Analyzing the Cascading Effect of Traffic Congestion Using LSTM Networks

Sanchita Basak[1], Abhishek Dubey[1], Bruno Leao[2]

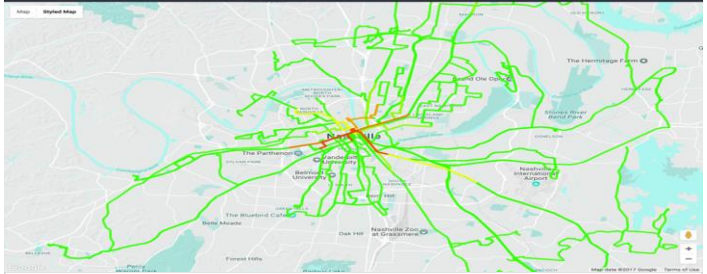
[1]Vanderbilt University, Nashville, TN

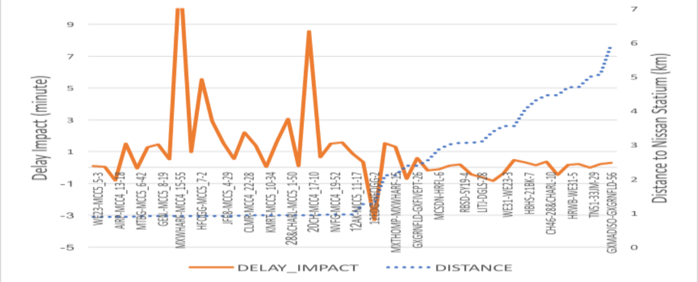
[2]Siemens, CT, Princeton, NJ

Outline

- Understanding the problem of traffic congestion cascade
- Research gap in analyzing and predicting the congestion cascade
- Our approach using Long Short Term Memory Networks
- Results from Nashville TN

Example of Traffic congestion caused due to football games in Nashville TN causing delay in travel time

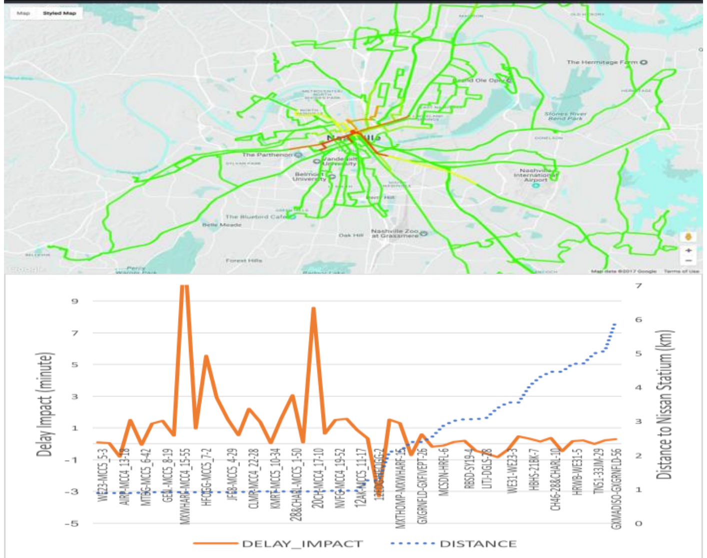




Outline

- Understanding the problem of Traffic Congestion Cascade
- Research Gap in Analyzing and Predicting the Congestion Cascade
- Our approach using Long Short Term Memory Networks
- Results from Nashville TN

Example of Traffic congestion caused due to football games in Nashville TN causing delay in travel time



