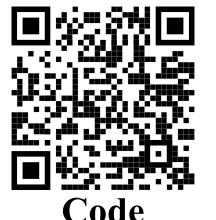
# CARD: Channel Aligned Robust Blend Transformer for Time Series Forecasting

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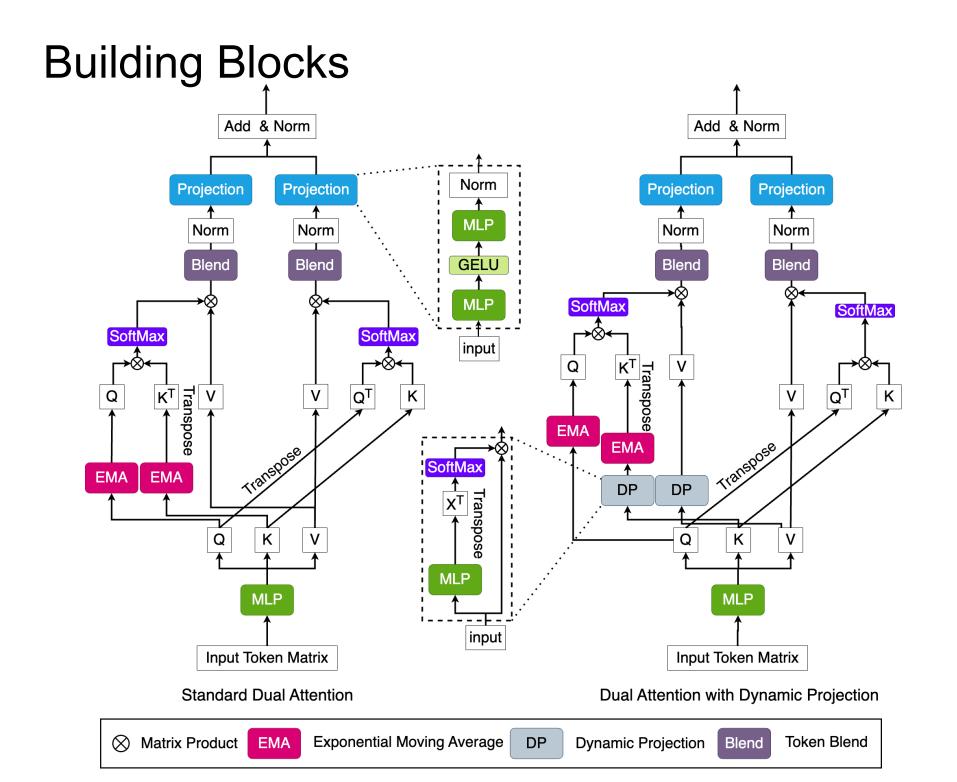




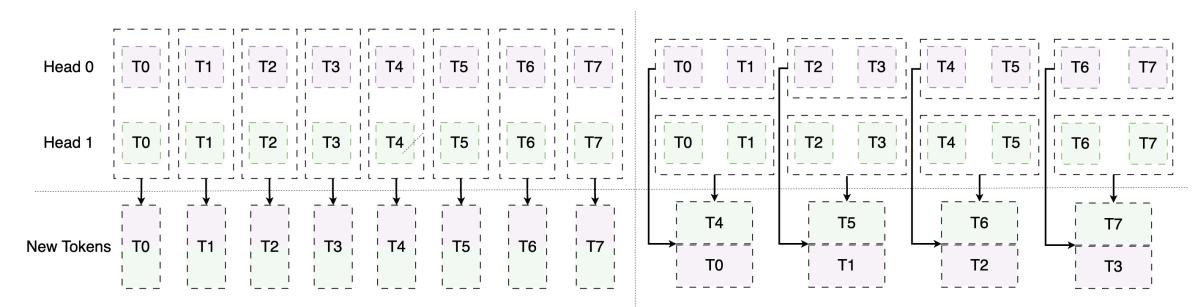
### Introduction & Contribution

Recent studies have demonstrated the great power of Transformer models for time series forecasting. One of the key elements that lead to the transformer's success is the channel-independent (CI) strategy to improve the training robustness. However, the ignorance of the correlation among different channels in CI would limit the model's forecasting capacity. In this work:

