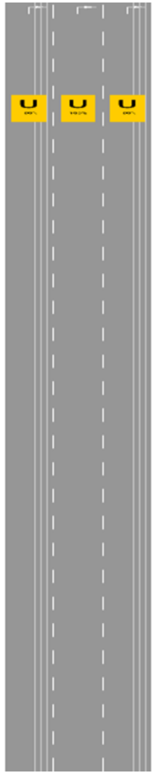
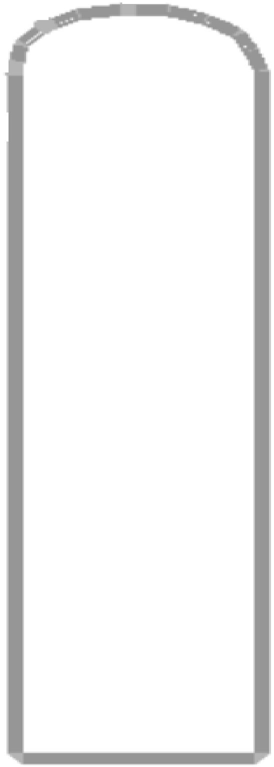
Collision Prediction Based On Semantic Relations

30220 - Master Thesis Presentation
Rakesh Allampally, Chemnitz, February 2021

Contents:

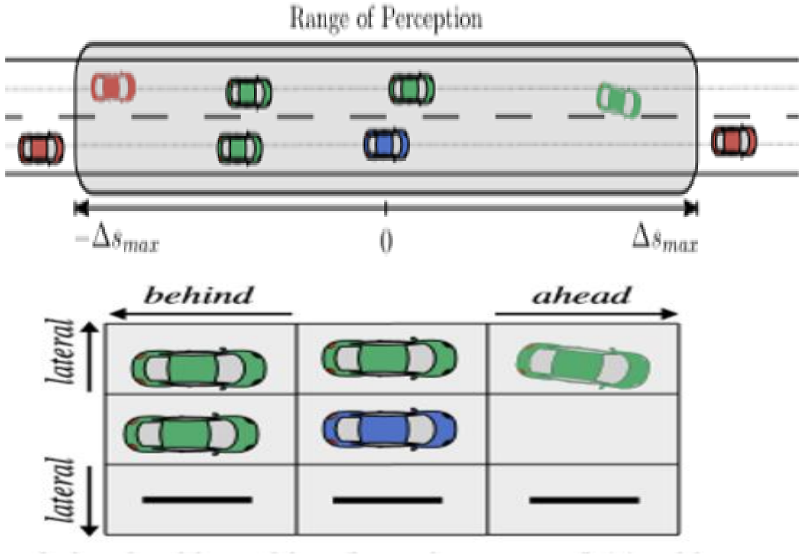
SUMO

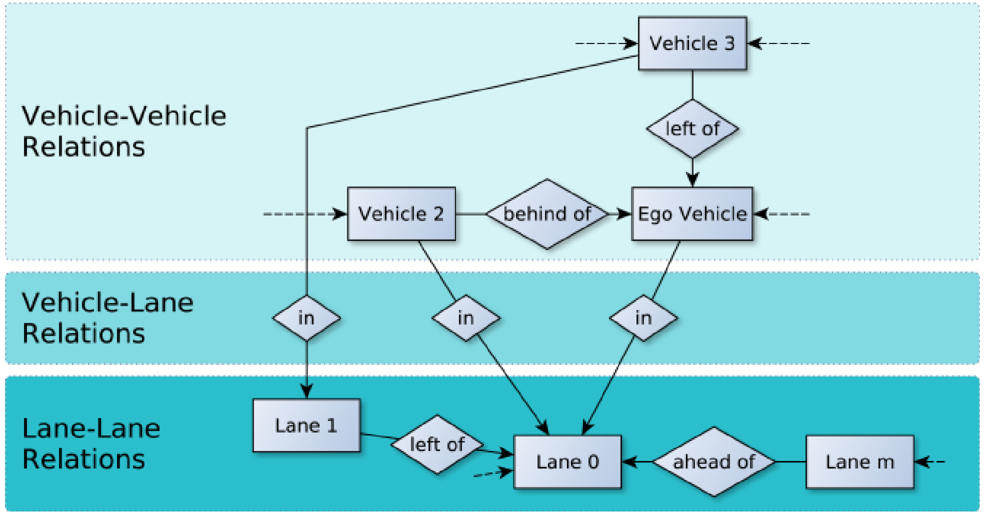




Highway Scenario in SUMO

Semantic Entity Relation (Approach-1)





Relational Grid Model [1]

→ **At each time step we get the information of all the objects in the scene and their relations**

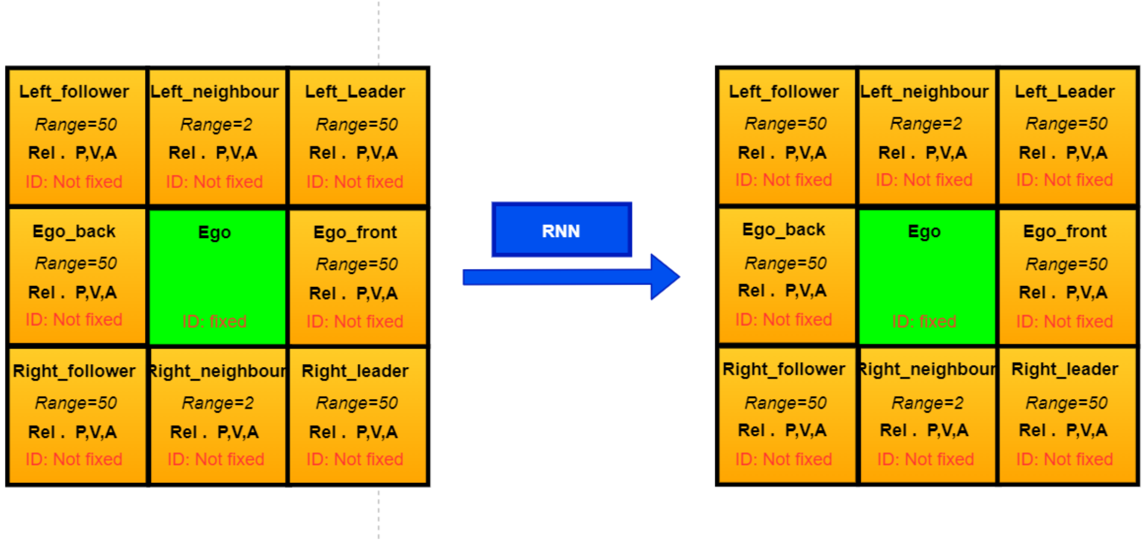
[1] https://www.groundai.com/project/adaptive-behavior-generation-for-autonomous-driving-using-deep-reinforcement-learning-with-compact-semantic-states/1

Goals

- **Use semantic entity relationship model to get complete overview of the scene.**
- **Use RNN to predict trajectory of all the vehicles in the scene by using the past trajectory.**
- **Finally, developed model test on various collision probable scenarios.**

