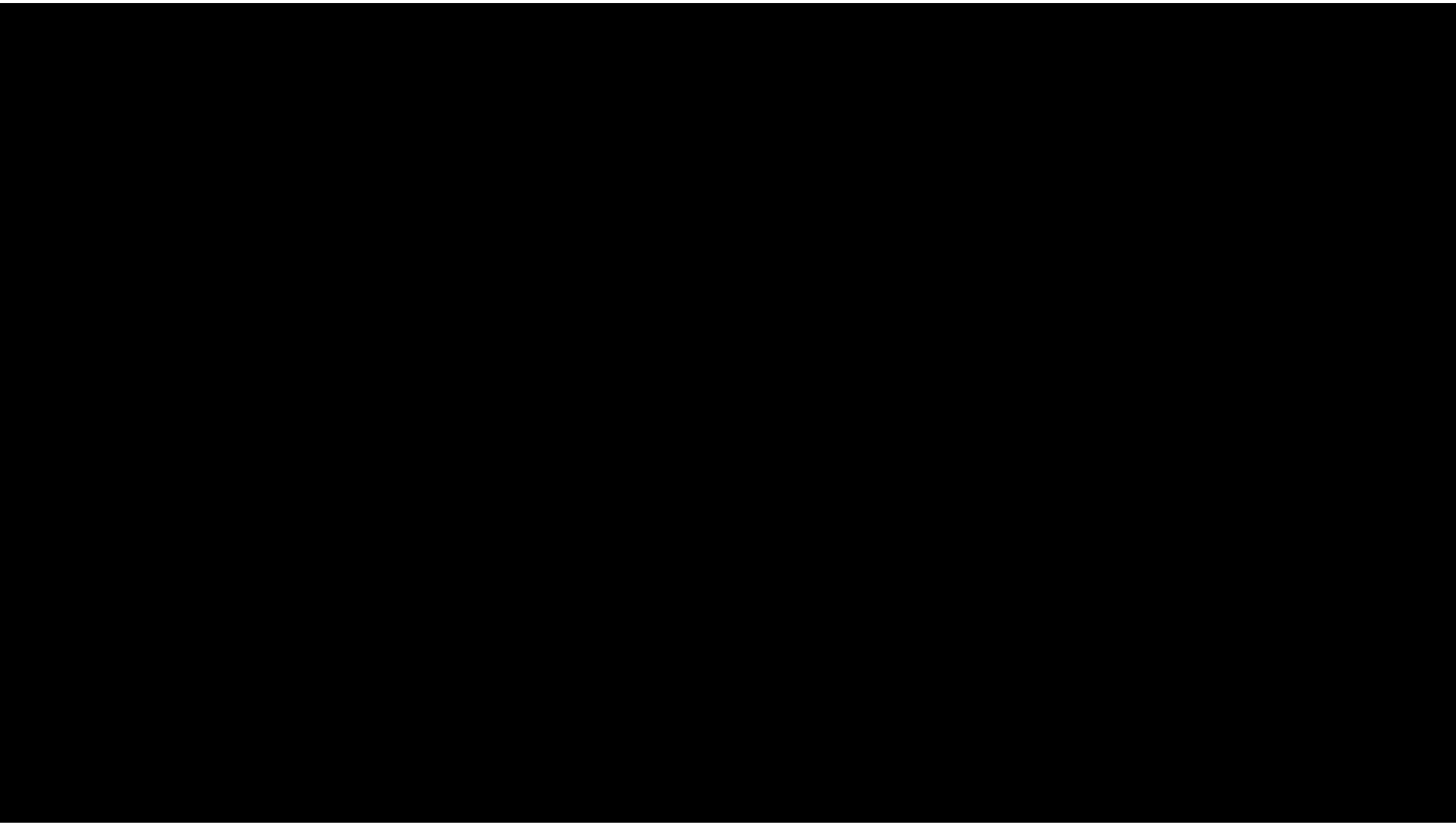
MACHINE LEARNING

CHAPTER 0: INTRODUCTION

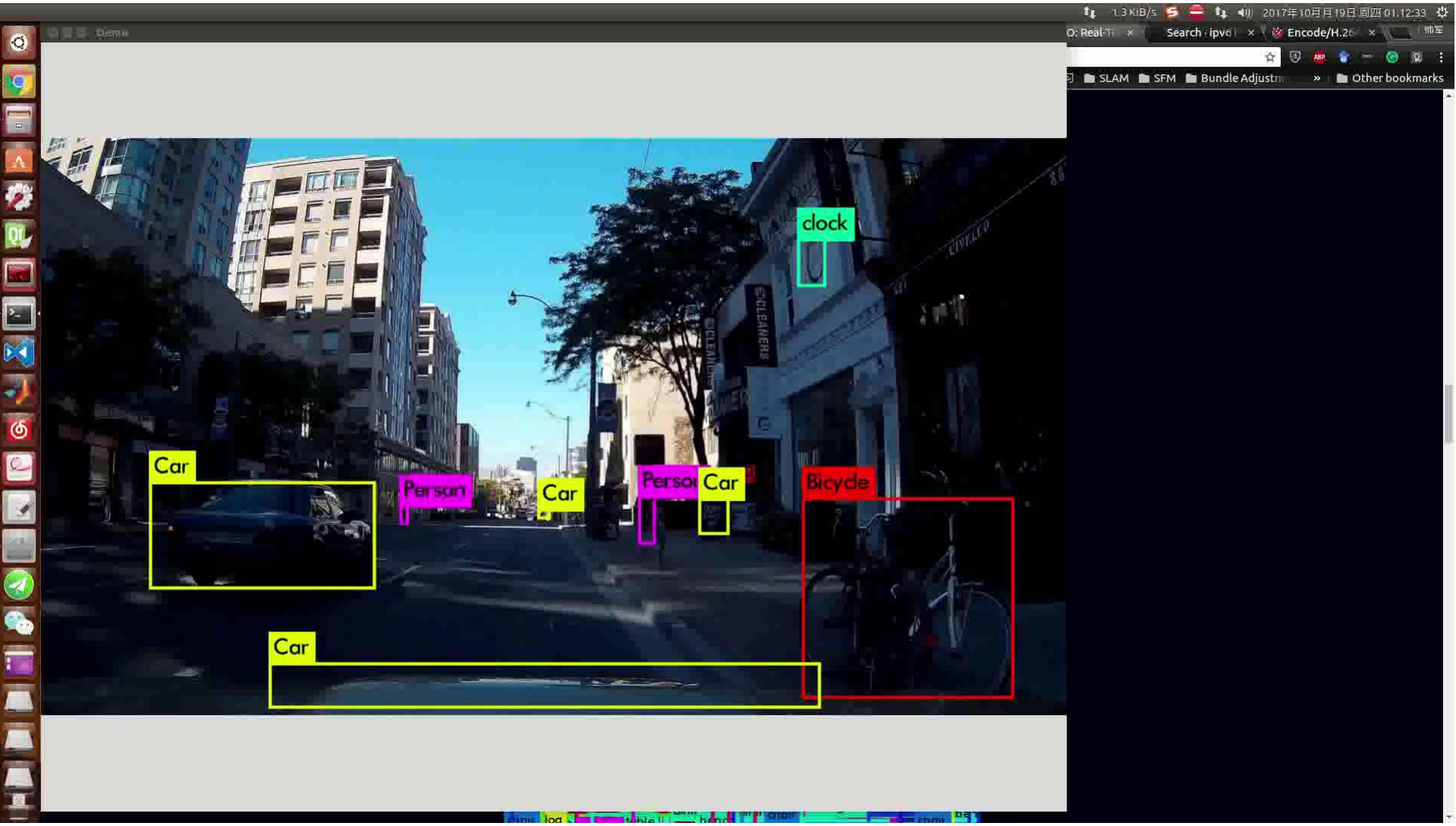
Outlines

- Framework
- Problem Statement
- Related Areas
- History
- Datasets and Learning Models
- Optimization Methods
- Algorithms
- Examples

