Multi-Object Tracking using Poisson Multi-Bernoulli Mixture Filtering for Autonomous Vehicles

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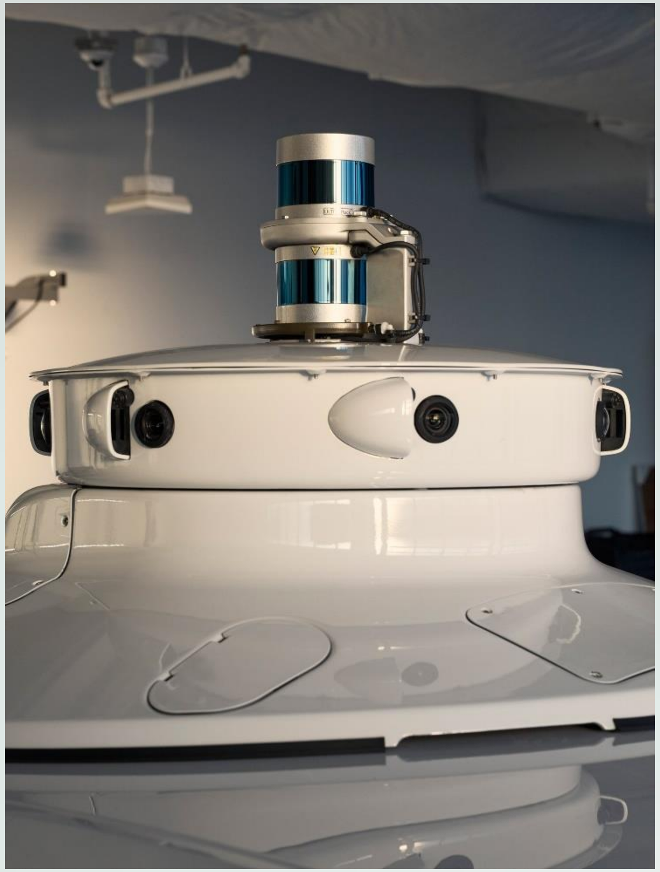
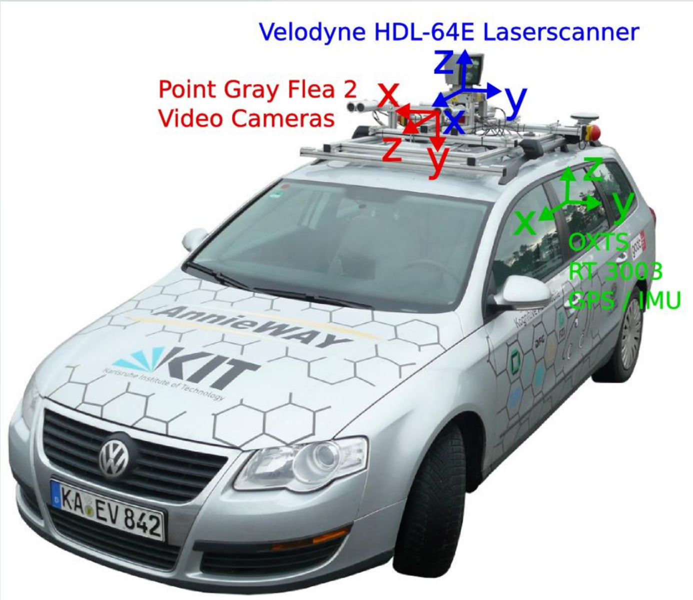
LiDAR Is Essential for 3D Perception



