Probabilistic Modeling of Vehicle Acceleration and State Propagation With Long Short-Term Memory Neural Networks

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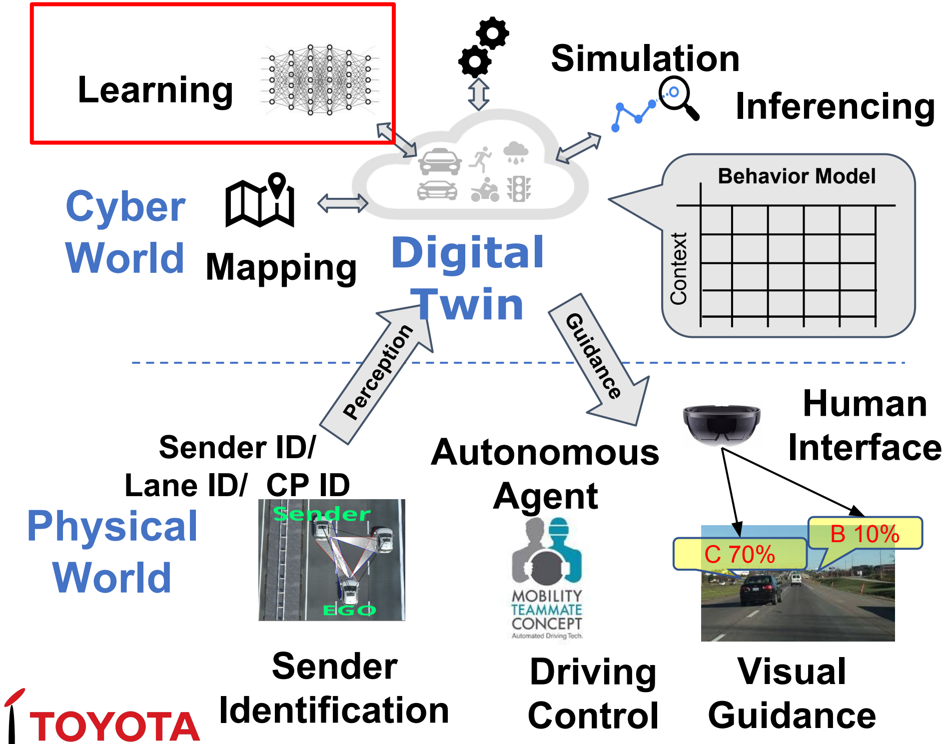
Research goals

- To predict vehicle one-dimensional (acceleration) trajectories given minimal observed vehicle traffic data
- From these acceleration predictions, we can generate future states and use these as input to propagate simulated vehicle trajectories

Motivation



- Intelligent Driver Assistance
- KT's research into freeway on-ramp merging
- Advanced cruise control

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Past research

- Fixed-form car-following models

$$a_n(t) = c v_n^m(t) \frac{\Delta v(t-T)}{\Delta x^l(t-T)}$$

- Deterministic car-following models

- Neural driving models

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Problem statement

Utilize Long Short-Term Memory (LSTM) neural networks to predict vehicle one-dimensional acceleration trajectories given minimal observed vehicle traffic data

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Approach

- Implement various LSTM neural networks that output acceleration distributions
- Consider acceleration and velocity of ego vehicle, as well as relative distance and relative speed difference between ego and other vehicles
- Not reliant on other vehicles sharing data
    - Could be improved given access to other vehicle’s data (occlusion)

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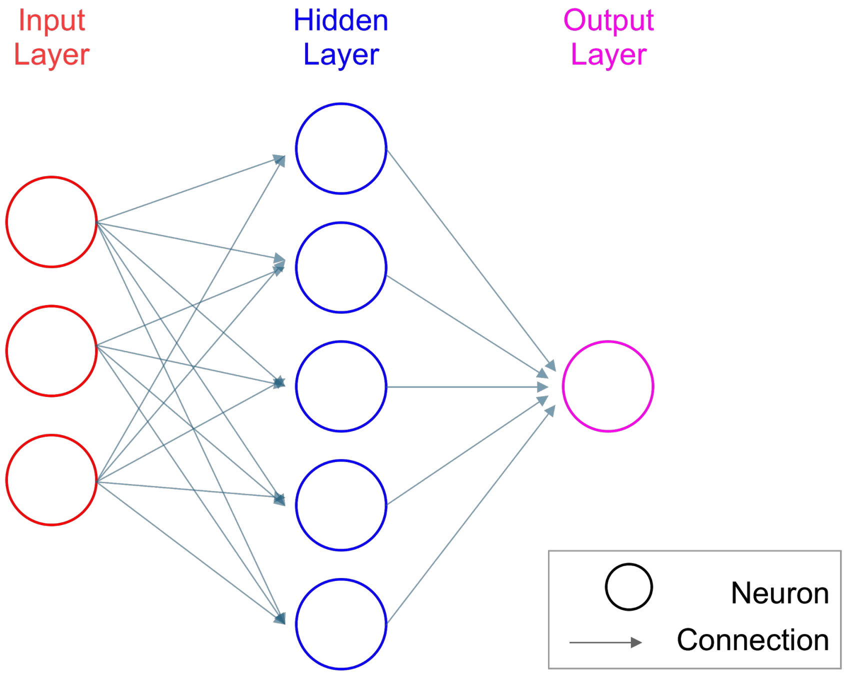
Neural Networks



