COSA: Context-aware Output-Space Adapter for Test-Time Adaptation in Time Series Forecasting

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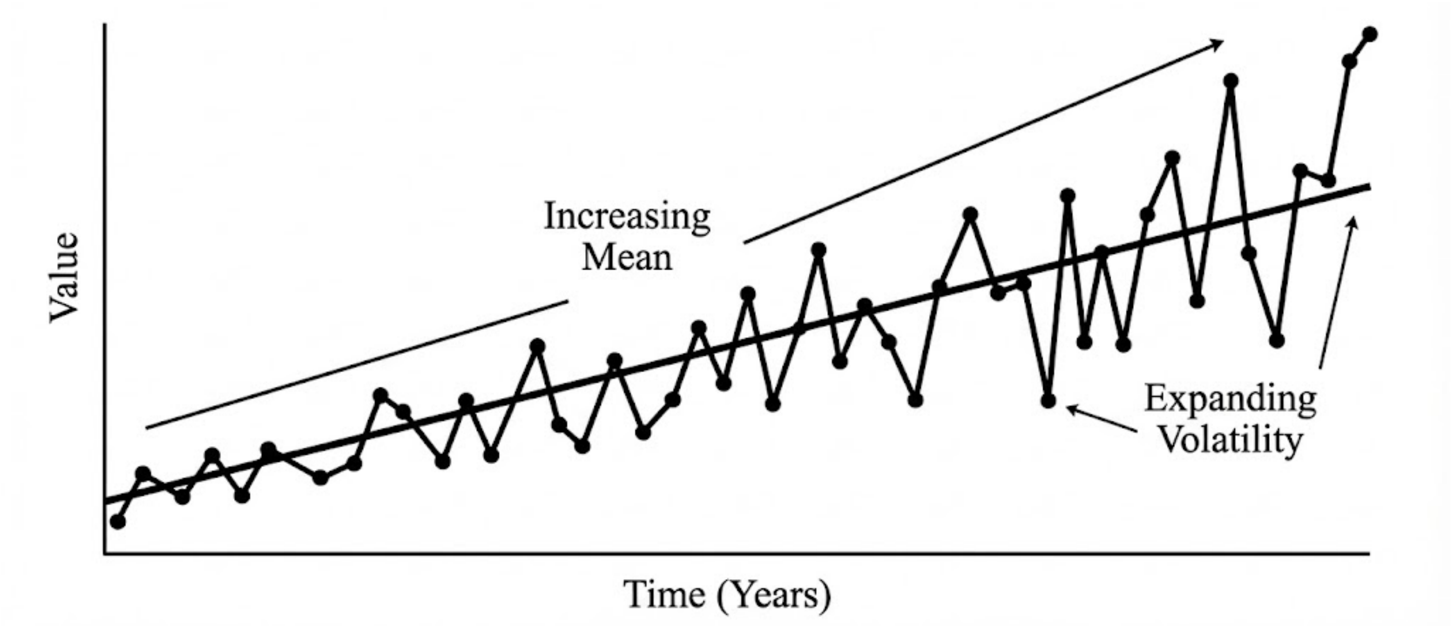
Background