Our Lab: Center for Intelligent Transportation



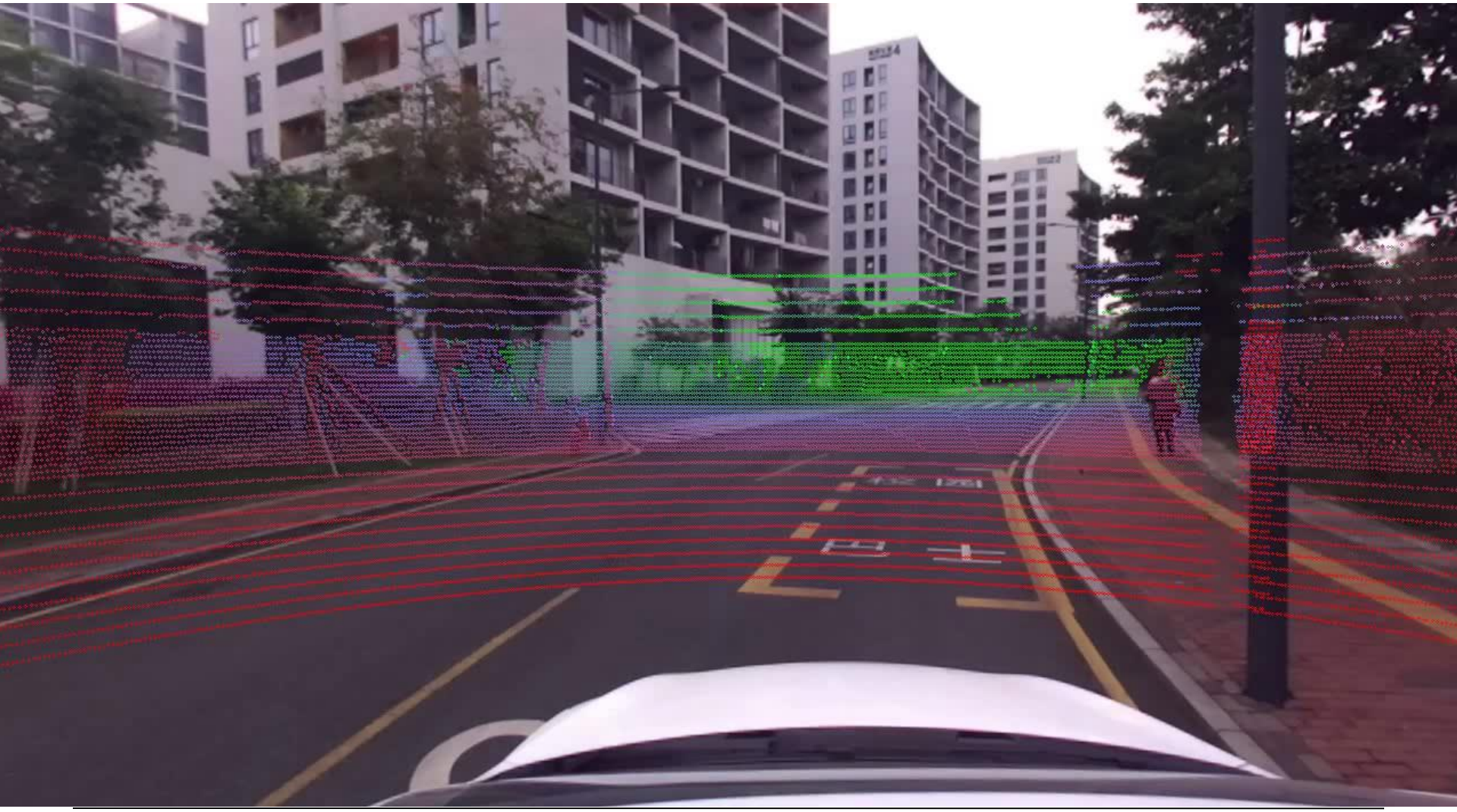
Object Detection-YOLOv3



Instance Segmentation

Lane & Sign Detection

2D-3D Fusion



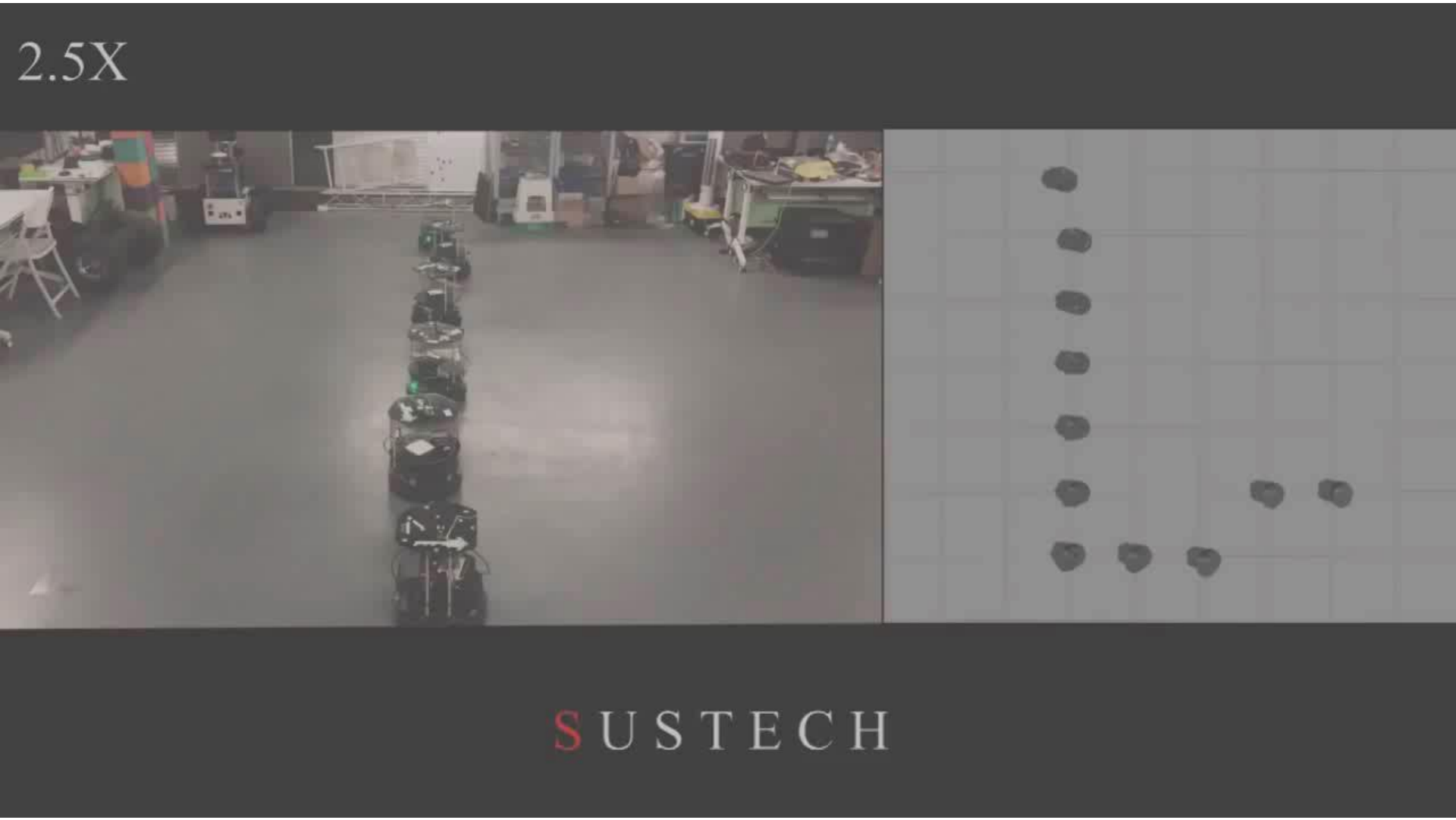
2D-3D Fusion for Tracking

Joint Multi-Object Detection and Tracking with Camera-LiDAR Fusion for Autonomous Driving

Kemiao Huang, Qi Hao*
Department of Computer Science and Engineering
