

SiT Dataset:

Socially interactive Pedestrian Trajectory Dataset for Social Navigation Robots

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SPA LAB
Signal Processing & Artificial-intelligence Laboratory

1. Challenges

- The Advent of diverse driving robots
 - Explosive growth of service robot market
- Insufficiency of comprehensive datasets for autonomous mobile robots
 - Necessity for socially interactive robots
 - Human Perception in 3D and movement prediction for safe and agile navigation



(a) Food delivering robot^[1]



(b) Serving robot^[2]



(c) Guide robot^[3]

1. Challenges: Pedestrian Trajectory Datasets

- Data collected from fixed positions, potentially restricting the range of data variability
- Hard to reflect *Human-Robot Interaction* (HRI)
- Mostly consisting of camera images and data on pedestrian location



(a) ETH-Hotel [4]



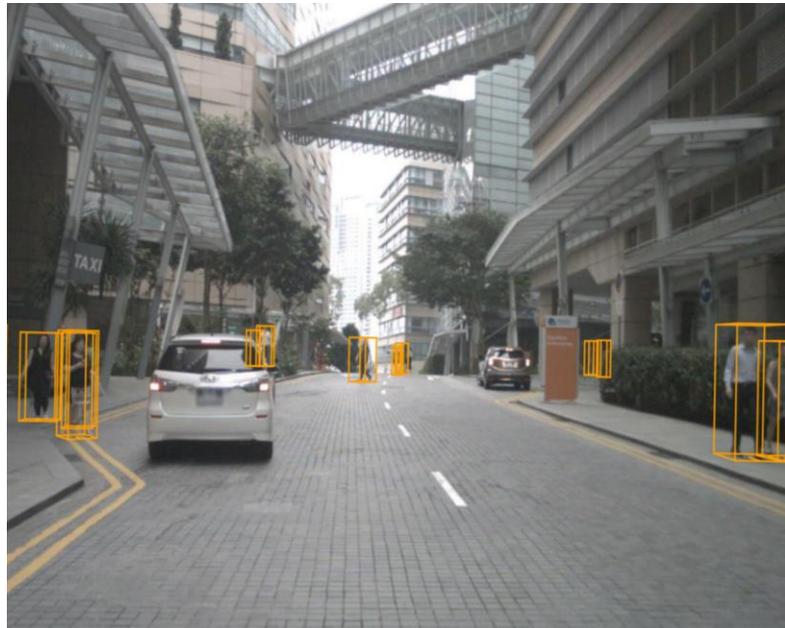
(b) UCY-Zara [5]



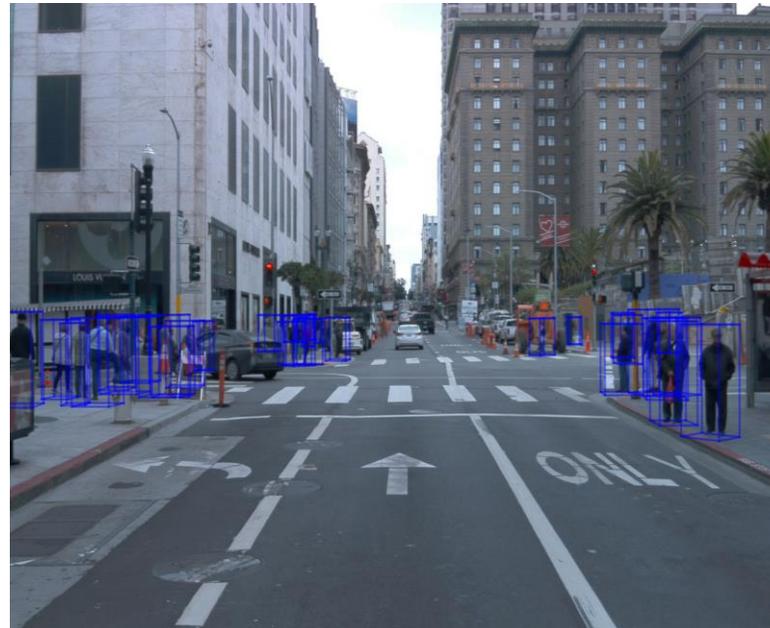
(c) SDD [6]

1. Challenges: Autonomous Driving Datasets

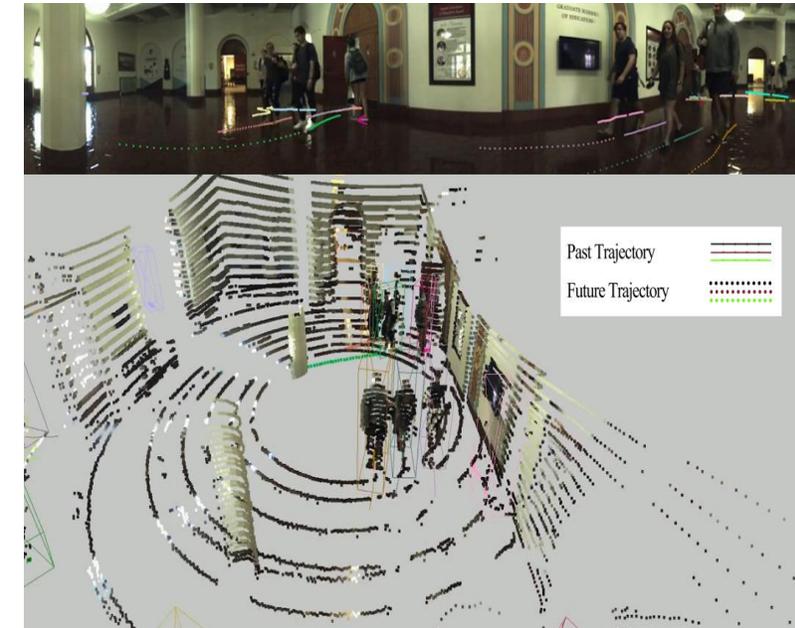
- Vehicle-centric on autonomous driving datasets rather than pedestrian-centric
 - A Shortage of vehicle-pedestrian interaction in autonomous driving datasets
 - Gaps in real-world robot and pedestrian interaction behavior
- Asynchronous multi-sensor data in robot-based datasets



(a) nuScenes^[7] (*vehicle-based*)



