



**ENGINEERING
HONORS PROGRAM**
UNIVERSITY OF MICHIGAN

Infrastructure-based Detection and Localization of Road Users for Cooperative Autonomous Driving

Lance Bassett (Honors Capstone), Advisor: Henry Liu, Rusheng Zhang
UMTRI, University of Michigan, Ann Arbor, Michigan

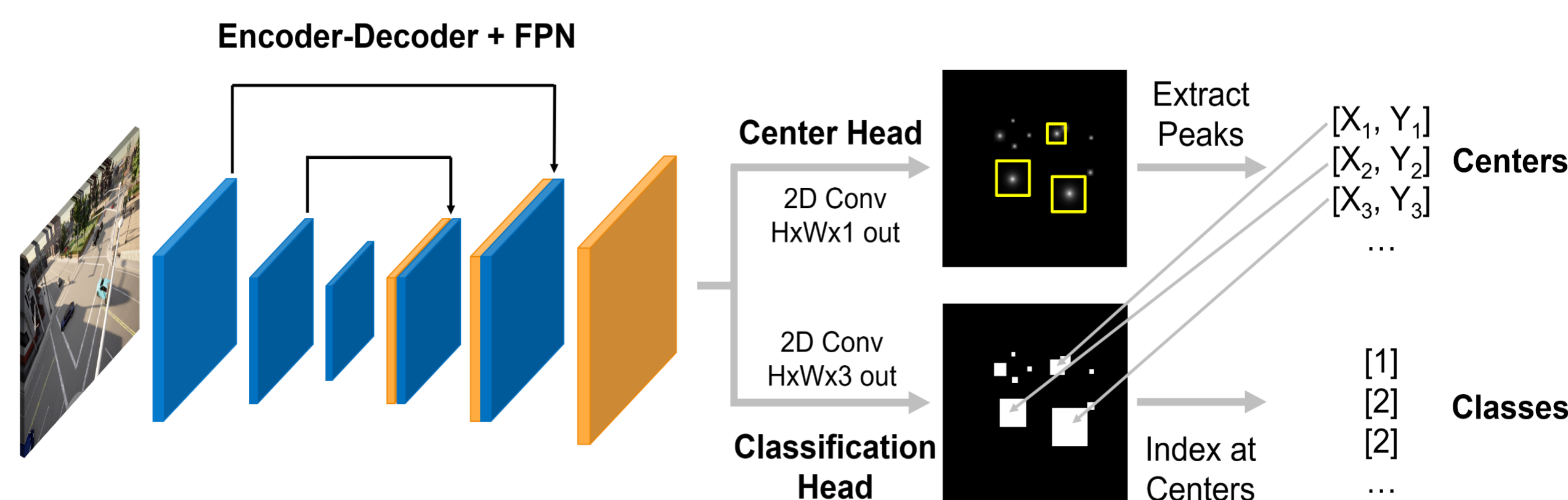
Introduction

Detection and localization of all road users is a difficult task to do well from a single on-road perspective (a vehicle's on-board sensors), but roadside units mounted in the infrastructure can provide a few distinct advantages. This project describes our detection pipeline and results, as well as some methods we use to improve results.

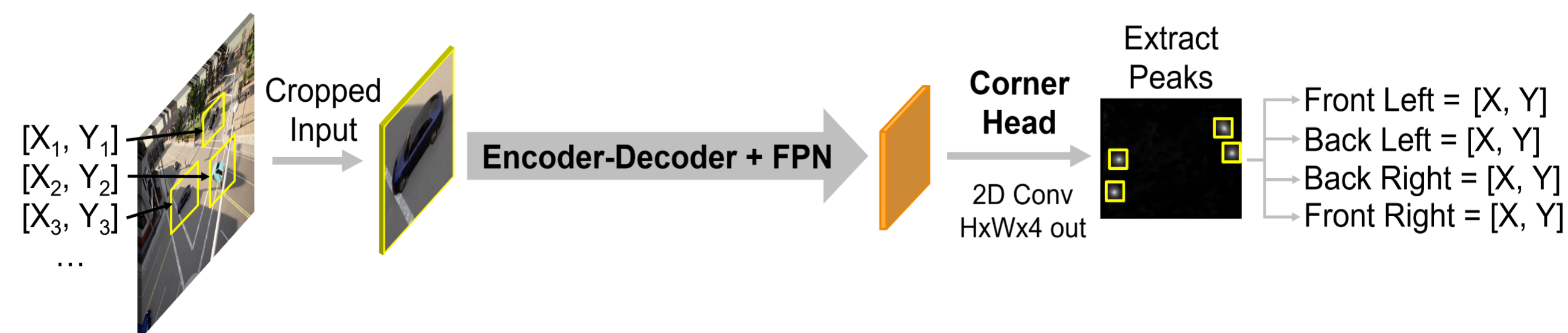


How it Works

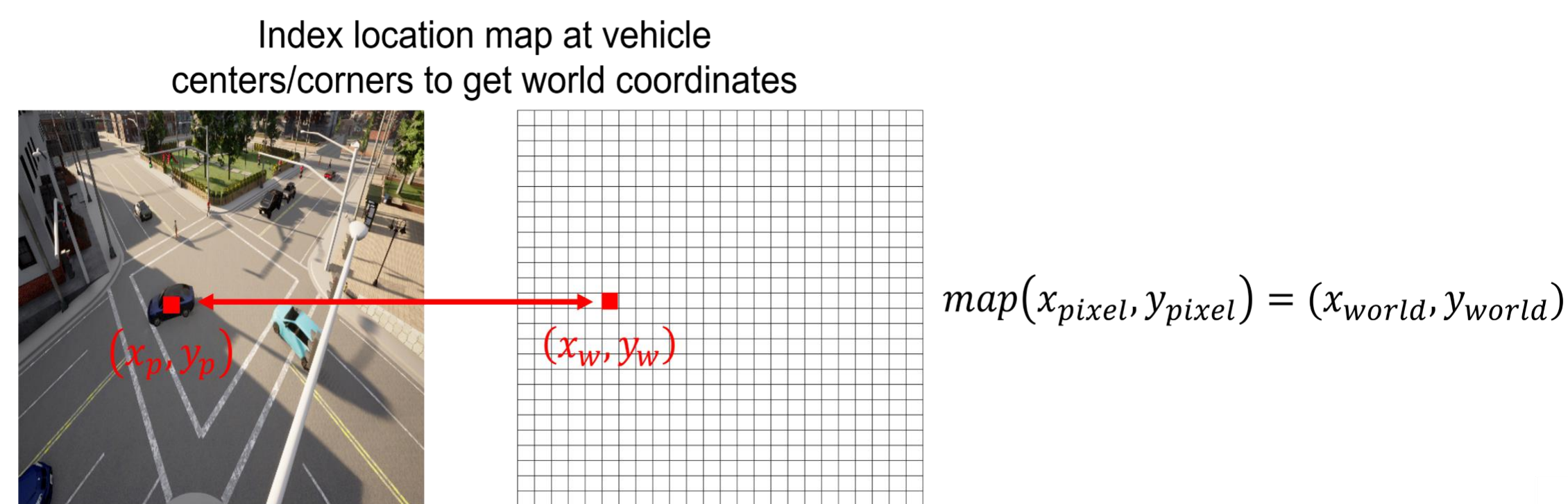
Stage 1: Center Prediction and Classification



