

An LSTM Network for highway trajectory prediction of a vehicle with given trajectories of the surrounding vehicles

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Outline



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- 3. Approach Used for Trajectory Prediction
- 4. Conclusion

1.1 Paper Chosen for Project



An LSTM Network for Highway Trajectory Prediction

This paper present a first step towards consistent trajectory prediction by introducing a long short-term memory (LSTM) neural network, which is capable of accurately predicting future longitudinal and lateral trajectories for vehicles on highway. Link: https://ieeexplore.ieee.org/abstract/document/8317913

1.2 Problem Statement



- We consider the problem of predicting future trajectories of vehicles driving on a highway, using previously observed data; these predictions can then be used to plan the motion of an autonomous vehicle.
- we consider a set of observable features I and a set of target outputs O to be predicted. We assume that the features can all be acquired simultaneously at regular intervals, We let $T = \{0, ..., K\}$ and for $x \in I, k \in T$.
- We denote by x_k the value of feature x observed k time steps earlier. Similarly, we denote by y_k the value of output $y \in O, k \in T$ time steps.

1.2 Problem Statement



▶ We use uppercase

$$X = (x_k)$$
, for $x \in I$, $k \in T$

and

$$Y = (y_k)$$
, for $y \in O$, $k \in T$

to respectively denote the tensors of the observed features and corresponding predicted outputs. We propose to use a machine learning approach, in which we train a regression function f such that the predicted outputs $\hat{Y} = f(X)$ match the actual values as closely as possible.

Our approach is to train a predictor for the trajectory of a single "target" vehicle; in order to only use data which can realistically be gathered, we limit the amount of available information to the vehicles immediately around the target vehicle.

1.3 Data-set Used



- ▶ We use the Next Generation Simulation (NGSIM) dataset, collected in 2005 by the United States Federal Highway Administration, which is one of the largest publicly available source of naturalistic driving data and, as such, has been widely studied in the literature
- we consider the US101 dataset which contains 45 minutes of trajectories for vehicles on the US101 highway, between 7:50am and 8:35am during the transition from fluid traffic to saturation at rush hour.
- In total, the dataset contains trajectories for more than 6000 individual vehicles, recorded at 10 Hz. The NGSIM dataset provides vehicle trajectories in the form of (X; Y) coordinates of the front center of the vehicle in a global frame, and of local (x; y) coordinates of the same point on a road-aligned frame.

1.3 Data-set Used



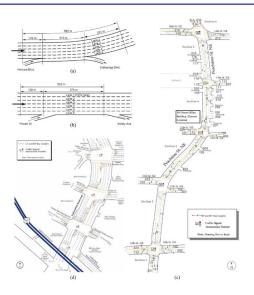


Fig1: Dataset Visualization
Autonomous Vehicles by Machine Learning Algorithms

1.4 Solution of Problem



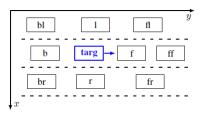
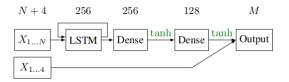


Fig2: Vehicle of interests around the Target Vehicle.



