Lane-changing Models, Data-driven model

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Publication

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Outline

1. Framework
2. Lane-changing decision: Deep Brief Network
3. Lane-changing implementation: Long Short-Term Memory
4. Validation

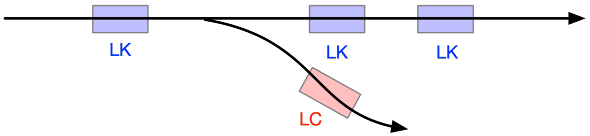
Framework

Two stages:

- LC Decision (LCD)
- LC Implementation (LCI)

Implementation in a multi-lane microscopic simulation

- Create a state label for each vehicle, namely, 'LC' or 'LK'
- Update the label of all vehicles, before updating positions
- Update the position of all vehicles



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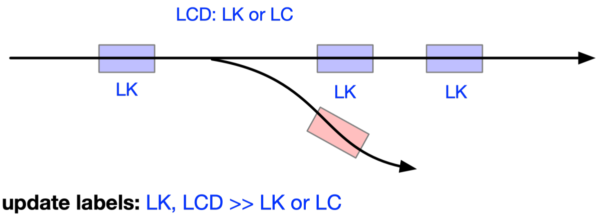

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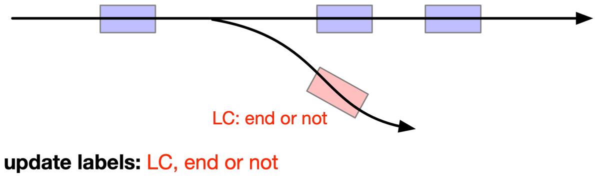

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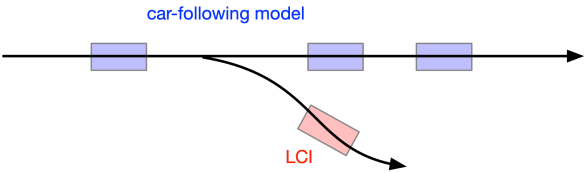


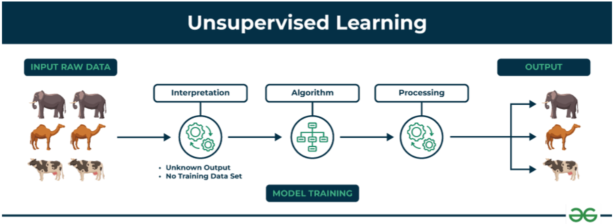
update positions

LCD: Deep Brief Network

- DBN is a generative graphical model developed by: Hinton et al, A fast learning algorithm for deep belief nets. Neural Comput, 2006 (Cited by 21,068)
- DBN can be trained layer-by-layer.
- DBN has simple network structure which can easily be designed in applications.
- In particular, the existing studies have been demonstrated that DBN can well predict stochastic events such as traffic accidents (Arief et al., 2016; Zhang et al., 2018).
- Therefore, this paper employs DBN to model LCD.

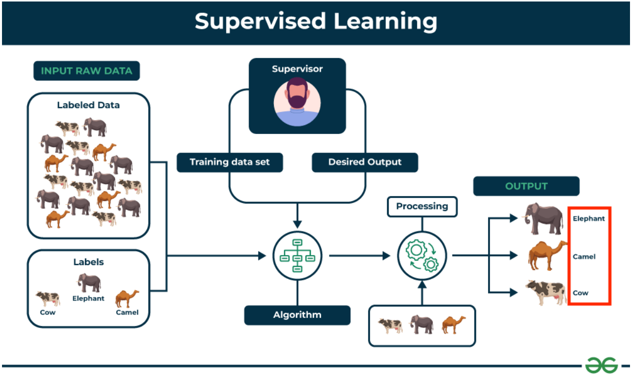
Unsupervised learning

Unsupervised learning is a type of machine learning that learns from data without human supervision.



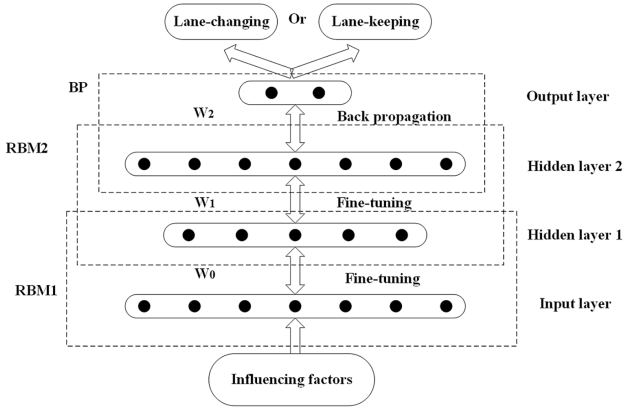
Supervised learning

Supervised learning is a category of machine learning that uses labeled datasets to train algorithms to predict outcomes and recognize patterns.