Source: WIRED

2 Velodyne LiDARs are installed on the top of Argo AI autonomous driving vehicle.



Source: KITTI Dataset

Source: MSU CANVAS

HDL-64E

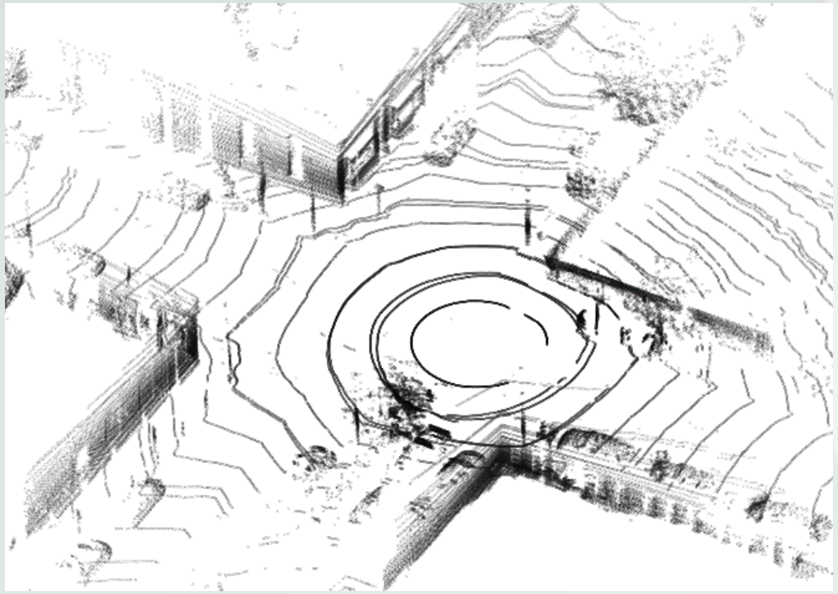
Source: Velodyne

VLP-16

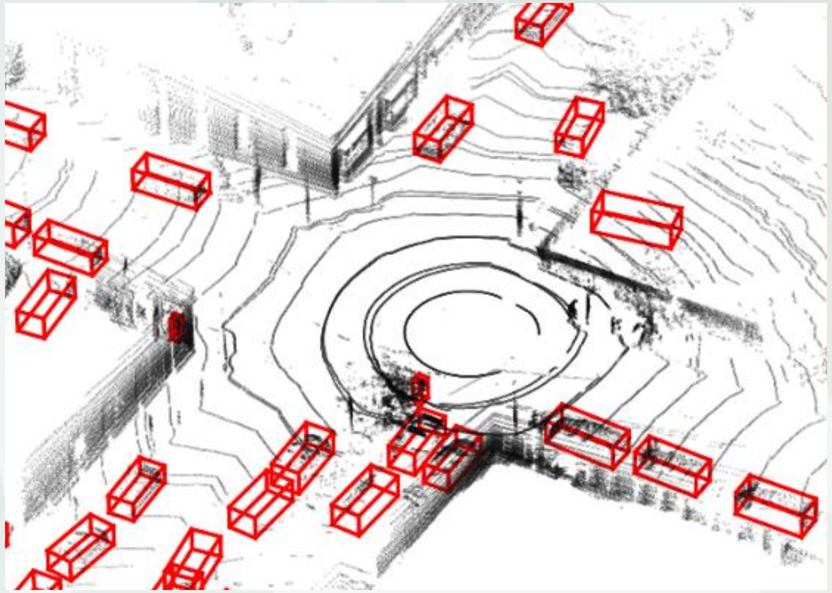
OS1

Source: Velodyne and Ouster

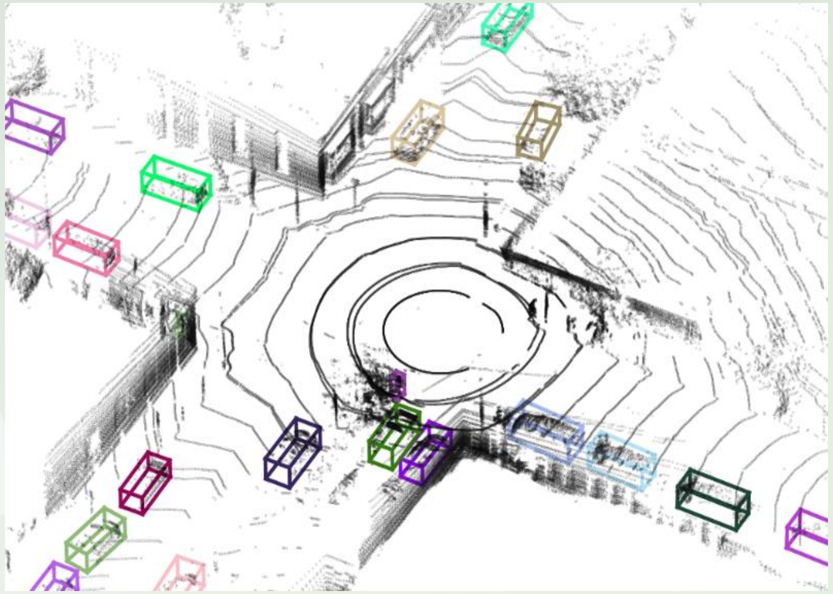
Multi-Object Tracking (MOT) – Main Challenges



