北京工業大學
BEIJINGUNIVERSITYOFTECHNOLOGY

TFB: Towards Comprehensive and Fair Benchmarking of Time Series Forecasting Methods

（迈向全面和公平的时间序列预测方法基准测试）

汇报人：闫林枝

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CONTENT

PART ONE

01

背景

数据领域覆盖不足

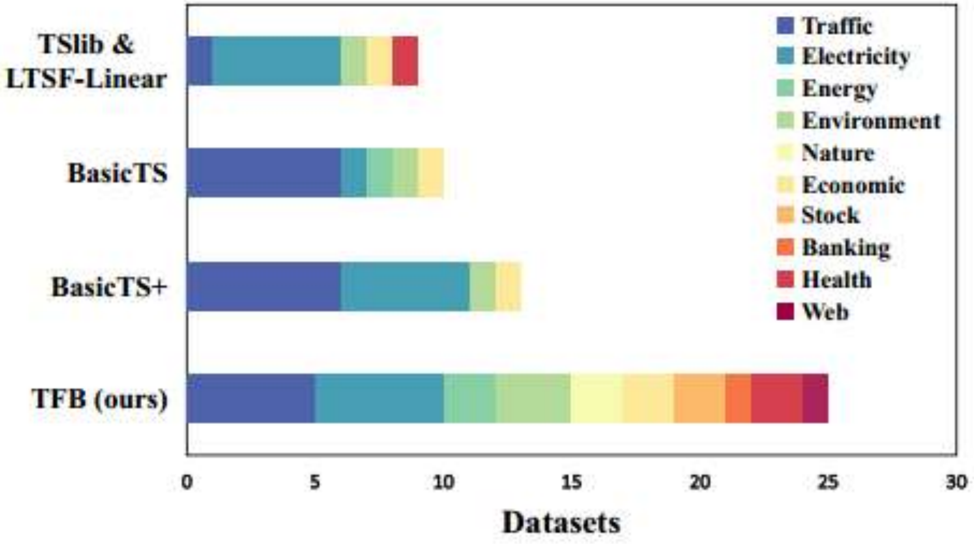


Figure 2: Statistics of data domains covered by existing multivariate time series benchmarks.

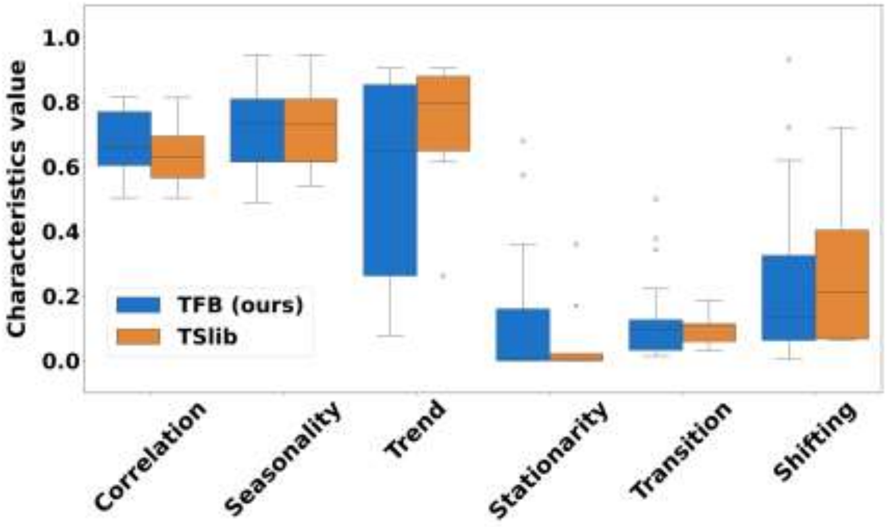


Figure 3: Box plot of the variations in normalized values of characteristics across the multivariate datasets in the TFB and TSlib.

✓ 结论：扩大数据集领域能够对方法性能进行更广泛的评估。

预备知识

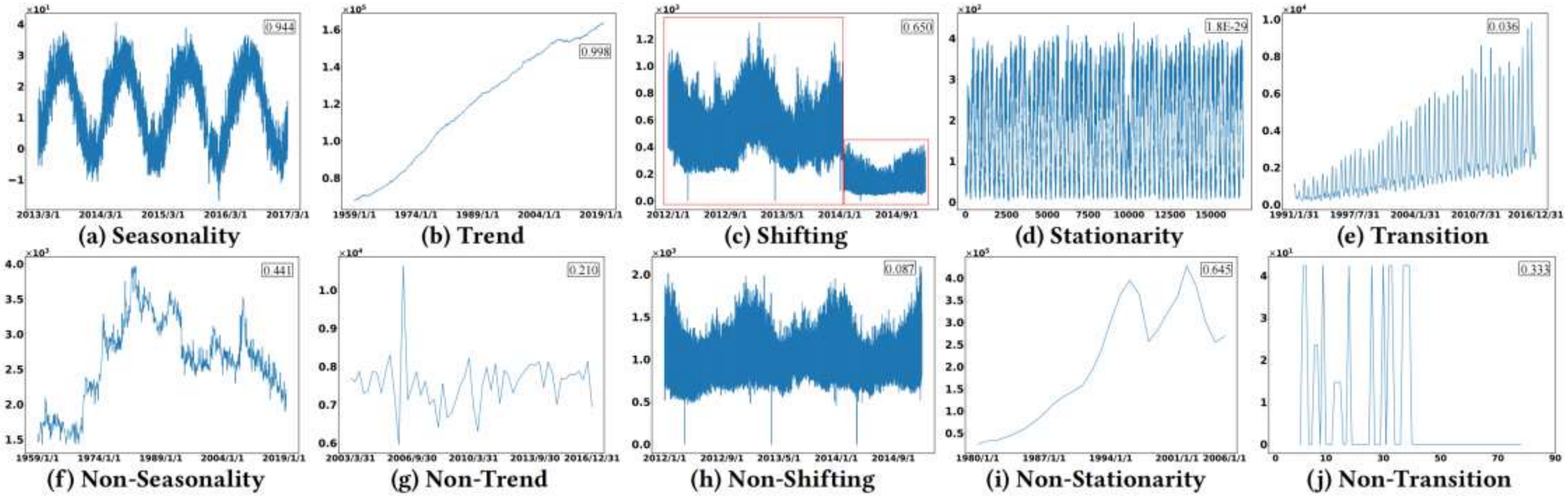


Figure 1: Visualization of data with different characteristics.

