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Chimera: Effectively Modeling Multivariate Time Series with 2-Dimensional State Space Models



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State Space Models (SSMs) are linear recurrent models that effectively compress information along the time dimension.

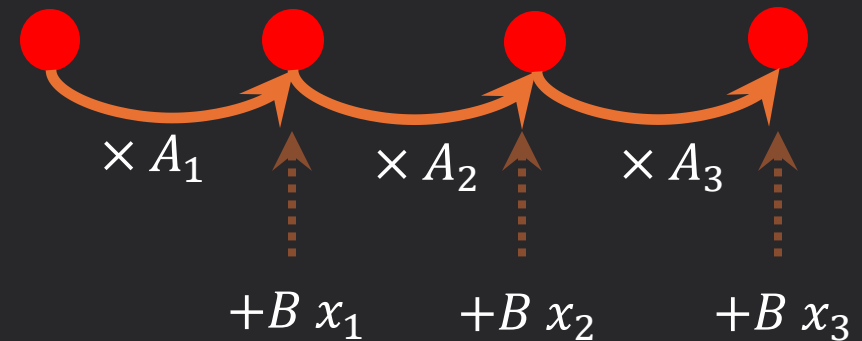
Are effective for modeling sequential data!

What happens when there 2D dependencies?

$$\frac{\partial}{\partial t} h(t) = A h(t) + B x(t)$$



$$h(t + 1) = A_t h(t) + B_t x(t)$$

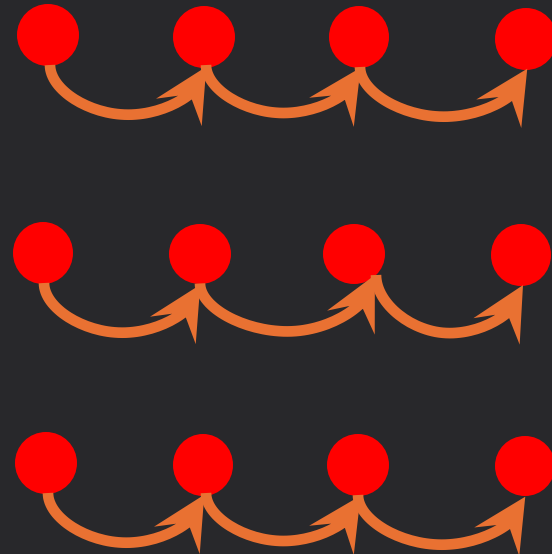


Idea 1:

Each channel is a separate variable!

Missing the dependencies of variates!

