

Frame 1

**Frame T** 

### LabelFormer: Object Trajectory Refinement for Offboard Perception from LiDAR Point Clouds



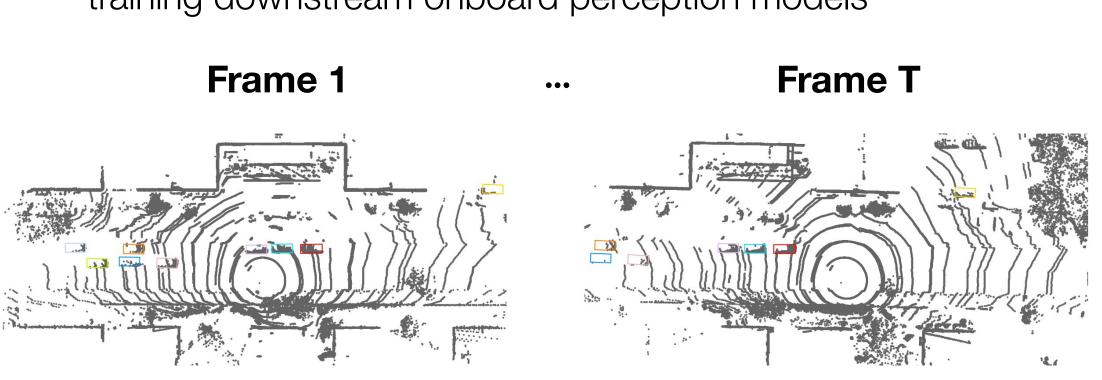
Anqi Joyce Yang, Sergio Casas, Nikita Dvornik, Sean Segal, Yuwen Xiong, Jordan Sir Kwang Hu, Carter Fang, Raquel Urtasun





### What is Offboard Perception?

- Motivation: Modern self-driving systems require a large set of annotated data, but human labelling is slow and costly
- **Task:** Automatically label object trajectories from LiDAR data
- **Setting:** Access to a limited set of human annotations, access to future observations, no real-time constraints
- Goal: Accurate bounding boxes + computationally cheap
- Application: Generate large-scale auto-labelled dataset for training downstream onboard perception models



