EVENTS: ReliablE in-Vehicle pErception and decisioN-making in complex environmenTal conditions

Javier Araluce, Tecnalia

12 de abril (Alcalá de Henares)

¿Quién es Javier Araluce?

Académico

- Grado en Ingeniería Electrónica y Automática Industrial
    - Automatización de un vehículo eléctrico
- Máster en Ingeniería Industrial: especialidad de Robótica y Percepción
    - Smart HMI for an autonomous vehicle
- Doctor en Electrónica: Sistemas Electrónicos Avanzados. Sistemas Inteligentes
    - Driver attention based on Deep Learning for a Smart Vehicle to Driver (V2D) interaction

Empresa

- Mettler-Toledo Safeline (Manchester)
- Asociación de bienes de equipo (Madrid)
- Tecnalia (Bilbao)

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Mi trabajo actual

- Líneas de investigación
  - Predicción de comportamientos
  - Detección de agentes 3D
  - Monitorización de ocupantes
    - Distracciones del conductor
    - Ocupación y estado de pasajeros
  - Percepción colaborativa
  - *Domain adaptation*

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Mi trabajo actual

- Proyectos
  - Financiación Publica Competitiva
    - **EVENTS**
    - Aware2All
    - AugmentedCCAM
    - SHELFY
  - Proyectos bajo contrato
    - DIVEC (Contratos con 3 clientes)
    - R3CAV

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Mi trabajo actual

- Alumnos
  - Alberto Justo (Alumno de doctorado)
    - Percepción colaborativa
    - Deep Learning
    - *Domain Adaptation*
    - Detección y Tracking

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EVENTS

- Objetivo: sistema de percepción y de decisión robusto que sea capaz de gestionar “eventos”
  - Eventos:
    - Interacción con otros agentes
    - Carreteras extrañas (obras…)
    - Baja visibilidad y cambios de clima
- Consorcio:
  - 11 empresas y centros de investigación
  - 8 países
- Datos:
  - 6,8 M € de presupuesto
  - 36 meses

Papel de Tecnalia

- Desarrollos
  - Predicción de la trayectoria de otros agentes (WP3)
  - Percepción aumentada por V2X (WP3)
  - Sistema de decisión (WP4)
  - Sistemas ante fallos en el control (WP4)
- Experimentos
  - Maniobra de platooning en rotonda
  - Maniobra de evitación de una zona de obras
  - Estimación del comportamiento de los agentes en una intersección

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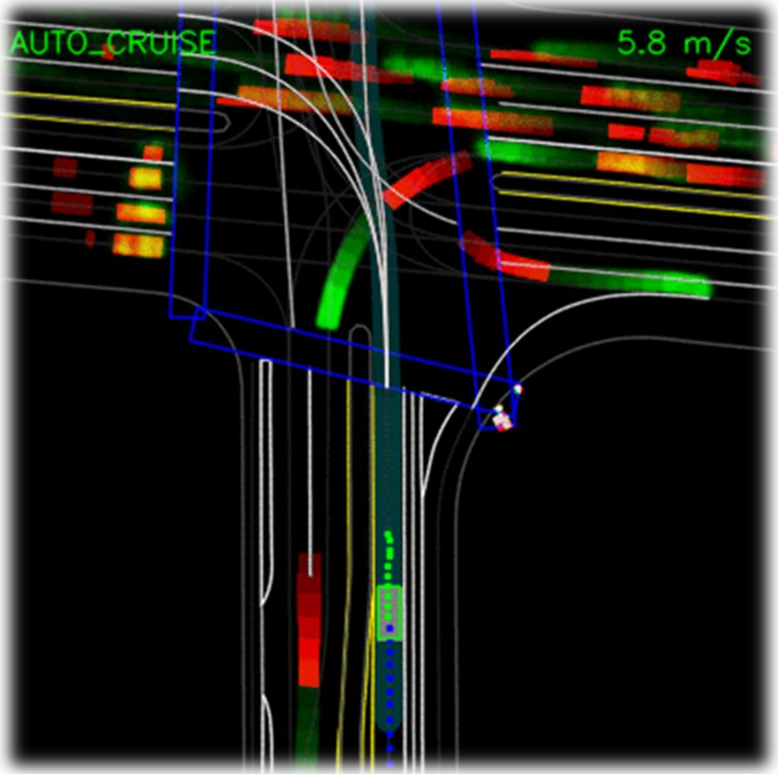
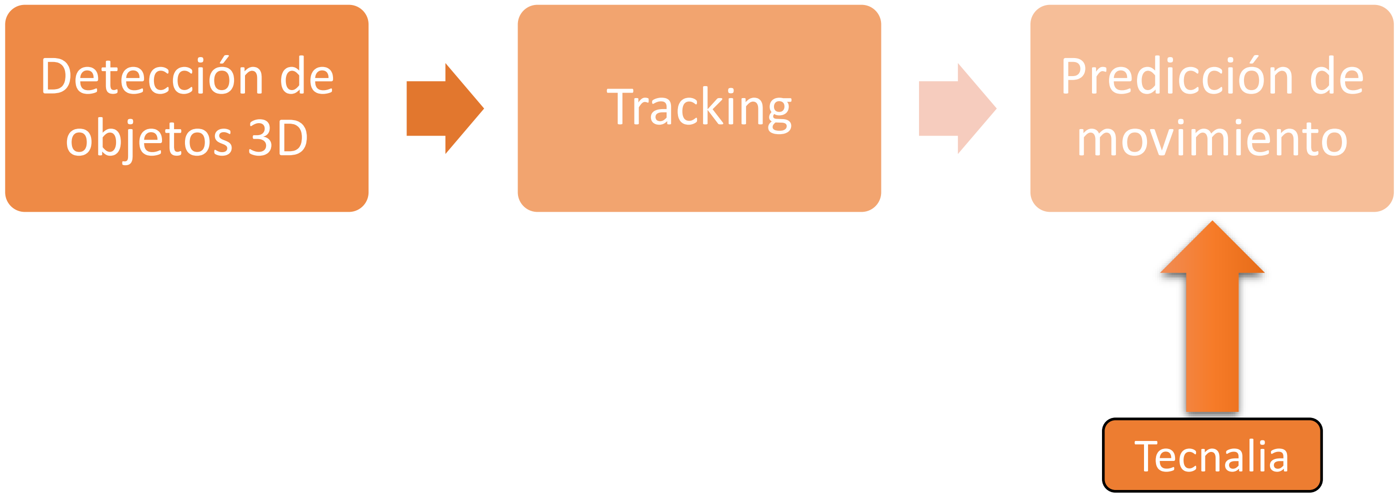
Percepción

- Predicción de movimiento de otros agentes (Motion Prediction)
  - Predecir las trayectorias de los agentes cercanos
  - Permite obtener un comportamiento predictivo



Sistema de percepción



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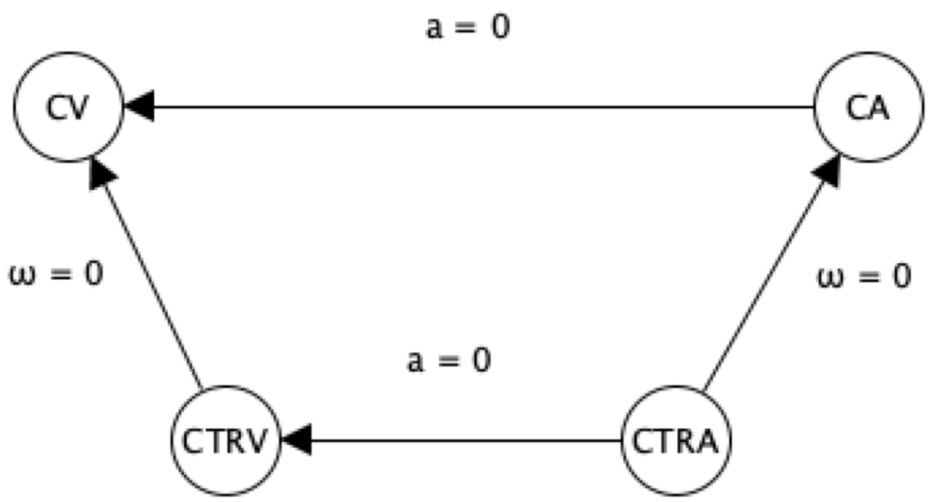
Motion Prediction

- Modelo físico clásico
- Utilizando el GT de nuestro simulador (CARLA)