Stage 2: Corner Prediction



Stage 2.1: Pixel to World Coordinate Translation



Stage 2.2: Corner Completion

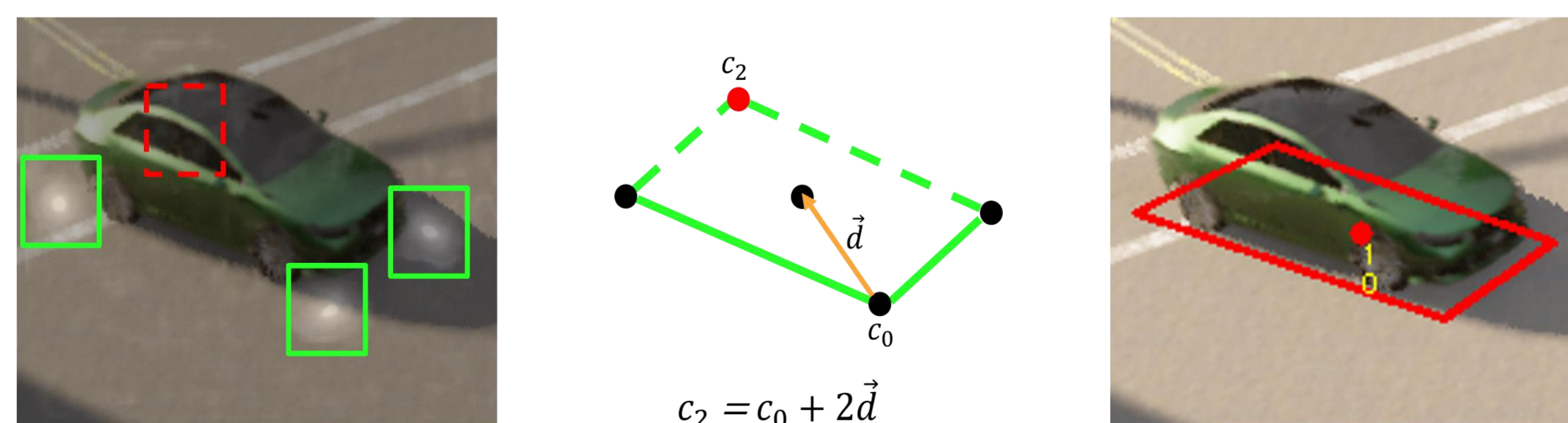
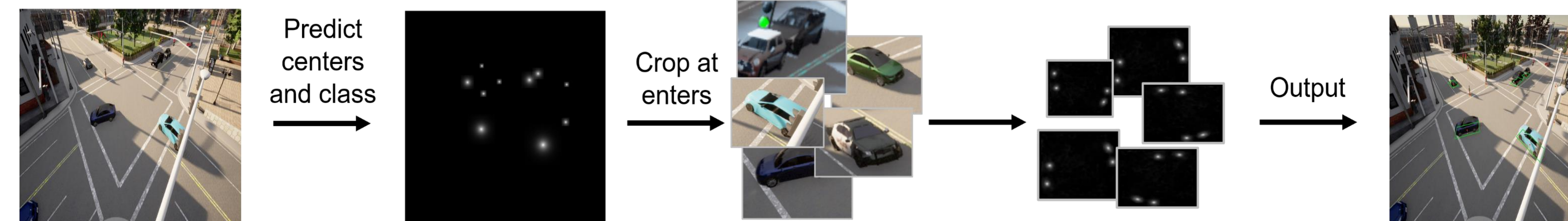


Figure 1: Example of missing vehicle missing corner and subsequent completed result.

Simple augmentation makes second stage robust to imperfect centers in first stage

Results and Discussion

Simplified Pipeline



Sample Results



Figure 2: Sample results from two stage model. Center stage trained on 4.2k examples, crop stage trained on 35k examples.

Performance Metrics

| Method | Center Pixel Error (px) | Corner Pixel Error (px) | Corner Global Error (m) |
|--------------|-------------------------|-------------------------|-------------------------|
| Two Stage | (2.657, 1.239) | (0.984, 1.776) | (0.153, 0.170) |
| Single Stage | (3.546, 1.197) | (1.471, 3.559) | (0.155, 0.207) |

Predicting corners on crops allows for subpixel accuracy and lower error in both pixel location and global location

Table 1: Errors for our two different methods of detection. Single stage predicts corners and centers in the same step.

| Method | Missed (n = 1936) | Detection Rate | Fixed |
|--------------|-------------------|----------------|-------|
| Two Stage | 26 | .987 | 72 |
| Single Stage | 48 | .975 | 25 |

Missed come from corner overlap and mismatches, which limits benefits of corner completion

Table 2: Detection rate for our two different methods of detection.

Center Jitter Augmentation

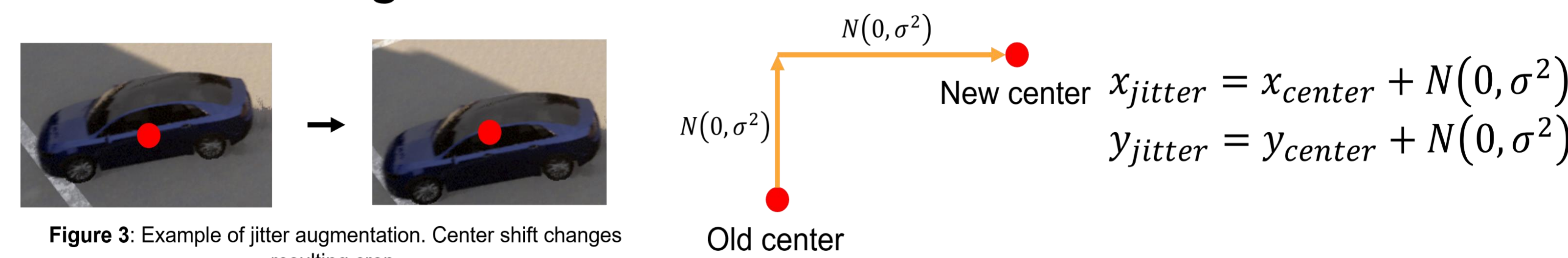
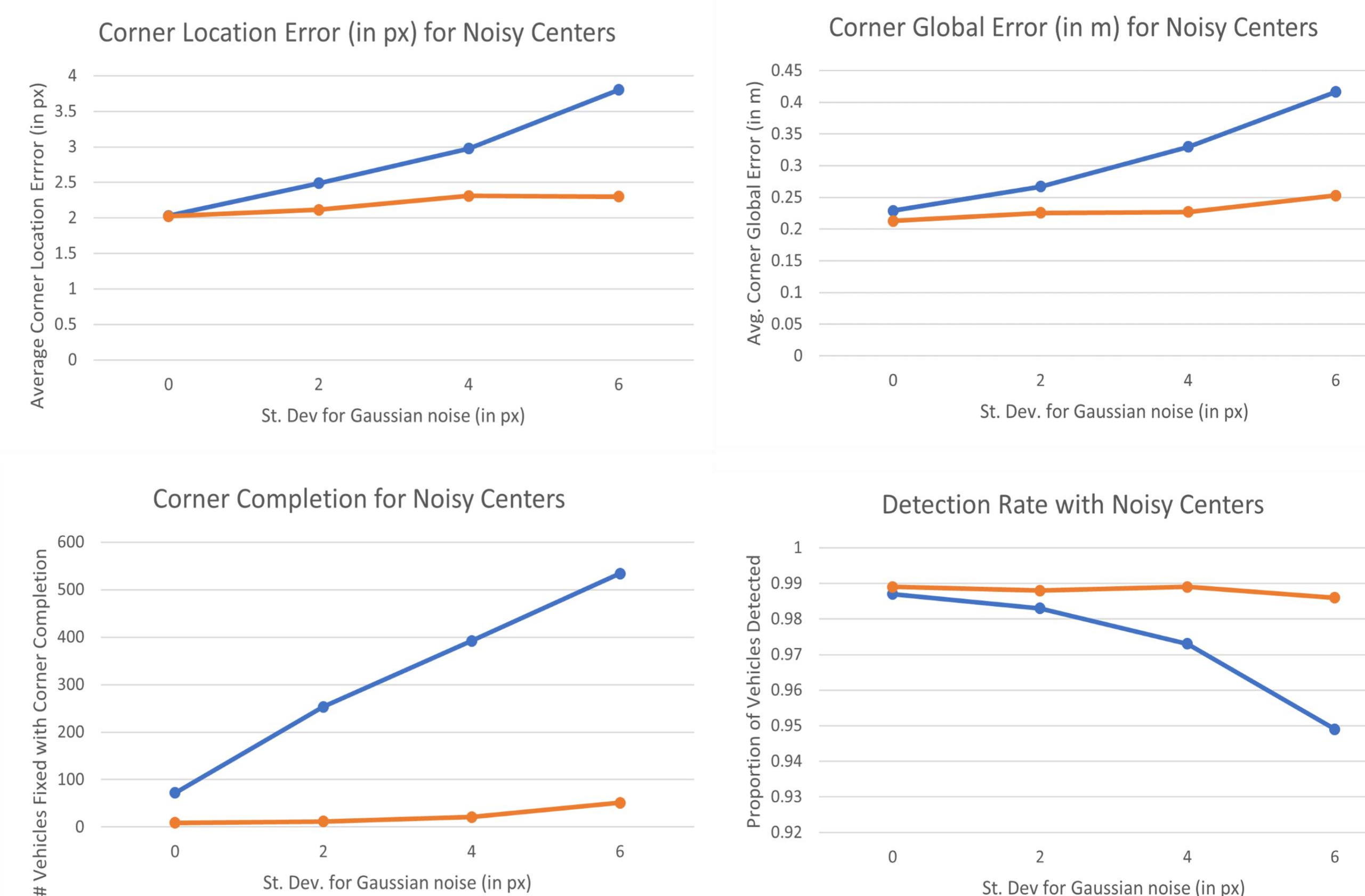


Figure 3: Example of jitter augmentation. Center shift changes resulting crop.

