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Short-term Traffic Prediction and Incident Detection with Traffic Detectors Using Recurrent Neural Network

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INTRODUCTION

Motivation:

- A need of processing information collected from roadway infrastructures and distributing real-time traveler information for proactive congestion and safety mitigation.
- Traffic detectors are widely used by different transportation agencies and are accessible as a prevailing source of descriptive traffic information.

Limitations of Past Studies:

- High-frequency (e.g., 30 second) flow, density and speed data required; no alternative measures explored.
- Incident data are assumed to be all inclusive requiring extensive manual efforts for inspections/verifications.

Objective:

Leverage existing traffic detector systems for automatic incident detection (AID) with traffic detector data in relatively low time resolution and with incomplete incident data.

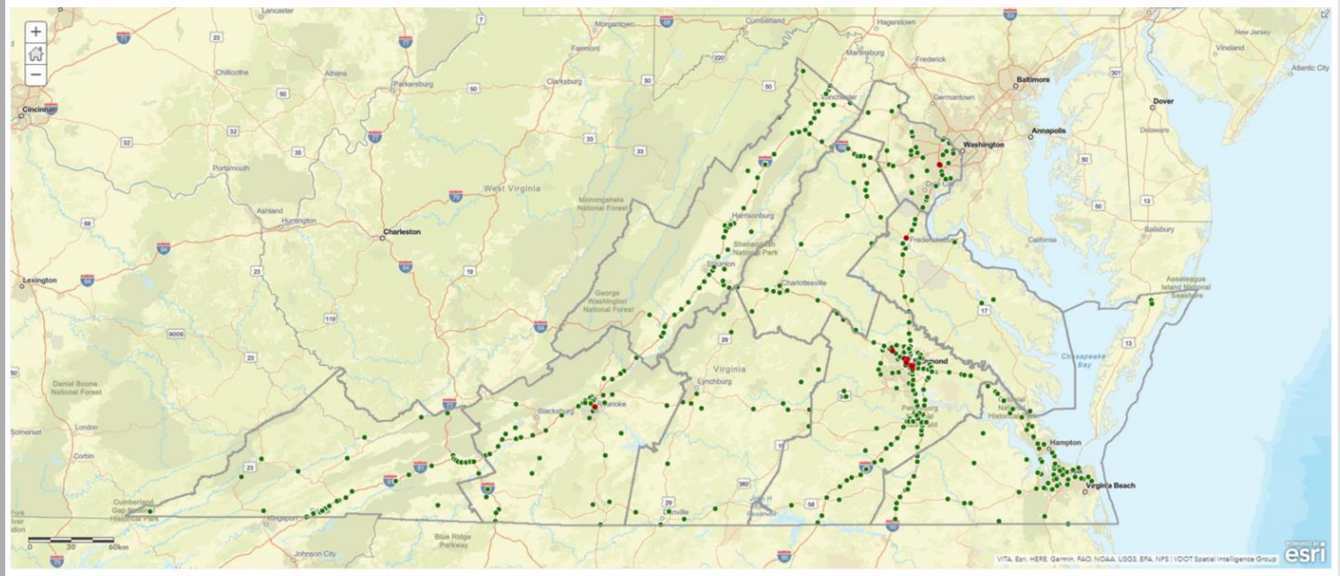


Figure 1. Spatial distribution of traffic detector stations in Virginia (Original Photo: © 2019 Esri®).

METHODOLOGY

Data Description:

- Traffic detector data (provided by Virginia Department of Transportation): continuously register the passing through vehicles and place them into different speed intervals. Data are archived every 5 or 15 minutes.
- Collision data (provided by Virginia Department of Motor Vehicles): time and location of each reported collision.

Definition and Assumption:

- Incidents refer to all types of traffic disruptive events leading to nonrecurrent changes in their surrounding traffic flow characteristics.
- Incident detection accuracy (in terms of both detection rate and false alarm rate) is positively related to the collision detection accuracy.

Balancing Problem:

- *Objective*: maximize the fraction of detected collisions to classified incidents.

METHODOLOGY (Continued)

- *Subject to:* collision detection rate should be greater than 80%; average number of classified incidents per day should be less than one.

Traffic Prediction Formulation:

- Structure of recurrent neural network (RNN):
  - Two direct temporal dependencies:
    - The nature of time series: the speed distribution of the next 15-minute period $(t+1)$ is dependent on the speed distribution of the present 15-minute period (t).
    - Repeating time-of-day and day-of-week traffic patterns: the speed distribution of the next 15-minute period is dependent on the speed distribution of the 15-minute period of the same time of day and same day of week in the past week ($t-m$, where $m = 60 \times 24 \times 7/15 - 1 = 671$).
  - Look-back steps of 3 accounting for the dynamics of traffic accumulation/dissipation.