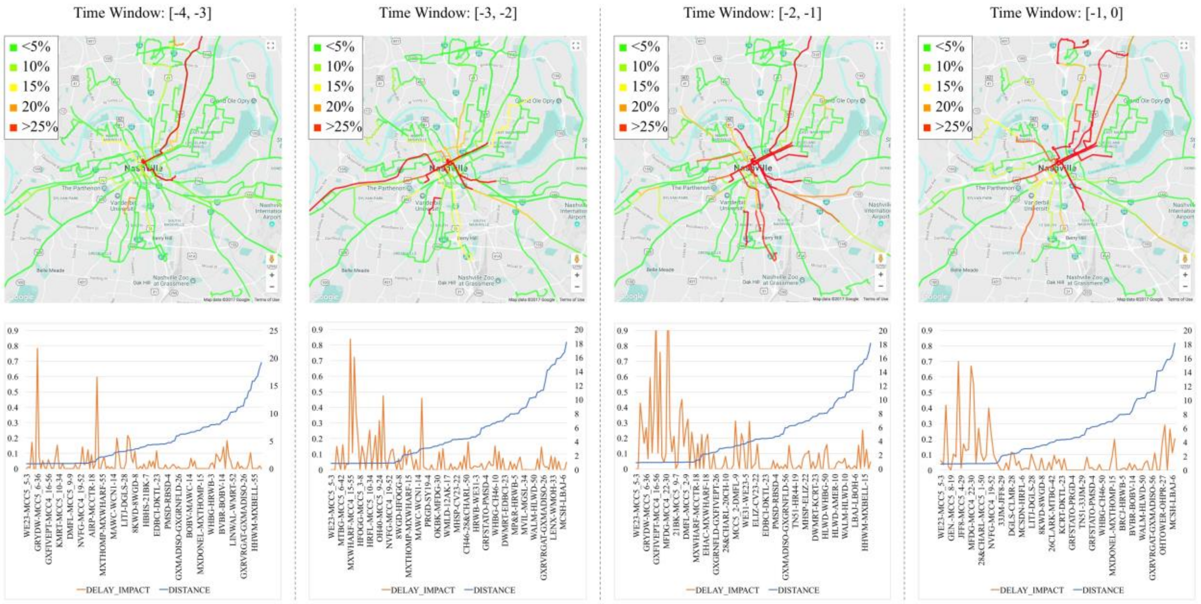
Traffic Congestions

Traffic congestion is a condition when the traffic demand approaches the capacity of the road.

Traffic Congestions

<u>Traffic congestion is a condition when the traffic demand approaches the capacity of the road.</u>

Cascading Failure: A process in an interconnected system where failure in one part of the system triggers failure in other parts of the system eventually.

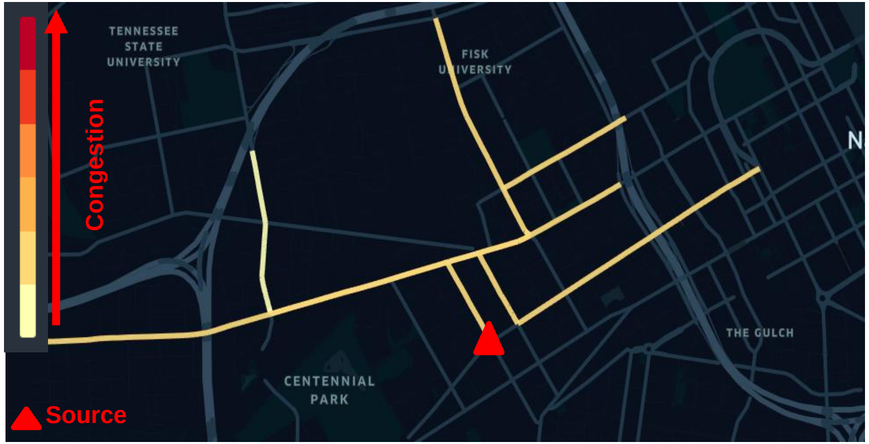


Traffic Congestions

<u>Traffic congestion is a condition when the traffic demand approaches the capacity of the road.</u>

Cascading Failure in Traffic: A process by which speed reduction propagates to roads that feed the traffic into current road.

Goal: Given the time of onset of speed reduction (< 60%) find the time when speed in neighboring segments will decrease

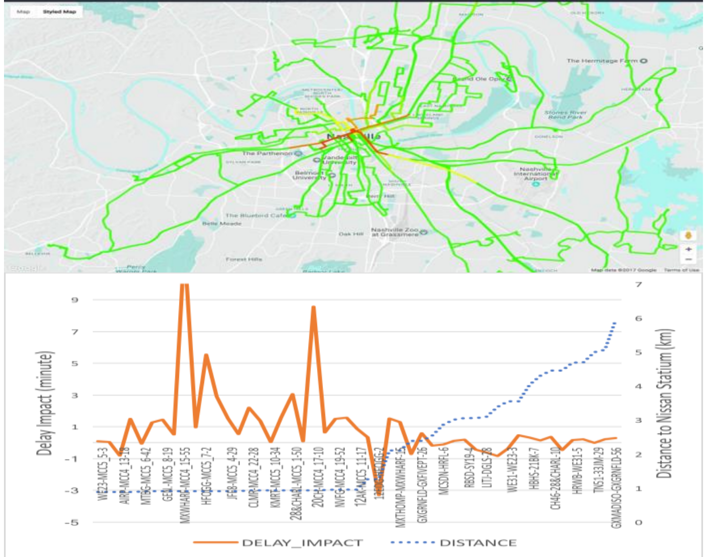


A sequence of congestion progression from Nashville, USA (~10 minute propagation delay) [compressed for video]