- We propose a Channel Aligned Robust Blend Transformer (CARD) which efficiently and robustly aligns the information among different channels and utilizes the multi-scale information.
- CARD demonstrates superior performance in several benchmark datasets for forecasting and other prediction-based tasks, outperforming the state-of-the-art models. Our studies have confirmed the effectiveness of the proposed model.
- We develop a robust signal decay-based loss function that utilizes signal decay to bolster the model's ability to concentrate on forecasting for the near future. Our empirical assessment has confirmed that this loss function is effective in improving the performance of other benchmark models as well.



Dual Attentions over both hidden dimension and token dimension



Standard Token Construction

Token Blend

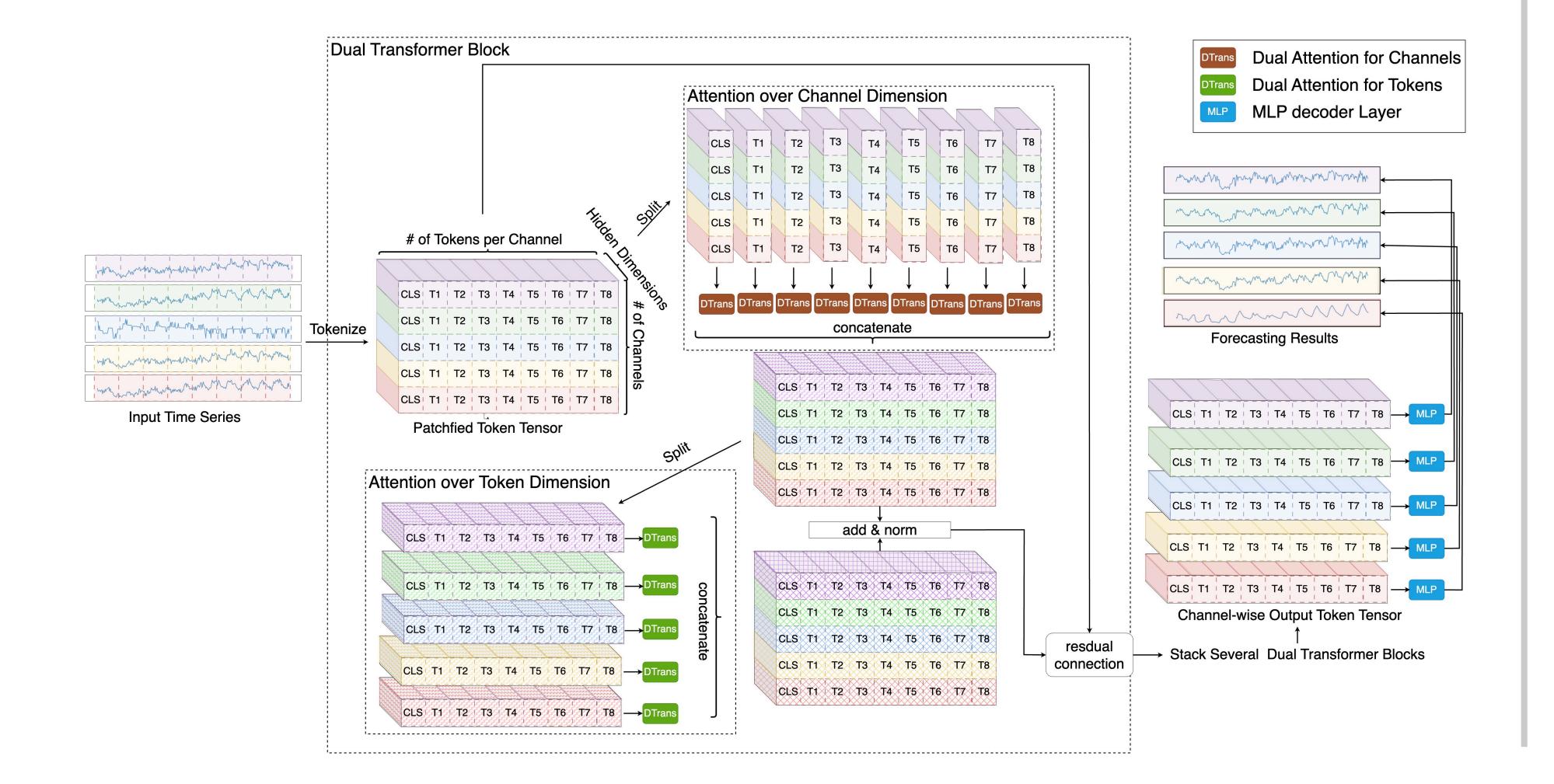
Multi-Resolution with Token Blend

$$\min \mathbb{E}_{\boldsymbol{A}} \left[ \frac{1}{L} \sum_{l=1}^{L} \| \hat{\boldsymbol{a}}_{t+l}(\boldsymbol{A}) - \boldsymbol{a}_{t+l}(\boldsymbol{A}) \|_{2}^{2} \right] \Rightarrow \min \mathbb{E}_{\boldsymbol{A}} \left[ \frac{1}{L} \sum_{l=1}^{L} l^{-1} \| \hat{\boldsymbol{a}}_{t+l}(\boldsymbol{A}) - \boldsymbol{a}_{t+l}(\boldsymbol{A}) \|_{2}^{2} \right]$$

$$\min \mathbb{E}_{\boldsymbol{A}} \left[ \frac{1}{L} \sum_{l=1}^{L} \| \hat{\boldsymbol{a}}_{t+l}(\boldsymbol{A}) - \boldsymbol{a}_{t+l}(\boldsymbol{A}) \|_{1} \right] \Rightarrow \min \mathbb{E}_{\boldsymbol{A}} \left[ \frac{1}{L} \sum_{l=1}^{L} l^{-1} \| \hat{\boldsymbol{a}}_{t+l}(\boldsymbol{A}) - \boldsymbol{a}_{t+l}(\boldsymbol{A}) \|_{1} \right]$$