Basic Overview of Approach

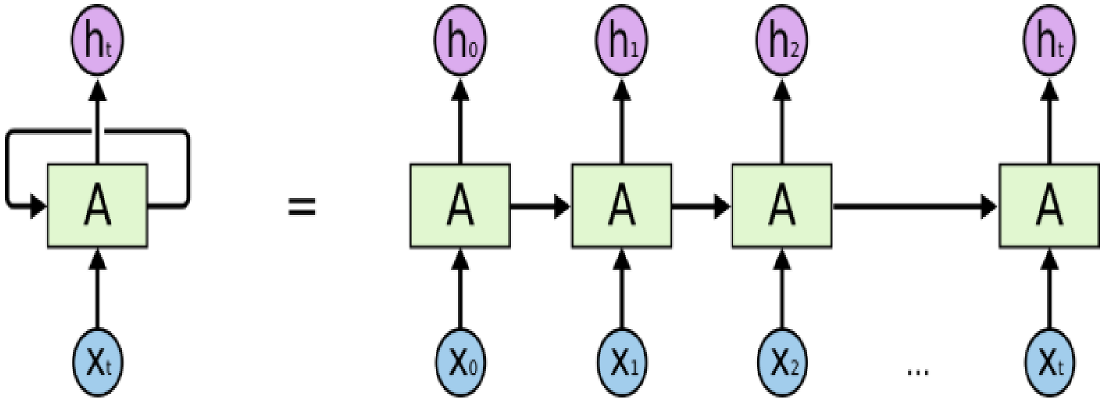
- For each time stamp, the Ego vehicle and its surroundings are considered.
- The surroundings are in the range of 50 meters.
- ID of the Ego vehicle is fixed but remaining vehicles IDs keeps changing.
- Rel. P, V, A = Relative position, velocity, acceleration with respect to Ego.



Relational Grid Model

Recurrent Neural Networks

- **The output from the previous step is fed as input to the current step along with the current Input.**
- **It has a hidden state, which remembers the information about a sequence.**
- **Hidden state at time 't',** $h_t = f\left(h_{t-1}, x_t\right)$
- x_t **= Input at time 't'**

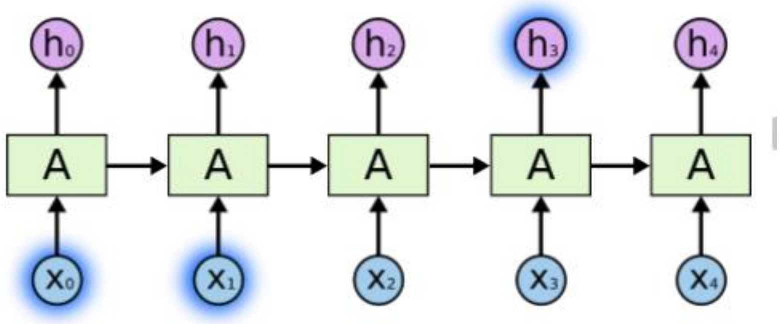


Recurrent Neural Networks [2]

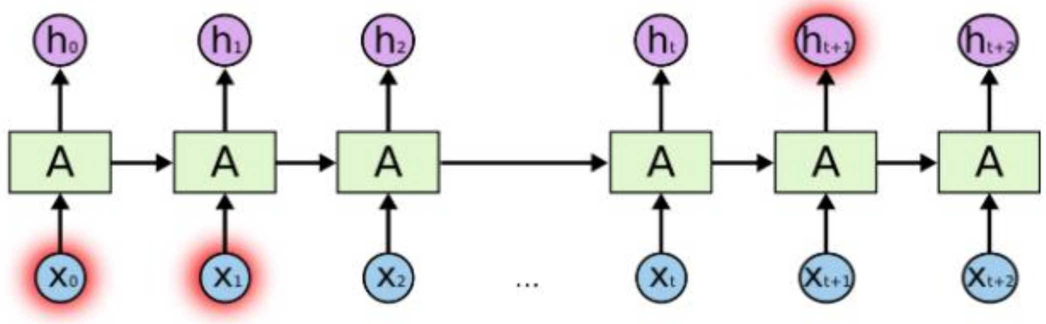
[2] https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Problem with RNN

The main problem of RNN is long term dependency.



Less Time Steps [2]

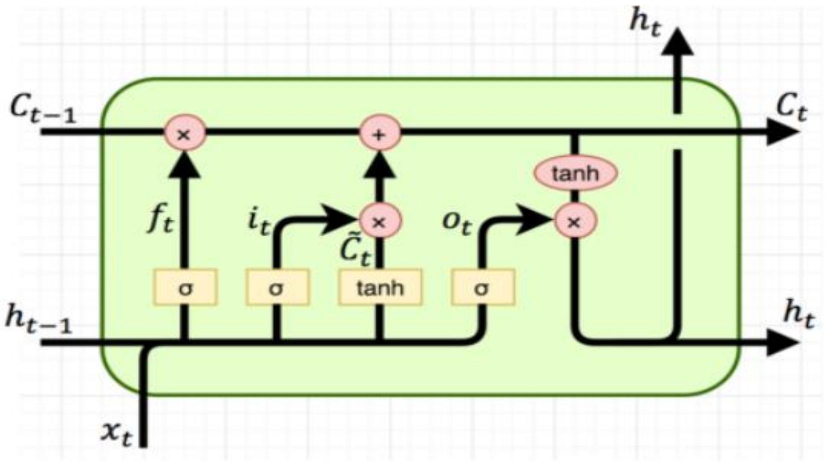


More Time Steps [2]

[2] https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Long Short Term Memory Network (LSTM)

- **In LSTM both cell state $'c_t'$, hidden state $'h_t'$ are passed to the next time step.**
- **Cell state acts as memory of the network and carries relevant information throughout processing of the sequence.**
- **In LSTM the the 3 gates namely Input gate, Forget gate, Ouptut gate decide which information is allowed on the cell state.**

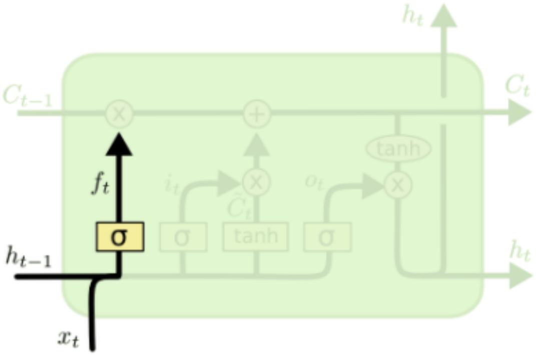


LSTM [2]

[2] https://colah.github.io/posts/2015-08-Understanding-LSTMs/

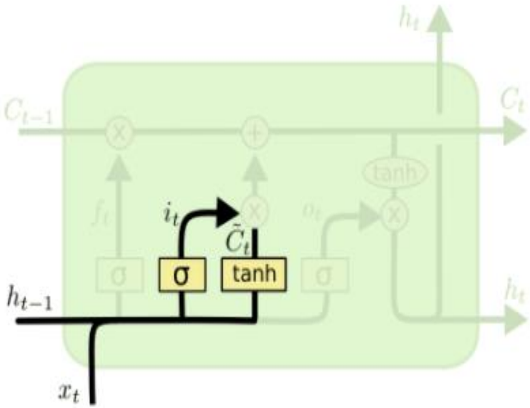
Long Short Term Memory Network (LSTM)