(b) Waymo Open^[8] (*vehicle-based*)



(c) JRDB^[9] (*robot-based*)

1. Challenges: Comparison with other datasets

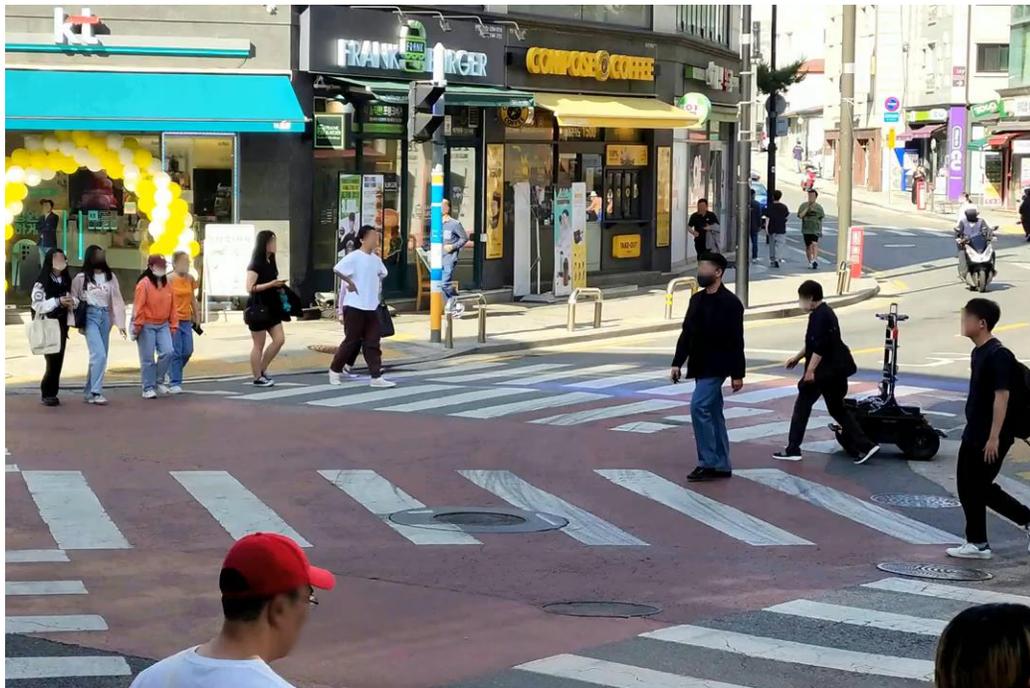
- Pedestrian trajectory datasets:
 - Data collected from fixed positions, potentially restricting the range of data variability
- Autonomous driving datasets:
 - Vehicle-centric on autonomous driving datasets rather than pedestrian-centric
 - Asynchronous multi-sensor data in robot-centric datasets

*†: Multi – layered map

Dataset	Platform	Task	Sync.	Map	E2E	Location
UCY	Fixed	Tracking, Prediction	-			Outdoor
ETH	Fixed	Tracking, Prediction	-			Outdoor
SDD	Fixed	Tracking, Prediction	-			Outdoor
nuScenes	Vehicle	Detection, Tracking, Prediction	✓	✓†		Outdoor
Waymo Open	Vehicle	Detection, Tracking, Prediction	✓	✓		Outdoor
Argoverse	Vehicle	Detection, Tracking, Prediction	✓	✓†	✓	Outdoor
JRDB	Robot	Detection, Tracking				Indoor & Outdoor
SiT(Ours)	Robot	Detection, Tracking, Prediction	✓	✓†	✓	Indoor & Outdoor

2. SiT Dataset: Real-world Context

- Collected data from dense areas like campuses and public roads
- Authentic Human-Robot Interactions in real-world settings
 - Capturing data without any actors or pre-arranged scenarios



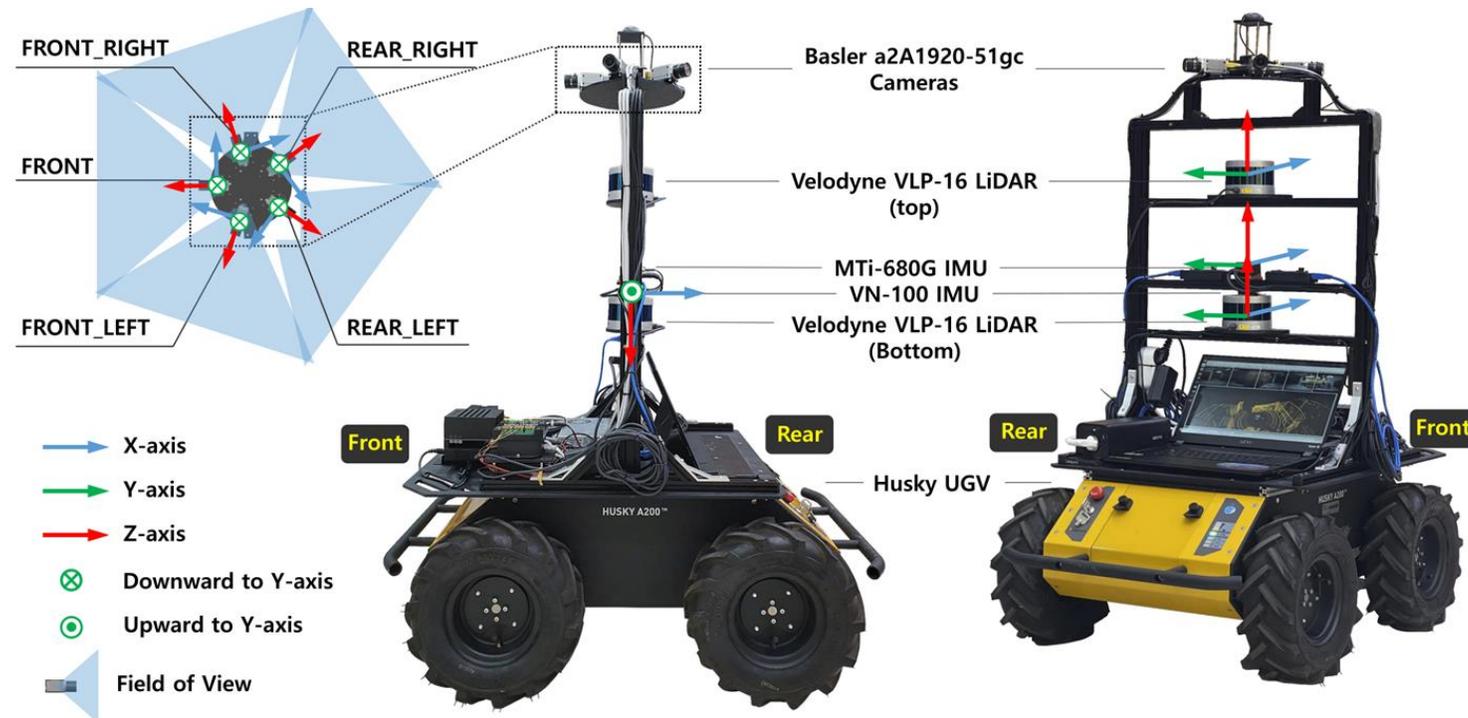
(a) Outdoor scene (*Crosswalk*)