Outline

- Understanding the problem of Traffic Congestion Cascade
- Research Gap in Analyzing and Predicting the Congestion Cascade
- Our approach using Long Short Term Memory Networks
- Results from Nashville TN

Example of Traffic congestion caused due to football games in Nashville TN causing delay in travel time



Congestion Forecasting Approaches

	Fei et al. [2]	Sole-Ribalta et al. [3]	Ma et al. [4]	Zhang et al. [5]
Approach	Model-driven	Model-driven	Data-driven	Data-driven
Accuracy	Average absolute error is 1.72 km/h	Provided parameterwise accuracy.	Prediction accuracy- 88.2%	Minimum wMSE is 0.0579
Computa-tional complexity	Huge	Moderate	Moderate	Huge
Generalizability	Not generalizable	Generalizable	Generalizable	Generalizable

[2] W. Fei, G. Song, J. Zang, Y. Gao, J. Sun, and L. Yu, "Framework model for time-variant propagation speed and congestion boundary by incident on expressways," IET Intelligent Transport Systems, vol. 11, no. 1, pp.10–17, 2017.
[3] A. Sole-Ribalta, S. Gomez, and A. Arenas, "A model to identify urban ´ traffic congestion hotspots in complex networks," Royal Society open science, vol. 3, 04 2016.
[4] X. Ma, H. Yu, Y. Wang, and Y. Wang, "Large-scale transportation network congestion evolution prediction using deep learning theory," PloS one, vol. 10, p. e0119044, 03 2015.
[5] S. L. Zhang, Y. Z. Yao, J. Hu, Y. Zhao, S. Li, and J. Hu, "Deep autoencoder neural networks for short-term traffic congestion prediction of transportation networks," in Sensors, 2019.

Problems with Model-driven approach:

- Hard to capture all modalities of such a system using a predetermined distributions.

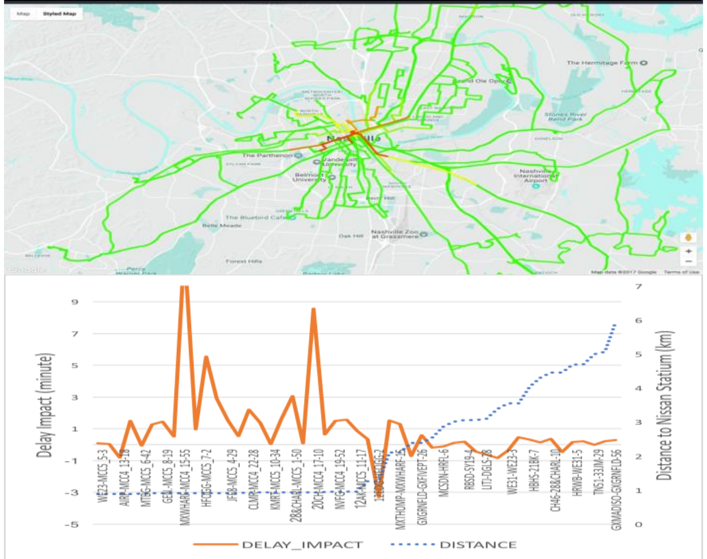
Problems with Data-driven approaches used:

- Homogenous architectures
- Ignoring intersection geometry

Outline

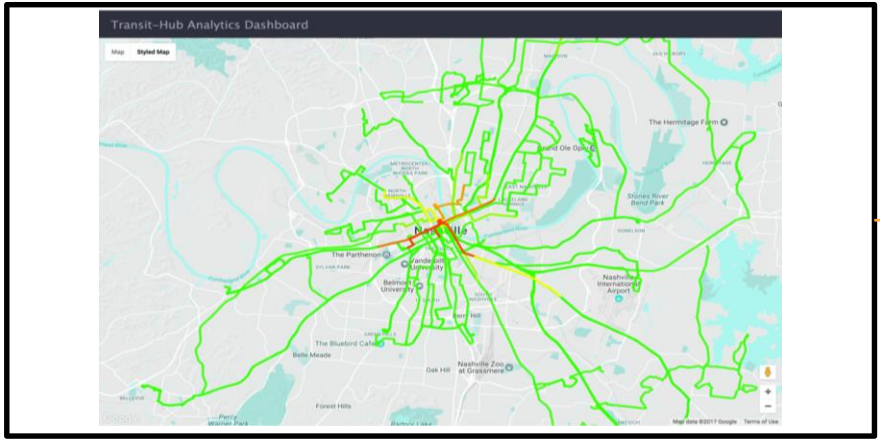
- Understanding the problem of Traffic Congestion Cascade
- Research Gap in Analyzing and Predicting the Congestion Cascade
- Our approach using Long Short Term Memory Networks
- Results from Nashville TN