Southern University of Science and Technology

Music Info: Digital Technology - AShamaluevMusic

Reinforcement Learning for Formation



Reinforcement Learning for Navigation

Adaptive Environment Modeling Based Reinforcement Learning (AEMCARL) for Collision Avoidance in Crowded Scenes

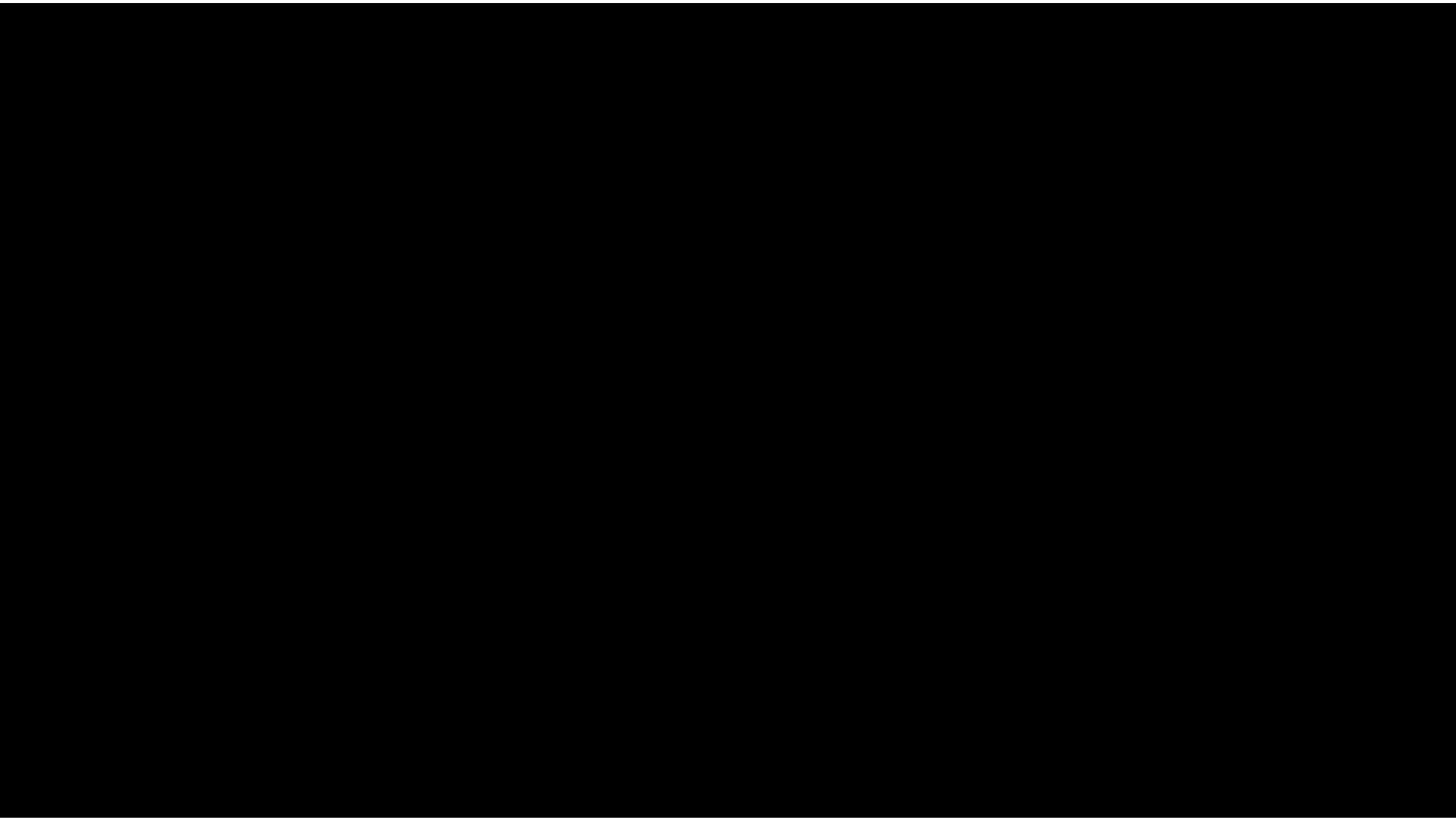
Shuaijun Wang, Rui Gao, Chenyang Li, Shengduo Chen, Ruihua Han, and Qi Hao*

