Pedestrian trajectory prediction

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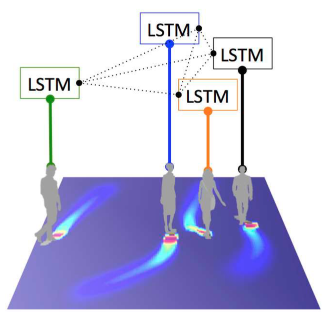
Introduction

- Trajectory prediction is crucial for improving autonomous vehicles behaviour
- Could enhance some situations seen in the ethical lectures
- The work field is still in development
- We choose to challenge two different models with the same inputs

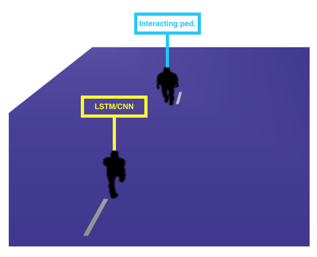
Previous Work [1]

- The prediction are done per frame: the goal is to determine multiple trajectory at the same time
- Introduction of a social pooling characteristics: if two pedestrian are side-by-side, they are grouped together



Idea for our Models

- Instead of focusing on frames, prediction focus on one pedestrian
- Special effort is put on pre-processing to make learning easier



Pre-processing

Goal: Normalize data such that every trajectory begin the same way, the model should learn more easily.

The preprocessing is divided in 5 steps:

1. Isolate each trajectory along with its interaction
2. Normalize the trajectories: the first point is at $(0, 0)$; the second is at $(0, y_1)$
3. Calculate axis velocities V_x and V_y
4. For each frame, if there is an interacting pedestrian we add his/her coordinates and speed otherwise we add zeros
5. Data augmentation: flip and add noise to trajectories

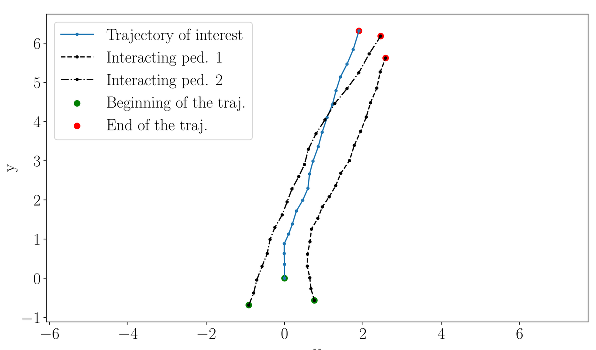


Figure 1: Example of one trajectory after pre-processing

Final shape of the data:

- Pedestrians ID
- Frame number
- Twenty sets of x and y coordinates per pedestrian

Frame Number	ID	x	y	V_x	V_y
0	i	0	0	0	0
10	i	0	y_1	0	V_{y_1}
⋮	⋮	⋮	⋮	⋮	⋮

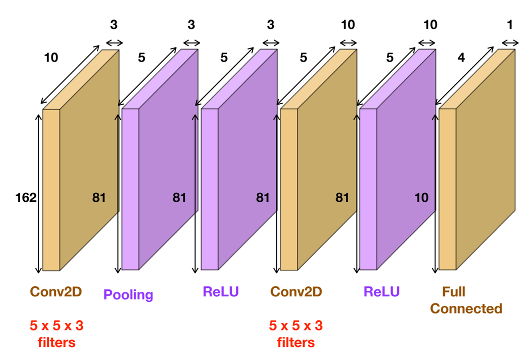
Objectives

- Train on the 10 first coordinates and speed and their interaction
- Predict the next 10
- Inputs have the following shape: $[10, N, 4 * N_{inter}]$

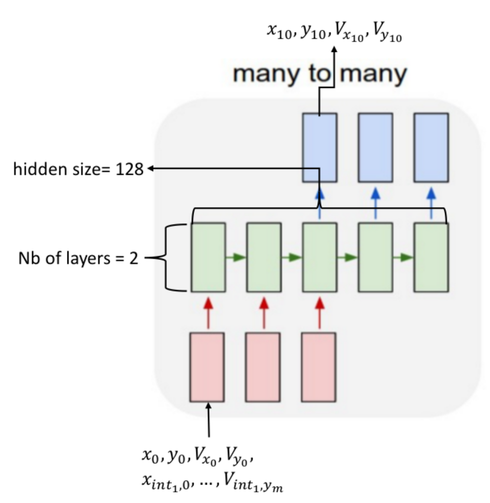
Models

Inputs: sequence of coordinates and velocities of the trajectory of interest and of the interacting trajectories
Outputs: sequence of predicted coordinates and velocities for the trajectory of interest.

