Using time-to-collision in the loss function of deep learning algorithm to improve pedestrian trajectory predictions

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Motivation

- **Pedestrian trajectory prediction** is a hot topic due to many real world applications like autonomous vehicles or social robots.
- **Deep Learning algorithms** have shown to outperform the physics-based models in terms of distance error.
- Nevertheless, the predictions show **too many collision and overlaps**, especially at higher densities.
- In this work, we want to implement **Time-To-Collision** into the architecture of the Deep learning algorithms to improve collision avoidance.

Objectives

- We train and test the algorithm with **ETH** and **UCY** pedestrian trajectory datasets.
- The predictions are evaluated with the distance based **average displacement error (ADE)** and a distance-based **collision metric (Col)**.
- We use the Social LSTM from Alahi et al. [1] as baseline and as core for the new TTC-SLSTM algorithm.
- The prediction results with **SLSTM and TTC-SLSTM are compared using the two evaluation metrics** ADE and Col.

TTC error metric

- The **TTC metric** estimates how long it would take for two pedestrians to collide with each other if they continue to move at their current velocity.
- Based on this concept, we create an sigmoidal error metric L_τ, **low TTC resulting in high loss**.

$$L_\tau = \frac{1}{1+\exp(-s(\tau-\delta))}$$

- *Idea*: **Penalize** predictions with **low TTC**

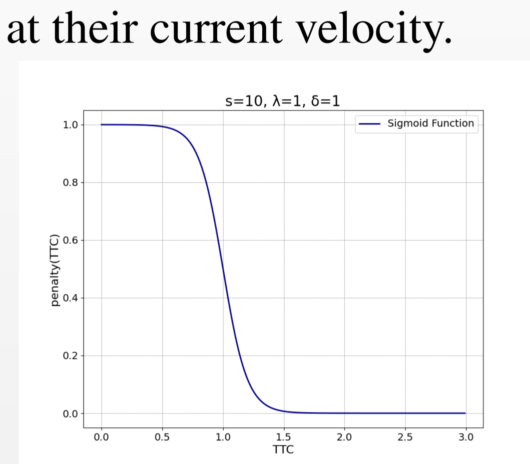

Fig. 1: TTC penalty function L_τ

New TTC-SLSTM algorithm

- The core of the TTC-SLSTM is the SLSTM. We keep the settings, but **add TTC in the loss function** L

$$L = ADE + \lambda L_\tau, \qquad \lambda \geq 0$$

- The **parameter** λ quantifies the **impact of TTC loss on the training** (see Fig.2).

Results

- We could improve the prediction for **both ADE and Col error metrics** (Fig. 2).
- With rising λ the metric Col **goes down continuously**. ADE decreases at first, but then starts to increase.
- Predictions are **more realistic** with better collision avoidance; see Fig. 3.