LCD: Deep Brief Network

The DBN training is unsupervised learning, and thus an NN structure based on the BP algorithm is added to the last layer for supervised learning.



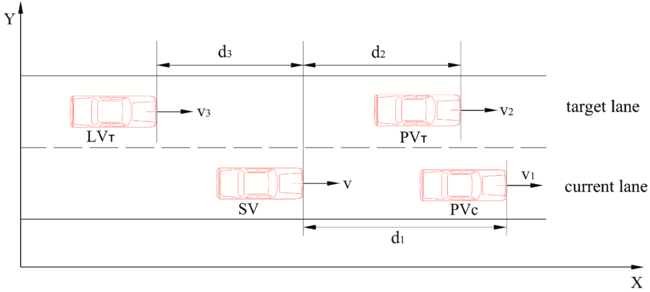
LCD: Deep Brief Network

Why unsupervised learning + supervised learning

- When using DBN for unsupervised learning, it learns the data distribution and extracts useful features, but these features might not be directly useful for our specific supervised task, i.e., we still don't know what it is (label).
- For instance, let's consider a handwritten digit recognition task; DBN might learn basic features like edges, lines, and shapes, but it doesn't know which features are most discriminative for distinguishing between, say, digits 1 & 7.
- To apply the features learned by DBN to a supervised learning task, we need to connect the output layer of the DBN to an additional neural network, which will take the features extracted by DBN and use them for classification.

LCD: Scenario

SV: Subject Vehicle, **PV**: Preceding Vehicle, **LV**: Lag Vehicle



LCD: Deep Brief Network

Input and output

	Variables	Variable descriptions
Inputs	$v(t_{LC} - t)$	Velocity of SV
	$\Delta v_1(t_{LC} - t)$	Velocity differences between SV and PV_c
	$\Delta v_2(t_{LC} - t)$	Velocity differences between SV and PV_T
	$\Delta v_3(t_{LC} - t)$	Velocity differences between SV and LV_T
	$d_1(t_{LC} - t)$	Space headway between SV and PV_c
	$d_2(t_{LC} - t)$	Space headway between SV and PV_T
	$d_3(t_{LC} - t)$	Space headway between SV and LV_T
Outputs	Dec	Binary decision: changing lane or not (Eq. (1))

LCD: Deep Brief Network

Performance evaluation

Mean Squared Error (MSE) is taken as the performance index in traing and testing the proposed DBN-based LCD model

$$\mathrm{MSE} = \frac{\sum_{k=1}^{M} (\mathrm{Dec}_k - \mathrm{Dec}'_k)^2}{M}$$

where M is the total number of trajectories that are used in the training and testing; Dec_k and Dec'_k are the ground-truth and predicted binary decision values at time step k.

The goal of training is to obtain the optimal θ such that the MSE can be minimized.

$$\min_{\theta \in \Omega} = \mathrm{MSE}_\theta$$

LCI: Long Short-Term Memory

- LSTM is an essential tool for processing sequential data due to its ability to handle long-term dependencies, prevent vanishing gradients, applicability to various sequence tasks, flexibility, and generalization ability. It has achieved significant success in various fields.
- Historical movements that are seconds before current time should be taken into account, since LC is a continuous driving process. Therefore, LSTM is employed to model the two-dimensional LC trajectory by taking its advantage in considering historical data.

Long short-term memory

S Hochreiter, J Schmidhuber - Neural computation, 1997 - ieeexplore.ieee.org

Learning to store information over extended time intervals by recurrent backpropagation takes a very **long** time, mostly because of insufficient, decaying error backflow. We briefly review …

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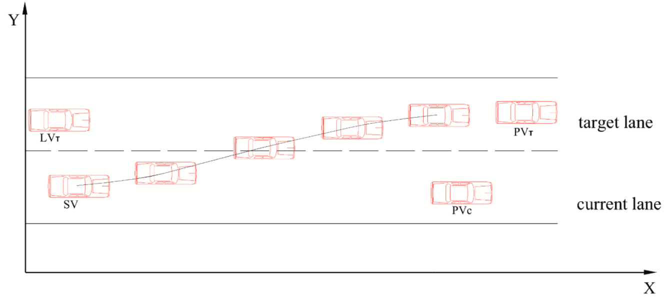
LCI: Scenario

