

# Enhancing Motion Prediction by a Cooperative Framework

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## Abstract

Cooperative Perception (CP) is a technique that enhances the on-board sensing and perception of automated vehicles by fusing data from multiple sources, such as other vehicles, roadside infrastructure, cloud/edge servers, among others. It can improve the performance of automated driving in complex scenarios, like unsignalled roundabouts or intersections where the visibility and awareness of other road users are limited. Motion Prediction (MP) is a key component of cooperative perception, as it enables the estimation and prediction of microscopic traffic states, such as the positions and speeds of all vehicles. It relies on information from other agents and their relationships among them, so the information provided by external sources is valuable because it enhances the understanding of the scene. In this paper, we present improved MP through Vehicle to Vehicle (V2V) communication. We have trained Hierarchical Vector Transformer (HiVT) to be a map-less solution that can be used in road domains. With this model, we have implemented and compared two association methods to evaluate our framework on a real V2V dataset (V2V4Real). Our evaluation concludes that our V2V MP improves performance due to better scene understanding over a single-vehicle MP.

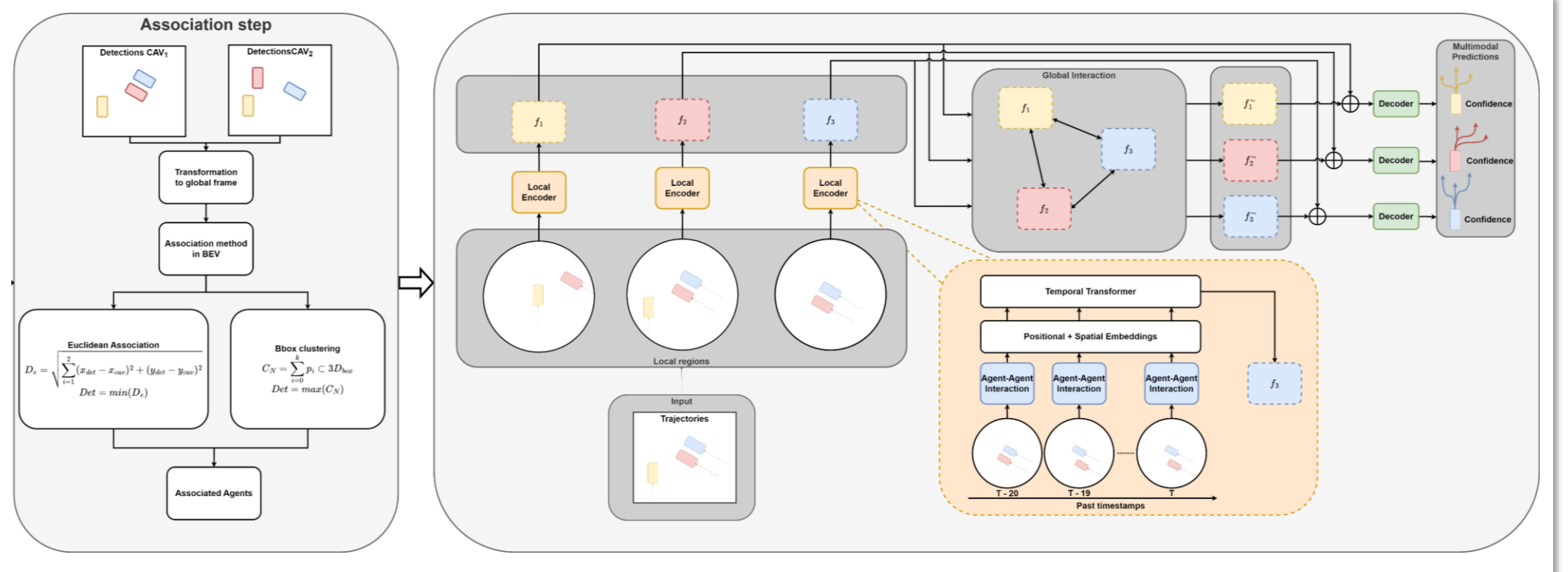
## Context

Cooperative Perception will help Connected Automated Vehicles (CAVs) improve their perception by considering other undetected agents in the environment. Motion Prediction will use this information as a more social context to predict future trajectories. This will help avoid occlusions due to a single vehicle perspective.