COSA

Evaluation

Conclusion

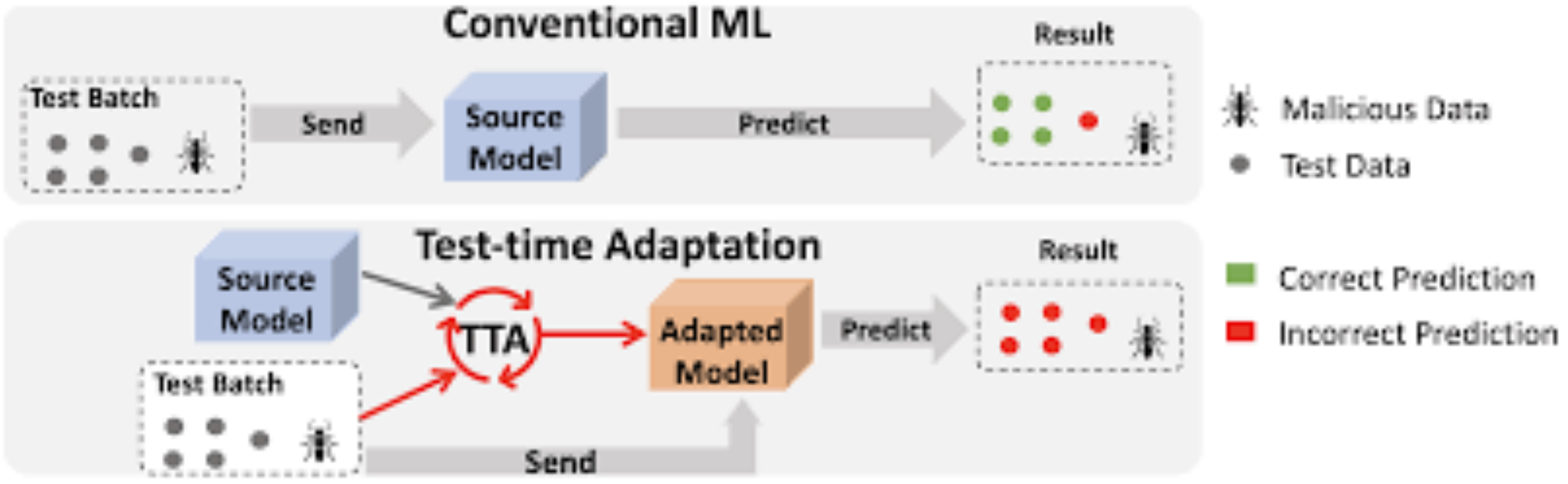
Background



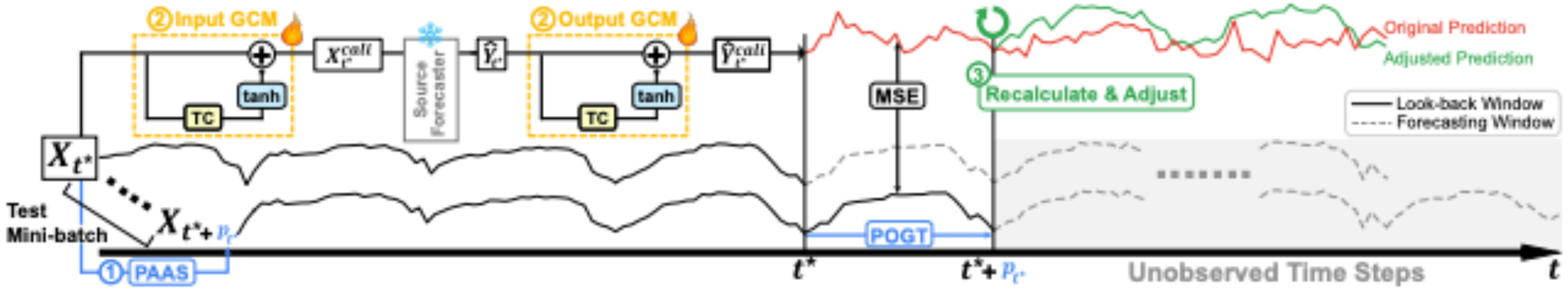
Non-stationarity of Time Series

Time series exhibits inherent non-stationarity,
which degrades the performance of deployed forecasting models.

To address non-stationarity,
Test-Time Adaptation (TTA) has been proposed,
which corrects prediction results during model inference
using only data observed at test time.



