Imperial College London

Short-Term Traffic Prediction: Modelling Temporal-Spatial Features in Local Highway Networks with Deep Neural Network

Jingqing Zhang,[1] Chao Wu,[1] and Yike Guo.[1]

[1] Data Science Institute, Imperial College London.

{ jingqing.zhang15, chao.wu, y.guo } @ imperial.ac.uk

Abstract

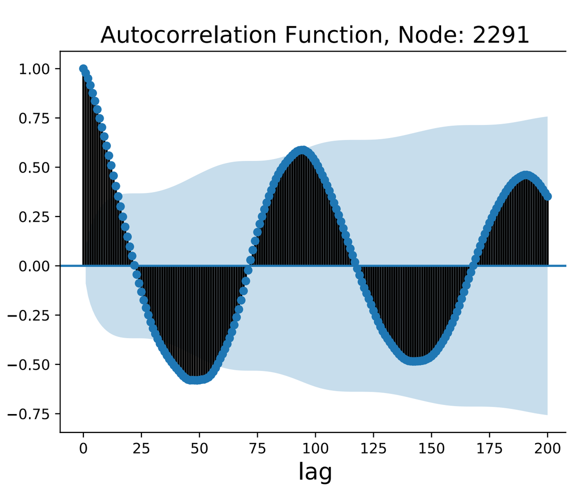
Both temporal and spatial features provide significant implications for short-term traffic volume prediction. The problem is challenging due to various non-linear temporal dynamics at different locations, complicated spatial dependencies and difficulty for longer-step ahead forecasting. We propose two deep learning models, CNN LSTM with attention mechanism (CNN-LSTM-Attn) and Temporal-Spatial-LSTM (TS-LSTM) to incorporate temporal and spatial correlations. Experiments show that both models outperform baselines on the Highways England dataset and the CNN-LSTM-Attn achieves lowest MAPE 9.26% on 2-hour traffic volume prediction. We also evaluate the CNN-LSTM-Attn on the KDDCUP17 dataset and our model defeats the model that got first place in the competition with lower MAPE 10.48%. Our models achieve 2-hour forecasting, which is longer than previous literature, with outstanding accuracy and robustness.

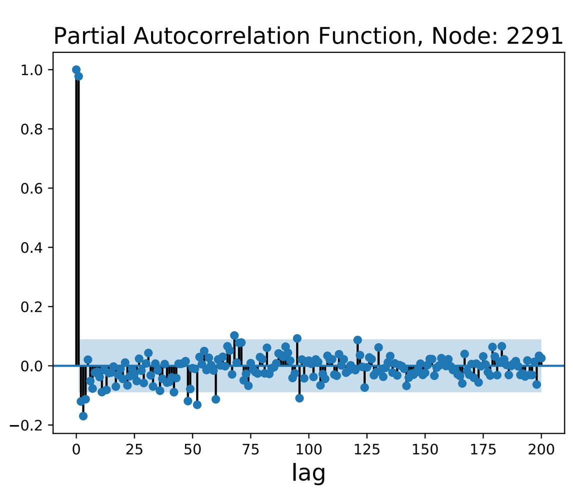
Dataset

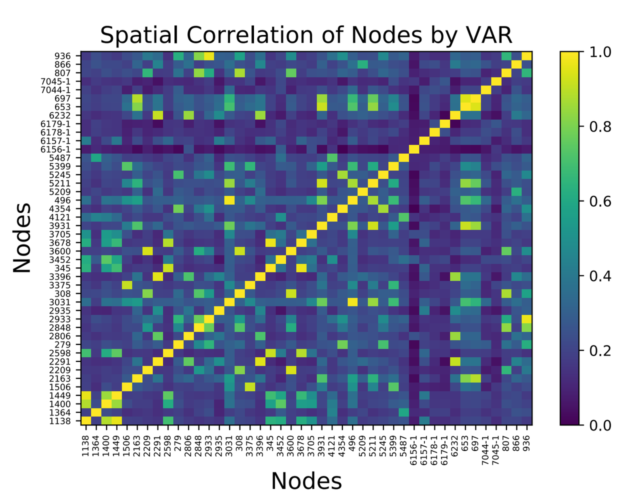
		Start	End	Full Batch Size
Highways England dataset	Train	01/01/2016	30/09/2016	1,136,290
	Valid	01/10/2016	31/12/2016	387,860
	Test	01/01/2017	30/06/2017	814,292
KDDCUP 17 dataset	Train	19/09/2016	10/10/2016	3456
	Valid	11/10/2016	17/10/2016	
	Test	18/10/2016	24/10/2016	14

