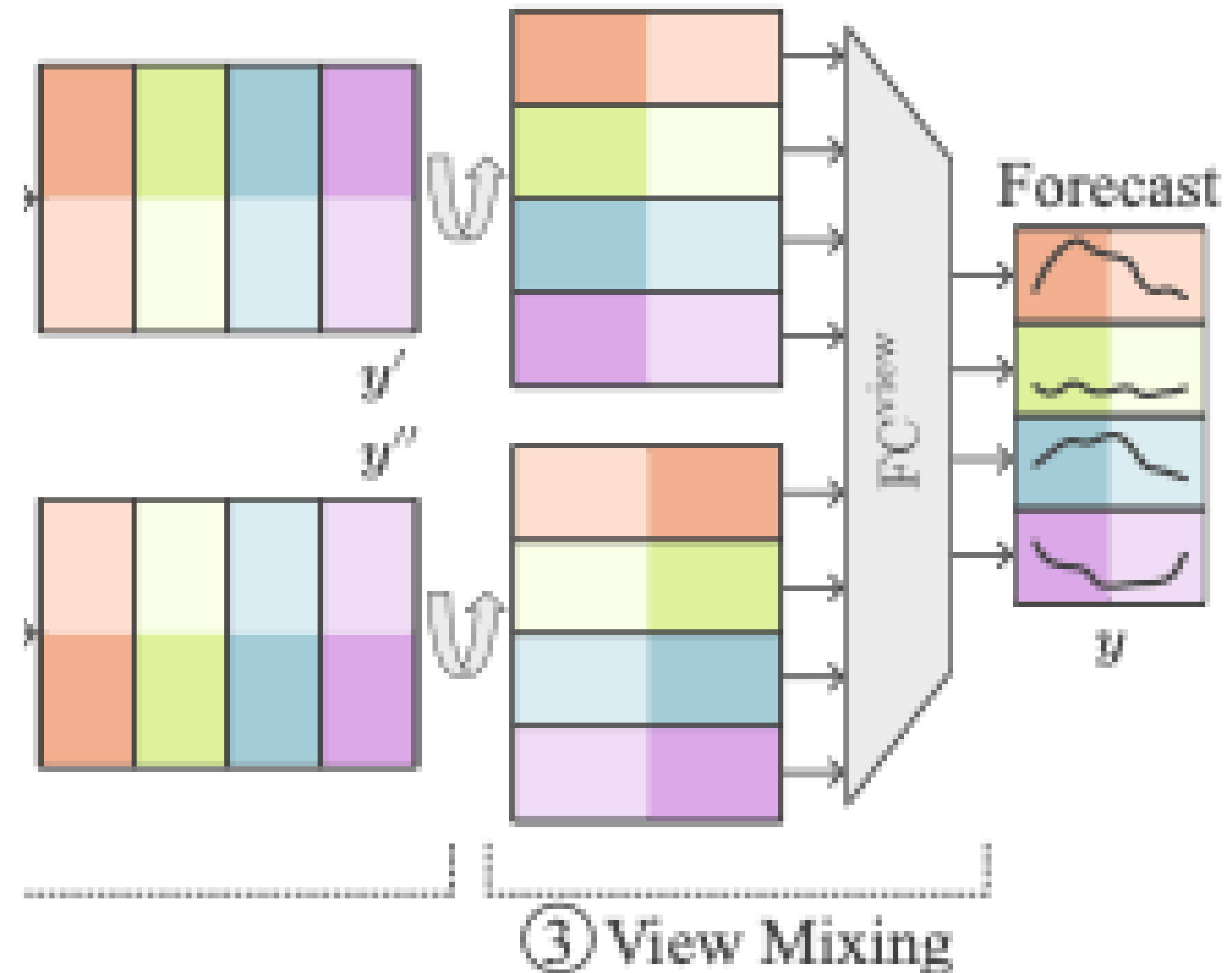
② Joint Mixing



# The Mixing Process

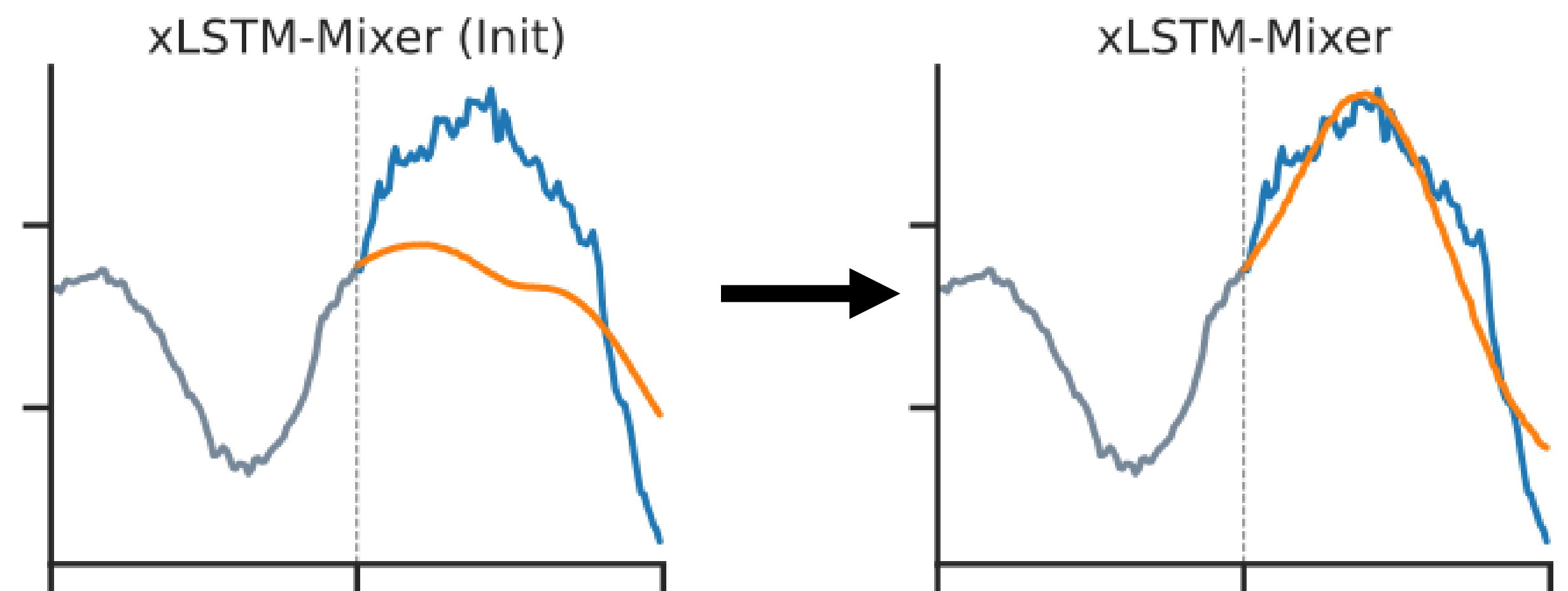
## View Mixing

- Start with a **shared linear forecast** (cheap, channel-independent).
- **Two views** (forward + reversed) → **view mixing** → final forecast.
- **Refine** it with xLSTM block(s) that mix time + variates.
- **Result:** As expressive as big models yet parameter-frugal like RNNs.



# Iterative refinement

- Think: '**rough guess** → **smarter correction**'.
- Early stage handles what's easy - xLSTM stages focus capacity on what's hard.
- Multi-view mixing regularizes and reduces parameters via shared weights.



# Benchmark Performance

- SOTA on standard multivariate benchmarks.
- Strong probabilistic forecasts on GIFT-Eval.
- Also works as an embedding model.

Models	Recurrent			Mixer			MLP		
	xLSTM-Mixer	xLSTMTime 2024	LSTM 1997†	TimeMix.++ 2025a	TimeMix. 2024a	TSMixer 2023c	CycleNet 2024	DLinear 2023	TiDE 2023
Dataset	MSE MAE	MSE MAE	MSE MAE	MSE MAE	MSE MAE	MSE MAE	MSE MAE	MSE MAE	MSE MAE
Weather	0.219 0.250	0.222 0.255	0.444 0.454	0.226 0.262	0.222 0.262	0.225 0.264	0.223 0.264	0.246 0.300	0.236 0.282
