

## VI. CONCLUSION AND FUTURE WORK

This paper presented a vectorized scenario description that provides a uniform way to describe both test and real-world scenarios, including spatial and temporal nuances. Unlike scenario description formats such as OpenScenario, which are intended for scenario definition, our vectorized scenario description is especially suitable for (predictive) analyses. We demonstrated this by generating and merging data from three functional scenarios to train the motion prediction model VectorNet. The results showed that VectorNet is able to predict an AV's trajectories based on both individual and multiple scenarios. Given existing data, a small amount of data is sufficient to enable generalization to new functional scenarios. Based on the predicted trajectories, evaluation metrics can also be predicted. Here, VectorNet partially achieves higher predictive performance than conventional regression metamodels. However, for our scenarios that inputs can still represent, the regression metamodels' overall performance is better.

Our results suggest that conventional search-based techniques are preferable for individual test campaigns with specified scenarios. However, our method can benefit from data accumulated during development and testing, and enables new use cases. For example, the behavior of AVs in specified test and real-world scenarios could be compared without scenario identification [24]. For this purpose, data from (virtual) tests could be combined to predict the behavior in real-world scenarios. If the actual behavior deviates from expectations, this indicates factors of reality that have not been thoroughly investigated in tests – a valuable hint for SOTIF area 3 [2].

Possible future work includes integrating dynamics models into the motion prediction to explicitly predict longitudinal and lateral behavior and enforce physically possible predictions. Probabilistic motion prediction models could account for uncertainties. The scenario embeddings could be extended to include inputs such as weather conditions and additional scenario elements such as traffic lights [7], [8]. The model could also be extended to predict logs and learn the behavior of other objects in the environment. This would allow studying interactions between the Ego and its environment.

In summary, integrating motion prediction into scenario-based testing is a promising direction to accelerate and fortify scenario-based testing by expanding the data pool for scenario selection and linking specified (virtual) and real-world tests.

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