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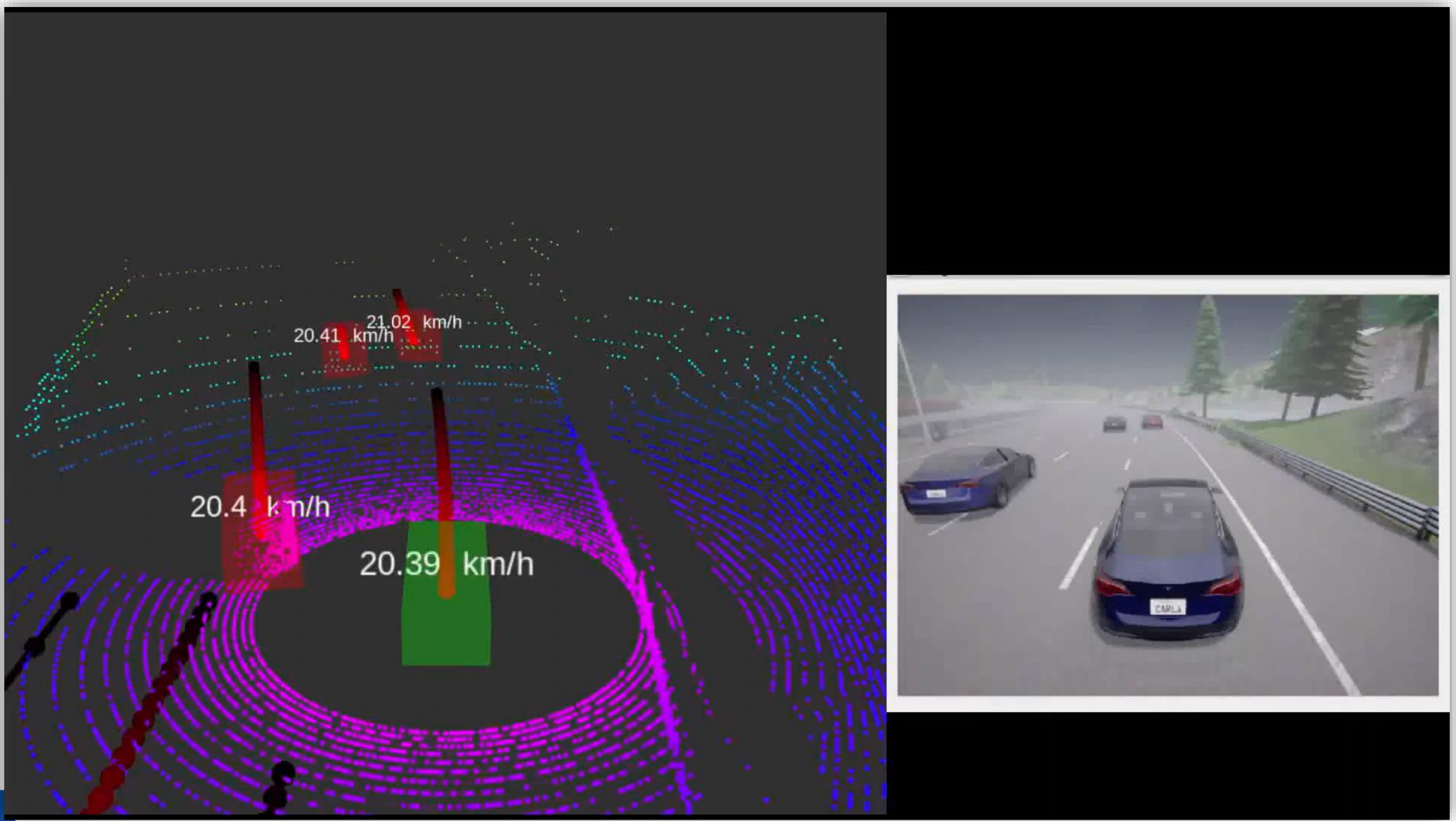
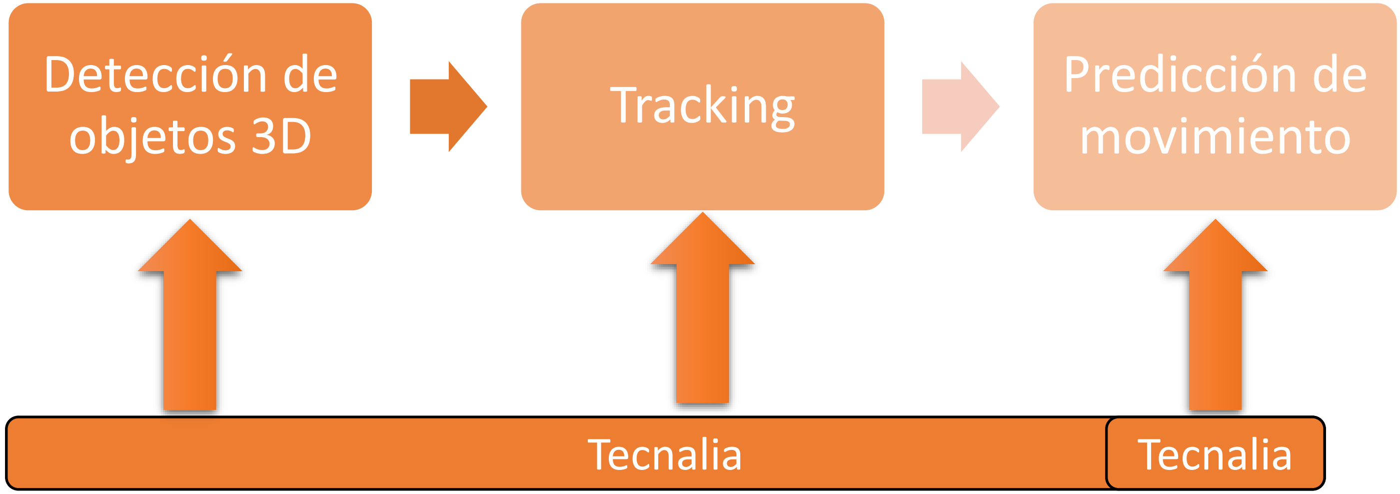
Motion Prediction



Sistema de percepción



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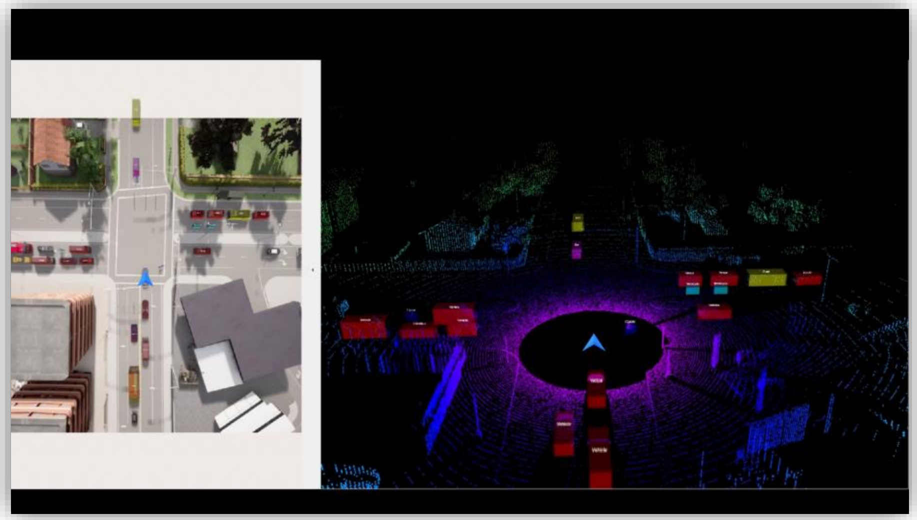
Detector 3D

- OpenPcdet
- PointPillars [1]
- Entrenado en dato sintético (SHIFT [2])



[1]: Lang, Alex H., et al. "Pointpillars: Fast encoders for object detection from point clouds." *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2019.
[2]: Sun, Tao, et al. "SHIFT: a synthetic driving dataset for continuous multi-task domain adaptation." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2022.

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Multi Object Tracking

- Algoritmo SORT
  - Algoritmo húngaro (asociaciones)
  - Filtro de Kalman (predicciones)

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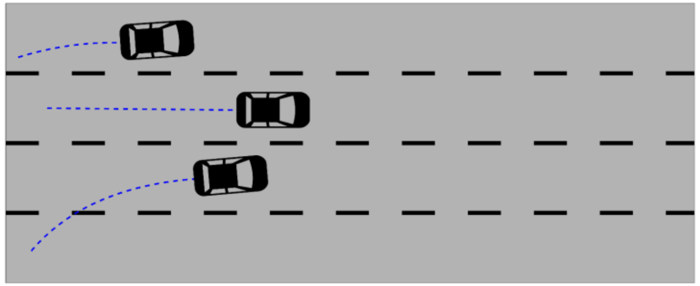
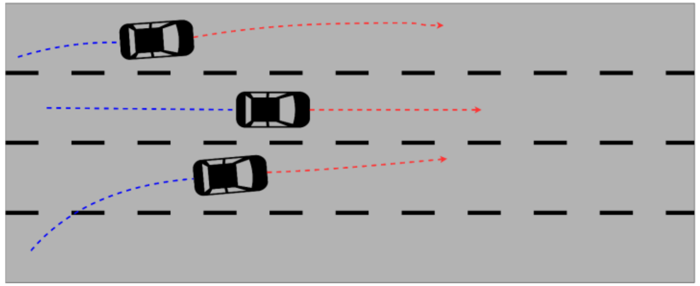
Motion Prediction

- Modelo físico clásico
- Utilizando el sistema de percepción



3D Object Detection (PointPillars) → Multi Object Tracking → Past Object trajectories (20 frames = 2 seconds) —[x, y, \theta, v a, \omega]→ CTRV/CTRA model → Future Object trajectories (30 frames = 3 seconds)



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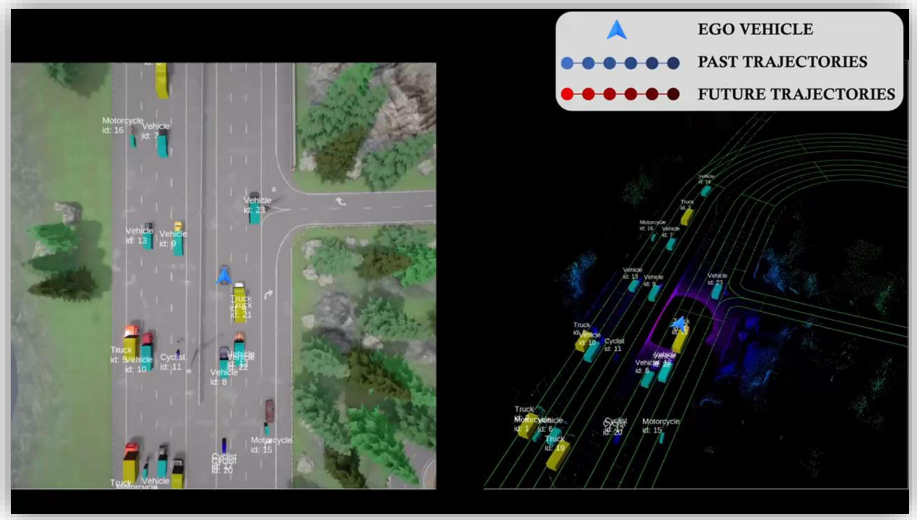
Motion Prediction

- Modelo físico clásico
- Utilizando el sistema de percepción



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Motion Prediction

Crat-Pred [1]

- Modelo social
- No depende de mapa
- 6 trayectorias
- 200 ms de inferencia (RTX 4000)
- Licencia: Creative Commons Attribution-NonCommercial 4.0 International

HiVT [2]

- Modelo social con mapa
- 6 trayectorias con confidencia
- 80 ms de inferencia (RTX 4000)
- Licencia: Apache

[1]: Schmidt, Julian, et al. "Crat-pred: Vehicle trajectory prediction with crystal graph convolutional neural networks and multi-head self-attention." *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, 2022.
[2]: Zhou, Zikang, et al. "Hivt: Hierarchical vector transformer for multi-agent motion prediction." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2022.

