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Tensorized LSTM with Adaptive Shared Memory for Learning Trends in Multivariate Time Series

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Motivation

☑ Trends Are Everywhere

System Monitoring

Trend:
Abnormal sensor signals

Health Care

Trend:
Irregular heart rate

Stock Market

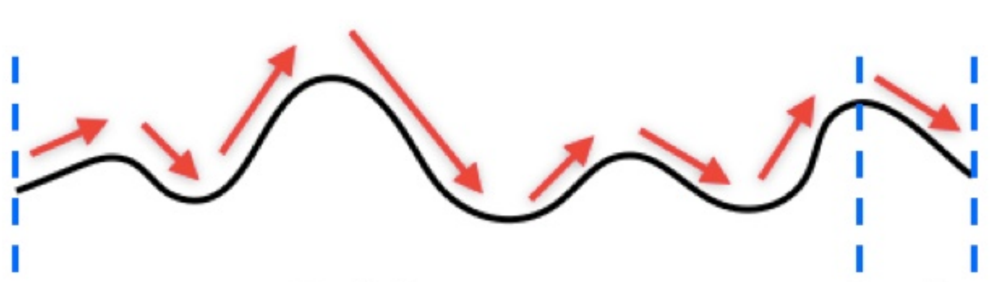
Trend:
Monotonous price

Gas Detection

Trend:
Gas Content

☑ Problem Definition

- Input: Multivariate time series
- Output:
  - Trends detected in training set
  - Trends predicted in testing set



Output: $(l_1, S_1), (l_2, S_2), \ldots, (l_n, S_n) \rightarrow (l_{n+1}, S_{n+1})$
where $l_k > \mu$, $|S_k| > \Theta$

☑ Challenges

- Trends are various
- Temporal patterns of time series are complex
- Data contain noisy
- Trends are multi-granularity

☑ Technical Highlights

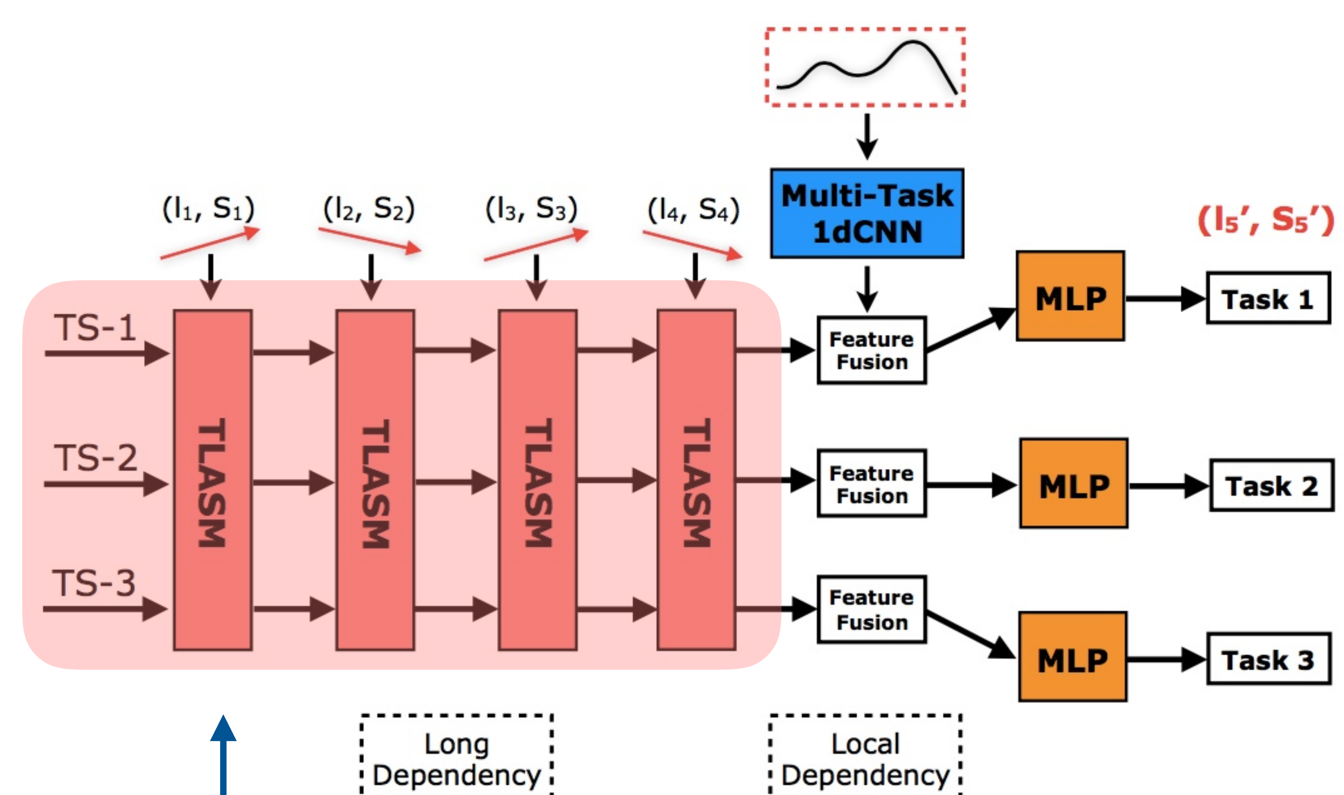
- A multi-task deep model
- Consider long- and short-term dependency
- Jointly achieve flexible parameter sharing and model the temporal patterns

