Rethinking the Power of Timestamps for Robust Time Series Forecasting: A Global-Local Fusion Perspective

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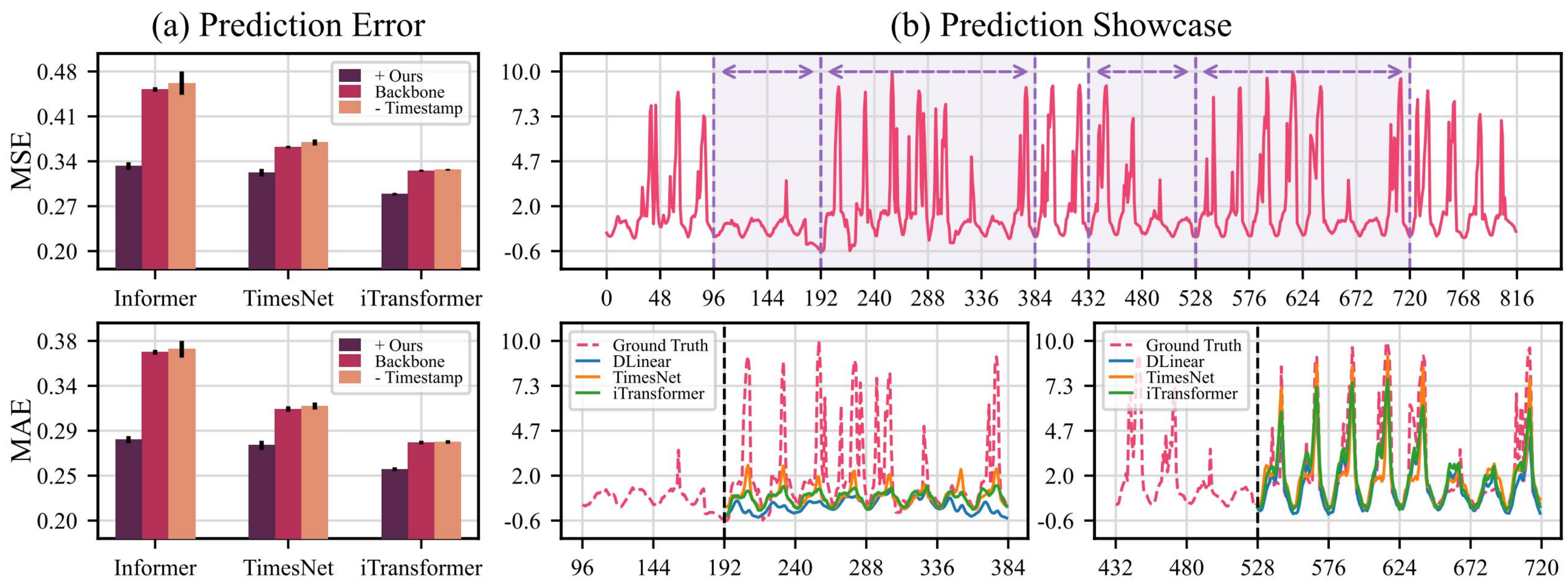
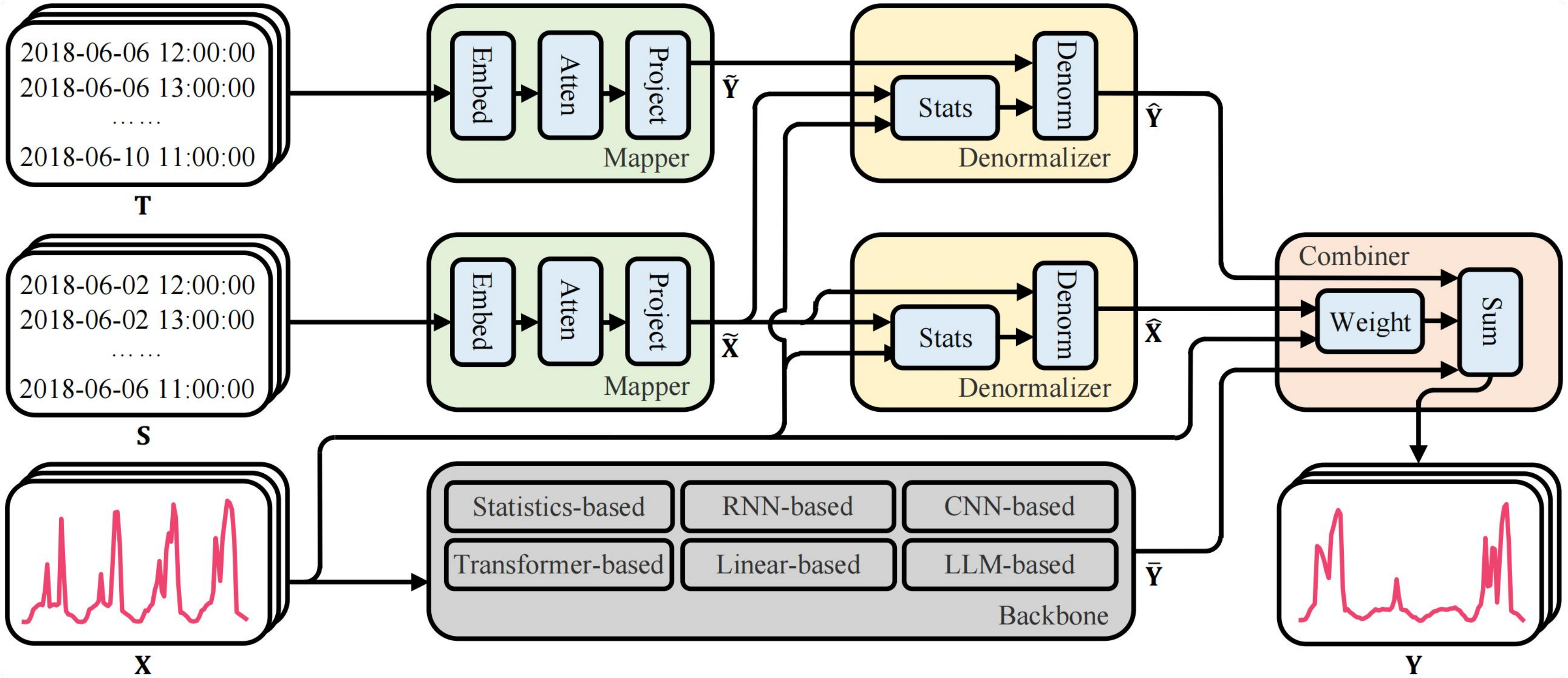
Motivation



