

# ACAV: A Framework for Automatic Causality Analysis in Autonomous Vehicle Accident Recordings

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# Autonomous Vehicle (AV)

## The Self-Driving Car Companies Going The Distance

Number of autonomous test miles and miles per disengagement (Dec 2019-Nov 2020)\*

			Miles	Miles per disengagement
Waymo (Alphabet)			628,839	29,945
Cruise (GM)			770,049	28,520
AutoX			40,734	20,367
Pony.AI			225,496	10,738
Argo.AI (Ford, VW)			21,037	10,519
WeRide			13,014	6,507
DiDi Chuxing			10,401	5,201
Nuro			55,370	5,034

\* Cases where a car's software detects a failure or a driver perceived a failure, resulting in control being seized by the driver.

Source: DMV California, via The Last Driver License Holder



statista



<https://www.statista.com/chart/17144/test-miles-and-reportable-miles-per-disengagement/>

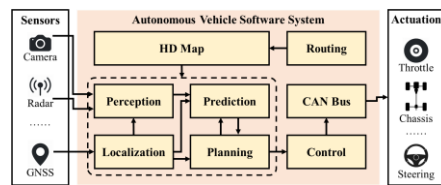
# Causality Analysis of AV Accidents



Autonomous Driving Crashes

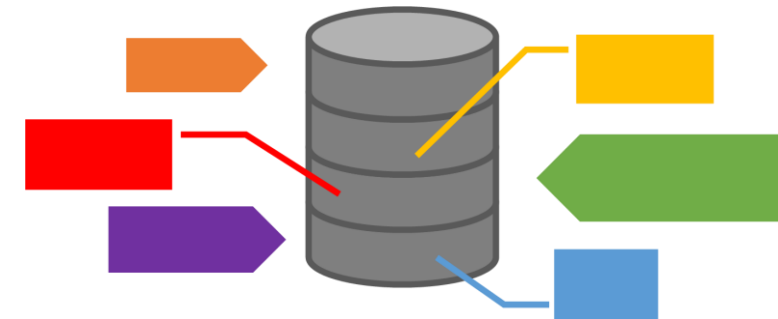
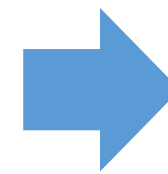