X=T + S + R

（Trend + Seasonality + Remainder）

- Stationarity：平稳性（弱平稳性），数据的统计特性（均值、方差、协方差）满足一定的条件，举个例子：股票收益率；
- Shifting：数据的分布范围、模式或者规律随时间改变的现象，比如温度变化，从10-20度变成了5-25度；
- Transition：捕获时间序列中存在的规则和可识别的固定特征，比如记录交通灯变化的规律；

对传统方法的刻板偏见

Table 1: VAR, LR versus other methods, using MAE as the evaluation metric and a forecasting horizon of 24 steps.

Datasets	VAR	LR	PatchTST	NLinear	FEDformer	Crossformer
NASDAQ	**0.462**	0.616	0.567	<u>0.522</u>	0.547	0.745
Wind	0.620	**0.583**	0.652	0.640	0.697	<u>0.590</u>
ILI	1.012	4.856	**0.835**	<u>0.919</u>	1.020	1.096

Table 3: Time series forecasting benchmark comparison.

Benchmark \ Property	Univariate forecasting	Multivariate forecasting	Statistical method	Machine learning method	Deep learning method	Taxonomy of data	Flexible & scalable pipeline
M3 [56]	√	×	√	√	×	×	×
M4 [57]	√	×	√	√	√	×	×
LTSF-Linear [98]	×	√	×	×	√	×	○
TSlib [89]	√	√	×	×	√	×	○
BasicTS [48]	×	√	×	√	√	×	○
BasicTS+ [76]	×	√	×	×	√	○	○
Monash [27]	√	×	√	√	×	×	○
Libra [3]	√	×	√	√	×	×	○
TFB (Ours)	√	√	√	√	√	√	√

× indicates absent, √ indicates present, ○ indicates incomplete.

✓ 结论：通过比较广泛的方法，有助于消除对传统方法的刻板偏见。

缺乏一致且灵活的pipeline

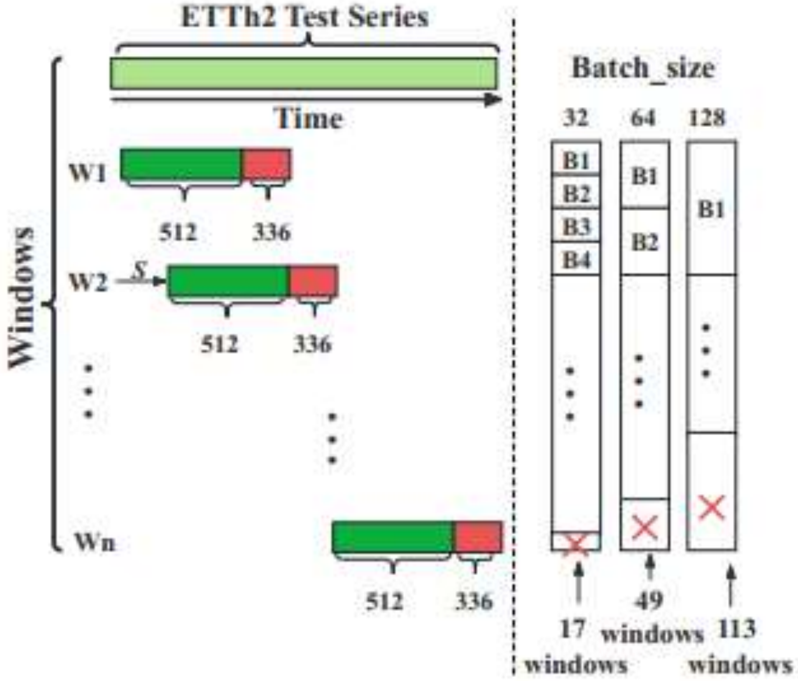


Figure 4: “Drop last” illustration.

Table 2: Impact of batch sizes with “drop last.”

Size	PatchTST	DLinear	FEDformer
1	0.4203	0.4874	**0.4120**
32	0.4138	0.4831	**0.4084**
64	**0.3999**	0.4726	0.4022
128	**0.3750**	0.4539	0.3921
256	**0.3561**	0.4360	0.3825
512	**0.3483**	0.4251	0.3736

✓ **结论**：确保一个一致和灵活的pipeline，以便在相同的环境中评估方法，从而提高研究结果的公平性。

02

PART THREE

方法

Datasets

- Univariate time series：8068个时间序列

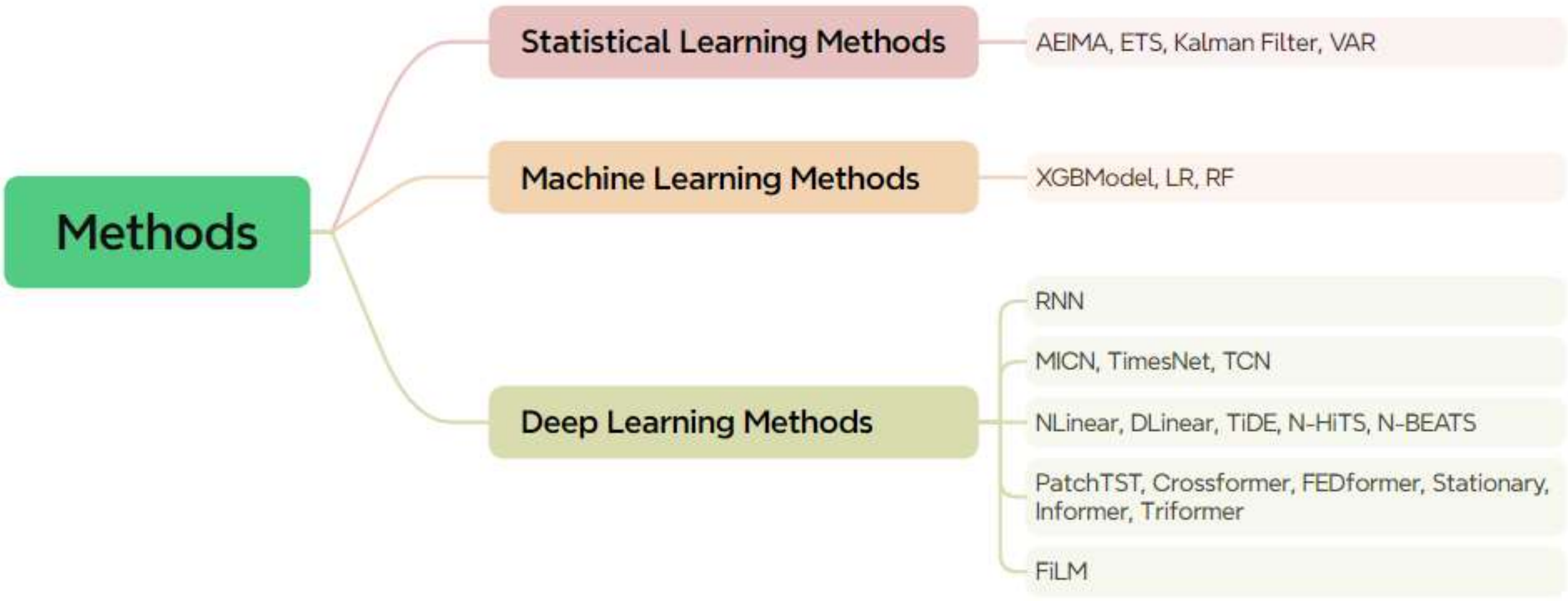
使用PFA（主特征分析）方法对每个数据集进行筛选和简化

- Multivariate time series：25个数据集
- 从Trend、Seasonality、Stationarity、Shifting、Transition、Correlation这几个方面对数据进行分类。

Table 5: Statistics of multivariate datasets.