➢ Despite the enormous advancements of previous research, most methods focus mainly on local data.

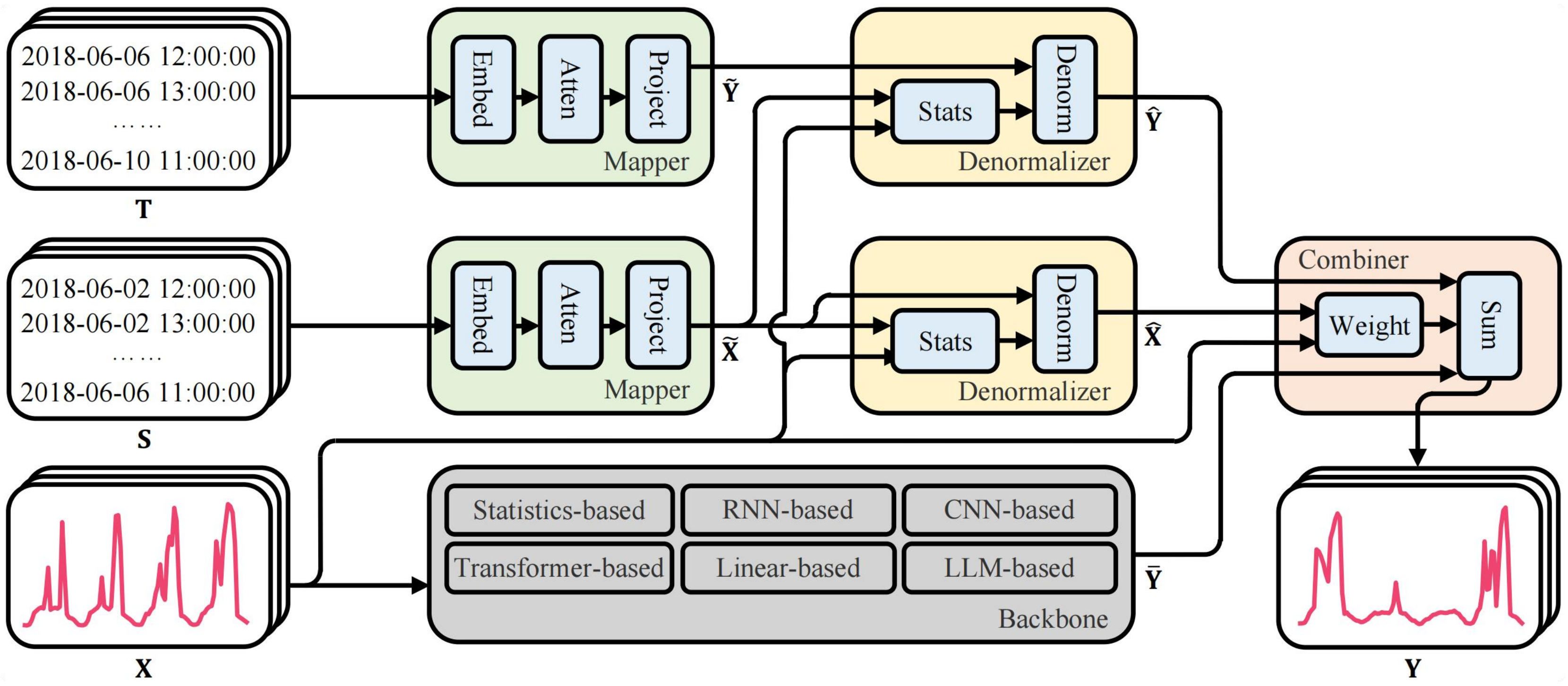
➢ When real-world data is polluted, the lack of global information weakens the robustness of predictions.