- **Forget Gate**



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

- **Input Gate**

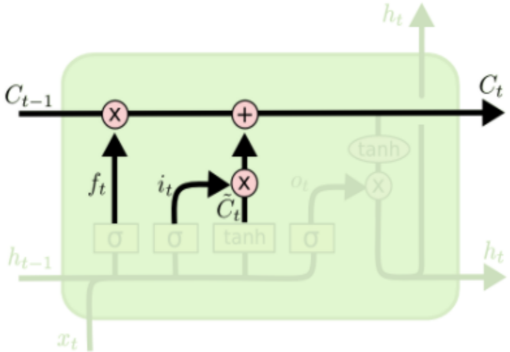


$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

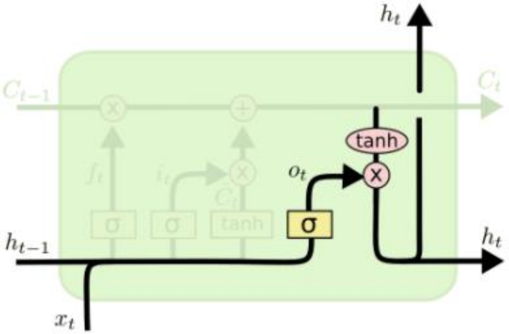
Long Short Term Memory Network (LSTM)

- **Updated Cell State**



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

- **Output Gate**



$$o_t = \sigma\left(W_o \left[h_{t-1}, x_t\right] + b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

Time Series Data:

- **Input data: t-39, t-39, t-38, ………., t-1, t [40 time-steps]**
- **For current models we get only single step prediction ahead.**
- **Predicted data : t+1 [1 time-step]**

Multi-step prediction:

To predict more than one step ahead, we should use multistep prediction.

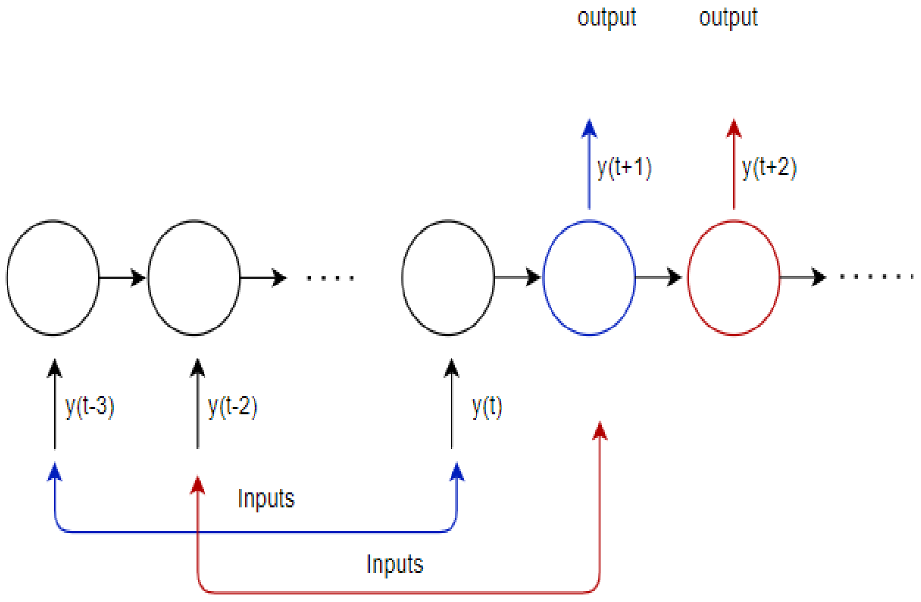
Some of the multi-step prediction models are:

1) Recursive Forecast

2) Encoder-Decoder

1) Recursive Forecast (Approach-1)

- **Input data: t-39, t-39, t-38, ………., t-1, t [40 time-steps]**
- **Predicted data : t+1 [1 time-step]**
- **<u>First iteration:</u>**
- **Input: t-38, ………., t-1, t, t+1 [40 time-steps]**
- **Predicted data : t+2 [1 time-step]**
- **<u>Second iteration:</u>**
- **Input: t-37, ………., t-1, t, t+1, t+2 [40 time-steps]**
- **Predicted data : t+3 [1 time-step]**



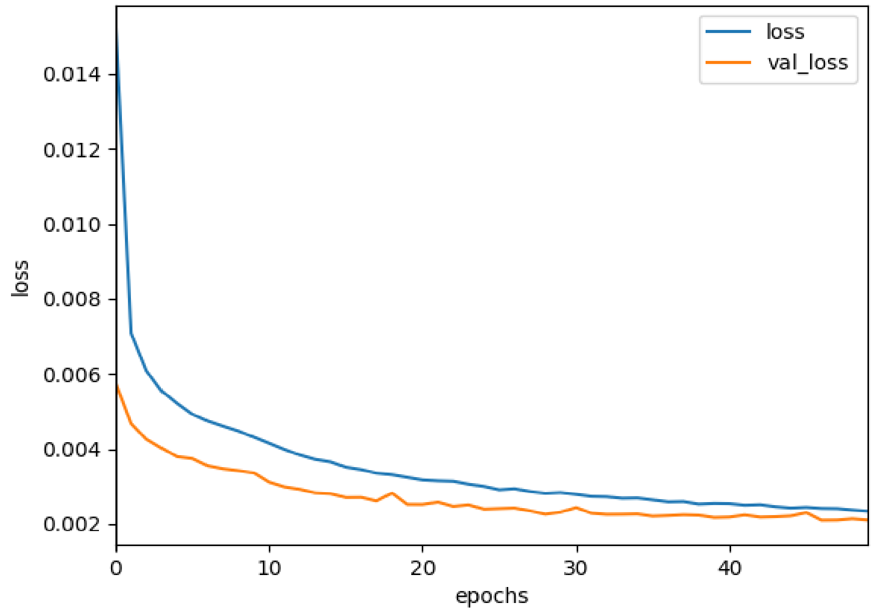
Recursive Forecast [3]

- **Repeat these for 20 iterations**
- **Predicted data : t+1, t+2, t+3, ………., t+20 [20 time-step]**

[3] A. Sorjamaa and A. Lendasse, “Time series prediction using dirrec strategy.,”inEsann, vol. 6, pp. 143–148, 2006.