Overview of Test-Time Adaptation



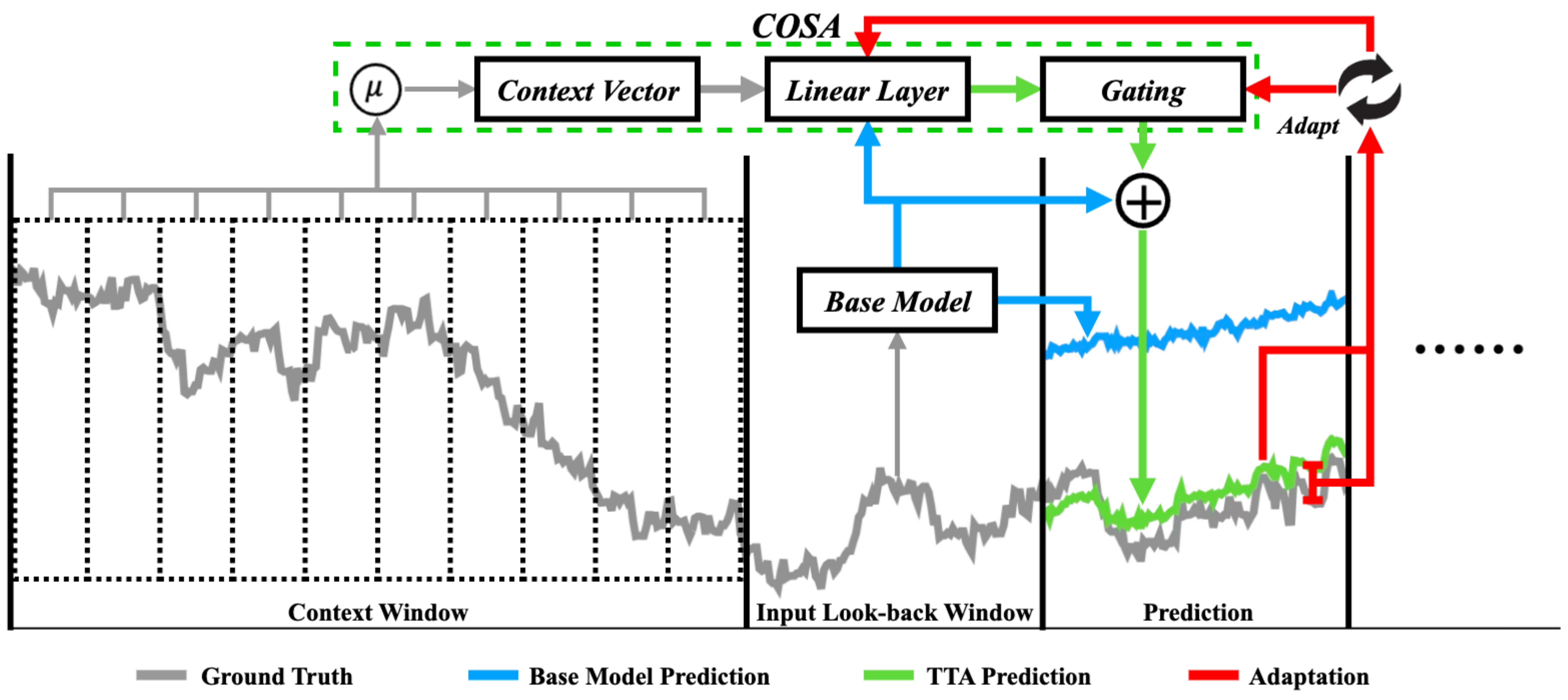
Overview of TAFAS

TAFAS (Kim et al., 2025) has been introduced TAFAS,
which performs distribution correction at the input and output
of a frozen source forecaster.