$$\frac{\partial}{\partial t_i} h(t_i) = A h(t_i) + B x(t_i)$$

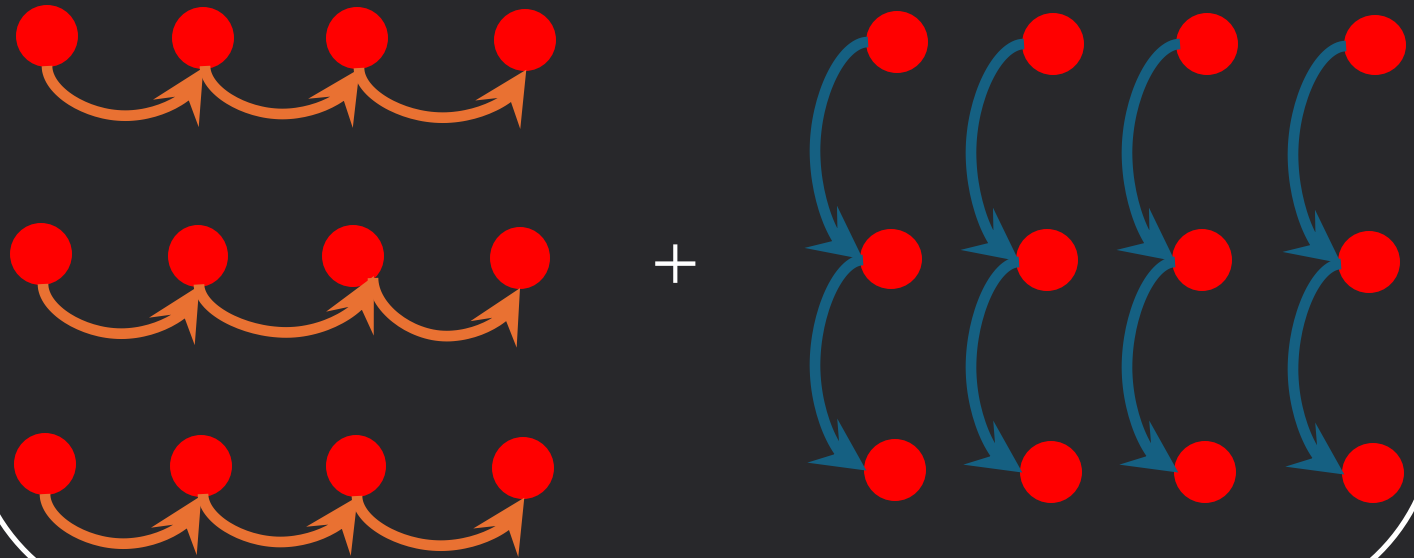


Idea 2:
Capture dependencies across both time and
variates but separately!

Missing inter-state dependencies!

$$\frac{\partial}{\partial t_i} h^{(1)}(t_i) = A^{(1)}h^{(1)}(t_i) + B^{(1)}x(t_i)$$

$$\frac{\partial}{\partial v_i} h^{(2)}(v_i) = A^{(2)}h^{(2)}(v_i) + B^{(2)}x(v_i)$$

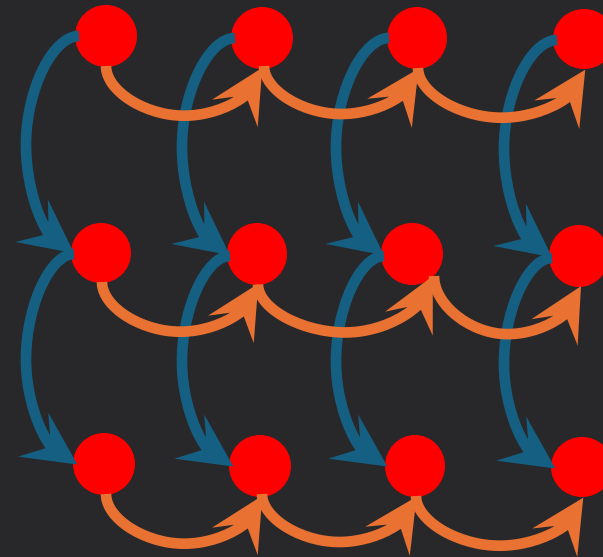


Idea 3:
Capture dependencies across both time and
variates (all together)!

Capture all complex dependencies!

$$\frac{\partial}{\partial t} h^{(1)}(t, v) = \left(A^{(1)} h^{(1)}(t, v), A^{(2)} h^{(2)}(t, v) \right) + B^{(1)} x(t, v)$$

$$\frac{\partial}{\partial v} h^{(2)}(t, v) = \left(A^{(3)} h^{(1)}(t, v), A^{(4)} h^{(2)}(t, v) \right) + B^{(2)} x(t, v)$$