Signal Decay based MSE/MAE Loss Functions

### Architecture Overview of CARD



## **Experimental Results**

Models	CARD	PatchTST	MIC	N   T	imesNet	Crossf	ormer	Dlinea	r   L	ightTS	FilM	ETSfo	rmer   I	EDformer
Metric   N	MSE MAE	MSE MAI	E MSE N	<b>ЛАЕ</b>  М	ISE MAE	EMSE	MAE	MSE M	AE MS	Е МАЕ	MSE MA	AE MSE	MAE I	MSE MAE
ETTm1  0	0.383   0.383	0.395 0.40	8 <u> 0.387</u> 0	.411 0.4	400 <u>0.406</u>	0.435	0.417	0.403 0.4	07 0.43	35 0.437	0.408 0.3	99 0.429	0.425 0	0.448 0.452
ETTm2  0	.271 0.316	0.283 0.32	7   0.284 0	.340 0.	291 0.333	8 0.609	0.521	0.350 0.4	01 0.40	09 0.436	0.287 0.3	28 0.292	0.342 0	0.305 0.349
ETTh1  0	0.443 <b>0.429</b>	0.455 <u>0.44</u>	<u>4</u>   <b>0.440</b> 0	.462 0.4	458 0.450	0 0.486	0.481	0.456 0.4	52 0.49	91 0.479	0.461 0.4	56 0.452	0.510 0	<b>.440</b> 0.460
ETTh2 0	0.367 0.390	0.384 0.40	6   0.402 0	.437 0.4	414 0.427	0.966	0.690	0.559 0.5	515 0.60	02 0.543	0.384 0.4	<u>06</u>  0.439	0.452 0	0.437 0.449
Weather 0	0.240 0.262	0.257 <u>0.28</u>	0 0.243 0	.299 0.:	259 0.287	0.250	0.310	0.265 0.3	317 0.20	51 0.312	0.269 0.3	39 0.271	0.334 0	0.309 0.360
Electricity 0	<b>0.169 0.258</b>  0	0.216 0.31	8 <u> 0.187</u> <u>0</u>	<u>.295</u>  0.	192 <u>0.295</u>	0.273	0.363	0.212 0.3	300 0.22	29 0.329	0.223 0.3	03 0.208	0.323 0	0.214 0.327
Traffic 0	0.450 0.278	0.488 0.32	7  0.542 0	.316 0.	620 0.336	0.593	0.332	0.625 0.3	883 0.62	22 0.392	0.639 0.3	89 0.621	0.396 0	0.610 0.376