Department of Computer Science and Engineering, Southern University of Science and Technology

SUSTech Autonomous Driving Challenge

demo video @南科大无人驾驶俱乐部

Federated Learning for Map Fusion



Datasets and Benchmark Metrics

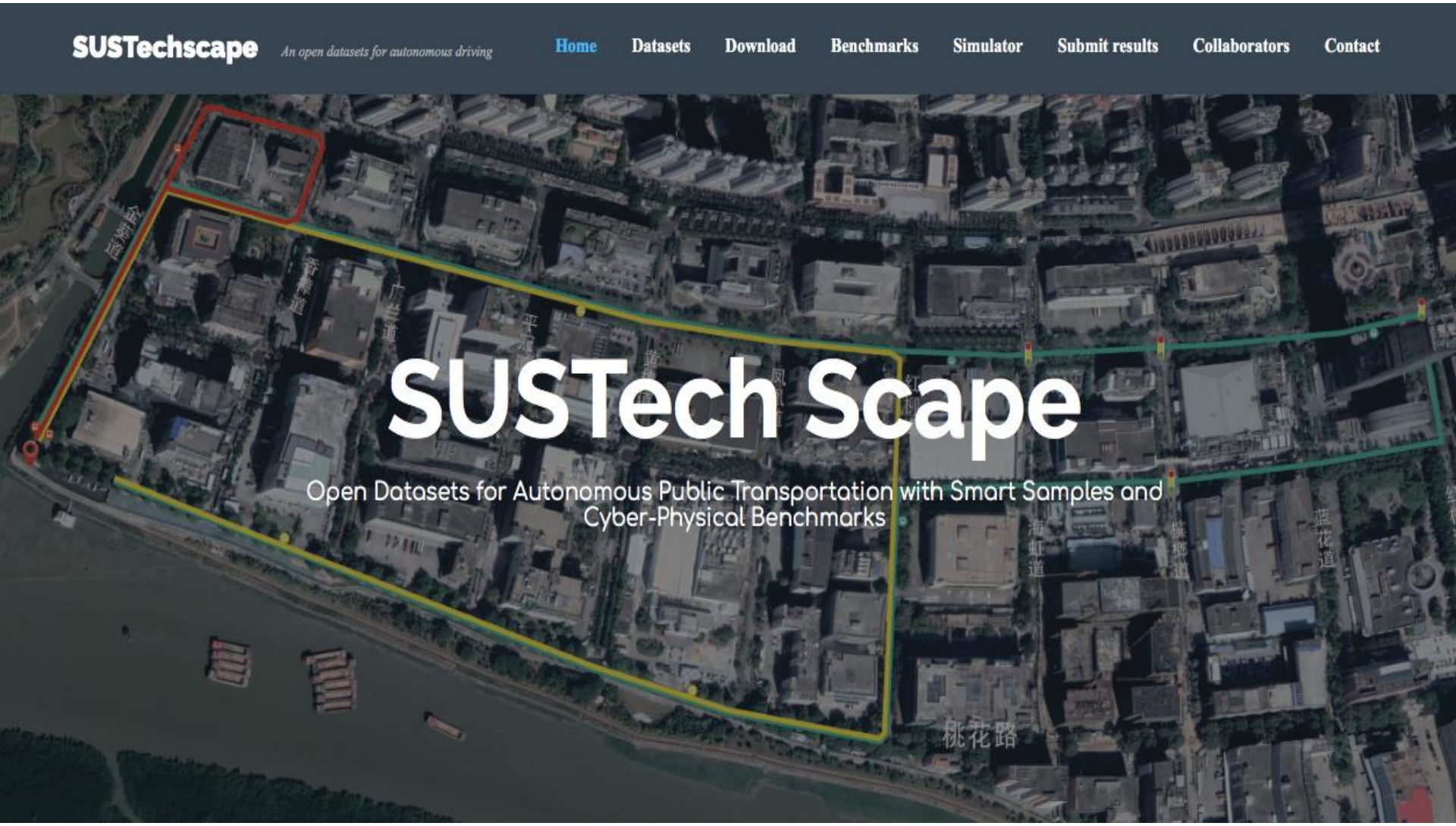
Datasets

- KITTI
- Udacity
- Waymo
- NuScences
- CityScapes
- Apolloscape
- SUSTech Scape

Metrics

- Correctness
- Robustness

Our Dataset: SUSTech Scape



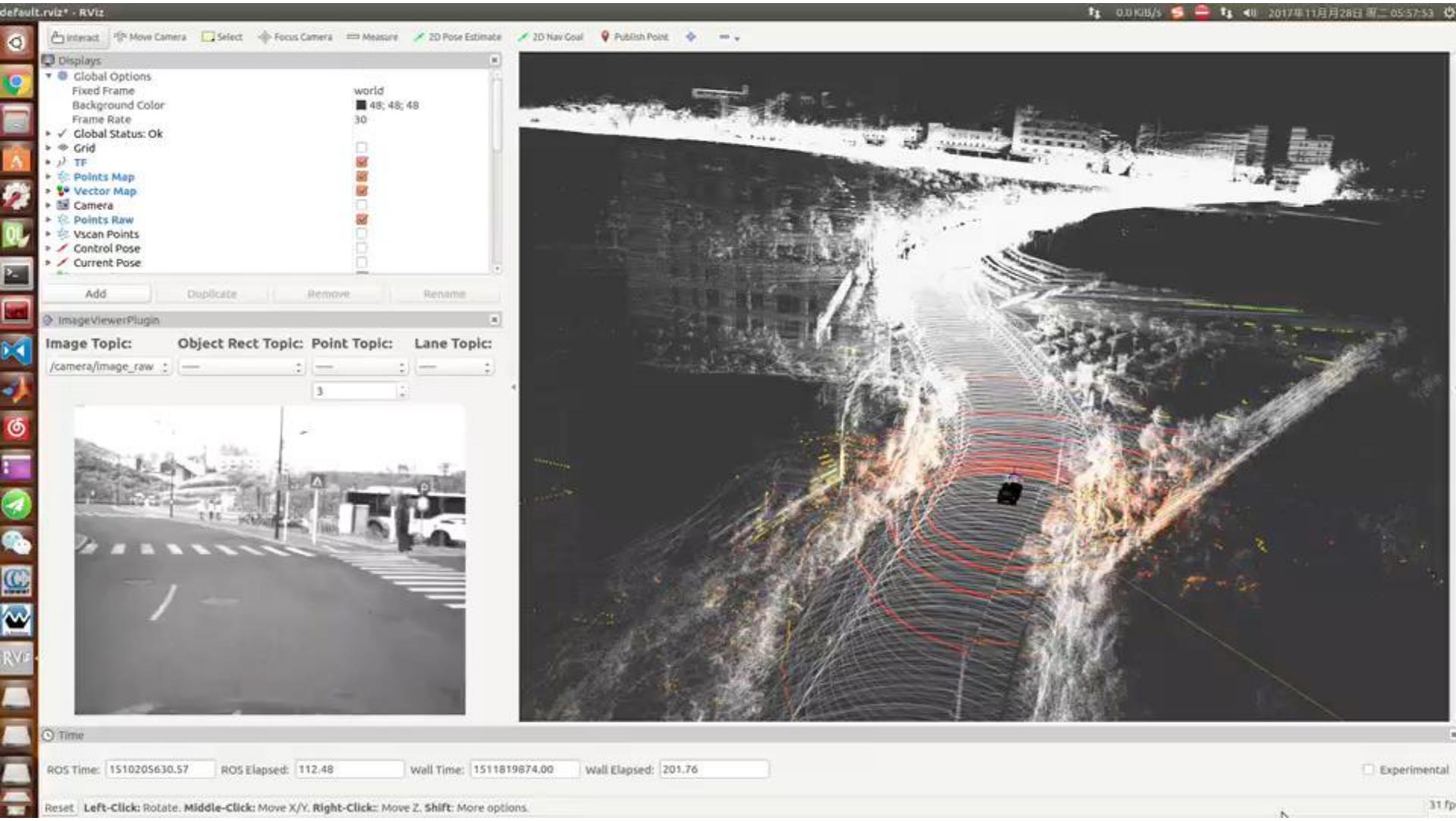
Datasets Comparison

Dataset	Sensors	Location Accuracy	Scene Diversity	Annotation				Driver	
				2D	3D	Video	Lane	Behav	Physi
KITTI	Cameras (6), Lidar (1)	cm	Regions Day time	box-15k, pixel-400	Box	no	no	no	no
Oxford RobotCar	Camera, Lidar	unknow	1 City, weather	no	no	no	no	no	no
TSD-max	Camera	m	Regions	box-10k	no	no	2D	no	no
CityScape	Camera	unknow	50 Cities, Season, weather, D&N	pixel-25k	no	no	no	no	no
Udacity	Camera, Lidar	unknow	1 City, sunny and overcast	box-25k	no	no	2D	no	no
Mapillary	Camera	m	Cities, season, weather, D&N	pixel-25k	no	no	2D, 2 classes	no	no
TorontoCity[1]	Camera, Lidar	cm	1 City	pixel	point	no	no	no	no
BDD100K	Camera, Lidar	m	4 Regions, weather, D&N	box-100k, pixel-10k	no	no	2D, 8 classes	no	no
ApolloScape	Cameras (6) Lidars (2) Cars (4)	cm	4 Regions, weather, D&N	pixel-140k resolution 2K	point	yes	2D, 3D, 28 classes	no	no
SUSTech Scape	Camera (6) Lidars (3) M-spectral Cameras (2) Buses (4) Taxis (4)	cm	1~5 Cities, weather, day and night	pixel-200k resolution <4K	point	yes	2D, 3D >28 classes	yes	yes