Baseline
Trained with Jitter (std 2)



Advantages

- Second stage crop more universally deployable

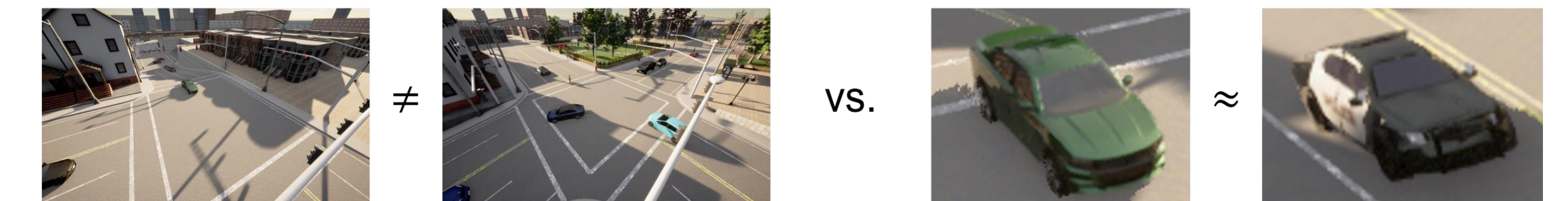
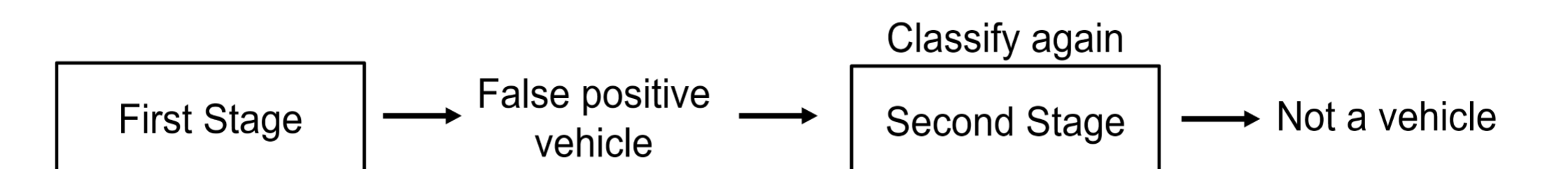


Figure 4: Comparison demonstrating low variability in crop of scene, despite high variability of actual scene.

- Second stage can refine first



- Capitalizes on fixed scene with preprocessed location maps
- Subpixel accuracy on cropped corners due to resize
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Future Work

- Real intersection data
- Comprehensive Comparison
- Refining Predictions
- Multi-scene crop training
- Crop-size index map

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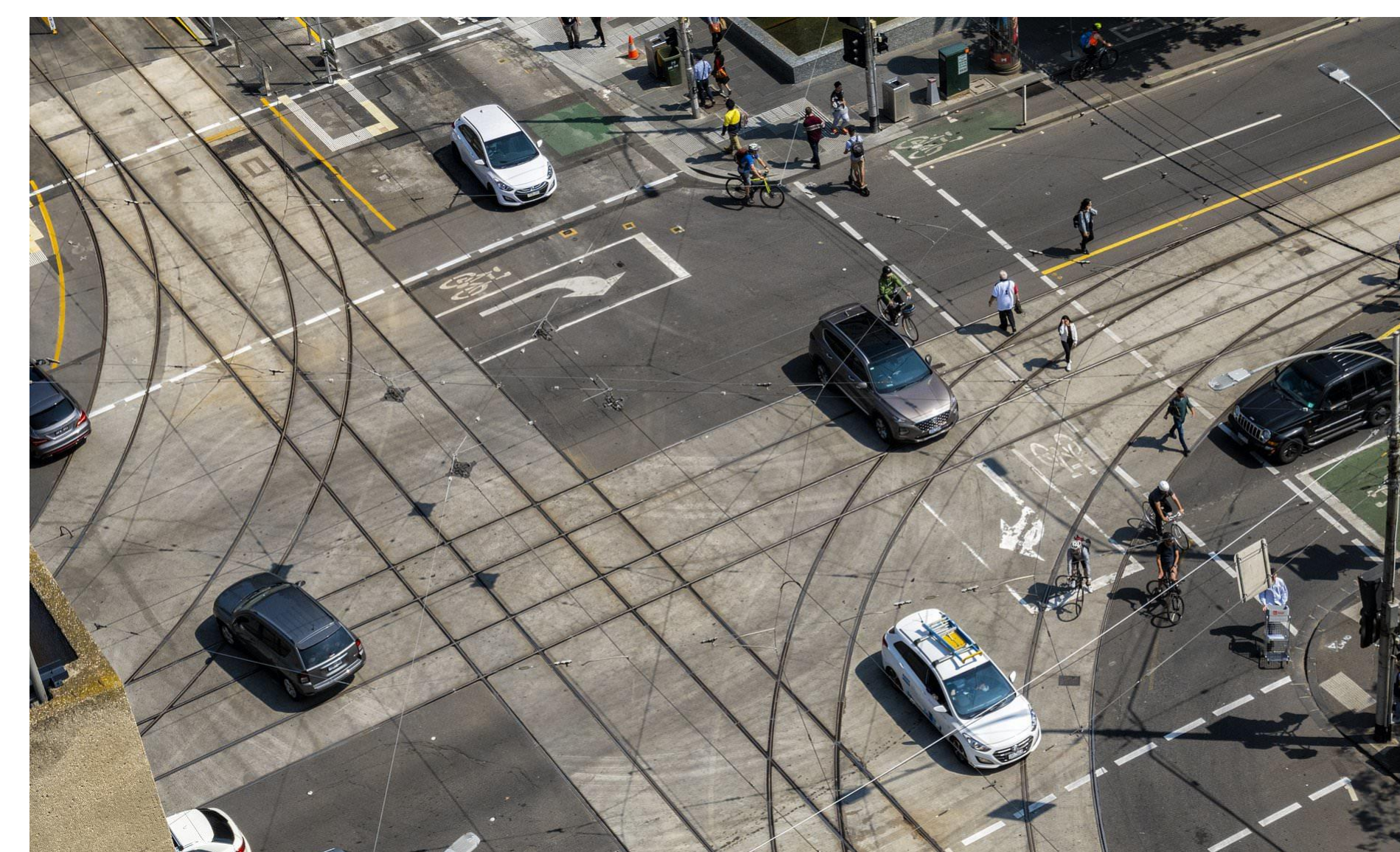
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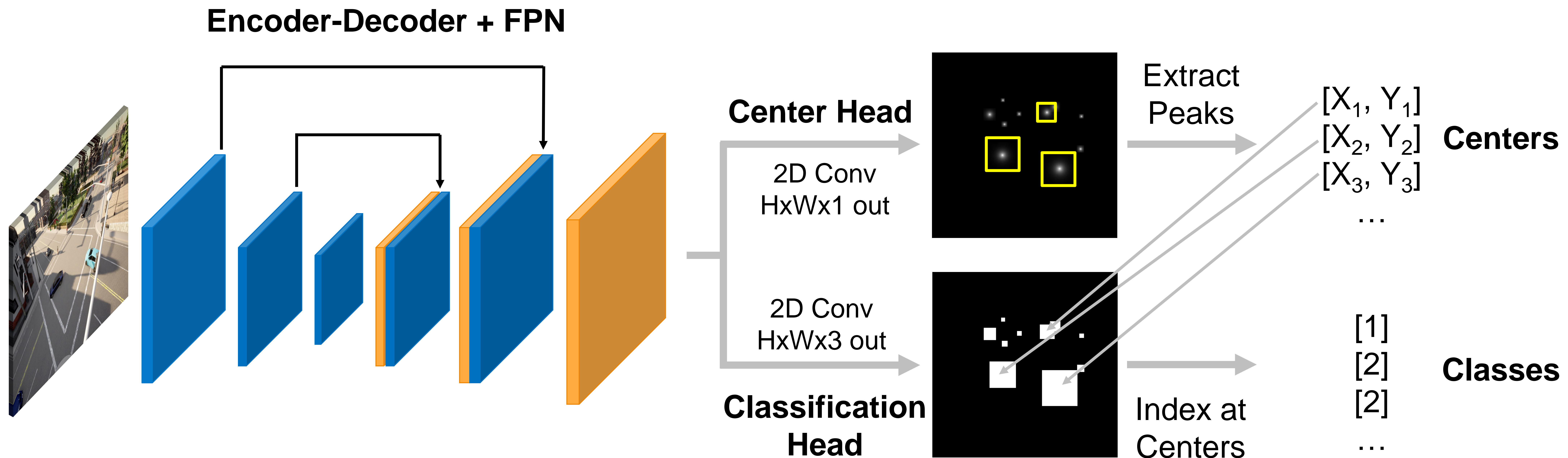


VS.