Causality Reports Of Accident



Vast amounts of driving recordings

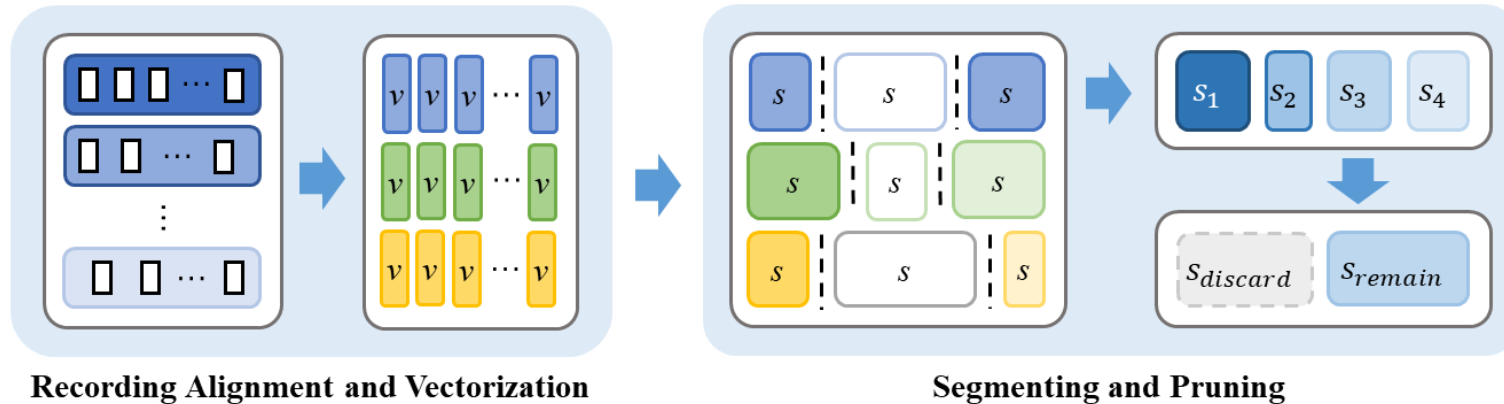
Use a recorder to obtain recordings



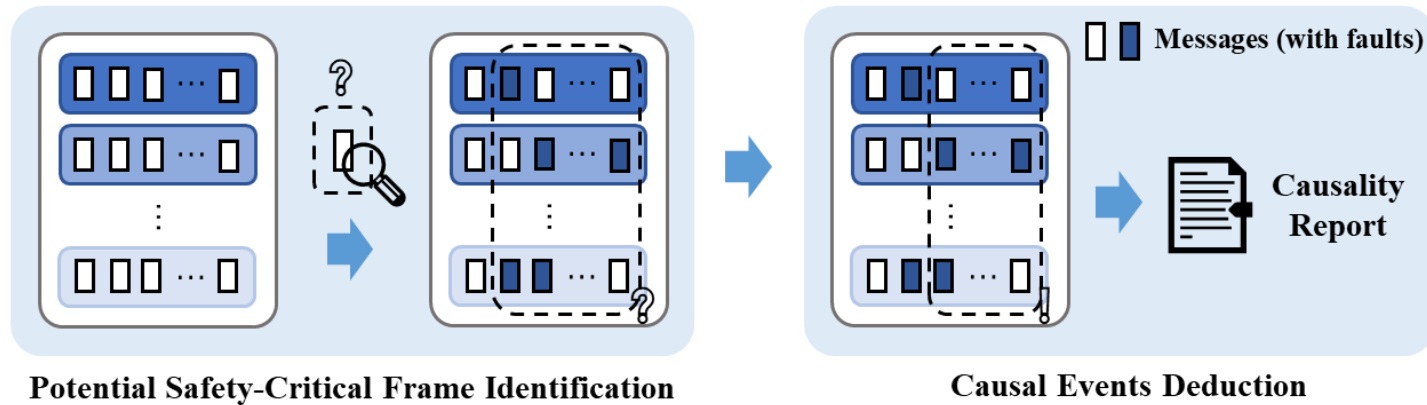
Data Labeling & Explanation

# Overview of ACAV

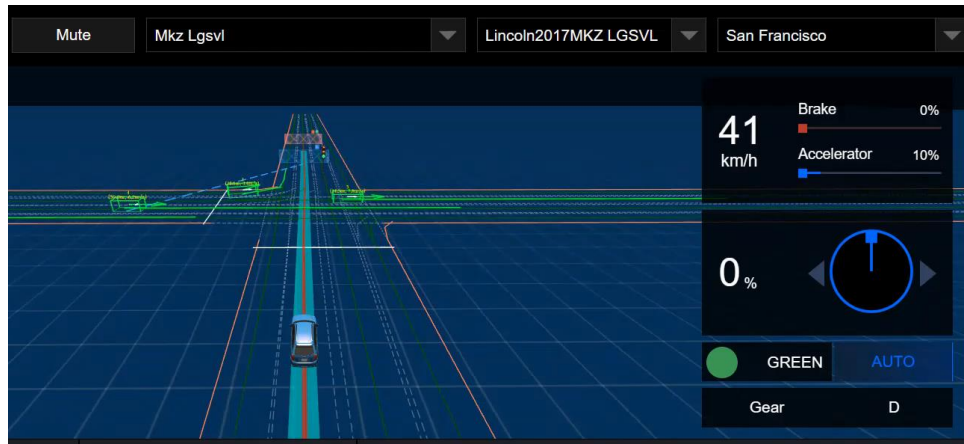
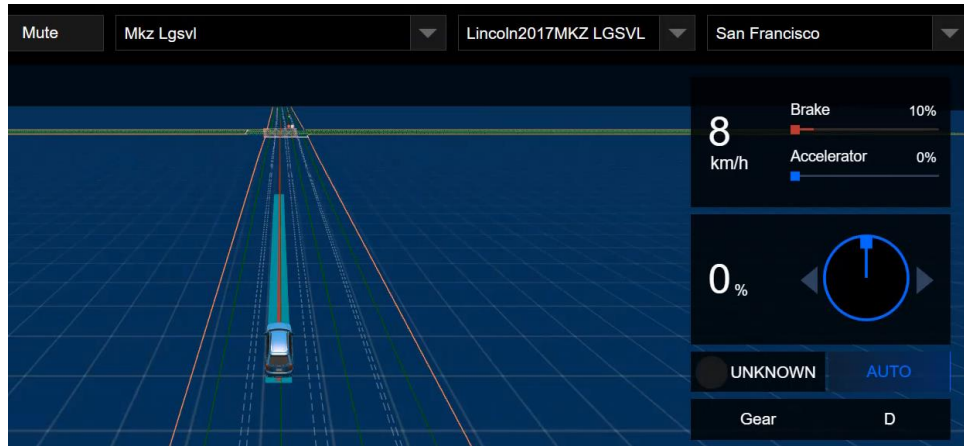
## The First Stage: Accident Recording Simplification



## The Second Stage: Causality Analysis



# Motivating Example

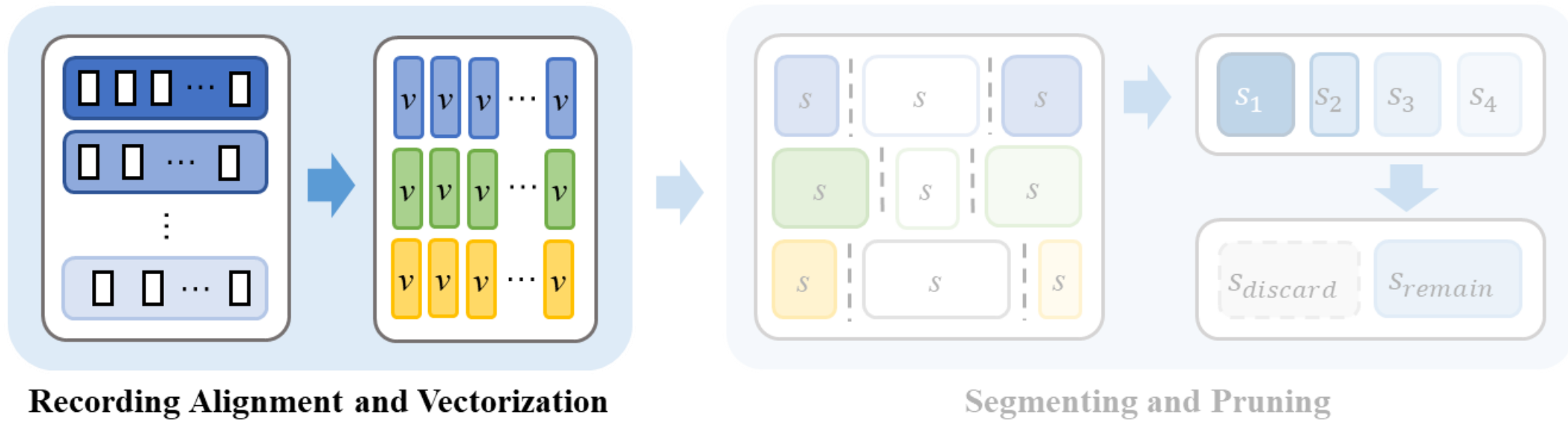


Time	Accident causal events	Details
0s	AV keeps safe distance from NPCs	--
0.4s	<b>Wrong motion planning;</b> AV <b>skidding</b> sometimes	Too fast or too slow <b>planning speed</b>
0.8s	<b>Wrong planning</b> caused by the wrong prediction; AV <b>skidding</b> sometimes	<b>For NPC 2:</b> wrong priority prediction; <b>For NPC 4:</b> improper 'overtake' decision; Too fast or too slow <b>planning speed</b>
2.6s	<b>Wrong motion planning;</b> AV <b>skidding</b> sometimes	Too fast or too slow <b>planning speed</b>
4.3s	Accident!	