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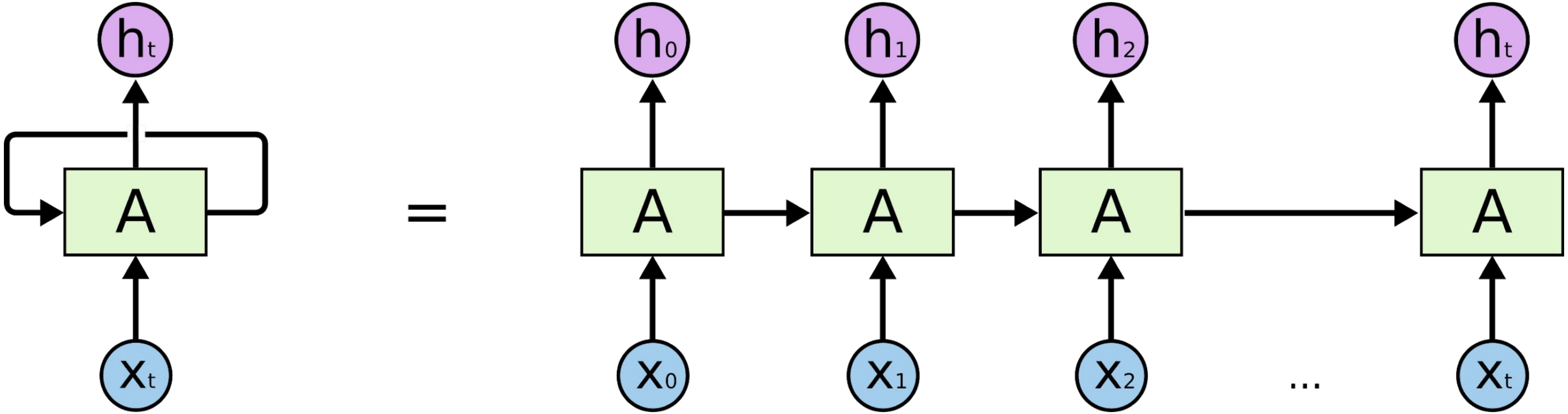
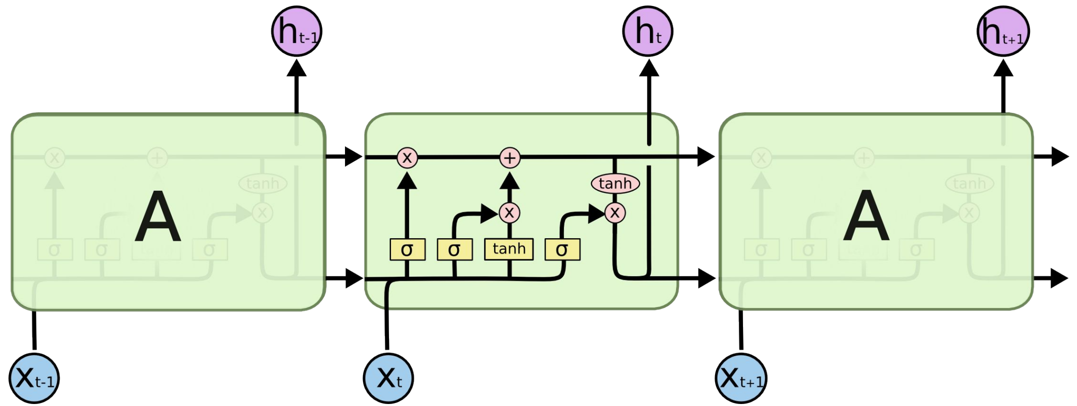
Basic Neural Network Structure

Recurrent Neural Networks (RNNs)



