DAIT Project

Pedestrian trajectory prediction

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23.05.2018

EPFL

Introduction

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- Trajectory prediction is crucial for improving autonomous vehicles behaviour

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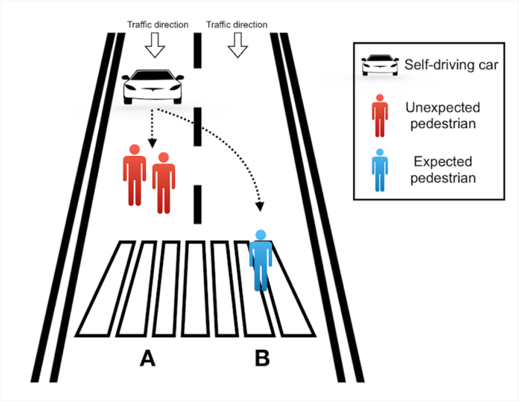


Image from lecture note 9

Introduction

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

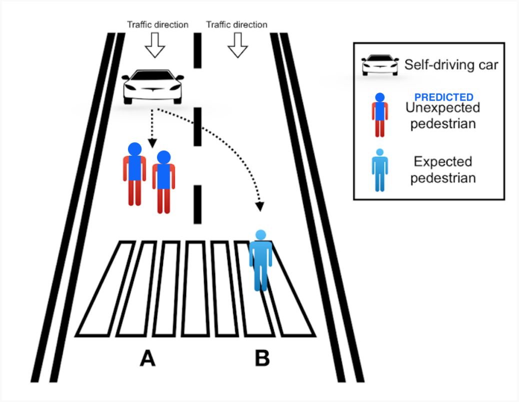
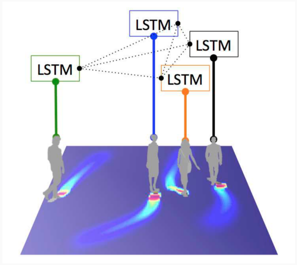


Image from lecture note 9

Previous work [1]

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

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



[1] Alahi et.al, **Social LSTM:Human Trajectory Prediction in Crowded Spaces**, 2016
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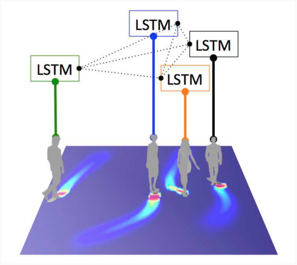
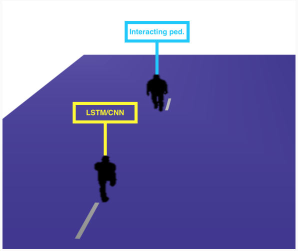


In our project, we use:

- One CNN, or one LSTM
- Prediction per pedestrian



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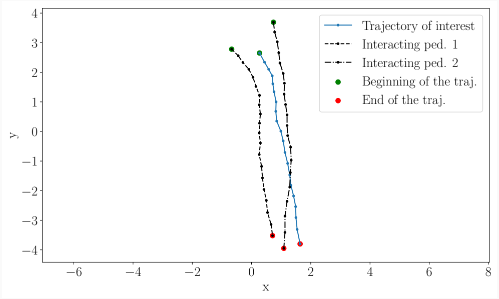
Data

Pre-processing

The preprocessing is divided in 5 steps:

1. Isolate each trajectory along with its interaction



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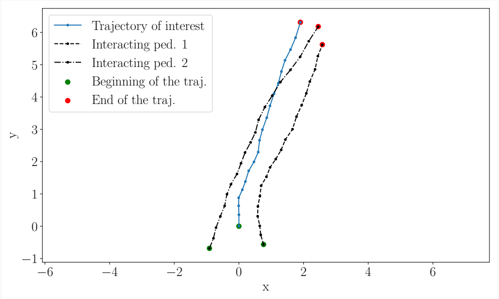
The preprocessing is divided in 5 steps:

1. Isolate each trajectory along with its interaction
2. Normalize the trajectories: the first point is at $(0, 0)$; the second is at $(0, y_1)$



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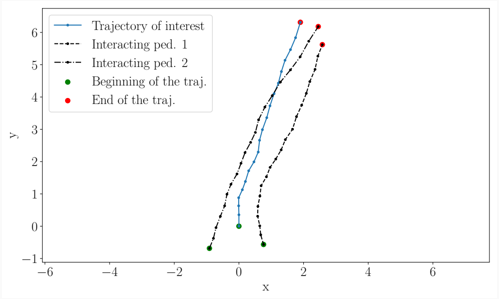