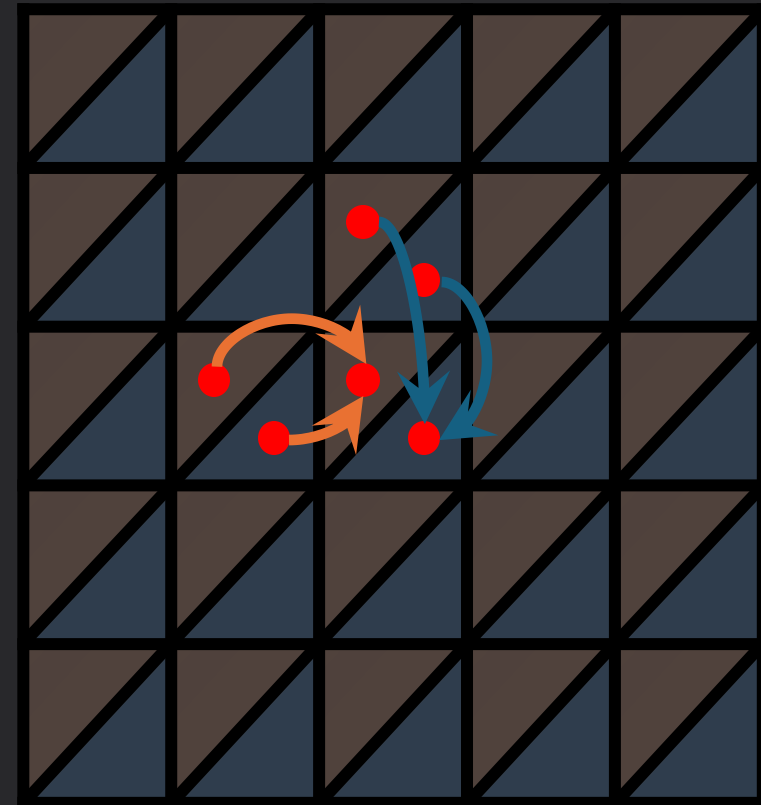


How does 2D recurrence look like?

Each hidden state is responsible to compress information across one dimension

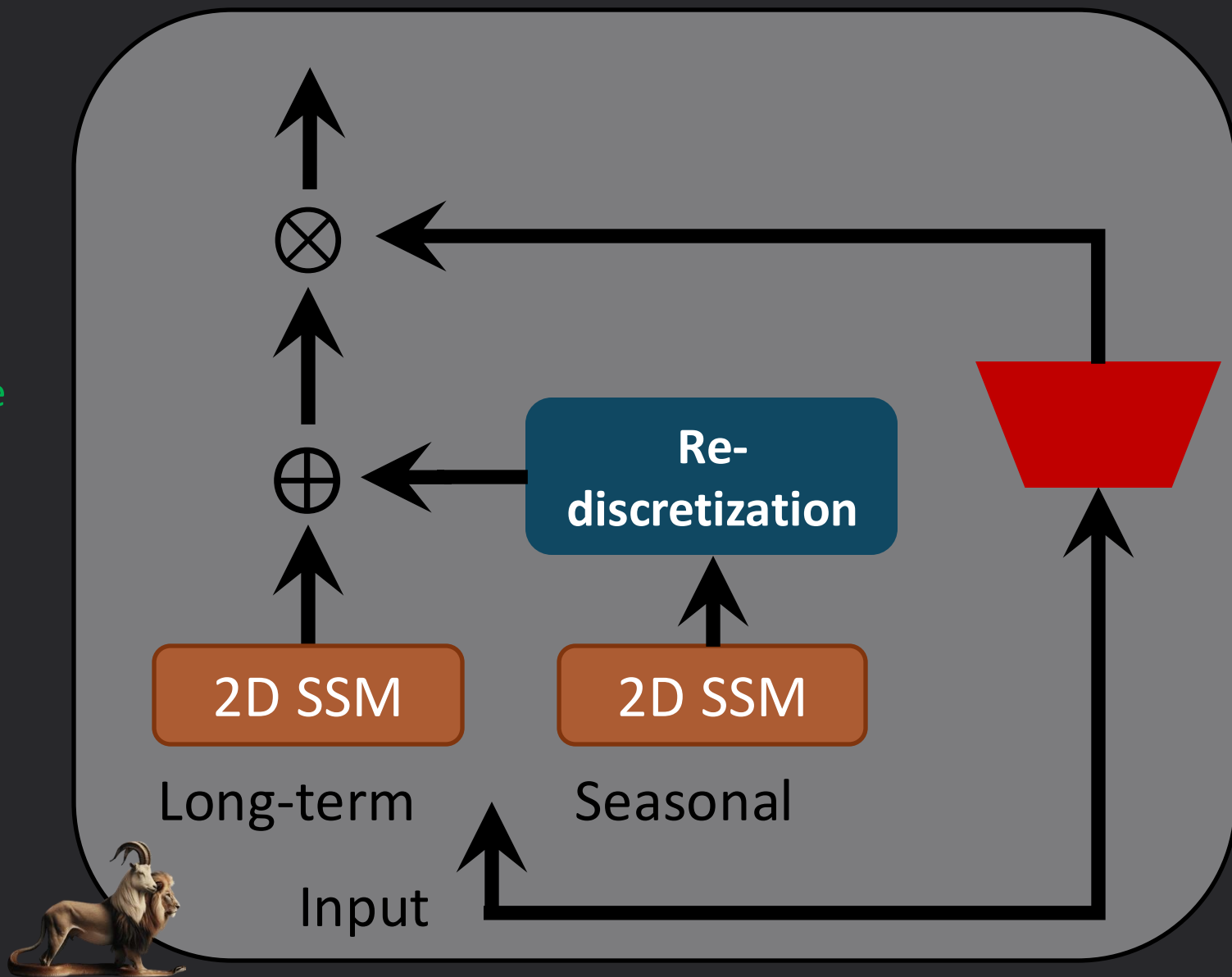
$$h^{(1)}(t + 1, v) = A^{(1)}h^{(1)}(t, v) + A^{(2)}h^{(2)}(t, v) + B^{(1)}x(t + 1, v)$$