Recurrent Neural Network Cell

Long Short-Term Memory (LSTM) Neural Networks



Long Short-Term Memory Neural Network Cell

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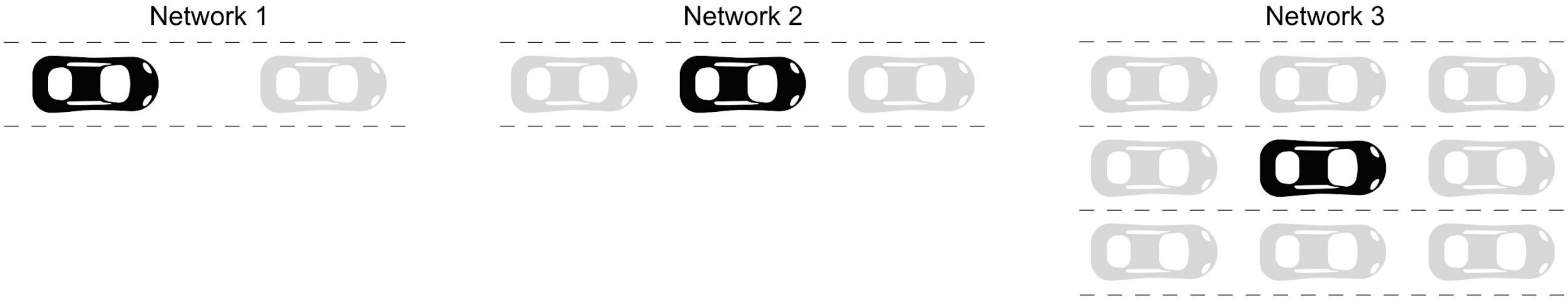
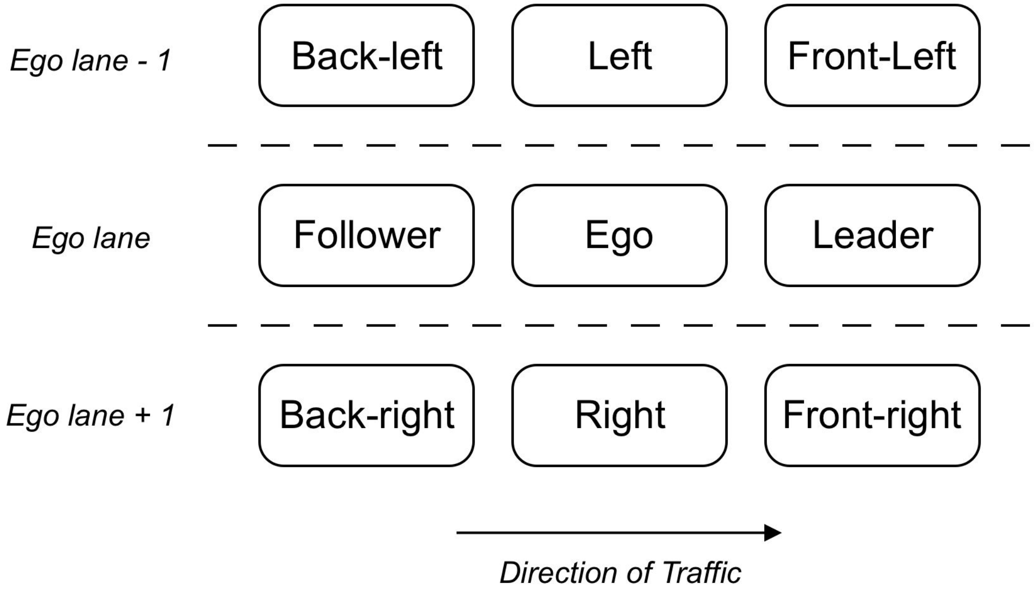
Input states



Inputs for 3 different networks, ego vehicle is black

Data preparation

- NGSIM highway I-80 reconstructed dataset, ~1million inputs



Neighboring vehicles grid

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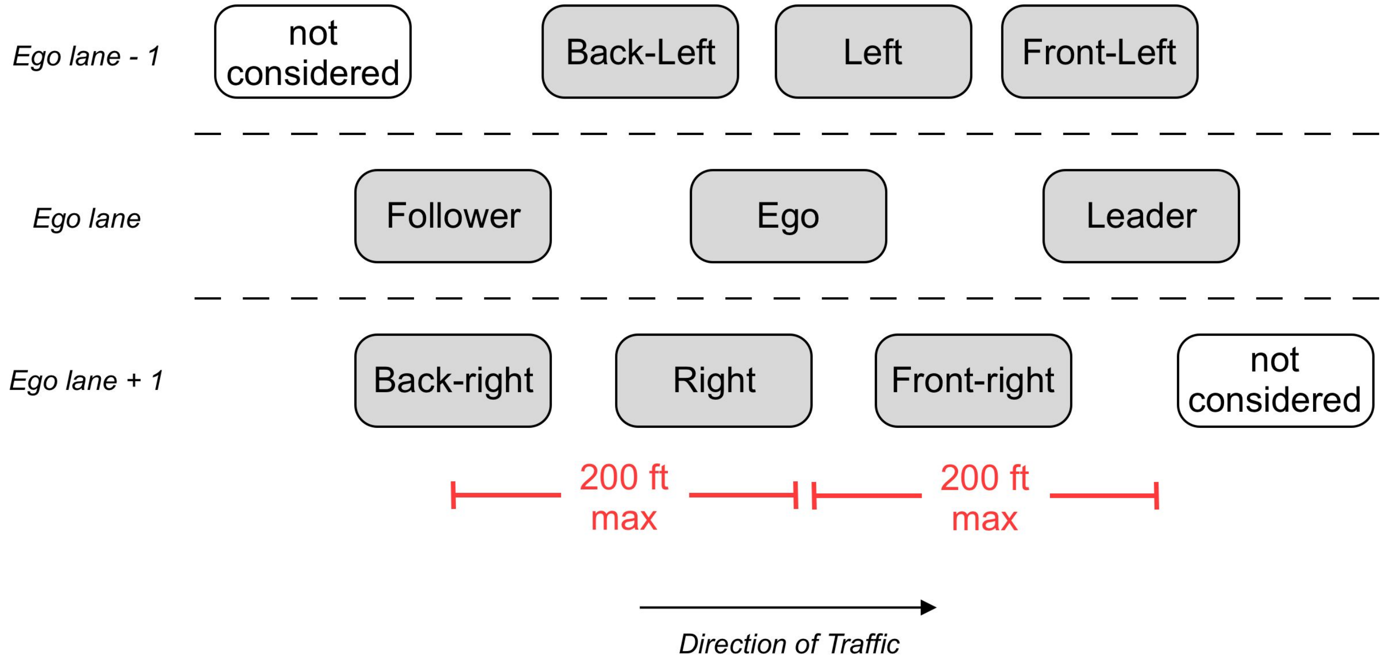
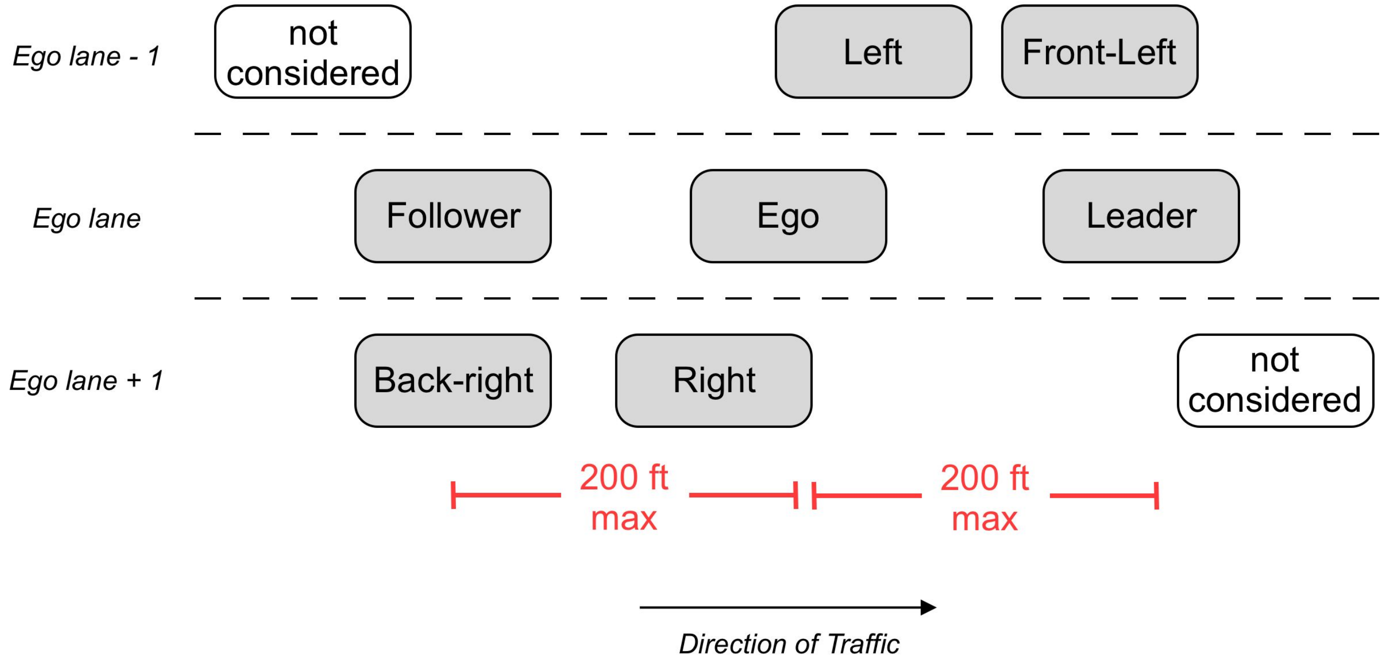
Data preparation