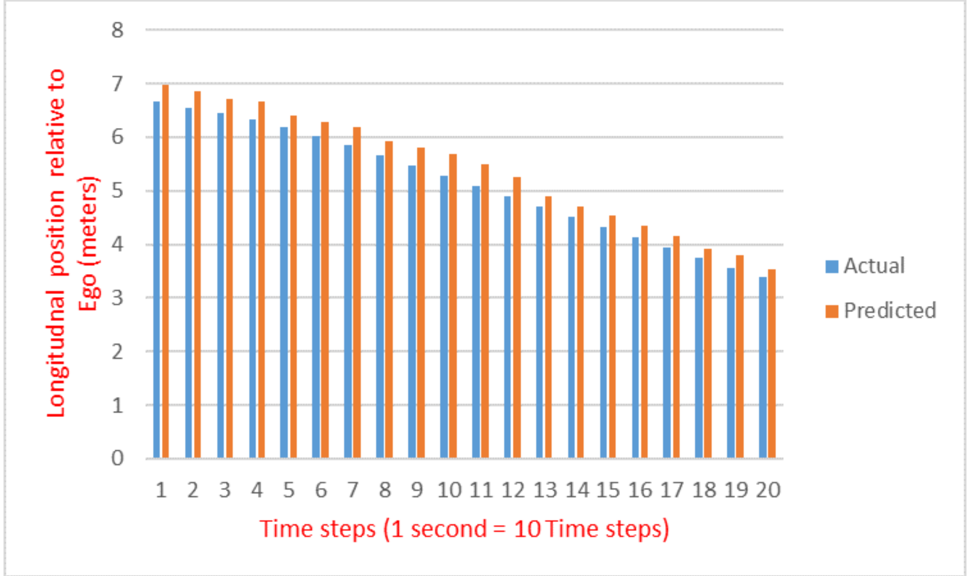
Recursive Forecast

- **Number of lstm layers = 2**
- **Number of neurons = 56**
- **Number of epochs = 50**
- **Time taken for each epoch = 32 seconds**
- **Trained scenes - 50**
- **Tested scenes - 15**

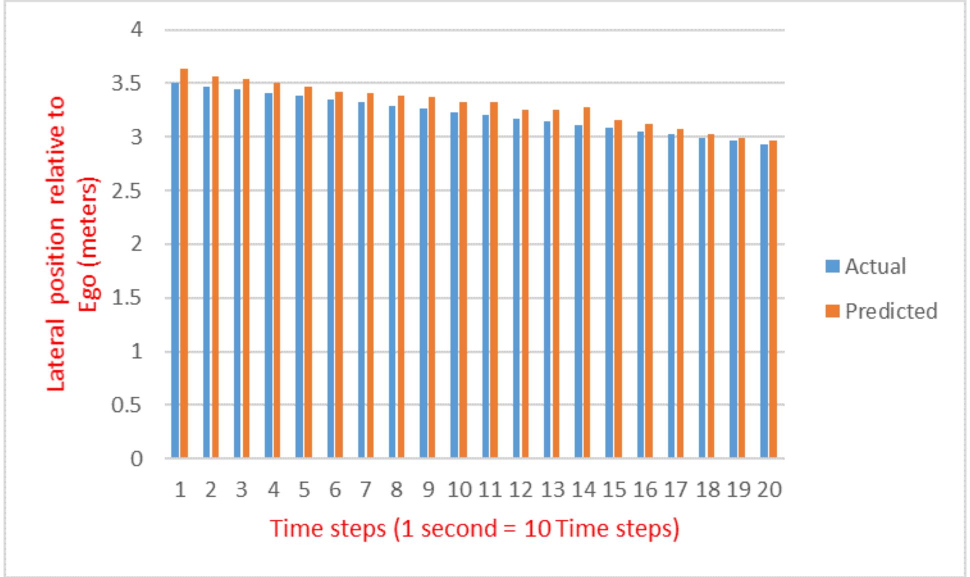


Training loss vs Validation loss

Prediction Result of Right-leader



Longitudinal Position Prediction



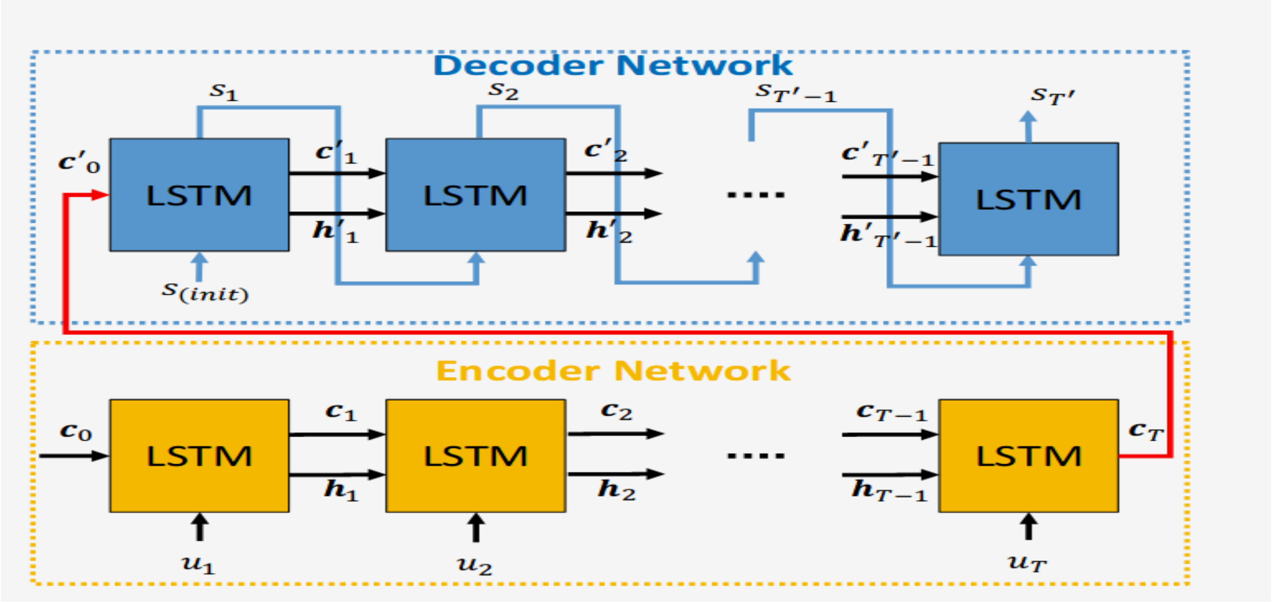
Lateral Position Prediction

- → **The longitudinal mean absolute error, e = 1.95 meters.**
- → **The lateral mean absolute error, e = 0.45 meters.**

2) Encoder-Decoder (Approach-1)

- **Input data:** $u_1, u_2, \ldots, u_T$
- **Predicted data :** $s_1, s_2, \ldots.., \; s_{T'}$
- **cell state :**$'c_t'$ **, hidden state :** $'h_t$'
- $'c_T'$ **is the final cell state vector of the Encoder,**

  which holds summary of input vector

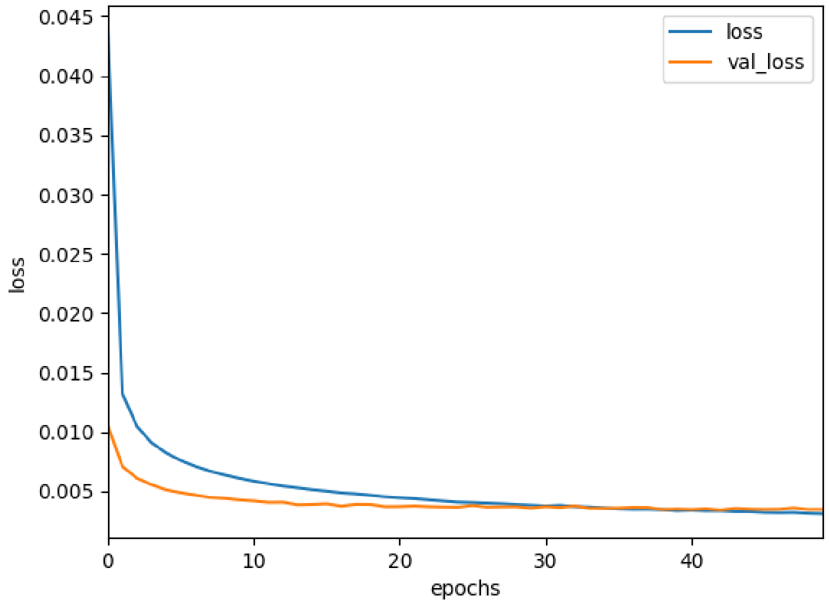


Encoder-Decoder LSTM [4]