$$h^{(2)}(t, v + 1) = A^{(3)}h^{(1)}(t, v) + A^{(4)}h^{(2)}(t, v) + B^{(1)}x(t, v + 1)$$



Chimera

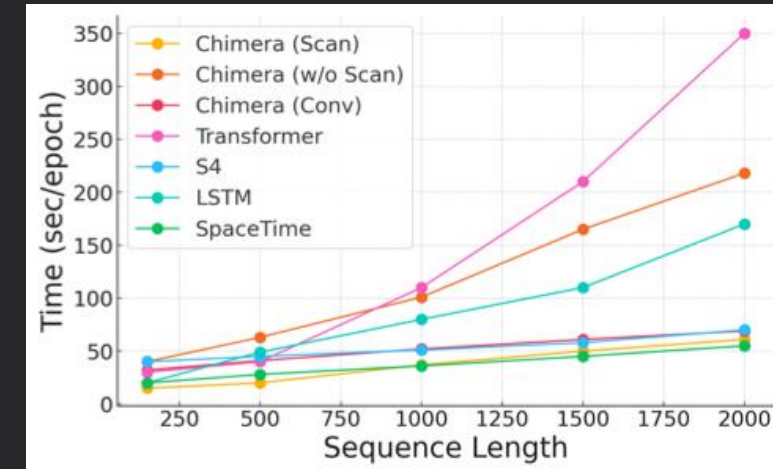
A Three-headed architecture that can capture both long-term and seasonal patterns.



Despite 2D dependencies, this process can be parallelized using the associative sum algorithms with * operators:

$$\begin{pmatrix} p_1 & p_2 & p_3 \\ p_4 & p_5 & p_6 \end{pmatrix} * \begin{pmatrix} q_1 & q_2 & q_3 \\ q_4 & q_5 & q_6 \end{pmatrix} \\ = \begin{pmatrix} q_1 \odot p_1 & q_2 \odot p_2 & q_1 \otimes p_3 + q_2 \otimes p_6 + q_3 \\ q_4 \odot p_4 & q_5 \odot p_5 & q_4 \otimes p_3 + q_5 \otimes p_6 + q_6 \end{pmatrix}$$

