MODELING INTERSECTION CONFLICTS FOR AUTONOMOUS VEHICLES WITH LOGISTIC REGRESSION

EDAN70 - Proyect in Computer Science

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Why Study Traffic Conflicts?

01

Increasing presence of AVs in everyday traffic

02

Intersections are critical conflict zones

03

Goal: Model and classify potential conflict patterns

AV Autonomous Vehicles

HD Human Driven Vehicles

Workflow

01

Dataset and parsing

02

Filtering Conflict Scenarios

03

Analyzing Motion Features

04

Training model

05

Result Analysis

01

Dataset and parsing

- Real Traffic situations
- Different agents (HVs, AVs, cyclists)
- Detailed movement data
- First step: Explore and understand

RomainLITUD/
conflict_resolution_data...

Conflict resolution dataset

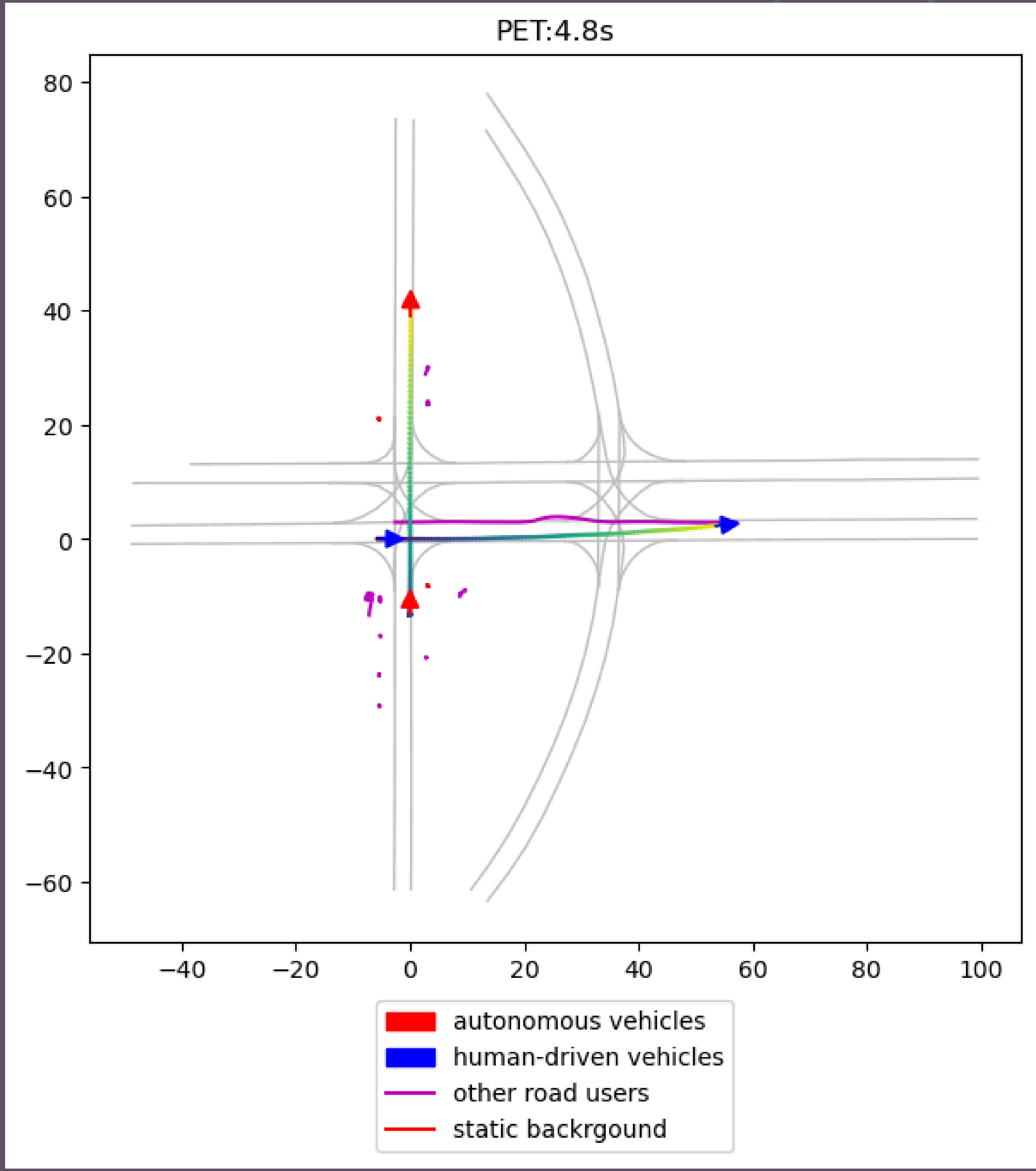
02

Intersection Scenario Filtering

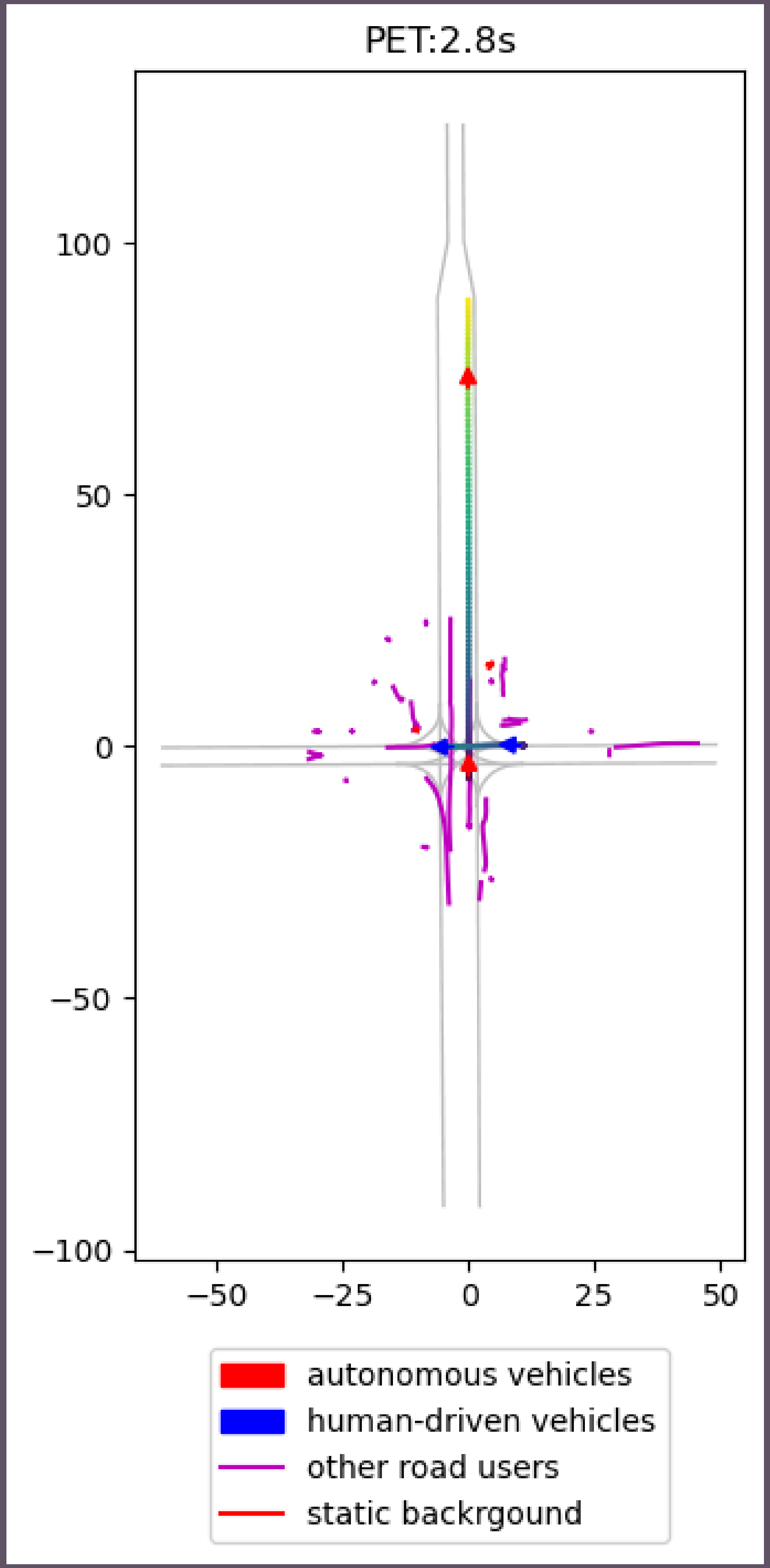
- Trajectory intersection
- Agent type filtering
- More than one agent

