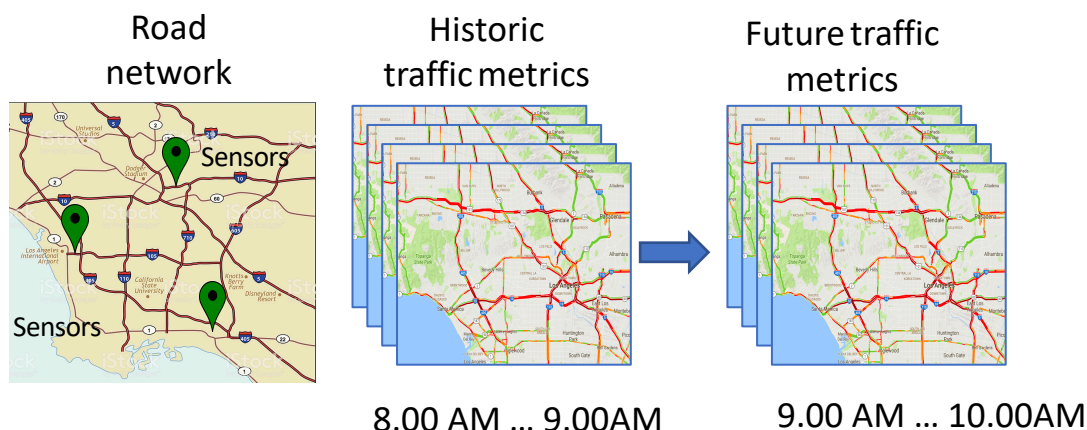


Transfer Learning with Graph Neural Networks for Short-Term Highway Traffic Forecasting

Tanwi Mallick¹, Prasanna Balaprakash¹, Eric Rask¹, and Jane Macfarlane²
¹Argonne National Laboratory and ²Lawrence Berkeley National Laboratory

Traffic forecasting:

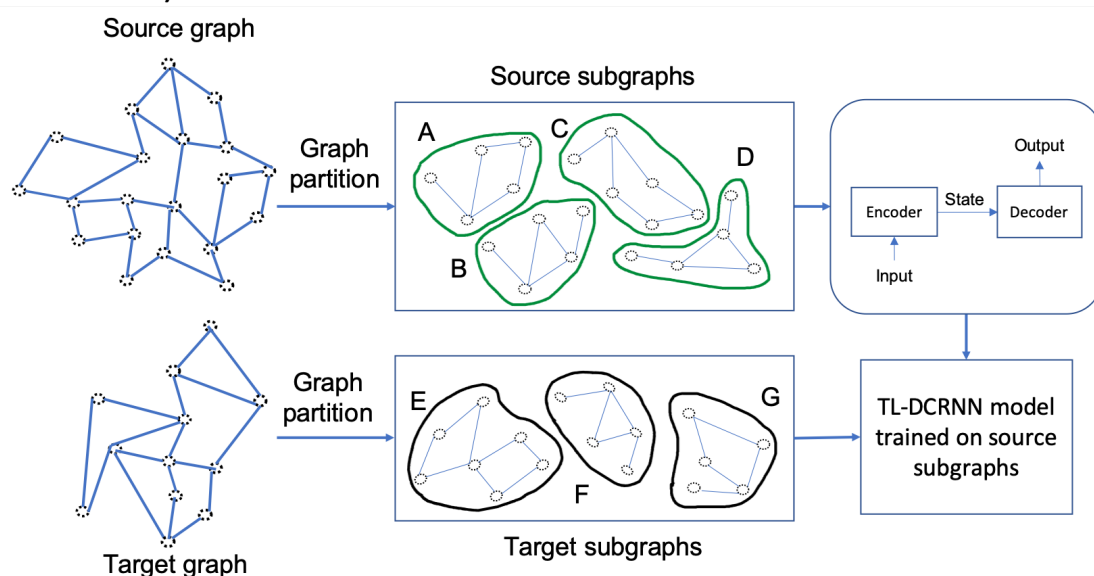
- Input: road network and past T' traffic speed
- Output: traffic speed for the next T steps