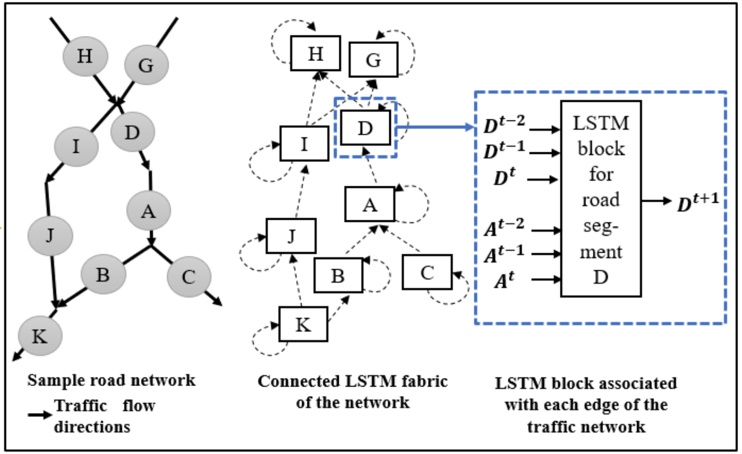
Example of Traffic congestion caused due to football games in Nashville TN causing delay in travel time



Our Approach

Model the road network as a sequence of Connected Long Short Term Memory Networks



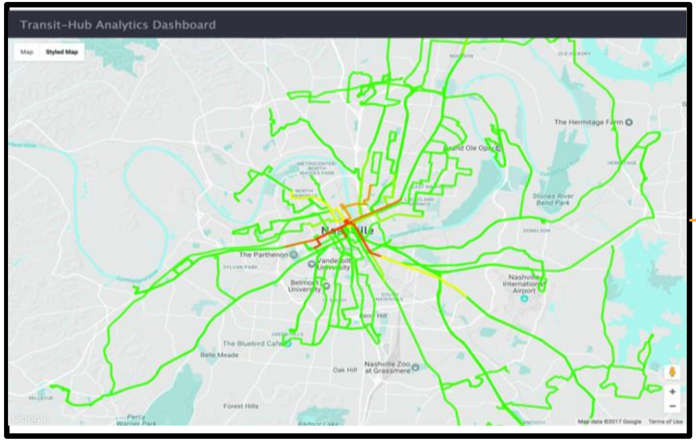


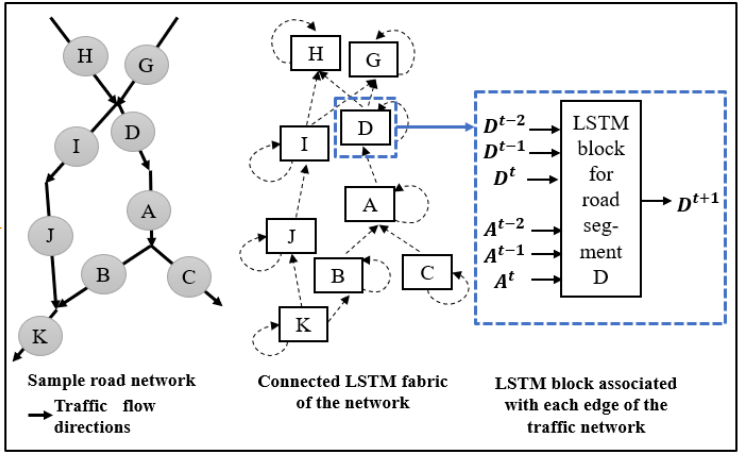
Total 3724 LSTM Neural Networks – one per road segment are modeled and deployed on a computing cluster in our lab

Bilayered LSTM architecture with each layer having 100 units
Loss function: Mean Squared Error between actual and predicted speed
Optimizer: Adam