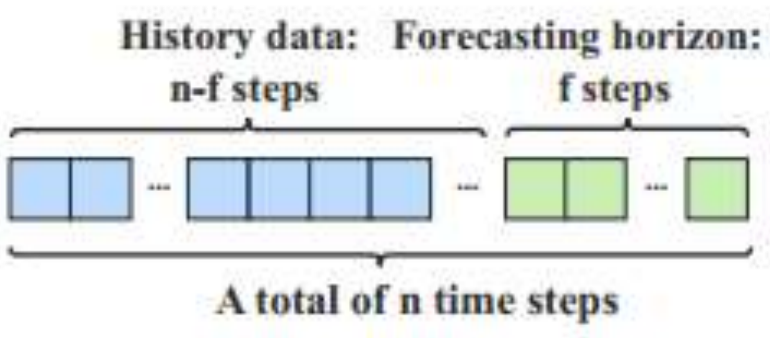
Dataset	Domain	Frequency	Lengths	Dim	Split
METR-LA [47]	Traffic	5 mins	34,272	207	7:1:2
PEMS-BAY [47]	Traffic	5 mins	52,116	325	7:1:2
PEMS04 [77]	Traffic	5 mins	16,992	307	6:2:2
PEMS08 [77]	Traffic	5 mins	17,856	170	6:2:2
Traffic [90]	Traffic	1 hour	17,544	862	7:1:2
ETTh1 [104]	Electricity	1 hour	14,400	7	6:2:2
ETTh2 [104]	Electricity	1 hour	14,400	7	6:2:2
ETTm1 [104]	Electricity	15 mins	57,600	7	6:2:2
ETTm2 [104]	Electricity	15 mins	57,600	7	6:2:2
Electricity [84]	Electricity	1 hour	26,304	321	7:1:2
Solar [43]	Energy	10 mins	52,560	137	6:2:2
Wind [46]	Energy	15 mins	48,673	7	7:1:2
Weather [90]	Environment	10 mins	52,696	21	7:1:2
AQShunyi [100]	Environment	1 hour	35,064	11	6:2:2
AQWan [100]	Environment	1 hour	35,064	11	6:2:2
ZafNoo [71]	Nature	30 mins	19,225	11	7:1:2
CzeLan [71]	Nature	30 mins	19,934	11	7:1:2
FRED-MD [58]	Economic	1 month	728	107	7:1:2
Exchange [43]	Economic	1 day	7,588	8	7:1:2
NASDAQ [23]	Stock	1 day	1,244	5	7:1:2
NYSE [23]	Stock	1 day	1,243	5	7:1:2
NN5 [80]	Banking	1 day	791	111	7:1:2
ILI [90]	Health	1 week	966	7	7:1:2
Covid-19 [68]	Health	1 day	1,392	948	7:1:2
Wike2000 [26]	Web	1 day	792	2,000	7:1:2

Methods


Methods
Statistical Learning Methods
AEIMA, ETS, Kalman Filter, VAR
Machine Learning Methods
XGBModel, LR, RF
Deep Learning Methods
RNN
MICN, TimesNet, TCN
NLinear, DLinear, TiDE, N-HiTS, N-BEATS
PatchTST, Crossformer, FEDformer, Stationary, Informer, Triformer
FiLM

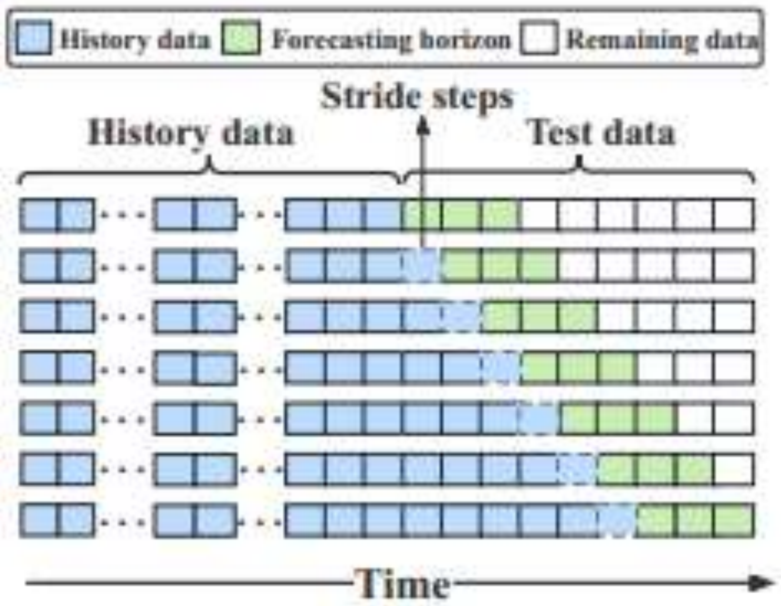
Evaluation strategies

固定预测



(a) Fixed Forecasting.

滚动预测



(b) Rolling Forecasting.

- 在滚动预测中，**统计学习方法**在每次滚动预测时重新训练，预测时覆盖所有历史数据；
- 而**深度学习方法**不重新训练，利用已经训练好的模型，在每次迭代中基于最后一段历史数据进行预测。

Evalution Metrics

- MAE：平均绝对误差
- MAPE：平均绝对百分比误差
- MSE：均方误差
- SMAPE：对称平均绝对百分比误差
- RMSE：均方根误差
- WAPE：加权绝对百分比误差
- MSMAPE：修正对称平均绝对百分比误差
- MASE：平均绝对缩放误差

$$MAE = \frac{1}{h}\sum_{k=1}^{h}|F_k - Y_k| \quad (7)$$

$$MAPE = \frac{1}{h}\sum_{k=1}^{h}\frac{|Y_k - F_k|}{Y_k} \times 100\% \quad (8)$$

$$MSE = \frac{1}{h}\sum_{k=1}^{h}(F_k - Y_k)^2 \quad (9)$$

$$SMAPE = \frac{100\%}{h}\sum_{k=1}^{h}\frac{|F_k - Y_k|}{\frac{|Y_k|+|F_k|}{2}} \quad (10)$$

$$RMSE = \sqrt{\frac{1}{h}\sum_{k=1}^{h}(F_k - Y_k)^2} \quad (11)$$

$$WAPE = \frac{\sum_{k=1}^{h}|Y_k - F_k|}{\sum_{k=1}^{h}|Y_k|} \quad (12)$$

$$MSMAPE = \frac{100\%}{h}\sum_{k=1}^{h}\frac{|F_k - Y_k|}{\max(|Y_k| + |F_k| + \epsilon, 0.5 + \epsilon)/2} \quad (13)$$

$$MASE = \frac{\sum_{k=M+1}^{M+h}|F_k - Y_k|}{\frac{h}{M-S}\sum_{k=S+1}^{M}|Y_k - Y_{k-S}|}, \quad (14)$$