Data Analysis

	Traffic Volume	Start of Peak Hours	End of Peak Hours
Workdays	0.00%	07:38	19:28
Weekends	10.87% less	11:03	19:56
Bank Holidays	14.76% less	11:24	19:47
School Holidays	0.92% more	07:44	19:17
Christmas Day	45.06% less	10:59	20:48
Christmas Period	20.02% less	11:26	19:05
New Year's Day	35.14% less	12:32	19:16







Problem Definition

Given a sequence of traffic volume observations $\{x_1, x_2, \dots x_t\}$ with a model $\mathcal{M}$ and its parameters θ

$$\tilde{x}_{t+1}, \tilde{x}_{t+2}, \dots, \tilde{x}_{t+H} = \underset{x_{t+1}, x_{t+2}, \dots, x_{t+H}}{\operatorname{argmax}} P(x_{t+1}, x_{t+2}, \dots, x_{t+H} | x_1, x_2, \dots x_t, \mathcal{M}, \theta)$$

If considering spatial correlations, $X_t = [x_t^1; x_t^2; \dots; x_t^N]$ concates N nodes

$$\tilde{X}_{t+1}, \tilde{X}_{t+2}, \dots, \tilde{X}_{t+H} = \underset{X_{t+1}, X_{t+2}, \dots, X_{t+H}}{\operatorname{argmax}} P(X_{t+1}, X_{t+2}, \dots, X_{t+H} | X_1, X_2, \dots X_t, \mathcal{M}, \theta)$$

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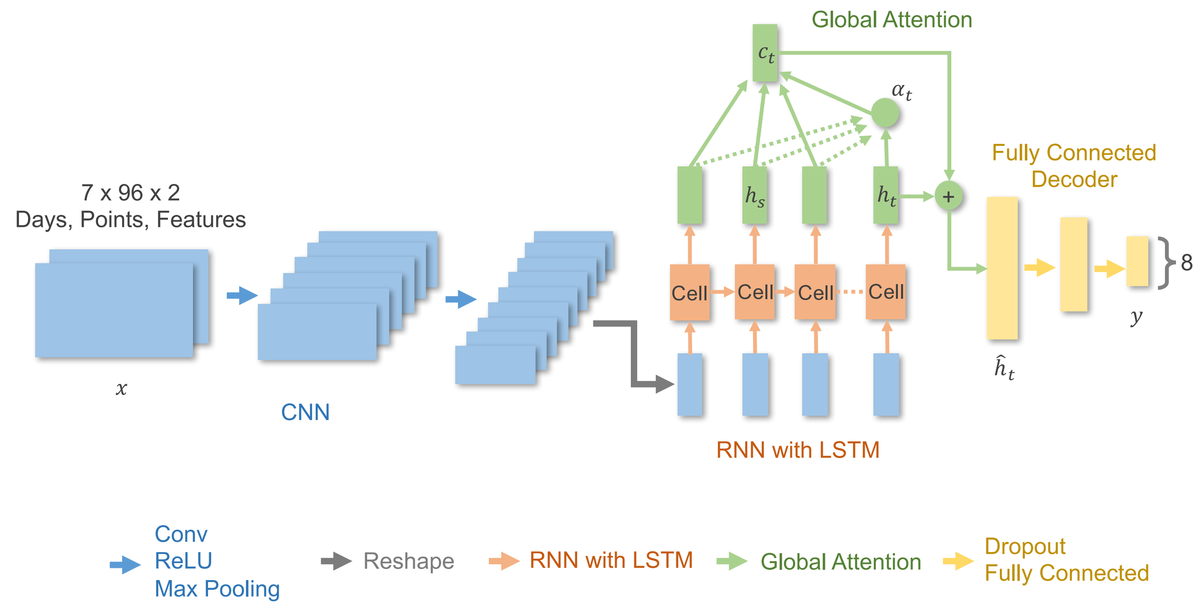
* More information about the project: https://jingqingz.github.io/projects/2017-09-EnglandHighway