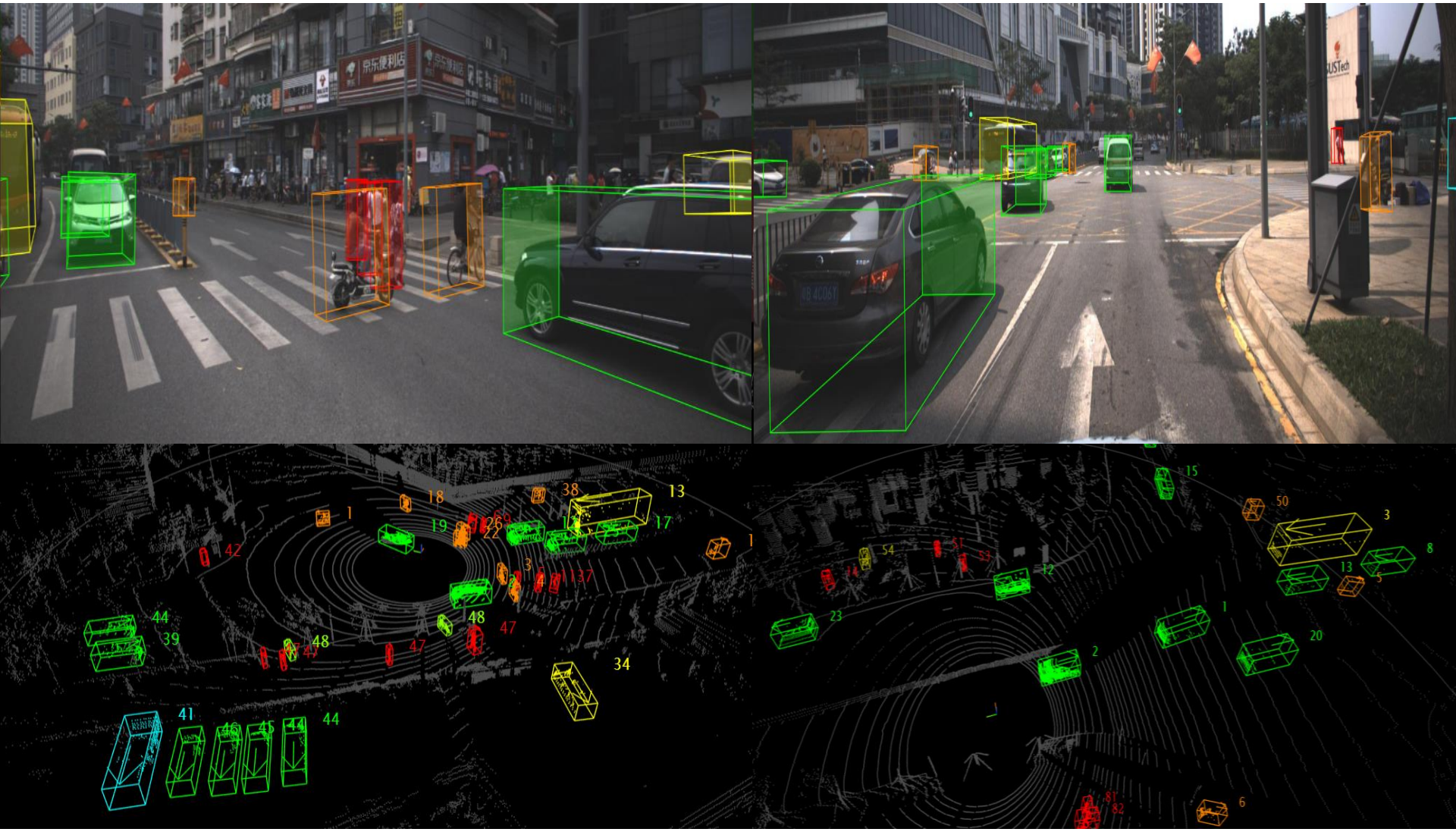
Benchmark Metrics

Evaluation Metrics			Methods	Measures	Subjects
Scene Processing	Scene flow	stereo disparity outliers [%] optical flow outliers [%] scene flow outlier [%]	Image, 3D Points Cloud Based Experiments	Optical and scene flow estimation errors, 3D reconstruction errors compared with ground truth	**Optical flow estimation, scene flow estimation, 2D-3D reconstruction algorithms**
	Depth	Scale invariant error [%] Relative squared error [%] Absolute squared error [%] Root mean squared error [%]			
Mapping & Localization Accuracy	Mapping	iRMSE [1/km] iMAE [1/km] RMSE [mm] MAE [mm]	Odometry (IMU, Camera) Readings and 3D Points Cloud Based Experiments	Environment mapping and vehicle localization under various scenarios and conditions	**SLAM, key frame selection, sensor fusion, optimization algorithms**
	Odometry	Translation errors [%] Rotation errors [deg/m]			
Energy Efficiency	Urban Area	Battery capacity [kW/h] Range [kM] Complete weight [t]	Testing Experiments	Current and power consumption of devices	**Power modes, battery management and Scheduling algorithms**
	Suburb Area				
	Hybrid Area				
System Scalability	Task completion time [h] Task completion distance [km] MTCA [km] MTDA [h]		Simulation Experiments in Different Scales	Predicted system performances in different scales of the vehicle fleet	**Communication protocols, group formation control, collaborative planning Algorithms**
System Reliability & Robustness	**Scenarios Overlap Rate[%] One Pass Rate[%] Defect resolution rate[%] Pressure running time[%]**		**Simulation Experiments under Complex Scenarios**	**Sharp turns, degraded marks, faulty signals, reckless driving, sensor failures**	**Sensor perception, motion planning, decision & control algorithms**

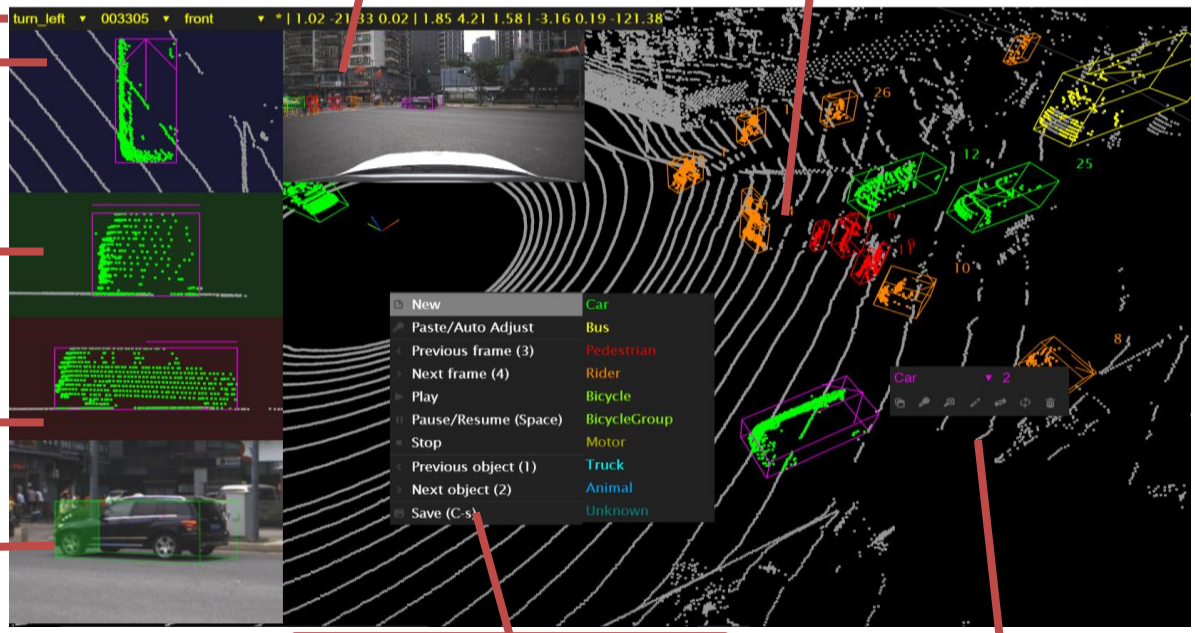
2D-3D Data


default.rviz* - RViz
Interact
Move Camera
Select
Focus Camera
Measure
2D Pose Estimate
2D Nav Goal
Publish Point
Displays
Global Options
Fixed Frame
world
Background Color
48; 48; 48
Frame Rate
30
Global Status: Ok
Grid
TF
Points Map
Vector Map
Camera
Points Raw
Vscan Points
Control Pose
Current Pose
Add
Duplicate
Remove
Rename
ImageViewerPlugin
Image Topic:
Object Rect Topic:
Point Topic:
Lane Topic:
/camera/image_raw
3
Time
ROS Time: 1510205630.57
ROS Elapsed: 112.48
Wall Time: 1511819874.00
Wall Elapsed: 201.76
Experimental
Reset
Left-Click: Rotate. Middle-Click: Move X/Y. Right-Click: Move Z. Shift: More options.