Problem: Forecast traffic in absence of location specific network and historical time series data

Proposed model:

Transfer learning Diffusion convolutional recurrent neural network (TL-DCRNN)



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Methodology:

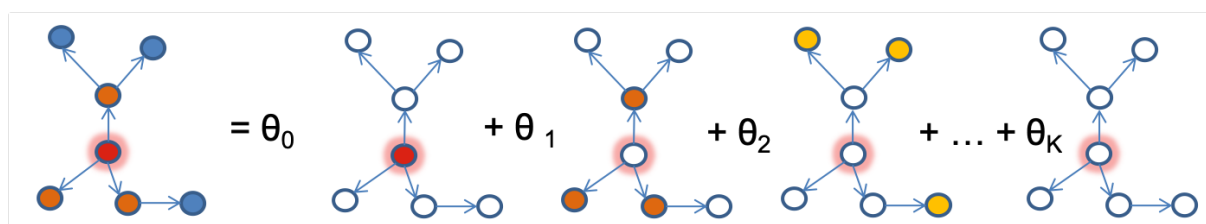
Capturing the road network in terms of graphs

- Transportation network as graph

- V = Vertices (sensors)

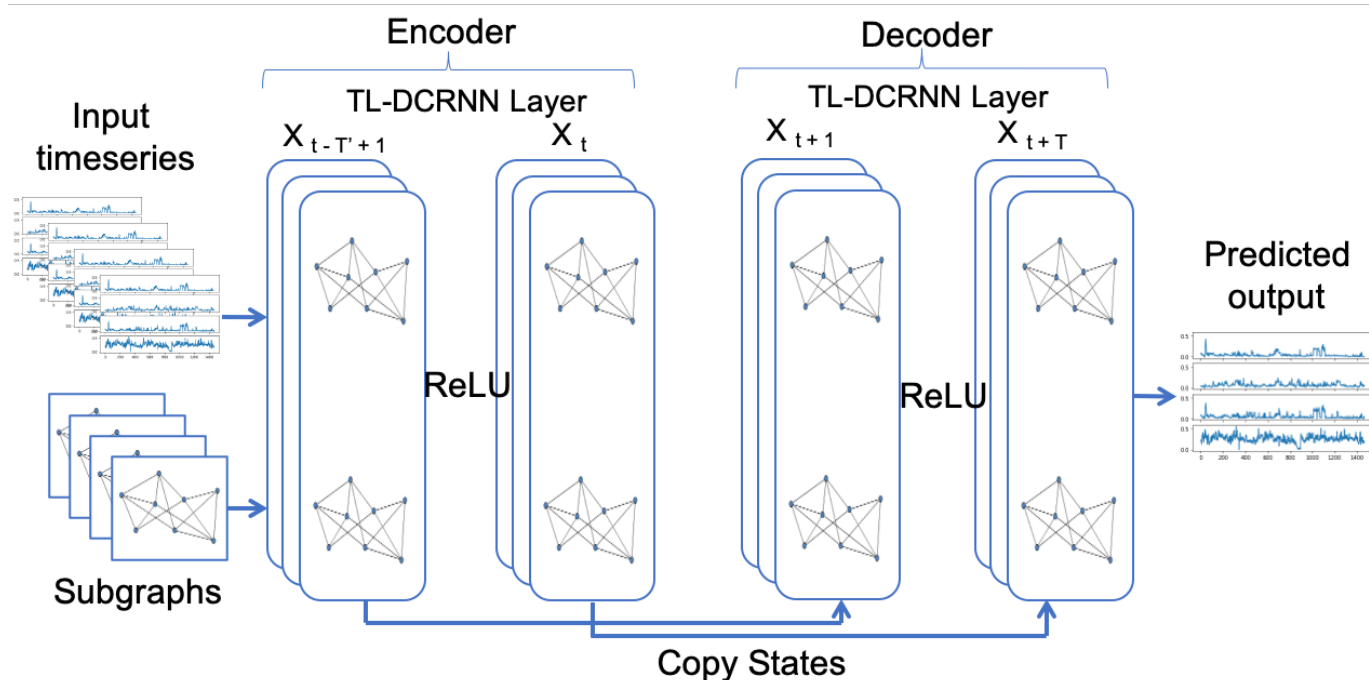
- E = Edges (roads)