(b) Indoor scene (*Hallway*)

2. SiT Dataset: Diverse Data Collection

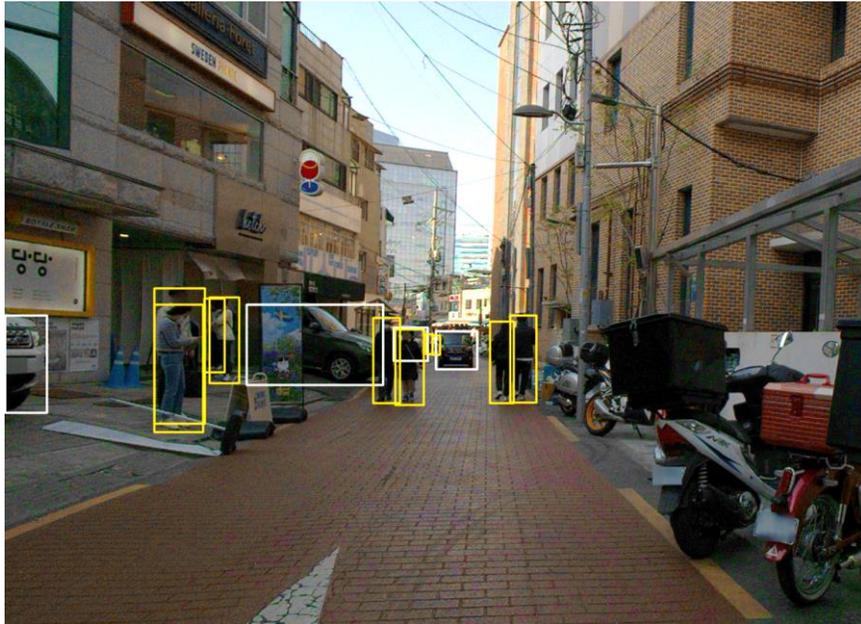
- Sequential raw data from various sensors
 - 60 scenes with 60K images and 12K point cloud frames at 10 Hz
- 2D and 3D bounding boxes for 6 classes
 - Car, bus, truck, pedestrian, cyclist, motorcyclist



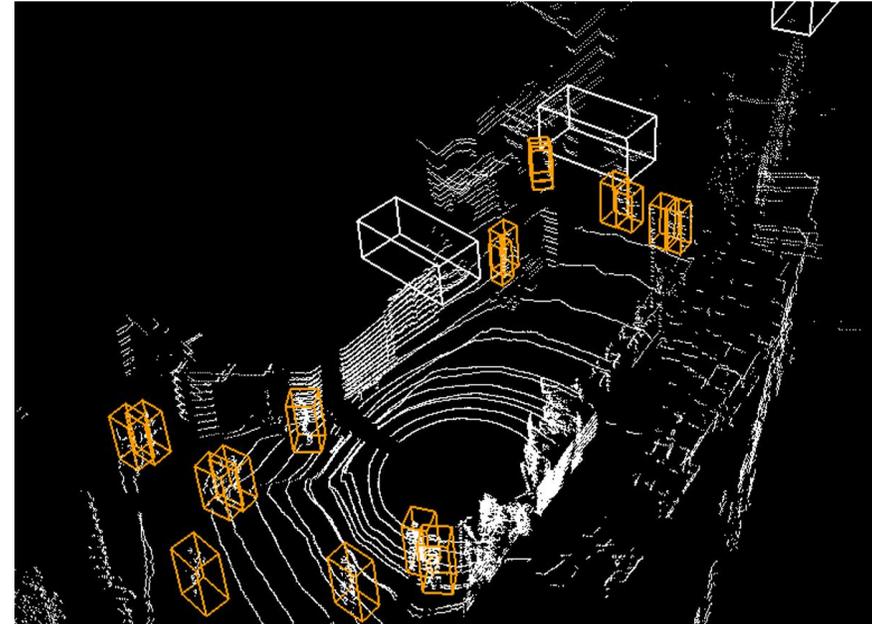
Husky UGV platform equipped with various sensors

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 - Car, bus, truck, pedestrian, cyclist, motorcyclist**



(a) 2D Bounding Boxes labeled on Image



(b) 3D Cuboid labeled on Point Clouds

2. SiT Dataset: Unique Features

- **Precise multi-sensor synchronization**
- Multi-layered indoor & outdoor semantic maps from SLAM
- Cover tasks from 3D detection to motion forecasting (End-to-end)
- Emphasis on *Human-Robot Interactions* (HRI)