Our Approach

$$s(e)^{c_t+p} = f\left(<s(e)>^{c_t}_{c_t-j},\ <\Upsilon_1 * s(neighbor_1)>^{c_t}_{c_t-j},\ \ <\Upsilon_2 * s(neighbor_2)>^{c_t}_{c_t-j}, \ldots\ldots <\Upsilon_n * s(neighbor_n)>^{c_t}_{c_t-j} \right)$$





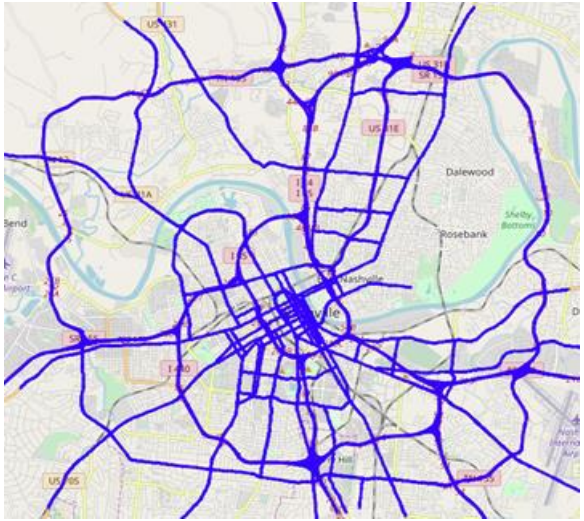
Each LSTM is trained with speed data from the city for about one month and is then checked for accuracy.

- We use the data from HERE API.
- Data from 01.01.2018 to 01.27.2018 is used for training the prediction architecture.
- Data from 01.28.2018 to 02.09.2018 is used for testing purposes.
- The speed data for each segment is normalized wrt. the average maximum speed per segment, i.e. the times when the jam factors are zero.

Our Approach

$$s(e)^{c_t+p} = f\left(<s(e)>_{c_t-j}^{c_t},\ <\Upsilon_1 * s(neighbor_1)>_{c_t-j}^{c_t},\ \ <\Upsilon_2 * s(neighbor_2)>_{c_t-j}^{c_t}, \ldots\ldots <\Upsilon_n * s(neighbor_n)>_{c_t-j}^{c_t} \right)$$

t : Timestep resolution (data sampling rate)
j : past timesteps
p : some timesteps in future
Υ_n: weighted constants to factor the influence of each neighbor class (categorized as 1-hop, 2-hop, 3-hop…)
s(x) : speed of a road segment x

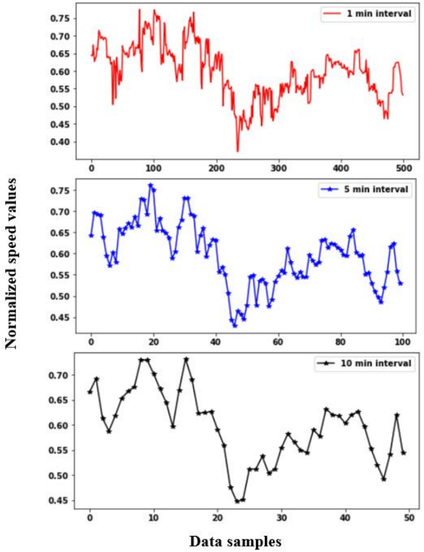


Region of Study: Nashville TMC map

Hyper-parameter Tuning

Selecting time constant :

a.
b.
c.



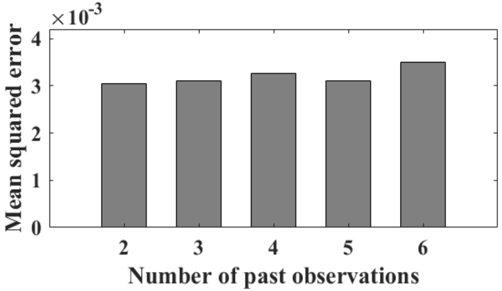
The MSE between the actual signal in plot ‘a’ and the regenerated signal of plot ‘a’ from the downsampled version in plot ‘c’ is only 0.00138.

We chose the timestep as 10 minutes for this work.

Various time constants at which the data can be sampled.

Selecting number of past observations :

- The MSE in predicting future speed does not decrease as we take more number of past data samples into account.
- Hence we choose past two observations for predicting the future traffic speed..