[4] https://www.semanticscholar.org/paper/Sequence-to-Sequence-Prediction-of-Vehicle-via-LSTM-Park-Kim/528f6933d246ff9d0918f2e936d7bfa79aa7fea9

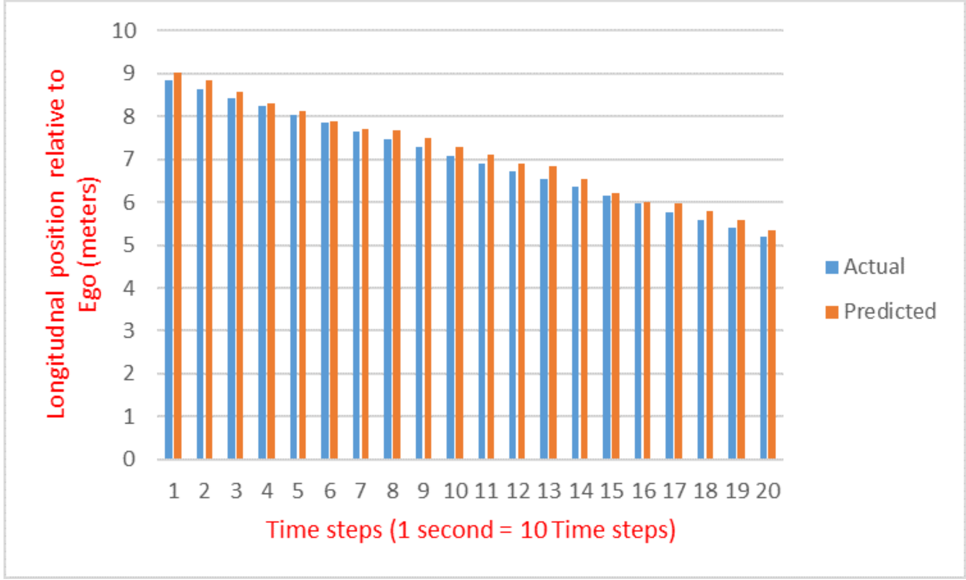
Encoder-Decoder

- **Number of LSTM Encoder-Decoder layer = 1**
- **Number of neurons = 256**
- **Number of epochs = 50**
- **Time taken for each epoch = 120 seconds**
- **Trained scenes - 50**
- **Tested scenes - 15**