Unified Pipeline

- **Data Layer**：数据标准化、评估和扩展的重要部分，保证数据集的质量和覆盖范围；
- **Method Layer**：为多种TSF方法提供支持，并且与第三方库兼容，支持DMS和IMS；
- **Evalution Layer**：提供全面的工具来评估不同时间序列预测方法的性能；
- **Reporting Layer**：日志记录确保过程的可追溯性，可视化工具增强对结果的理解。

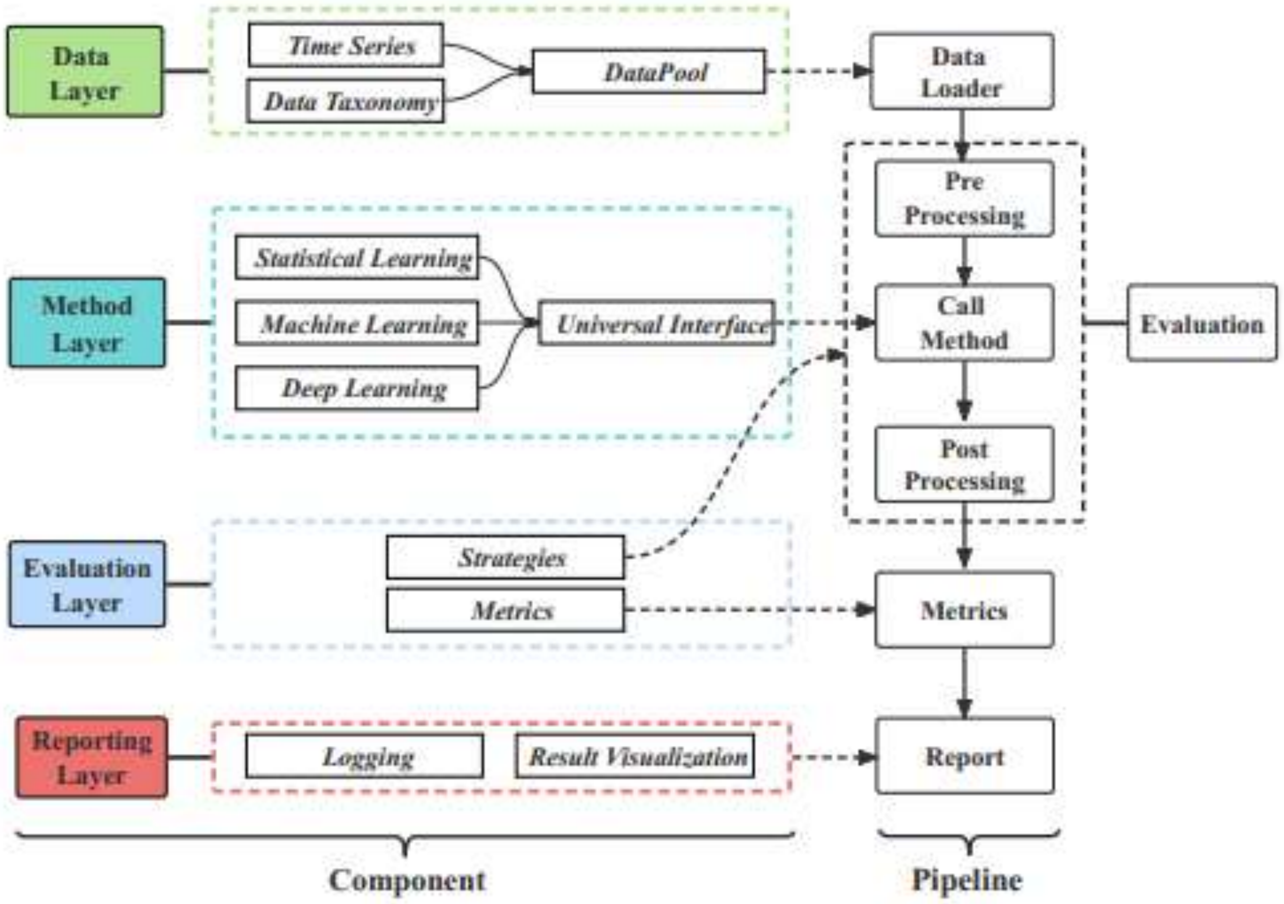


Figure 7: The TFB pipeline.

P

ART FOUR

03

实验

单变量时间序列预测

Table 6: Univariate forecasting results.