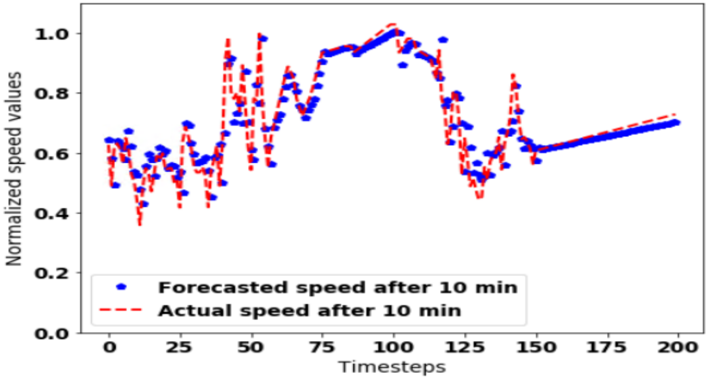


Comparison of MSE for different number of past observations

Traffic Speed Prediction Performances

Training:

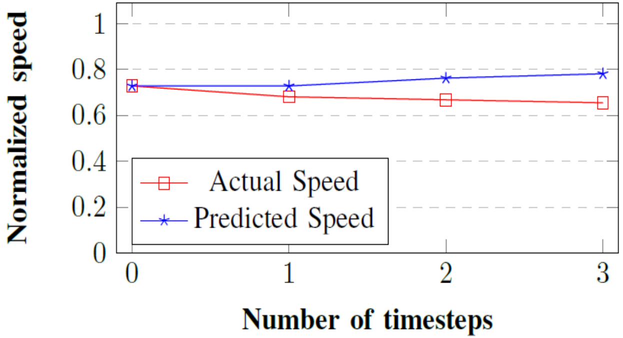
We train the traffic speed predictors with data from normally operating traffic conditions and not from the specific cascade events. We only use that for testing purposes.



Forecasting traffic speed 10 minutes in advance for a road segment having *five* neighbors

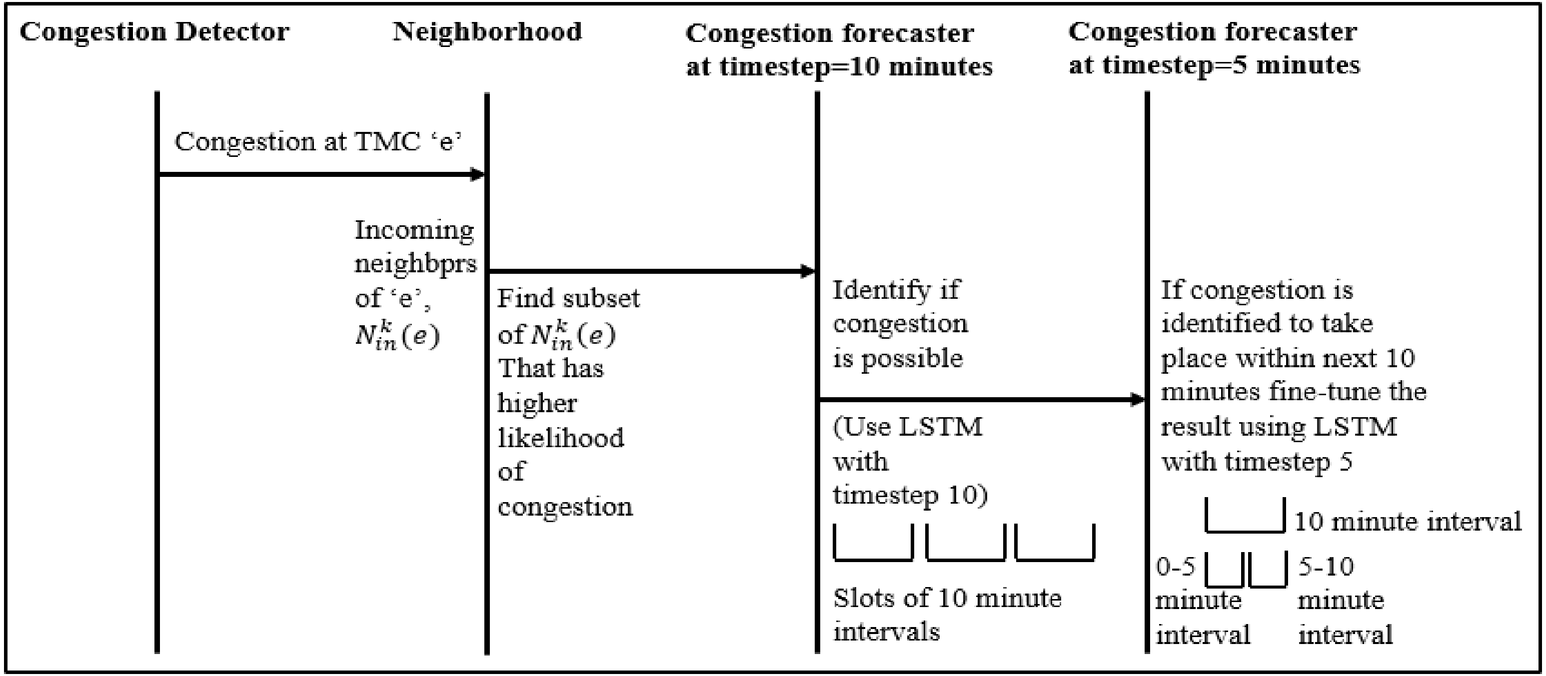
Predicting multiple timestesps ahead using connected LSTM fabric:

To predict 'k' number of timesteps ahead from current time, we require the information upto k-hop neighbors of a target road.



Predicting normalized traffic speed of TMC upto three timesteps, i.e., 30 minutes ahead from current time.

Congestion Forecasting Framework

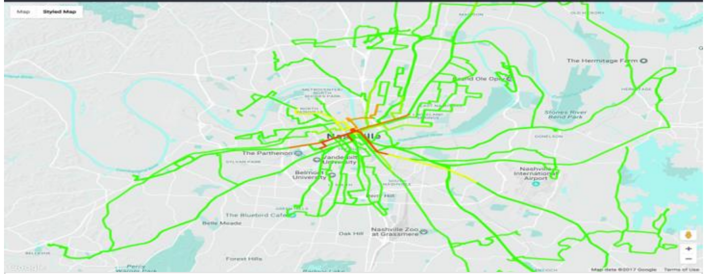


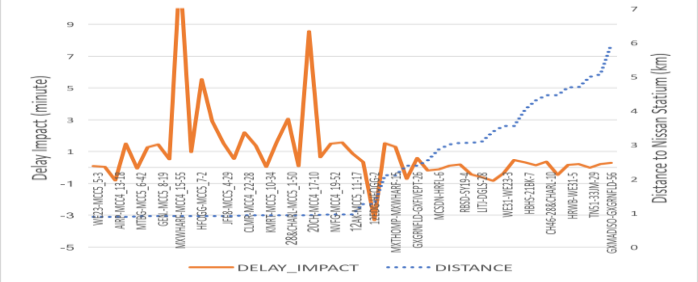
An illustration of the overall congestion forecasting framework

Outline

- Understanding the problem of Traffic Congestion Cascade
- Research Gap in Analyzing and Predicting the Congestion Cascade
- Our approach using Long Short Term Memory Networks
- Results from Nashville TN

Example of Traffic congestion caused due to football games in Nashville TN causing delay in travel time



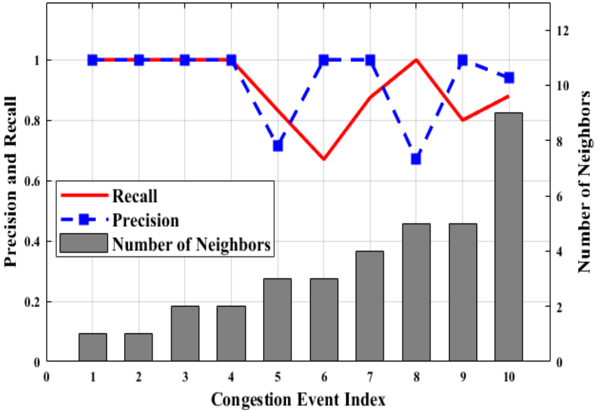


Testing on Several Congestion Events

We identify ten cascade events from Nashville and show the experimental results on applying the congestion forecasting framework.