Boundary of 200 feet

Data preparation



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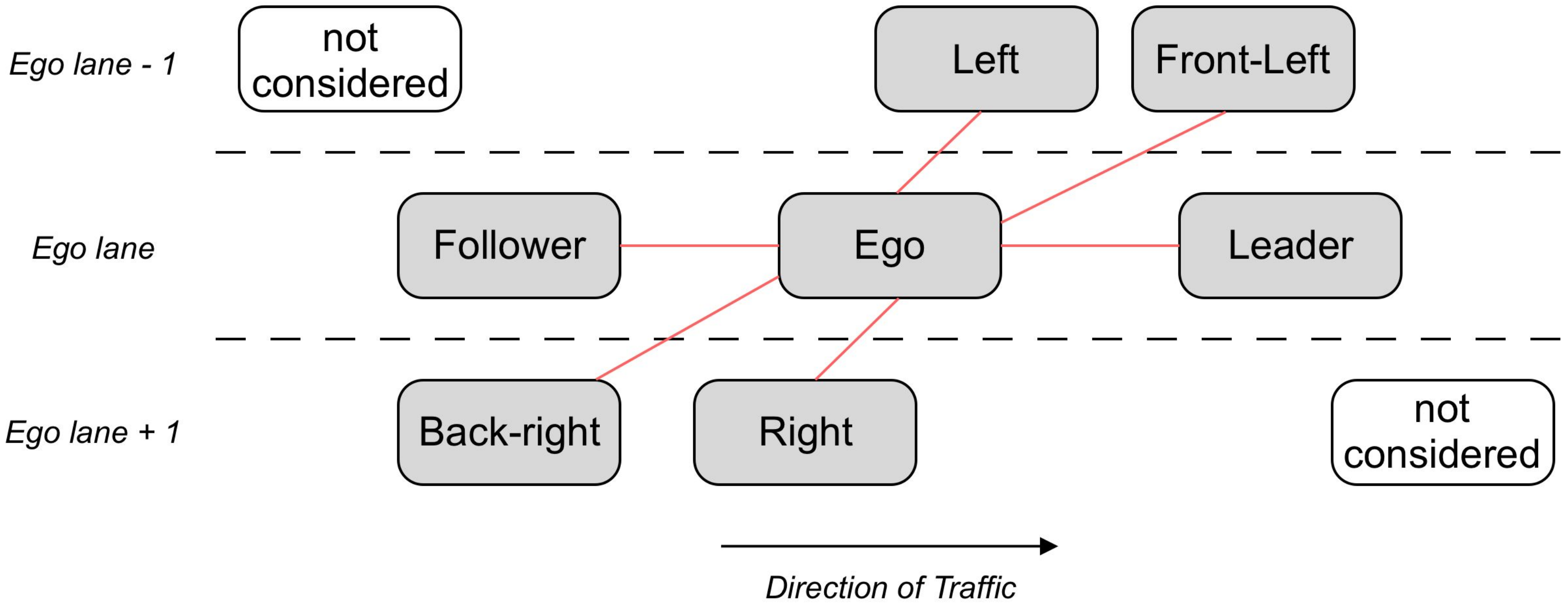
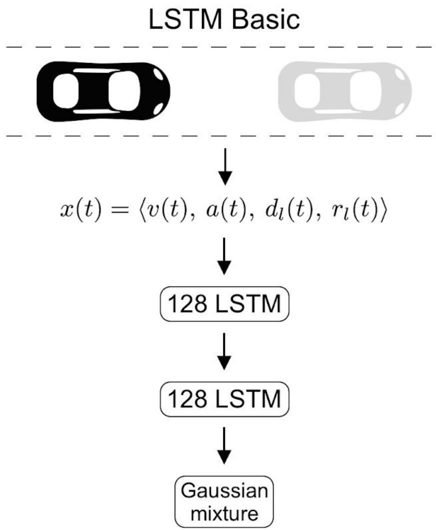
Max of 8 neighbors within boundary considered