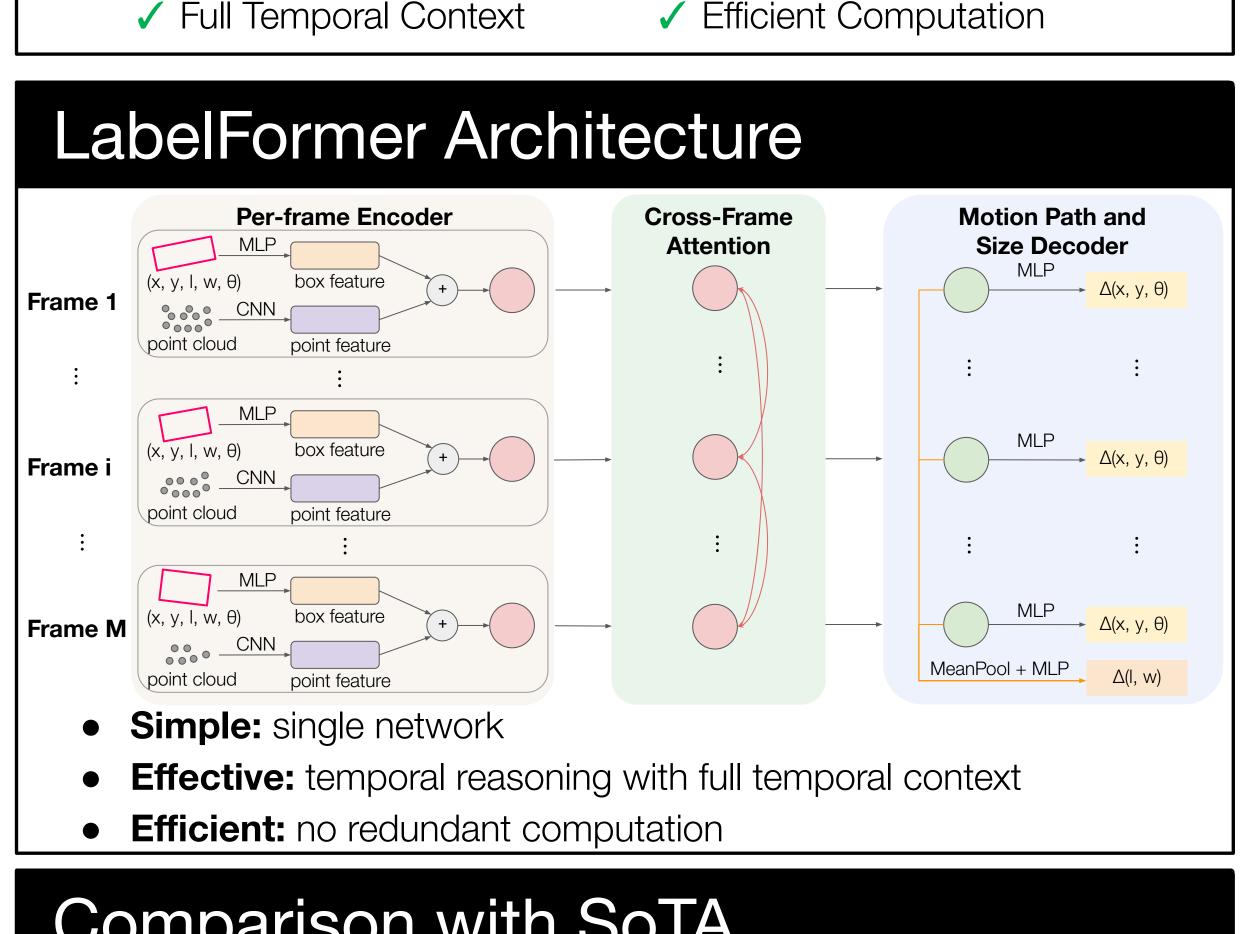
Two-Stage Auto-labelling Paradigm

First Stage: Coarse Initialization

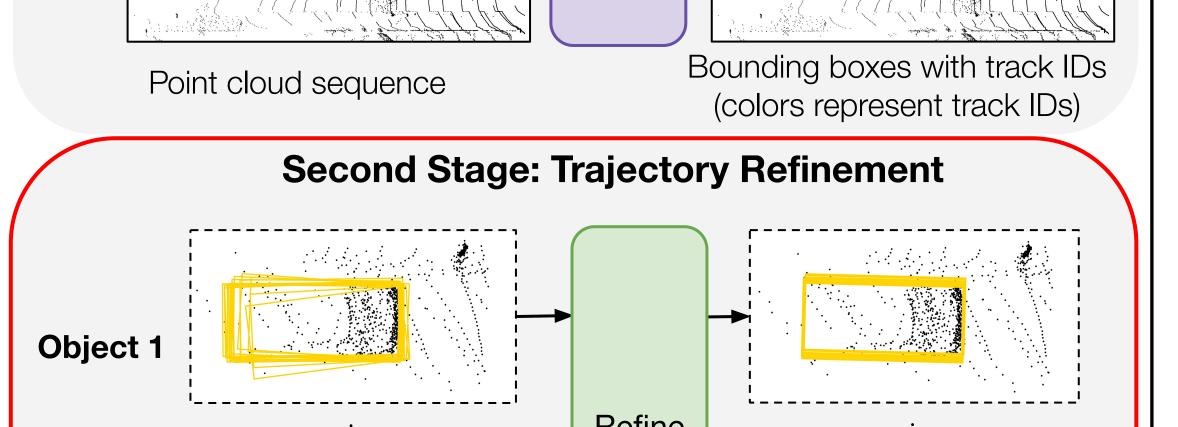
Detect

Track

# Intuition behind LabelFormer Window-based Refinement Sliding Window Init \*\* Limited Temporal Context \*\* Redundant Computation Trajectory-level Refinement Init \*\* Full Temporal Context \*\* Efficient Computation



## Qualitative Results Init Mean IoU: 72.12 3DAL Mean IoU: 81.15 Auto4D Mean IoU: 84.38 Init Mean IoU: 63.06 in the state of th



Object N

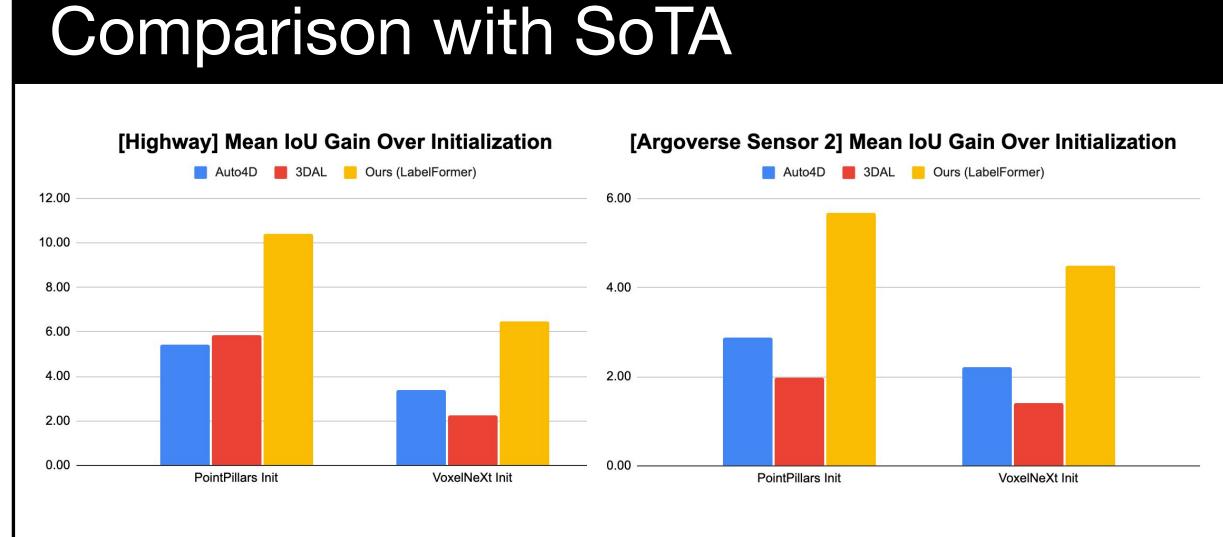
Refine Tracks

Initial object-based tracks with

Refine dobject-based tracks

In this work we tackle the second-stage object trajectory refinement.

point observations in global frame



### Downstream Evaluation

We apply different auto-labellers to augment the Highway dataset. With a larger annotated dataset, we train a downstream onboard object detector.

Auto-Label	Mean AP	AP@0.5	AP@0.7	AP@0.8
N/A	82.98	91.62	79.17	55.97
Init	83.63	92.67	79.51	55.30
Auto4D	83.42	92.71	79.32	55.07
3DAL	83.64	92.66	79.76	55.79
Ours	84.81	92.91	80.91	<b>59.00</b>