DAIT Project

Trajectory Preduiction for Human-Human Interaction

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Introduction

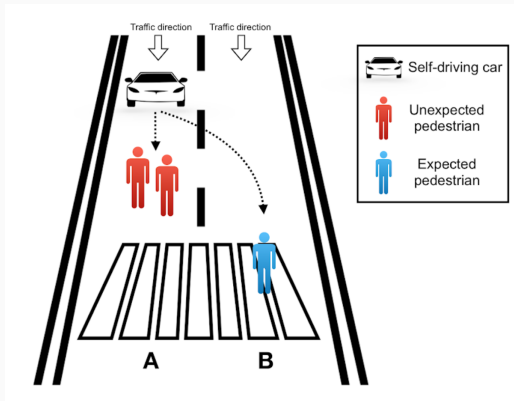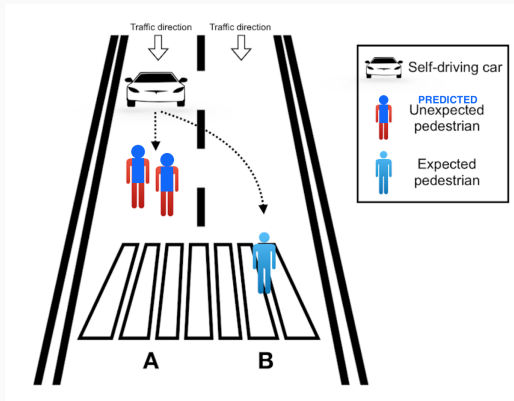- Trajectory prediction is crucial for improving autonomous vehicles behaviour
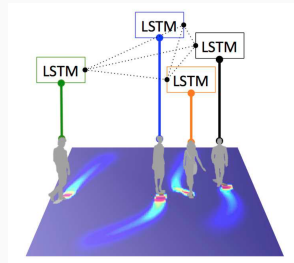
- Trajectory prediction is crucial for improving autonomous vehicles behaviour
- Could avoid situations seen in the ethical lectures

Previous work Social LSTM : Human Trajectory Prediction in Crowded Spaces

In their project, they used different components to make the structure:
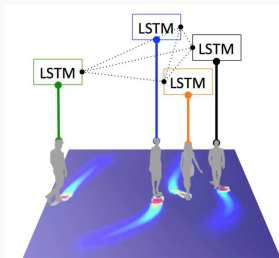
- One LSTM per pedestrian
- Social Pooling
- Prediction per frame

# Previous work Social LSTM : Human Trajectory Prediction in Crowded Spaces

In their project, they used different components to make the structure:

- One LSTM per pedestrian
- Social Pooling
- Prediction per frame

In our project we only use:

- One CNN, or one LSTM
- Prediction per pedestrian

Images from Social LSTM:Human Trajectory Prediction in Crowded Spaces and courses lecture
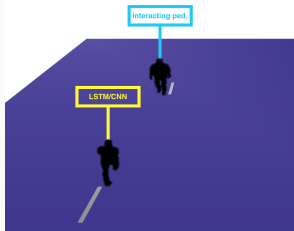
Data

Pre-processing

The preprocessing is divided in 4 steps:

1. We isolate each trajectory along with his interaction, that is the other trajectories that are around within the same frames

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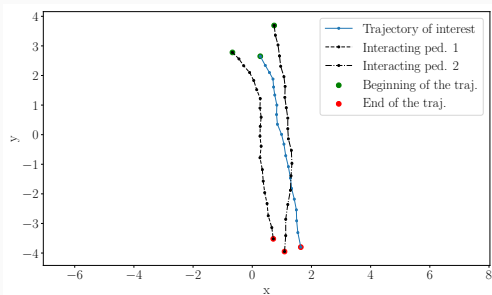2. We normalize the trajectories such that the first point is at $(0,0)$ and the second is at $(0, y_1)$

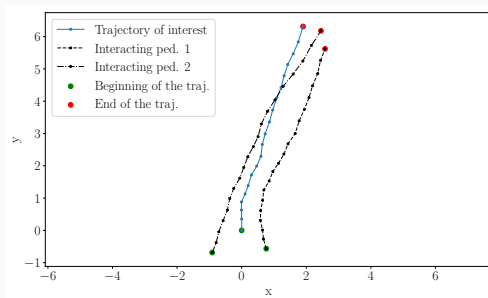## Pre-processing

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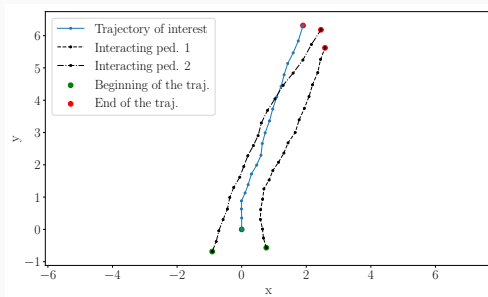The preprocessing is divided in 4 steps:

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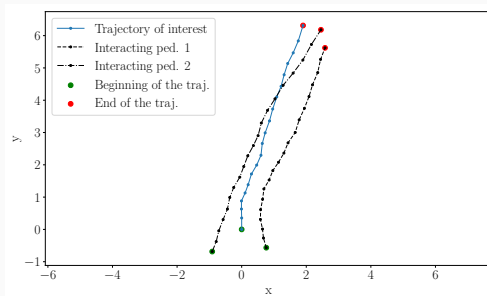
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5. Data augmentation (flip and add noise) cf. last slide
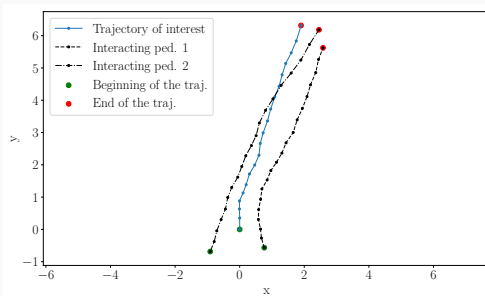
Data

We have a file with:

- Pedestrians ID

- Frame number

- Twenty sets of x and y coordinates per pedestrian

Frame Number	ID	x	y	V_x	V_y
⋮	⋮	⋮	⋮	⋮	⋮

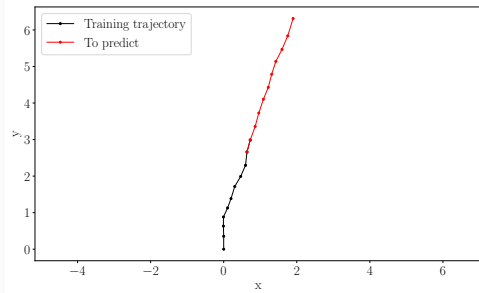## Data

We have a file with:

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

We want :

- Train on the 10 first coordinates
- Predict the next 10

Frame Number	ID	x	y	V_x	V_y
⋮	⋮	⋮	⋮	⋮	⋮

Example of trajectory to predict

Outputs structure

Finally our inputs have the following shape: $[10, N, 4 * N_{inter}]$, with

- 10: sequence length
- N: The number of data
- $4 * N_{inter}$: 4 (being the x and y coordinates and V_x and V_y velocities) times the number of pedestrians interacting with the one of interest.

The four different cases are:

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 $L_3 = (X - X_{t-1} + V_t * 0.4)^2$

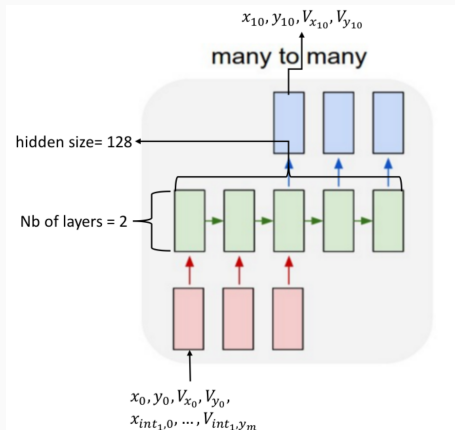The fourth case ensure that coordinates and speeds are not predicted independently.

Models

CNN

Define CNN

LSTM

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

Results

Results: Introduction

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

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

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

Results for both models:

- 3 Types of trajectory defined: Static, linear and non-linear trajectories
- Mean and Final displacements

Results

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

		CNN				LSTM			
		Type 1	Type 2	Type 3	Total	Type 1	Type 2	Type 3	Total
Coord.	Mean					1.16	0.768	0.817	0.837
	Final					1.269	0.911	1.087	1.011
Speed	Mean					0.742	0.397	0.448	**0.461**
	Final					1.433	0.716	0.874	**0.863**
2 Loss	Mean					0.519	0.484	0.568	0.511
	Final					0.979	0.871	1.093	0.946
3 Loss	Mean					0.537	0.473	0.576	0.51
	Final					0.992	0.86	1.125	0.95

Results

Discussion

Representation

Representation

Dynamic Representation

Discussion