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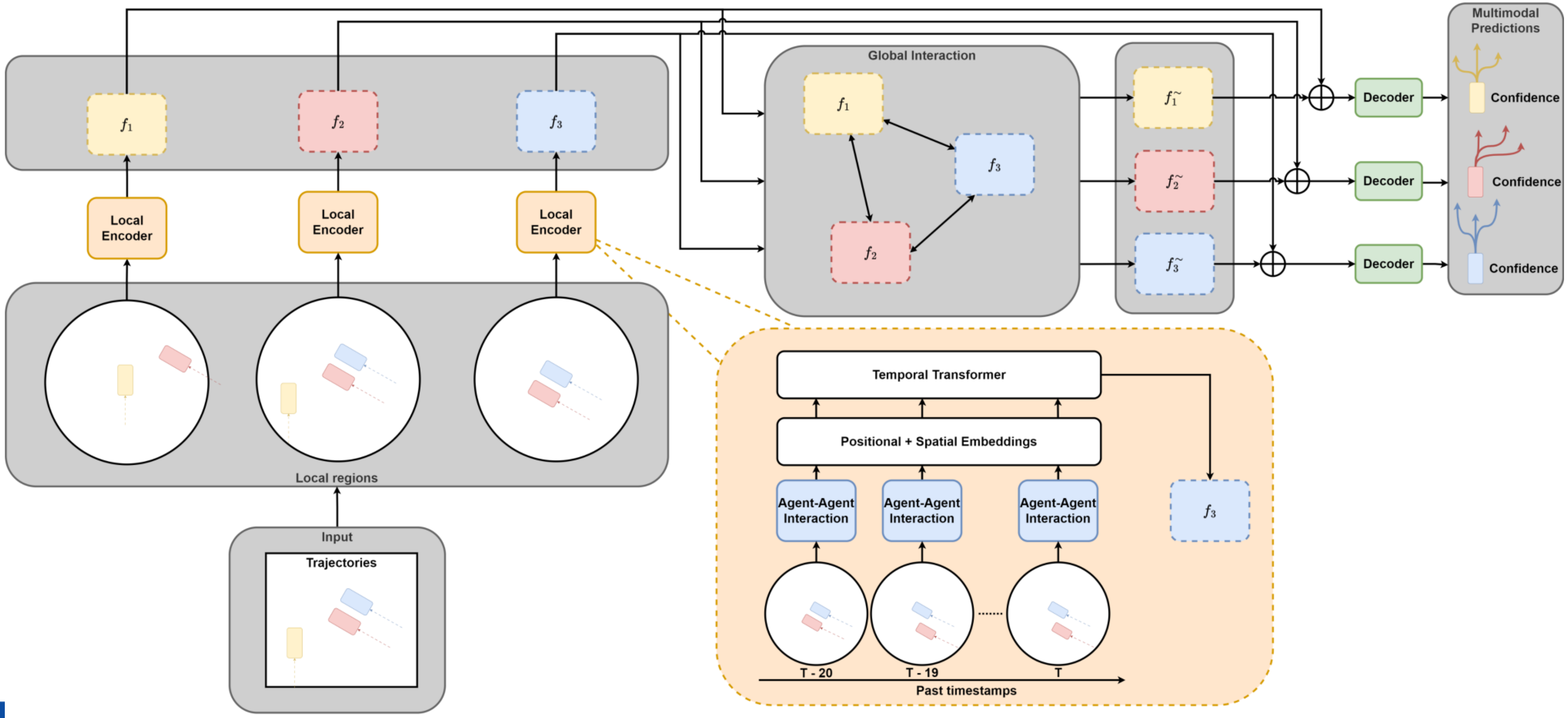
Motion Prediction

- HiVT



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Motion Prediction

- Información social: relación entre agentes
- Resultados de validación en Argoverse 1
  - minADE: mínimo error medio
  - minFDE: mínimo error final
  - MR: % de rutas con un desplazamiento final mayor a 2 metros

Model	Map	minADE ↓	minFDE ↓	MR (%) ↓
HiVT-64 [7]	✓	0.69	1.04	0.10
HiVT-128 [7]	✓	**0.66**	**0.96**	**0.09**
Crat-Pred [28]	✗	0.85	1.44	0.17
HiVT-64 (ours)	✗	0.76	1.24	0.14

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Motion Prediction

Información de mapa

Pros

- Soluciones más precisas
- Contexto espacial
- Tienes una ligera información del futuro. En casos normales

Contras

- Poco escalable:
  - Muchos formatos
- Información difícil de manejar

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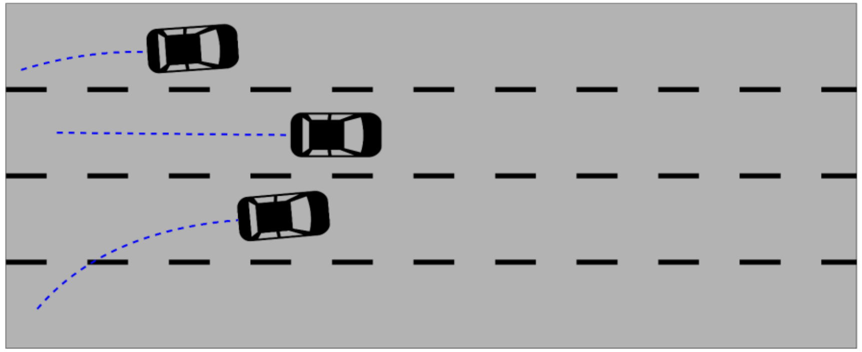
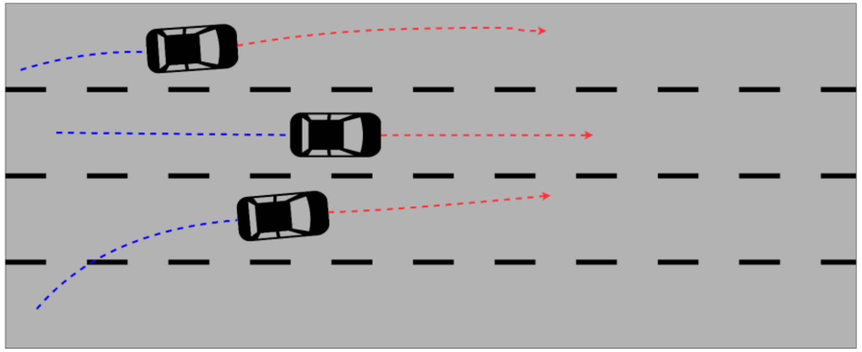
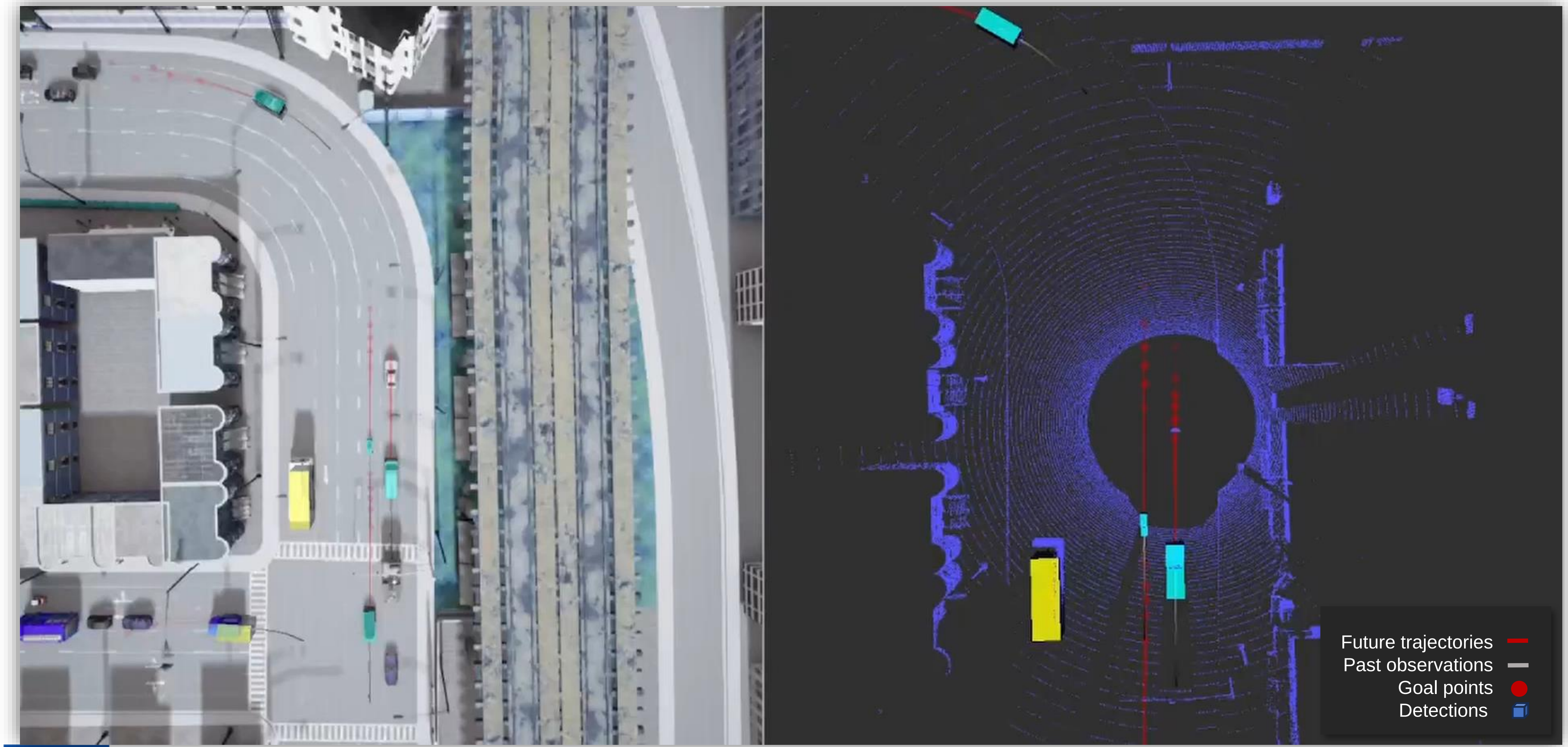
Motion Prediction