1.5 Results by Author



TABLE I RMS error for the tested models

	Prediction horizon						
Model	1s	28	3 s	4 s	6 s	88	10 s
Reference*	0.11	0.25	0.33	0.40	0.53	0.60	0.73
Type*	0.39	0.39	0.44	0.48	0.53	0.63	0.69
No ff*	0.14	0.24	0.33	0.41	0.54	0.65	0.76
No bypass	0.80	0.82	0.85	0.88	0.93	0.97	1.03
Bypass before	0.33	0.38	0.43	0.46	0.52	0.61	0.68
Lin. activ.	1.38	1.39	1.40	1.42	1.46	1.51	1.56
2 LSTMs	1.25	1.26	1.28	1.29	1.33	1.37	1.41
3 dense*	0.34	0.38	0.44	0.50	0.59	0.70	0.72
[14]	0.11	0.32	0.71		not available		
Bagged	0.17	0.25	0.33	0.40	0.46	0.57	0.65
				10000000			
	(a) Late	eral posi		ors are			22000
Model	(a) Late	2s				8s	10 s
Model Reference*		- 14	Predi	ction ho	rizon	8 s	
	1s	2 s	Predi	ction ho	erizon 6 s	-	2.96
Reference*	1 s	2 s	Predi 3 s	4s	6 s	2.60	2.96
Reference* Type*	1 s 0.71 0.65	2 s 0.99 0.88	3 s 1.25 1.05	4 s 1.49 1.25	6 s 2.10 1.75	2.60	2.96 2.74 2.84
Reference* Type* No ff*	1s 0.71 0.65 0.67	2s 0.99 0.88 0.91	3 s 1.25 1.05 1.16 1.55 1.06	4 s 1.49 1.25 1.44	6 s 2.10 1.75 1.98	2.60 2.28 2.43	2.96 2.74 2.84 2.89
Reference* Type* No ff* No bypass	1 s 0.71 0.65 0.67 1.50	2 s 0.99 0.88 0.91 1.50 0.90 1.10	3 s 1.25 1.05 1.16 1.55	1.49 1.25 1.44 1.66	6 s 2.10 1.75 1.98 2.05	2.60 2.28 2.43 2.50	2.96 2.74 2.84 2.89 2.78 2.94
Reference* Type* No ff* No bypass Bypass before	1 s 0.71 0.65 0.67 1.50 0.78	2s 0.99 0.88 0.91 1.50 0.90 1.10 1.14	3 s 1.25 1.05 1.16 1.55 1.06	1.49 1.25 1.44 1.66 1.26 1.56 1.71	6 s 2.10 1.75 1.98 2.05 1.76	2.60 2.28 2.43 2.50 2.30	2.96 2.74 2.84 2.89 2.78 2.94
Reference* Type* No ff* No bypass Bypass before Lin. activ.	1 s 0.71 0.65 0.67 1.50 0.78 0.77	2 s 0.99 0.88 0.91 1.50 0.90 1.10	Predi 3 s 1.25 1.05 1.16 1.55 1.06 1.34	1.49 1.25 1.44 1.66 1.26 1.56	6 s 2.10 1.75 1.98 2.05 1.76 2.08	2.60 2.28 2.43 2.50 2.30 2.58	2.96 2.74 2.84 2.89 2.78 2.94 3.17 2.77

(b) Longitudinal speed (errors are in m s-1)

Fig4: Error Values.



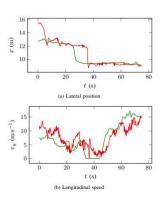


Fig5: Output: Represented in Normalized Values

Outline



1. Introduction

- 2. Trajectory Planning and Prediction
 - 2.1 What is trajectory planning?
 - 2.2 Types of trajectory prediction
 - 2.3 What is time series data?
 - 2.4 Possible approach
- 3. Approach Used for Trajectory Prediction
- 4 Conclusion

2.1 What is trajectory planning?



- Trajectory planning is moving from point A to point B while avoiding collisions over time. This can be computed in both discrete and continuous methods. Trajectory planning is a major area in robotics as it gives way to autonomous vehicles.
- ▶ Trajectory planning is sometimes referred to as motion planning and erroneously as path planning. Trajectory planning is distinct from path planning in that it is parametrized by time. Essentially trajectory planning encompasses path planning in addition to planning how to move based on velocity, time, and kinematics.

2.2 Types of trajectory prediction



There can be two possibilities:

- First is that the initial trajectory of the vehicle and surrounding is given and then predict the future motion.
- Second is that the trajectory of all surrounding vehicles are given and predict the motion of target, without any information given about target vehicle. (This one is used for this project)

2.3 What is time series data?



- ▶ A time series is a series of data points indexed (or listed or graphed) in time order. Most commonly, a time series is a sequence taken at successive equally spaced points in time. Thus it is a sequence of discrete-time data.
- Because this is discrete data some sort of filtering is required to filter noise. In this application savitzky golay filter is used to remove noise from calculated difference values.