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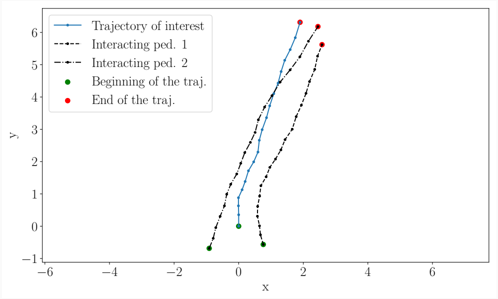
4. For each frame, if there is an interacting pedestrian we add his/her coordinates and speed otherwise we add zeros



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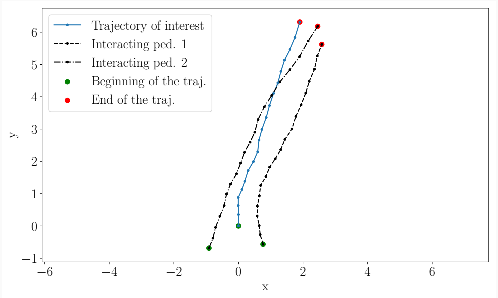
5. Data augmentation: flip and add noise to trajectories



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
0	i	0	0	0	0
10	i	0	y_1	0	V_{y_1}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$

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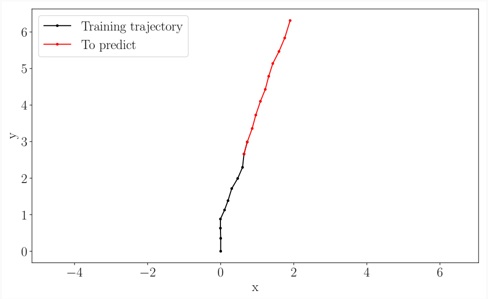
We want :

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

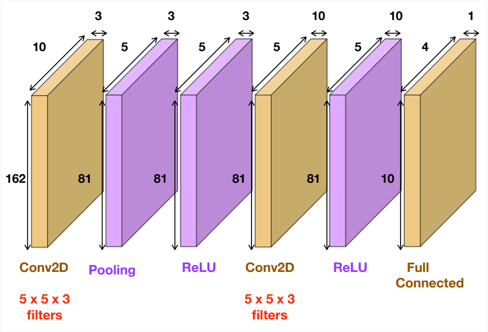
Example of trajectory to predict



Models

CNN

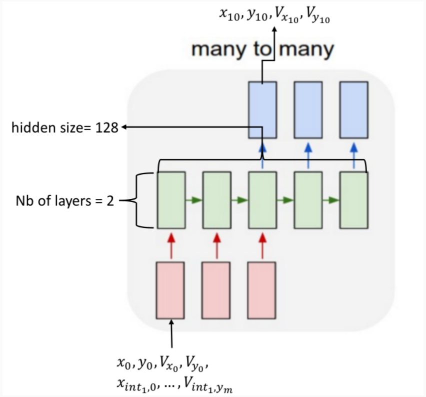
CNN architecture:



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

LSTM

LSTM architecture:



$x_{10}, y_{10}, V_{x_{10}}, V_{y_{10}}$
many to many
hidden size= 128
Nb of layers = 2
$x_0, y_0, V_{x_0}, V_{y_0},$
$x_{int_1,0}, \dots, V_{int_1,y_m}$

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

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: Introduction

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

Each case is tested on four trajectory types:

1. Static
2. Linear trajectories
3. Non-linear trajectories
4. All of them together

Results: Table

Results with linear prediction:

- 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**	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

Results: Discussion

LSTM and CNN comparison:

- For both LSTM and CNN, the "2 Losses" model have the better results
- For the CNN, results are much higher $\Rightarrow$ the absence of memory is really penalising