ACAV <https://acav2023.github.io/merging1.html>

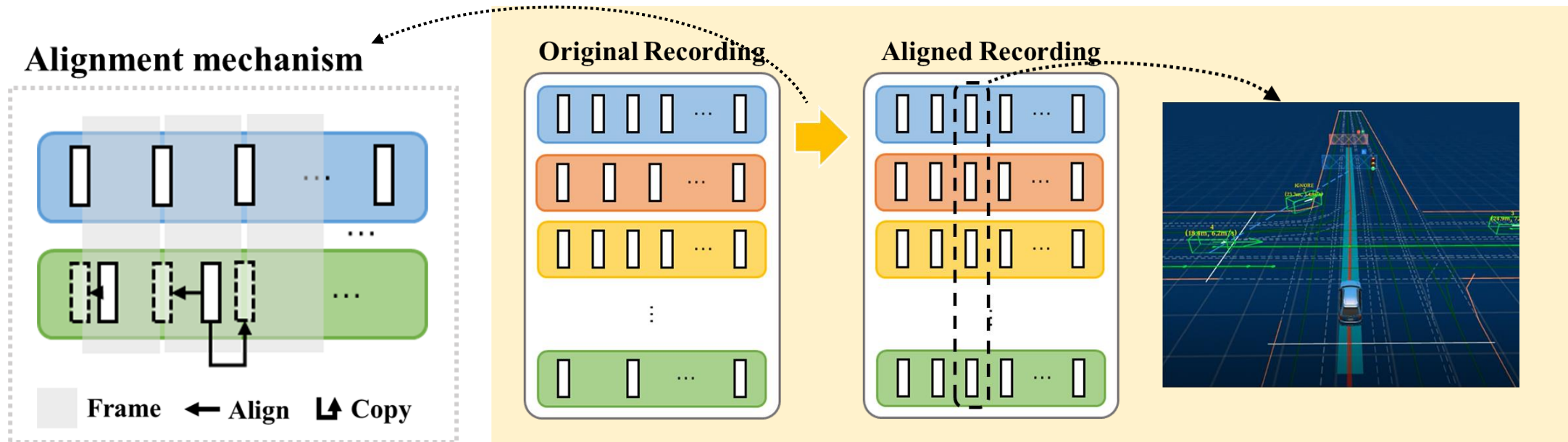
# ACAV Framework: Stage #1

## The First Stage: Accident Recording Simplification



# Stage #1: Alignment and Vectorization

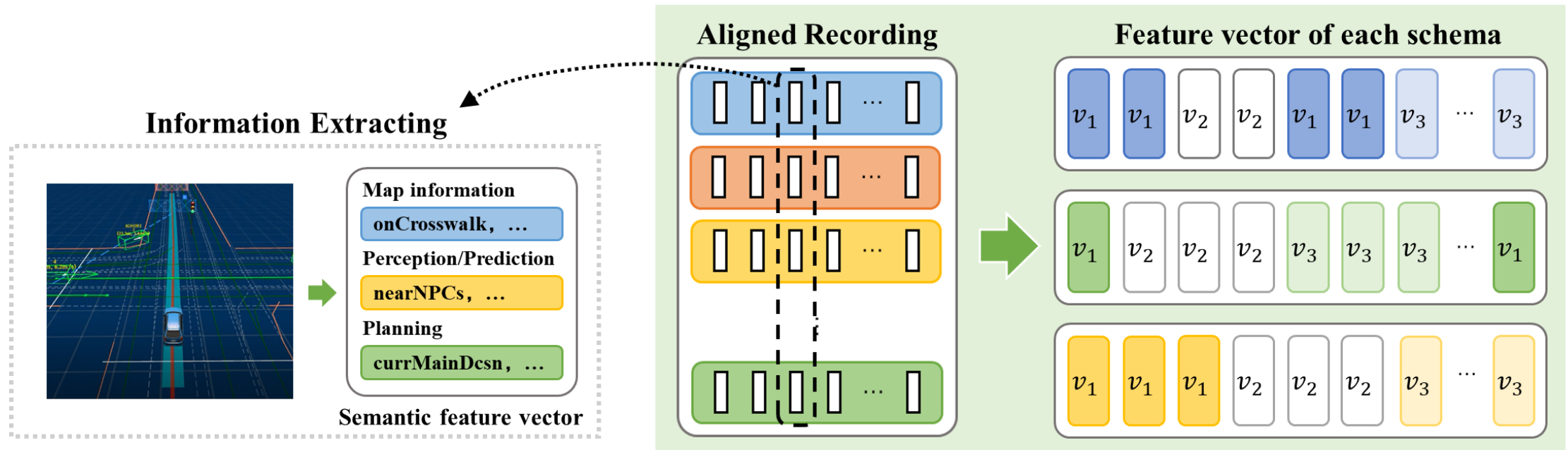
- Consider five channels: map, localization, perception, prediction, planning.
- Divide the recording into a list of frames.





# Stage #1: Alignment and Vectorization

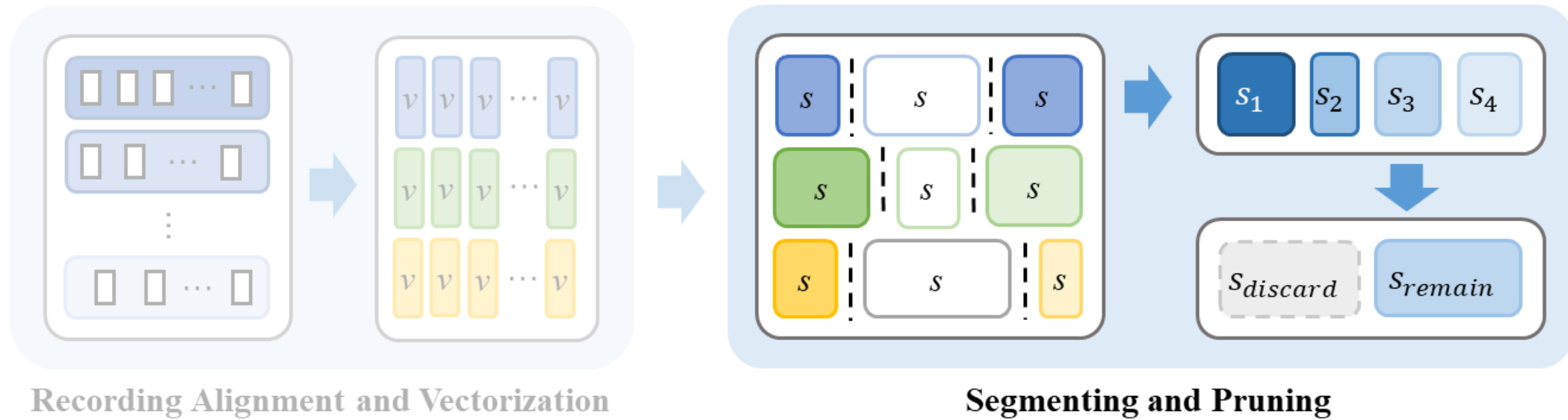
- Extract semantic information according to three feature extraction schemas.