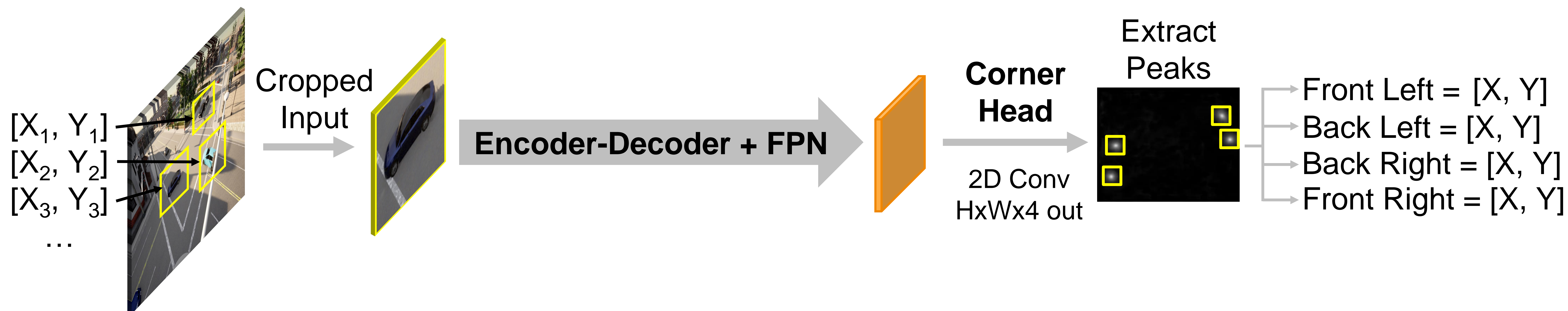


How it Works

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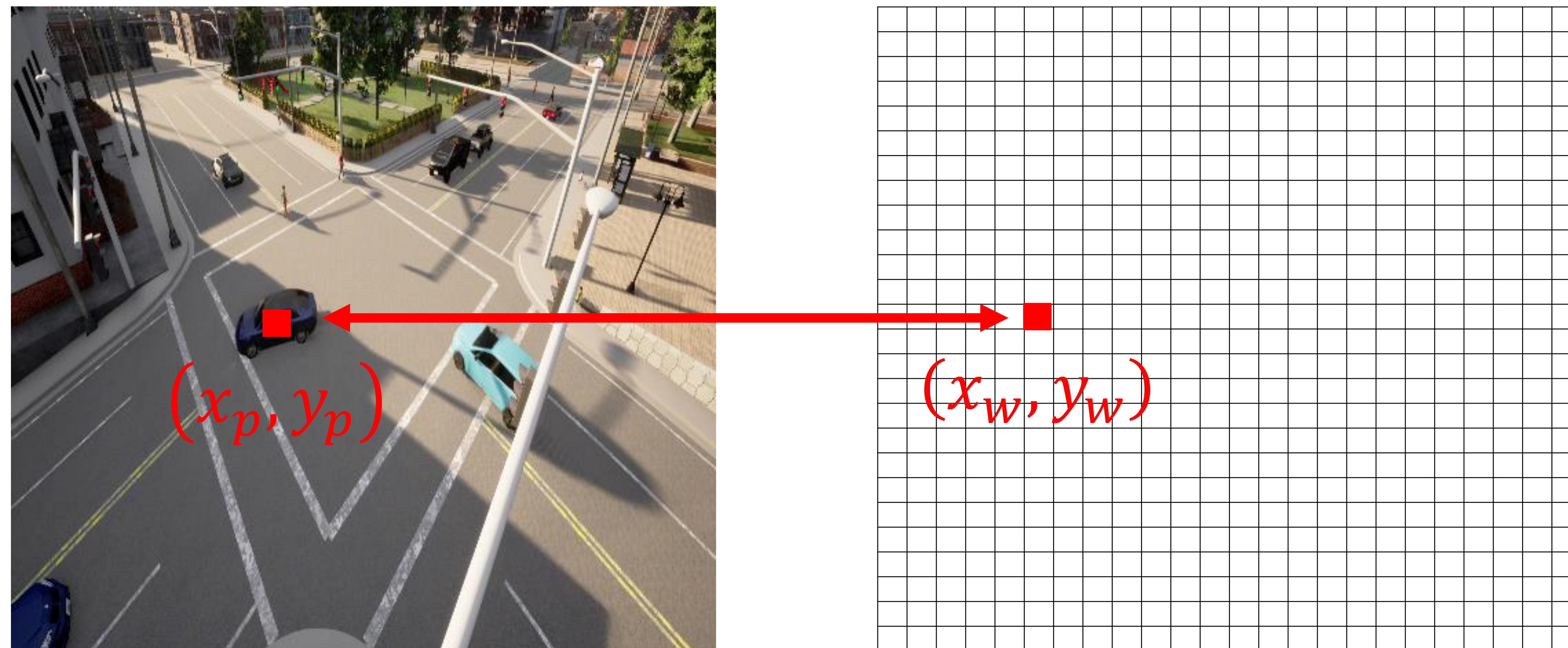