LiDAR-based 3D Object Detection (PointPillars) → Multi Object Tracking (tracking by detection) → Past Object trajectories (20 frames = 2 seconds) → HiVT map-less → Future Object trajectories (30 frames = 3 seconds)





Motion Prediction



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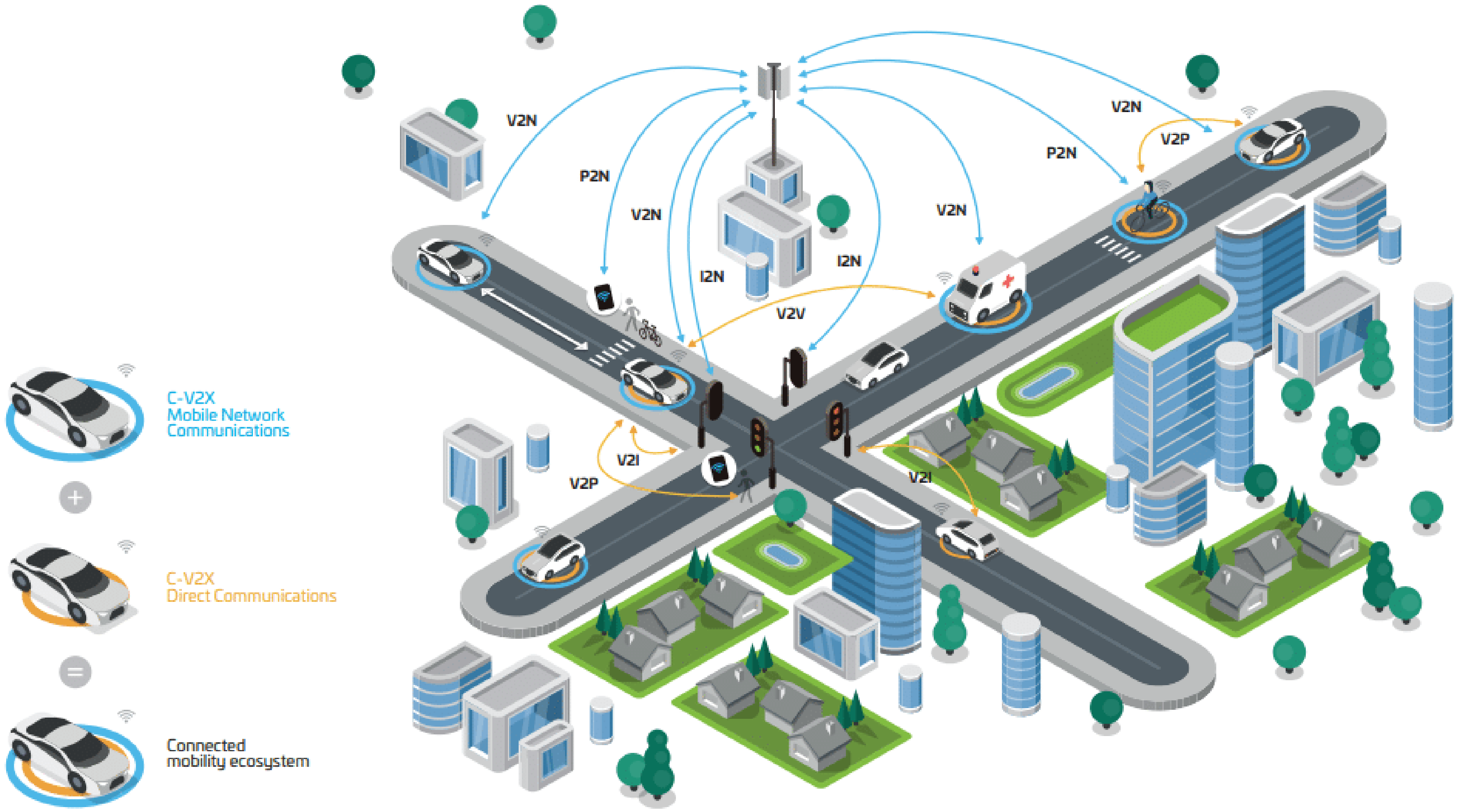
Percepción aumentada por V2X



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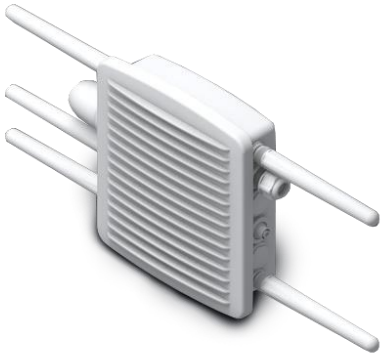
Percepción aumentada por V2X

- Hardware:
  - OBU: OnBoard Unit
  - RSU: Road Side Unit
- Software:
  - ETSI messages
    - CAM: Cooperative Awareness Message
    - CPM: Collective Perception Message



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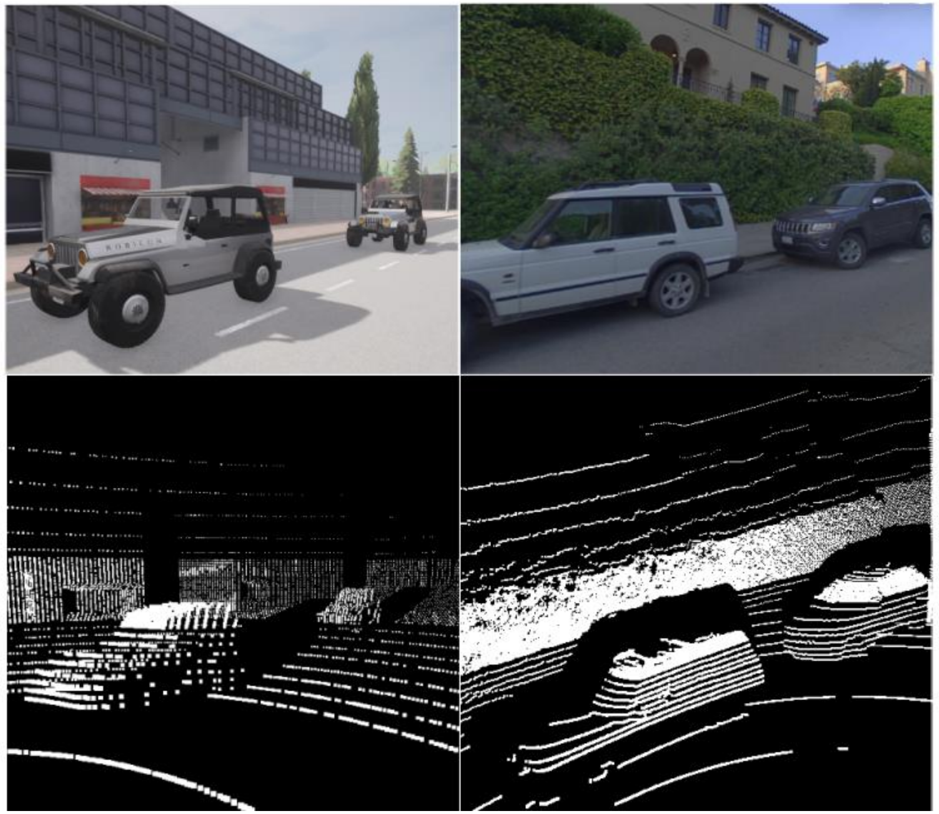
Simulación realista

- El LiDAR en CARLA no es "realista"
- Los sistemas basados en LiDAR no son trasladables a otros entornos
- Problema de *Domain Adaptation*



- Alberto Justo , Javier Araluce , Mario Rodríguez-Arozamena , Leonardo Gonzalez and Sergio Díaz, "SimBusters: Bridging Simulation Gaps in Intelligent Vehicles Perception", in 2024 IEEE Intelligent Vehicles Symposium (IV), IEEE, June 2024.

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SimBusters: Bridging Simulation Gaps in Intelligent Vehicles Perception

- CARLA genera la nube por Ray tracing.
- Depende de:
  - Ángulo de azimuth (θ)
  - Ángulo polar ($\emptyset$)
  - Distancia obtenida por ray casting (r_i)
- En CARLA son ideales
- Distribuciones uniformes y consistentes
- Esto no es realista

$$p_i = \begin{pmatrix} x \\ y \\ z \end{pmatrix} = r_i \begin{pmatrix} \cos(\phi)\cos(\theta) \\ \cos(\phi)\sin(\theta) \\ \sin(\phi) \end{pmatrix}$$

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SimBusters: Bridging Simulation Gaps in Intelligent Vehicles Perception

- Intensidad se calcula con Beer-Lambert Law
  - I: intensidad
  - I_o: intensidad inicial antes de entrar al material
  - a: coeficiente del medio
  - d: espesor del medio que la luz atraviesa

$$\frac{I}{I_0} = e^{-a \cdot d}$$

- CARLA lo codifica utilizando el RGB en una imagen virtual

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SimBusters: Bridging Simulation Gaps in Intelligent Vehicles Perception

- PCSim [1]: simula diferentes LiDARs del mercado
  - Ángulo de azimuth (θ)
  - Ángulo polar (Ø)
  - Distancia obtenida por ray casting (r_i)
  - La intensidad es simulada en valores de *drop-off*
  - La intensidad en cada sensor tiene unas cotas diferentes
- Normalización de la Intensidad

$$I_{\text{normalized}} = \frac{(I_{\text{raw}} - I_{\text{min}}) \times (R_{\text{max}} - R_{\text{min}})}{I_{\text{max}} - I_{\text{min}}} + R_{\text{min}}$$

[1] X. Cai et al, "Analyzing infrastructure lidar placement with realistic lidar simulation library," in 2023 IEEE International Conference on Robotics and Automation (ICRA), IEEE, May 2023.