Methodology



- ➢ **Attention-based Mapper**
- ➢ **Robust Denormalizer**
- ➢ **Adaptive Combiner**

Methodology

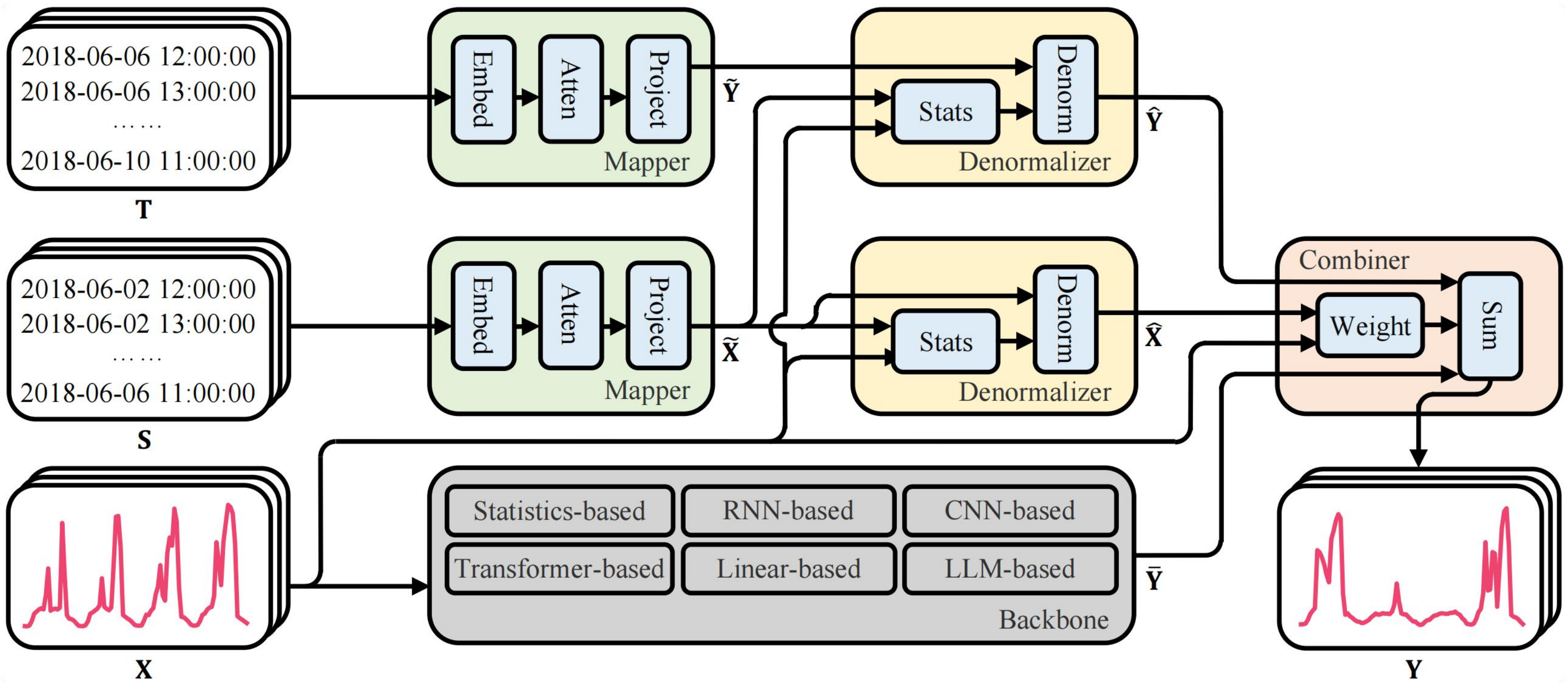


➢ **Attention-based Mapper**
Captures the timestamp dependencies via attention, creating standard-distribution initial history and future mappings.