raw 3D point cloud



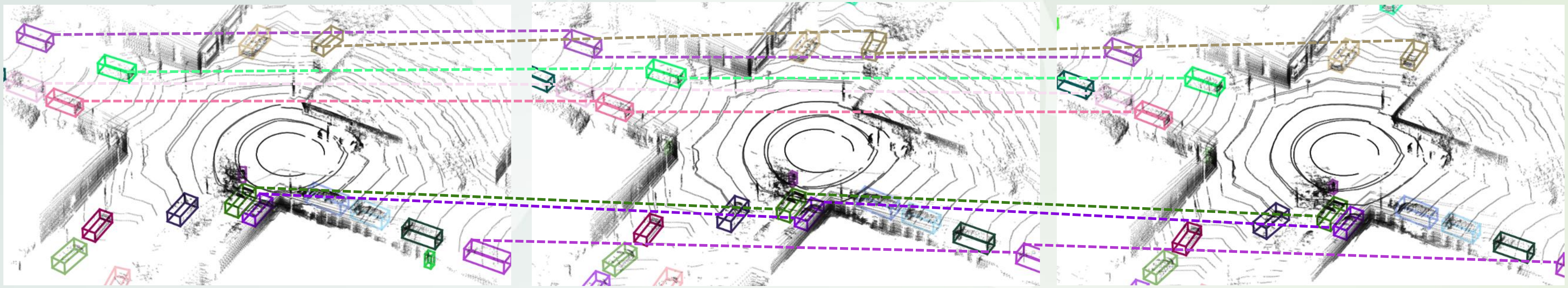
noisy input detections (cars)



ground truth (cars)

Multi-Object Tracking (MOT) – Main Challenges

- Uncertainty in the number of objects
- Uncertainty regarding when and where the objects may appear and disappear
- Uncertainty in objects' states



Random-Finite-Sets (RFS) and Multi-Object Tracking (MOT)

- Random-Finite-Set (RFS) based approaches have shown a great deal of promise in addressing all of the MOT uncertainties.
- RFS-based MOT algorithms have been shown to be very effective for radar-based MOT applications.
- To the best of our knowledge, RFS-based approaches have not been well explored for 3D LiDAR-based tracking-by-detection systems.

Our Contributions

- We propose an RFS-based tracker to solve the autonomous driving MOT problem using 3D LiDAR and learning-based detectors.
- Our RFS-based tracker is in low-complexity and can run in real-time on a standard desktop computer.
- We validate and test our tracker using two extensive open datasets provided by two industry leaders – Waymo and Argoverse.

Random Finite Set (RFS) based Multi-Object Tracking (MOT)

Random Finite Set (RFS): Definition

A random process whose possible outcomes are sets with a number of unique elements.

