# VizAV: Visualizing Autonomous Vehicle Data

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# INTRODUCTION

This project explores a large-scale for autonomous driving dataset to better understand how self-driving vehicles perceive and react to their surroundings.

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The Lyft L5 Prediction Dataset, which contains over 100GB of semantic maps and time series motion data collected from real urban driving scenarios.
To analyze and visualize this data, an interactive 3D visualization platform called **VizViewer** is used, supporting synchronized maps, charts, and feature filtering.
This combination makes it possible to gain insights into vehicle behavior, traffic patterns, and how surrounding agents – like cars and pedestrians – move in complex environments.

VizViewer Scene Visualization

# PROBLEM STATEMENT

Self-driving vehicles must safely and accurately navigate complex environments populated with other moving agents, such as cars, bicycles, and pedestrians.
To achieve this, autonomous systems need to **predict the future movements** of these agents in real-time.
This challenge depends on:

- **High-quality training data** that reflects real-world driving scenarios
- **Advanced tools** for analyzing and visualizing traffic dynamics and agent interactions

Project Objective:
To visualize and analyze motion data from real-world driving scenes in order to improve our understanding of autonomous vehicle decision-making and path planning.

# DATASET Structure

## THE LYFT L5 PREDICTION DATASET CONTAINS TWO MAIN TYPES OF DATA:

### STATIC ENVIRONMENT – SEMANTIC MAP

- Represents the fixed elements of the driving environment.
- Includes: road geometry, traffic signs, lane directions, and traffic light positions.
- Used to understand the context in which vehicles operate.

### DYNAMIC ENVIRONMENT – SCENE DATAABASE

- Captures time-varying elements in real-world driving.
- Includes the data about varying driving conditions such as the location and speeds of nearby pedestrians or vehicles, as well as the color of an upcoming traffic light.

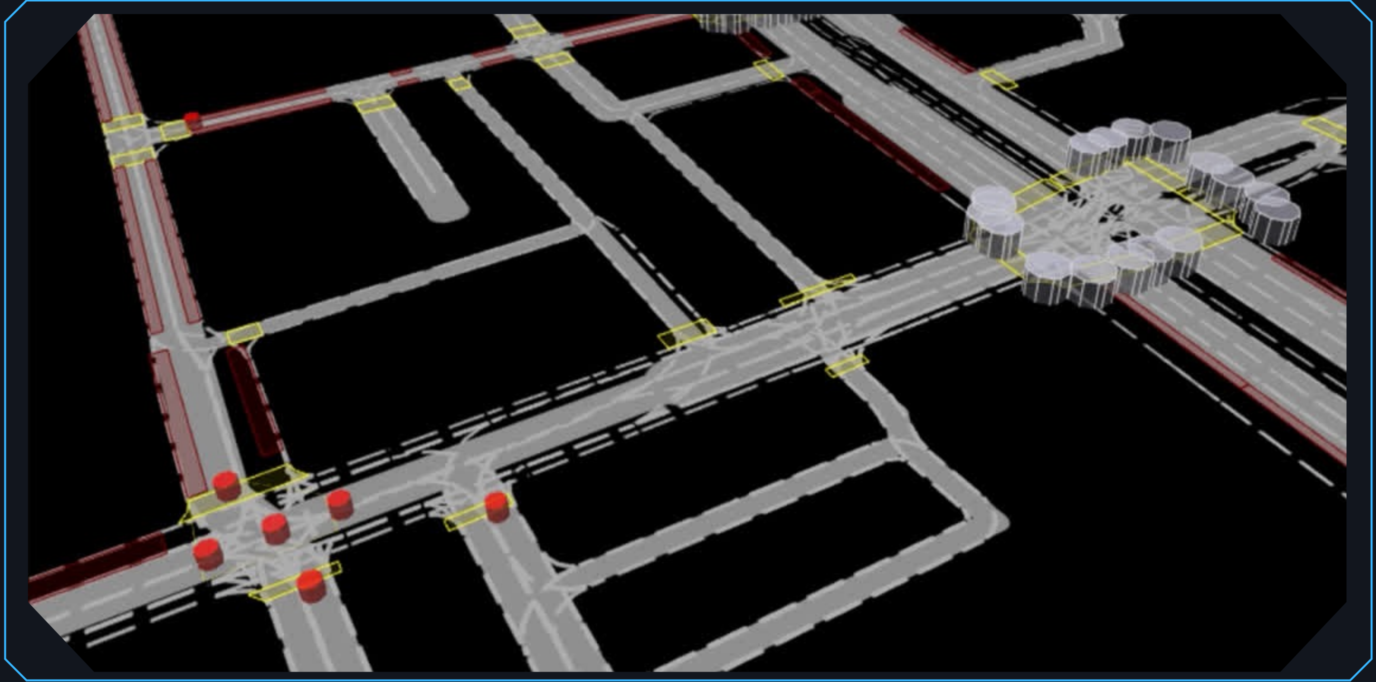
This dual structure allows both context-aware navigation and dynamic motion prediction.

***Ego Vehicle-** The autonomous vehicle collecting the data – serves as the central reference point for all observations and predictions.