SV: Subject Vehicle, **PV**: Preceding Vehicle, **LV**: Lag Vehicle



LCI: Long Short-Term Memory

Input and output

	Variables	Variable descriptions
Inputs	$v(t)$	Velocity of SV
	$v_1(t)$	Velocity of PV_c
	$v_2(t)$	Velocity of PV_T
	$v_3(t)$	Velocity of LV_T
	$d_1(t)$	Space headway between SV and PV_c
	$d_2(t)$	Space headway between SV and PV_T
	$d_3(t)$	Space headway between SV and LV_T
	$x(t)$	Longitudinal position of the subject vehicle
	$y(t)$	Lateral position of the subject vehicle
	X	Historical longitudinal positions
	Y	Historical longitudinal positions
Outputs	$x(t+\Delta t)$	Longitudinal position of the subject vehicle at next time step
	$y(t+\Delta t)$	Lateral position of the subject vehicle at next time step

LCI: Long Short-Term Memory

Performance evaluation

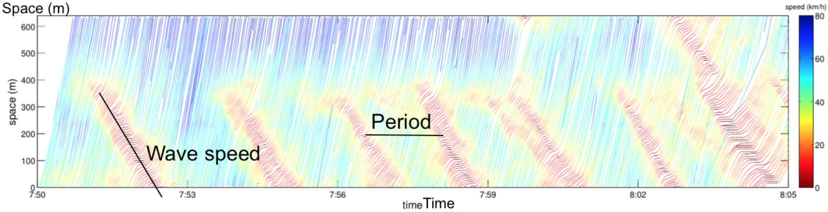
Mean Squared Error (MSE) is taken as the performance index in traing and testing the proposed LSTM-based LCI model

$$\text{MSE} = \frac{\sum_{k=1}^{T}[(x_k - x'_k)^2 + (y_k - y'_k)^2]}{T}$$

where T is the number of time intervals discretizing the LC process; x_k and x'_k are the ground-truth and simulated longitudinal positions at time step k; y_k and y'_k are the ground-truth and simulated lateral positions at time step k

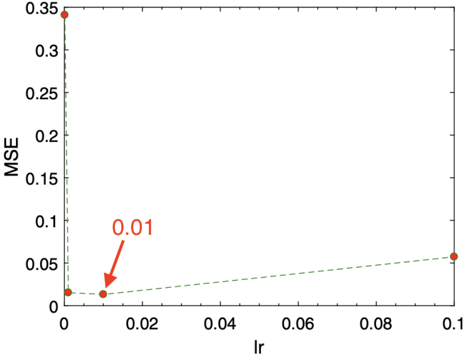
Validation - LCD: Data

- NGSIM: US-101 and I-80
- Lanes 1-4
- 1078 LC vehicles
- 1120 LK vehicles: spatiotemporal neighbor of the LC vehicles



Validation - LCD: Learning Rate

Learning rate determines the size of the steps taken to adjust the model parameters during training (like searching in feasible region). It controls the magnitude of parameter updates in each iteration. If too small, the model may converge too slowly; vice versa.



Validation - LCD: Cross-validation

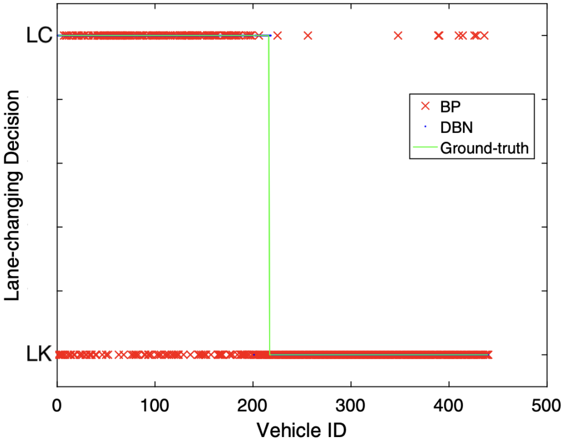
80% training, 20% testing — standard

	MSE	Accuracy
Training 1	0.0132	99.32%
Training 2	0.0148	97.05%
Training 3	0.0158	96.59%
Training 4	0.0135	98.64%
Training 5	0.0160	96.82%

Model	MSE	Accuracy
DBN (Test 1)	0.0132	99.32% †
DBN (Test 2)	0.0168	96.04%
DBN (Test 3)	0.0162	96.14%
DBN (Test 4)	0.0169	95.16%
DBN (Test 5)	0.0143	97.73%
BP	0.3102	76.82%
Logit	0.39	61.30%

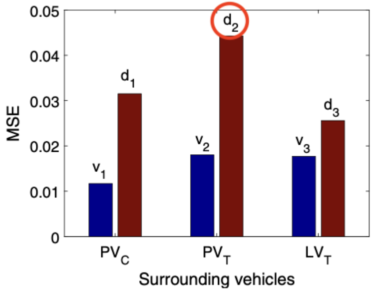
Validation - LCD

All 440 testing samples: DBN (2 miss) vs. BP (102 miss)