2.4 Possible approach



- One of the appeals of RNNs is the idea that they might be able to connect previous information to the present task, such as using previous video frames might inform the understanding of the present frame.
- ➤ Sometimes, we only need to look at recent information to perform the present task. RNNs can learn to use the past information.
- The LSTM network can perform this task of prediction of time series very efficiently because of its capability to forget the unused information in a long time series.

Outline



- 1. Introduction
- Trajectory Planning and Prediction
- 3. Approach Used for Trajectory Prediction
 - 3.1 What is LSTM network?
 - 3.2 Data-set pre-processing
 - 3.3 Feature Vector creation
 - 3.4 Network Architecture
 - 3.5 Results
- 4. Conclusion

3.1 What is LSTM network?



- Long Short Term Memory networks usually just called "LSTMs" – are a special kind of RNN, capable of learning long-term dependencies.
- ► LSTMs are explicitly designed to avoid the long-term dependency problem. Remembering information for long periods of time is practically their default behavior, not something they struggle to learn.

3.1 What is LSTM network?



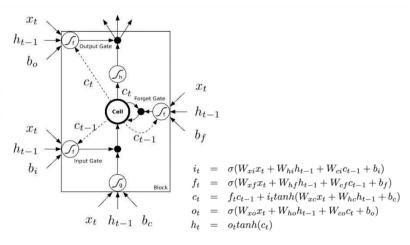


Fig6: Basic LSTM cell

3.2 Data-set pre-processing



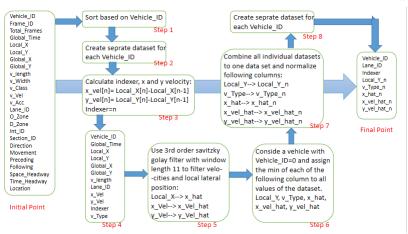


Fig7: Preprocessing Steps

3.2 Data-set pre-processing



- ➤ Step 0: First step is to figure out what are the important parameters required from initial data set to final data set.
- Step 1: Sort the dataset based on vehicle ids given.
- Step 2: Create separate csv file for each dataset with number of rows equal to minimum number of instances available for a vehicle out of all 600 vehicles. This step is done so that the feature vector has constant dimension. Also it will hep in velocity calculation in each direction
- ➤ Step 3: Calculate lateral x and longitudinal y direction velocities for all the vehicles and assign an indexer to each row because the time difference from the given global time is not possible to be calculated. Each index represents 100ms time.
- ➤ Step 4: Store the velocities and Index values in the dataset and drop the columns which are not required.

3.2 Data-set pre-processing



- ➤ Step 5: As the velocities are the first difference of the position values some noise will automatically gets included in the signal. To filter the velocities Savitzky-Golay filter is used, which is explained in more detail in Sub-Section ??. Then the nun filetred values are replaced by the filtered values.
- ➤ Step 6: As the network will only take values between range {0,1}, the normalization of the values is required. To achieve this a new dataset is created manually with vehicle id 0..
- Step 7: Now the data of all the vehicle ids is concatenated to normalize the required columns. After normalization the non-normalized values are replaced by normalized values.
- ▶ Step 8: Sort the dataset again based on vehicle ids given as it was done in Step 1. Now we have the final datasets for all the vehicles which will be used to create input feature vector as shown in Figure 3.

3.3 Feature Vector creation



For the target vehicle, we define the following features:

- local lateral position x_{targ}, to account for different behaviors depending on the driving lane,
- local longitudinal position y_{targ} , to account for different behaviors when approaching the merging lane,
- ▶ lateral and longitudinal velocities $v_{x_{targ}}$ and $v_{y_{targ}}$,
- type (motorcycle, car or truck), encoded respectively as 1, 2 or 3.