Stage 2: Corner Prediction



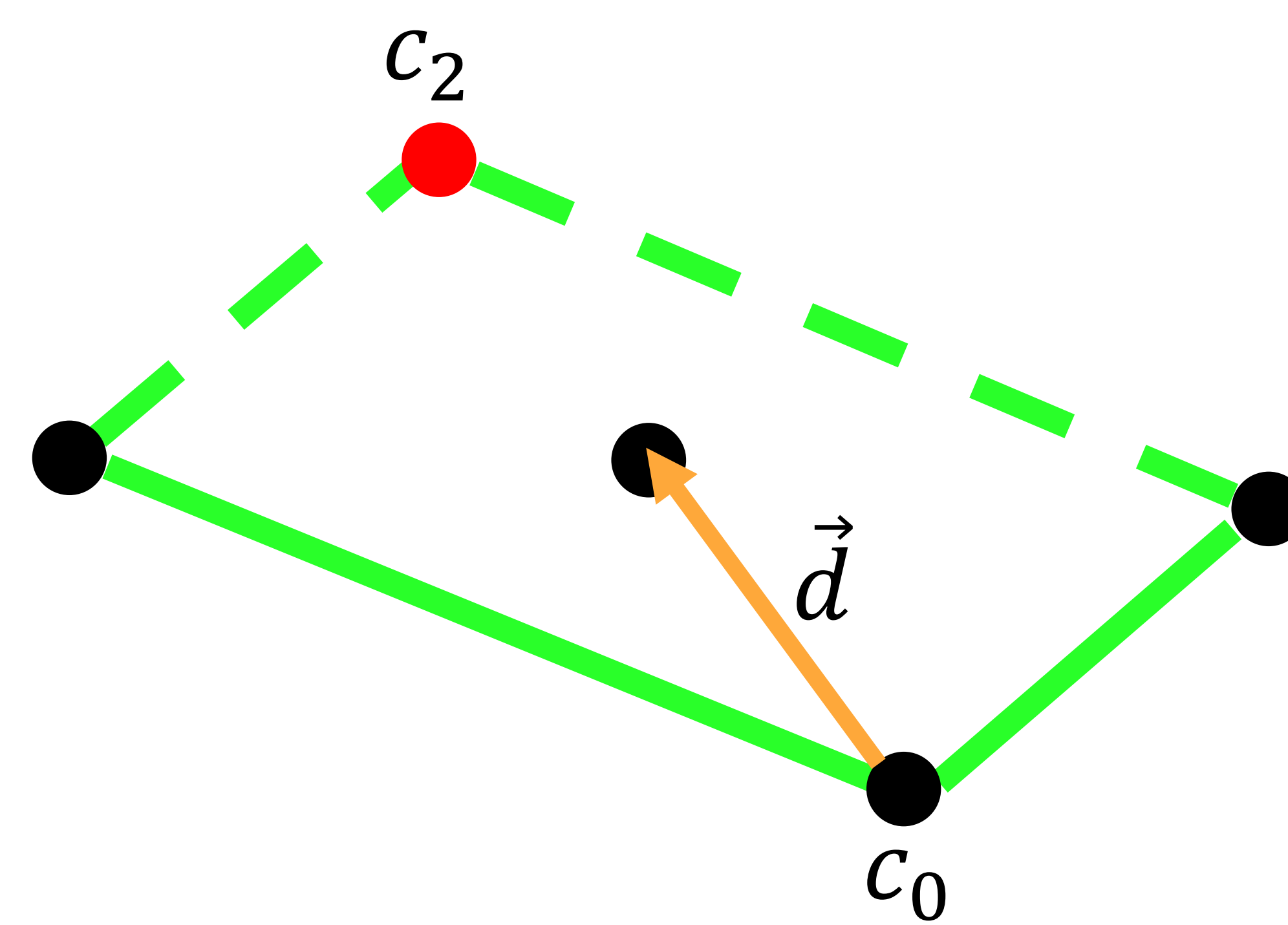
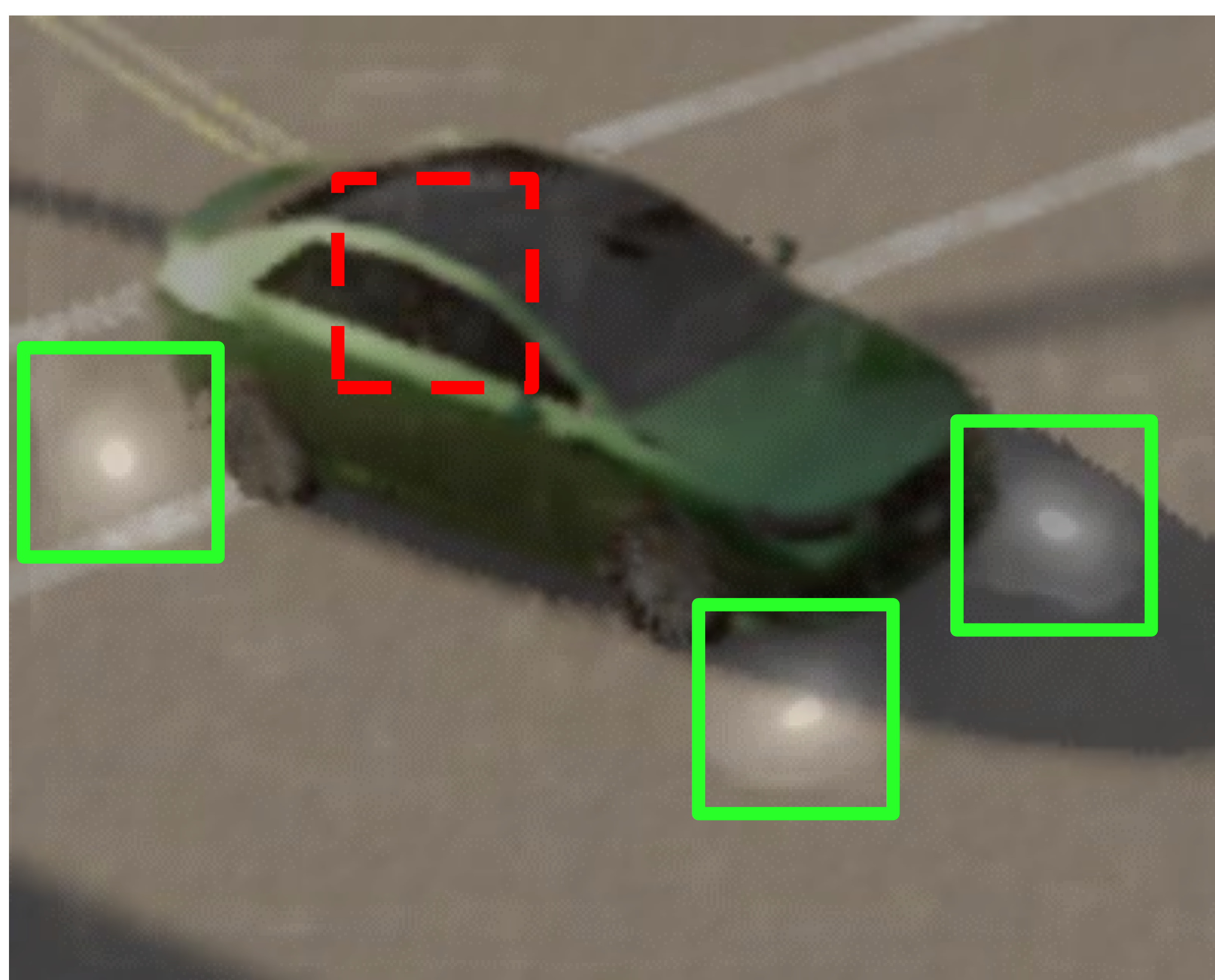
Stage 2.1: Pixel to World Coordinate Translation

Index location map at vehicle centers/corners to get world coordinates



$$\text{map}(x_{\text{pixel}}, y_{\text{pixel}}) = (x_{\text{world}}, y_{\text{world}})$$

Stage 2.2: Corner Completion



$$c_2 = c_0 + 2\vec{d}$$

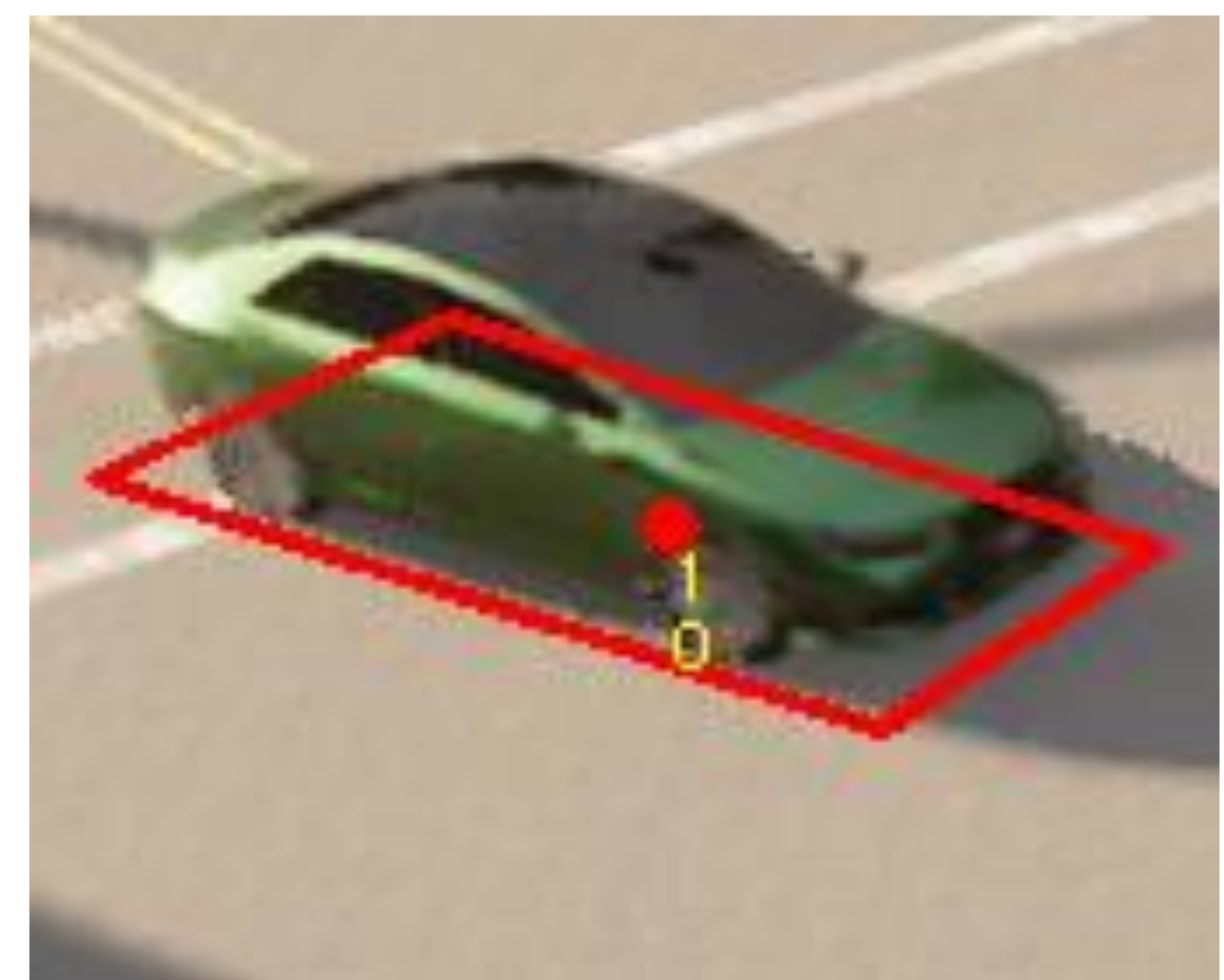
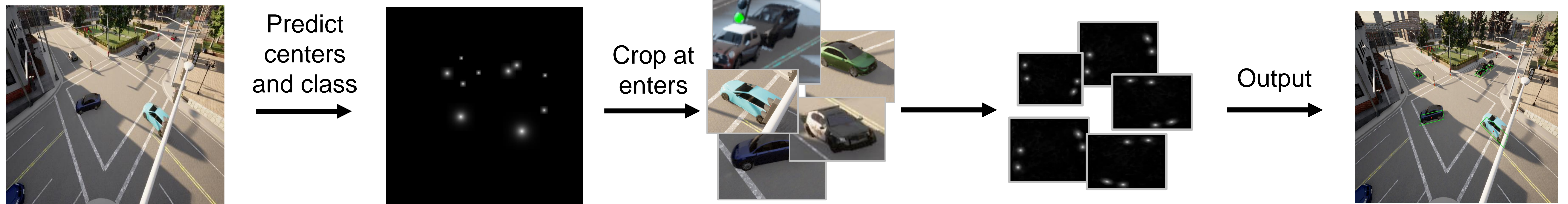