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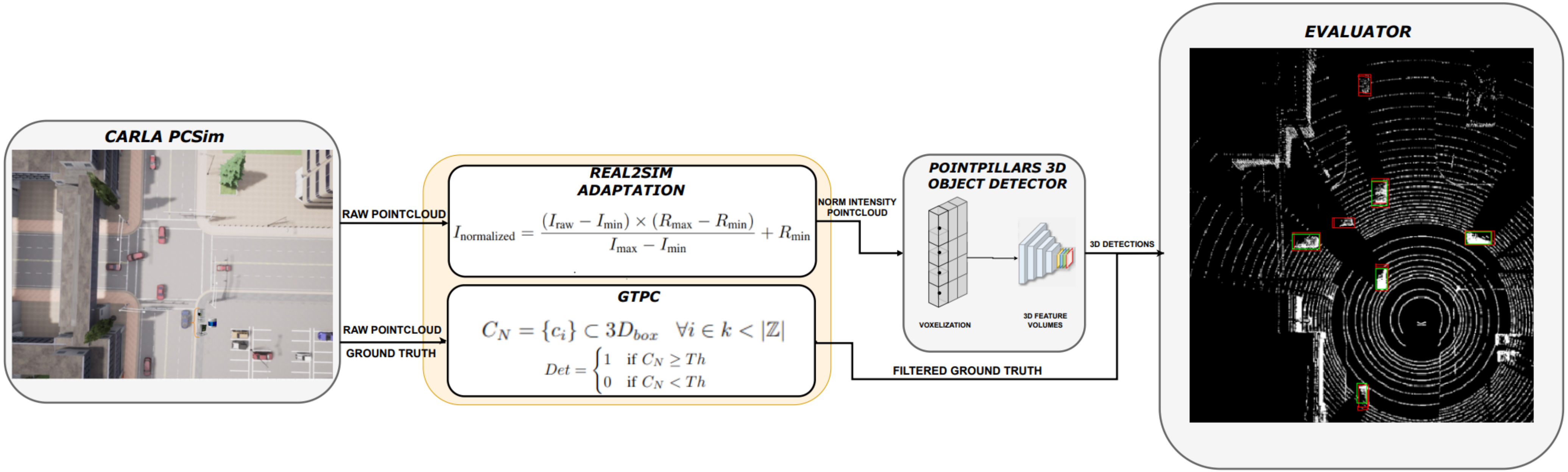
SimBusters: Bridging Simulation Gaps in Intelligent Vehicles Perception



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SimBusters: Bridging Simulation Gaps in Intelligent Vehicles Perception

- Datasets

Dataset	LiDAR	Channels	vFOV(º)	Range(m)	Frames	BBoxes
KITTI [29]	Velodyne HDL-64	64	27	120	7.4k	80k
NuScenes [17]	Velodyne HDL-32	32	41	100	390k	1.4M
Pandaset [12]	Hesai Pandar64	64	40	200	16k	-

Dataset	IoU	mAP@0.7
KITTI	0.7	0.39
NuScenes	0.84	0.68
Pandaset	0.88	0.71

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SimBusters: Bridging Simulation Gaps in Intelligent Vehicles Perception

- Resultados

Dataset	PCSim LiDAR	DA	IoU	mAP@0.7
KITTI	HDL-64	-	0.67	0.34
	HDL-64	Real2Sim	**0.71**	**0.43**
NuScenes	HDL-32	-	0.77	0.59
	HDL-32	Real2Sim	0.77	0.59
	CARLA-32	-	0.76	0.54
	CARLA-32	Real2Sim	0.76	0.54
Pandaset	Pandar64	-	0.86	0.65
	Pandar64	Real2Sim	**0.88**	**0.73**

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SimBusters: Bridging Simulation Gaps in Intelligent Vehicles Perception

- Resultados

Dataset	PCSim LiDAR	DA	IoU	mAP@0.7
KITTI	HDL-64	-	↓4.29%	↓12.34%
	HDL-64	Real2Sim	**↑1.42%**	**↑10.26%**
NuScenes	HDL-32	-	↓8.33%	↓13.23%
	HDL-32	Real2Sim	↓8.33%	↓13.23%
	CARLA-32	-	↓9.52%	↓20.58%
	CARLA-32	Real2Sim	↓9.52%	↓20.58%
Pandaset	Pandar64	-	↓2.27%	↓8.45%
	Pandar64	Real2Sim	**0.0%**	**↑2.81%**

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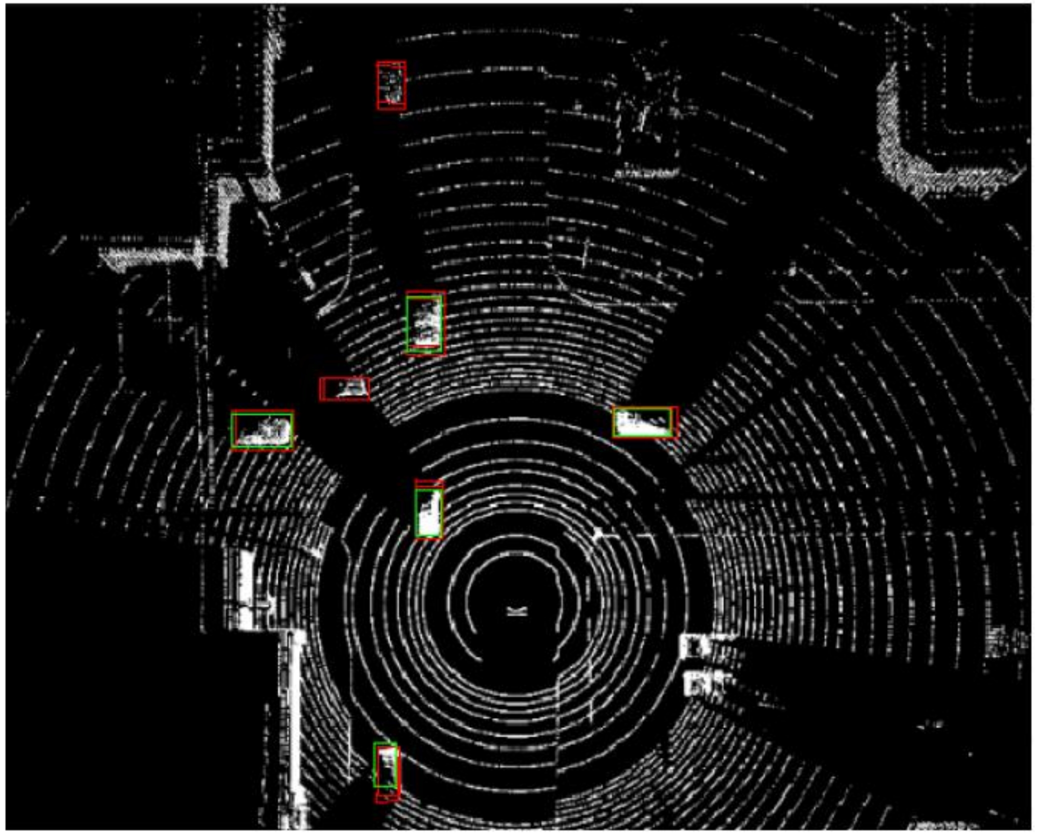
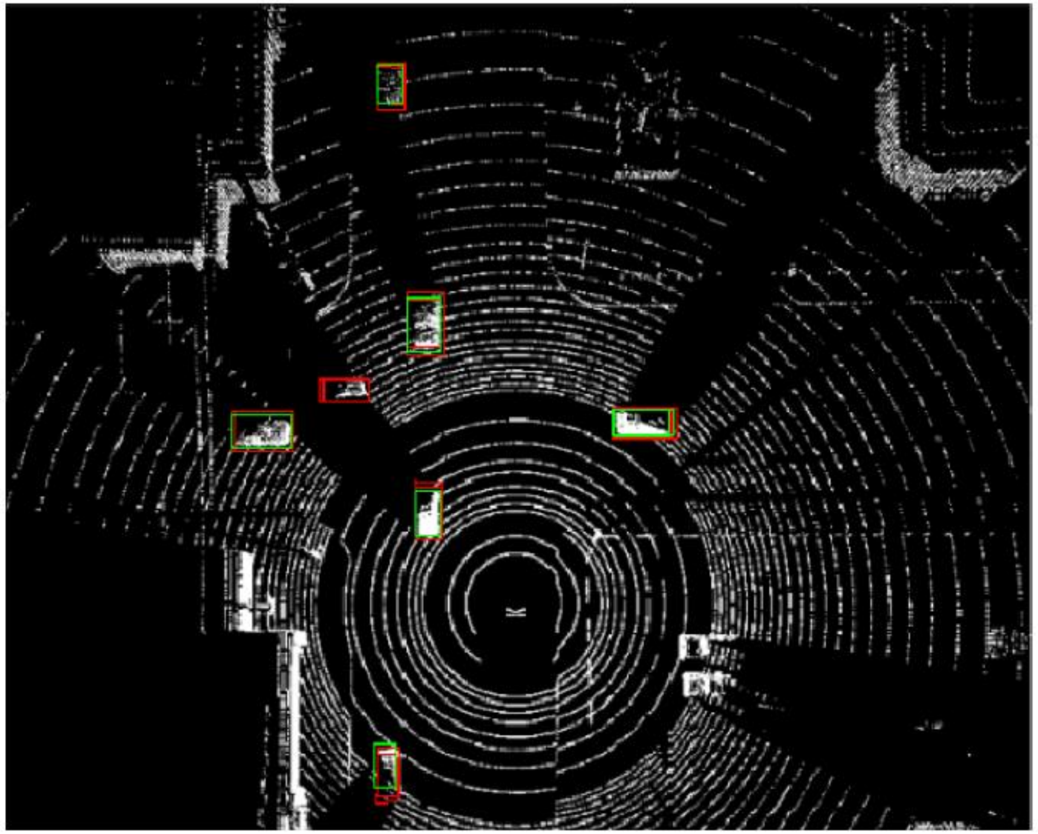
SimBusters: Bridging Simulation Gaps in Intelligent Vehicles Perception