## Framework

- ⚡ Detections from two CAVs are shared with the framework. We transform all the detections into the same coordinate system using the transformation matrices provided by the dataset. As we carry out the prediction in Bird's Eye View (BEV), we have disregarded the z coordinate.
- ⚡ We evaluated two association methods: Euclidean distance to CAV and bounding box clustering. The first measures the distance to the CAV and takes the closer one. The second counts the points in the point cloud that fall within the bounding box.
- ⚡ The filtered detections are fed into our HiVT proposal, which has been trained to be a mapless solution that can be implemented in different domains.

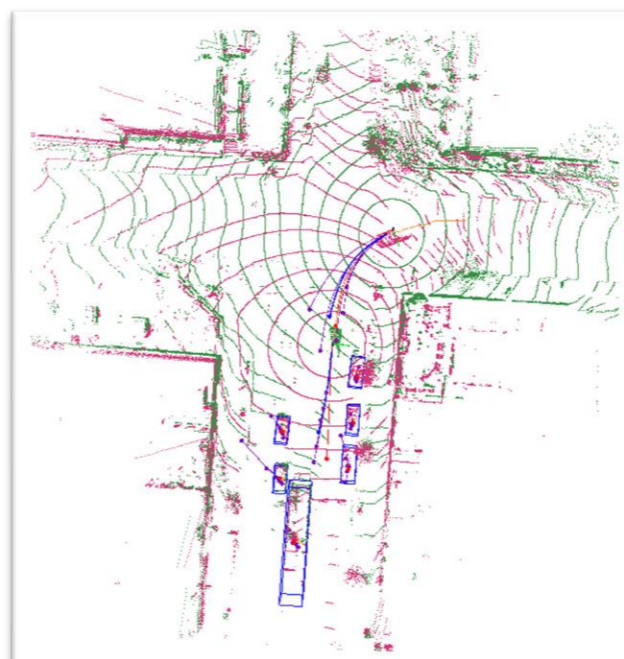
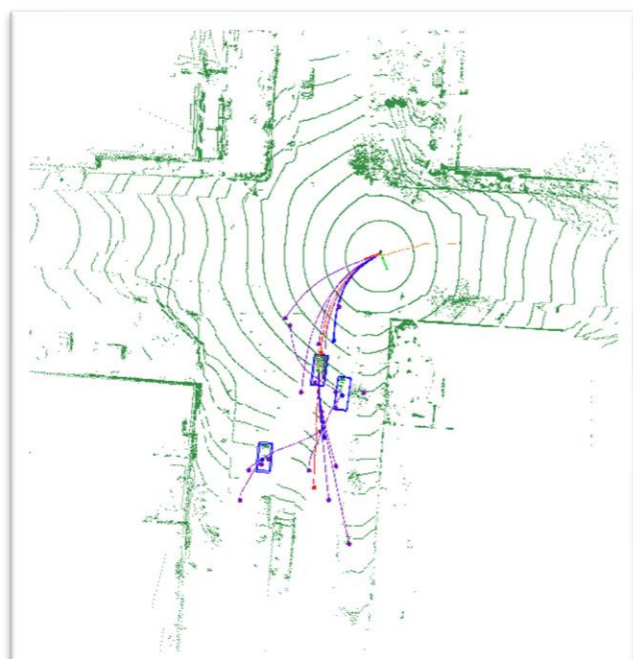


## Results

CAVs	Fusion	ViewPoint	N actors	brier-minADE			brier-minFDE		
				Absolute	Relative actors	Improvement	Absolute	Relative actors	Improvement
Tesla	-	Tesla	7.74	1.80	0.23	-	2.88	0.37	-
Astuff	-	Astuff	8.45	1.88	0.22	-	2.96	0.35	-
Tesla & Astuff	-	Tesla	14.58	2.00	0.14	-	3.17	0.22	-
Tesla & Astuff	Euclidean	Tesla	10.13	1.92	0.19	18%	3.02	0.30	20%
Tesla & Astuff	Bbox clustering	Tesla	10.19	1.92	0.19	19%	3.03	0.30	20%
Tesla & Astuff	-	Astuff	14.58	2.00	0.14	-	3.18	0.22	-
Tesla & Astuff	Euclidean	Astuff	10.13	1.92	0.19	15%	3.04	0.30	14%
Tesla & Astuff	Bbox clustering	Astuff	10.19	1.93	0.19	15%	3.05	0.30	15%

## Conclusions

- We have adapted and trained HiVT in Argoverse 1 to be a map-less solution model that we can use in other domains where the map is not available.
- Two association methods for CP: Euclidean distance to the connected vehicle and bounding box clustering.
- Evaluation in a novel V2V real dataset (V2V4Real) with an extensive comparison of different options.



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