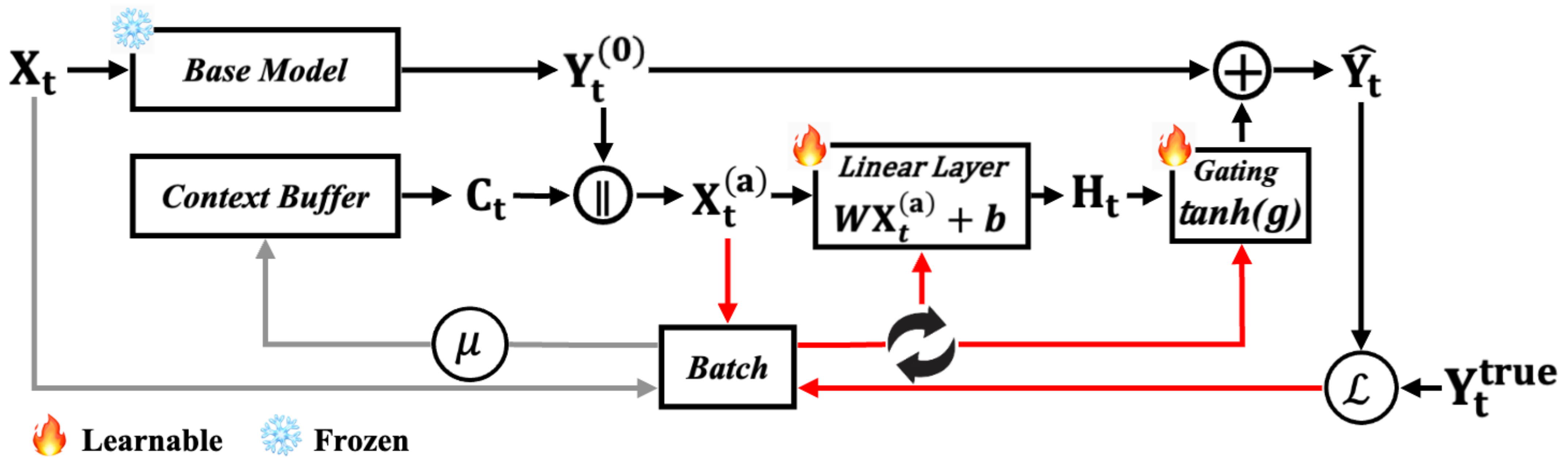
However, the dual-adapter scheme of TAFAS involves design complexity and
create uncertainty about the impact of input transformations on internal model representations.

To this end, we propose Context-aware Output-Space Adapter (COSA),
which offers a direct output-space correction approach that operates with minimal computational overhead.

COSA



Overview of COSA



Detailed Architecture of COSA

COSA consists of …

- **Context Vector: Summarizes observed ground truth.**
- **Linear Residual Layer: Computes a correction residual via linear transformation of the concatenated base model prediction and context vector.**
- **Gating: Controls correction strength within [-1, 1] via tanh(g) to prevent overcorrection.**
- **CALR: Combines cosine annealing with loss-trend-based dynamic adjustment for fast and stable convergence within few adaptation steps**

Evaluation

Table 2: Prediction accuracy comparison. Standard deviations less than 0.001 are omitted.