# Semantic Map VS. Scene Database

## STATIC ENVIRONMENT – SEMANTIC MAP

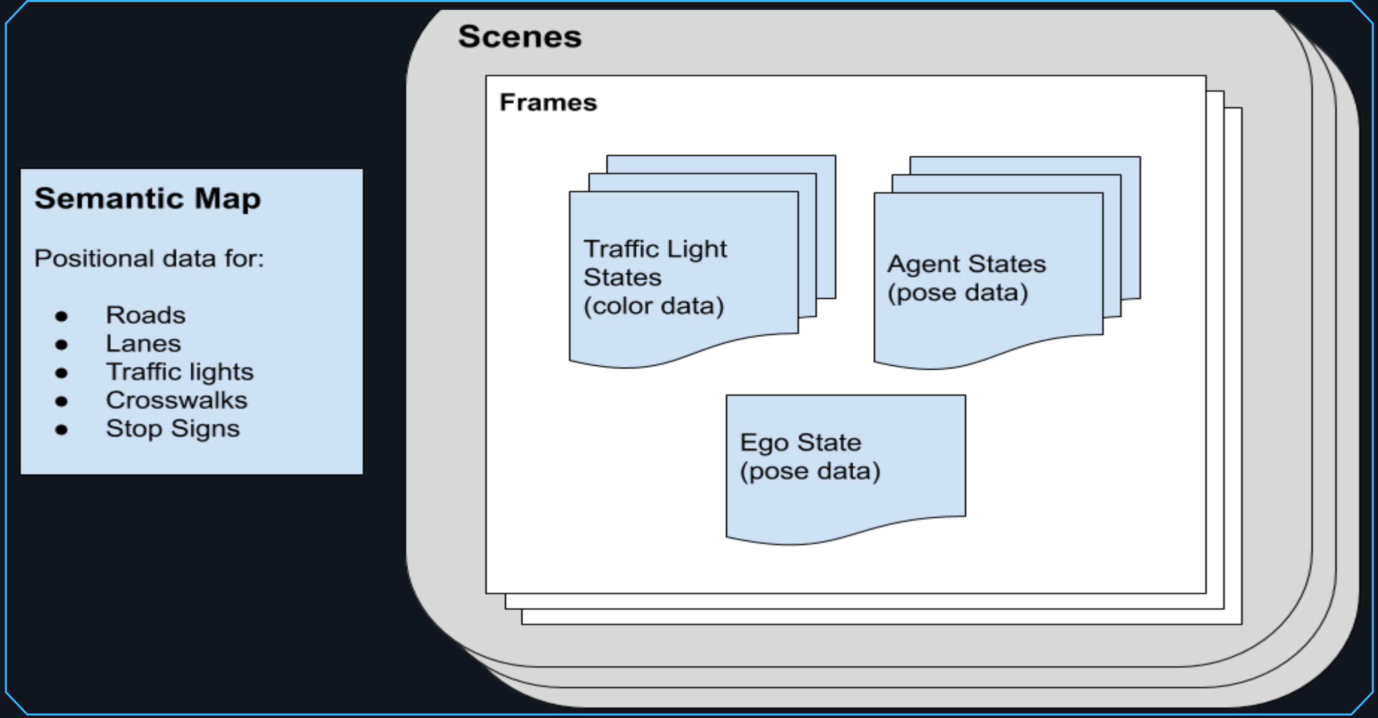
- 2D annotated map of roads, lanes, traffic control elements, speed limits, parking zones and more.
- Provides centimeter-level accuracy for static objects.
- Helps offload perception tasks from the AV by predefining the driving environment.



**Semantic Map Visualization – roads/lane lines, parking zones, crosswalks, stop signs, traffic lights (gray cylinders)**

## DYNAMIC ENVIRONMENT – SCENE DATABASE

- Encodes time-series data of:
  - Ego vehicle (position, orientation)
  - Agents (class, position, size)
  - Traffic light state
- Data is organized by frames (single timestamps) and scenes (sequences of frames).
- Scenes are the atomic training units for ML models to ensure motion consistency across time.




**Structural Diagram of the L5 Prediction Dataset**

# WHAT IS VIZVIEWER?

- VizViewer is a **web-based interactive platform** for visualizing and analyzing large, multi-modal datasets – like those used in autonomous driving.
- It combines data processing, communication, and visualization tools into one easy to use dashboard interface.

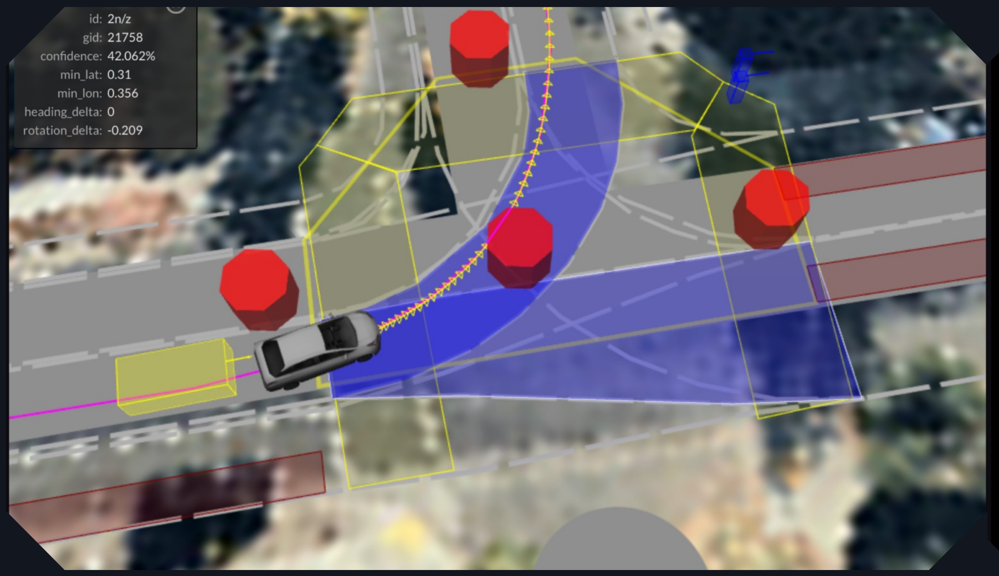
- Supports integration with Python and Jupyter Notebooks.
- Helps explore dense, complex data to gain insights, debug models, and build better training sets.
- Designed for collaborative and efficient data analysis workflows.

