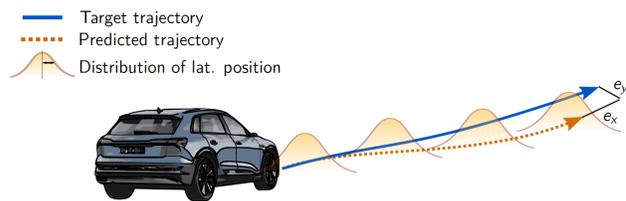


Representation Learning and Latent Spaces for Trajectory Prediction in Automated Driving

Overview

- Identifying novel approaches and representations for predicting vehicle trajectories that benefit from interpretability.
 - Focus: Long-term prediction periods (≥ 1 s).
 - Problem: Long-term prediction highly depends on the scenario context. To include context information into predictions, the applied AI algorithms/architectures unavoidably require to be complex to a certain extent and therefore are not interpretable. However, complex AI-based architectures are hard to trust blindly for such high stake decisions.
 - Solution: Find appropriate representations, structures and architectures that enable partial interpretability by still providing good performance.
- Shaping (latent) representations in order to gain interpretability.

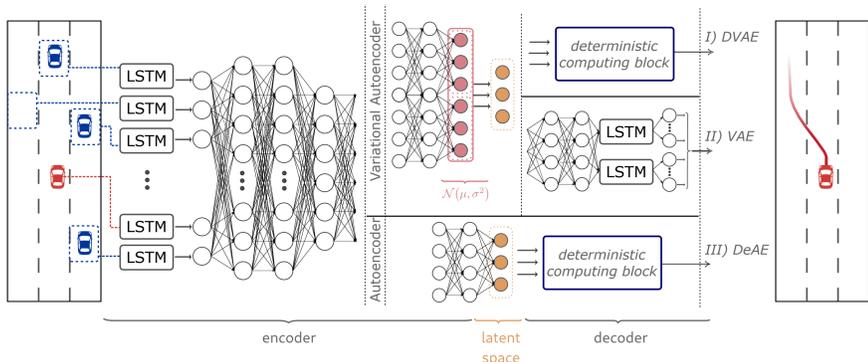


Methods

Expert knowledge-assisted predictions[1]

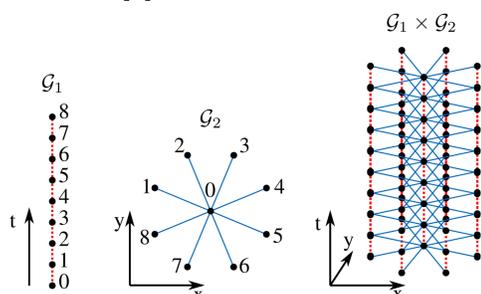
- Train an autoencoder using \mathcal{D} to perform the mapping $\mathbf{X} \mapsto \mathbf{z}$ (encoder) and $\mathbf{z} \mapsto \mathbf{X}_{rec}$ (decoder).
- The encoder is implemented using state of the art AI to grasp the context information of a traffic scenario.
- The decoder part is implemented model-based by using expert-knowledge. Its output is the long-term trajectory prediction.
- Due to the decoder setup, the latent space \mathbf{z} holds a specific and interpretable meaning (e. g. acceleration).
- This method is called a *Descriptive (Variational) Autoencoder*, short *DVAE*.

$$\mathbf{x} = v_0 \mathbf{t} + 0.5 z_1 \mathbf{t}^2 \quad \mathbf{y} = \frac{z_2}{1 + \exp(-\text{relu}(z_2 \boldsymbol{\tau}))}$$



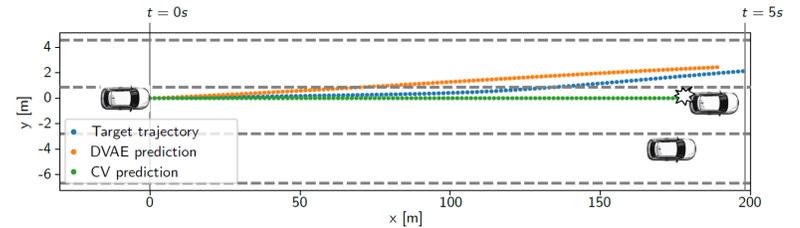
Graph-based scenario representations

- Use graph structures and graph transformations to represent traffic scenarios.[2]
- Apply novel methods like *Graph Neural Networks* to predict intentions and gain interpretability.[3]

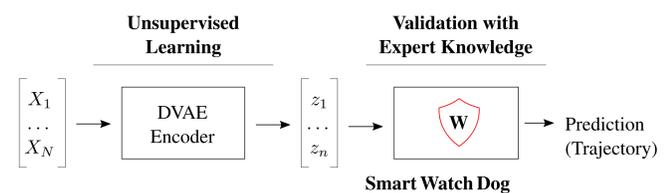


Results

- Evaluation of the proposed DVAE shows, that its prediction accuracy is similar to their non-interpretable counterparts and superior to simple model-based methods like the Constant Velocity (CV) model.



- The training can be done completely unsupervised.
- The resulting latent space is interpretable, which allows prediction validation by rules in the latent space ('Watch-Dog').
- Interpretability contributes towards the use of AI in safety critical applications. Predictions can be evaluated regarding their validity. Physically impossible or unlikely predictions can be detected and declared as untrustworthy.

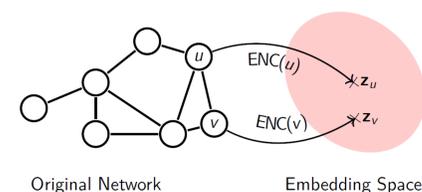


Possible Approaches to Generate Watch Dog for Validation

- Bounds for the latent space parameters based on physical constraints.
- Physical model of the relation between the latent parameters.
- Evaluate the predicted trajectory by checking if the vehicle will stay on the road and avoid collisions.

Outlook

In future work, the goal is to introduce more sophisticated motion calculations within the decoder part to improve prediction performance. A more general decoder design is necessary to enable the networks' usage for all traffic situations and not to be limited to highway-alike scenarios. Current efforts are evaluating the usage of graph structures for the prediction task. First results support this research direction showing that both interpretability and performance can benefit from representations in graph structures.



References

References

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