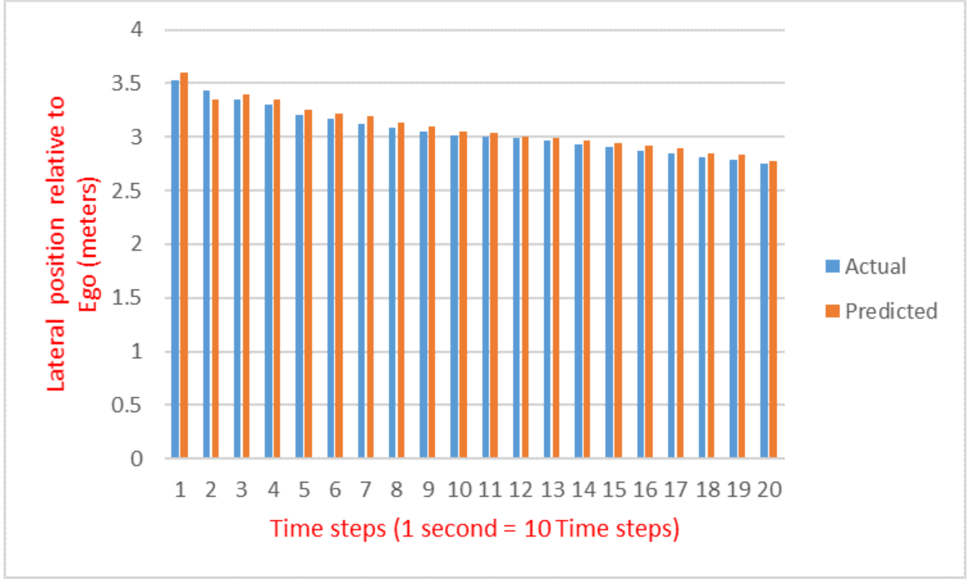


Training loss vs Validation loss

Prediction Result of Right-leader



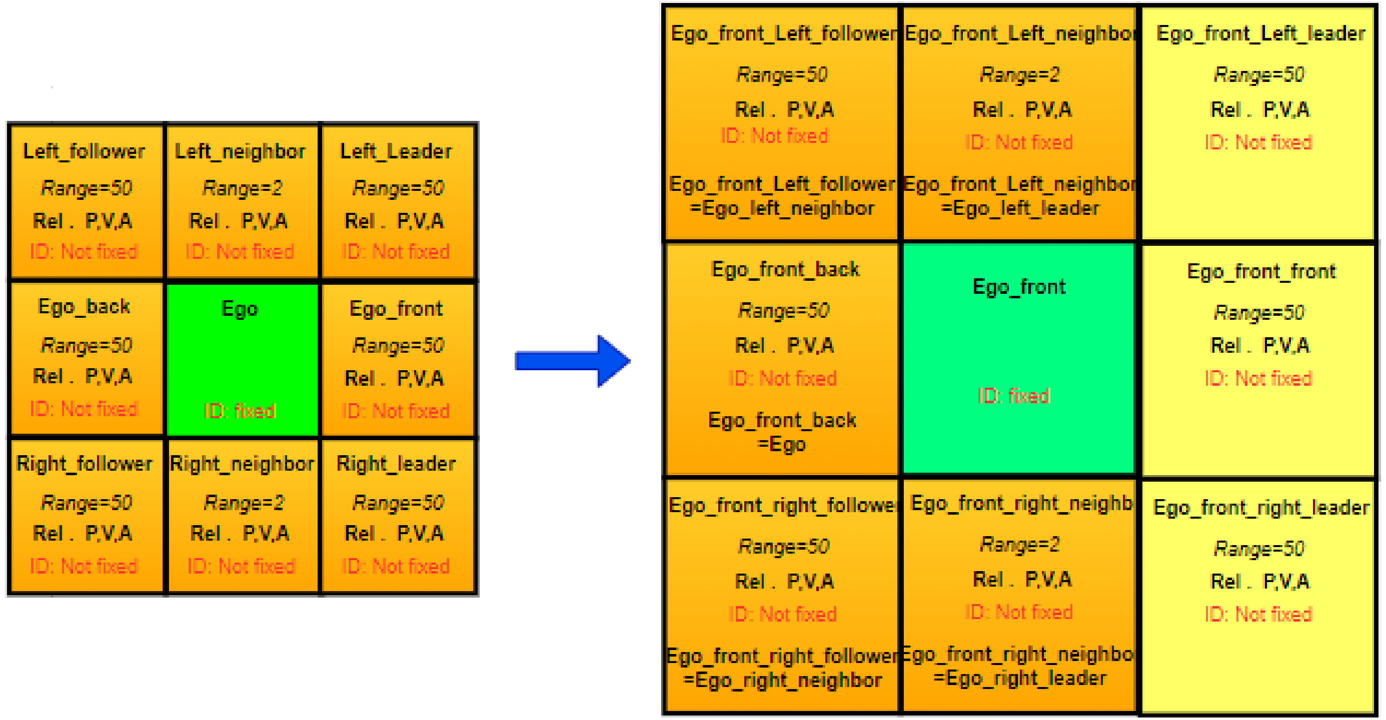
Longitudinal Position Prediction



Lateral Position Prediction

- → **The longitudinal mean absolute error, e = 1.4 meters.**
- → **The lateral mean absolute error, e = 0.3 meters.**

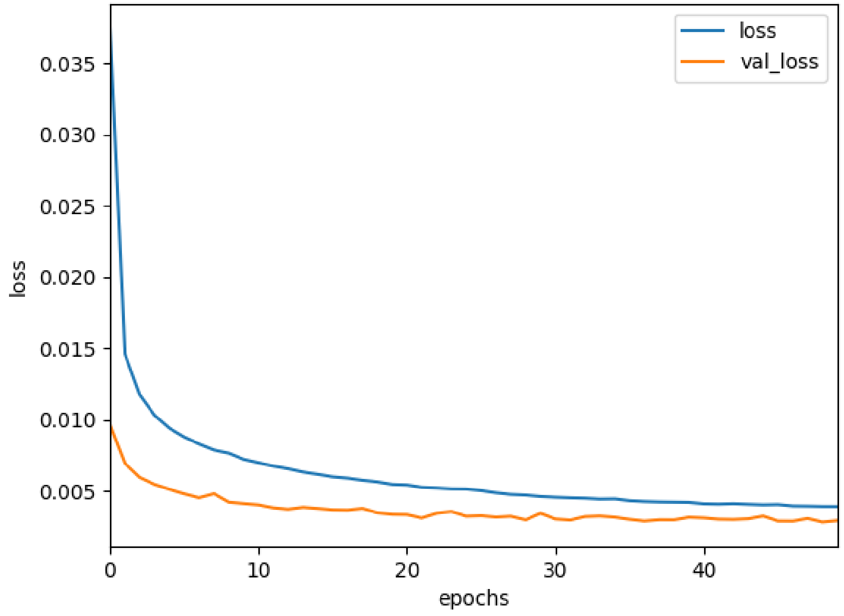
Entity Relation for Single Vehicle (Approach-2)



Approach-2 Overview

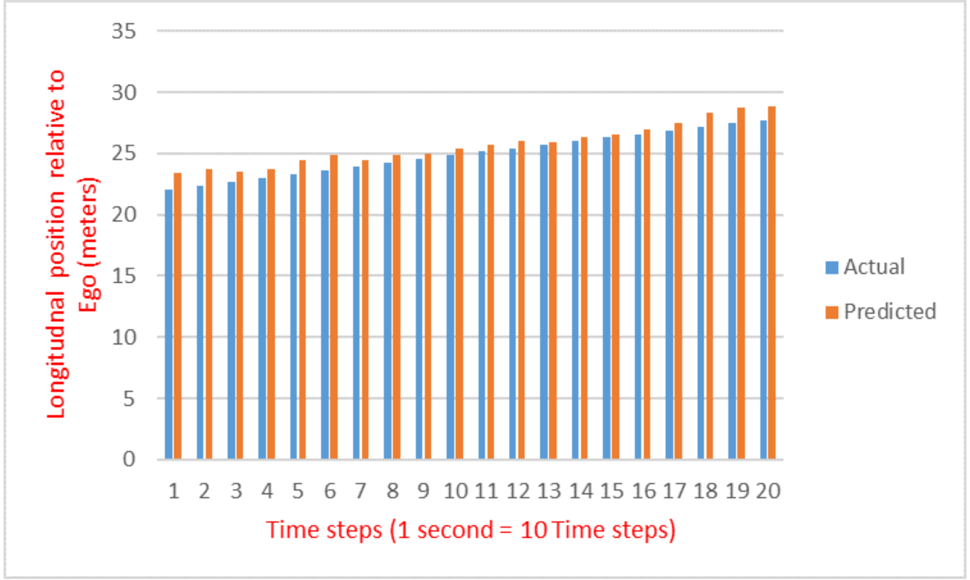
Encoder-Decoder

- **Number of LSTM Encoder-Decoder layer = 1**
- **Number of neurons = 512**
- **Number of epochs = 50**
- **Time taken for each epoch = 50 seconds**
- **Trained scenes - 50**
- **Tested scenes - 15**



Training loss vs Validation loss

Prediction Result of Ego-front

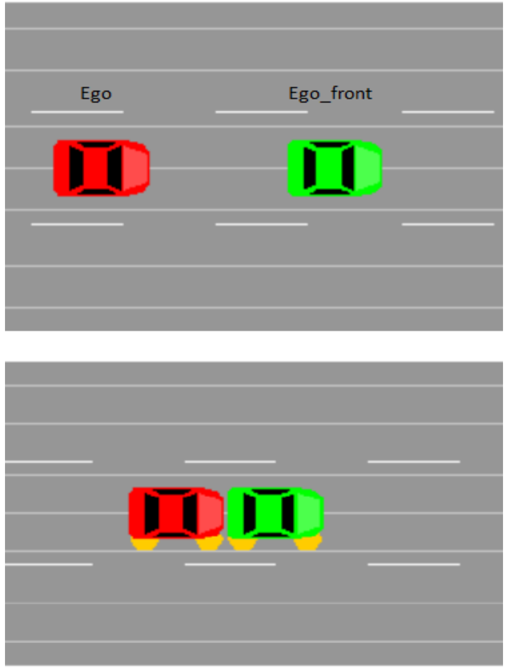


Longitudinal Position Prediction

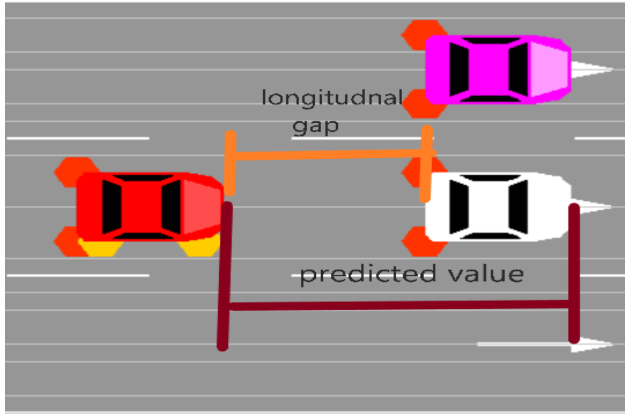
→ **The longitudinal mean absolute error, e = 1.6 meters.**