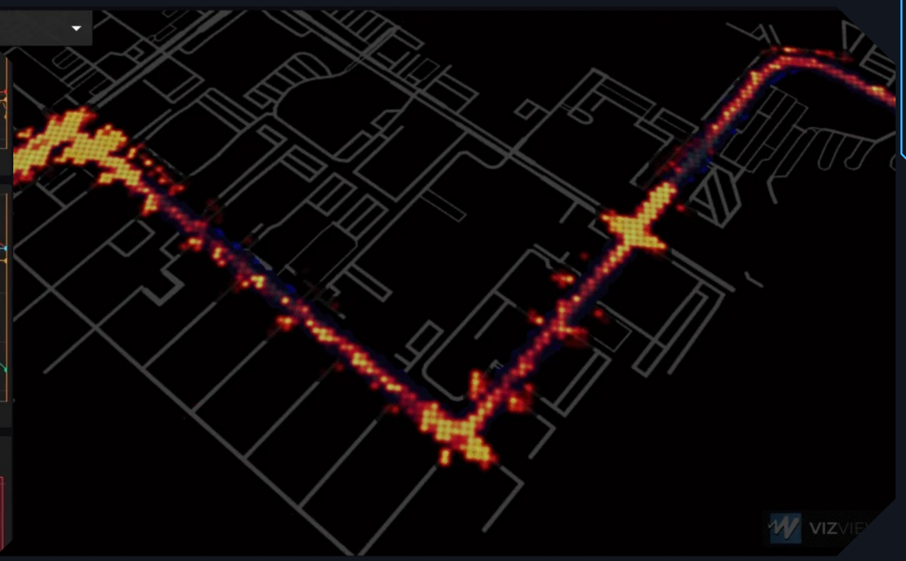
3D SEMANTIC MAP VISUALIZATION

SYNCHRONIZED TIME-SERIES GRAPHS

OBJECT SELECTION AND FILTERING

HEATMAPS TO IDENTIFY SPATIAL PATTERNS

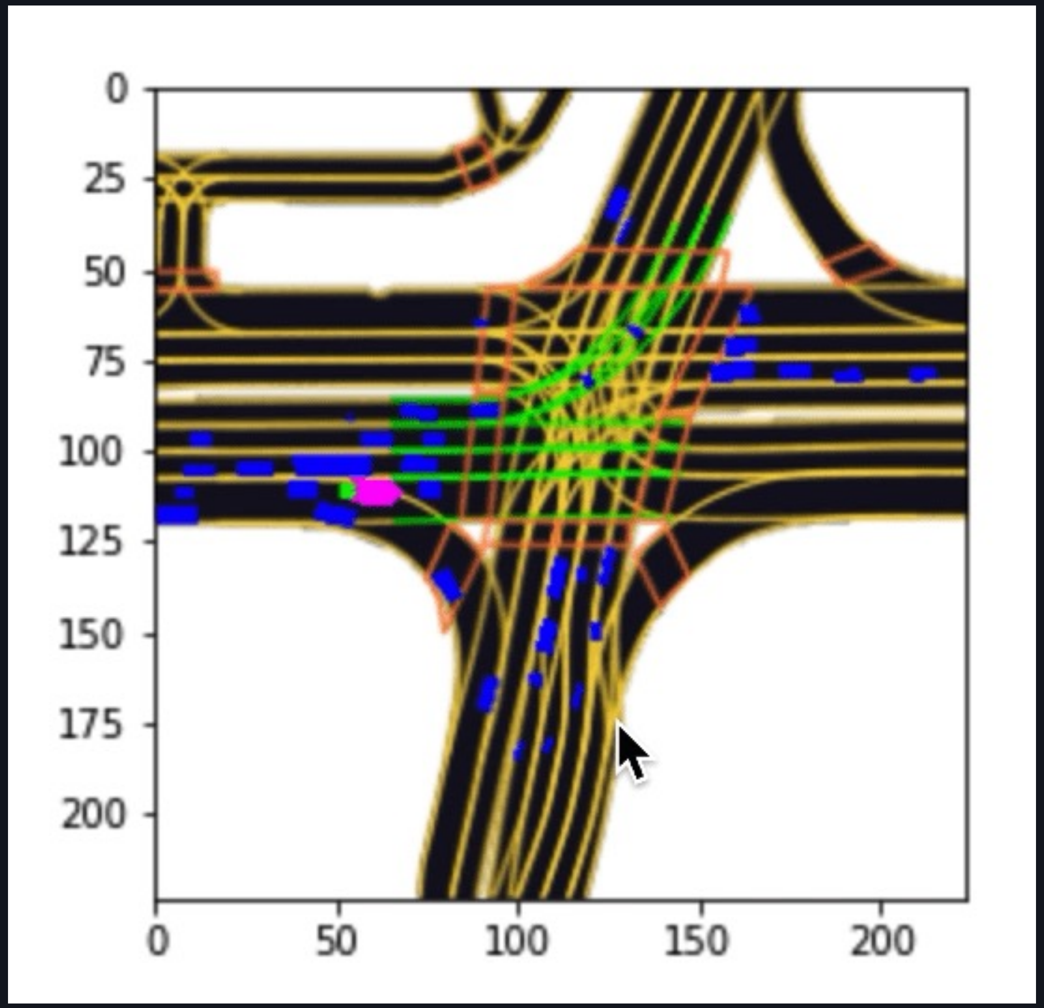


# SEMANTIC MAP VISUALIZATION

- The L5 Prediction Dataset Kit includes a basic tool for rendering semantic maps and scene data together.
- It generates static images showing:
  - Roads
  - Lane lines
  - Traffic control elements
  - Dynamic traffic states (red lanes when the light is red)

- These images can be merged to create short animated clips of driving scenes.




- THESE MAPS HELP PROVIDE CONTEXT IN WHICH AUTONOMOUS VEHICLES OPERATE, REDUCING THE NEED FOR REAL-TIME INTERPRETATION BY ONBOARD SENSORS.

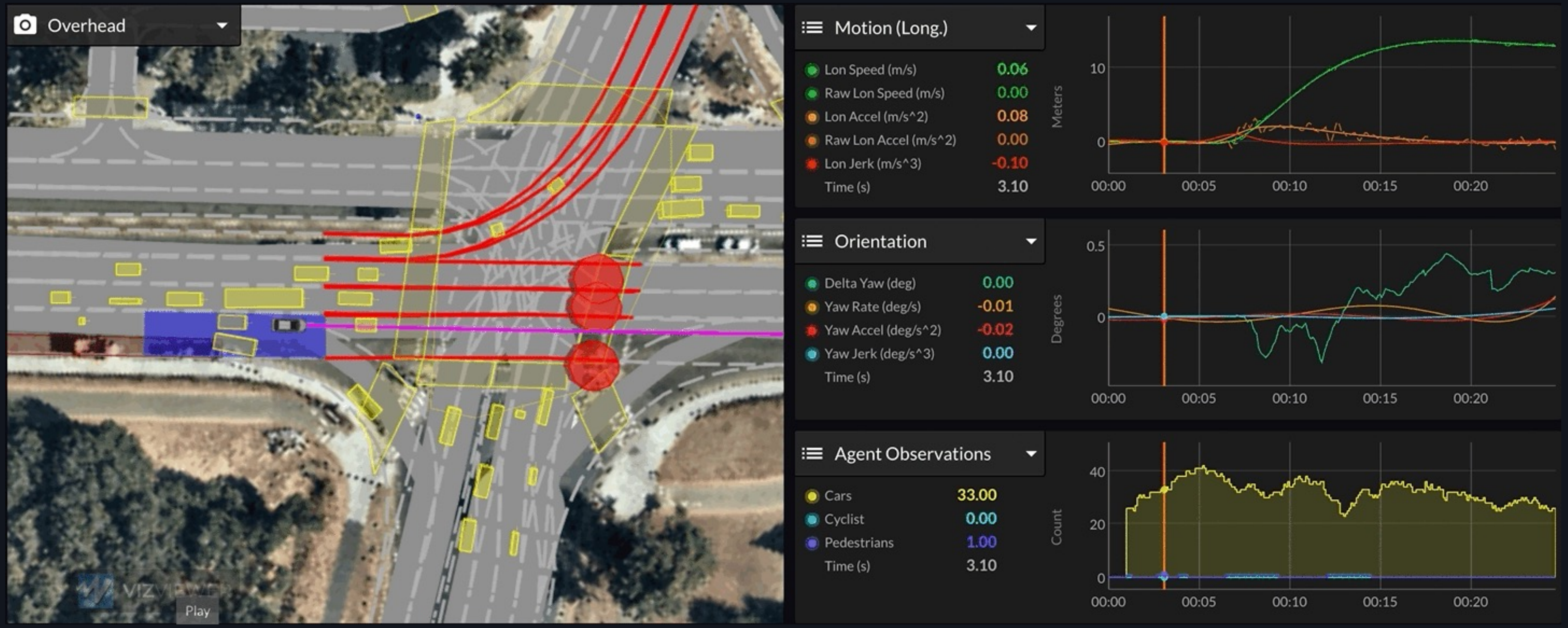
# Exploring Driving Scenarios with VizViewer

- VizViewer offers an interactive 3D mapping tool with:
  - Free navigation, zooming, and layer control (vector/satellite)
  - Clickable elements to view detailed metadata
  - Enables filtering scenes by geographic features (intersections, multilane turns)
  - Integrates with Python:
    - Define feature-based queries (roads with 3–5 lanes).

```
# example query command for marking roads with 3 to 5 lanes

vv.semantic_query({ "where":
"msg.kind == 'road' &amp;&amp; msg.num_lanes >= 3 &amp;&amp; msg.num_lanes <= 5"
})
```

    - Render search results directly in the VizViewer dashboard.
- VIZVIEWER'S INTERACTIVE TOOLS HELP IDENTIFY RELEVANT DATA SEGMENTS WITHIN THE SEMANTIC MAP, IMPROVING TRAINING SET SELECTION AND STREAMLINING THE DEBUGGING AND EVALUATION OF PREDICTIVE MODELS.