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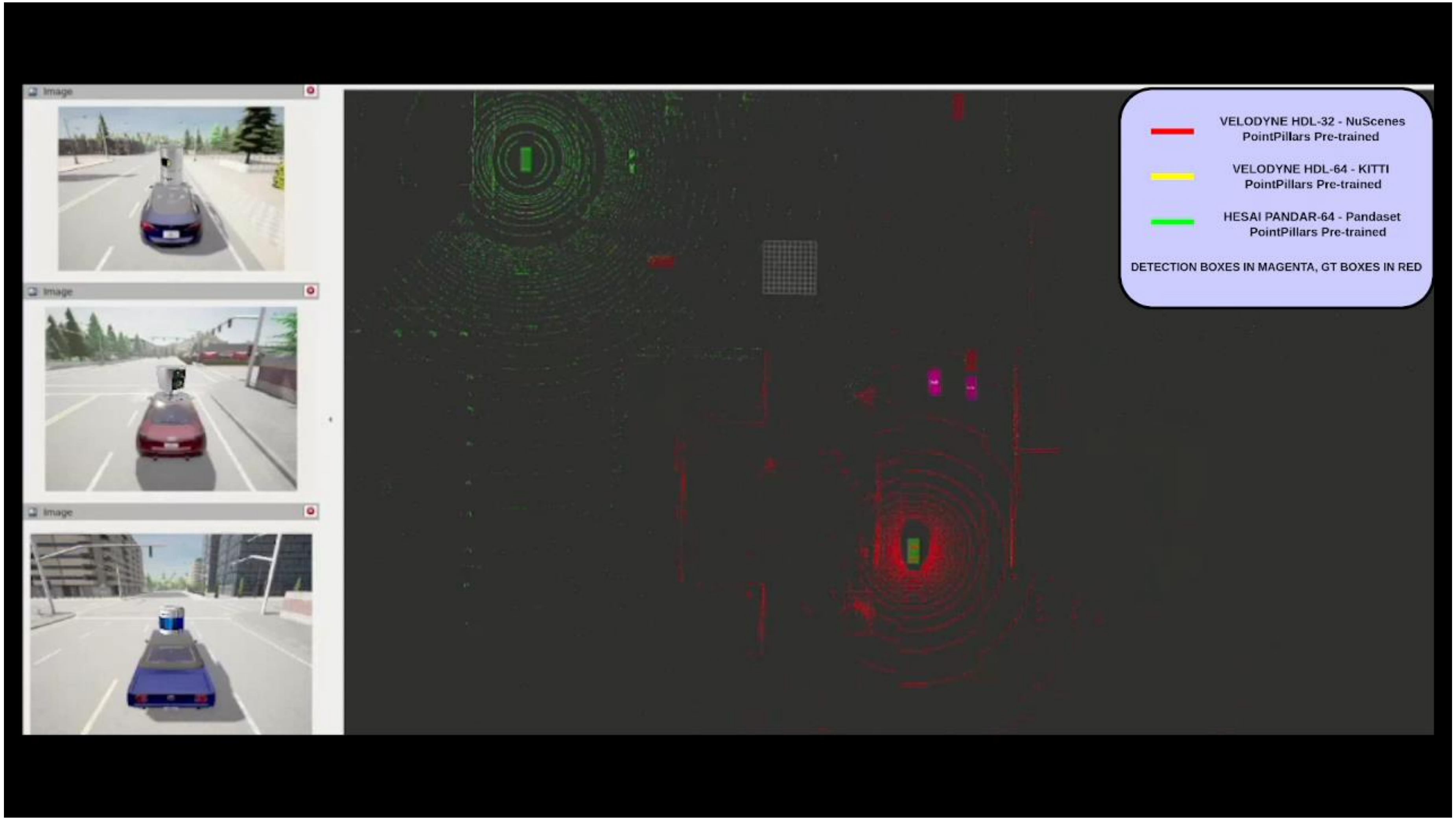
SimBusters: Bridging Simulation Gaps in Intelligent Vehicles Perception



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SimBusters: Bridging Simulation Gaps in Intelligent Vehicles Perception

- Conclusiones
  - Reducción del *gap* entre simulación y real
  - Método de *Domain Adaptation*
  - Futuro necesario para poder realizar más simulaciones

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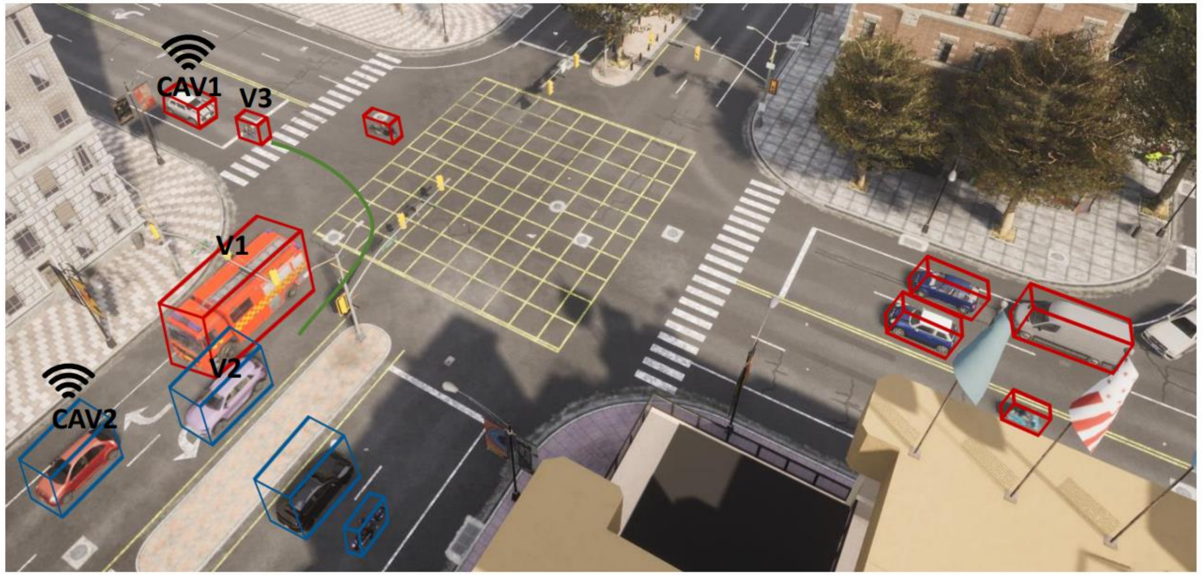
Motion Prediction colaborativo

- Problemas de oclusiones
- Información más lejana
- Más contexto social



- Javier Araluce, Alberto Justo, Asier Arizala, Leonardo Gonzalez and Sergio Díaz, “Enhancing Motion Prediction by a Cooperative Framework”, in 2024 IEEE Intelligent Vehicles Symposium (IV), IEEE, June 2024.

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Enhanced Motion Prediction by Cooperative Framework

- Fusión de detecciones
  - Distancia euclídea

$$D_e = \sqrt{(x_{det} - x_{cav})^2 + (y_{det} - y_{cav})^2}$$

$$det = argmin(D_e^A, D_e^B)$$

  - *Bounding box clustering*

$$P = \{p_i\} \subset 3D_{box}^A \quad \forall i \in k < |\mathbb{Z}|$$

$$Q = \{q_j\} \subset 3D_{box}^B \quad \forall j \in l < |\mathbb{Z}|$$

$$det = max(\{dim(P), dim(Q)\})$$

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Enhanced Motion Prediction by Cooperative Framework

TABLE I: Comparison between Cooperative Perception-related Datasets.

Dataset	Real/Sim	V2X	Size (km)	Lidar pcds	Maps	3D boxes	Classes	Locations
OPV2V [19]	Sim	V2V	-	11k	Yes	230k	1	CARLA
V2X-Sim [20]	Sim	V2V&I	-	10k	Yes	26.6k	1	CARLA
V2XSet [21]	Sim	V2V&I	-	11k	Yes	230k	1	CARLA
A9 Intersection [23]	Real	V2I	-	4.8k	No	57.4k	10	Hanover, Germany
DAIR-V2X [24]	Real	V2I	20	39k	No	464k	10	Beijing, CN
V2X-Seq [25]	Real	V2V&I	-	210k (seq)	No	20,301k (2D)	8	Beijing, CN
V2V4Real [15]	Real	V2V	410	20k	Yes*	240k	5	Ohio, USA

Notes: * indicates that the map are listed as public but they have not been released by the day of this work.