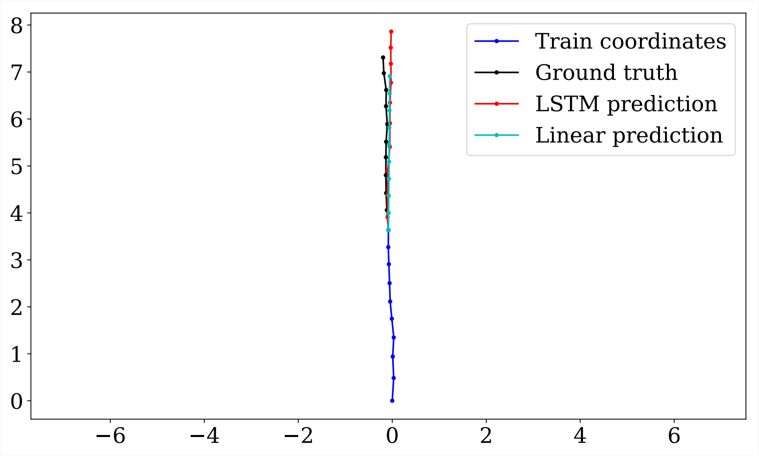
LSTM and linear prediction comparison:

- Except for the first type trajectory, our "2 Losses" LSTM have better results
- Even for static trajectory, the LSTM tries to predict dynamic trajectory

Representation

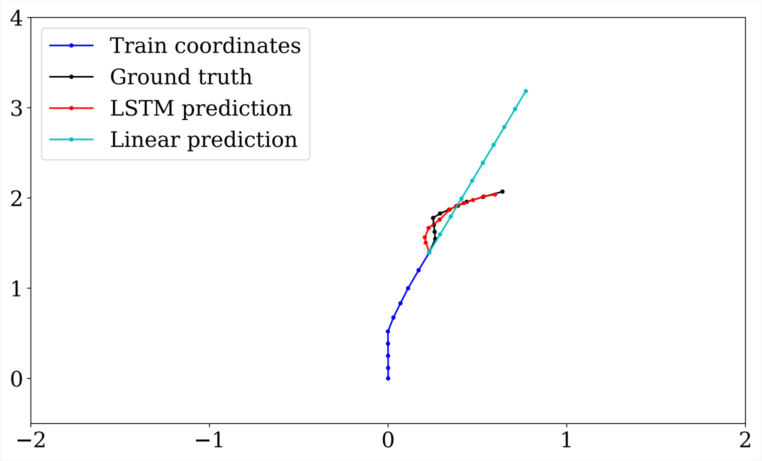
Representation: a few examples

Linear trajectory:



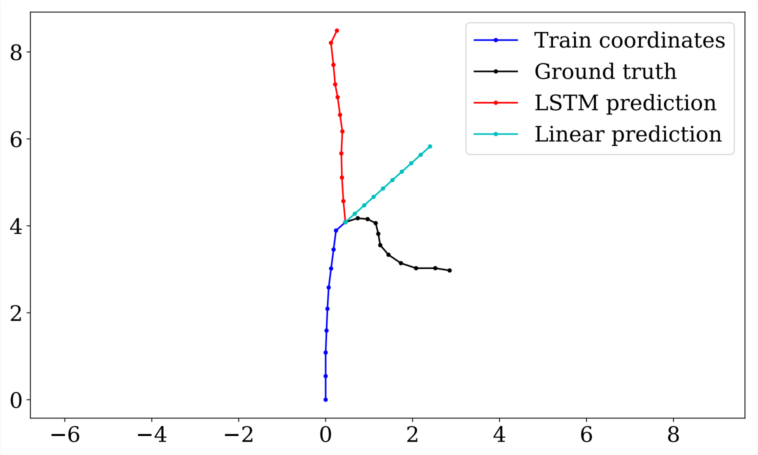
Representation: a few examples

Non-linear trajectory:

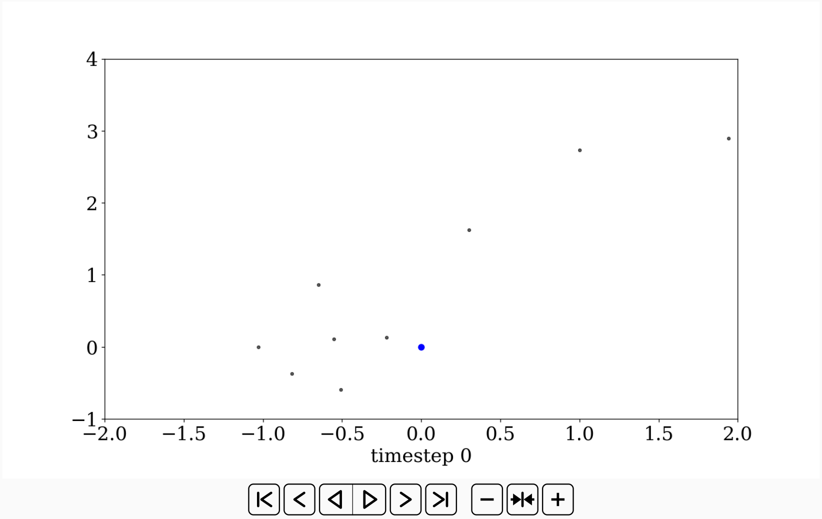


Representation: a few examples

But sometimes prediction fails:



Dynamic Representation



Conclusion

What can we conclude ?

- CNN is not well structured for this application
- LSTM gives better trajectories compare to the other models
- Models struggle to predict the statics trajectories

What can be debated ?

- The inputs of the CNN model can be improved
- The inputs can be discussed concerning the initialisation of the matrix of interactions
- Our data augmentation can be discussed

Annex

Data Augmentation

The data augmentation is divided in two steps:

1. Flipping the trajectory, i.e $x = -x$ and $y = y$
2. Add noise to all points (except two first): $0 < \epsilon_x < 0.1$ and $0 < \epsilon_y < 0.1$. Only for type 2 and 3 trajectory, otherwise for type 1, trajectory become unrealistic.

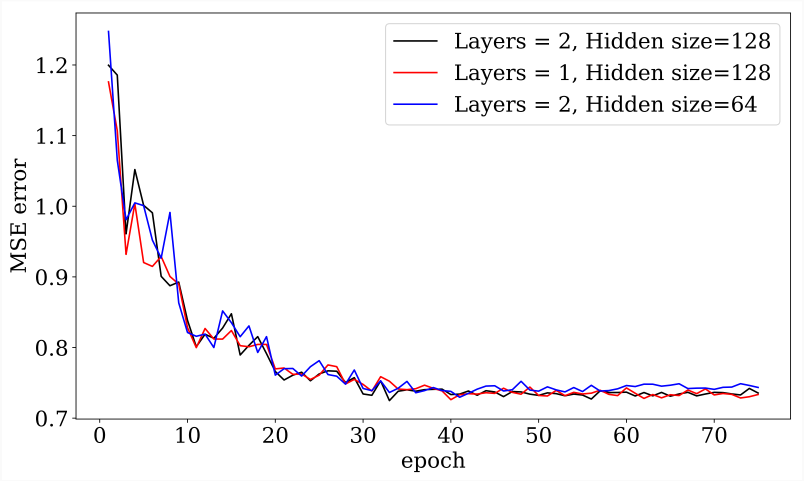
What is the problem:

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.

The first problem is hard to overcome. The solution would be to not flip the trajectory $\Rightarrow$ we tried and with less data, we have worst prediction.
The second problem is not a really one. Trajectory are often similar for a lot of them, the issue can be problematic for "unconventional" trajectories, and the model can "learn by heart" the output.

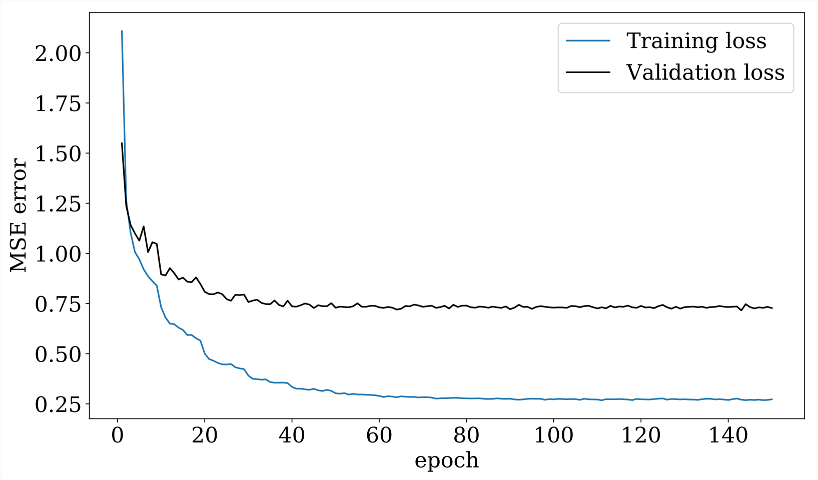
Hyperparameters LSTM

Loss validation depending on the hyperparameters:



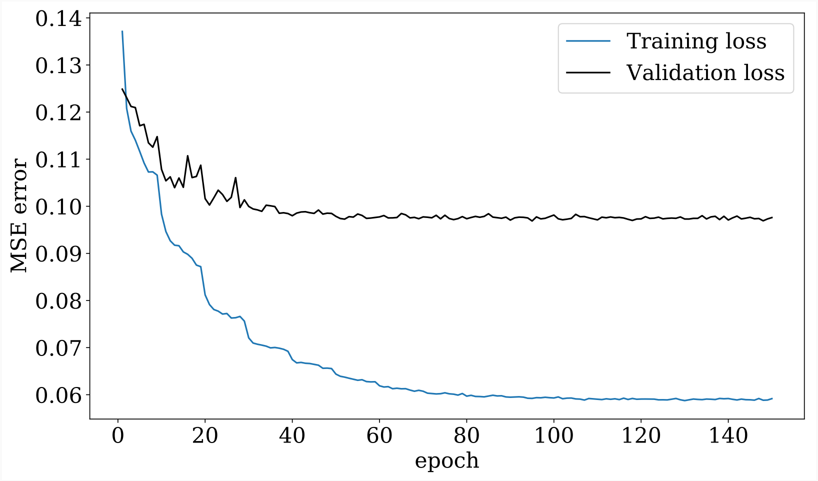
Loss Functions: Coordinates model

Coordinates model:



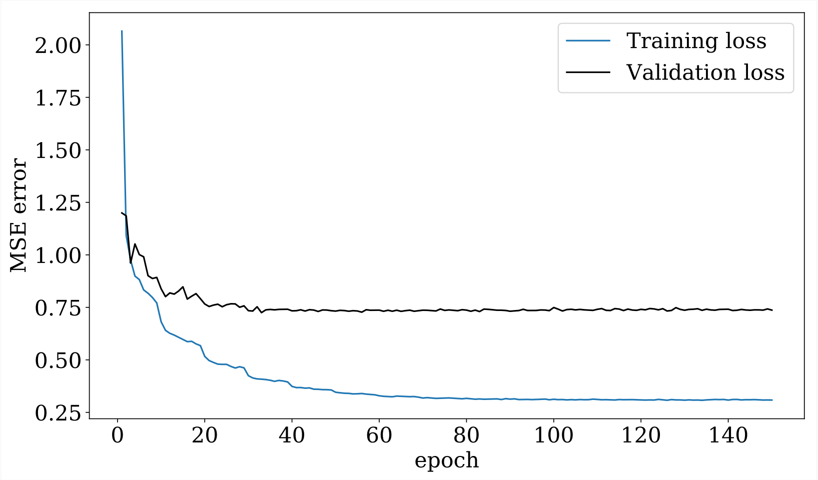
Loss Functions: Speed model

Speed model:



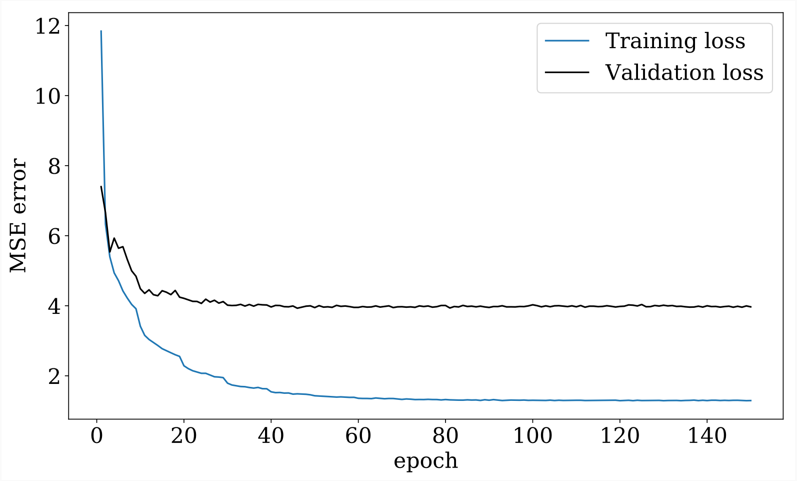
Loss Functions: 2 Loss model

2 Loss model:



Loss Functions: 3 Loss model

3 Loss model:


Training loss
Validation loss
MSE error
epoch