Goal: Detect situations where two vehicles intersect paths

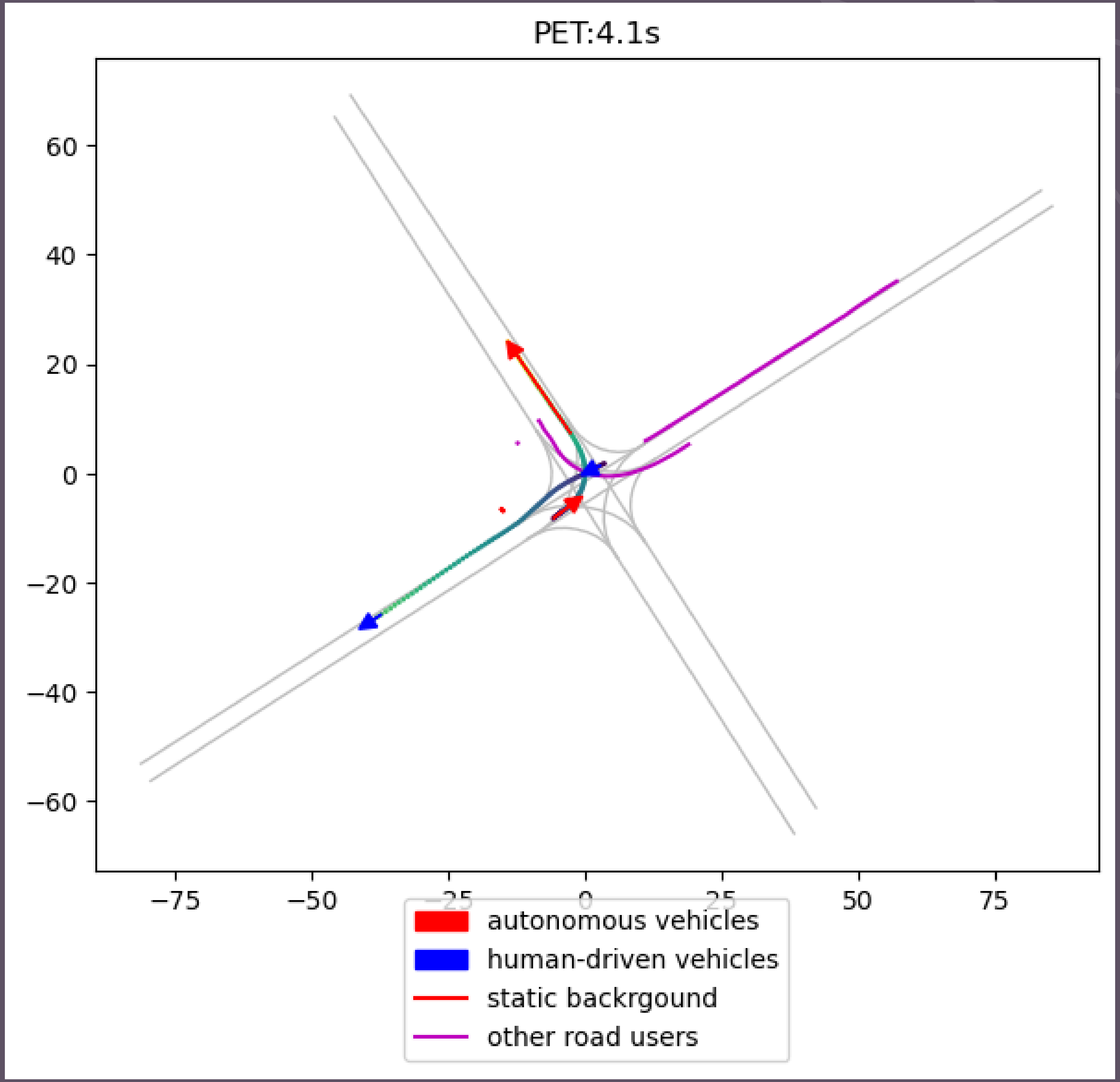
Vehicle approaching from the left



Vechicle approaching from the right



AV crossing HD trayectory



Trajectory points: position over time

Velocity & direction

PET: Post-Encroachment Time (conflict risk indicator)

Relative movement:

- Angle difference between agents
- Distance at closest point

Agent metadata: Types (AV, HV), sizes, IDs

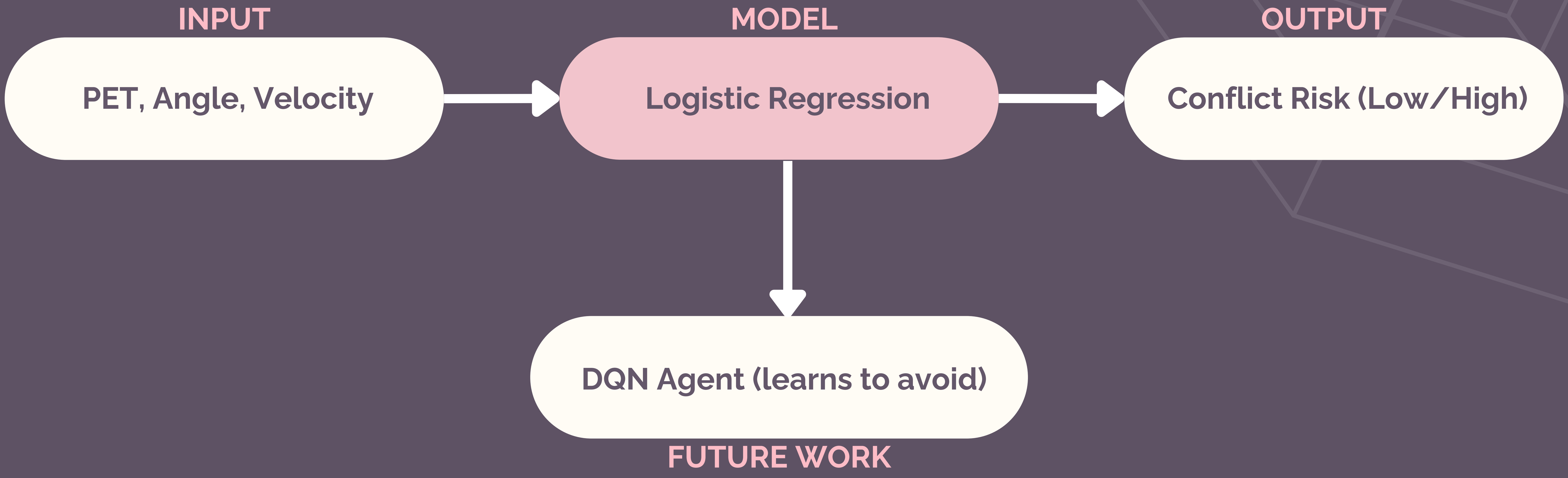
03

Analyzing Motion Features

Extract key properties from each scenario

Feature	Value
Agent 1 Type	AV
Agent 2 Type	HV
PET (s)	1.8
Angle Diff	92°
Min Distance	2.1m

From features to risk classification and control



Logistic Regression

Binary classification
Conflict vs No Conflict

Input Features:

- PET (Post-Encroachment Time)
- Direction angle difference
- Velocity of each agent
- Minimum distance between agents
- Relative time to intersection

Output:

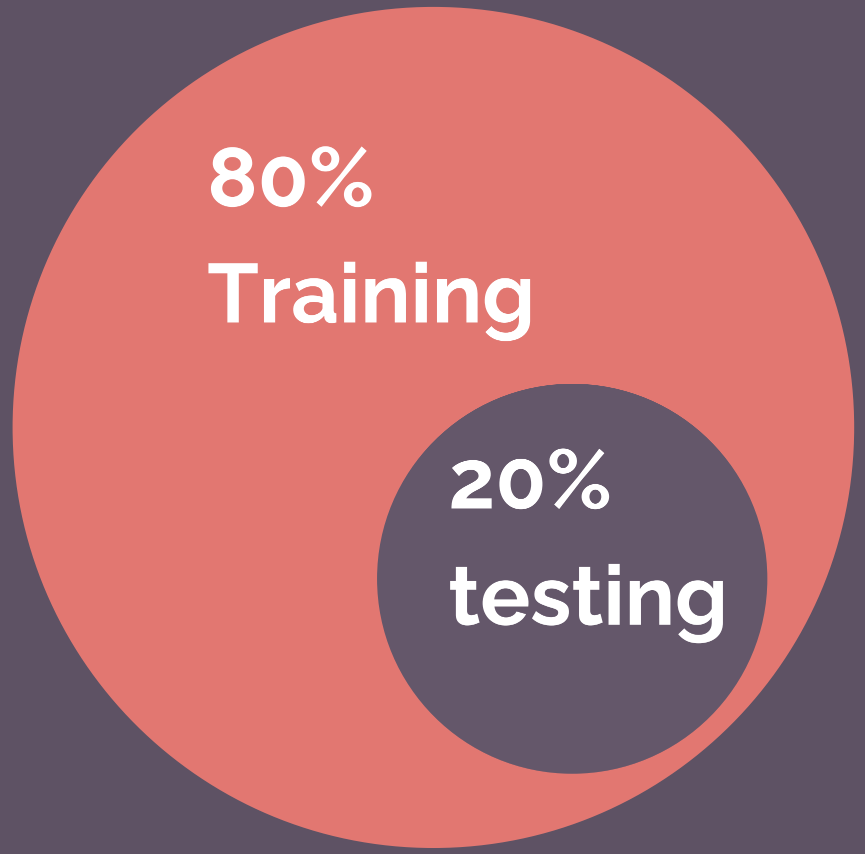
- Probability of conflict
- Threshold used to classify

$$P(\text{conflict}) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots)}}$$

04

Training the Model

- Dataset: Filtered conflict scenarios
- Train/test split: 80/20
- Features used: PET, angle difference, min distance, velocity, relative time



Total available scenarios: 3385

Class distribution in dataset:
No Conflict (0): 3318
Conflict (1): 67

Training samples: 2708
Test samples: 677

After SMOTE in Training Set:
No Conflict (0): 2654
Conflict (1): 2654

SMOTE
(Synthetic Minority Over-sampling Technique)
Generates synthetic examples rather than duplicating existing ones.

mblearn.over_sampling

05

Result Analysis

Classification Report (Test Set):

	Precision	Recall	f1-score
No Conflict	1	0.98	0.99
Conflict	0.57	1	0.72
accuracy			0.99
macro avg	0.78	0.99	0.86
weighted avg	0.99	0.99	0.99