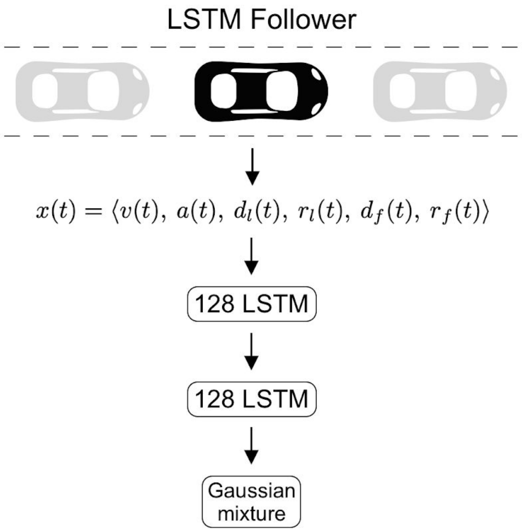
Data preparation

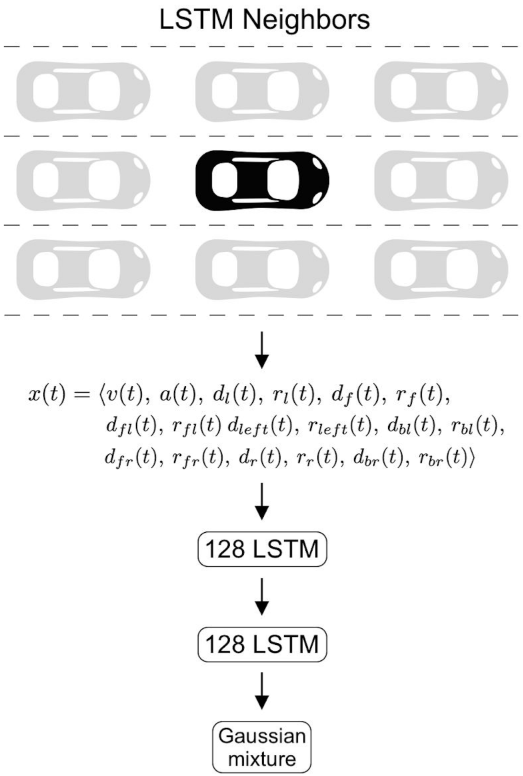


RADAR/LIDAR detection

Network architecture







Networks from input to output

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Hyperparameter details

- Variables that determine network behavior, set before training and adjusted
- Learning rate 4×10^{-3}
- Decay at a rate of 0.97 starting after third epoch of training
- 2 LSTM layers, 128 neurons each
- Dropout rate 0.25
  - Counters overfitting by reducing chance of co-adaption
- Models trained for 10 epochs or until learning stabilized

Experiments

- Models trained and evaluated on ability to predict future timestep acceleration distributions and produce “realistic” trajectories
- 10-fold cross validation
- Training:
  - First 2 seconds of input data used to initialize internal state of LSTM network
  - Learned on last 10 seconds of each trajectory
    - ~8,000 10-second trajectories to learn on
- Testing:
  - Initial 2 seconds of true data supplied to network
  - Network output acceleration distributions for each timestep
  - At each timestep, 50 samples taken from distribution, input state for subsequent timestep generated

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Evaluation metrics

- Root mean squared error (RMSE)

$$RMSE = \sqrt{\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(v_H^{(i)} - \hat{v}_H^{(i,j)})^2}$$

- Ability to produce realistic trajectories
  - Frequency of negative distance headway
  - Frequency of negative speed