Dataset		Metric	PatchTST	Crossformer	FEDformer	Stationary	Informer	Triformer	DLinear	NLinear	TiDE	N-BEATS	N-HiTS	TimesNet	TCN	RNN	FiLM	LR	RF	XGB	ARIMA	ETS	KF
Seasonality	√	mase	1.660	29.704	2.100	2.384	2.390	19.378	2.409	2.850	2.074	2.081	2.189	1.446	24.159	30.231	1.882	7.8e+9	1.649	1.715	2.830	4.091	9.002
		msmape	12.263	161.074	19.041	15.190	14.301	107.957	19.628	20.938	14.566	15.794	13.557	10.927	121.335	149.830	13.537	19.183	12.790	13.404	19.868	26.386	57.409
		Ranks	167	14	59	40	85	15	22	45	162	168	213	314	14	8	141	603	425	250	225	92	43
	×	mase	1.639	23.704	1.879	1.638	1.601	16.496	1.949	1.733	2.526	1.677	1.678	1.478	15.441	23.889	1.769	2.5e+10	1.731	1.814	1.496	1.544	3.318
		msmape	21.671	166.859	26.766	22.050	21.413	138.945	26.966	27.154	30.968	25.705	24.127	20.497	140.174	162.648	22.331	33.413	25.316	26.838	24.491	25.190	44.551
		Ranks	214	35	208	200	303	72	61	157	189	383	556	371	64	40	138	326	423	273	355	268	292
Trend	√	mase	2.220	41.287	2.758	2.651	2.658	28.091	3.016	2.914	3.316	2.512	2.553	1.911	28.716	44.365	2.492	7.9e+9	2.271	2.355	2.822	3.615	8.486
		msmape	10.679	184.125	13.917	11.709	11.216	133.424	14.435	13.463	13.747	11.583	11.090	9.247	136.243	180.218	11.442	16.920	10.832	11.221	11.686	12.986	50.062
		Ranks	201	2	114	113	188	20	51	113	201	270	375	402	6	2	162	737	298	246	403	222	123
	×	mase	1.007	8.941	1.077	1.127	1.064	5.878	1.131	1.326	1.272	1.073	1.116	0.968	7.718	8.282	1.052	3.1e+10	1.059	1.127	1.104	1.311	2.185
		msmape	26.261	142.824	34.808	27.894	26.993	119.760	34.972	37.374	36.802	33.385	30.053	25.243	129.153	136.076	27.307	40.210	31.262	33.307	35.019	39.814	48.911
		Ranks	180	47	153	127	200	67	32	89	150	281	394	283	72	46	117	192	550	277	177	138	212
Stationarity	√	mase	1.004	9.380	1.057	1.132	1.133	6.309	1.139	1.290	1.343	1.162	1.212	0.961	7.870	8.305	1.066	15.848	1.043	1.100	1.257	1.618	3.172
		msmape	27.024	135.888	35.122	28.539	27.546	114.323	35.434	37.306	37.594	33.519	31.080	26.120	122.194	129.738	28.172	38.320	32.232	34.281	36.212	41.513	52.234
		Ranks	154	45	128	105	177	67	24	69	124	214	285	242	66	42	99	197	444	219	150	117	180
	×	mase	2.065	36.826	2.553	2.451	2.408	24.945	2.768	2.732	3.007	2.269	2.305	1.793	25.907	39.090	2.297	3.1e+10	2.125	2.214	2.500	3.118	7.032
		msmape	12.206	183.264	16.425	13.397	12.904	135.177	16.800	16.610	16.225	14.325	12.885	10.754	139.836	178.312	12.940	21.168	12.853	13.455	13.942	15.365	47.757
		Ranks	227	4	139	135	211	20	59	133	227	337	484	443	12	6	180	732	404	304	430	243	155
Transition	√	mase	1.397	19.759	1.571	1.744	1.779	11.972	1.820	1.985	1.827	1.543	1.601	1.282	13.744	19.901	1.505	5.7e+4	1.380	1.474	1.930	2.723	3.998
		msmape	21.932	155.700	24.803	23.707	22.978	117.240	25.741	29.013	27.664	23.031	22.672	20.869	125.136	150.624	22.973	29.179	23.002	24.545	25.020	28.725	45.521
		Ranks	242	44	187	153	263	79	44	121	230	373	527	464	73	48	187	560	533	382	304	186	166
	×	mase	2.102	37.372	2.676	2.277	2.136	27.831	2.682	2.489	3.303	2.358	2.371	1.799	27.987	39.651	2.369	5.3e+10	2.278	2.323	2.157	2.172	8.259
		msmape	10.984	180.775	21.932	11.399	10.860	144.591	21.216	17.039	19.143	19.785	15.284	9.435	146.942	173.676	11.622	25.629	15.905	16.404	18.520	20.089	56.754
		Ranks	139	5	80	87	125	8	39	81	121	178	242	221	5	0	92	369	315	141	276	174	169
Shifting	√	mase	2.138	36.092	2.646	2.507	2.314	25.570	2.823	2.747	2.975	2.289	2.345	1.857	24.925	37.921	2.352	3.7e+10	2.224	2.306	2.331	2.799	6.862
		msmape	13.453	173.924	19.874	14.454	13.509	133.554	19.930	19.013	17.860	16.573	14.248	11.873	137.113	167.496	14.074	21.775	14.877	16.159	17.550	20.517	50.844
		Ranks	181	13	107	86	194	27	47	123	173	268	380	384	14	18	143	556	401	220	370	227	157
	×	mase	1.142	15.639	1.262	1.355	1.485	9.401	1.410	1.563	1.709	1.363	1.390	1.062	12.499	15.066	1.257	7.4e+4	1.159	1.229	1.681	2.248	4.122
		msmape	22.763	155.031	27.811	24.258	23.983	120.183	28.465	30.674	31.618	27.347	26.022	21.881	128.544	148.943	23.945	34.251	26.254	27.310	28.022	30.950	48.150
		Ranks	200	36	160	154	194	60	36	79	178	283	389	301	64	30	136	373	447	303	210	133	178

- ✓ MSMAPE：在数据集上实现最佳性能的次数
- ✓ Rank：模型在不同评估指标上的排名

- 机器学习方法更适合于特定的场景；
- LR在具有季节性、趋势和shifting特征的时间序列上表现好，而RF则相反；
- LR比RF更适合于没有平稳性的数据；
- LR和RF对Transition很敏感，特性越强越好。
- ✓ 这些结果为选择特定环境的正确方法提供了指导。

多变量时间序列预测

- ✓ 没有一种方法在所有数据集上都能达到最佳性能；
- ✓ 基于Transformer的方法在趋势较弱的数据集上通常优于其他方法；
- ✓ 基于线性的方法往往在具有强趋势的数据集上表现得较好；
- ✓ 最近的方法并不总是优于早期的研究。

Table 7: Multivariate forecasting results I.