sklearn.metrics

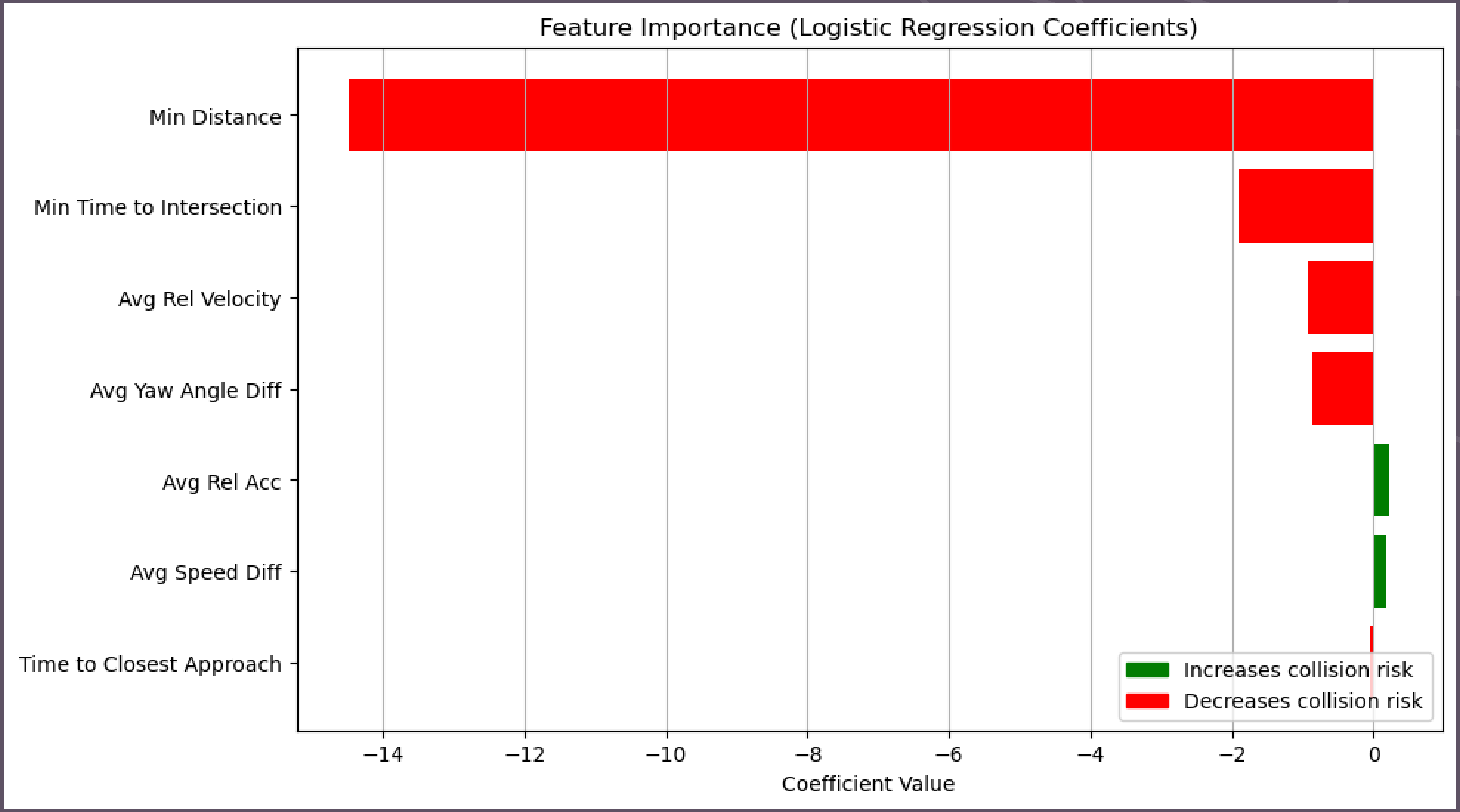
over-warning is far better than under-warning