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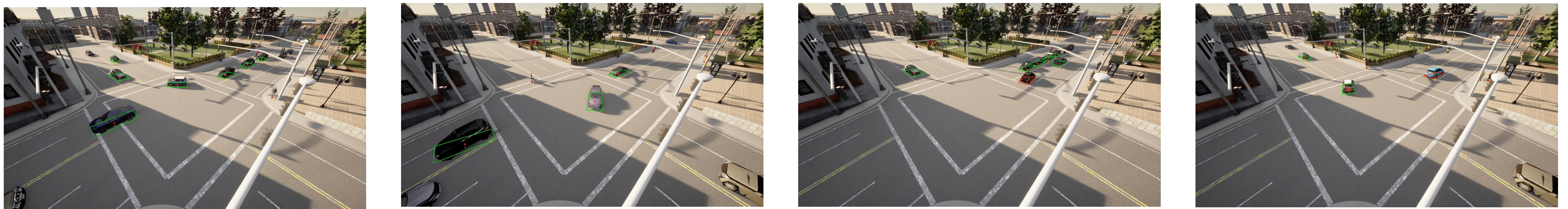


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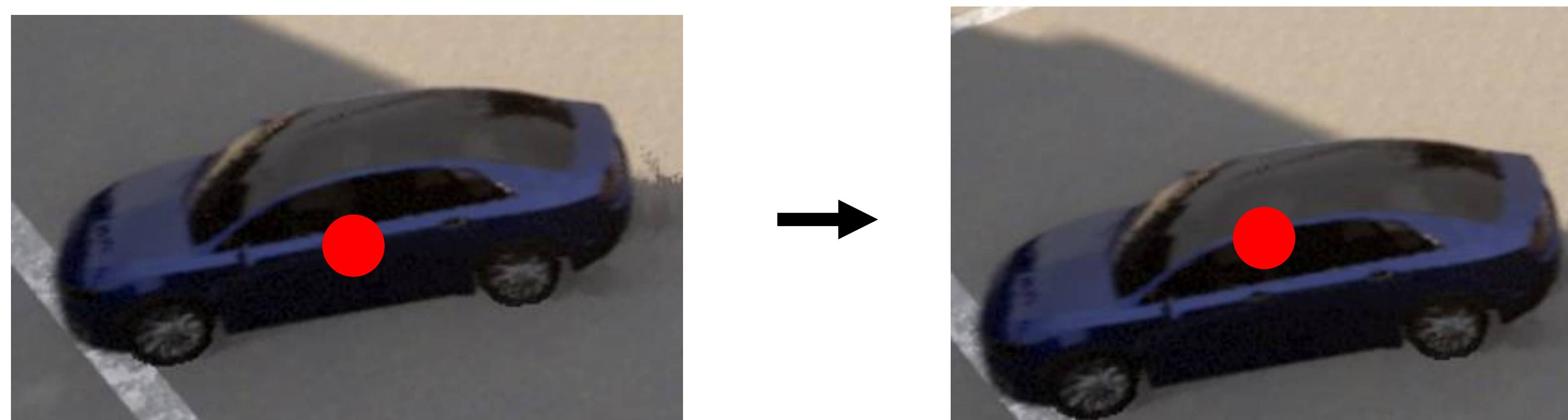
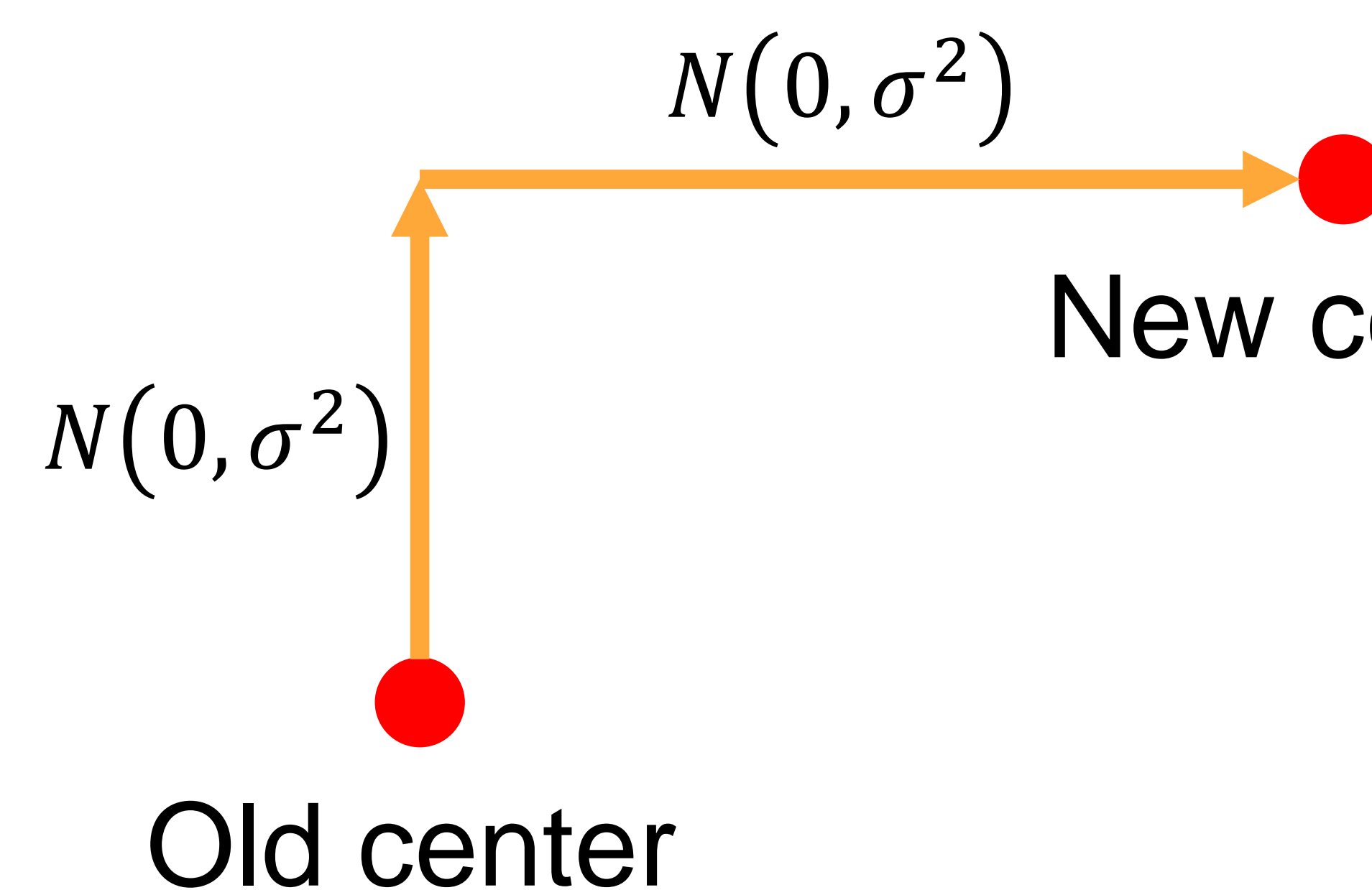