Electricity	0.153 0.245	0.157 0.250	0.559 0.549	0.165 0.253	0.156 0.246	0.160 0.256	0.156 0.251	0.166 0.264	0.159 0.257
Traffic	0.392 0.253	0.391 0.261	1.011 0.541	0.416 0.264	0.387 0.262	0.408 0.284	0.403 0.282	0.434 0.295	0.356 0.261
ETTh1	0.397 0.420	0.408 0.428	1.198 0.821	0.419 0.432	0.411 0.423	0.412 0.428	0.435 0.440	0.423 0.437	0.419 0.430
ETTh2	0.340 0.382	0.346 0.386	3.095 1.352	0.339 0.380	0.316 0.384	0.355 0.401	0.367 0.405	0.431 0.447	0.345 0.394
ETTm1	0.339 0.366	0.347 0.372	1.142 0.782	0.369 0.378	0.348 0.375	0.347 0.375	0.360 0.388	0.357 0.379	0.355 0.378
ETTm2	0.248 0.307	0.254 0.310	2.395 1.177	0.269 0.320	0.256 0.315	0.267 0.322	0.263 0.324	0.267 0.332	0.249 0.312
Wins	11 16	0 2	0 0	0 2	2 2	0 0	1 0	0 0	5 1

Model	MASE ↓	CRPS ↓	Rank (CRPS) ↓
TiRex	0.724	0.498	1
xLSTM-Mixer (ours)	0.780	0.510	2
TEMPO_ensemble	0.862	0.514	3
Toto_Open_Base_1.0	0.750	0.517	4
TabPFN-TS	0.771	0.544	5
YingLong_300m	0.798	0.548	6
timesfm_2_0_500m	0.758	0.550	7
YingLong_110m	0.809	0.557	8
sundial_base_128m	0.750	0.559	9
YingLong_50m	0.822	0.567	10

# Take-home

- New: **3 Step-mixing** for multivariate forecasting.
- Cheap base forecast, then xLSTM refines.
- Two views regularize + reduce params.
- Delivers **SOTA accuracy with tiny memory footprint.**