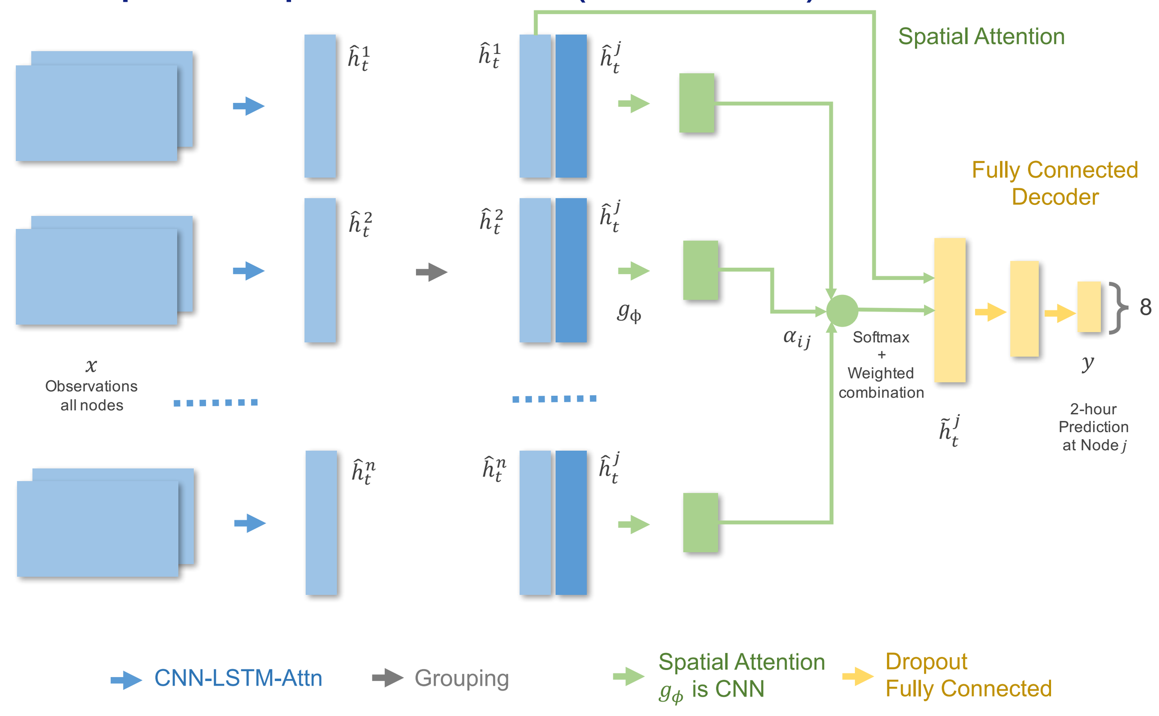
Methodologies

CNN-LSTM with Attention (CNN-LSTM-Attn)



- CNN Embedding
- RNN with LSTM
- Global Attention
  - $\alpha_t(s) = \frac{\exp(score(h_s, h_t))}{\sum_{s'} \exp(score(h_{s'}, h_t))}$
  - $score(h_s, h_t) = h_s^T W_\alpha h_t$
  - $c_t = \sum_s \alpha_t(s) h_s$
  - $\hat{h}_t = [c_t; h_t]$
- Fully Connected Decoder
  - Predict 2-hour together
- One model for the whole highway network

Temporal-Spatial-LSTM (TS-LSTM)