CNN

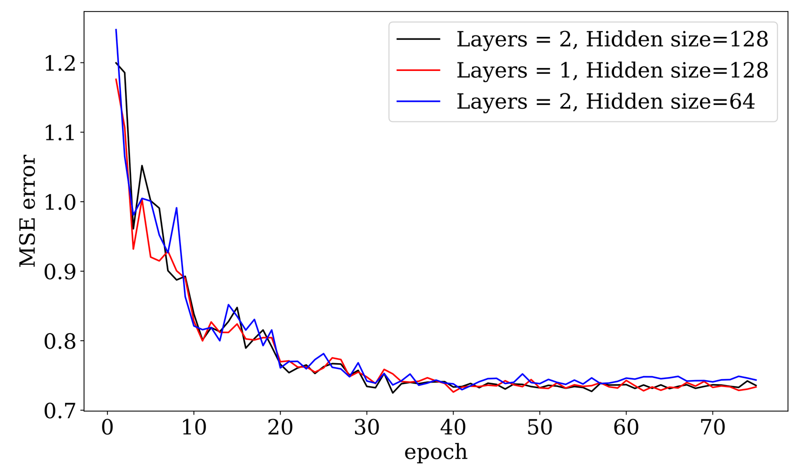


LSTM



Hyper-parameters test

Tests to choose the bests hyper-parameters of the LSTM:



Results

Precision indicators

To calculate the correctness of the prediction two indicators are used:

1. The final displacement error: $e_{fin} = \sqrt{(X_{gt,n} - X_{pred,n})^2}$
2. The mean displacement error: $e_{mean} = \sqrt{\frac{\sum_{i=0}^{n}(X_{gt,i} - X_{pred,i})^2}{(n)}}$

Post-processing

Depending on the inputs two ways are possible to find the predicted coordinates:

1. If the coordinates are predicted: directly use them
2. If the velocities are predicted: $X_t = X_{t-1} + V_t \cdot 0.4$, with 0.4 the time between two frames in seconds

Model tests case

Four different cases, that corresponds to four losses, are tested for each model:

1. Predict coordinates with loss defines as $L_1 = (X - X_{pred})^2$ with $X = [x, y]$
2. Predict speeds with loss defines as $L_2 = (V - V_{pred})^2$ with $V = [V_x, V_y]$
3. Predict both coordinates and speeds with loss defines as $L = L_1 + L_2$
4. Predict both coordinates and speeds with loss defines as $L = L_1 + L_2 + L_3$, with $L_3 = (X - X_{t-1} + V_t * 0.4)^2$

Trajectory type

1. Static
2. Linear trajectories
3. Non-linear trajectories

Linear prediction results

- Type 1: *Mean* = 0.141, *Final* = 0.322
- Type 2: *Mean* = 0.541, *Final* = 0.93
- Type 3: *Mean* = 0.651, *Final* = 1.457
- Total: *Mean* = 0.512, *Final* = 0.982