- A = Weighted adjacency matrix (A function of the road network distance)



Out-degree In-degree

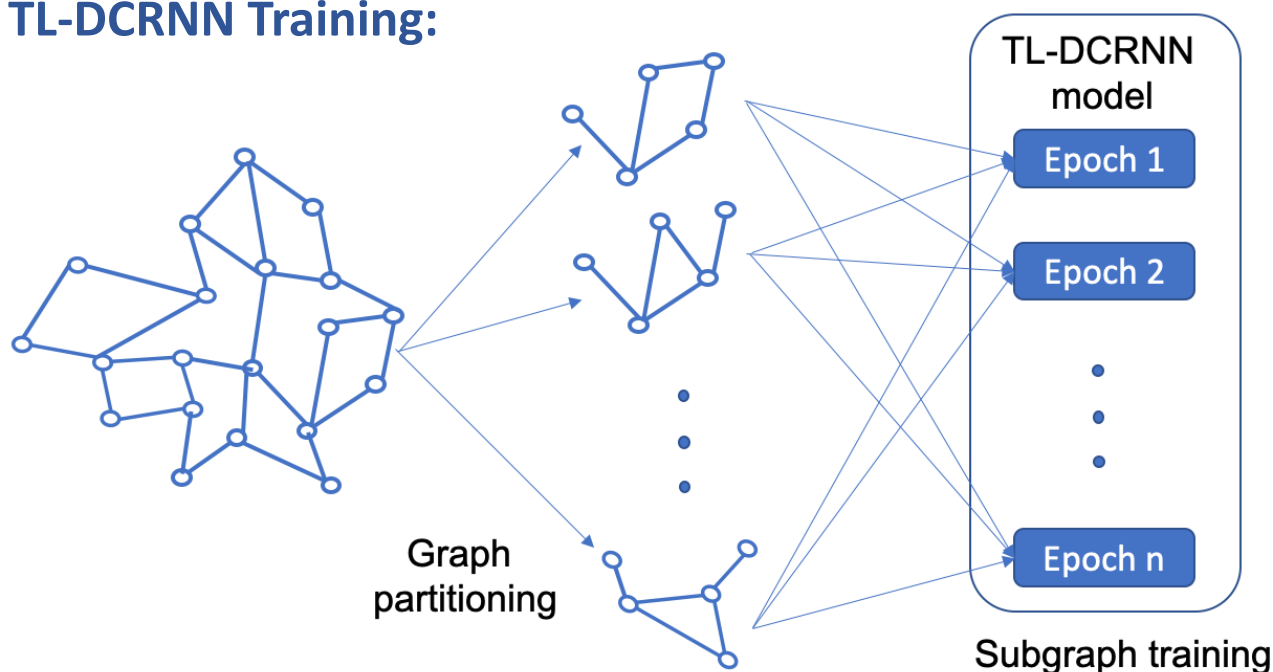
$$X_{:,p} \star_{\mathcal{G}} f_{\theta} = \sum_{k=0}^{K-1} \left(\theta_{k,1} (\mathbf{D}_O^{-1} \mathbf{A})^k + \theta_{k,2} (\mathbf{D}_I^{-1} \mathbf{A}^T)^k \right) X_{:,p}$$



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TL-DCRNN Training:

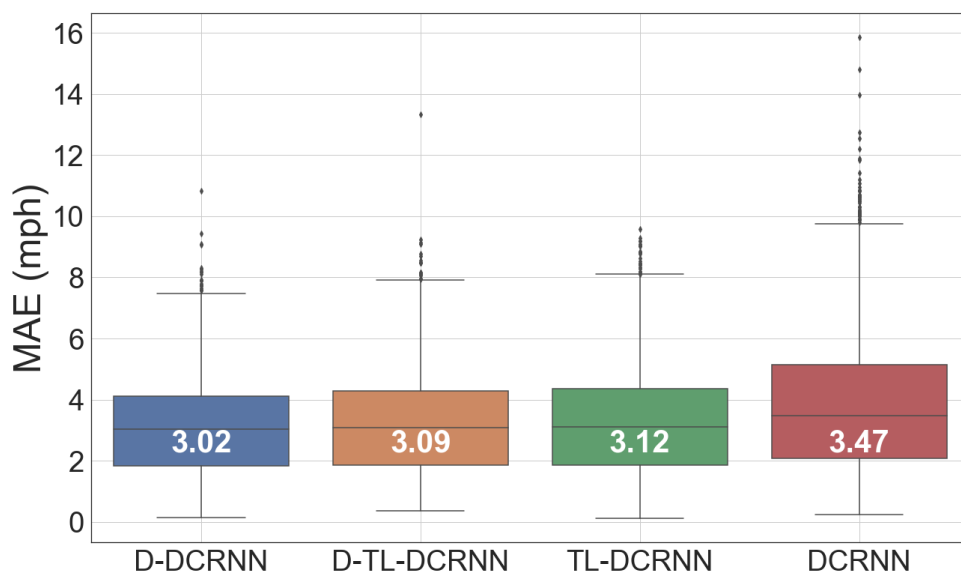


Results:

Transfer learning between LA and SFO regions

PeMS dataset 2018: LA (2,716 sensors) and SFO (2,382 sensors)

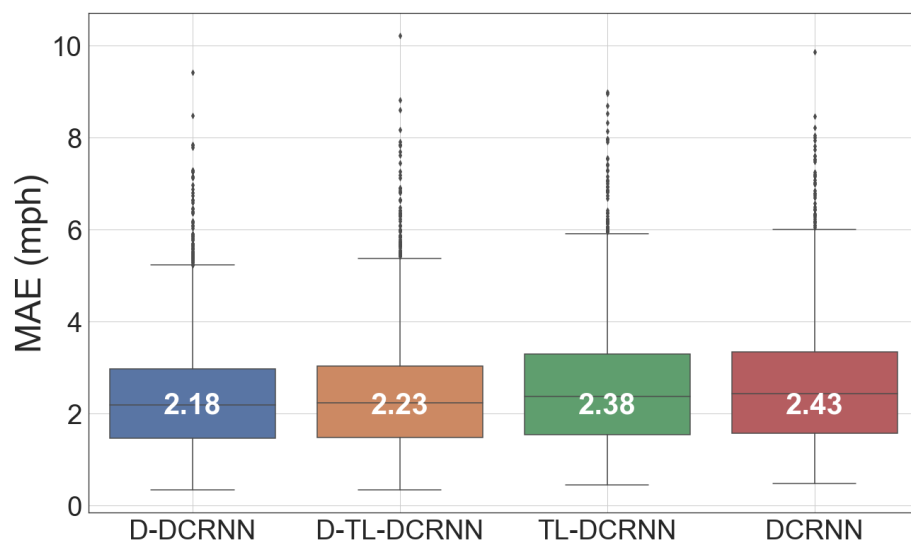
- D-DCRNN and D-TL-DCRNN trained on LA data and tested on the LA data
- TL-DCRNN and DCRNN trained on SFO data and tested on the LA data



Transfer Learning with Graph Neural Networks for Short-Term Highway Traffic Forecasting