➢ **Robust Denormalizer**

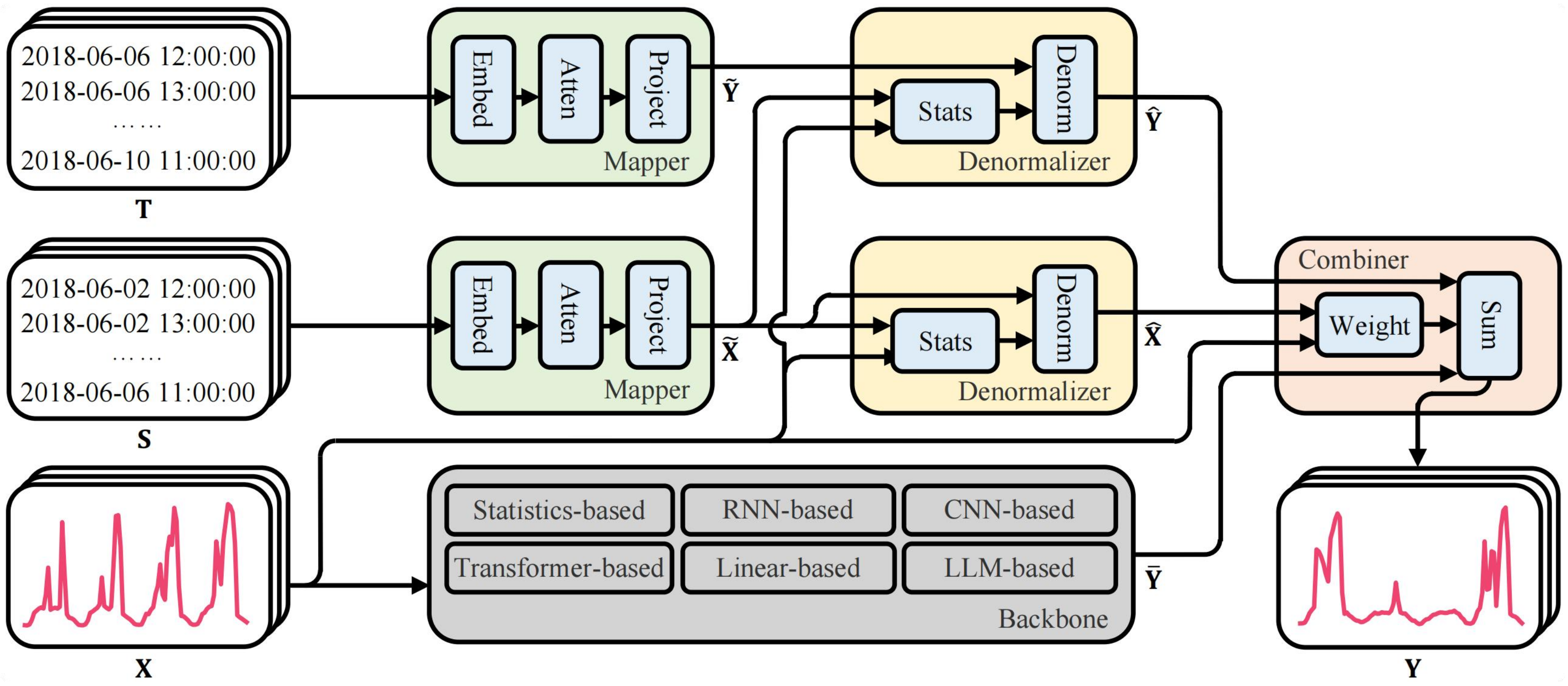
➢ **Adaptive Combiner**

Methodology



- **Attention-based Mapper**
- **Robust Denormalizer**
  Inverse normalizes the initial mappings using quantile deviation from historical observations, mitigating data drift.
- **Adaptive Combiner**