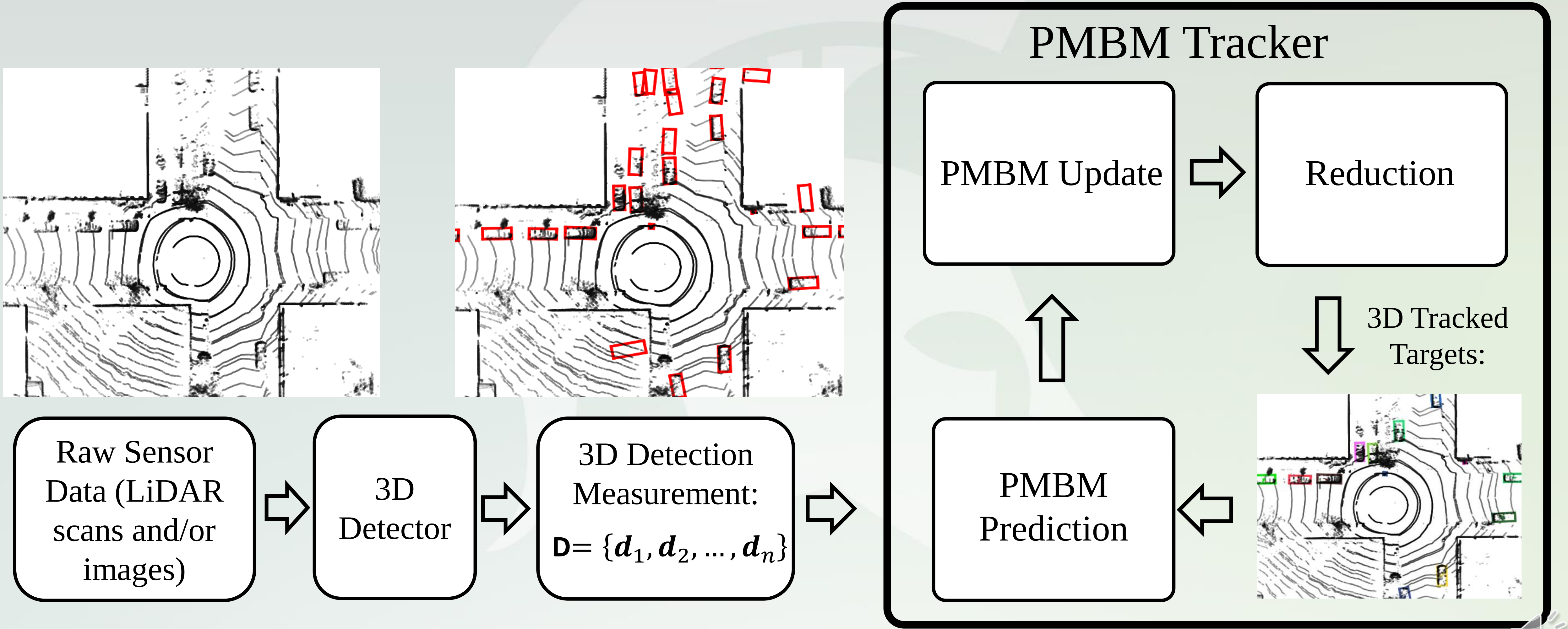
- In an RFS, $\mathbf{x} = \{x^1, \ldots x^N\}$, both the number of elements and the elements themselves are random.

Detected and Undetected Objects

- **Detected Objects ($\mathbf{x}^d$):** Tracked objects that have been detected at least once.
  - Multi-Bernoulli Mixture (MBM) RFS is used to represent detected objects.

- **Undetected Objects ($\mathbf{x}^u$):** Potential objects that have not been detected.
  - Poisson RFS, also named Poisson Point Process (PPP) is used to model undetected objects.