		Transformer-based					Linear-based					MLP-based				
		iTransformer					DLinear					FreTS				
		Baseline	TAFAS	PETSA	COSA-F	COSA-P	Baseline	TAFAS	PETSA	COSA-F	COSA-P	Baseline	TAFAS	PETSA	COSA-F	COSA-P
ETTh1	96	.4507	.4411	.4393	.4368	**.4363**	.4695	.4618	.4594	.4574	**.4482**	.4462	.4403	.4387	.4384	**.4371**
	192	.5078	.4928	.4949	.4961	**.4919**	.5213	.5117	.5118	.5066	**.5050**	.5022	.4954	.4942	.4951	**.4940**
	336	.5658	.5629	.5640	.5651	**.5300**	.5659	.5604	.5617	.5528	**.5456**	.5544	.5521	.5527	**.5467**	.5351
	720	.7038	.6612	.6596	.5958	**.5638**	.7117	.6820	.6743	.6107	**.5896**	.7182	.6852	.6846	.6259	**.5959**
ETTh2	96	.2577	.2549	.2551	.2504	**.2493**	.2323	.2303	.2306	.2300	**.2281**	.2384	.2367	.2364	.2367	**.2350**
	192	.3161	.3010	.3006	.2983	**.2947**	.2862	.2842	.2876	.2827	**.2819**	.2866	.2824	.2832	**.2816**	.2824
	336	.3545	.3352	.3348	.3241	**.3339**	.3252	.3185	.3184	**.3050**	.3083	.3317	.3229	.3233	**.3031**	.3153
	720	.4276	.4023	.4043	**.3487**	.3591	.4087	.3873	.3853	**.3062**	.3477	.4119	.3857	.3860	**.3169**	.3399
ETTm1	96	.3823	.3558	.3570	**.3447**	.3455	.3715	.3497	.3524	**.3456**	.3475	.3675	.3582	.3583	**.3520**	.3525
	192	.4423	.4146	.4142	**.4124**	.4140	.4438	.4166	.4178	**.4113**	.4122	.4325	.4212	.4198	**.4150**	.4212
	336	.5093	.4754	.4751	**.4569**	.4643	.5183	.4799	.4803	**.4753**	.4858	.5005	.4827	.4789	**.4661**	.4775
	720	.6065	.5562	.5553	**.4773**	.5102	.5929	.5488	.5532	**.4774**	.4991	.5704	.5486	.5476	**.4718**	.4982
ETTm2	96	.1647	.1634	.1637	**.1627**	.1632	.1598	.1584	.1584	**.1583**	.1586	.1581	.1572	.1572	**.1568**	.1569
	192	.2209	.2183	.2173	**.2171**	.2173	.1930	.1913	.1913	**.1904**	.1905	.1923	.1909	.1908	**.1905**	.1908
	336	.2727	.2630	.2592	**.2435**	.2535	.2324	.2289	.2292	**.2083**	.2242	.2320	.2288	.2289	**.2098**	.2211
	720	.3451	.3305	.3332	**.2477**	.2606	.3062	.2968	.2963	**.2215**	.2316	.3012	.2916	.2926	**.2158**	.2314
Exchange Rate	96	.0882	.0876	.0885	**.0818**	.0837	.0913	.0885	.0878	**.0812**	.0834	.0828	.0799	.0803	**.0744**	.0766
	192	.1811	.1686	.1740	**.1403**	.1479	.1827	.1760	.1730	**.1459**	.1519	.1734	.1665	.1648	**.1366**	.1499
	336	.3428	.3079	.3097	**.2089**	.2624	.3277	.2941	.2920	**.2039**	.2480	.3240	.2930	.2923	**.2053**	.2461
	720	.8540	.8322	.8004	**.3421**	.4460	.8873	.8762	.8781	**.3494**	.4481	.8368	.8273	.8067	**.3352**	.4458
Weather	96	.1755	.1664	.1674	**.1597**	.1617	.1954	.1796	.1823	**.1773**	.1793	.1856	.1759	.1765	**.1724**	.1737
	192	.2232	.2101	.2128	**.2067**	.2088	.2403	.2244	.2254	**.2216**	.2217	.2310	.2165	.2192	**.2135**	.2189
	336	.2800	.2614	.2665	**.2503**	.2515	.2918	.2709	.2740	**.2567**	.2626	.2843	.2653	.2681	**.2561**	.2587
	720	.3571	.3458	.3459	**.2480**	.2730	.3643	.3500	.3497	**.2581**	.2708	.3599	.3490	.3488	**.2573**	.2692

