

## Why Unsupervised Object Detection?

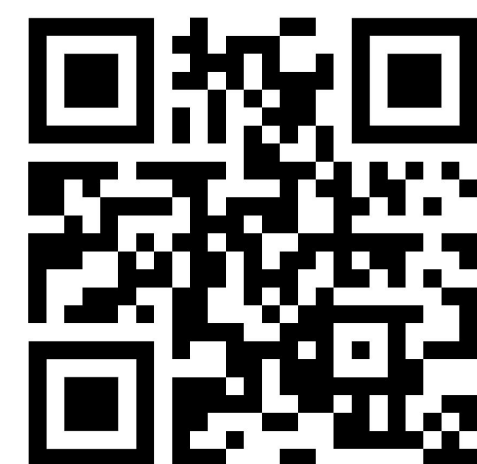
- Obtaining human annotations is costly and tedious.
- Most existing visual data is **unlabeled**.
- Humans and animals learn to perceive objects without explicit labels at all.
- In this paper, we study **unsupervised object detection** from **LiDAR point clouds** in **real-world self-driving scenes**.

## Intuition behind OYSTER

- Construct an **object discovery loop** where the detector is **iteratively re-trained on pseudo-labels of increasingly higher quality** as self-training goes on.

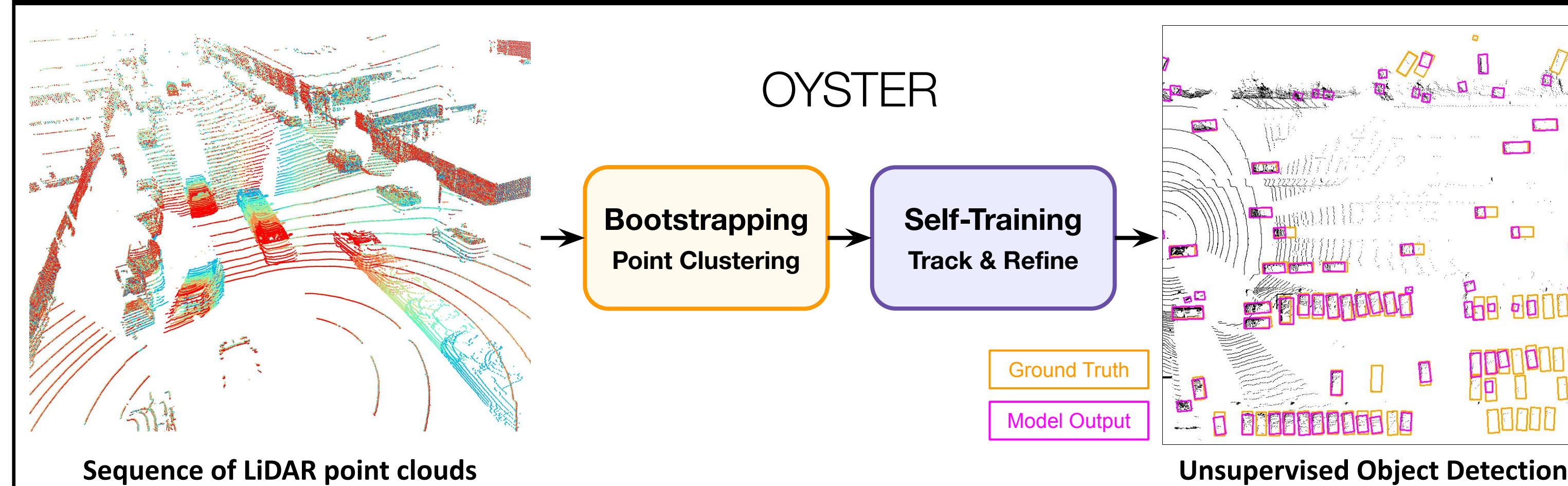


Evolution of our self-training pseudo-labels, starting from very noisy point clusters.