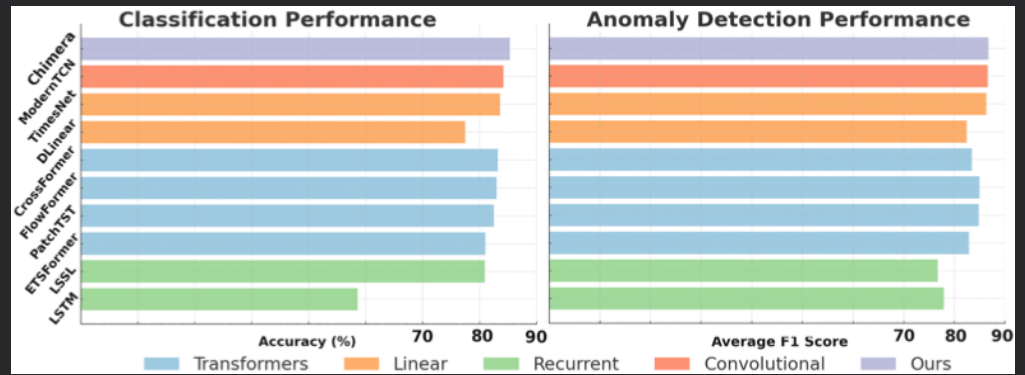
* is associative!



Strong results in long-term and short-term forecasting as well as classification and anomaly detection tasks!

	Chimera (ours)		TSM2 [2024]		Simba [2024]		TCN [2024]		iTransformer [2024]		RLinear [2023]		PatchTST [2023]		Crossformer [2023]		TiDE [2023]		TimesNet [2023]		DLinear [2023]	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETTm1	0.355	0.381	0.361	-	0.383	0.396	0.351	0.381	0.407	0.410	0.414	0.407	0.387	0.400	0.513	0.496	0.419	0.419	0.400	0.406	0.403	0.407
ETTm2	0.252	0.317	0.267	-	0.271	0.327	0.253	0.314	0.288	0.332	0.286	0.327	0.281	0.326	0.757	0.610	0.358	0.404	0.291	0.333	0.350	0.401
ETTh1	0.408	0.425	0.403	-	0.441	0.432	0.404	0.420	0.454	0.447	0.446	0.434	0.469	0.454	0.529	0.522	0.541	0.507	0.458	0.450	0.456	0.452
ETTh2	0.321	0.377	0.333	-	0.361	0.391	0.322	0.379	0.383	0.407	0.374	0.398	0.387	0.407	0.942	0.684	0.611	0.550	0.414	0.427	0.559	0.515
ECL	0.154	0.249	0.169	-	0.185	0.274	0.156	0.253	0.178	0.270	0.219	0.298	0.205	0.290	0.244	0.334	0.251	0.344	0.192	0.295	0.212	0.300
Exchange	0.311	0.358	0.443	-	-	-	0.302	0.366	0.360	0.403	0.378	0.417	0.367	0.404	0.940	0.707	0.370	0.413	0.416	0.443	0.354	0.414
Traffic	0.403	0.286	0.420	-	0.493	0.291	0.398	0.270	0.428	0.282	0.626	0.378	0.481	0.304	0.550	0.304	0.760	0.473	0.620	0.336	0.625	0.383
Weather	0.219	0.258	0.239	-	0.255	0.280	0.224	0.264	0.258	0.278	0.272	0.291	0.259	0.281	0.259	0.315	0.271	0.320	0.259	0.287	0.265	0.317
1 st Count	4	5	1	-	0	0	3	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Models		Chimera (ours)	ModernTCN [2024]	PatchTST [2023]	TimesNet [2023]	N-HiTS [2022]	N-BEATS* [2019]	ETS* [2022]	LightTS [2022]	DLinear [2023]	FED* [2022]	Stationary [2022]	Auto* [2021]	Pyra* [2021]	In* [2021]	Re* [2020]	LSTM [1997]
Weighted Average	SMAPE	11.618	11.698	11.807	11.829	11.927	11.851	14.718	13.525	13.639	12.840	12.780	12.909	16.987	14.086	18.200	160.031
	MASE	1.528	1.556	1.590	1.585	1.613	1.599	2.408	2.111	2.095	1.701	1.756	1.771	3.265	2.718	4.223	25.788
	OWA	0.827	0.838	0.851	0.851	0.861	0.855	1.172	1.051	1.051	0.918	0.930	0.939	1.480	1.230	1.775	12.642



Thank You!