BasicTS: An Open-Source Standard Time Series Forecasting Benchmark

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1 EXPERIMENTS

1.1 Baselines

- **HI** [3]:
- **AR**:
- **VAR**:
- **Graph WaveNet** [9]: Graph WaveNet stacks Gated TCN and GCN layer by layer to jointly capture the spatial and temporal dependencies.
- **DCRNN** [7]:
- **AGCRN** [1]:
- **D^{2}STGNN**
- **MTGNN** [8]
- **STNorm** [4]

1.2 Datasets

1.2.1 Short-term Multivariate Time Series Forecasting. The statistical information is summarized in Table 1.

- **METR-LA** is a public traffic speed dataset collected from loop-detectors located on the LA County road network [6]. Specifically, METR-LA contains data of 207 selected sensors over a period of 4 months from Mar 1st 2012 to Jun 30th 2012 [7]. The traffic information is recorded at the rate of every 5 minutes, and the total number of time slices is 34,272.
- **PEMS-BAY** is a public traffic speed dataset collected from California Transportation Agencies (CalTrans) Performance Measurement System (PeMS) [2]. Specifically, PEMS-BAY contains data of 325 sensors in the Bay Area over a period of 6 months from Jan 1st 2017 to May 31th 2017 [7]. The traffic information is recorded at the rate of every 5 minutes, and the total number of time slices is 52,116.
- **PEMS04** is a public traffic flow dataset collected from California Transportation Agencies (CalTrans) Performance Measurement System (PeMS) [2]. Specifically, PEMS04 contains data of 307 sensors in the District04 over a period of 2 months from Jan 1st 2018 to Feb 28th 2018 [5]. The traffic information is recorded at the rate of every 5 minutes, and the total number of time slices is 16,992.
- **PEMS08** is a public traffic flow dataset collected from California Transportation Agencies (CalTrans) Performance Measurement System (PeMS) [2]. Specifically, PEMS08 contains data of 170 sensors in the District08 over a period of 2 months from July 1st 2018 to Aug 31th 2018 [5]. The traffic information is recorded at the rate of every 5 minutes, and the total number of time slices is 17,833.

1.2.2 Long-term Multivariate Time Series Forecasting.

- **ETTHh$_1$**
- **ETTHh$_2$**
- **ETTHm$_1$**
- **Electricity**

Table 1: Statistics of datasets.

Dataset	# Time Step	# Node	Sample Rate	Time Span
METR-LA	34272	207	5mins	4 mouths
PEMS-BAY	52116	325	5mins	6 mouths
PEMS04	16992	307	5mins	2 mouths
PEMS08	17833	170	5mins	2 mouths

1.3 Metrics

1.4 Main Results

1.5 Efficiency

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Table 2: Short-term multivariate time series forecasting on the METR-LA, PEMS-BAY, PEMS04, PEMS08 datasets.