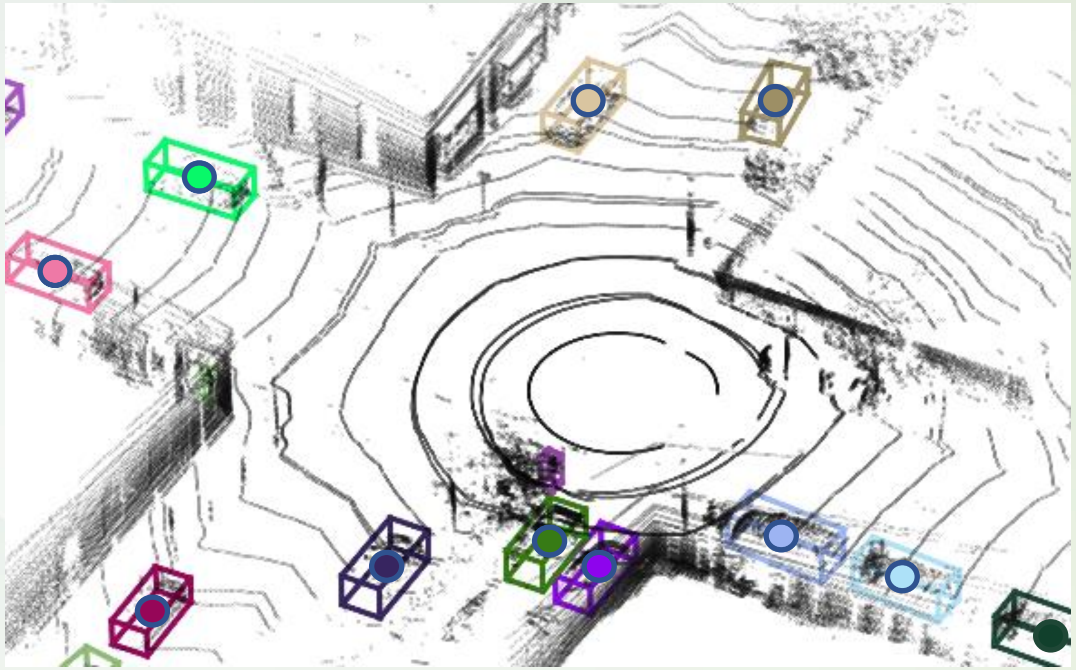
Proposed Poisson Multi-Bernoulli Mixture (PMBM) Tracker:System Architecture



Proposed Poisson Multi-Bernoulli Mixture (PMBM) Tracker: Object State

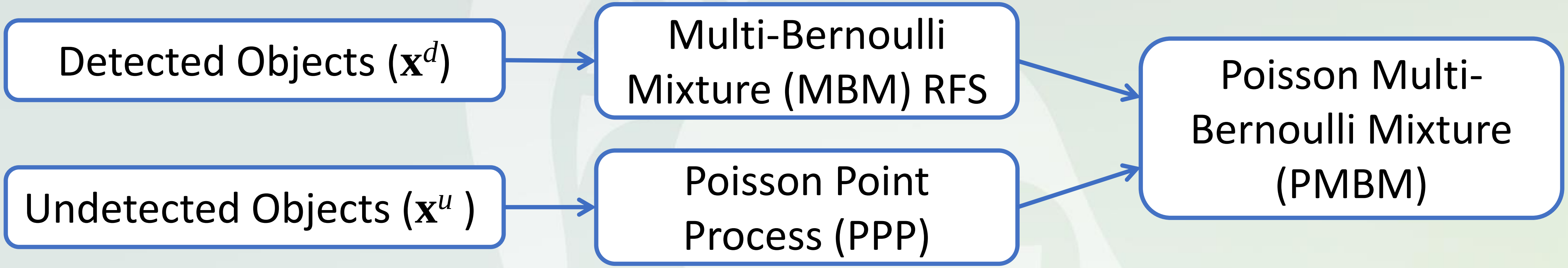
Under this work, our PMBM tracker is designed as a point-based tracker. The object state used in this work is defined as $\mathbf{x} = [x, y, v_x, v_y]$

- z value does not change dramatically for consecutive frames.
- The dimension of the objects are already precise from a neural network-based 3D detector.
- Reducing the state dimension inherently enables the tracking system operate at a lower computational cost for real-time performance.



Proposed Poisson Multi-Bernoulli Mixture (PMBM) Tracker: Density

In our RFS-based tracker, Poisson point process (PPP) is used to represent Undetected Objects, multi-Bernoulli mixture (MBM) RFS is used to model Detected Objects.