# ACAV Framework: Stage #1

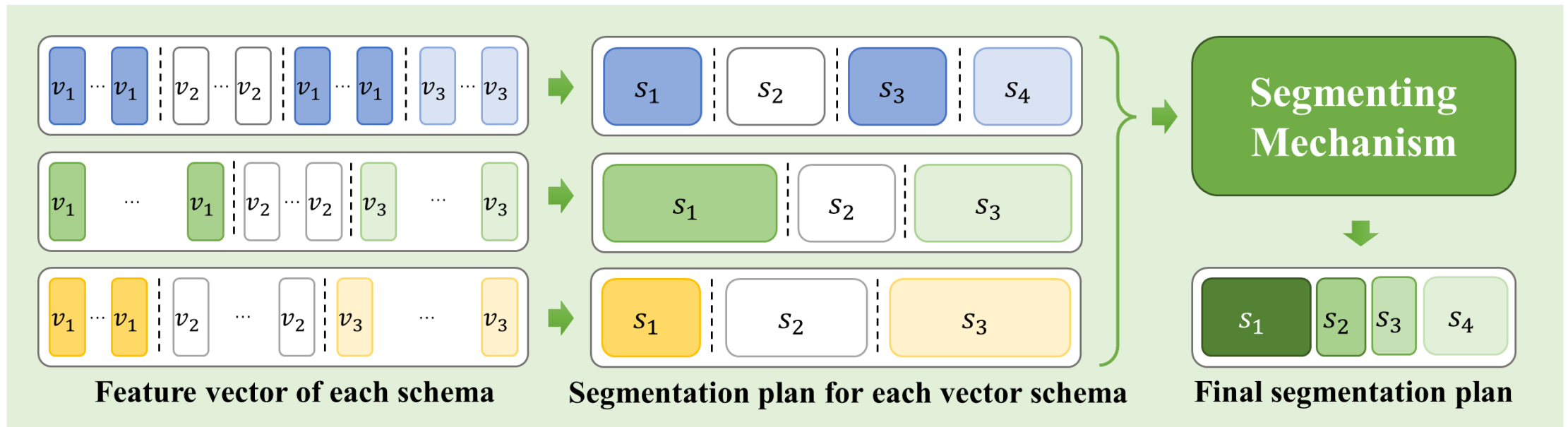
## The First Stage: Accident Recording Simplification



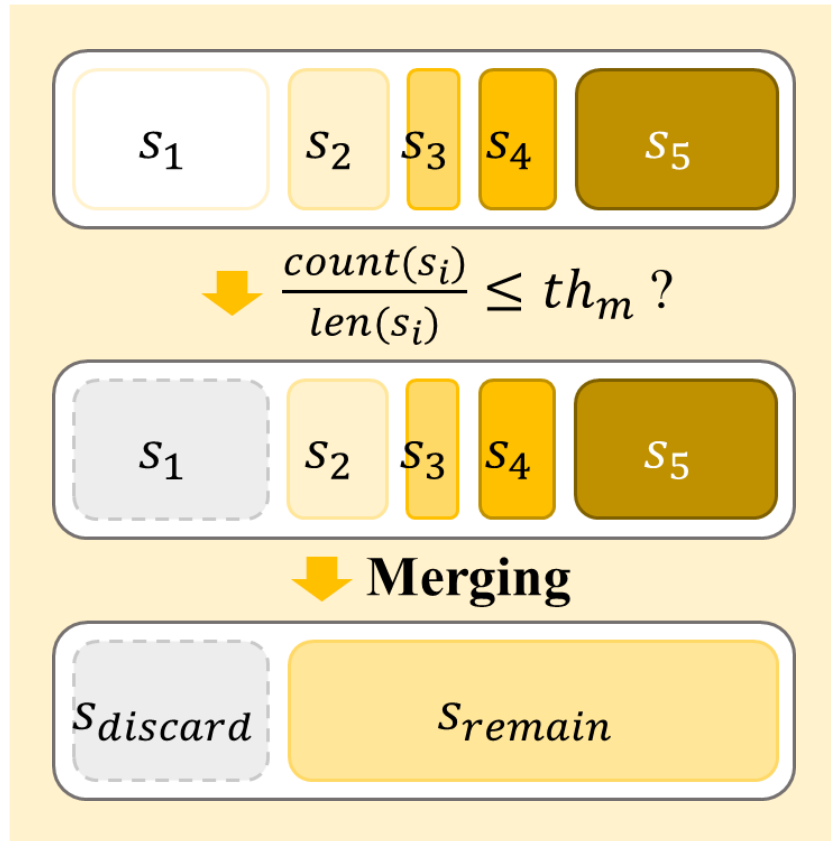
# Stage #1: Segmenting and Pruning

- Segmenting Mechanism:

$$\text{voting}(v_{map}, v_{perc}, v_{pred}) := \sum_{c \in C} w_c \times v_c \geq \frac{1}{2} \sum_{c \in C} w_c, \quad C = \{map, perc, pred\}$$