Model		PatchTST		Crossformer		FEDformer		Informer		Triformer		DLinear		NLinear		MICN		TimesNet		TCN		FiLM		RNN		LR		VAR	
Metrics		mae	mse	mae	mse	mae	mse	mae	mse	mae	mse	mae	mse	mae	mse	mae	mse	mae	mse	mae	mse	mae	mse	mae	mse	mae	mse	mae	mse
PEMS04	96	0.280	0.161	0.224	0.112	0.565	0.573	0.304	0.189	0.325	0.218	0.296	0.196	0.294	0.202	0.318	0.199	0.266	0.159	0.291	0.168	0.297	0.204	0.916	1.318	0.474	0.423	0.313	0.192
	192	0.290	0.178	0.236	0.134	0.624	0.655	0.335	0.229	0.353	0.257	0.310	0.213	0.305	0.223	0.380	0.290	0.282	0.179	0.303	0.188	0.307	0.219	0.933	1.359	0.497	0.465	0.336	0.216
	336	0.302	0.193	0.286	0.190	0.920	1.365	0.323	0.217	0.347	0.250	0.327	0.235	0.324	0.245	0.453	0.384	0.269	0.169	0.336	0.237	0.327	0.243	0.939	1.373	0.519	0.513	0.362	0.245
	720	0.338	0.233	0.331	0.235	0.728	0.873	0.391	0.310	0.375	0.284	0.395	0.327	0.396	0.350	0.629	0.677	0.286	0.187	0.354	0.246	0.386	0.322	0.938	1.372	0.658	0.831	0.409	0.298
PEMS-BAY	96	0.361	0.567	0.326	0.492	0.540	0.815	0.435	0.844	0.472	0.785	0.404	0.628	0.404	0.642	0.398	0.664	0.429	0.908	0.680	1.300	0.429	0.660	0.659	1.198	1.192	2.934	0.516	0.761
	192	0.382	0.619	0.336	0.490	0.583	0.872	0.461	0.912	0.500	0.854	0.419	0.666	0.420	0.687	0.429	0.727	0.448	0.997	0.710	1.327	0.404	0.677	0.659	1.201	1.176	2.776	0.545	0.863
	336	0.403	0.670	0.342	0.529	0.609	1.026	0.447	0.834	0.477	0.805	0.439	0.710	0.438	0.735	0.481	0.919	0.429	0.893	0.573	1.040	0.421	0.726	0.660	1.204	1.071	2.310	0.581	0.966
	720	0.448	0.795	0.494	0.850	0.659	1.124	0.498	1.005	0.519	0.900	0.508	0.872	0.516	0.929	0.596	1.105	0.447	0.962	0.544	1.089	0.482	0.895	0.660	1.210	0.959	1.844	0.617	1.082
METR-LA	96	0.629	1.058	0.633	1.232	0.770	1.335	0.664	1.375	0.640	1.048	0.658	1.009	0.650	1.044	0.685	1.256	0.640	1.323	0.716	1.409	0.682	1.282	0.774	1.668	1.968	7.219	0.706	1.100
	192	0.676	1.177	0.663	1.312	0.887	1.645	0.707	1.554	0.714	1.222	0.716	1.148	0.720	1.218	0.701	1.359	0.681	1.490	0.860	1.715	0.733	1.223	0.784	1.727	1.955	6.797	0.754	1.276
	336	0.733	1.300	0.711	1.367	0.840	1.687	0.721	1.615	0.735	1.286	0.742	1.241	0.758	1.339	0.741	1.390	0.688	1.502	0.899	1.811	0.745	1.323	0.791	1.765	1.762	5.511	0.786	1.375
	720	0.779	1.466	0.773	1.516	0.962	2.018	0.805	1.878	0.782	1.437	0.793	1.415	0.874	1.656	0.780	1.486	0.784	1.801	0.854	1.898	0.825	1.574	0.809	1.849	1.382	3.472	0.817	1.478
PEMS08	96	0.272	0.163	0.226	0.119	0.568	0.623	0.345	0.247	0.329	0.226	0.321	0.241	0.317	0.259	0.403	0.310	0.296	0.213	0.393	0.299	0.320	0.252	0.879	1.071	4.198	78.523	0.363	0.267
	192	0.295	0.201	0.259	0.151	0.690	0.782	0.409	0.351	0.365	0.279	0.342	0.273	0.338	0.300	0.408	0.346	0.321	0.264	0.393	0.289	0.341	0.290	0.880	1.072	4.919	52.019	0.435	0.393
	336	0.311	0.225	0.276	0.180	0.859	1.256	0.386	0.342	0.365	0.287	0.362	0.299	0.358	0.325	0.438	0.358	0.315	0.264	0.446	0.394	0.360	0.309	0.880	1.074	3.205	20.396	0.474	0.467
	720	0.347	0.264	0.332	0.254	0.706	0.843	0.467	0.461	0.398	0.330	0.429	0.378	0.426	0.403	0.641	0.732	0.343	0.311	0.470	0.466	0.413	0.365	0.883	1.080	2.331	10.680	0.556	0.591
Traffic	96	0.271	0.379	0.282	0.514	0.365	0.593	0.371	0.664	0.323	0.589	0.282	0.410	0.279	0.410	0.295	0.494	0.313	0.600	0.606	1.139	0.284	0.411	1.604	5.834	0.548	0.799	1.056	2.355
	192	0.277	0.394	0.273	0.501	0.375	0.614	0.396	0.724	0.325	0.597	0.288	0.423	0.284	0.423	0.301	0.521	0.328	0.619	0.559	1.040	0.283	0.406	2.120	8.563	0.551	0.794	0.869	1.751
	336	0.281	0.404	0.279	0.507	0.373	0.609	0.435	0.796	0.332	0.617	0.296	0.436	0.291	0.436	0.309	0.552	0.330	0.627	0.540	1.006	0.298	0.425	2.405	10.153	0.552	0.802	0.752	1.397
	720	0.302	0.442	0.301	0.571	0.394	0.646	0.453	0.823	0.350	0.650	0.315	0.466	0.308	0.464	0.328	0.569	0.342	0.659	0.626	1.063	0.370	0.523	2.644	11.596	0.568	0.837	0.644	1.113
Solar	96	0.273	0.190	0.230	0.166	0.530	0.509	0.373	0.338	0.279	0.225	0.287	0.216	0.254	0.222	0.250	0.193	0.330	0.285	0.265	0.206	0.256	0.225	2.271	6.661	0.365	0.235	0.593	0.556
	192	0.302	0.204	0.251	0.214	0.500	0.474	0.391	0.375	0.295	0.250	0.305	0.244	0.269	0.252	0.270	0.225	0.342	0.309	0.347	0.304	0.276	0.266	2.258	6.457	0.369	0.253	0.686	0.668
	336	0.293	0.212	0.260	0.203	0.439	0.338	0.416	0.417	0.298	0.261	0.319	0.263	0.282	0.273	0.301	0.250	0.365	0.335	0.306	0.279	0.299	0.308	2.291	6.604	0.402	0.291	0.724	0.710
	720	0.310	0.221	0.721	0.735	0.459	0.365	0.407	0.390	0.292	0.258	0.324	0.264	0.282	0.273	0.362	0.323	0.355	0.346	0.269	0.296	0.300	0.310	2.321	6.743	0.452	0.333	0.751	0.738
ETTm1	96	0.343	0.290	0.361	0.310	0.465	0.467	0.424	0.430	0.384	0.342	0.343	0.299	0.343	0.301	0.349	0.303	0.398	0.377	0.643	0.700	0.343	0.301	0.908	2.087	0.393	0.359	0.678	0.889
	192	0.368	0.329	0.402	0.363	0.524	0.610	0.479	0.550	0.415	0.389	0.364	0.334	0.365	0.337	0.368	0.335	0.411	0.405	0.616	0.698	0.365	0.339	1.121	2.961	0.442	0.434	0.762	1.031
	336	0.390	0.360	0.430	0.408	0.544	0.618	0.529	0.654	0.446	0.427	0.384	0.365	0.384	0.371	0.388	0.366	0.437	0.443	0.764	0.900	0.384	0.373	1.394	4.439	0.488	0.503	0.803	1.093