Index	Congestion source (ID)	Congestion source (Road name)	Date	Time	1-hop neighbors		2-hop neighbors		3-hop neighbors	
					Actual	Predicted	Actual	Predicted	Actual	Predicted
1	7413+3.57391	Hillsboro Pike	02.01.2018	16:30	16:40	16:40	-	-	-	-
2	4564+0.68565	I-24	01.30.2018	18:00	18:20	18:20	-	-	-	-
3	4418-0.94469	Charlotte Avenue	01.29.2018	16:20	16:30	16:30	16:40	16:40	-	-
4	4470+1.91003	I-24	02.02.2018	14:40	14:50	14:50	-	-	-	-
5	6847-1.51788	Memorial Boulevard	01.31.2018	15:00	15:00	15:10	15:30 15:30	15:20 15:20	-	-
6	6841+0.23911	South Church Street	02.09.2018	14:10	14:20 14:50	14:20 15:00	15:00	15:10	-	-
7	5041+1.16158	Dickerson Pike	01.30.2018	15:20	15:20 15:20 15:50	15:20 15:20 16:00	16:00	16:00	-	-
8	6017+0.46437	US 231	02.05.2018	06:30	06:50 - 07:20	06:50 07:10 07:10	07:40 07:50	07:30 07:50	-	-
9	8649-0.30317	West End Avenue	02.09.2018	10:40	11:00 11:10	11:00 11:10	10:40 11:10 11:20	10:50 11:20 11:20	-	-
10	13710-0.32285	21st Ave North	02.02.2018	06:50	06:50	06:50	07:00 07:40	07:00 07:20	07:00 07:10 07:30 07:30 07:20 07:30	07:00 07:00 07:30 07:30 07:20 07:30

The table shows the actual and predicted time of onset of congestion measured in steps of 10 minutes.

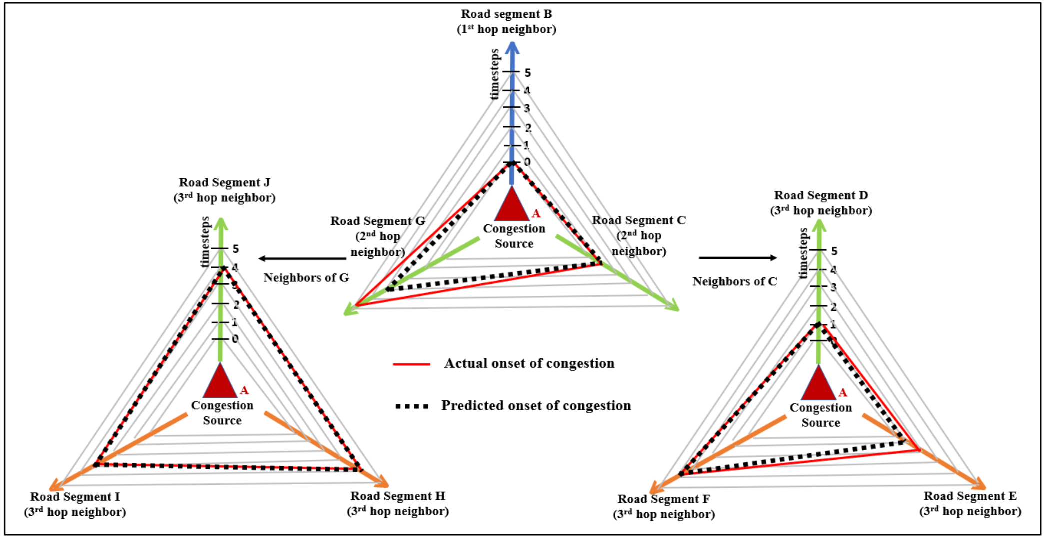


The figure shows an average precision of 0.9269 and recall of 0.9118 obtained in identifying the onset of congestion.

Fine-tuning Forecasting Results at 5 minutes Resolution

Neighbors of TMC '13710-0.32285'	Actual	Predicted
B	06:40-06:45	06:40-06:45
C	06:50-06:55	06:55-07:00
G	07:45-07:40	07:10-07:15
D	06:55-07:00	06:50-06:55
E	07:05-07:10	06:55-07:00
F	07:20-07:25	07:20-07:25
J	07:20-07:25	07:20-07:25
H	07:10-07:15	07:10-07:15
I	07:20-07:25	07:20-07:25

The actual and predicted time for onset of congestion calculated at 5 minute resolution



Radar chart showing the accuracy of forecasting results

The average precision and recall for identifying the onset of congestion in 5 minute resolution are calculated as 0.75 and 0.92.

Summary

- We demonstrated mechanisms for spatiotemporal modelling of traffic network learning the distribution of traffic speed of a road segment as a function of its neighboring segments.
- We developed a traffic congestion forecasting framework based on city-level connected fabric of multiple LSTM models.
- We took into account the likelihood of congestion propagation for each of the neighboring segments of any congestion source and identified the onset of congestion at each of them with an average precision of 0.9269 and an average recall of 0.9118 tested on ten congestion events.
- This approach is generalizable and serves the purpose of forecasting the onset of congestion in advance, so that traffic routing algorithms can divert the traffic away from the roads to be congested in near future.
- In future, we plan to extend this framework to predict cascading effects of failure in other networked systems such as electrical grids and water networks using similar approach.