The Architecture of DeepTrends

☑ Generate trends via l_2 filtering

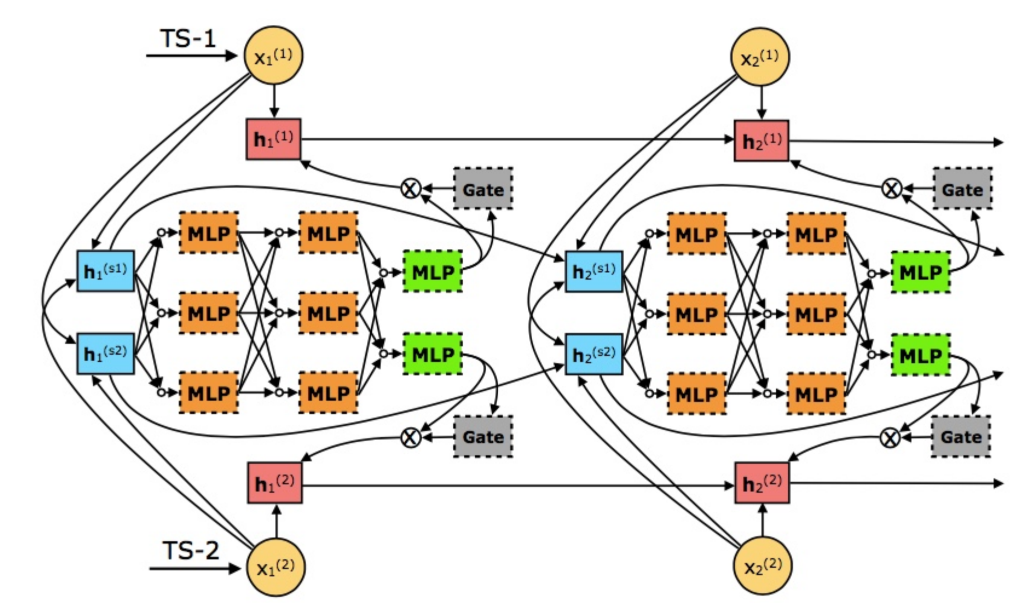
$$\sum_{t=1}^{T} \|\hat{\mathbf{x}}_t - \mathbf{x}_t\|_2^2 + \mu \sum_{t=2}^{T-1} \|\hat{\mathbf{x}}_{t-1} - 2\hat{\mathbf{x}}_t + \hat{\mathbf{x}}_{t+1}\|_2$$

☑ Predict trends via DeepTrends

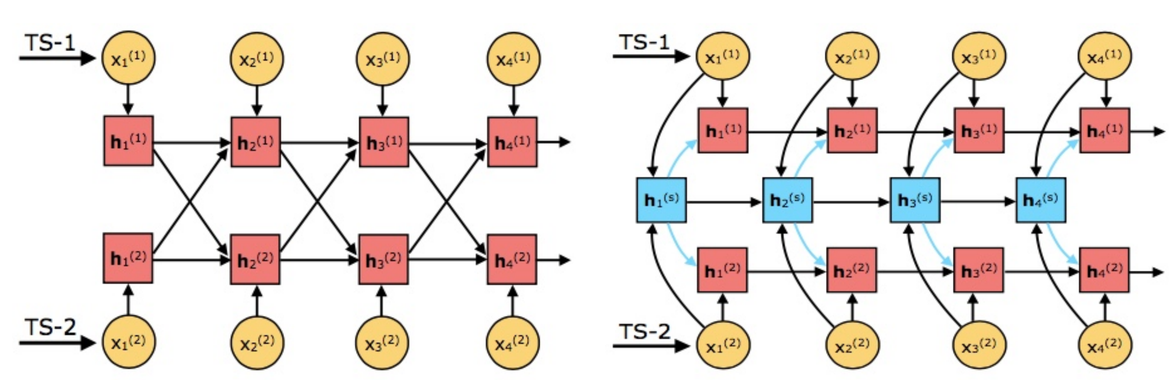


Tensorize the hidden states to learn the time series-specific representation, such that the hidden representation of each time series can be learned exclusively based on the data from that time series