Dataset Annotation



Dataset Annotation Tools



Scene & frame navigation
Box information
Camera selection

Photo context
Freely resizable
Auto-follow target obj.

Colored objects

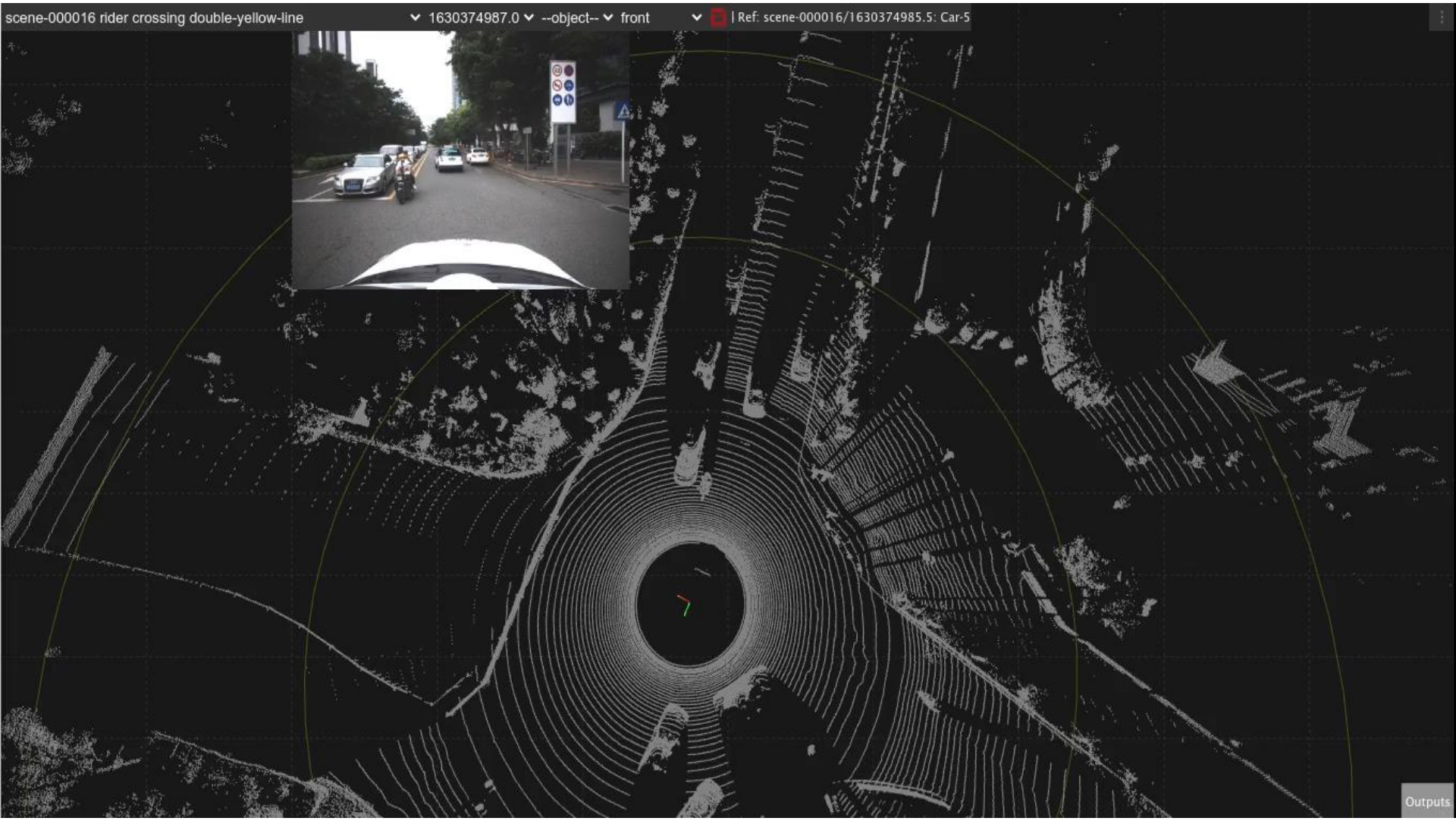
Projective view
Auto-shrink
Rotation
Resize
Move
Keyboard fine-tune

Auto-focused target object

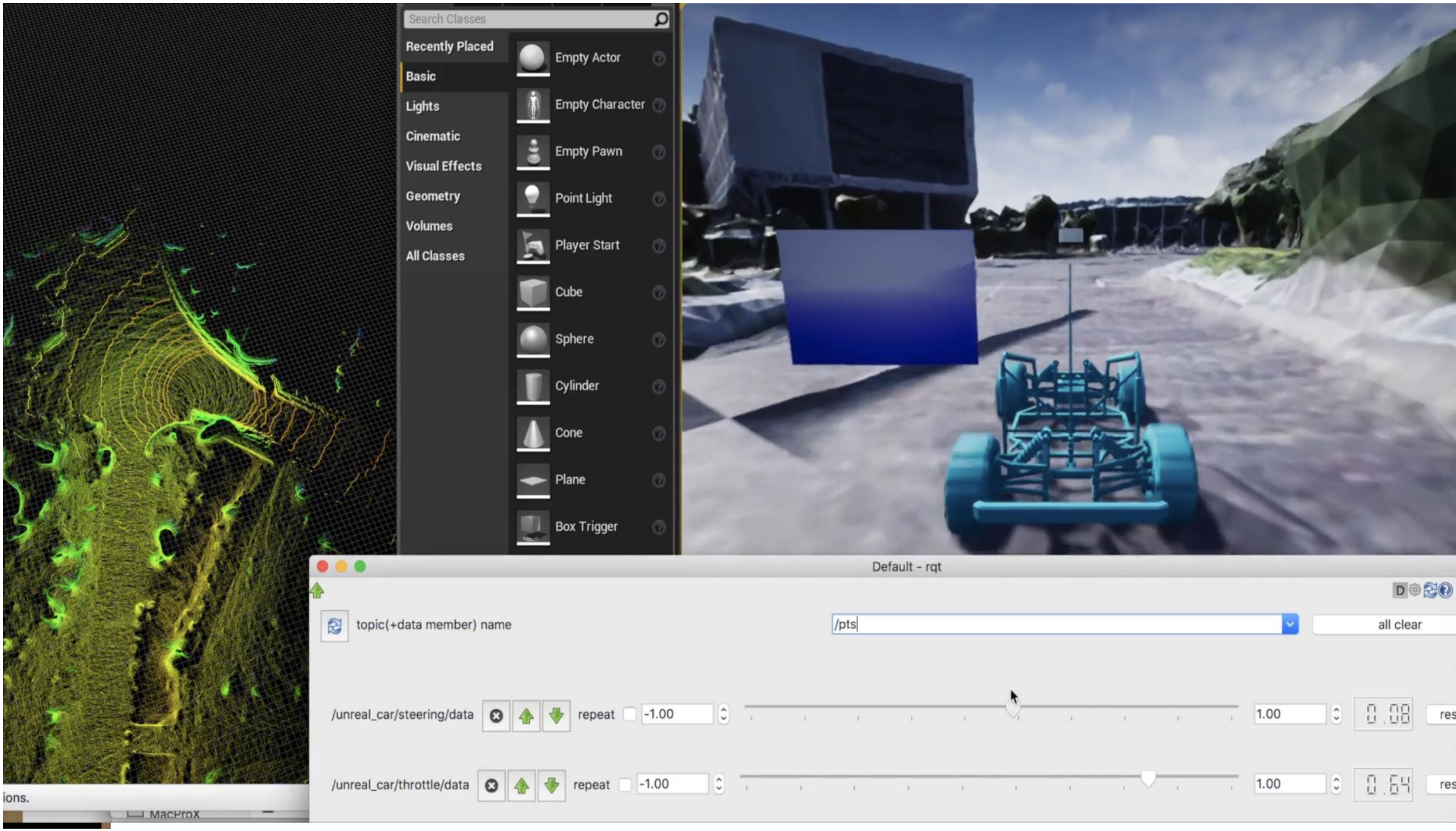
Context menu
Frame/obj. navigation
Stream play/stop
New/paste/save