	720	0.422	0.416	0.637	0.777	0.551	0.615	0.578	0.714	0.484	0.488	0.415	0.418	0.415	0.426	0.423	0.409	0.464	0.495	0.779	0.979	0.414	0.423	1.594	5.515	0.568	0.632	0.826	1.111
Weather	96	0.196	0.149	0.212	0.146	0.292	0.223	0.255	0.218	0.231	0.168	0.230	0.170	0.222	0.179	0.232	0.172	0.219	0.170	0.332	0.262	0.229	0.178	0.545	0.543	0.293	0.201	0.401	0.360
	192	0.240	0.193	0.261	0.195	0.322	0.252	0.306	0.269	0.279	0.216	0.267	0.212	0.261	0.218	0.270	0.214	0.264	0.222	0.447	0.420	0.263	0.218	0.545	0.544	0.330	0.240	0.453	0.413
	336	0.281	0.244	0.325	0.268	0.371	0.327	0.340	0.320	0.322	0.271	0.305	0.257	0.296	0.266	0.309	0.259	0.310	0.293	0.496	0.509	0.295	0.266	0.548	0.549	0.379	0.303	0.491	0.459
	720	0.332	0.314	0.380	0.330	0.419	0.424	0.390	0.392	0.379	0.358	0.356	0.318	0.344	0.334	0.342	0.308	0.355	0.360	0.474	0.499	0.340	0.332	0.548	0.549	0.447	0.396	0.539	0.529
ILI	24	0.835	1.840	1.096	2.981	1.020	2.400	1.151	2.738	1.728	6.044	1.031	2.208	0.919	1.998	1.020	2.279	0.926	2.009	1.419	4.194	1.011	2.454	3.125	15.131	4.856	47.856	1.012	2.429
	36	0.845	1.724	1.162	3.295	1.005	2.410	1.145	2.890	1.762	6.226	0.981	2.032	0.916	1.920	1.085	2.451	0.997	2.552	1.514	4.999	1.016	2.412	3.133	15.196	3.803	31.573	1.081	2.851
	48	0.863	1.762	1.230	3.586	1.033	2.592	1.136	2.742	1.764	6.230	1.063	2.209	0.924	1.895	1.077	2.440	0.919	1.956	1.458	4.636	1.040	2.398	3.152	15.340	3.173	18.711	1.130	3.060
	60	0.894	1.752	1.256	3.693	1.070	2.539	1.139	2.825	1.828	6.596	1.086	2.292	0.947	1.964	1.009	2.305	0.962	2.178	1.639	5.676	0.969	2.227	3.203	15.704	3.057	17.222	1.152	3.151
Electricity	96	0.233	0.133	0.237	0.135	0.302	0.186	0.321	0.214	0.285	0.185	0.237	0.140	0.236	0.141	0.262	0.156	0.267	0.164	0.433	0.371	0.246	0.154	1.651	4.368	0.631	0.731	0.359	0.264
	192	0.248	0.150	0.262	0.160	0.315	0.201	0.350	0.245	0.297	0.196	0.250	0.154	0.248	0.155	0.285	0.173	0.280	0.180	0.435	0.371	0.261	0.168	1.657	4.392	0.651	0.771	0.370	0.282
	336	0.267	0.168	0.282	0.182	0.330	0.218	0.393	0.294	0.315	0.215	0.268	0.169	0.264	0.171	0.296	0.184	0.292	0.190	0.442	0.371	0.284	0.189	1.663	4.415	1.004	1.796	0.380	0.296
	720	0.295	0.202	0.337	0.246	0.350	0.241	0.393	0.306	0.348	0.265	0.301	0.204	0.297	0.210	0.311	0.203	0.307	0.209	0.468	0.420	0.340	0.249	1.670	4.445	1.039	1.931	0.399	0.320
ETTh1	96	0.396	0.376	0.426	0.405	0.419	0.379	0.563	0.709	0.424	0.399	0.392	0.371	0.393	0.372	0.413	0.377	0.412	0.389	0.676	0.780	0.395	0.372	1.093	2.778	0.440	0.420	0.708	0.923
	192	0.416	0.399	0.442	0.413	0.443	0.419	0.570	0.724	0.448	0.444	0.413	0.404	0.413	0.405	0.435	0.405	0.443	0.440	0.723	0.870	0.423	0.415	1.561	5.760	0.506	0.512	0.770	1.025
	336	0.432	0.418	0.460	0.442	0.464	0.455	0.581	0.732	0.479	0.492	0.435	0.434	0.427	0.429	0.446	0.426	0.465	0.482	0.775	0.978	0.446	0.449	1.912	8.029	0.584	0.633	0.799	1.058
	720	0.469	0.450	0.539	0.550	0.488	0.474	0.616	0.760	0.528	0.549	0.489	0.469	0.452	0.436	0.500	0.483	0.501	0.525	0.804	1.006	0.472	0.461	2.359	11.006	0.699	0.808	0.810	1.057
Exchange	96	0.200	0.083	0.364	0.248	0.267	0.136	0.254	0.122	0.336	0.219	0.204	0.082	0.204	0.085	0.208	0.082	0.238	0.109	0.671	0.727	0.212	0.092	0.700	0.831	0.331	0.226	0.263	0.135
	192	0.298	0.176	0.511	0.474	0.353	0.239	0.324	0.197	0.509	0.483	0.325	0.186	0.297	0.175	0.302	0.163	0.331	0.213	0.876	1.175	0.308	0.182	1.019	1.633	0.550	0.625	0.399	0.298
	336	0.397	0.301	0.723	0.829	0.486	0.438	0.421	0.330	0.681	0.812	0.435	0.328	0.409	0.320	0.420	0.298	0.435	0.358	1.065	1.763	0.409	0.318	1.289	2.489	0.740	1.071	0.548	0.540
	720	0.693	0.847	0.998	1.491	0.811	1.117	0.609	0.615	0.887	1.346	0.679	0.801	0.689	0.834	0.686	0.797	0.764	1.004	1.308	2.550	0.677	0.808	1.545	3.346	0.841	1.189	0.776	1.079
ETTm2	96	0.254	0.165	0.359	0.263	0.306	0.219	0.302	0.216	0.357	0.298	0.255	0.164	0.252	0.163	0.273	0.175	0.266	0.190	0.805	0.989	0.254	0.165	1.233	3.444	0.284	0.188	0.370	0.288
	192	0.292	0.221	0.425	0.361	0.357	0.294	0.367	0.324	0.460	0.491	0.304	0.224	0.290	0.218	0.323	0.241	0.308	0.251	0.939	1.368	0.292	0.218	1.484	4.724	0.342	0.259	0.485	0.481
	336	0.325	0.275	0.496	0.469	0.401	0.362	0.429	0.424	0.557	0.726	0.337	0.277	0.326	0.273	0.373	0.312	0.350	0.322	1.044	1.635	0.329	0.277	1.601	5.309	0.402	0.336	0.621	0.775
	720	0.380	0.360	0.857	1.263	0.450	0.459	0.500	0.581	0.863	2.009	0.401	0.371	0.382	0.361	0.492	0.491	0.403	0.414	1.968	5.564	0.374	0.327	1.670	5.670	0.496	0.470	0.833	1.333
ETTh2	96	0.339	0.277	0.557	0.611	0.380	0.338	0.402	0.378	0.828	1.894	0.368	0.302	0.338	0.275	0.392	0.339	0.363	0.319	1.092	1.706	0.347	0.284	1.444	4.642	0.411	0.336	0.437	0.377
	192	0.381	0.345	0.651	0.810	0.428	0.415	0.449	0.462	0.908	2.115	0.433	0.405	0.379	0.336	0.434	0.412	0.416	0.411	1.701	4.123	0.401	0.358	1.846	7.099	0.468	0.414	0.575	0.611
	336	0.404	0.368	0.698	0.928	0.451	0.378	0.449	0.426	0.875	1.816	0.490	0.496	0.403	0.362	0.490	0.497	0.443	0.415	1.619	3.371	0.425	0.372	2.007	8.134	0.521	0.478	0.738	0.973
	720	0.432	0.397	0.775	1.094	0.485	0.479	0.449	0.401	0.931	1.698	0.622	0.766	0.437	0.396	0.605	0.732	0.445	0.429	1.786	4.166	0.454	0.427	2.295	9.981	0.645	0.666	0.953	1.585