Datasets	Methods	@Horizon 3			@Horizon 6			@Horizon 12			Overall (12 Horizon)		
		MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE
METR-LA	HI	6.80	14.21	16.72%	6.80	14.21	16.72%	6.80	14.20	10.15%	6.80	14.21	16.72%
	Graph WaveNet	2.69	5.15	6.96%	3.08	6.21	8.47%	3.53	7.30	10.15%	3.04	6.15	8.31%
	DCRNN	2.67	5.16	6.86%	3.07	6.29	8.42%	3.57	7.56	10.37%	3.04	6.26	8.33%
	AGCRN	2.88	5.57	7.72%	3.26	6.61	9.17%	3.67	7.60	10.74%	3.20	6.50	9.00%
	MTGNN	2.71	5.22	6.89%	3.07	6.23	8.27%	3.51	7.28	9.90%	3.04	6.17	8.15%
	STNorm	2.82	5.55	7.48%	3.19	6.59	9.00%	3.56	7.47	10.51%	3.12	6.45	8.77%
	D^2STGNN	2.56	4.90	6.52%	2.90	5.90	7.88%	3.34	7.02	9.63%	2.87	5.88	7.79%
PEMS-BAY	HI	3.06	7.05	6.85%	3.06	7.04	6.84%	3.05	7.03	6.83%	3.05	7.05	6.84%
	Graph WaveNet	1.30	2.80	2.69%	1.65	3.75	3.65%	1.97	4.58	4.63%	1.59	3.69	3.52%
	DCRNN	1.31	2.80	2.73%	1.66	3.81	3.75%	1.98	4.64	4.73%	1.60	3.74	3.61%
	AGCRN	1.37	2.93	2.95%	1.70	3.89	3.88%	1.99	4.64	4.72%	1.63	3.78	3.73%
	MTGNN	1.34	2.84	2.80%	1.67	3.79	3.74%	1.97	4.55	4.57%	1.60	3.70	3.57%
	STNorm	1.34	2.88	2.82%	1.67	3.83	3.75%	1.96	4.52	4.62%	1.60	3.71	3.60%
	D^2STGNN	1.25	2.65	2.62%	1.58	3.63	3.57%	1.86	4.37	4.44%	1.52	3.55	3.50%
PEMS03	HI	32.46	49.78	30.58%	32.45	49.76	30.59%	32.44	49.75	30.63%	32.45	49.76	30.60%
	Graph WaveNet	13.37	23.04	13.90%	14.51	25.29	14.85%	16.16	27.91	16.12%	14.48	25.19	14.67%
	DCRNN	14.16	24.61	14.21%	15.41	27.01	15.07%	17.31	30.05	16.71%	15.37	26.92	15.10%
	AGCRN	14.22	25.02	13.40%	15.47	27.28	14.43%	17.09	28.78	16.43%	15.41	27.15	14.76%
	MTGNN	13.71	23.04	14.84%	14.87	25.94	15.12%	16.50	28.76	16.88%	14.80	25.65	15.04%
	STNorm	14.23	24.05	13.98%	15.45	26.54	14.49%	17.08	29.42	15.73%	15.34	26.33	14.56%
	D^2STGNN	13.42	23.11	13.71%	14.71	25.61	14.73%	16.62	28.69	16.64%	14.72	25.61	14.70%
PEMS04	HI	42.33	61.64	29.90%	42.35	61.66	29.92%	42.38	61.67	29.96%	42.35	61.66	29.92%
	Graph WaveNet	18.00	28.83	13.64%	18.96	30.33	14.23%	20.53	32.54	15.41%	18.97	30.32	14.26%
	DCRNN	18.53	29.61	12.71%	21.67	31.37	13.45%	21.67	34.19	15.03%	19.71	31.43	13.54%
	AGCRN	18.52	29.79	12.31%	19.45	31.45	12.82%	20.64	33.31	13.74%	19.36	31.28	12.81%
	MTGNN	18.65	30.13	13.32%	19.48	32.02	14.08%	20.96	34.66	14.96%	19.50	32.00	14.04%
	STNorm	18.28	29.70	12.28%	18.92	31.12	12.71%	20.20	32.91	13.43%	18.96	30.98	12.69%
	D^2STGNN	17.44	28.48	11.91%	18.20	29.91	12.29%	19.31	31.68	12.99%	18.15	29.80	12.25%
PEMS07	HI	49.02	71.15	22.73%	49.04	71.18	22.75%	49.06	71.21	22.79%	49.03	71.18	22.75%
	Graph WaveNet	18.69	30.69	8.02%	20.26	33.37	8.56%	22.79	37.11	9.73%	20.25	33.32	8.63%
	DCRNN	XXX	XXX	XXX%	XXX	XXX	XXX%	XXX	XXX	XXX%	XXX	XXX	XXX%
	AGCRN	19.31	31.68	8.18%	20.70	34.52	8.66%	22.74	37.94	9.71%	20.64	34.39	8.74%
	MTGNN	19.23	31.15	8.55%	20.83	33.93	9.30%	23.60	38.1	10.10%	20.94	34.03	9.10%
	STNorm	19.15	31.70	8.26%	20.63	35.10	8.84%	22.60	38.65	9.60%	20.52	34.85	8.77%
	D^2STGNN	18.56	30.52	7.79%	20.10	33.15	8.41%	22.30	36.73	9.40%	20.05	33.08	8.42%
PEMS08	HI	36.65	50.44	21.60%	36.66	50.45	21.63%	36.68	50.46	21.68%	36.66	50.45	21.63%
	Graph WaveNet	13.72	21.71	8.80%	14.67	23.50	9.49%	16.15	25.85	10.74%	14.67	23.47	9.52%
	DCRNN	14.16	22.20	9.31%	15.24	24.26	9.90%	17.70	27.14	11.13%	15.26	24.28	9.96%
	AGCRN	14.51	22.87	9.34%	15.66	25.00	10.34%	17.49	27.93	11.72%	15.65	24.99	10.17%
	MTGNN	14.30	22.55	10.56%	15.25	24.41	10.54%	16.80	26.96	10.9%	15.31	24.42	10.70%
	STNorm	14.44	22.68	9.22%	15.53	25.07	9.94%	17.20	27.86	11.3%	15.54	25.01	10.00%
	D^2STGNN	13.24	21.83	8.47%	14.19	23.98	9.09%	15.50	26.43	9.9%	14.20	23.95	9.10%