VizViewer alternative 3D view of the same scene from L5 Kit, with synchronized plots and selectable bounding boxes

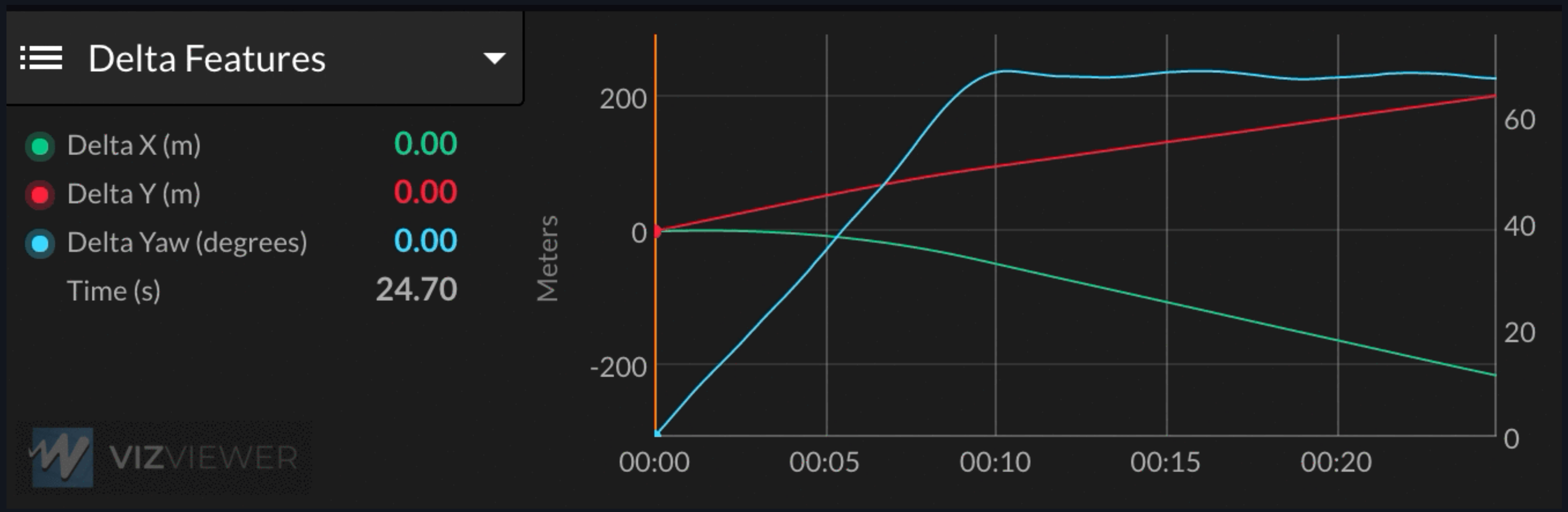

Highlighting roads on the semantic map by decreasing the minimum number of lanes from 7 to 1

# DERIVING AUGMENTED FEATURES FROM RAW DATA

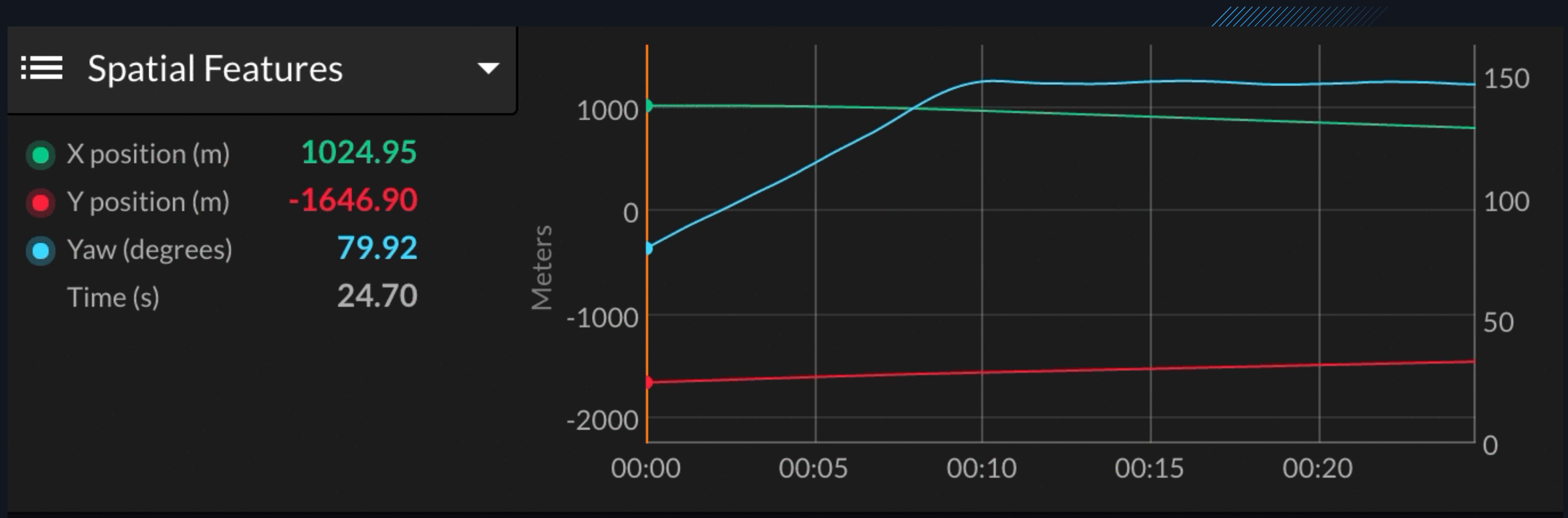
## TO BETTER UNDERSTAND AND MODEL VEHICLE BEHAVIOR, WE CAN DERIVE MOTION-RELATED FEATURES FROM THE RAW POSITION AND ORIENTATION DATA:

Examples of derived features:

- Longitudinal / Lateral speed and acceleration
- Yaw rate, yaw acceleration, and jerk (rate of change)
- Distance to stop signs, lane center offset
- Relative position to other agents and map elements



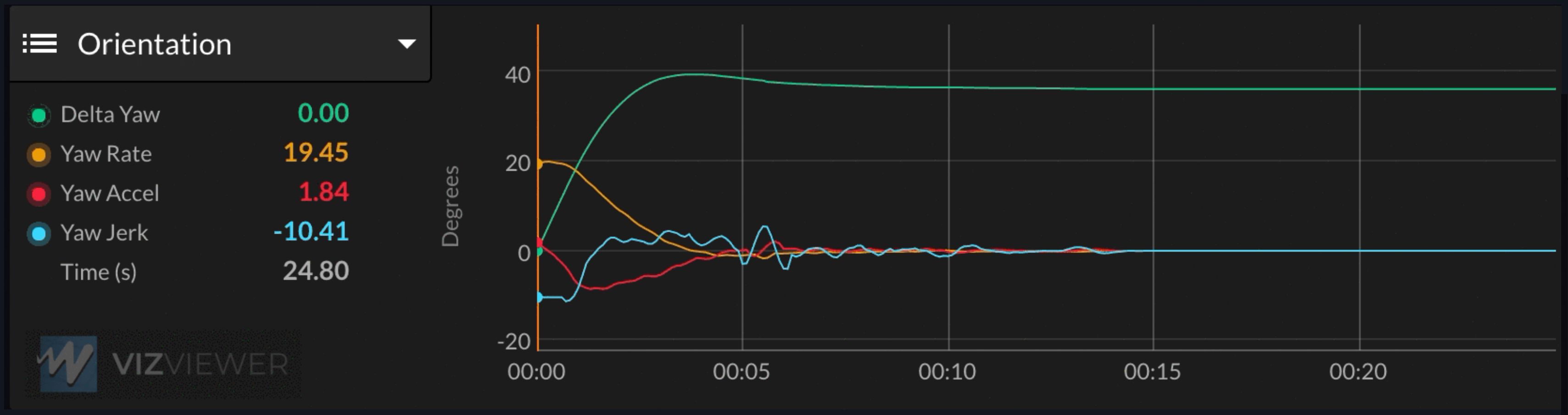

VizViewer: Raw dynamic data, plotting x, y positions, and yaw along a curved path.



# MODELING INTERACTIONS BETWEEN OBJECTS

## IN ADDITION TO INDIVIDUAL OBJECT DYNAMICS AUGMENTED FEATURES CAN DESCRIBE AUGMENTED FEATURES HELP IMPROVE THE QUALITY OF TRAINING DATA BY:

- KEY RELATIONAL FEATURES INCLUDE:
  - Relative distance and speed between ego vehicle & other agents.
  - Distance to traffic lights, stop lines, and crosswalks.
  - Position and orientation relative to lane geometry.
- THESE FEATURES ENABLE THE MODEL TO:
  - Anticipate interactions (slow down near pedestrians).
  - Understand contextual cues (curves, intersections).
  - Generate safer, more human-like planning behavior.





VizViewer: Plots of motion and orientation for a sample scene with a left turn.

# WHY FEATURE AUGMENTATION MATTERS

AUGMENTED FEATURES HELP IMPROVE THE QUALITY OF TRAINING DATA BY:

- Building more accurate prediction models.
- Debugging abnormal behaviors in scenes.
- Standardizing scene comparisons.
- Highlighting underlying patterns in time series data.

SMOOTHING TECHNIQUES REDUCE NOISE AND IMPROVE MODEL CONVERGENCE.

```python
import numpy as np
from scipy.interpolate import splprep

"""
   yaws - numpy array to yaw values for each frame
   t - timestamps for each frame
"""

weights = np.ones(len(t))
smooth = len(self.weights)
# higher order polynomial of odd degree for good fit
degree = 5
tck, u = splprep(yaws, weights, t, k=degree, s=smooth)
yaws_spline = splprep(yaws, t, weights=weights, degree=5, smooth=smooth)
yaw_rate = yaws_spline(deriv=1)
# calculate 2nd order derivatives
yaw_accel = yaws_spline(deriv=2)
# calculate 3rd order derivatives
yaw_jerk = yaws_spline(deriv=3)
```

HERE IS AN EXAMPLE OF HOW THE ARGUMENTED VALUES WERE SMOOTED USING PYTHON

# SCENE-LEVEL VISUALIZATION

- VizViewer allows users to interactively explore scenes on a clickable map.
- By selecting a path, we can view detailed plots of the ego vehicle's motion along with surrounding agents.