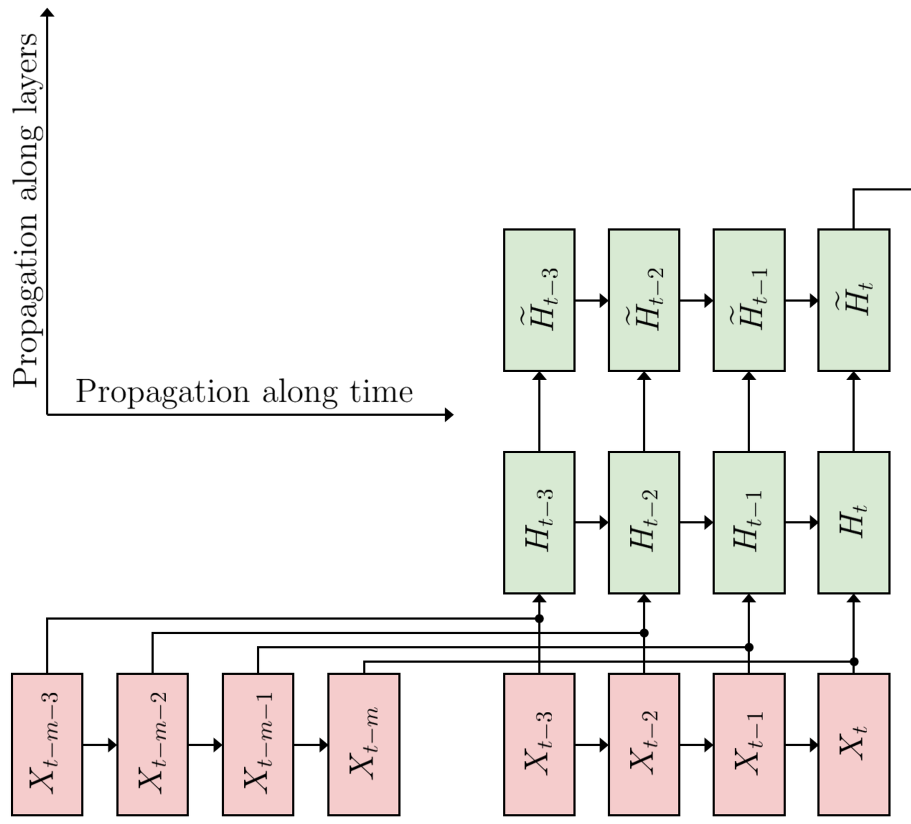


Figure 2. Structure of the applied RNN for traffic prediction.