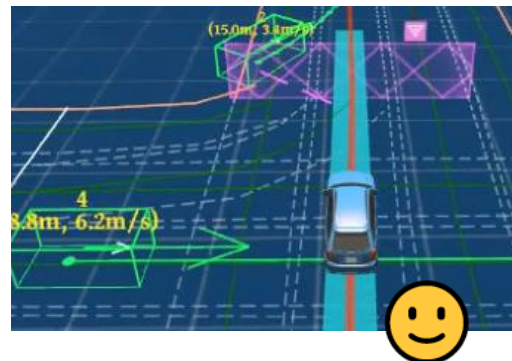


# Stage #1: Segmenting and Pruning



## Irrelevant Frame:

- Road Area
- Not near a stop sign
- No NPCs



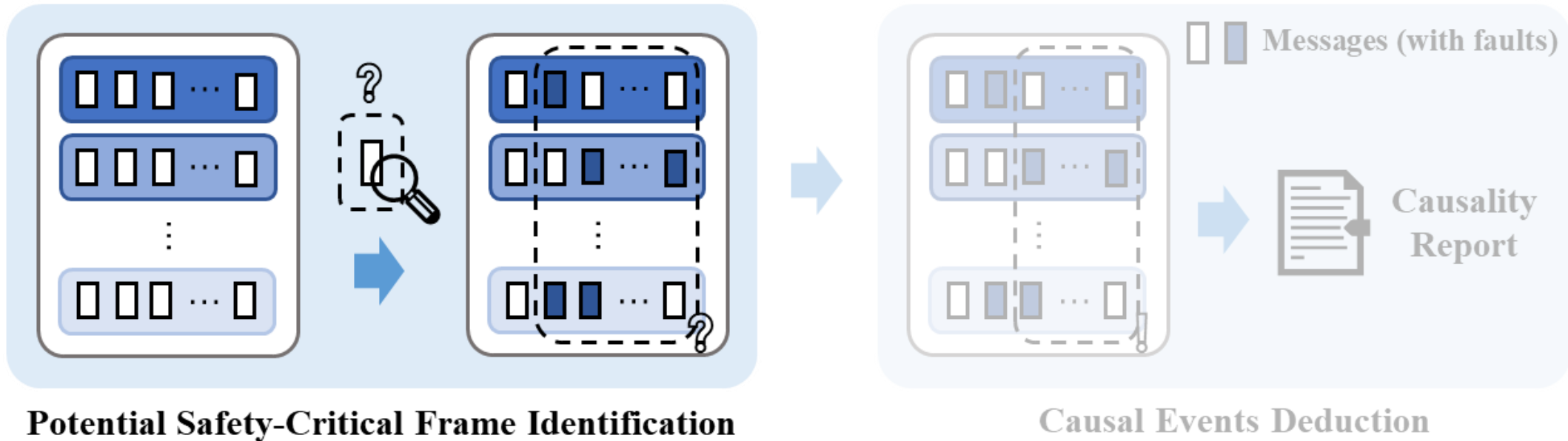
## Relevant Frame:

- Junction/Crosswalk area
- Near NPCs
- Interact with NPCs

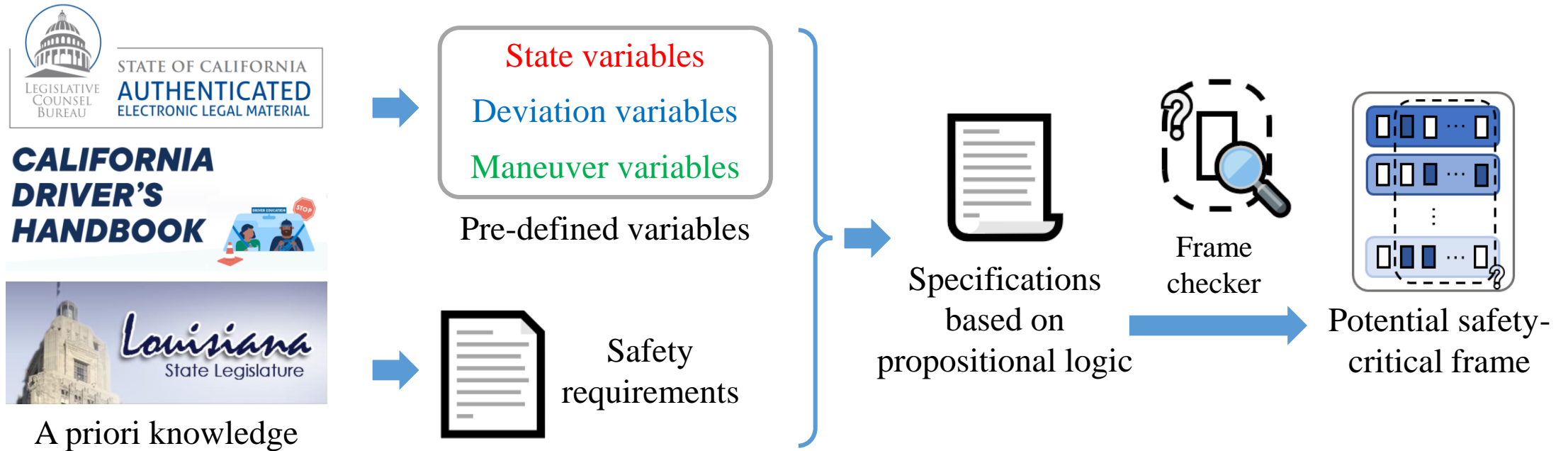
$\text{count}(S)$ : compute the irrelevant frame ratio for a segment  $S$

# ACAV Framework: Stage #2

## The Second Stage: Causality Analysis



# Stage #2: Potential Frame Identification



# Stage #2: Potential Frame Identification

- Example

*Navigating the Roads (Section 9, Navigating the Roads, California Driver's Handbook):*

Before you **pass**, look ahead for road conditions and traffic that could cause other vehicles to move into your lane. Only pass when it is safe. Do not pass:

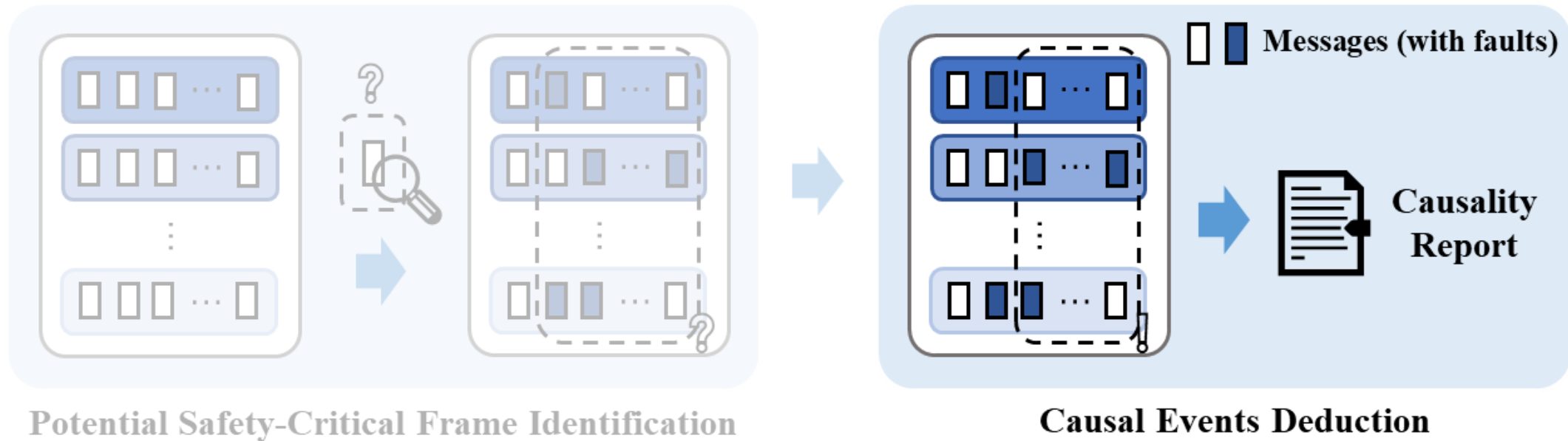
- Within 100 feet of or in an **intersection**, bridge, tunnel, railroad crossing, or other hazardous area.
- At **crossroads** and driveways.

$$\text{ImpropOvtkDecn}(x) := (\text{av.onJct} \vee \text{av.OnCswk}) \wedge \text{DecnOvtk}(x)$$