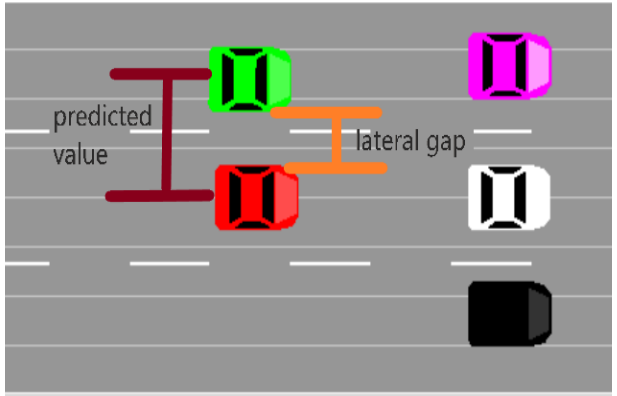
Test Scene 1

Timesteps	Ego-front longitudnal-rel.dis	Collision
1	6.21172	no
2	5.85035	no
3	5.7419	no
4	5.70345	no
5	5.69375	no
6	5.64261	no
7	5.61264	no
8	5.59091	no
9	5.48739	no
10	5.45261	no
11	5.37689	no
12	5.29039	no
13	5.21326	no
14	5.15562	no
15	5.10761	no
16	5.05938	no
17	5.01106	no
18	4.98278	yes
19	4.91463	yes
20	4.86067	yes



Ego-front collision

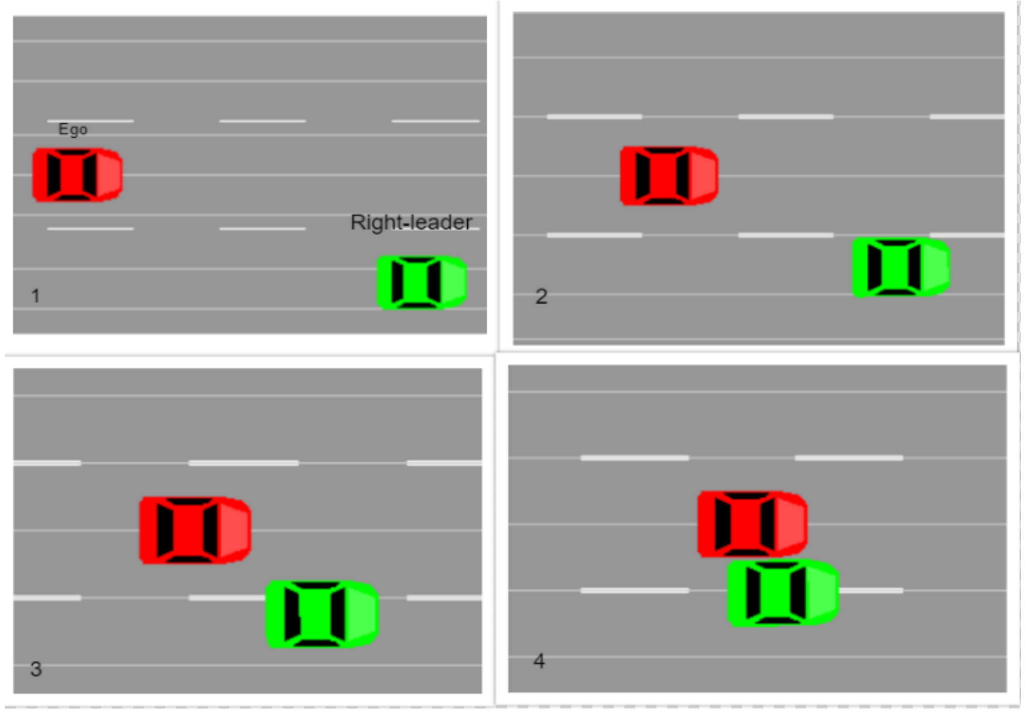




Threshold = 2 meters (longitudnal)
Threshold = 1 meter (lateral)

Test Scene 2

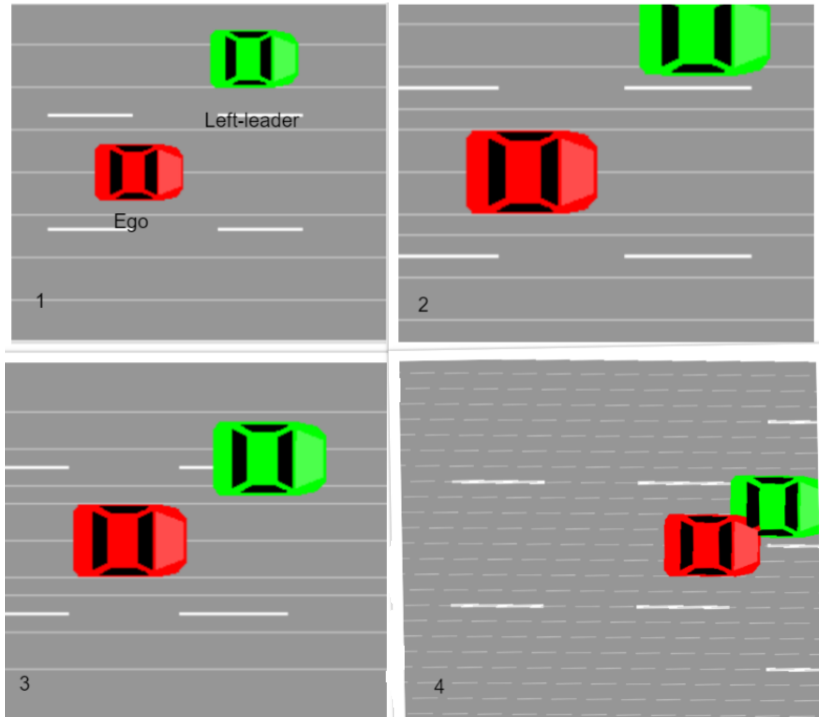
Timesteps	Right-leader longitudnal-rel.dis	Right-leader lateral-rel.dis	Collision
1	8.98553	3.27502	no
2	8.77917	3.20633	no
3	8.38899	3.19225	no
4	8.0025	3.14882	no
5	7.66269	3.09943	no
6	7.35827	3.06147	no
7	7.08136	3.03082	no
8	6.82799	2.98466	no
9	6.59545	2.88135	no
10	6.38199	2.8601	no
11	6.18689	2.84076	no
12	6.00869	2.82302	no
13	5.84593	2.80661	no
14	5.69776	2.79146	no
15	5.5633	2.7775	no
16	5.33165	2.76465	no
17	5.13119	2.75286	no
18	5.03315	2.74207	no
19	4.94445	2.73223	yes
20	4.77496	2.72326	yes