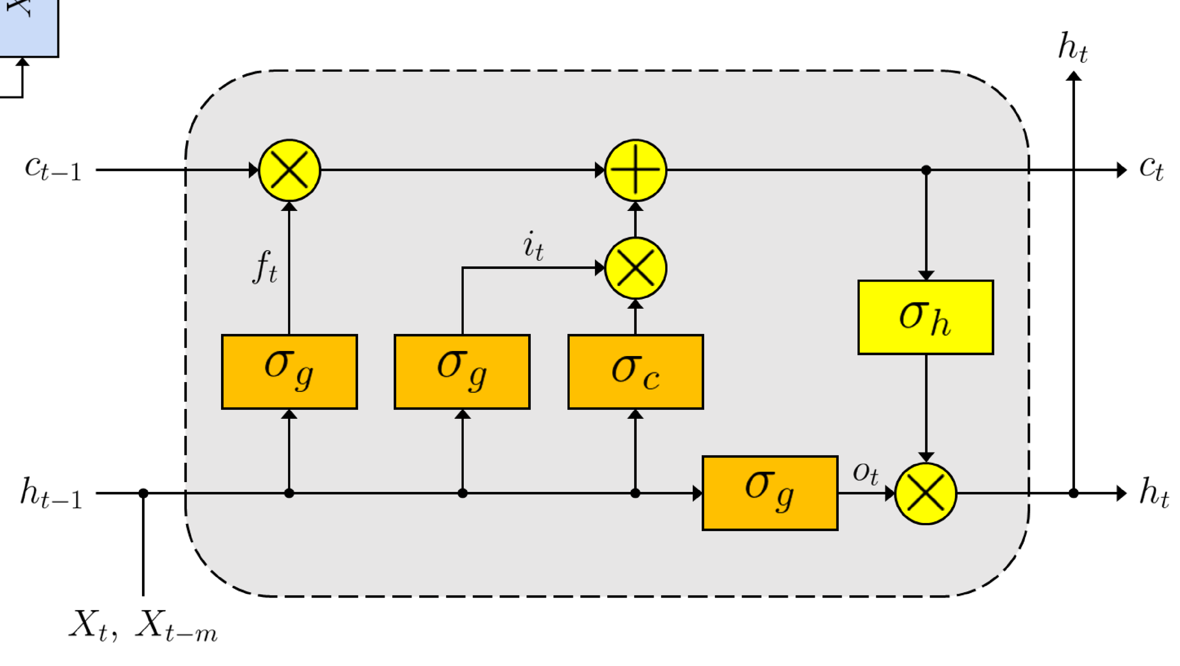


Figure 3. Illustration of the LSTM neural functionality (Gers et al., 1999).

- Long short-term memory (LSTM) neurons:

$$f_t = \sigma_g\left(W_f \tilde{X}_t + U_f h_{t-1} + b_f\right) \quad (1)$$
$$i_t = \sigma_g\left(W_i \tilde{X}_t + U_i h_{t-1} + b_i\right) \quad (2)$$
$$o_t = \sigma_g\left(W_o \tilde{X}_t + U_o h_{t-1} + b_o\right) \quad (3)$$
$$c_t = f_t \circ c_{t-1} + i_t \circ \sigma_c\left(W_c \tilde{X}_t + U_c h_{t-1} + b_c\right) \quad (4)$$
$$h_t = o_t \circ \sigma_h(c_t) \quad (5)$$

f_t, i_t and o_t ...... activation vectors for forget gate, input gate and output gate, respectively.

$\sigma_g(\cdot)$, $\sigma_c(\cdot)$, $\sigma_h(\cdot)$ ...... gate activation function, cell state activation function, output activation function, respectively.

$\tilde{X}_t$ ...... input vector.

h_t ...... output vector.

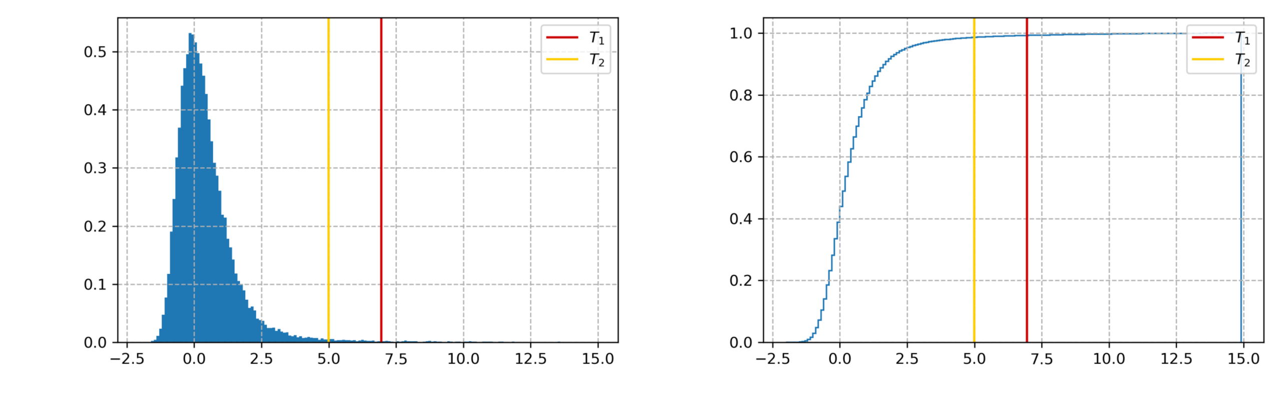
W's, U's and b's ...... the learned weight matrices and bias vectors.

Incident Detection Formulation:

- Measure of normality:
  - RMSE is adopted to evaluate the deviation from the predicted speed distribution to the observed speed distribution.
  - RMSE is further standardized by its time-of-day and weekday/weekend specific median and interquartile range (IQR).
- Outlier (incident) identification:
  - Incidents can be seen as the extreme cases in terms of the deviations from the original predictions to the actual observations, thus the derived standardized RMSEs.
  - Percentile values of standardized RMSEs adopted as incident-warning thresholds after calibration.
  - Two thresholds, T_1 (one-step check) and T_2 (two-consecutive-step check), are established for a timelier detection with less false alarms.