- This scene-level analysis helps detect patterns such as:
  - Reduced speed near intersections
  - Higher agent density in crowded or urban areas
  - Increased yaw rate or lateral velocity on curves
  - Non-standard behavior in complex traffic situations

- These observations can guide:
  - Feature engineering (deriving new motion metrics)
  - Training data selection (focusing on specific scenarios)
  - Model debugging (isolating scenes with unexpected behavior)


VizViewer demo of multiple layouts with customizable views.

Heatmaps in VizViewer help visualize how vehicle behavior varies across the map by location.

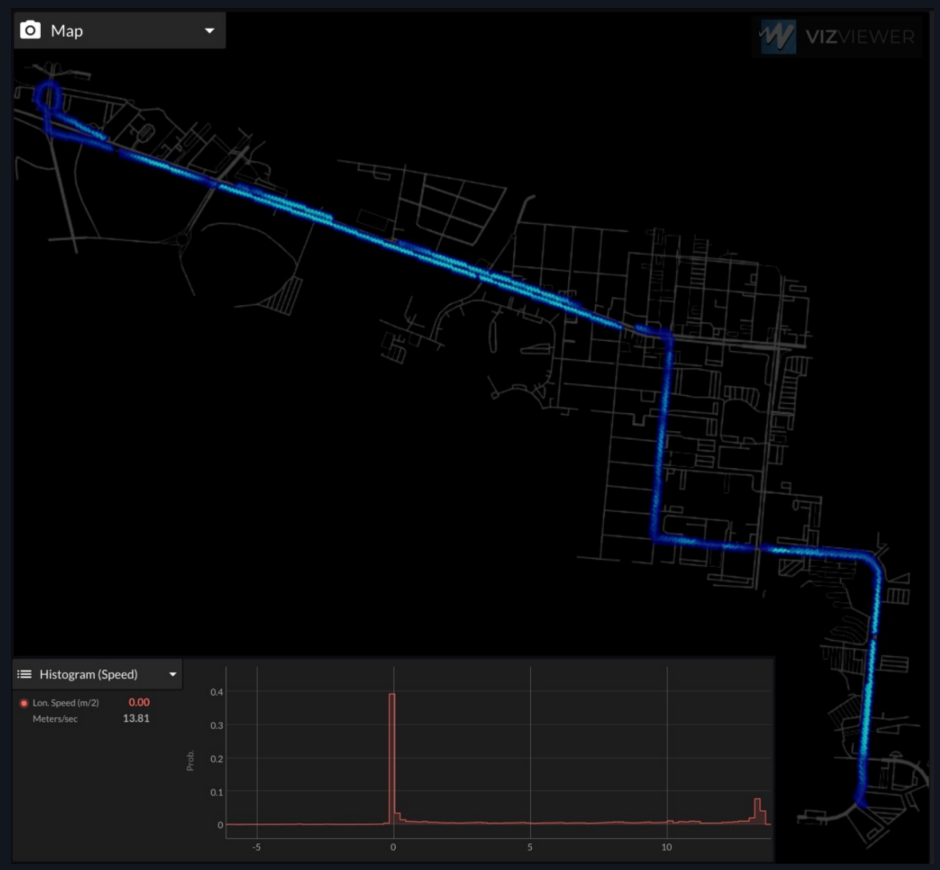
Key insights from heatmap analysis include:

- **Speed patterns by location:**
brighter areas = high-speed roads, darker = slow side streets
- **Agent observation continuity:**
longer tracking sequences are rarer but more valuable for training.
- **Correlation between speed and agent density:**
intersections often show low ego speed and high agent density, useful for modeling interactions in complex traffic scenarios.

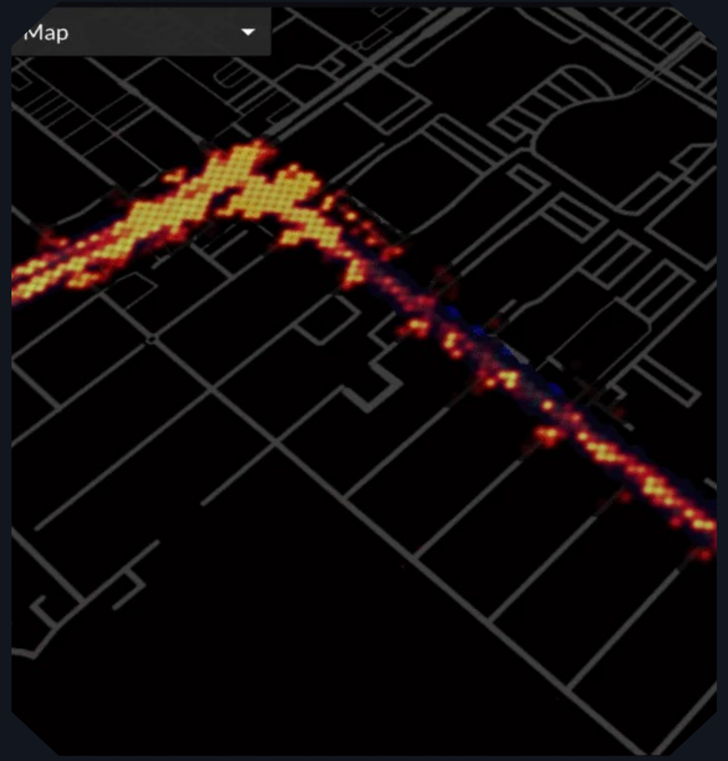
- Heatmaps improves feature engineering by revealing behavior patterns, and supports balanced and diverse training set construction

HEATMAPS OFFER A POWERFUL TOOL TO EXPLORE DATA COVERAGE, DISTRIBUTION, AND POTENTIAL BIASES IN YOUR DATASET.