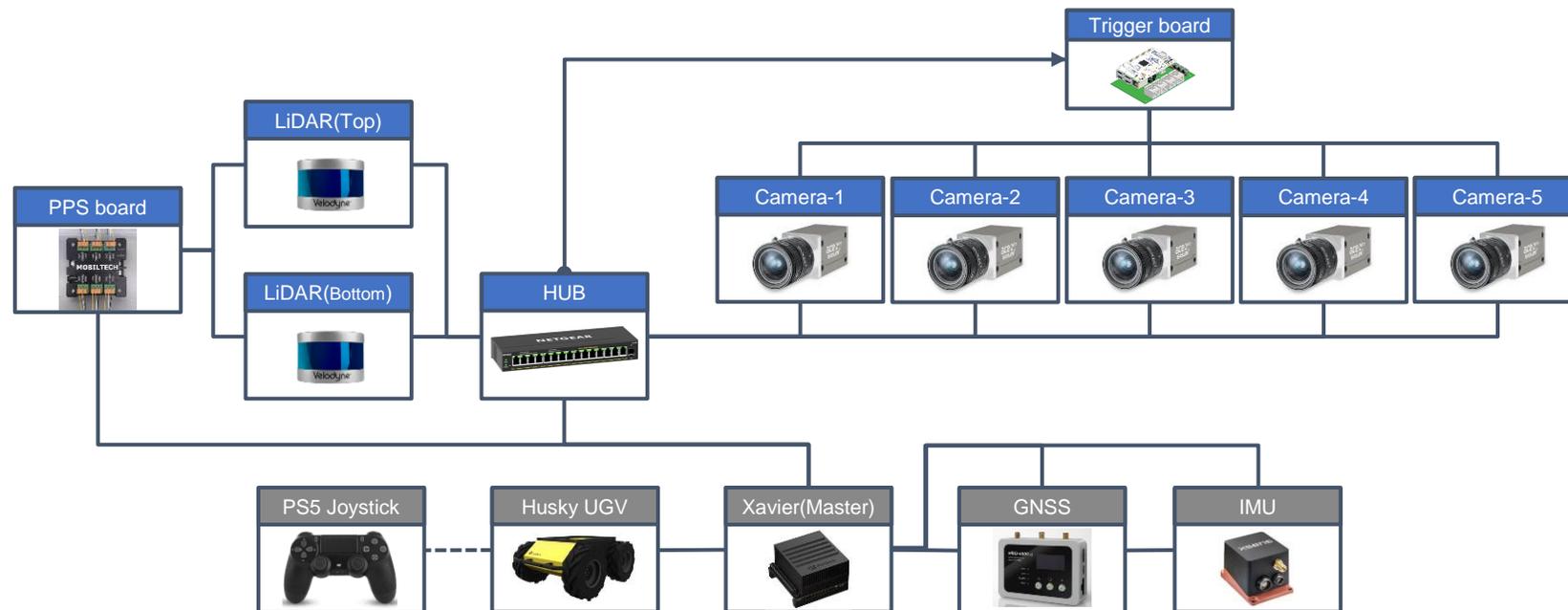
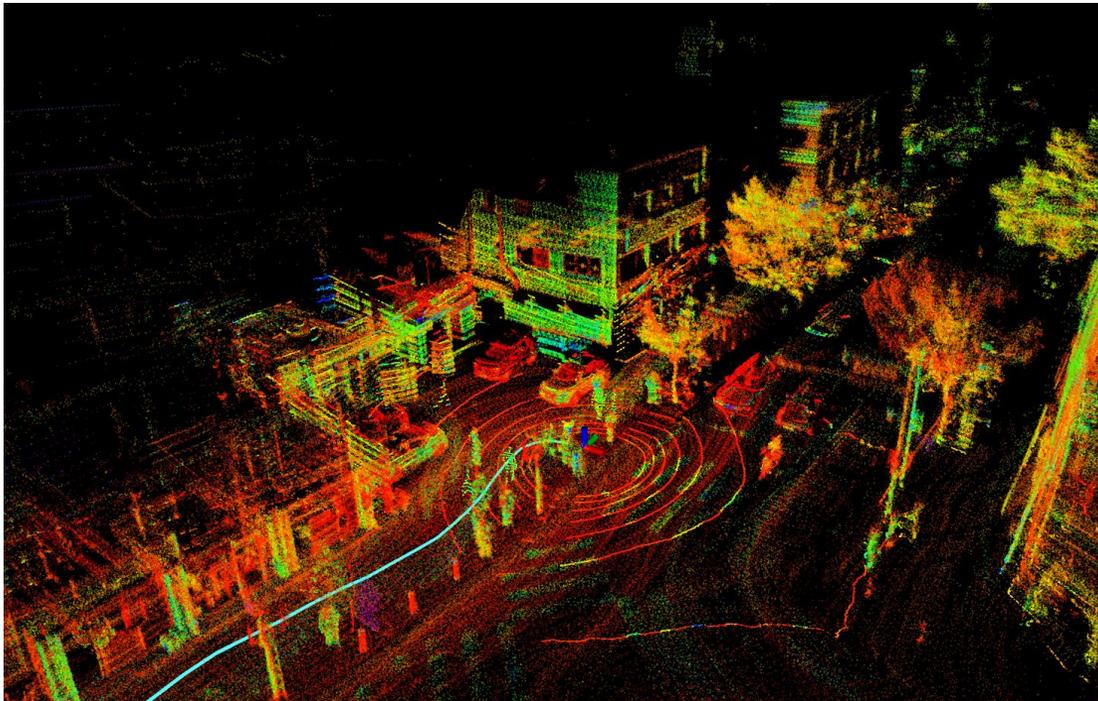