Methodology



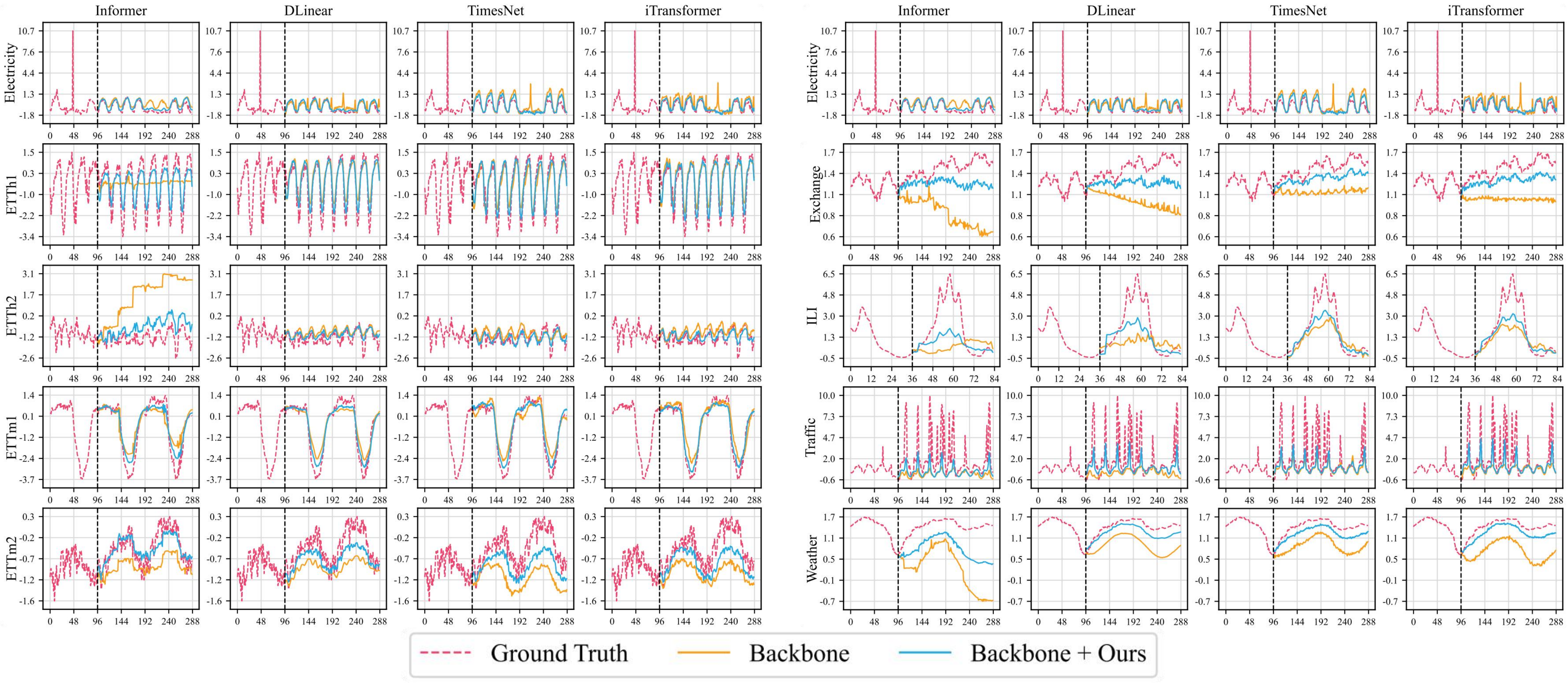
- **Attention-based Mapper**
- **Robust Denormalizer**
- **Adaptive Combiner**
  Adjusts weights of global mapping and local prediction based on the differences between final mapping and historical observations, yielding final prediction.