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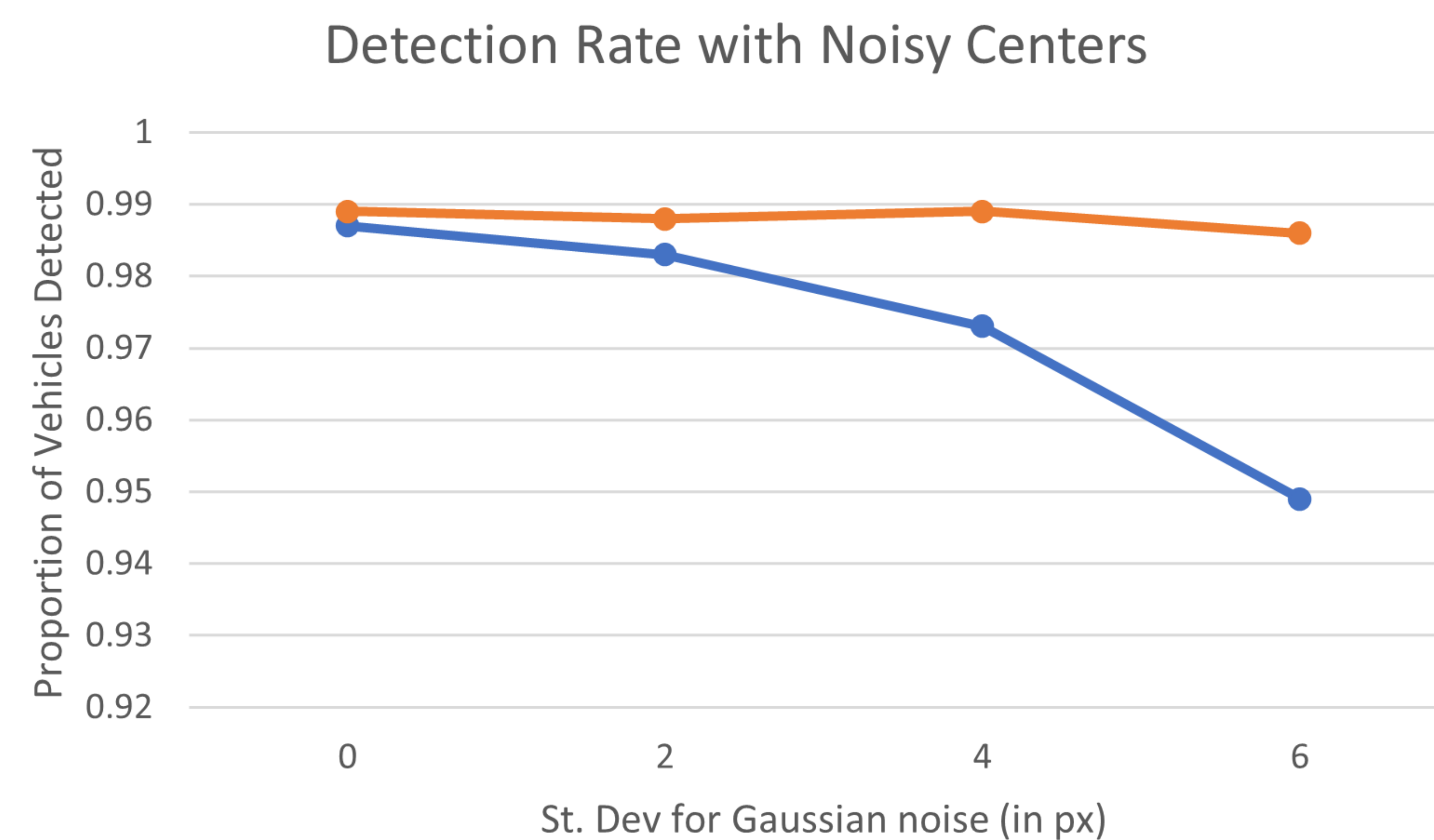
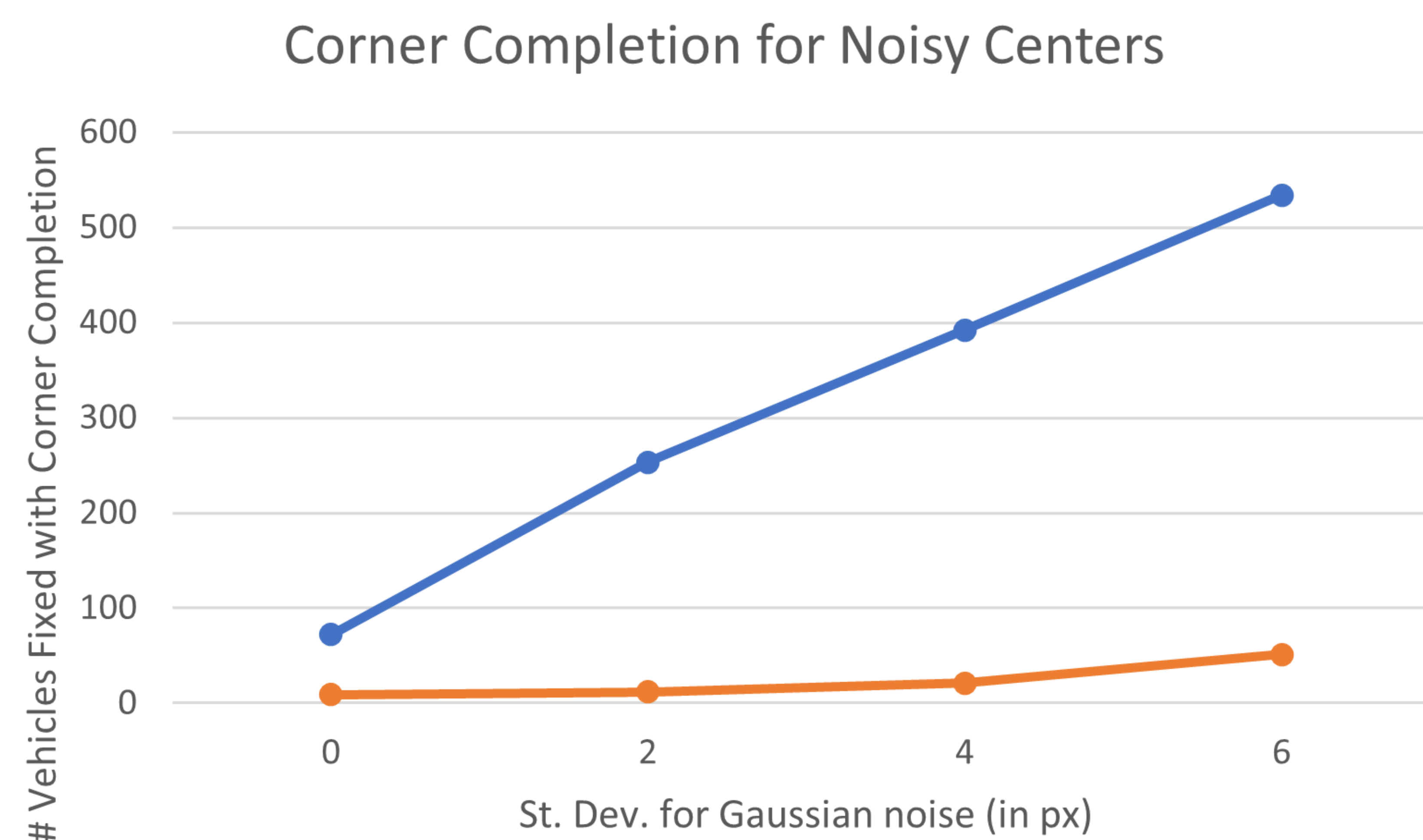
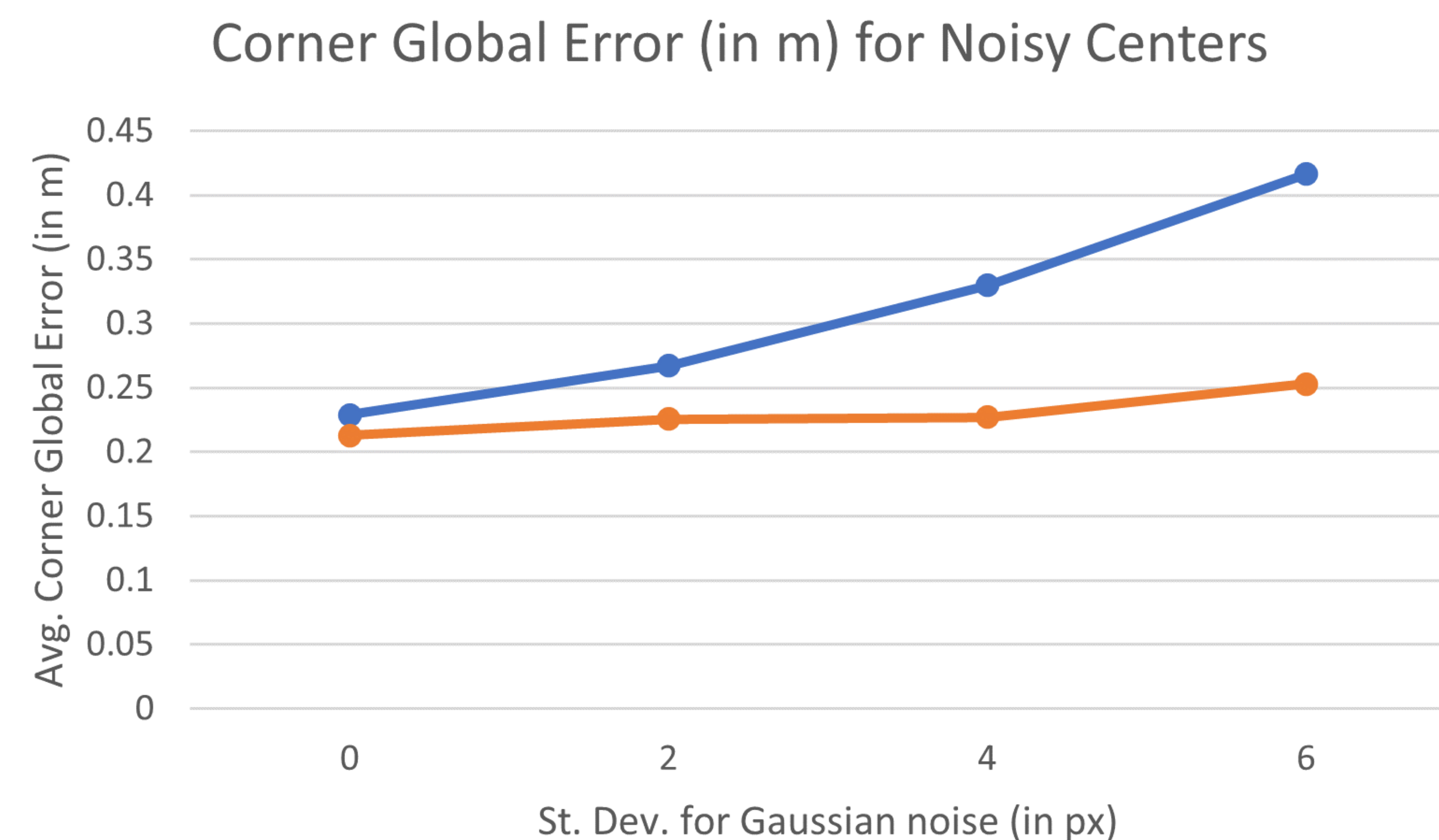
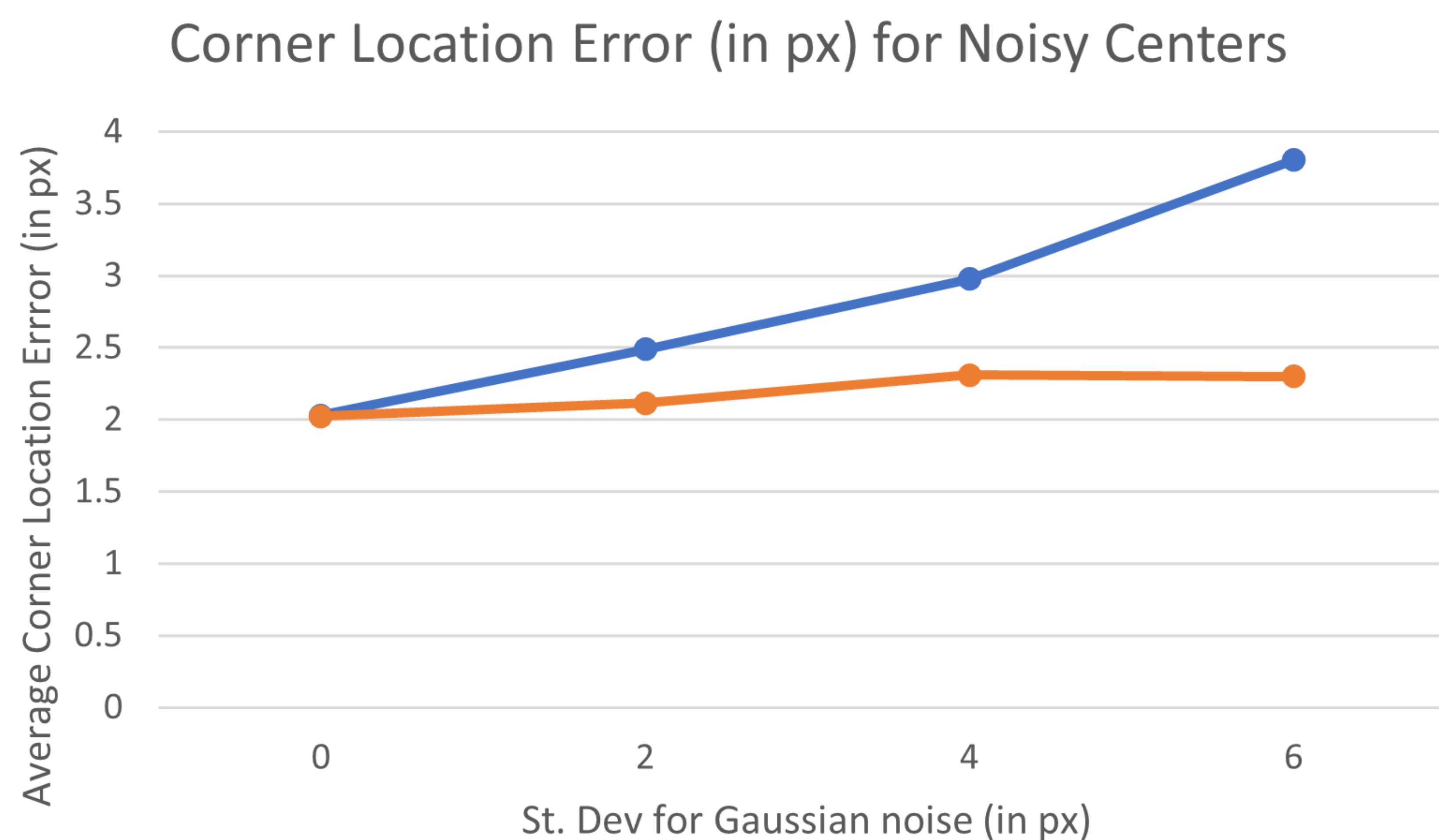