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		Baseline	TAFAS	PETSA	COSA-F	COSA-P	Baseline	TAFAS	PETSA	COSA-F	COSA-P	Baseline	TAFAS	PETSA	COSA-F	COSA-P
ETTh1	96	.4312	.4262	.4269	.4242	**.4238**	.4511	.4409	.4391	.4390	**.4372**	.5103	.4901	.4898	.4693	**.4684**
	192	.4955	.4865	.4854	.4830	**.4805**	.5046	.4934	.4937	.4915	**.4906**	.5954	.5617	.5620	.5372	**.5328**
	336	.5559	.5478	.5475	.5438	**.5320**	.5510	.5440	.5465	.5385	**.5320**	.6615	.6387	.6420	.5950	**.5878**
	720	.7117	.6860	.6822	.6113	**.5822**	.6997	.6630	.6431	.5969	**.5733**	.9233	.8142	.8375	.7001	**.6504**
ETTh2	96	.2362	.2351	.2362	.2349	**.2343**	.2306	.2285	.2288	**.2232**	.2265	.2582	.2551	.2552	.2492	**.2485**
	192	.2826	.2758	.2773	.2665	**.2608**	.2839	.2824	.2848	.2796	**.2791**	.3282	.3179	.3258	.3049	**.3017**
	336	.3199	.3125	.3132	**.2971**	.2978	.3258	.3182	.3189	**.3003**	.3043	.3732	.3482	.3497	**.3241**	.3310
	720	.4264	.4005	.4012	**.3233**	.3428	.4162	.3908	.3884	**.3177**	.3453	.4617	.4474	.4473	**.3650**	.3885
ETTm1	96	.4024	.3894	.3937	**.3625**	.3626	.3710	.3506	.3536	**.3454**	.3475	.4354	.3951	.3951	.3837	**.3831**
	192	.4512	.4372	.4413	**.4250**	.4258	.4439	.4160	.4184	**.4115**	.4119	.4855	.4566	.4574	**.4476**	.4514
	336	.5081	.4905	.4946	**.4568**	.4697	.5182	.4787	.4792	**.4748**	.4749	.5556	.5108	.5082	**.4832**	.5054
	720	.5629	.5427	.5462	**.4681**	.4882	.5922	.5478	.5522	**.4763**	.5007	.6212	.5756	.5778	**.5029**	.5225
ETTm2	96	.1584	.1581	.1583	**.1558**	.1562	.1602	.1590	.1589	**.1582**	.1586	.1710	.1711	.1730	**.1702**	.1704
	192	.2059	.2036	.2037	**.2007**	.2022	.1936	.1921	.1919	**.1906**	.1907	.2121	**.2102**	.2126	**.2102**	.2120
	336	.2458	.2451	.2452	**.2258**	.2352	.2331	.2299	.2302	**.2131**	.2226	.2530	.2501	.2520	**.2337**	.2351
	720	.3268	.3268	.3256	**.2446**	.2645	.3066	.2986	.2971	**.2171**	.2349	.3327	.3220	.3131	**.2477**	.2643
Exchange Rate	96	.0867	.0843	.0837	**.0765**	.0788	.0814	.0792	.0798	**.0756**	.0773	.1151	.1087	.1146	**.0955**	.1008
	192	.1877	.1805	.1832	**.1464**	.1570	.1727	.1658	.1653	**.1393**	.1457	.2150	.2198	.1999	**.1663**	.1722
	336	.3389	.3275	.3300	**.1983**	.2445	.3226	.2877	.2898	**.2020**	.2323	.3950	.3047	.3100	**.2119**	.2660
	720	.8648	.8659	.8643	**.3543**	.4662	.8366	.8138	.8149	**.3444**	.4541	1.0259	.7191	.7805	**.3871**	.4815
Weather	96	.1742	.1724	.1743	**.1624**	.1634	.1957	.1807	.1795	**.1772**	.1803	.1757	.1853	.1970	**.1636**	.1651
	192	.2195	.2147	.2167	**.2006**	.2108	.2404	.2244	.2274	**.2223**	.2237	.2237	.2161	.2265	**.2082**	.2120
	336	.2766	.2666	.2701	**.2451**	.2488	.2921	.2714	.2748	**.2551**	.2642	.2812	.2746	.2788	**.2729**	.2737
	720	.3544	.3383	.3442	**.2590**	.2713	.3644	.3466	.3493	**.2579**	.2708	.3508	.3573	.3681	**.2582**	.2855

COSA-F (Fixed): Uses a **fixed batch size of B=48**
COSA-P (Periodic): Sets **batch size B dynamically using PAAS,** adjusting adaptation frequency based on the data's frequency patterns

Key Findings:

- COSA achieves the **best performance** across all 6 datasets, 4 horizons, and 6 base models.
- **10.48%–13.05% improvement** over SOTA TTA methods (TAFAS, PETSA).
- **13.91%–17.03% improvement** over baselines without TTA.
- Gains are architecture-agnostic.
- Largest improvements at horizon 720**, up to 32.24%** over baseline.
- Inference time of only **1.25ms/batch**, achieving **88.59%–90.10% faster inference** than prior SOTA TTA methods

Conclusion

Conclusion

- COSA: minimal, plug-and-play output adapter that directly corrects frozen model predictions
- Consistent gains across all architectures and datasets with negligible overhead

Future Work:

- Extending to partial ground truth for real-time deployment
- Adaptive context length and hybrid adapters for complex distribution shifts

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