Experiment

Method		Informer		+ Ours		DLinear		+ Ours		TimesNet		+ Ours		iTransformer		+ Ours		Impr.
		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	
Electricity	96	0.333	0.414	**0.217**	**0.323**	0.196	0.283	**0.147**	**0.238**	0.175	0.280	**0.154**	**0.248**	0.153	0.246	**0.120**	**0.198**	15.7%
	192	0.362	0.444	**0.220**	**0.329**	0.196	0.286	**0.172**	**0.253**	0.191	0.293	**0.169**	**0.261**	0.167	0.259	**0.143**	**0.216**	
	336	0.352	0.434	**0.230**	**0.337**	0.208	0.301	**0.197**	**0.274**	0.211	0.310	**0.185**	**0.276**	0.183	0.276	**0.168**	**0.240**	
	720	0.364	0.443	**0.247**	**0.351**	0.239	0.331	**0.239**	**0.308**	0.235	0.326	**0.226**	**0.303**	0.220	0.310	**0.217**	**0.279**	
ETTh1	96	0.926	0.736	**0.609**	**0.569**	0.409	0.440	**0.391**	**0.418**	0.453	0.481	**0.435**	**0.464**	0.420	0.454	**0.411**	**0.441**	8.8%
	192	1.235	0.844	**0.831**	**0.680**	0.457	0.475	**0.446**	**0.457**	0.533	0.531	**0.520**	**0.517**	0.494	0.502	**0.474**	**0.482**	
	336	1.354	0.875	**0.882**	**0.698**	0.500	0.506	**0.492**	**0.488**	0.621	0.580	**0.596**	**0.560**	0.538	0.528	**0.534**	**0.519**	
	720	1.264	0.857	**0.937**	**0.730**	0.610	0.576	**0.609**	**0.556**	0.844	0.697	**0.773**	**0.661**	0.716	0.629	**0.704**	**0.615**	
ETTh2	96	0.708	0.549	**0.422**	**0.443**	0.159	0.278	**0.128**	**0.205**	0.183	0.298	**0.174**	**0.276**	0.177	0.287	**0.172**	**0.271**	12.1%
	192	1.133	0.688	**0.860**	**0.599**	0.187	0.309	**0.165**	**0.238**	0.218	0.329	**0.204**	**0.306**	0.199	0.311	**0.196**	**0.295**	
	336	0.997	0.667	**0.747**	**0.570**	0.207	0.330	**0.206**	**0.265**	0.240	0.346	**0.219**	**0.319**	0.220	0.329	**0.213**	**0.306**	
	720	1.607	0.815	**1.255**	**0.720**	0.262	0.378	**0.214**	**0.288**	0.281	0.376	**0.278**	**0.363**	0.271	0.366	**0.270**	**0.356**	
ETTm1	96	0.593	0.548	**0.503**	**0.486**	0.339	0.388	**0.309**	**0.353**	0.449	0.448	**0.381**	**0.398**	0.383	0.415	**0.349**	**0.386**	8.1%
	192	0.611	0.576	**0.534**	**0.525**	0.394	0.418	**0.362**	**0.386**	0.448	0.461	**0.440**	**0.432**	0.429	0.445	**0.403**	**0.420**	
	336	0.888	0.726	**0.707**	**0.628**	0.450	0.451	**0.442**	**0.432**	0.550	0.504	**0.494**	**0.462**	0.485	0.479	**0.468**	**0.460**	
	720	1.037	0.786	**0.925**	**0.719**	0.508	0.493	**0.493**	**0.467**	0.619	0.559	**0.563**	**0.507**	0.566	0.532	**0.564**	**0.519**	
ETTm2	96	0.186	0.311	**0.147**	**0.266**	0.115	0.232	**0.080**	**0.165**	0.121	0.234	**0.110**	**0.212**	0.120	0.235	**0.111**	**0.221**	12.1%
	192	0.242	0.348	**0.230**	**0.341**	0.143	0.261	**0.109**	**0.193**	0.155	0.267	**0.136**	**0.239**	0.149	0.266	**0.144**	**0.252**	