Models results

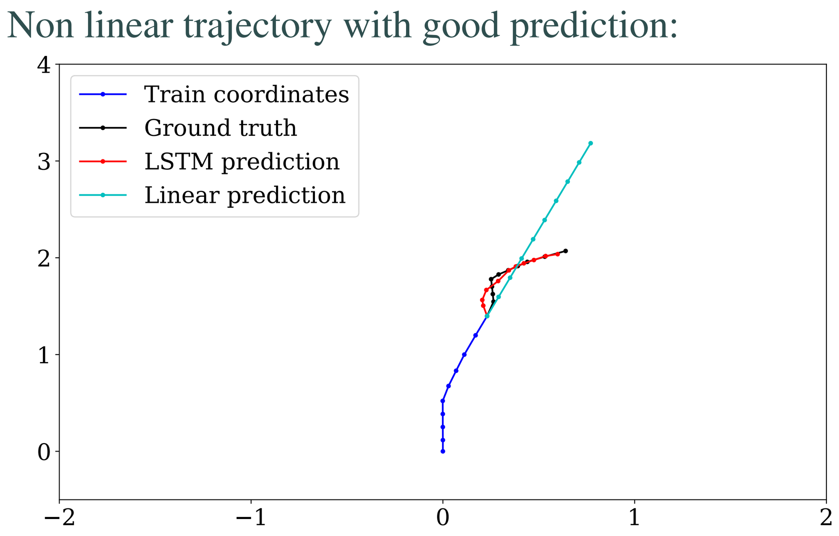
		CNN				LSTM			
		Type 1	Type 2	Type 3	Total	Type 1	Type 2	Type 3	Total
Coord.	Mean	4.696	5.144	4.674	4.176	1.309	0.777	0.862	0.877
	Final	10.246	7.009	10.501	5.602	1.385	0.92	1.108	1.037
Speed	Mean	0.567	5.133	1.911	4.17	0.726	0.573	0.651	0.616
	Final	0.77	6.971	3.882	5.587	1.412	1.045	1.231	1.148
2 Losses	Mean	1.269	5.134	1.762	**4.163**	0.695	0.532	0.627	**0.581**
	Final	2.727	6.978	3.546	**5.57**	1.302	0.963	1.2	**1.076**
3 Losses	Mean	0.549	5.135	3.829	4.163	0.748	0.607	0.681	0.647
	Final	0.758	6.983	4.962	5.573	1.364	1.072	1.308	1.177

Observation

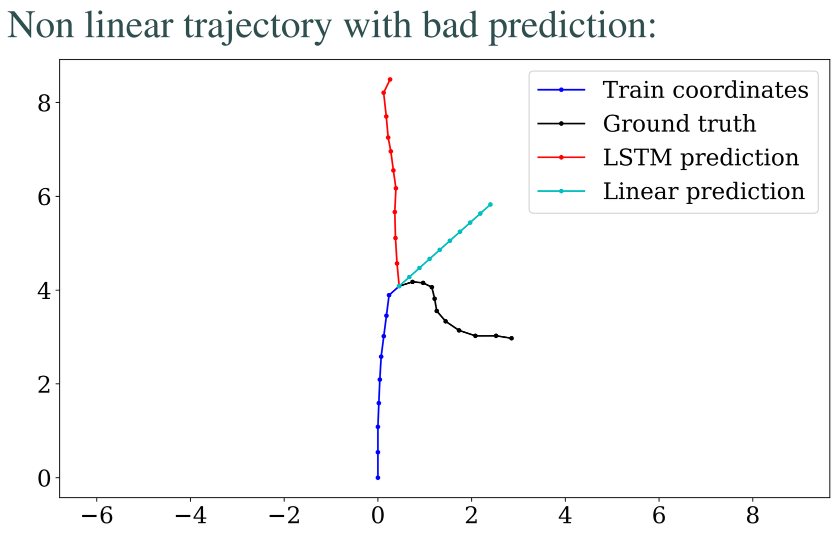
- Best results are the same for both models: case with two losses, one for coordinates and the other for velocities
- LSTM has much better results than CNN: memory capacities of the cells is useful in sequence to sequence prediction
- Three losses model might be too complicated for learning
- Good results for type 2 and 3 trajectories but struggle for type 1
- Global results is better with linear prediction, but without type 1 LSTM is better

Representation

Non linear trajectory with good prediction:



Non linear trajectory with bad prediction:



Issues

Data Augmentation

1. Flipping trajectories can remove behavioural pattern. If pedestrians tend to deviate on the right (or left) to avoid interaction, this pattern is lost.
2. Adding noise doesn't change much the trajectory: two very similar trajectories can be in the train AND in the test set.
3. Random data choice can create overfitting.

Trajnet challenge

1. Results cannot be entered for the challenge
2. Small modifications are needed to satisfy the challenge criterion

Future work

1. Test model without normalising step of the preprocessing: see the impact of this step on the learning
2. Change the way of selecting data to avoid redondance in train, validation and test sets

References

[1] Ramanathan V. Robicquet A. Fei-Fei L. Alahi A., Goel K. and Savarese S. Social lstm: Human trajectory prediction in crowded spaces. June 2016.

[2] Alex Graves. Generating sequences with recurrent neural networks. *CoRR*, abs/1308.0850, 2013.

[3] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural Comput.*, 9(8):1735–1780, November 1997.