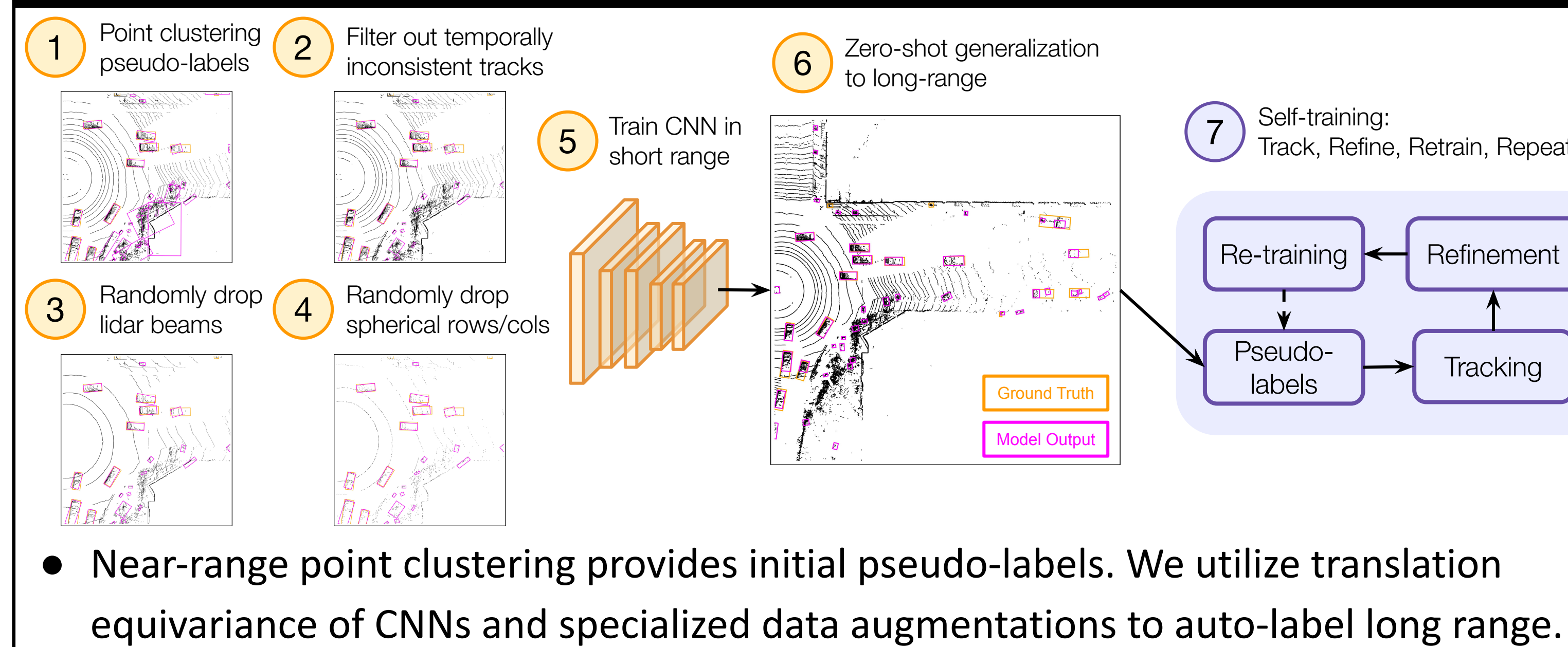


Website:

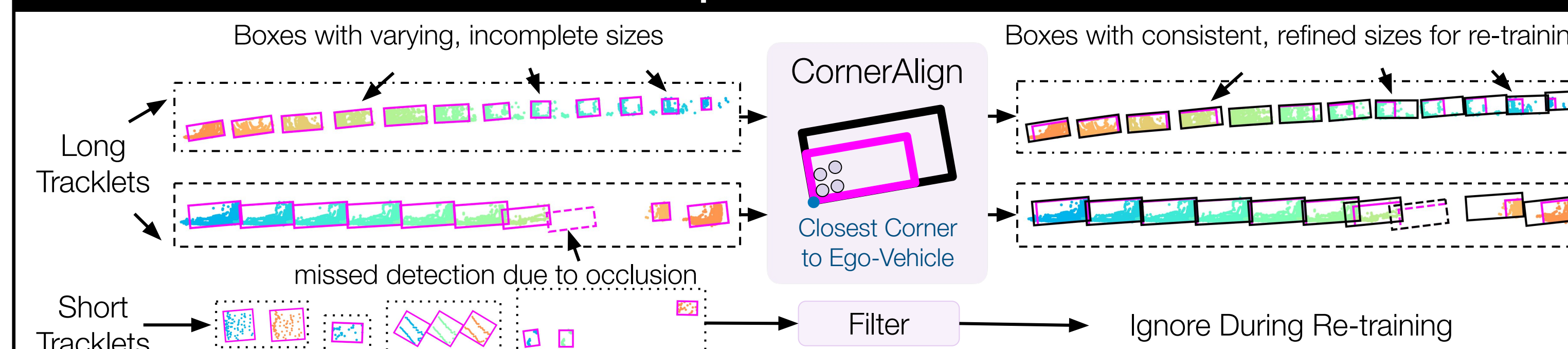
## Object Discovery via Spatio-Temporal Refinement



## OYSTER: Bootstrapping + Self-Training



## Track, Refine, Retrain, Repeat



- We use an unsupervised offline **tracker** to find object tracks of various lengths, discard short tracks, **refine** long tracks, **re-train** on refined pseudo-labels, **repeat**.
- Refinement uses temporal consistency of object tracks as a self-supervision signal: objects tend to stay the same 3D size and move in a temporally consistent way.

## Results



	AP @ IoU			Recall @ IoU			AP @ IoU			Recall @ IoU		
	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7
DBSCAN [17]	3.5	1.1	0.3	28.6	15.9	8.3	2.1	1.0	0.4	26.4	17.9	10.9
DBSCAN + init-train	21.6	12.0	6.4	42.0	26.0	13.8	15.5	10.7	5.7	29.7	19.3	10.1
DBSCAN + self-train [66]	20.1	12.3	6.3	42.2	26.1	13.5	12.5	9.1	5.5	30.1	19.6	10.3
PP score [66]	6.4	2.0	0.4	32.8	18.7	8.8	5.5	2.5	0.9	33.7	22.8	13.8
PP score + init-train [66]	28.4	14.0	4.9	47.4	26.6	12.5	24.4	15.8	7.4	43.9	27.4	14.2
MODEST [66] (1 traversal)	22.8	7.5	2.8	49.7	28.9	14.9	20.6	9.9	2.7	47.0	28.6	13.0
Ours	43.5	29.5	18.1	62.8	44.8	28.1	35.4	24.5	12.9	55.1	37.5	21.4

PandaSet results

Argoverse2 Sensor results