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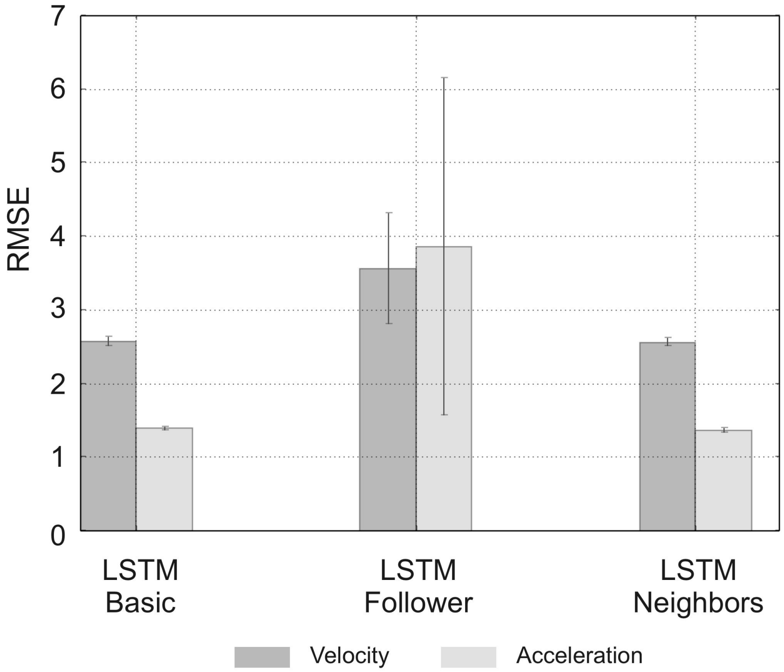
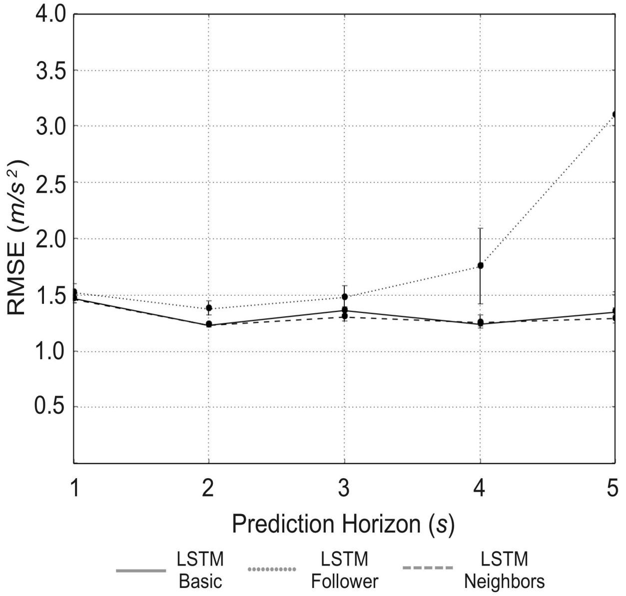
Results: Error

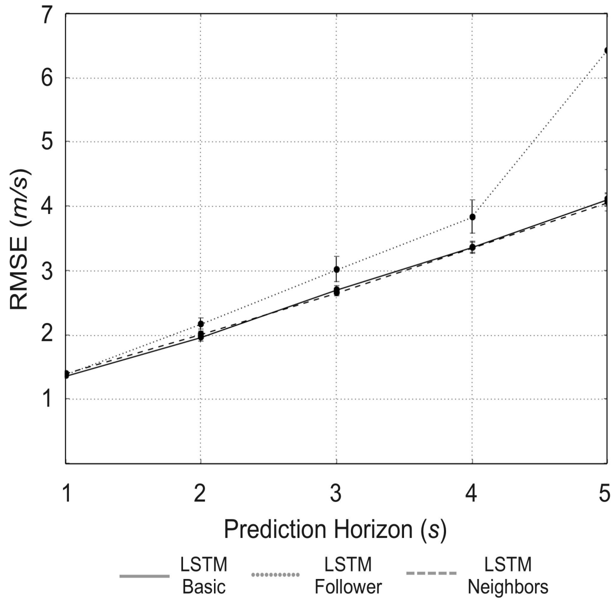
- LSTM Neighbors and LSTM Basic have relatively identical RMSE
- LSTM Follower performs worse
  - Interestingly, because its input state is LSTM Basic's input state plus Follower distance headway and relative speed difference