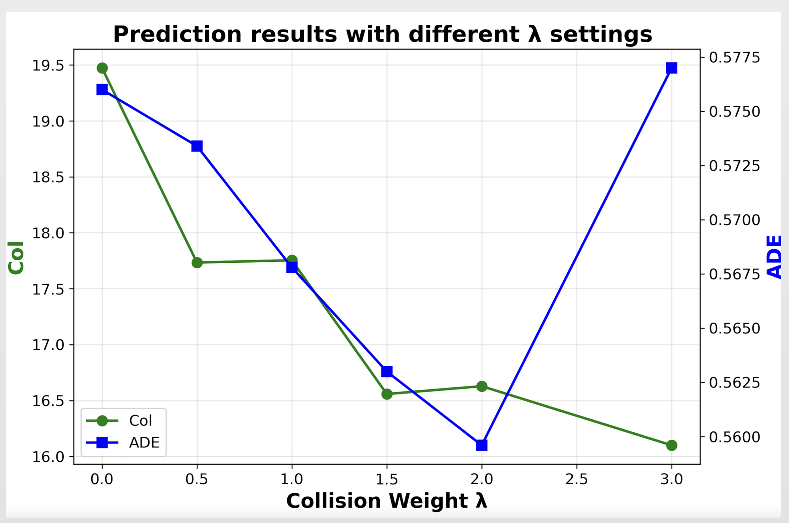

Fig. 2: Testing prediction error metrics against λ

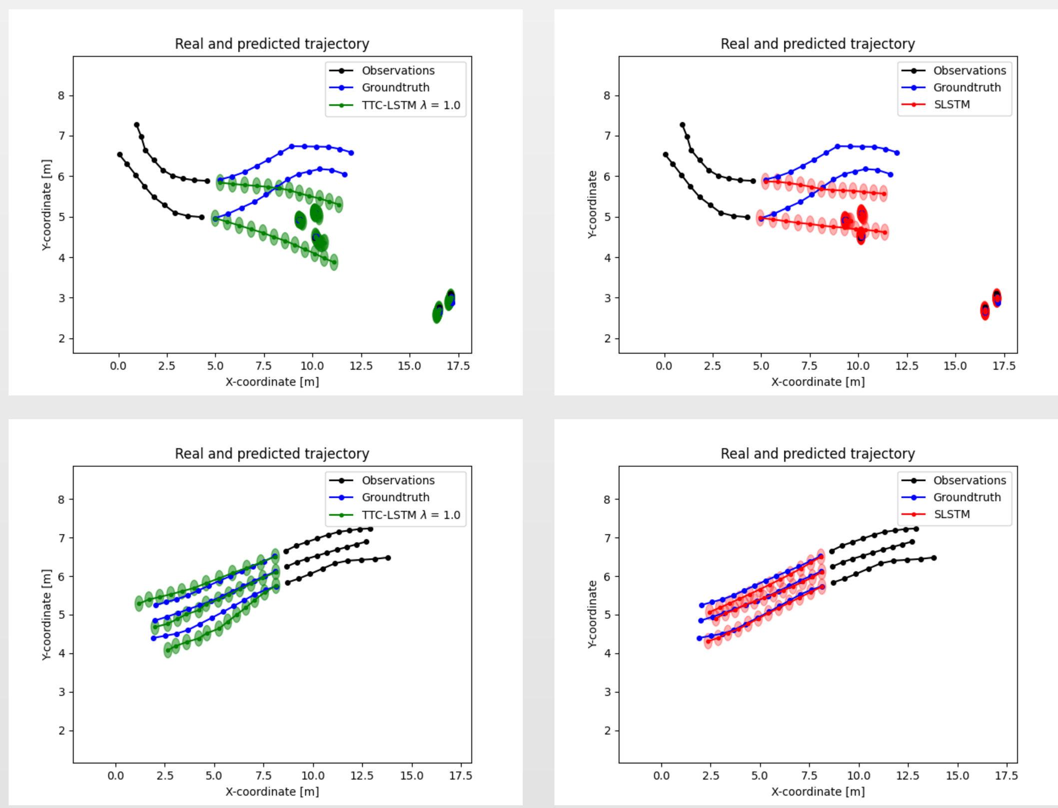

Fig. 3: Trajectory predictions with TTC-SLSTM and SLSTM

Future works

By incorporating not only the distance-error metric, but also the TTC error metric into the training loss function, we could significantly improve the trajectory predictions.

In further work we aim to:

- Investigate whether the predictions improve in different environments and especially **higher densities**.
- Explore the performance of **other hybrid deep learning architectures** including time-to-collision and pedestrian-related metrics.

References

[1] Alahi, A., Goel, K., Ramanathan, V., Robicquet, A., Fei-Fei, L., & Savarese, S. (2016). Social lstm: Human trajectory prediction in crowded spaces. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 961-971).

[2] Karamouzas, I., Skinner, B., & Guy, S. J. (2014). Universal power law governing pedestrian interactions. *Physical review letters*, 113(23), 238701.

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