☑ Core module: TLASM



To learn the sequential dependency of historical trends

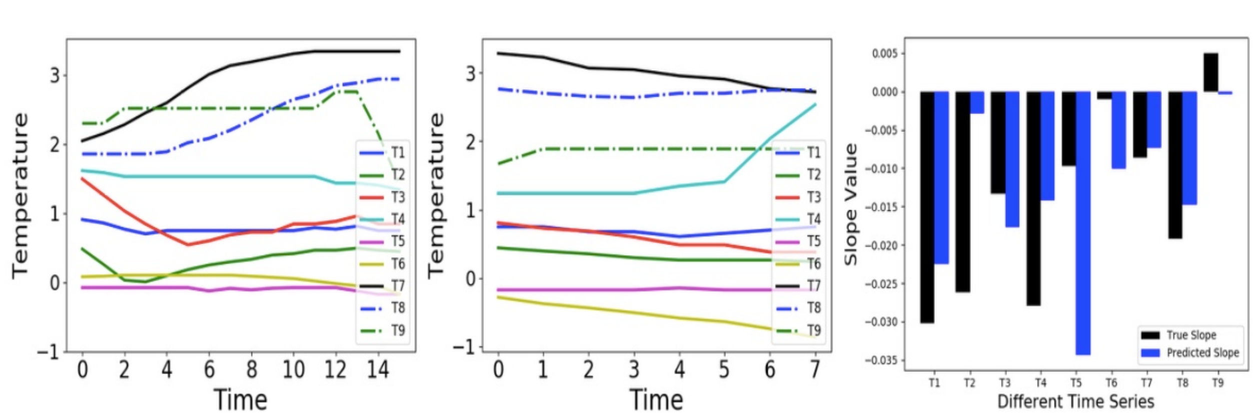


(a) Basic MTL (b) Enhanced MTL

Two typical architectures for modeling the temporal patterns of two time series with multi-task learning

Experiments

Dataset	Traffic			Exchange-Rate			Solar-Power		
μ	10	40	100	2	6	20	400	600	800
# Trends	5187	3755	1499	2312	1508	925	13957	8554	4856
# Time Steps	17544			7588			52560		
# Time Series	9			7			9		



(a) Local data (b) Future data (c) True slope v.s. Predicted slope

Visualization of the trend slope prediction

Dataset		Traffic			Exchange-Rate			Solar-Power		
		Duration								
		μ			μ			μ		
Methods	Metrics	10	50	170	2	6	20	400	600	800
CNN	Rmse	2.1215	3.9815	12.4465	3.5391	6.1490	10.0548	10.0505	15.4735	20.4078
	Rrse	1.0265	1.3997	2.0688	26.5035	29.3988	31.4994	2.4176	2.3791	2.5307
LSTM	Rmse	2.0466	3.2263	9.0031	3.0915	5.2540	9.0721	8.9872	13.0804	18.5547
	Rrse	0.9583	0.8745	0.9000	1.8089	1.7093	1.3682	1.1360	1.1401	1.2885
CLSTM	Rmse	2.2803	3.9689	10.3119	3.4449	5.8263	9.3573	8.9829	13.6282	19.1766
	Rrse	1.4100	0.9491	1.6693	1.9105	1.7658	14.4338	1.1832	1.6952	1.2246
TreNet	Rmse	1.9428	3.0801	9.4828	3.0865	5.2595	**8.1762**	9.0520	12.9362	18.7838
	Rrse	0.8959	0.7253	0.8561	1.8188	1.7208	1.3823	1.1911	1.1852	1.2383
LSTM-m	Rmse	2.3541	3.2469	9.8074	3.9940	5.2879	8.3240	8.0060	12.7251	19.2483
	Rrse	0.8733	0.7145	0.8474	1.3344	1.6351	1.3863	0.8539	0.9683	1.1861
TreNet-m	Rmse	2.2255	3.3440	10.6698	3.9548	7.2710	8.7669	7.9072	12.8988	19.3374
	Rrse	0.8530	**0.7074**	0.8994	1.2471	1.2502	1.2278	0.8433	0.9657	1.2025
ME-LSTM	Rmse	1.7984	3.0551	11.7528	3.0501	5.6678	8.3554	7.5384	12.1377	19.4335
	Rrse	0.6829	0.7654	0.9819	1.7857	1.1985	1.2548	0.8897	0.8400	1.0669
DTrends-L	Rmse	2.2076	3.3460	11.4092	3.7655	5.4440	8.6764	7.7359	12.3016	20.7890
	Rrse	0.8191	0.7724	0.8953	1.2020	1.1670	1.0719	0.8037	0.8973	1.1171
DTrends-C	Rmse	1.8120	3.0253	10.5177	3.1496	5.8344	8.3924	7.5047	9.8812	15.6963
	Rrse	0.6595	0.7762	0.8543	1.1326	1.1973	1.0718	0.8293	0.5995	0.82948
DeepTrends	Rmse	**1.7587**	**3.0182**	**9.4343**	**2.9920**	**5.1705**	8.2209	**7.4439**	**8.3247**	**13.5987**
	Rrse	**0.6087**	0.7544	**0.8412**	**1.1232**	**1.1615**	**1.0668**	**0.8011**	**0.5647**	**0.7114**

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