RMSE for acceleration & velocity predictions

Results: Error

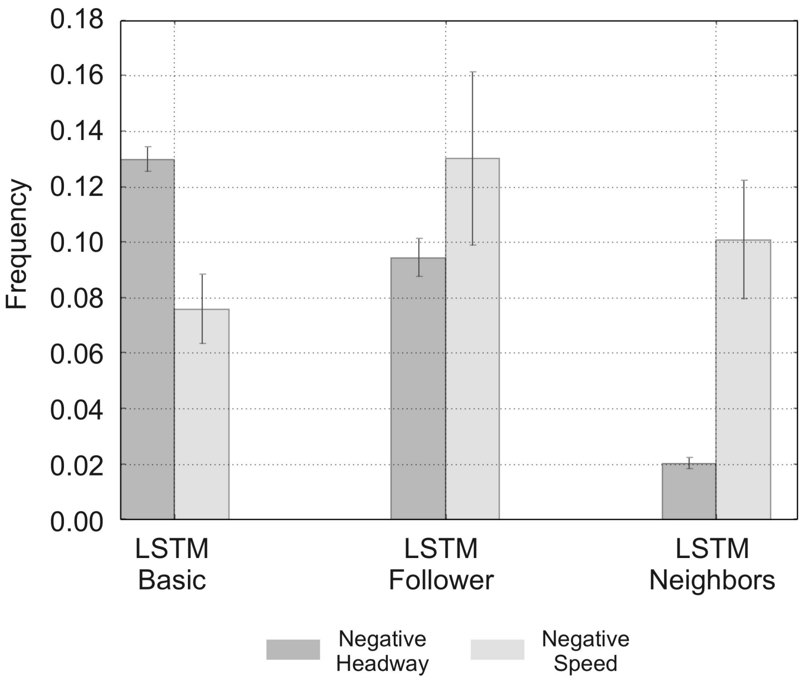




RMSE across prediction horizons

Results: Negative state values

- Negative state values correspond to unrealistic simulated trajectories
- Negative headway distance corresponds to a collision
- Negative speed corresponds to driving in reverse



Frequency of negative state values

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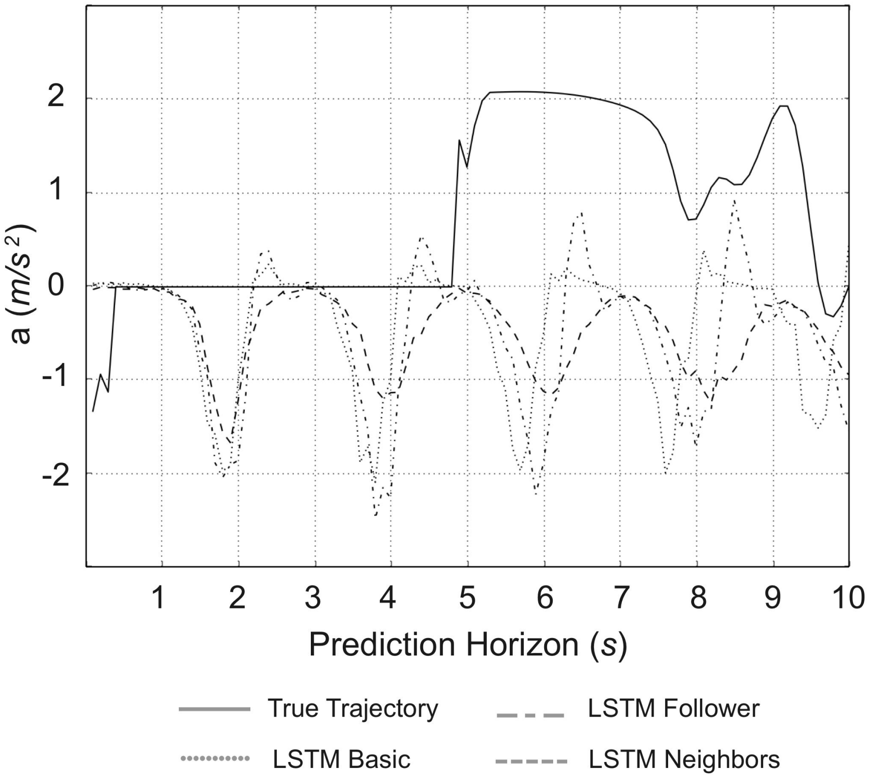
Results: Trajectory comparison



Networks perform poorly when predicting uncommon trajectories

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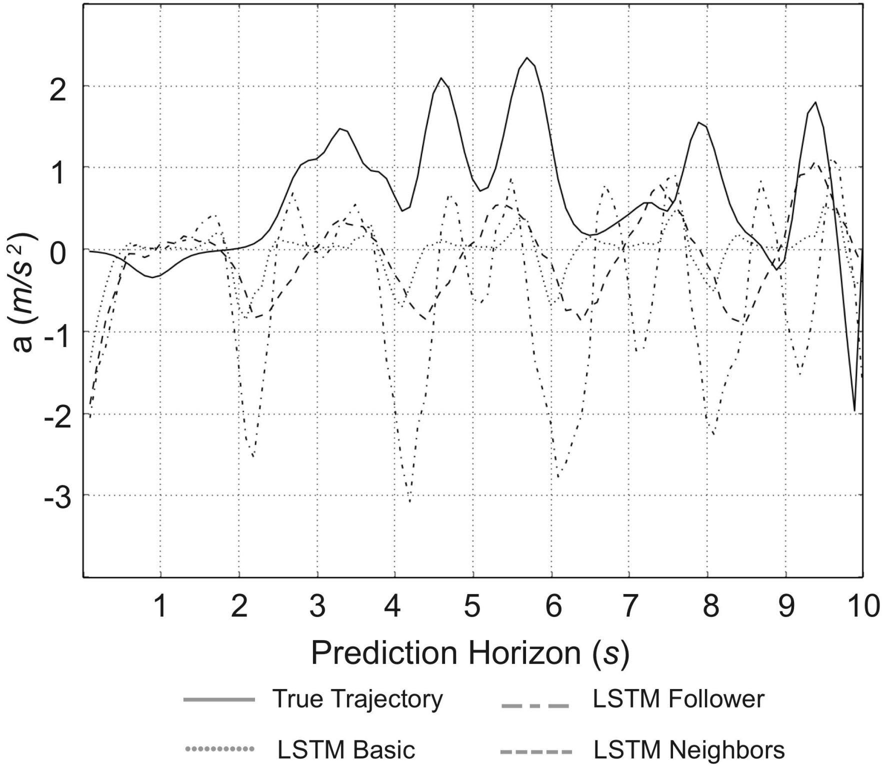
Results: Trajectory comparison