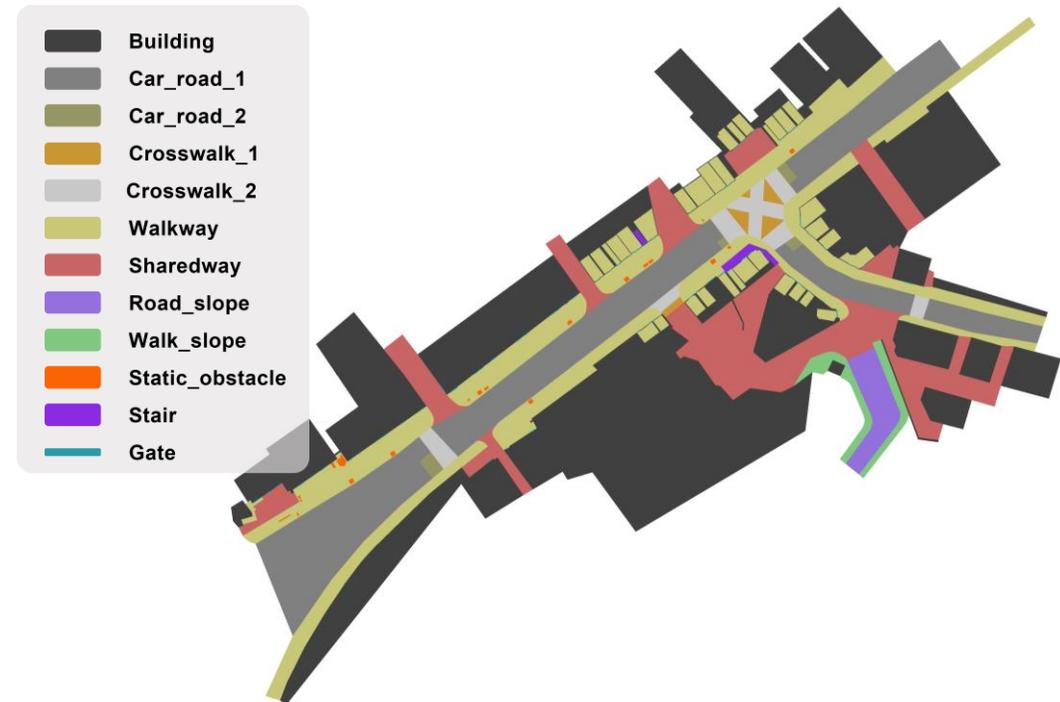
Diagram for multi-sensor synchronization

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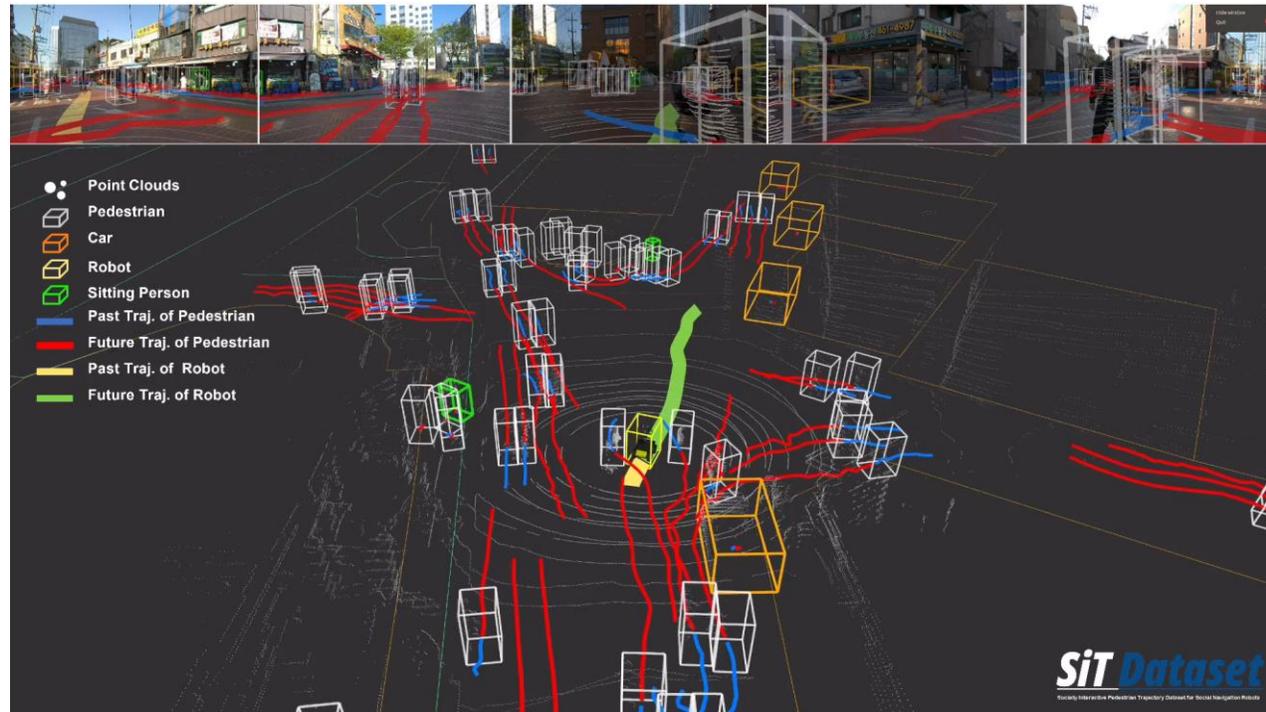
(a) SLAM-based 3D Point Cloud map



(b) 12-layered semantic map of outdoor scene

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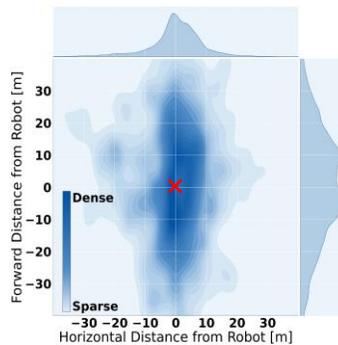
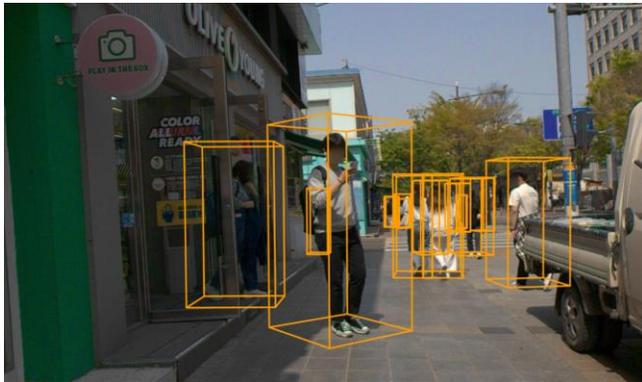


Visualization of SiT dataset of outdoor scene (*Cafe_Street_3*)