For each vehicle $p \in \{bl; b; br; l; f; r; fl; fr; ff\}$, we define the following features:

- lateral velocity v_{x_p} ,
- ▶ longitudinal velocity relative to targ: $v_{y_p} = v_{y_{targ}} v_{y_p}$,
- ▶ lateral distance from targ: $x_p = x_p x_{targ}$,
- ▶ longitudinal distance from targ: $y_p = y_p y_{targ}$,
- type (motorcycle, car or truck), encoded respectively as 1, 2 or 3.

3.3 Feature Vector creation



As per the matrix represented in Fig2 Input Feature Vector:

$$\begin{split} X &= \left(y_{targ}, v_{x_{targ}}, v_{type_{targ}}, \right. \\ &v_{x_{fl}}, \Delta v_{y_{fl}}, \Delta x_{fl}, \Delta y_{fl}, v_{type_{fl}}, \\ &v_{x_{ff}}, \Delta v_{y_{ff}}, \Delta x_{ff}, \Delta y_{ff}, v_{type_{ff}}, \\ &v_{x_{fr}}, \Delta v_{y_{fr}}, \Delta x_{fr}, \Delta y_{fr}, v_{type_{fr}}, \\ &v_{x_{f}}, \Delta v_{y_{fr}}, \Delta x_{l}, \Delta y_{l}, v_{type_{l}}, \\ &v_{x_{f}}, \Delta v_{y_{f}}, \Delta x_{l}, \Delta y_{l}, v_{type_{l}}, \\ &v_{x_{f}}, \Delta v_{y_{f}}, \Delta x_{f}, \Delta y_{f}, v_{type_{f}}, \\ &v_{x_{f}}, \Delta v_{y_{fr}}, \Delta x_{r}, \Delta y_{r}, v_{type_{r}}, \\ &v_{x_{bl}}, \Delta v_{y_{bl}}, \Delta x_{bl}, \Delta y_{bl}, v_{type_{bl}}, \\ &v_{x_{b}}, \Delta v_{y_{b}}, \Delta x_{b}, \Delta y_{b}, v_{type_{br}}, \\ &v_{x_{br}}, \Delta v_{y_{br}}, \Delta x_{br}, \Delta y_{br}, v_{type_{br}}) \\ \text{Output Vector:} \\ &Y &= \left(x_{targ}, v_{v_{targ}}\right) \end{split}$$

Target Vehicle
Front Left Vehicle
Front Front Vehicle
Front Right Vehicle
Left Vehicle
Front Vehicle
Right Vehicle
Back Left Vehicle
Back Vehicle
Back Right Vehicle

Target Vehicle

3.4 Network Architecture



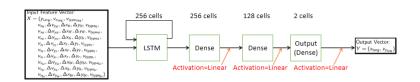


Fig8:Network Used

- ► Network is same except the first four instances are not directly given to output layer
- The activation are not tanh but linear in this network.
- Dense/fully connected layer: A linear operation on the layer's input vector.

3.4 Network Architecture



Model: "sequential_1"		
Layer (type)	Output Shape	Param #
lstm_1 (LSTM)	(None, 1500, 256)	312320
dense_1 (Dense)	(None, 1500, 256)	65792
dense_2 (Dense)	(None, 1500, 128)	32896
dense_3 (Dense)	(None, 1500, 2)	258
Total params: 411,266 Trainable params: 411,266 Non-trainable params: 0		
None		

Fig9:Network Definition

3.4 Network Architecture



TABLE I Hyper Parameters for Model Layers

Layer N	Vame	lstm_l	dense_l	dense_2	dense_3
S.No.	Parameter	Values	Values	Values	Values
1	units	256	256	128	2
2	activation	-	linear	linear	linear
3	use_bias	-	True	True	True
4	kernel_initializer	-	'glorot_uniform'	'glorot_uniform'	'glorot_uniform'
5	bias_initializer	-	'zeros'	'zeros'	'zeros'
6	kernel_regularizer	-	None	None	None
7	bias_regularizer	-	None	None	None
8	activity_regularizer	-	None	None	None
9	kernel_constraint	-	None	None	None
10	bias_constraint	-	None	None	None