# ACAV Framework: Stage #2

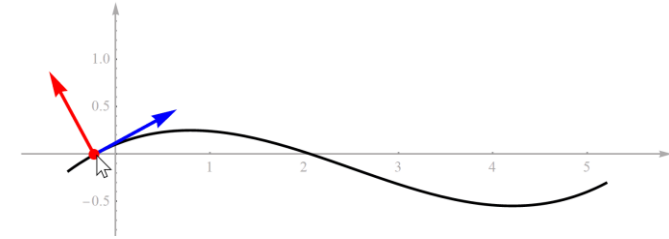
## The Second Stage: Causality Analysis



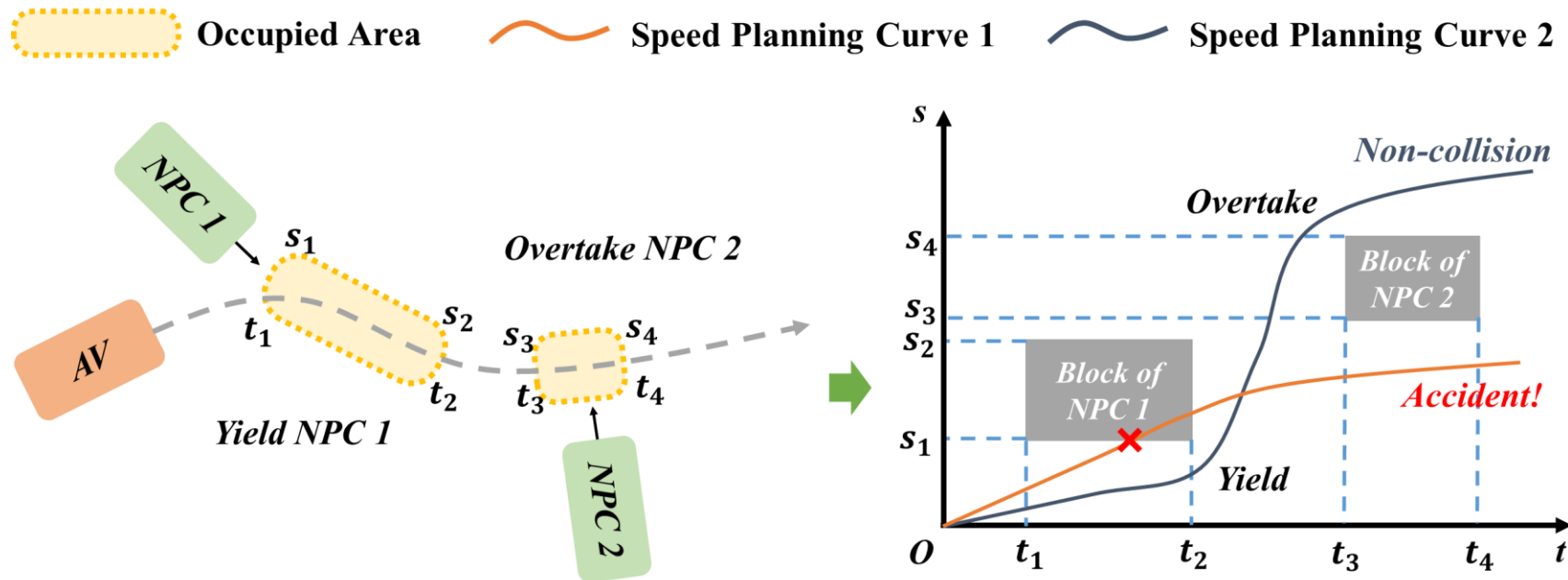


# Stage #2: Causal Events Deduction

For a vehicle: motions = longitudinal motions + lateral motions



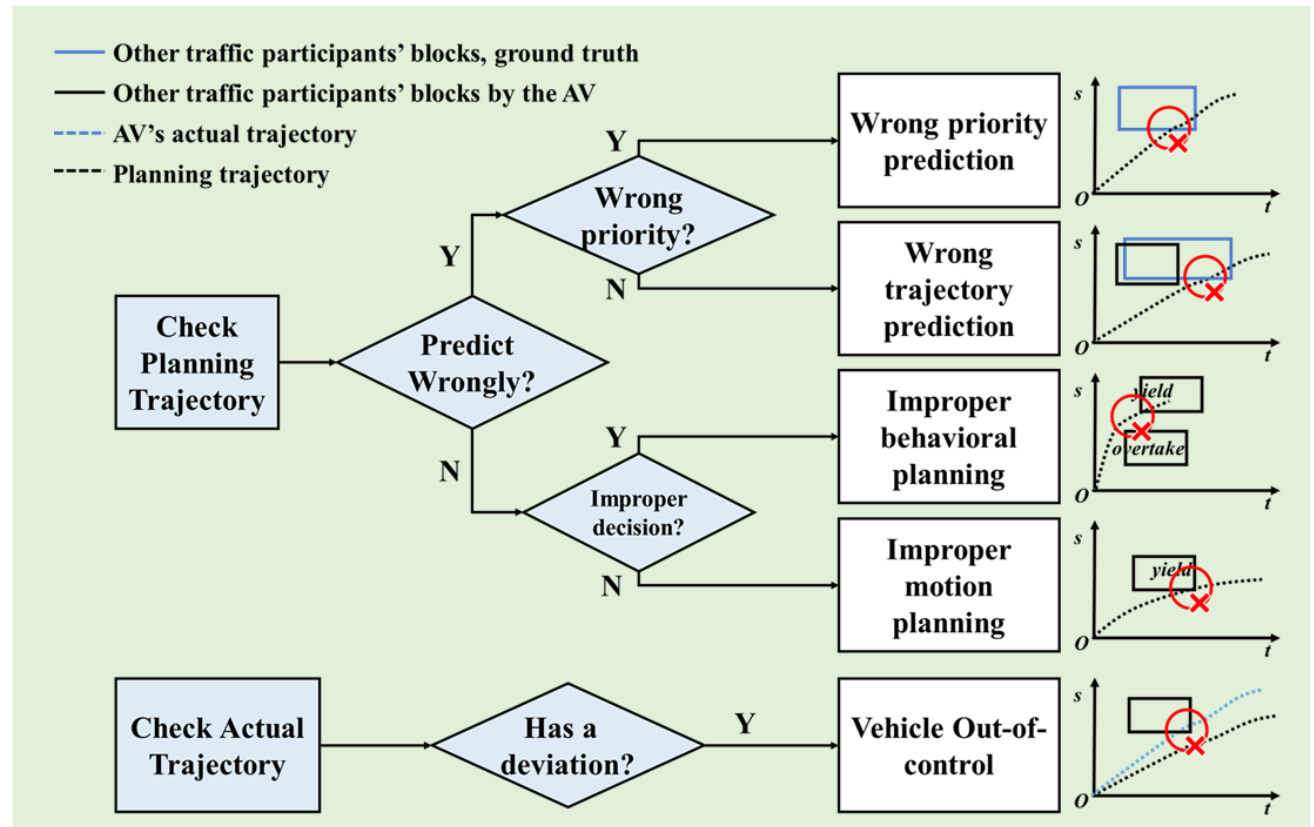
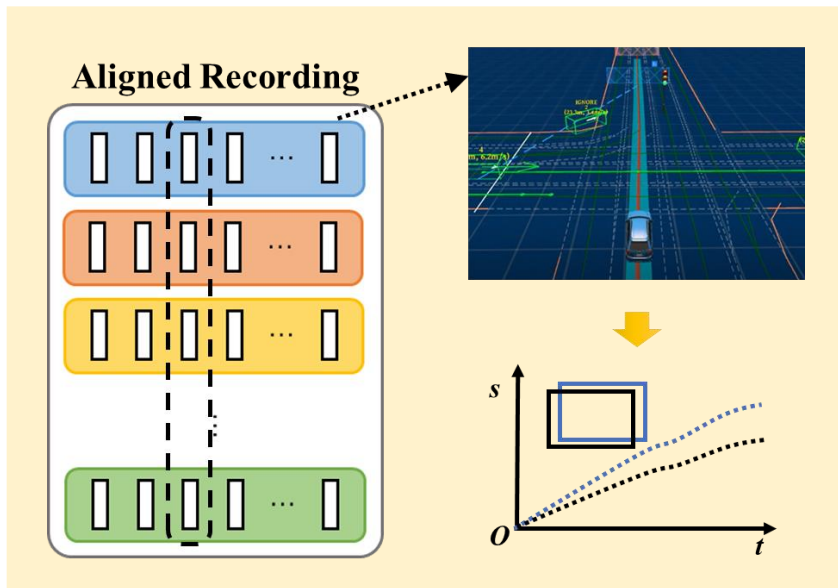
Depicting the AV's longitudinal planning states with Station-Time graph (ST graph)



# Stage #2: Causal Events Deduction

- Restore ST graph + Causality Analysis Tool (CAT)

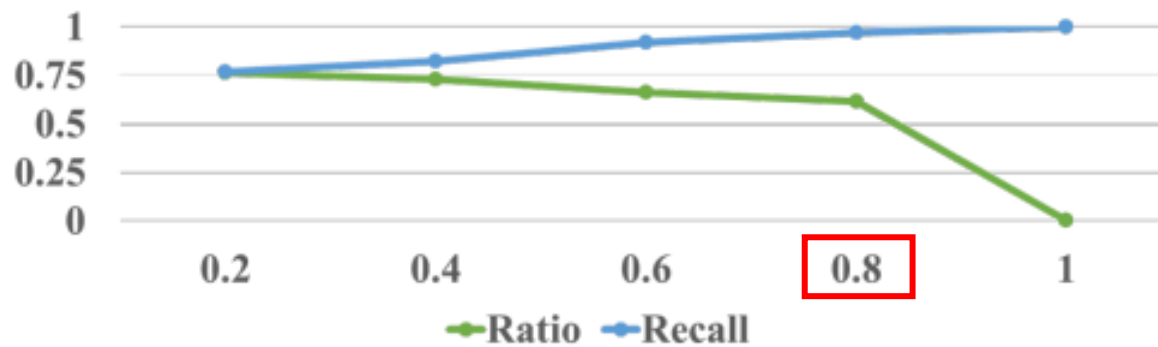
CAT compare and analyze the ST graph from the AV perspective against the ground truth, frame by frame.



# Evaluation

**RQ1:** Which **combination of weights** for feature vector categories and which **threshold** in the “segmenting and pruning” phase is the most **effective**?