	336	0.454	0.466	**0.308**	**0.380**	0.176	0.294	**0.148**	**0.229**	0.190	0.293	**0.175**	**0.269**	0.185	0.293	**0.182**	**0.283**	
	720	0.861	0.616	**0.719**	**0.561**	0.225	0.340	**0.221**	**0.274**	0.242	0.334	**0.225**	**0.309**	0.233	0.333	**0.232**	**0.327**	
Exchange	96	0.735	0.728	**0.223**	**0.391**	0.051	0.164	**0.046**	**0.155**	0.076	0.198	**0.066**	**0.177**	0.058	0.172	**0.051**	**0.158**	16.4%
	192	1.016	0.861	**0.421**	**0.547**	0.099	0.238	**0.093**	**0.225**	0.135	0.272	**0.115**	**0.242**	0.113	0.245	**0.108**	**0.231**	
	336	1.331	0.971	**0.691**	**0.694**	0.174	0.317	**0.161**	**0.299**	0.237	0.363	**0.219**	**0.336**	0.210	0.339	**0.196**	**0.314**	
	720	2.054	1.263	**1.152**	**0.922**	0.314	0.446	**0.308**	**0.439**	0.636	0.618	**0.595**	**0.582**	0.517	0.551	**0.510**	**0.529**	
ILI	24	3.374	1.356	**2.487**	**1.106**	2.087	1.131	**1.875**	**0.963**	1.478	0.713	**1.333**	**0.684**	1.148	0.659	**1.129**	**0.658**	9.9%
	36	3.094	1.293	**2.617**	**1.157**	2.065	1.107	**1.756**	**0.957**	1.294	0.748	**1.204**	**0.695**	1.061	0.695	**1.039**	**0.682**	
	48	3.383	1.370	**2.879**	**1.230**	2.059	1.088	**1.639**	**0.912**	1.280	0.736	**1.278**	**0.721**	1.209	0.735	**1.164**	**0.715**	
	60	3.610	1.415	**3.086**	**1.274**	2.186	1.097	**1.644**	**0.889**	1.291	0.773	**1.191**	**0.713**	1.222	0.758	**1.196**	**0.731**	
Traffic	96	0.467	0.375	**0.352**	**0.297**	0.482	0.378	**0.301**	**0.260**	0.360	0.314	**0.322**	**0.278**	0.308	0.272	**0.283**	**0.249**	19.5%
	192	0.455	0.371	**0.343**	**0.288**	0.449	0.356	**0.302**	**0.261**	0.364	0.314	**0.325**	**0.277**	0.327	0.279	**0.291**	**0.253**	
	336	0.462	0.378	**0.335**	**0.281**	0.453	0.358	**0.306**	**0.263**	0.373	0.320	**0.331**	**0.282**	0.338	0.285	**0.301**	**0.259**	
	720	0.495	0.400	**0.340**	**0.287**	0.475	0.374	**0.327**	**0.278**	0.396	0.337	**0.339**	**0.289**	0.357	0.302	**0.320**	**0.273**	
Weather	96	1.422	0.867	**0.642**	**0.554**	0.198	0.258	**0.176**	**0.244**	0.188	0.238	**0.171**	**0.226**	0.178	0.223	**0.159**	**0.220**	9.6%
	192	1.429	0.880	**0.877**	**0.664**	0.237	0.296	**0.219**	**0.280**	0.234	0.278	**0.233**	**0.277**	0.231	0.268	**0.214**	**0.265**	
	336	1.796	1.008	**1.506**	**0.851**	0.282	0.333	**0.265**	**0.312**	0.293	0.317	**0.288**	**0.314**	0.289	0.310	**0.273**	**0.306**	
	720	1.542	0.946	**1.427**	**0.853**	0.343	0.379	**0.330**	**0.360**	0.368	0.365	**0.364**	**0.362**	0.370	0.363	**0.352**	**0.355**	
Impr.		23.8%				13.1%				7.5%				5.5%				12.5%