RESULTS

Statistics of Standardized RMSEs:



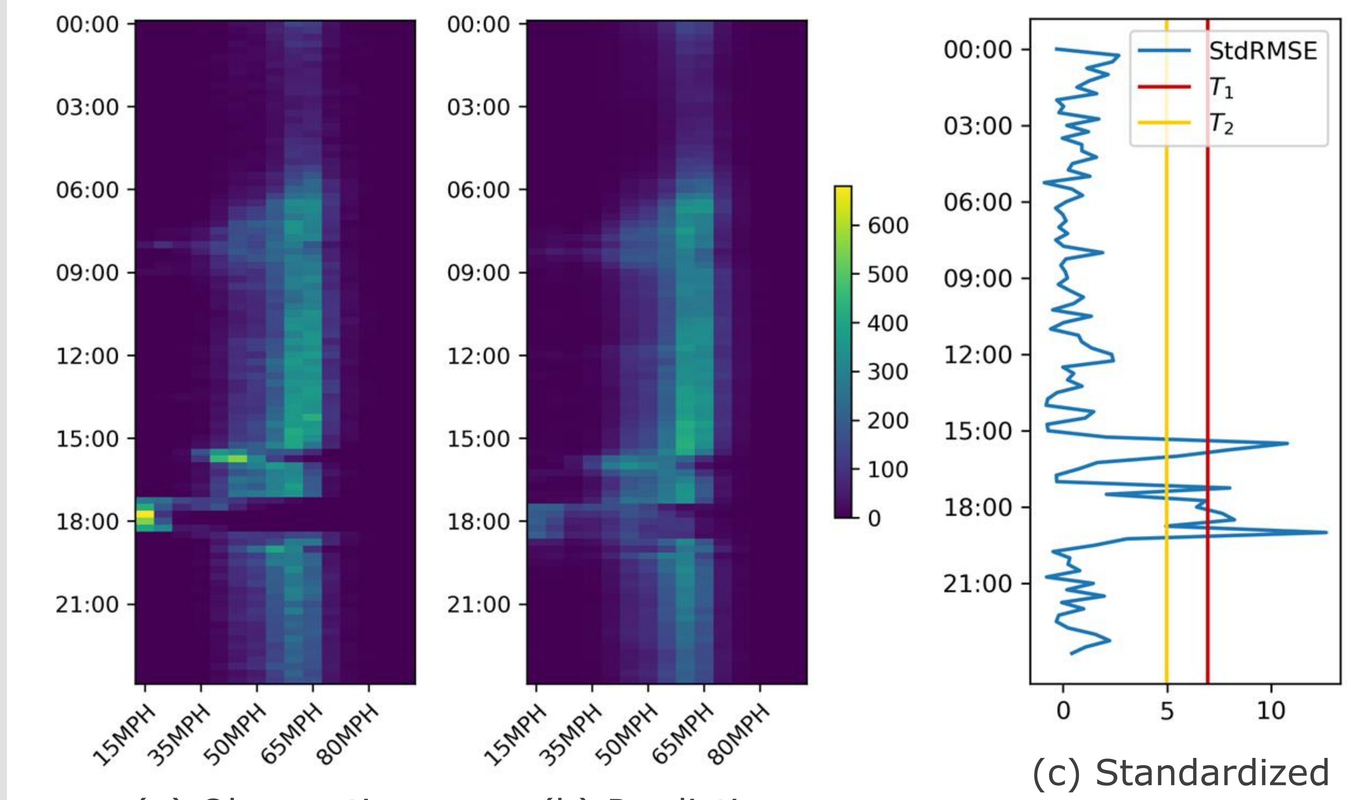
(a) Probability distribution function (PDF)   (b) Cumulative distribution function (CDF)

Figure 4. Statistical distributions of the standardized RMSE.

Detection Results:

Table 1. Comparison of Detection Results Between the proposed LSTM-RNN Algorithm and a Benchmark Algorithm

	Number of Documented Collisions	Number of Detected Collisions	Collision Detection Rate	Number of Classified Incidents	Collision to Incident Fraction	Incident Time Fraction
LSTM-RNN Algorithm	282	241	85.5%	4554	0.053	0.013
Benchmark Algorithm	282	231	81.9%	11763	0.020	0.087



(a) Observation   (b) Prediction   (c) Standardized RMSE

Figure 5. Illustration of incident detection.

CONCLUSIONS

Detection Results:

- Over 85% of the collisions can be detected.
- Detected collisions consist 5.3% of the classified incidents.
- Incident time occupies 1.3% of the total testing period.

Limitation and Future Research Direction:

- Only one incident type—collision—was analyzed. Data libraries of other types of traffic disruptive events, e.g., inclement weather and work zones, should be mined.
- Further classify incidents into different categories based on their spatial and temporal characteristics.

Reference:
Gers, F. A., Schmidhuber, J., and Cummins, F. (1999). Learning to forget: Continual prediction with LSTM. In 9th International Conference on Artificial Neural Network, Edinburgh, United Kingdom, 850-855.