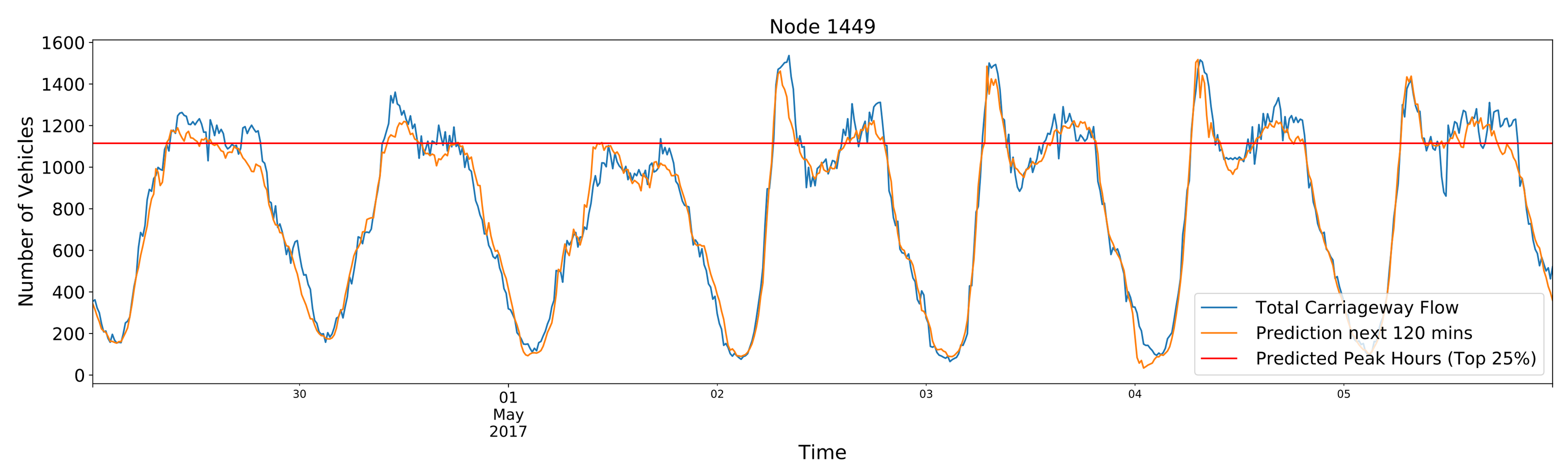


- CNN-LSTM-Attn
  - Applied on all locations
- Spatial Relational Module
  - For a specific location j
  - $\alpha_{ij} = \frac{\exp(g_\phi(\hat{h}_t^i, \hat{h}_t^j))}{\sum_{i'} \exp(g_\phi(\hat{h}_t^{i'}, \hat{h}_t^j))}$
  - $\tilde{h}_t^j = \sum_i \alpha_{ij} \hat{h}_t^i$
- Fully Connected Decoder
  - Predict 2-hour together
- Prior Knowledge not necessary

Experiments

Highways England dataset: 2-hour prediction with error rate (MAPE)

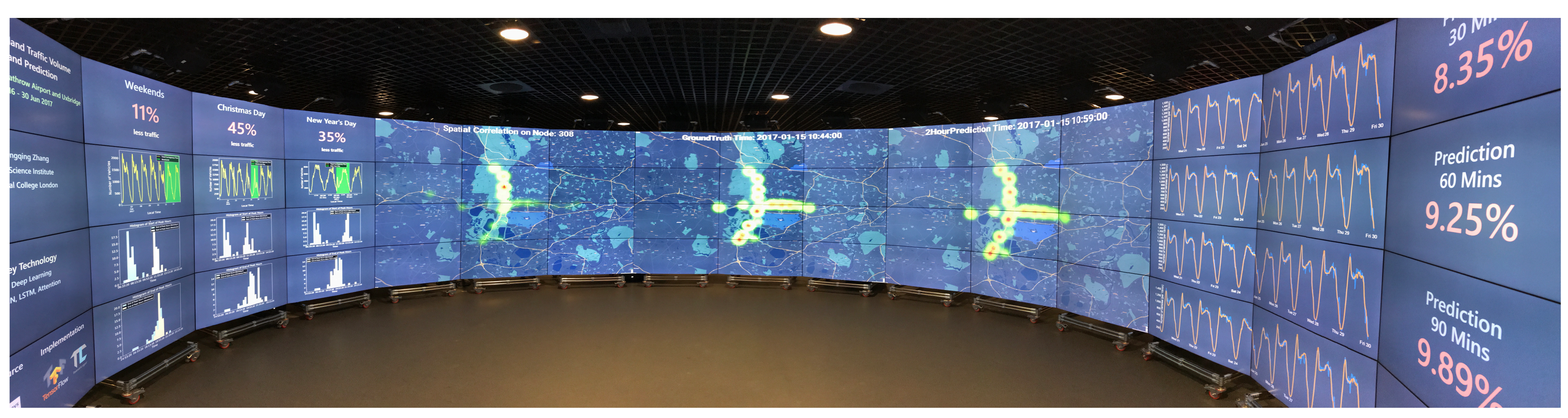
Prediction	SARIMA	VAR	GP	SVR	LSTM	CNN-LSTM-Attn	TS-LSTM
15-min		8.99	12.15	9.48	7.73	**7.54**	8.53
30-min		12.06	19.16	13.23	8.77	**8.35**	8.50
45-min		15.09	25.47	17.01	9.51	**8.88**	9.17
60-min		18.37	31.17	20.94	10.02	**9.25**	9.86
75-min		21.93	36.27	25.14	10.42	**9.60**	10.33
90-min		25.74	40.87	29.47	10.74	**9.89**	10.59
105-min		29.77	45.03	33.97	11.04	**10.12**	11.05
120-min		33.93	48.82	38.64	11.54	**10.44**	12.07
Overall	22.00	20.73	32.37	23.48	9.97	**9.26**	10.01



KDDCUP 17 dataset: 2-hour prediction with error rate (MAPE)

	CNN-LSTM-Attn	The-Model-Got-1st-Place
MAPE	**10.48**	12.03

Visualisation: Global Data Observatory



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