$$x_{jitter} = x_{center} + N(0, \sigma^2)$$

$$y_{jitter} = y_{center} + N(0, \sigma^2)$$

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—●— Trained with Jitter (std 2)

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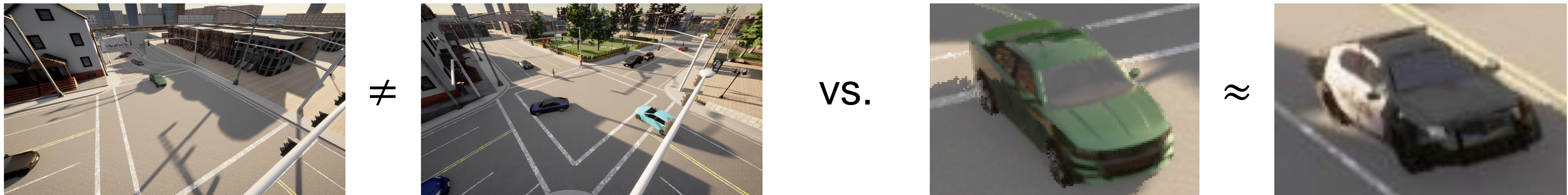
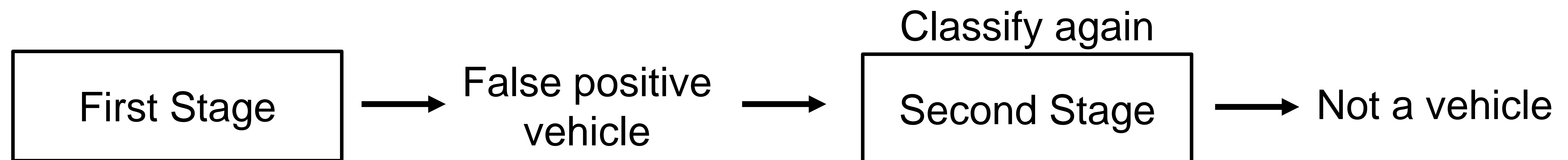


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