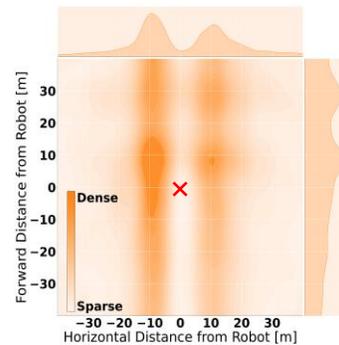
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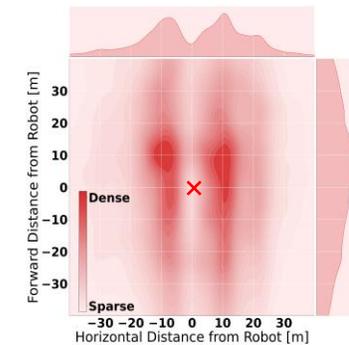
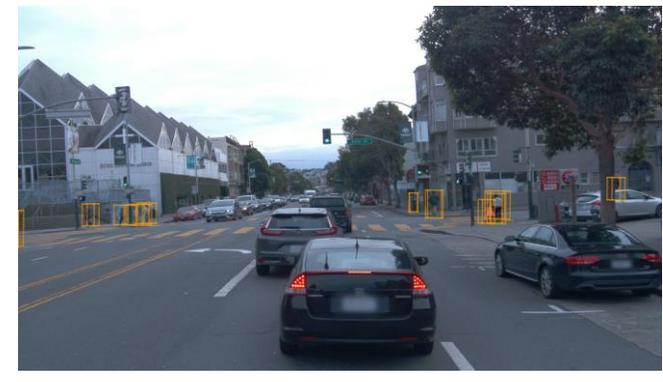
 : 3D Cuboid of Pedestrian
 : Position of ego vehicle



(a) SiT (Ours)



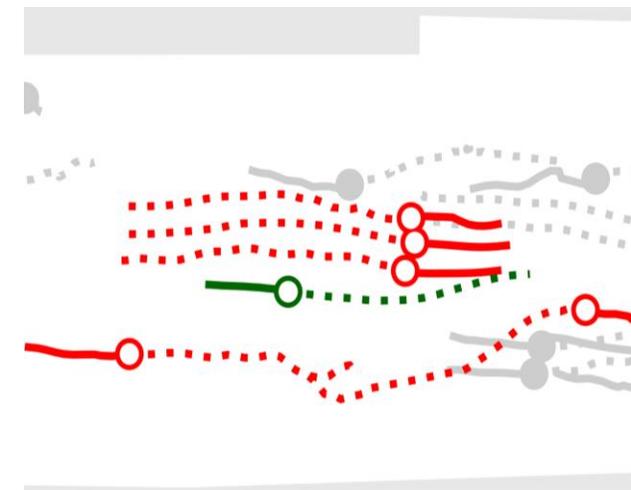
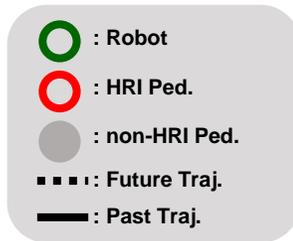
(b) nuScenes^[7]



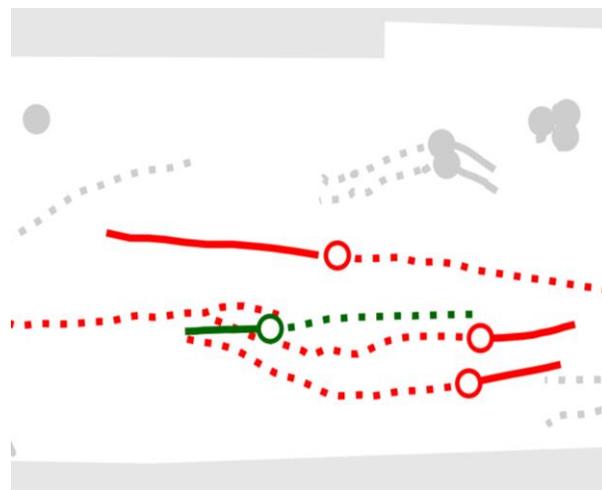
(c) Waymo Open^[8]

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- **Emphasis on *Human-Robot Interactions (HRI)***