Floating fast toolbox

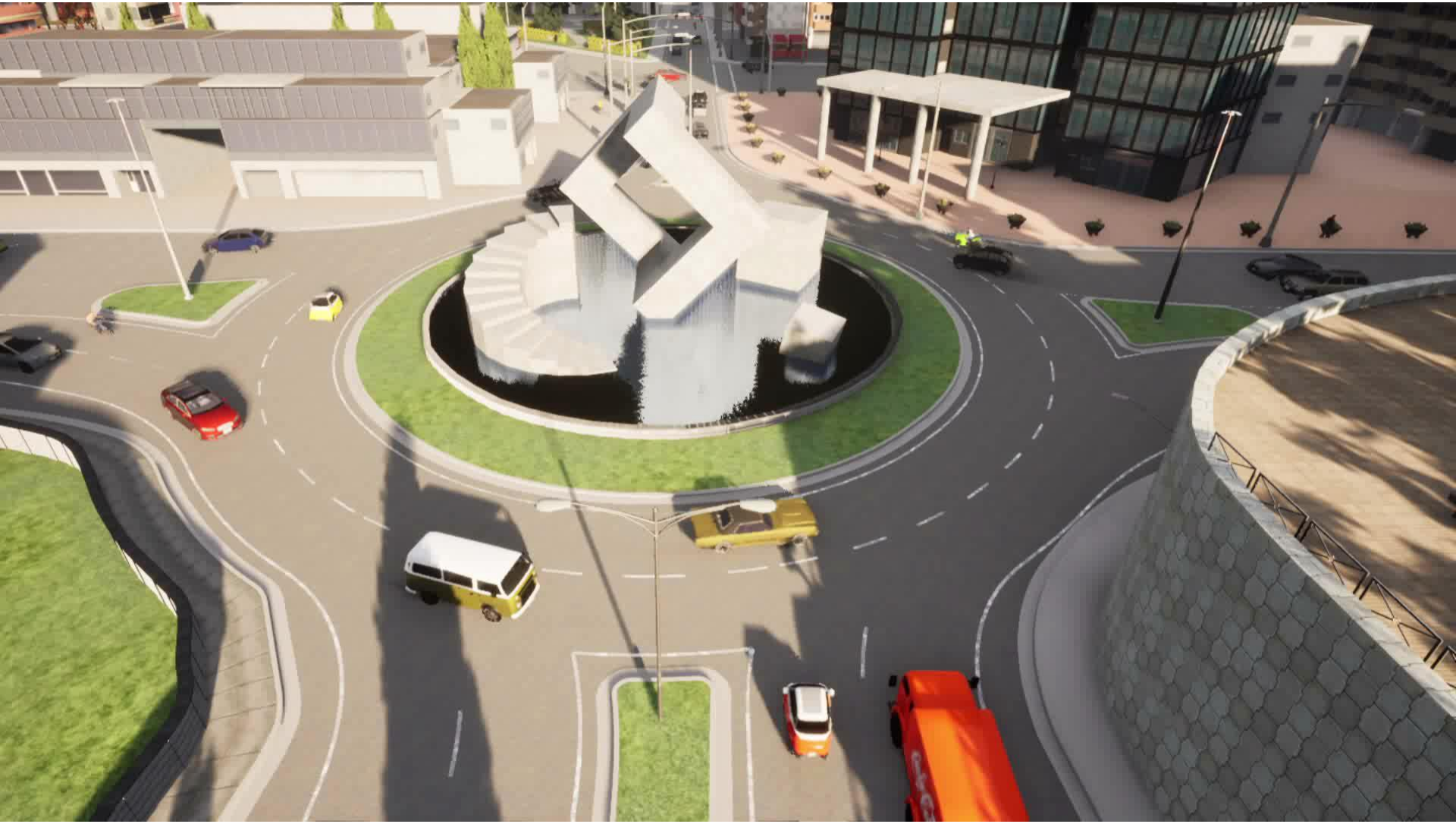
Out Platform: SUSTech POINTS



Out Simulator: SUSTech PAVALION



Simulator: CARLA+Autoware



Simulator: CARLA+Autoware

Simulator: CARLA+Autoware

More Reading and Multimedia Materials

Books： 《人类简史》《奇点将近》《终极算法》《人工智能时代》《2050》《情感机器》《数学之美》

Movies： “Blade Runner” “AI” “Prometheus” “Covenant” “Ex Machina” “She” “2001：Space Odyssey” “The Matrix” “I，Robot” “Bicentennial Man” “Terminator”

TV Series： “West World” “Humans” “Black Mirrors”

More Course Links

Stanford Machine Learning：
https://see.stanford.edu/Course/CS229/47

MIT Machine Learning： https://ocw.mit.edu/courses/electrical-engineering-and-computer-science/6-867-machine-learning-fall-2006/index.htm

Stanford CNN for Vision： http://cs231n.stanford.edu

Stanford Deep Learning: http://cs230.stanford.edu/syllabus.html

MIT Deep Learning: http://introtodeeplearning.com/