#### Long term Forecasting with 96 input length

Models		CARD	PatchTST	MICN	TimesNet	N-HiTS	N-BEATS	EETSformer	LightTS	Dlinear	FEDformer	Autoformer	Informer
Yearly	SMAPE MASE OWA		$\begin{array}{ c c }\hline 13.258\\ \hline 2.985\\ \hline 0.781\\ \hline \end{array}$	14.935 3.523 0.900	13.387 2.996 0.786	13.418 3.045 0.793	13.436 3.043 0.794	18.009 4.487 1.115	14.247 3.109 0.827	16.965 4.283 1.058	13.728 3.048 0.803	13.974 3.134 0.822	14.727 3.418 0.881
Quarterly	SMAPE MASE OWA		1.212	11.452 1.389 1.026	10.100 1.182 0.890	10.202 1.194 0.899	10.124 1.169 0.886	13.376 1.906 1.302	11.364 1.328 1.000	12.145 1.520 1.106	10.792 1.283 0.958	11.338 1.365 1.012	11.360 1.401 1.027
Monthly	SMAPE MASE OWA		0.930	13.773 1.076 0.983	12.670 0.933 0.878	12.791 0.969 0.899	12.667 0.937 0.880	14.588 1.368 1.149	14.014 1.053 0.981	13.514 1.037 0.956	14.260 1.102 1.012	13.958 1.103 1.002	14.062 1.141 1.024
Others	SMAPE MASE OWA	4.522 3.021 0.962	3.238	6.716 4.717 1.451	4.891 3.302 1.035	5.061   3.216   1.040	4.925 3.391 1.053	7.267 5.240 1.591	15.880 11.434 3.474	6.709   4.953   1.487	4.954 3.264 1.036	5.458 3.865 1.187	24.460 20.960 5.879
Avg	SMAPE MASE OWA		1.590	13.130 1.896 0.980	11.829 1.585 0.851	11.927 1.613 0.861	11.851 1.599 0.855	14.718 2.408 1.172	13.252 2.111 1.051	13.639 2.095 1.051	12.840 1.701 0.918	12.909 1.771 0.939	14.086 2.718 1.230

#### Short term M4 forecasting

Models	CARD I	PatchTST	T MICN T	TimesNe	t Cr	ossform	er E	TSforme	r LightTS	Dlinear	FEDforme	er S	tationary	Autoforme	er Informe
SMD	0.872	<u>0.866</u>	0.800	0.858		0.778		0.831	0.825	0.771	0.851		0.847	0.851	0.855
MSL	0.817	0.823	0.816	0.852		0.820		<u>0.850</u>	0.790	0.849	0.786		0.775	0.791	0.841
SMAP	0.857	0.695	0.656	<u>0.715</u>		0.674		0.695	0.692	0.693	0.708		0.711	0.711	0.699
SWaT	0.945	0.909	0.875	0.921		0.886		0.849	0.933	0.875	0.932		0.799	0.927	0.814
PSM	0.957	0.951	0.933	0.975		0.921		0.918	0.972	0.936	0.972		0.973	0.933	0.771
Avg	0.890	0.849	0.816	0.864		0.816		0.829	0.842	0.825	0.849		0.821	0.843	0.789

Forecasting based anomaly detection