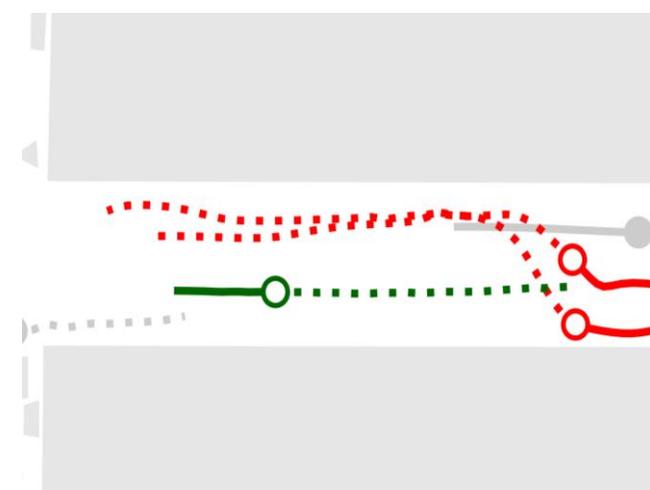
(a) Approach



(b) Followed by Pedestrians



(c) Avoidance by Robot



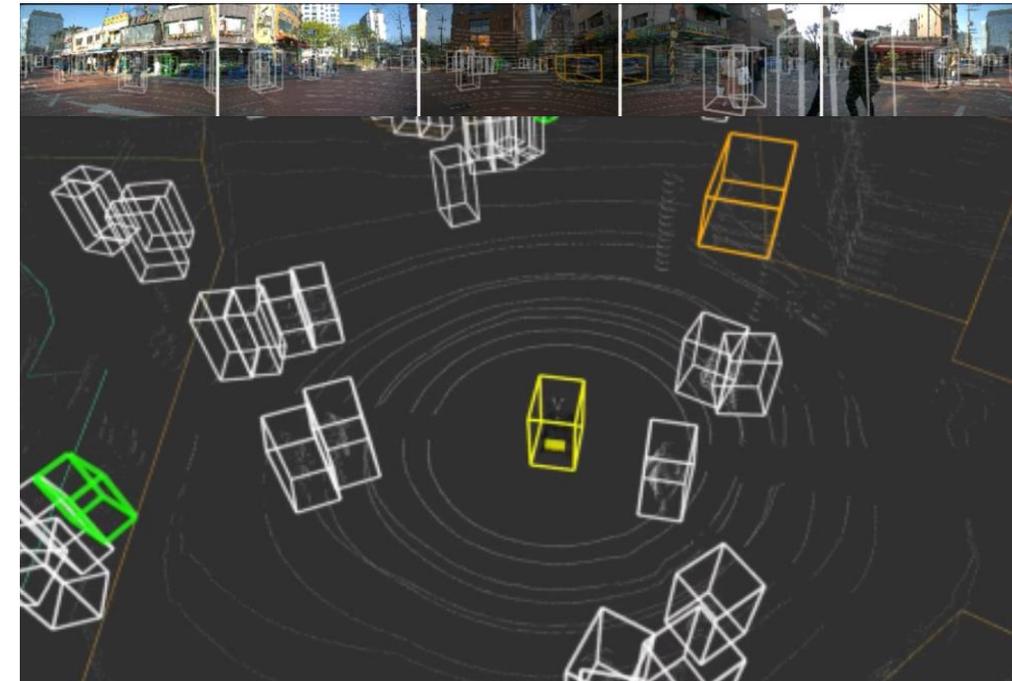
(d) Avoidance by Pedestrians

3. Benchmarks & Challenges

- 3D object detection based on image and point clouds
- 3D multi-object tracking
- Trajectory prediction
- End-to-end 3D detection to motion forecasting
- Challenges open on Eval.AI (*Feb. 2024*)

Methods	Modality	mAP \uparrow	AP(0.25) \uparrow	AP(0.5) \uparrow	AP(1.0) \uparrow	AP(2.0) \uparrow
FCOS3D [33]	Camera	0.244	0.024	0.159	0.329	0.463
PointPillars [15]	LiDAR	0.351	0.260	0.354	0.374	0.418
Centerpoint-P [39]	LiDAR	0.414	0.300	0.424	0.446	0.486
Centerpoint-V [39]	LiDAR	0.518	0.397	0.531	0.553	0.592
TransFusion-P [2]	LiDAR+Camera	0.390	0.248	0.371	0.437	0.507
TransFusion-V [2]	LiDAR+Camera	0.531	0.318	0.536	0.607	0.665

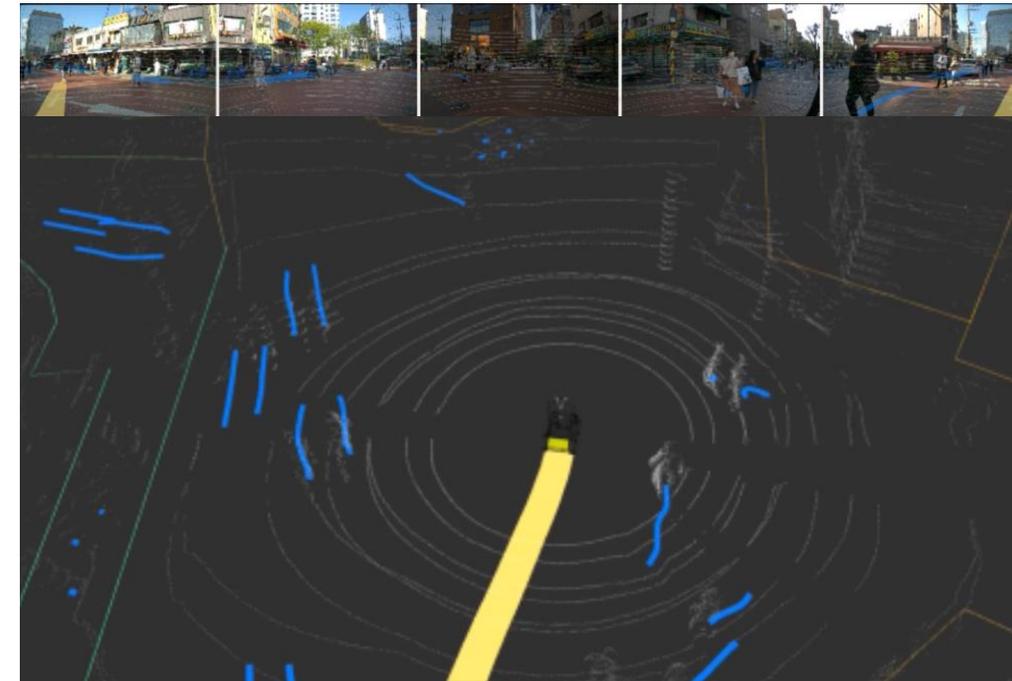
Evaluation of 3D pedestrian detection baselines.



3D cuboids on each object

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Past trajectories of each object

Methods	sAMOTA \uparrow	AMOTA \uparrow	AMOTP(m) \downarrow	MOTA \uparrow	MOTP(m) \downarrow	IDS \downarrow
PointPillars [15] + AB3DMOT [34]	0.4110	0.1047	0.3580	0.4086	1.0277	1048
Centerpoint Detector [39] + AB3DMOT [34]	0.4841	0.1398	0.3958	0.4586	0.9836	554
Centerpoint Tracker [39]	0.6070	0.2007	0.2679	0.4760	0.5140	1136

Evaluation of 3D pedestrian tracking baselines.

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Methods	Map	ADE ₅ ↓	FDE ₅ ↓	ADE ₂₀ ↓	FDE ₂₀ ↓
Social-LSTM [1]		1.638	3.121	1.630	3.103
Y-Net [22]		1.527	2.802	0.836	1.878
Y-Net [22]	✓	1.361	2.624	0.675	1.547
NSP-SFM [41]		1.346	2.261	0.634	1.087
NSP-SFM [41]	✓	1.061	1.818	0.517	0.925

Evaluation of pedestrian trajectory prediction baselines



Past and future trajectories of each objects

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- 3D object detection based on image and point clouds
- 3D multi-object tracking
- Trajectory prediction
- **End-to-end 3D detection to motion forecasting**
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Methods	mAP \uparrow	mAP _f \uparrow	ADE ₅ \downarrow	FDE ₅ \downarrow
FaF [21]	0.490	0.079	1.915	3.273
FutureDet-P [26]	0.209	0.037	2.532	4.537
FutureDet-V [26]	0.408	0.053	2.416	4.409