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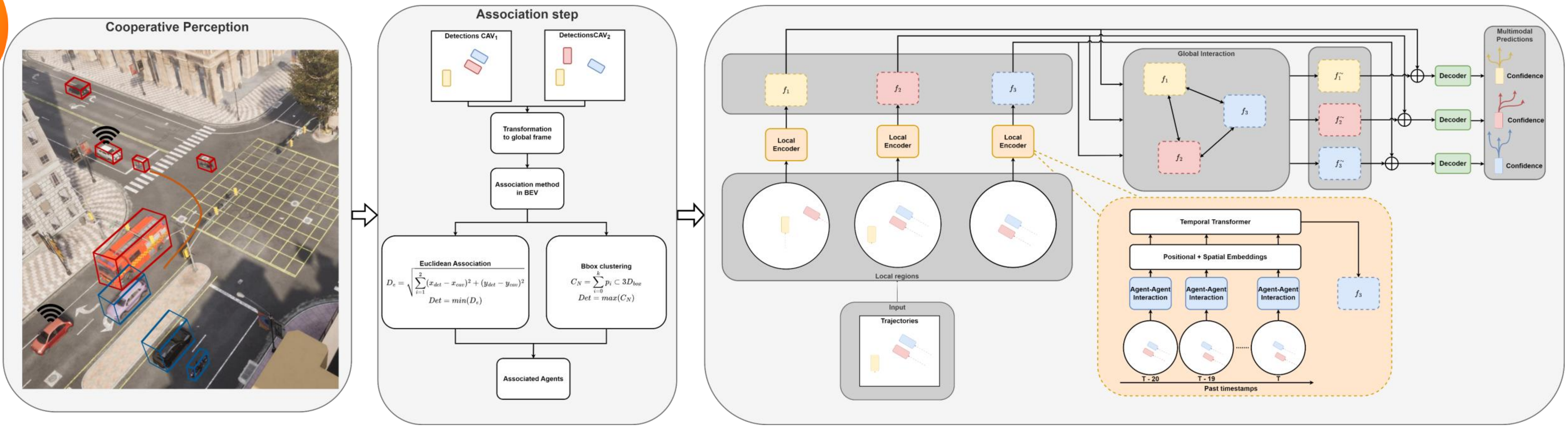
Enhanced Motion Prediction by Cooperative Framework

EVENTS



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Enhanced Motion Prediction by Cooperative Framework

TABLE III: Comparison of methods on the V2V4Real dataset. We show the CAVs, the association method, the viewpoint, the number of actors considered and the performance metrics. The ”-” denotes that there is no association method used.

CAVs	Association	Viewpoint	Number Actors	minADE (m) ↓	minFDE (m) ↓	MR ↓	p-minADE ↓	p-minFDE ↓	p-MR ↓	brier-minADE (m) ↓	brier-minFDE (m) ↓
Tesla	-	Tesla	7.74	**1.14**	**2.22**	**0.32**	**2.84**	**3.91**	**0.87**	**1.80**	**2.88**
Astuff	-	Astuff	8.45	1.22	2.30	0.33	2.90	3.99	**0.87**	1.88	2.96
V2V	-	Tesla	14.58	1.34	2.51	0.33	3.02	4.19	**0.87**	2.00	3.17
V2V	Euclidean	Tesla	10.19	1.26	2.37	**0.32**	2.95	4.05	**0.87**	1.92	3.02
V2V	Bbox clustering	Tesla	10.19	1.26	2.37	**0.32**	2.95	4.06	**0.87**	1.92	3.03
V2V	-	Astuff	14.58	1.34	2.52	0.33	3.03	4.21	**0.87**	2.00	3.18
V2V	Euclidean	Astuff	10.19	1.27	2.38	**0.32**	2.95	4.07	**0.87**	1.92	3.04
V2V	Bbox clustering	Astuff	10.19	1.27	2.39	0.33	2.96	4.08	**0.87**	1.93	3.05

TABLE IV: Comparison of methods on the V2V4Real dataset normalised by the number of actors in the scene. We show the CAVs, the association method, the viewpoint and the performance metrics. The ”-” denotes that there is no association method used.

CAVs	Association	Viewpoint	minADE ↓	minFDE ↓	MR ↓	p-minADE ↓	p-minFDE ↓	p-MR ↓	brier-minADE ↓	brier-minFDE ↓
Tesla	-	Tesla	0.15	0.29	0.04	0.37	0.51	0.11	0.23	0.37
Astuff	-	Astuff	0.14	0.27	0.04	0.34	0.47	0.10	0.22	0.35
V2V	Euclidean	Tesla	**0.12**	**0.23**	**0.03**	**0.29**	**0.40**	**0.09**	**0.19**	**0.30**
V2V	Bbox clustering	Tesla	**0.12**	**0.23**	**0.03**	**0.29**	**0.40**	**0.09**	**0.19**	**0.30**
V2V	Euclidean	Astuff	0.13	0.24	**0.03**	**0.29**	**0.40**	**0.09**	**0.19**	**0.30**
V2V	Bbox clustering	Astuff	**0.12**	**0.23**	**0.03**	**0.29**	**0.40**	**0.09**	**0.19**	**0.30**

TABLE V: Increased performance through our V2V framework compared to a single vehicle, taking into account the number of vehicles. We show the comparison, the association method, the main CAV and the performance metrics.

Comparison	Association	Viewpoint	minADE	minFDE	MR	p-minADE	p-minFDE	p-MR	brier-minADE	brier-minFDE
V2V vs Tesla	Euclidean	Tesla	**16%**	**19%**	**22%**	**21%**	**21%**	**24%**	**19%**	**20%**
V2V vs Tesla	Bbox clustering	Tesla	**16%**	**19%**	**22%**	**21%**	**21%**	**24%**	**19%**	**20%**
V2V vs Astuff	Euclidean	Astuff	13%	14%	19%	15%	15%	17%	14%	14%
V2V vs Astuff	Bbox clustering	Astuff	14%	14%	19%	16%	15%	17%	15%	15%

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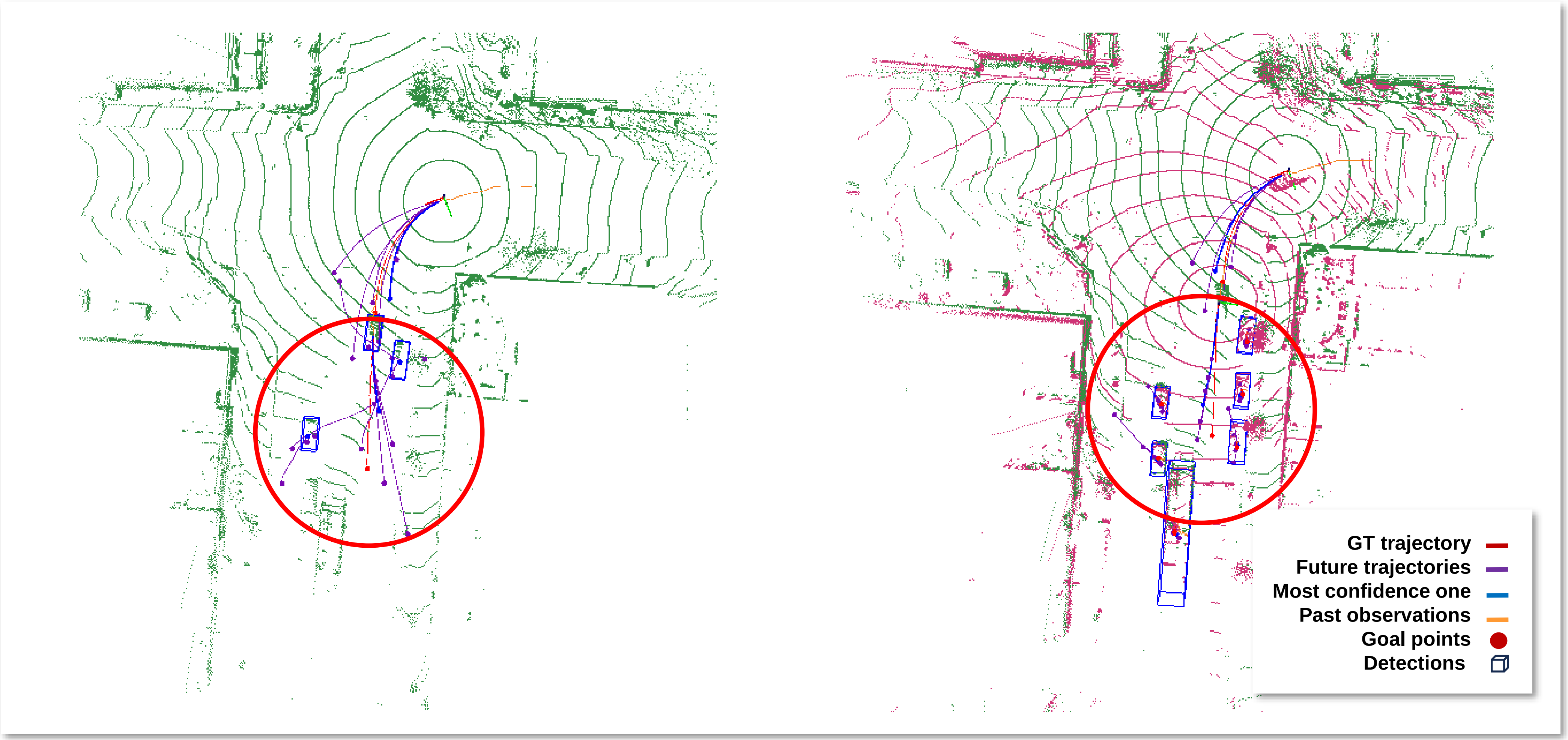
Qualitative results



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Enhanced Motion Prediction by Cooperative Framework

- Conclusiones
  - HiVT en un ambiente colaborativo
  - Dos métodos de asociación
  - V2V ayuda en Motion Prediction

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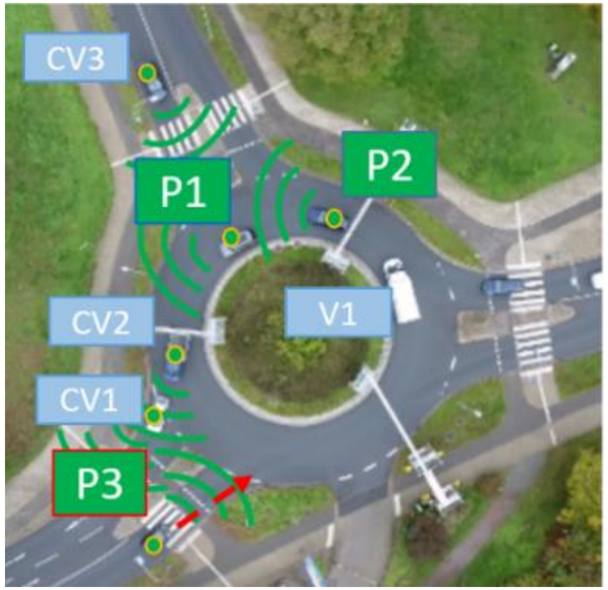
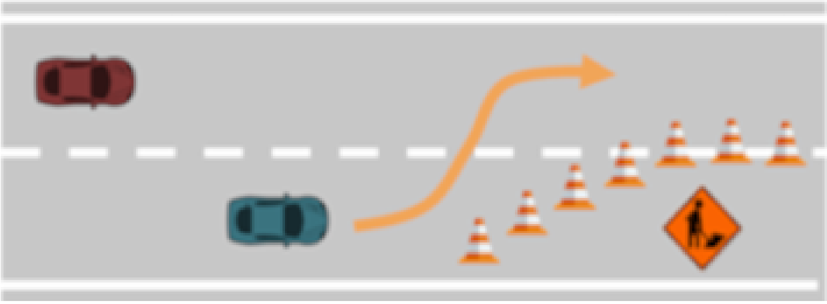
Experimentos/Demos