Right-leader collision

Test Scene 3

TimeSteps	Left-Leader Longitudnal-Rel.dis	Left-leader Lateral-Rel.dis	Collision
1	6.56429	3.30372	no
2	6.30603	3.19894	no
3	6.17009	3.11077	no
4	5.97004	3.11188	no
5	5.82791	3.09694	no
6	5.60086	3.08242	no
7	5.56867	3.06297	no
8	5.53605	3.04207	no
9	5.50785	3.02133	no
10	5.48097	3.00075	no
11	5.45348	2.98033	no
12	5.40478	2.96037	no
13	5.35604	2.9415	no
14	5.30787	2.92394	no
15	5.24092	2.90786	no
16	5.11557	2.89329	no
17	4.99921	2.88023	yes
18	4.92061	2.86861	yes
19	4.85113	2.85834	yes
20	4.63361	2.8493	yes

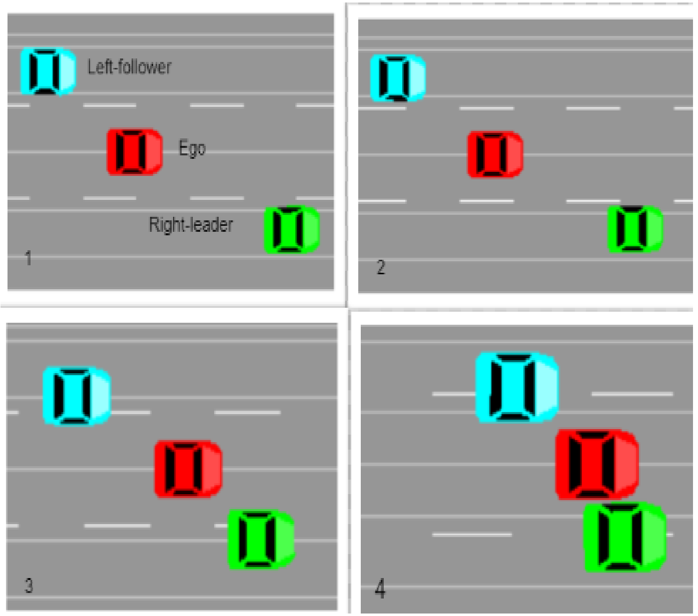


Left-leader collision

Test Scene 4

TimeSteps	Right-leader Longitudnal-Rel.dis	Right-leader Lateral-Rel.dis	Collision
1	7.50952	3.22498	no
2	7.22883	3.09501	no
3	6.94186	2.96499	no
4	6.75093	2.93502	no
5	6.45908	2.905	no
6	6.26165	2.87497	no
7	6.06723	2.845	no
8	5.88189	2.81498	no
9	5.69097	2.78501	no
10	5.49353	2.75499	no
11	5.35889	2.72502	no
12	5.20425	2.69499	no
13	5.12797	2.66503	no
14	5.01193	2.635	no
15	4.84008	2.60498	yes
16	4.6552	2.57501	yes
17	4.47335	2.54498	yes
18	4.29289	2.51502	yes
19	4.09243	2.48499	yes
20	3.92825	2.45503	yes

TimeSteps	Left-follower Longitudnal-Rel.dis	Left-follower Lateral-Rel.dis	Collision
1	7.17251	3.11502	no
2	7.09674	3.08502	no
3	7.03811	3.05497	no
4	6.86283	3.02498	no
5	6.679	2.99499	no
6	6.58946	2.96499	no
7	6.49041	2.935	no
8	6.37805	2.905	no
9	6.25903	2.87501	no
10	6.12146	2.84501	no
11	5.99247	2.81502	no
12	5.84588	2.78503	no
13	5.69549	2.75498	no
14	5.64129	2.72498	no
15	5.57663	2.69499	no
16	5.50057	2.665	no
17	5.41404	2.635	no
18	5.31611	2.60501	no
19	5.15676	2.57501	no
20	4.98266	2.54502	yes

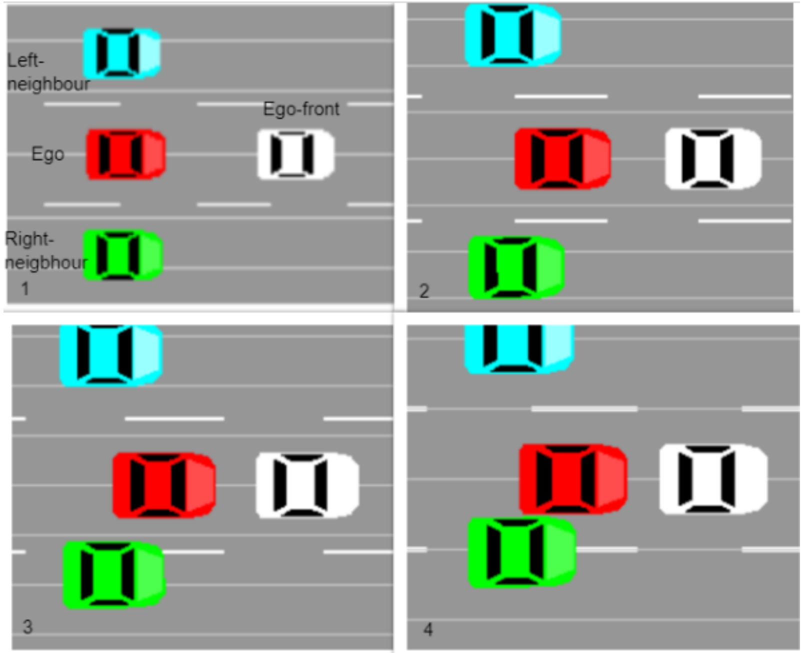


Right-leader & Left-follower collision

Test Scene 5

Timesteps	Ego-front longitudnal-rel.dis	Collision
1	6.58173	no
2	6.49644	no
3	6.34544	no
4	6.26993	no
5	6.16465	no
6	6.08657	no
7	6.01948	no
8	5.96038	no
9	5.90939	no
10	5.84971	no
11	5.75315	no
12	5.66705	no
13	5.57458	no
14	5.46864	no
15	5.38008	no
16	5.26197	no
17	5.18261	no
18	5.09299	no
19	5.01323	no
20	4.96834	yes

TimeSteps	Right-neighbour Longitudnal-Rel.dis	Right-neighbour Lateral-Rel.dis	Collision
1	1.49281	3.6135	no
2	1.5096	3.57498	no
3	1.52107	3.52501	no
4	1.52957	3.45498	no
5	1.53181	3.39502	no
6	1.52662	3.36499	no
7	1.51725	3.33503	no
8	1.50377	3.315	no
9	1.50124	3.25497	no
10	1.5096	3.20501	no
11	1.51033	3.17498	no
12	1.50261	3.12502	no
13	1.50297	3.07499	no
14	1.51566	3.03502	no
15	1.5251	3.00115	no
16	1.52698	2.99497	yes
17	1.51919	2.94501	yes
18	1.51674	2.89498	yes
19	1.52416	2.84501	yes
20	1.52734	2.80499	yes



Right-neighbour & Ego-front collision

Conclusion & Future Work

- **The mean absolute error is minimal for semantic entity relationship’s based encoder-decoder model.**
- **This can be deployed in real-world autonomous driving cars, by predicting the collision in advance can help to minimize the accidents.**

Kontakt

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