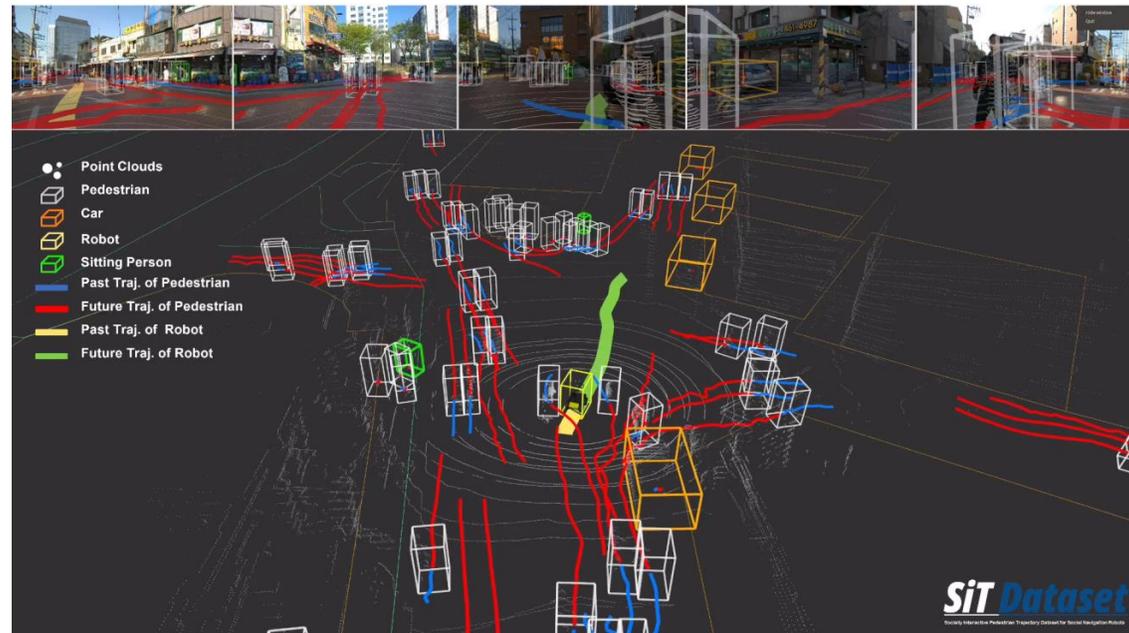
Evaluation of end-to-end motion prediction baselines.



3D cuboids, past and future trajectories of each object

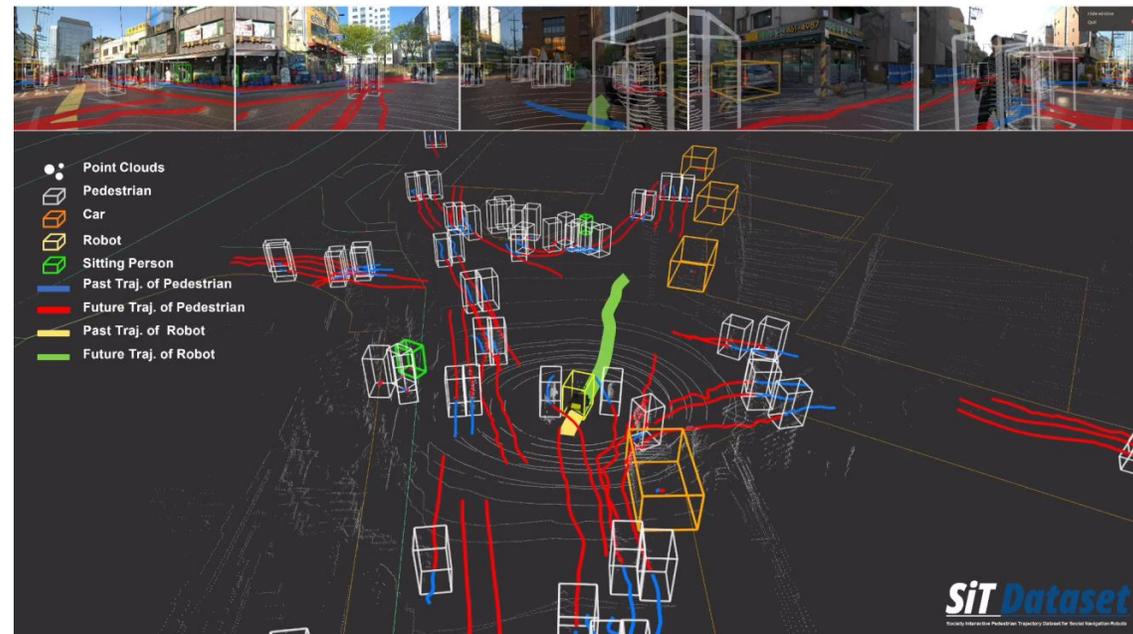
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- 3D object detection based on image and point clouds
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- Trajectory prediction
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- **Challenges open on Eval.AI (Feb. 2024)**



4. Conclusion

- **SiT Dataset:** Socially interactive Pedestrian Trajectory Dataset for Social Navigation Robots
 - Include diverse pedestrian trajectories captured in human-robot interactive scenarios
 - High-quality 2D and 3D annotations for various perception tasks
 - 12-layered semantic maps covering a wide range of scene information
 - Facilitate design of end-to-end motion prediction models



References

- [1] Starship: food delivering robot, https://en.wikipedia.org/wiki/Delivery_robot
- [2] Dadawan: serving robot, <https://www.businessinsider.com/robot-serves-food-takes-temperatures-covid-19-in-the-netherlands-2020-6#next-the-human-staff-still-have-to-actually-take-orders-from-a-safe-distance-6>
- [3] Airstar: guide robot, <https://m.hankookilbo.com/News/Read/201807111499787598>
- [4] ETH-Hotel, <https://icu.ee.ethz.ch/research/datasets.html>
- [5] UCY-Zara, <https://www.youtube.com/watch?v=jyKO4rGDn0o>
- [6] SDD, <https://www.youtube.com/watch?v=c6xQ6iz6wH8>
- [7] nuScenes, <https://www.nuscenes.org/>
- [8] Waymo Open, <https://waymo.com/open/>
- [9] JRDB, <https://jrdb.erc.monash.edu/>

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