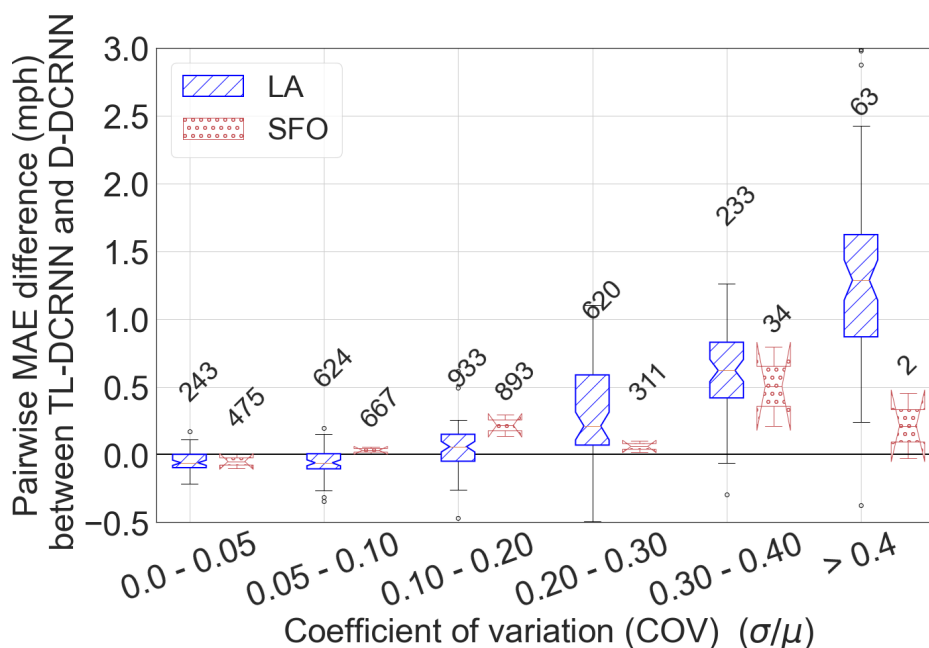
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- D-DCRNN and D-TL-DCRNN trained on SFO data and tested on the SFO data
- TL-DCRNN and DCRNN trained LA data and tested on the SFO data



TL-DCRNN outperformed DCRNN on LA and SFO

Pairwise MAE differences between TL-DCRNN and D-DCRNN and with respect to Coefficient of variance (COV) values



These results imply that when the traffic is less dynamic, transfer learning will be as good as the direct learning.

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Comparison with other methods:

- TL-DCRNN trained on LA dataset and tested on the PEMS-BAY
- Other models trained and tested on PEMS-BAY

TL-DCRNN
outperformed
number of traffic
forecasting
methods

Method	MAE	RMSE	MAPE
Training and testing on PEMS-BAY			
ARIMA [13]	3.38	6.50	8.30%
SVR [14]	3.28	7.08	8.00%
FNN [15]	2.46	4.98	5.89%
FC-LSTM [4]	2.37	4.96	5.70%
STGCN [16]	2.49	5.69	5.79%
DCRNN [6]	2.07	4.74	4.90%
GMAN [17]	1.86	4.32	4.31%
Training on LA and testing on PEMS-BAY			
TL-DCRNN	2.13 ± 1.09	5.23 ± 2.29	5.55 ± 4.34

All models are trained on LA dataset and tested on the PEMS-BAY

Models	MAE	RMSE	MAPE
STGCN [16]	6.53 ± 2.69	10.07 ± 3.47	13.31 ± 6.38 %
FC-LSTM [4]	4.69 ± 1.79	8.48 ± 3.17	12.32 ± 8.78 %
GMAN [17]	4.05 ± 1.56	7.57 ± 2.51	8.5 ± 4.58 %
DCRNN [6]	3.3 ± 1.24	6.91 ± 2.19	8.21 ± 5.57 %
TL-DCRNN	2.13 ± 1.09	5.23 ± 2.29	5.55 ± 4.34 %

TL-DCRNN outperformed all state-of-the-art traffic forecasting methods in a transfer learning setting

Conclusion and future work:

- TL-DCRNN allow practitioners to apply data-driven methods trained on datasets collected elsewhere
- Enabling a wide range of transportation system operations operate efficiently in reduced infrastructure and data acquisition cost
- In future, we will work on deployment strategies for traffic management systems across the country