LSTM Follower exaggerates predictions

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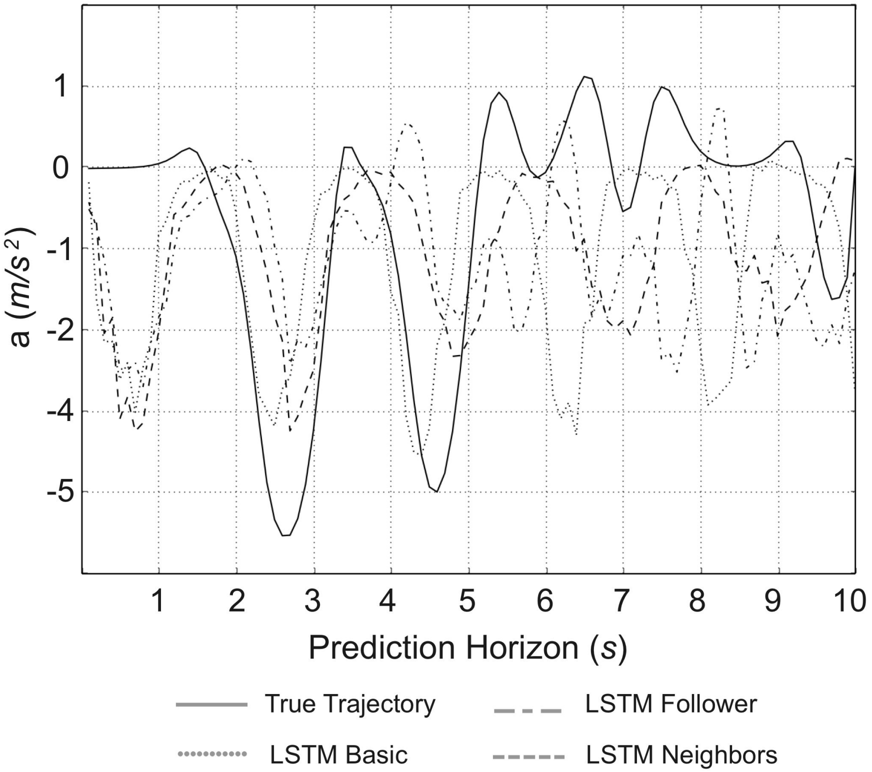
Results: Trajectory comparison



Accurate in first 5 seconds

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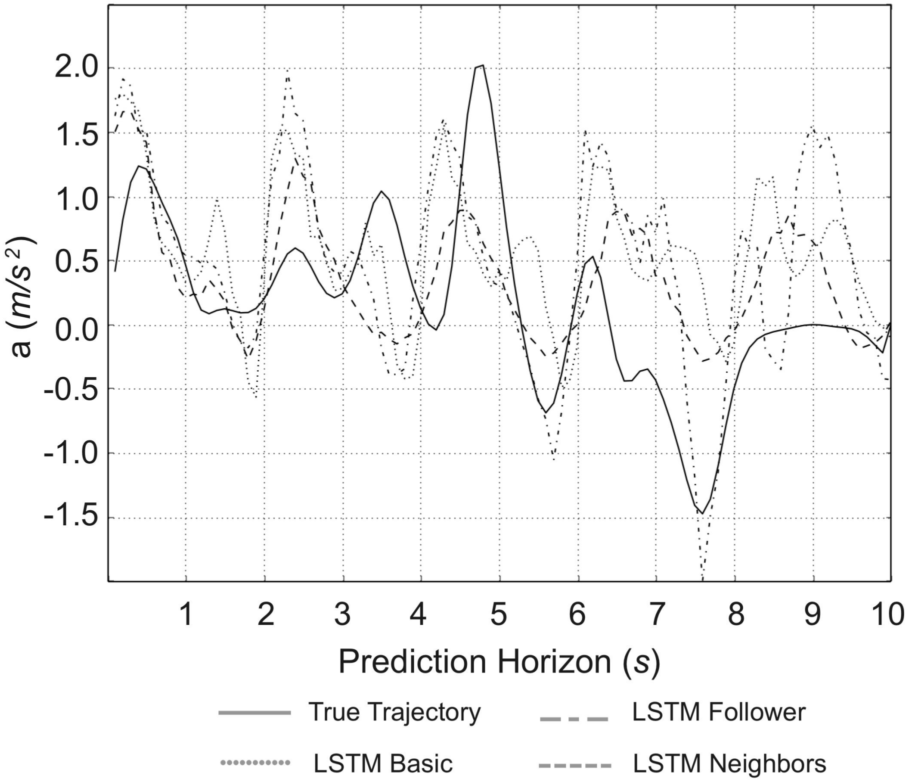
Results: Trajectory comparison



Accurate in first 5 seconds

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Conclusion

- LSTM Neighbors most successful
- Networks are capable of complex prediction and simulation in one dimension
- Generating distributions allows for generalizability
- High level: method to generate vehicle trajectories with low collision rate

Future work

- Network to predict lane changing behavior
  - Relatively simple based off current method
  - Need to define “lane changing” in terms that a network could learn from
- Unity Sender Identification Simulator
  - Visualize real and simulated trajectories
- Use networks to generate data

Thanks!