05

Result Analysis

05

Result Analysis

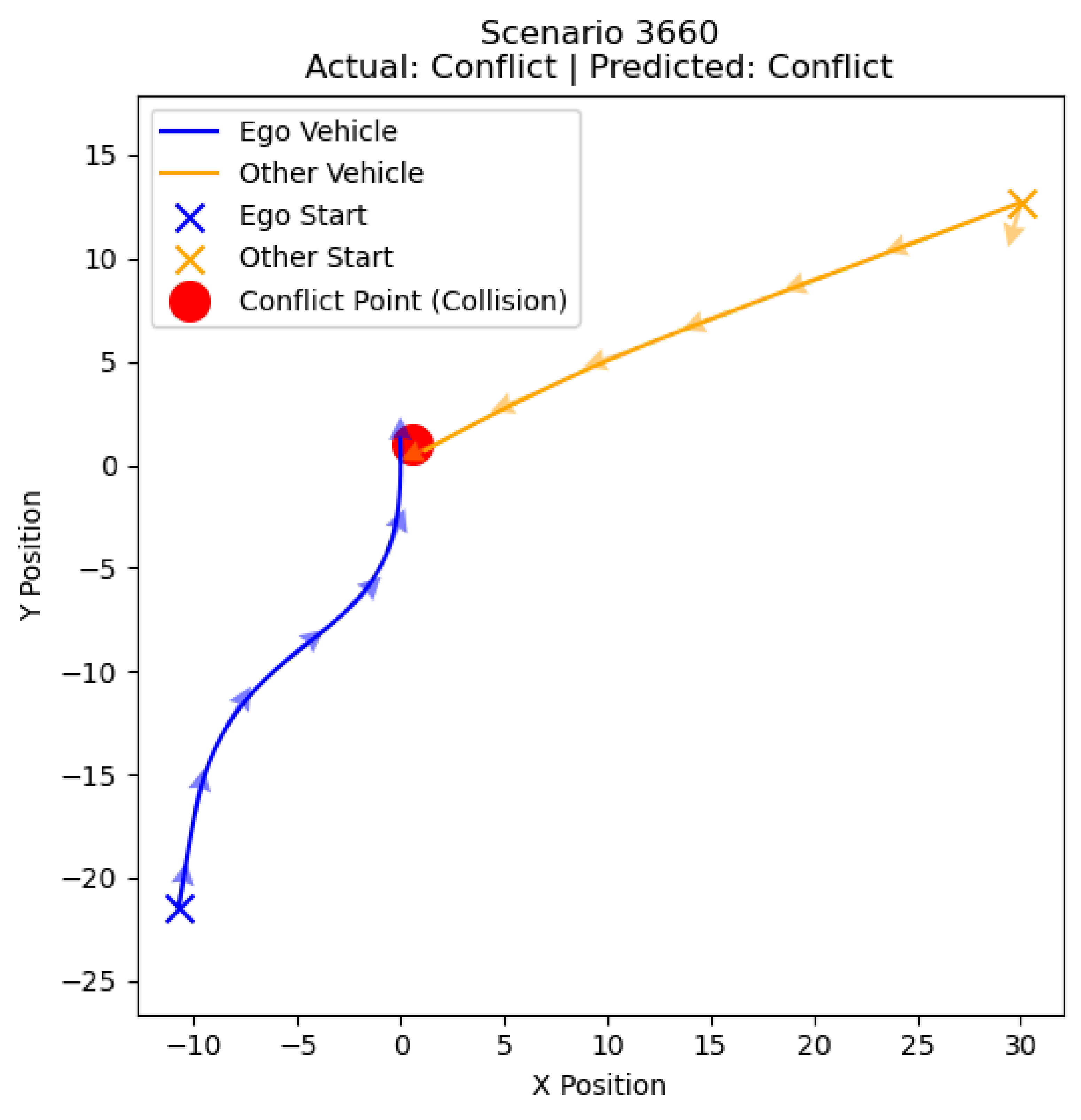


Red bars → the feature reduces conflict risk as it increases.

Green bars → the feature increases conflict risk as it increases.

06

Example of correct detection conflict



Scenario 3660:
Actual: Conflict
Predicted: Conflict
Intersection Point: [0.58121824 0.98074023]
Conflict Time: 0.63
Ego Speed at Conflict: 5.62 m/s
Other Speed at Conflict: 2.90 m/s
Collision: Yes

Conclusion and Key Takeaways

Our model successfully identifies intersection conflicts with 99% accuracy and perfect recall (100%)

Key features (PET, distance, angle) provide interpretable risk assessment

Great potential for enhancing traffic safety through AI algorithms

Future Work

01

Incorporate more complex models for improved performance

02

Leverage additional features

03

Expand dataset with more diverse and rare conflict scenarios

THANK YOU FOR LISTENING!
ANY QUESTIONS?