Fig10:Hyper Parameters of layers



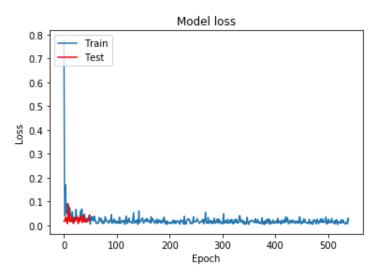


Fig11: Loss Function



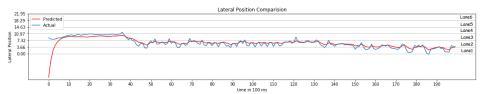


Fig12: Result1



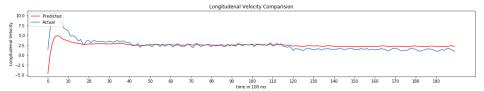


Fig13: Result2

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- 1. Introduction
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- 4. Conclusion

4. Conclusion



- our goal was to predict the future trajectory of the target vehicle. Since the region of interest spans roughly 1km longitudinally,
- The values of the longitudinal position can become quite large; for this reason, we prefer to predict future longitudinal velocities $\hat{v}_{y_{targ}}$ instead. Since the lateral position is bounded,
- we directly use $\hat{\mathbf{x}}_{targ}$ for the output. In order to have different horizons of prediction, we choose a vector of outputs $\{\hat{\mathbf{x}}_{k_{targ}}; \hat{\mathbf{v}}_{y_{k_{targ}}}\}$ for k=1:K consisting in values taken k seconds in the time.

4. Conclusion



To visualize the results in actual units the output of the neural network must be denormalized. To do this following calculations and values(from Table 1) are used:

Values used for Denormalization(for vehicle 595)

S.No.	Quantity	Value
1	X _{targ_{min}}	-28.43 m
2	X _{targ_{max}}	30.33 m
3	$\epsilon_{X_{targ}}$	10.10 m
4	V _{ytarg_{min}}	-13.38 m/s
5	V _{ytargmax}	38.07 m/s
6	$\epsilon_{\textit{V}_{\textit{y}_{targ}}}$	1.94 m/s

4 Conclusion



The prediction is done for 20 seconds. Actual values are calculated from predictions using these formulas:

$$\begin{aligned} x_{targ_{actual}} &= ((x_{targ_{normalized}} + \epsilon_{x_{targ_{normalized}}}) * (x_{targ_{max}} - x_{targ_{min}}) + x_{targ_{min}}) \\ v_{y_{targ_{actual}}} &= ((v_{y_{targ_{normalized}}} + \epsilon_{v_{y_{targ_{normalized}}}}) * (v_{y_{targ_{max}}} - v_{y_{targ_{min}}}) + v_{y_{targ_{min}}}) \end{aligned}$$

As visible in calculation by adding the average error value in the prediction the actual error remaining is very less, which is given in Table 2.

Final Errors(for vehicle 595)

S.No.	Quantity	Value
1	$\epsilon_{X_{targ}}$	-2.7755575615628914e-17 m
2	$\epsilon_{v_{y_{targ}}}$	-5.662137425588298e-15 m/s

4. Conclusion



- ▶ As we can see in Figure 12 and 13 the accuracy level is very high. Due to initialization with minimum values it takes almost 1 second for the predictions to reach minimum amount of accuracy after that the difference between signals are very less.
- ▶ In Figure 12 as we can see that the predicted lateral position is almost same as the actual values, Also to visualize the maneuvers y axis is divided based on lanes so that the lane changing maneuver can be visualized.
- In figure 13 we can see that the actual velocity of the vehicle and the predicted velocity are almost same. Also due to filtering the little changes in velocity is removed but still the the network predicts the velocity around the actual value with almost zero error.

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