Performance on different characteristics

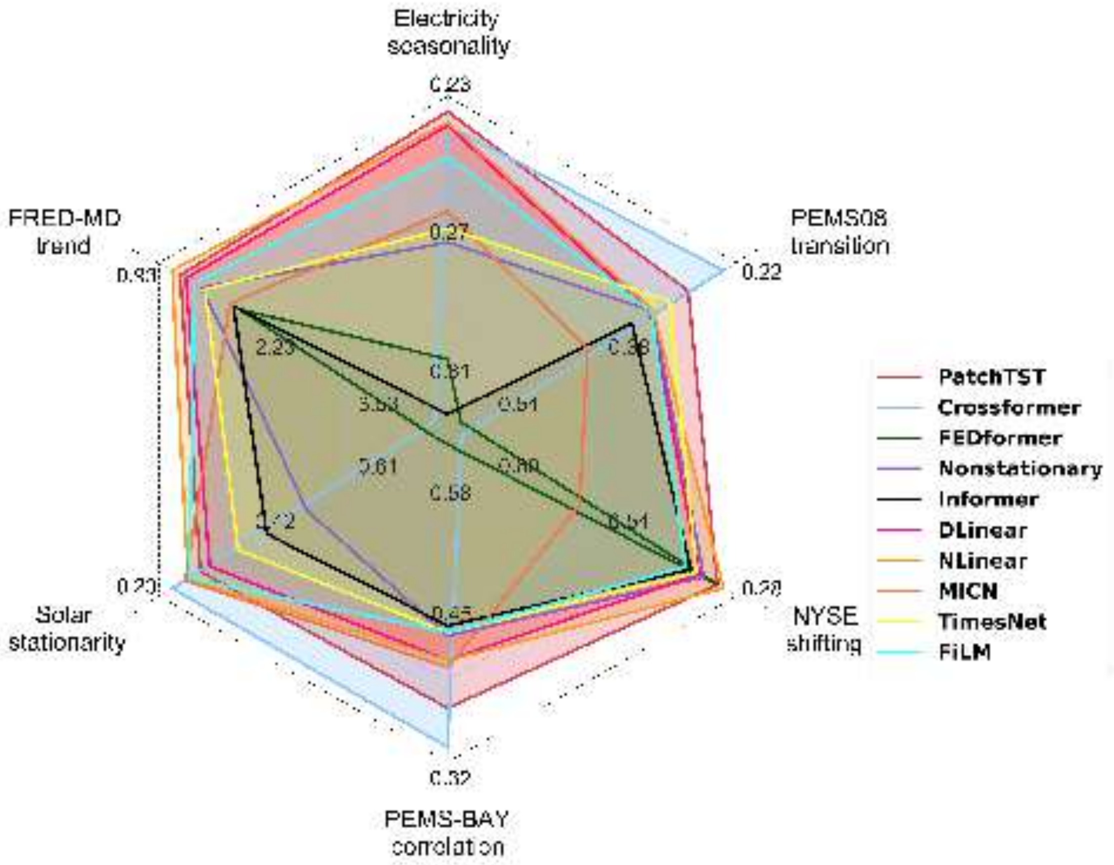


Figure 8: MAE results of methods across six characteristics.

- ✓ 没有一种深度学习方法在所有数据集上都表现出色；
- ✓ Crossformer在transition非常明显、数据最平稳和数据最相关的数据集上表现出卓越的性能，但是在处理具有其他特征的时间序列时，性能不如其他方法；
- ✓ PatchTST在具有强季节性的数据集上达到最佳性能；

VS

- **研究不同数据特征对Transformer和linear methods的影响**

✓ 每种方法在具有不同特征的数据集上表现出不同的优势;

✓ 当数据集呈现增加趋势或显著变化时，基于线性的方法更有效;

✓ 在表现出明显的季节性、平稳性和非线性模式，以及更明显的模式或强烈的内部相似性的数据集上，基于transformer的方法优于基于linear的方法.

- **多变量数据依赖性对多变量时间序列的影响**

✓ 在设计新的预测方法时，应注意充分利用变量之间的关系，从而更准确地捕捉数据集中的底层结构和模式;

✓ 当数据集中的相关性不明显时，考虑到变量依赖性可能模型效果不会变好。

- **多变量预测中运行时间和参数的性能**

✓ 考虑运行时间和参数数量时，基于线性的方法优于基于cnn和基于变压器的方法

05

PART FIVE

结论

结论

TFB解决了3个问题

- ✓ 为了缓解数据集覆盖领域不足的问题，本文收集了10个不同领域的**数据集**，涵盖交通、电力、能源、环境、自然、经济、股票、银行、健康和web；
- ✓ 为了消除对传统方法的偏见，TFB涵盖了多种**方法**，包括统计学习、机器学习和深度学习方法，并伴有各种评估策略和指标；
- ✓ 为了解决pipeline不一致和不灵活的问题，TFB提供了一种新的灵活且可扩展的**pipeline**，消除了偏差，并为性能比较提供了更好的基础。

感谢观看！

汇报人：闫林枝

> GOODBYE <