PMBM Density: $$PMBM_t(\mathbf{x}) = \sum_{\mathbf{x}^u \uplus \mathbf{x}^d = \mathbf{x}} PPP_t(\mathbf{x}^u)MBM_t(\mathbf{x}^d)$$

Proposed Poisson Multi-Bernoulli Mixture (PMBM) Tracker: Prediction

Conjugacy property of PMBM filter: If the prior is in PMBM form, then the distribution after Bayesian prediction and update steps will also be PMBM form.

PMBM prediction: $$PMBM_{t+1|t}(\mathbf{x}_{t+1}) = \int p(\mathbf{x}_{t+1} \mid \mathbf{x}_t) PMBM_{t|t}(\mathbf{x}_t) \delta \mathbf{x}_t$$

$p(\mathbf{x}_{t+1} \mid \mathbf{x}_t)$: the transition density. It contains probability of survival Ps and state transition density $\pi_{t+1}(\mathbf{x}_{t+1} \mid \mathbf{x}_t)$, constant velocity model is used for this work.

Proposed Poisson Multi-Bernoulli Mixture (PMBM) Tracker: Update

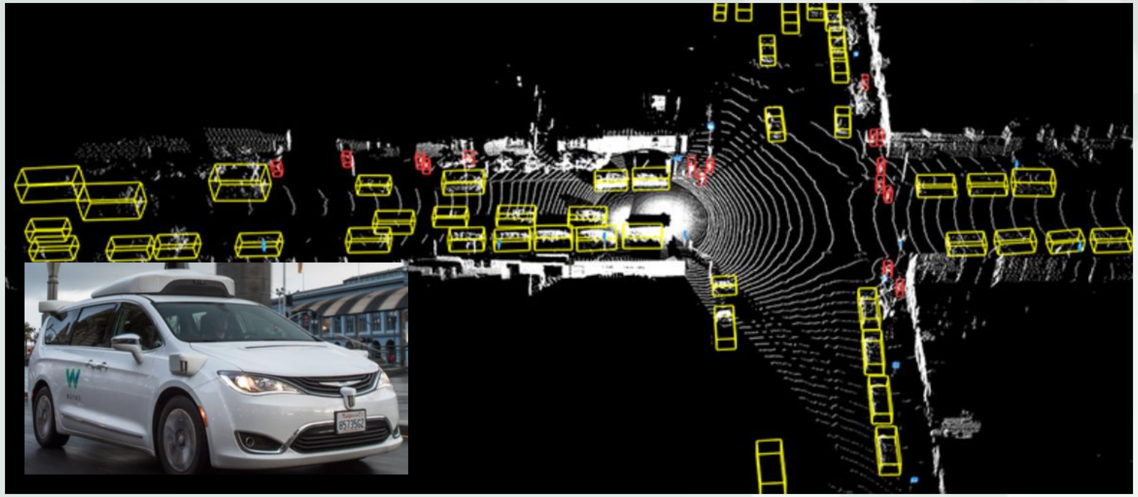
By adding information from the measurement model $p(\mathbf{z}_t|\mathbf{x}_t)$, the PMBM density can be updated with:

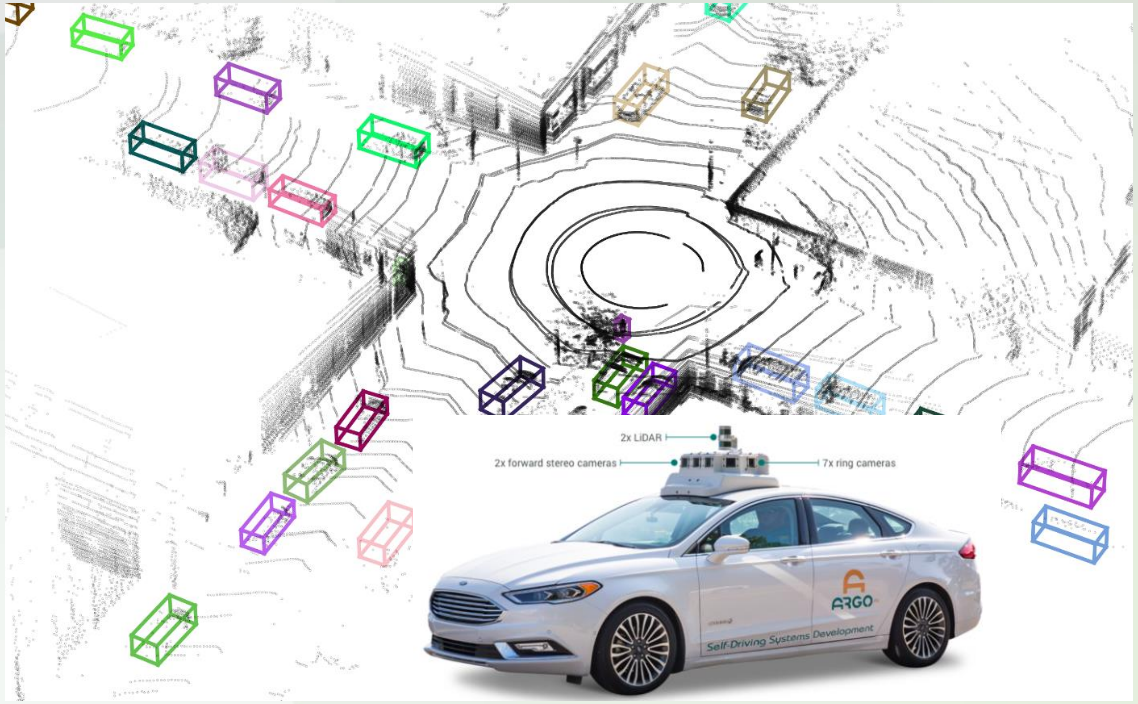
$$PMBM_{t+1|t+1}(\mathbf{x}_{t+1}) = \frac{p(\mathbf{z}_{t+1} \mid \mathbf{x}_{t+1}) PMBM_{t+1|t}(\mathbf{x}_{t+1})}{\int p(\mathbf{z}_{t+1} \mid \mathbf{x}'_{t+1}) PMBM_{t+1|t}(\mathbf{x}'_{t+1}) \delta \mathbf{x}'_t}$$

(1) Update of Undetected Objects without associated detections/measurements.
(2) Update of Undetected Objects with associated detections/measurements
-> Update of new objects tracked for the first time.
(3) Update of Detected Objects without associated detections/measurements.
(4) Update of Detected Objects with associated detections/measurements.

Experimental Results

Dataset: Waymo and Argoverse





Waymo dataset contains 40,400 frames in validation set and 30,000 frames in test set.

Argoverse dataset has 5,000 frames in validation set and 4,200 frames in test set.

Experimental Results -- Waymo

Method	Split	Class	MOTA (Primary) (%)	MOTP	False Positive (%)	Misses (%)
Waymo Baseline	test	All	25.92	0.263	13.98	64.55
Argoverse Baseline	test	All	29.14	0.270	17.14	53.47
Probabilistic KF [2]	test	All	36.57	0.270	8.32	54.02
Our PMBM tracker	test	All	**38.51**	0.270	7.74	52.86

[2] Chiu, Hsu-kuang, Antonio Prioletti, Jie Li, and Jeannette Bohg. "Probabilistic 3d multi-object tracking for autonomous driving." *arXiv preprint arXiv:2001.05673* (2020).

Experimental Results -- Argoverse

Method	Split	Class	MOTA (Primary) (%)	MOTP	#False Positive	#Misses
Argoverse Baseline	test	Vehicle	65.90	0.34	15,693	23,594
Our PMBM tracker	test	Vehicle	**71.67**	0.34	8,278	24,165
Argoverse Baseline	test	Pedestrian	48.31	0.37	4,933	25,780
Our PMBM tracker	test	Pedestrian	**48.56**	0.4	5,924	24,278

Thank you!

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