Extensive experiments conducted on nine real-world datasets demonstrate that **GLAFF** significantly enhances the average performance of widely used mainstream forecasting models by **12.5%**, surpassing the previous state-of-the-art method by **5.5%**.

Experiment

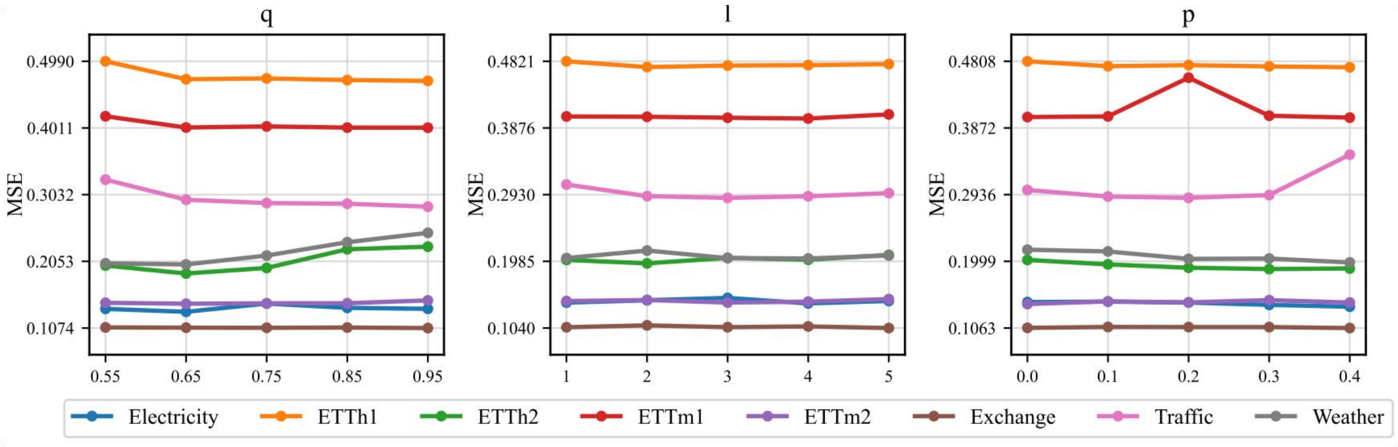

Informer
DLinear
TimesNet
iTransformer
Informer
DLinear
TimesNet
iTransformer
Electricity
ETTh1
ETTh2
ETTm1
ETTm2
Electricity
Exchange
ILI
Traffic
Weather
Ground Truth
Backbone
Backbone + Ours

Experiment

Ablation Studies

Method		iTransformer MSE	iTransformer MAE	**+ Ours** MSE	**+ Ours** MAE	w/o Backbone MSE	w/o Backbone MAE	w/o Attention MSE	w/o Attention MAE	w/o Quantile MSE	w/o Quantile MAE	w/o Adaptive MSE	w/o Adaptive MAE
Electricity	96	0.1525	0.2460	**0.1197**	**0.1979**	0.2058	0.2663	0.1518	0.2450	0.1467	0.2465	0.1574	0.2502
	192	0.1674	0.2593	**0.1434**	**0.2157**	0.2097	0.2793	0.1684	0.2610	0.1677	0.2662	0.1740	0.2662
	336	0.1830	0.2762	**0.1683**	**0.2395**	0.2454	0.3014	0.1832	0.2775	0.1993	0.2954	0.1953	0.2877
	720	0.2199	0.3097	**0.2169**	**0.2786**	0.2984	0.3386	0.2182	0.3092	0.2593	0.3403	0.2330	0.3171
Traffic	96	0.3084	0.2717	**0.2828**	**0.2485**	0.3348	0.2723	0.3172	0.2806	0.2909	0.2684	0.2930	0.2612
	192	0.3267	0.2794	**0.2909**	**0.2528**	0.3387	0.2736	0.3357	0.2884	0.2948	0.2737	0.2970	0.2610
	336	0.3381	0.2850	**0.3005**	**0.2594**	0.3460	0.2794	0.3482	0.2958	0.3023	0.2804	0.3082	0.2706
	720	0.3574	0.3015	**0.3201**	**0.2730**	0.3558	0.2906	0.3684	0.3113	0.3249	0.2984	0.3212	0.2819
Weather	96	0.1784	0.2229	**0.1587**	**0.2199**	0.2382	0.2695	0.1780	0.2214	0.1811	0.2270	0.1914	0.2379
	192	0.2308	0.2675	**0.2138**	**0.2654**	0.2882	0.3105	0.2383	0.2733	0.2364	0.2768	0.2489	0.2832
	336	0.2892	0.3099	**0.2733**	**0.3058**	0.3381	0.3414	0.2932	0.3146	0.2905	0.3134	0.3070	0.3251
	720	0.3701	0.3634	**0.3520**	**0.3547**	0.4011	0.3813	0.3752	0.3664	0.3727	0.3649	0.3829	0.3722
Avg.		0.2602	0.2827	**0.2367**	**0.2593**	0.3000	0.3004	0.2646	0.2870	0.2555	0.2876	0.2591	0.2845

Hyperparameter Analyses



Thanks for you listening!

For further questions welcome to discuss via E-mail

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or GitHub issues

https://github.com/ForestsKing/GLAFF