Weight Ratio (map:perc:pln)	1:1:0	1:0:1	0:1:1	<b>1:1:1</b>	2:1:1	1:2:1	<b>1:1:2</b>
Ratio	74.64%	96.43%	74.64%	<b>50.03%</b>	60.26%	74.64%	<b>62.23%</b>
Recall	79.62%	11:06%	79.62%	<b>93.01%</b>	89.19%	79.62%	<b>94.41%</b>



# Evaluation

**RQ2:** Does the ACAV **effectively** simplify accident recording compared to other approaches?

**RQ3:** How many **different causal events** can the causality analysis of ACAV automatically identify?

	ACAV	STRaP	Length: 4s	Length: 8s	Length: 12s	Length: 16s
Ratio	62.23%	60.57%	76.74%	54.40%	32.64%	16.29%
Recall	94.41%	30.81%	72.26%	82.92%	86.85%	91.35%

	Wrong Priority Prediction	Wrong Trajectory Prediction	Wrong Behavioral Planning	Wrong Motion Planning	Vehicle Out-of-control
<b>Total</b>	<b>26</b>	<b>51</b>	<b>17</b>	<b>67</b>	<b>103</b>
Intersection	0	0	6	27	39
Merging	20	27	4	23	30
Tailgating	6	24	7	17	34

# Evaluation

**RQ4:** To what extent can the ACAV **accurately** identify causal events?

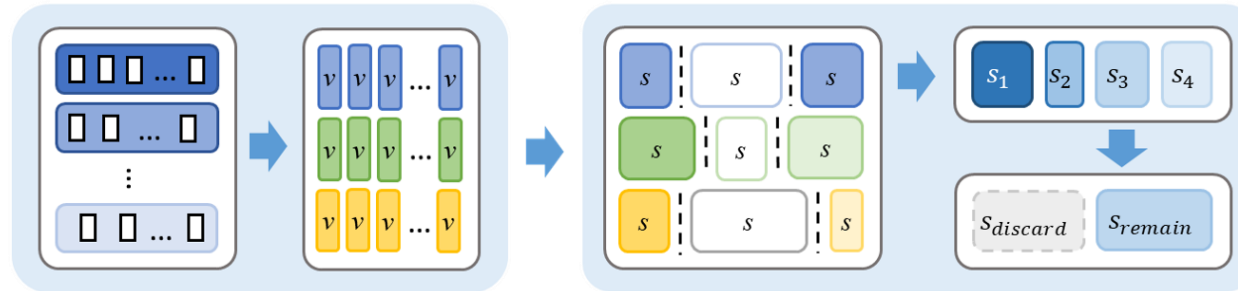
Location	Prediction Module			Planning Module						
Fault Types	F1	F2	Total	F3	F4	F5	F6	F7	F8	Total
Numbers	155	126	281	132	146	202	166	145	134	925
Precision (%)	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Recall (%)	100.00	90.00	95.97	87.61	73.98	89.70	86.72	77.19	77.19	82.56
Accuracy (%)	100.00	92.06	<b>96.44</b>	89.39	<b>78.08</b>	91.58	89.76	82.07	80.60	<b>85.73</b>

Fault Type	Location	Description
F1	AssignIgnoreLevel()@obstacle_prioritizer.cc	Assign 'ignore' priority to all the detected NPCs by default.
F2	PredictObstacle()@predictor_manager.cc	Assign improper trajectory prediction models to NPCs to get erroneous trajectory prediction.
F3	MakeStaticObstacleDecision()@path_decider.cc	Make 'ignore' decisions to all the static NPCs near the AV's planned trajectory.
F4	MakeObjectDecision()@speed_decider.cc	Make 'follow' decisions to any NPCs in front of the AV which tend to stop, instead of 'stop' decisions or changing lanes.
F5	MakeObjectDecision()@speed_decider.cc	Make 'ignore' decisions to an NPC ahead of the AV, if the AV is not following or keeping distance from it.
F6	MakeObjectDecision()@speed_decider.cc	Make 'yield' decisions to a high-speed NPC accelerating ahead of the AV, which leads to AV's low speed in a fast lane.
F7	MakeObjectDecision()@speed_decider.cc	Make 'overtake' decisions to any NPC if it is near the AV.
F8	GetSpeedLimits()@speed_limit_decider.cc	Keep a high speed even being close to NPCs.

# Conclusion

- ACAV, an automated framework for determining the causal events in AV accidents
- Implementation ACAV in both Apollo and Autoware.universe
- Causal events identification in 103 of 110 accident recordings

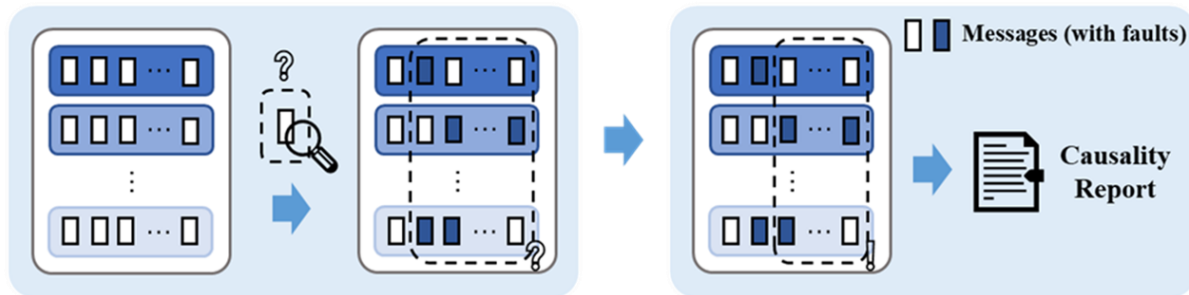
## The First Stage: Accident Recording Simplification



Recording Alignment and Vectorization

Segmenting and Pruning

## The Second Stage: Causality Analysis



Potential Safety-Critical Frame Identification

Causal Events Deduction

## Main Contributions:

- A mechanism for identifying recording segments related to the accident
- A tool for identifying safety-critical frames by leveraging ST graphs
- The first framework for AV accident analysis and explanation

# Thank You for Listening!