# HEATMAPS & HISTOGRAMS Analysis




VizViewer: Velocity heatmap and histogram. High speeds are brighter blue.



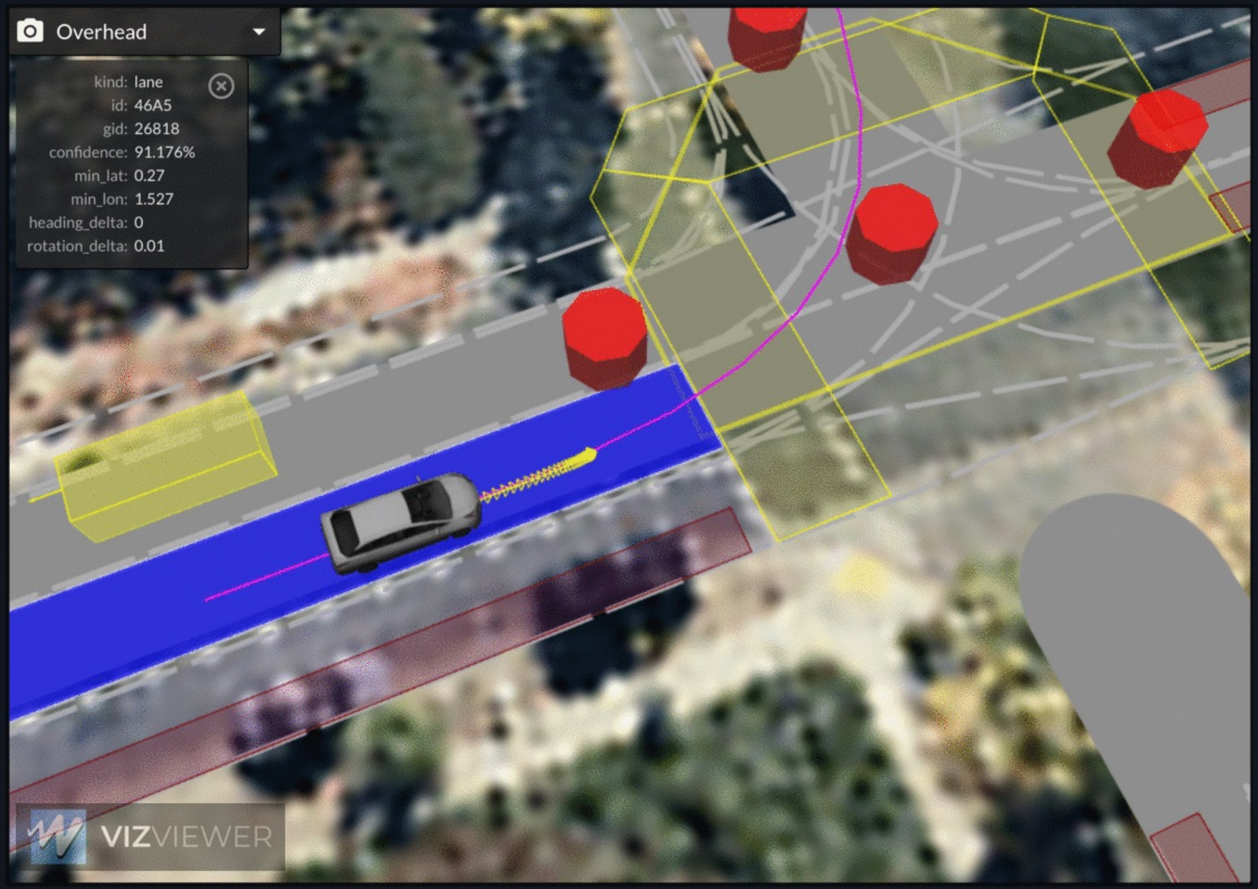

Velocity (blue) vs. agent density (red/yellow); agent observations are clustered near intersection/turns, where lower speeds are likely.

# PREDICTING VEHICLE PATHS USING SCENE DATA

Using scene data and semantic maps, we can train a model to predict a vehicle’s future path.

VizViewer helps visualize and evaluate these predictions through an interactive 3d scene view:

- Lane-level path predictions displayed with color-coded confidence (darker blue = higher confidence).
- Ability to observe path changes over time as the vehicle moves through the environment
- Interactive UI to:
  - Click on paths to see raw model outputs
  - Track how predictions shift as context changes




the system correctly predicted a left turn before it occurred, indicating strong contextual understanding.

# CONCLUSION

- VIZVIEWER PROVIDES A POWERFUL PLATFORM FOR ANALYZING AUTONOMOUS DRIVING DATASETS.
- IT ENABLES BETTER UNDERSTANDING OF VEHICLE DYNAMICS AND AGENT INTERACTIONS.
- HELPS GENERATE, TEST, AND DEBUG TRAINING DATA FOR MOTION PREDICTION MODELS

FUTURE DIRECTION:

- USE THIS APPROACH TO TRAIN AND EVALUATE FULL PATH PREDICTION MODELS BASED ON REAL-WORLD DATA, WITH EXPECTATIONS FOR DATA EXPANSION AND IMPROVED LABELING IN THE FUTURE.

The presentation recording