Validation - LCD: Insights

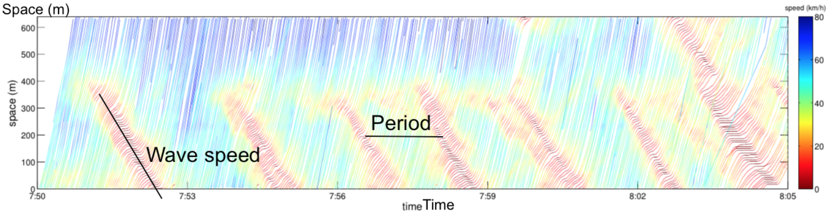
It is known that LCD mainly depend on the conditions of the surrounding vehicles. However, it is unclear which one of the surrounding vehicles has the most essential impact on LCD.



The incremental MSE when one variable of the surrounding vehicle is removed answers the question

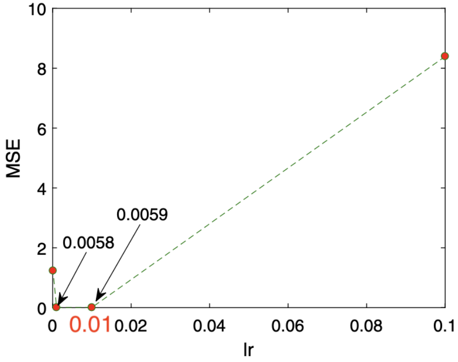
Validation - LCI: Data

- NGSIM: US-101 and I-80
- Lanes 1-4
- 530 LC vehicles: filtered from 1078
- 90% training, 10% testing



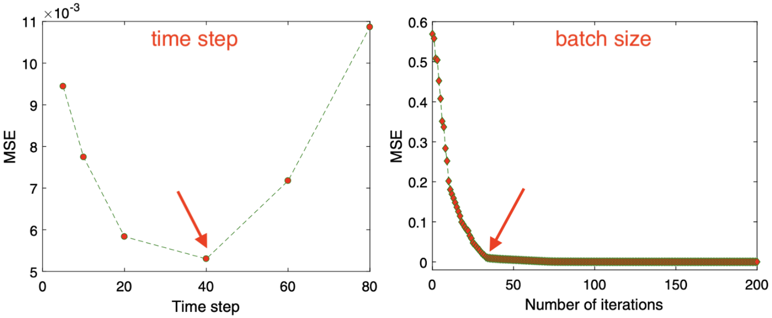
Validation - LCI: Learning Rate

Learning rate determines the size of the steps taken to adjust the model parameters during training (like searching in feasible region). It controls the magnitude of parameter updates in each iteration. If too small, the model may converge too slowly; vice versa.

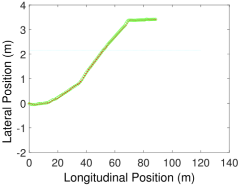


Validation - LCI: Other parameters

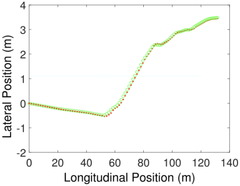
Time Step & Batch Size



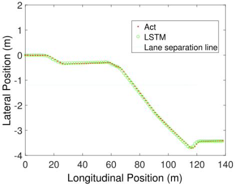
Validation - LCI



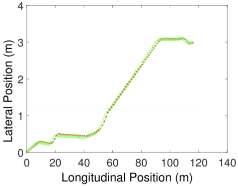
(a) Vehicle ID: 26



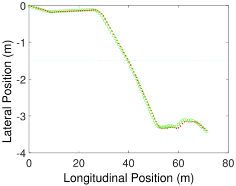
(b) Vehicle ID: 11



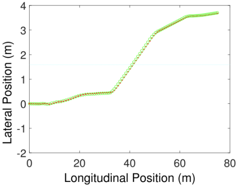
(c) Vehicle ID: 3



(d) Vehicle ID: 21

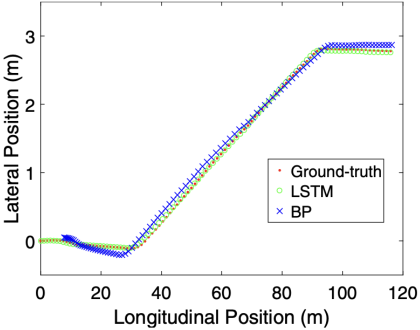


(e) Vehicle ID: 41



(f) Vehicle ID: 53

Validation - LCI: LSTM vs. BP



Thank you!