- Tres experimentos:
  - EXP2: rotonda con un platoon roto
  - EXP4: zona de obras
  - EXP5: negociar la entrada en una intersección





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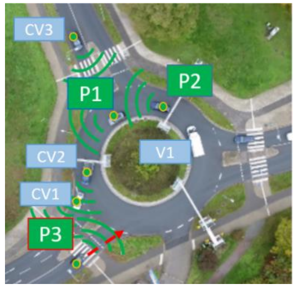
EXP2



- P1, P2 & CV: Simulados en Carla

- P3: Renault Twizy

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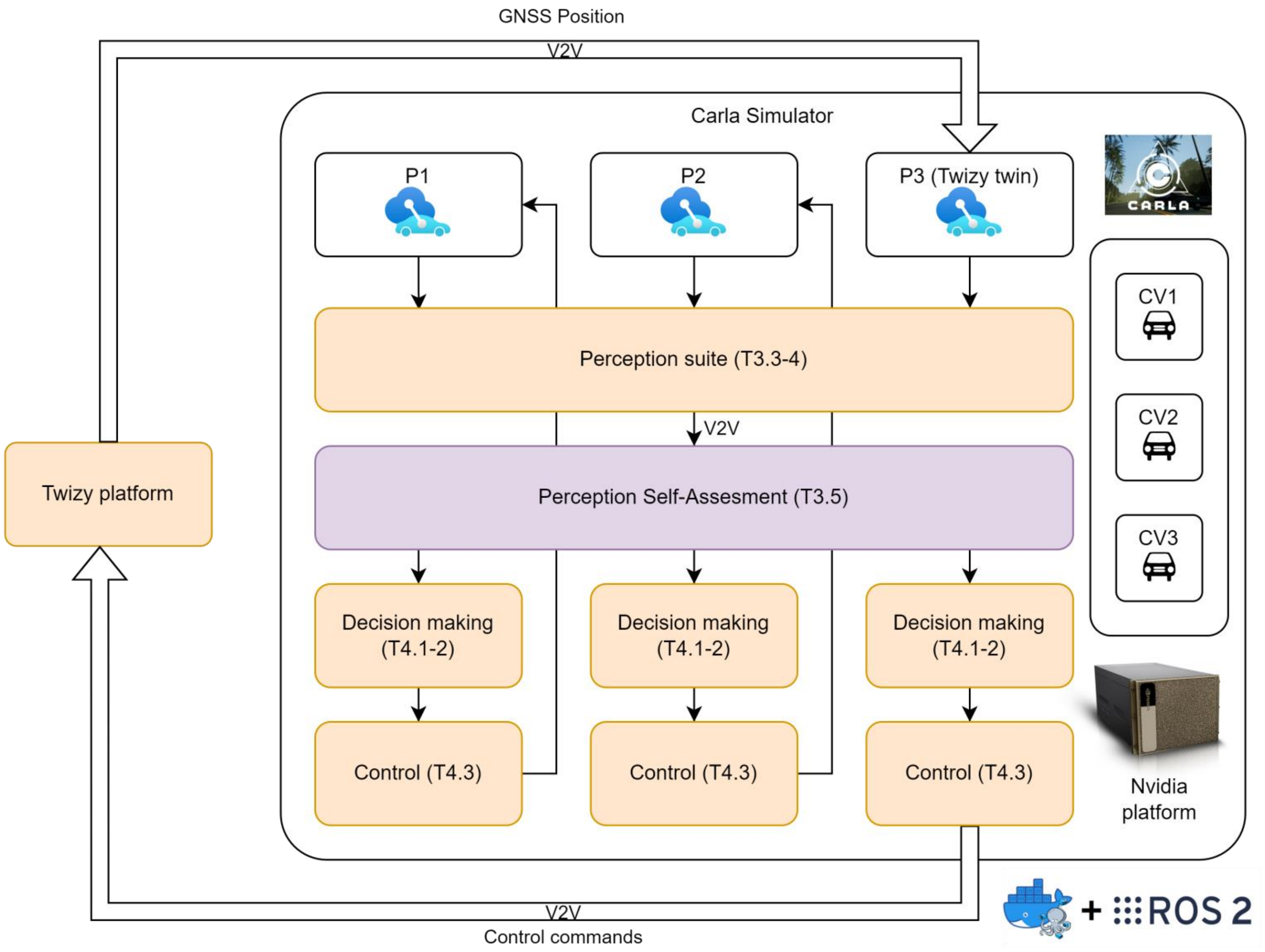
EXP2



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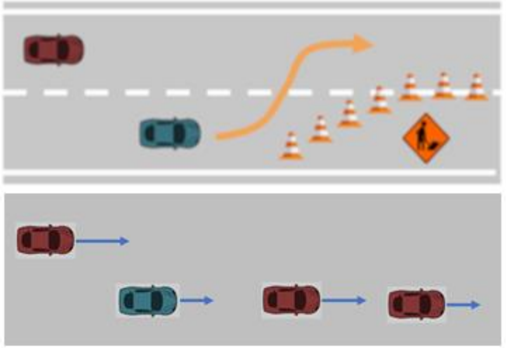
EXP4

- Un coche en manual detecta una zona de obras
  - Nosotros lo replicamos en un ambiente controlado utilizando sus detecciones



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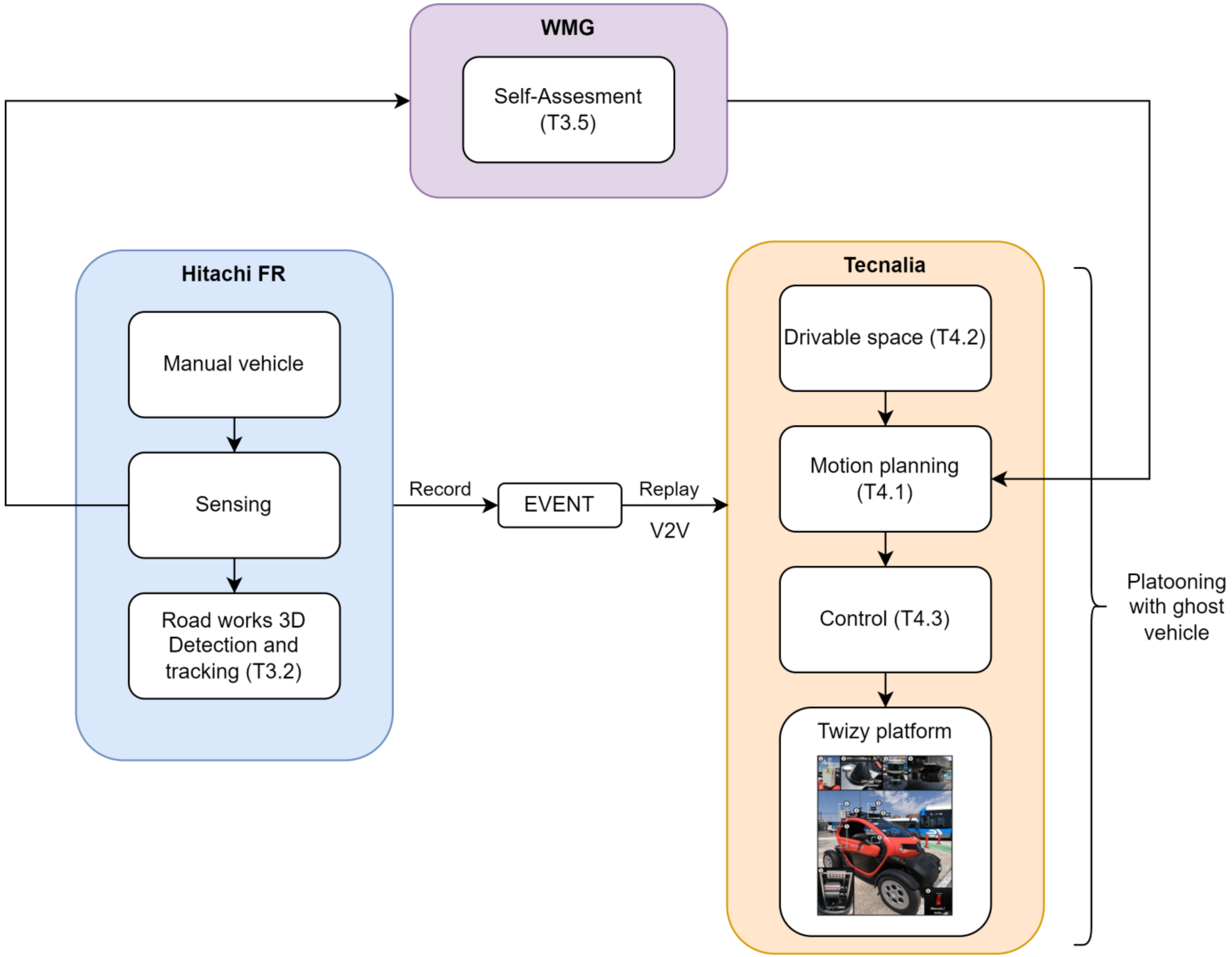
EXP4



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Thank you for your attention!

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