

# Rigorous Simulation-based Testing for Autonomous Driving Systems Targeting the Achilles' Heel of Four Open Autopilots

(arXiv:2405.16914 [cs.SE])

Joseph Sifakis

Verimag, June 28, 2024

Changwen Li  
Rongjie Yan  
Jian Zhang

- Validation of ADS
- Compositional Testing
- Test Methodology
- Experimental Results
- Discussion

# Validation of ADS – Validation Methods

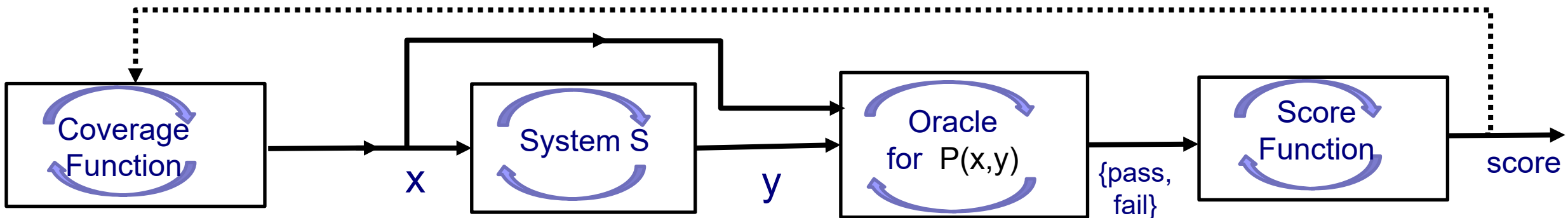
- ❑ To validate that "a system S satisfies a property P", systems engineering following epistemic imperatives
  - requires not only that P be rigorously defined, but also that a falsifiable validation method be provided.
  - uses verification or testing techniques.

- ❑ Verification consists in comparing a model of S against some specification of P.
  - can examine the whole system behavior described by a model and determine about the validity of its properties
  - can validate properties involving universal quantification, e.g. that all system states are safe, or that for any system run there exists a rejuvenation state.
  - is a symbolic (reasoning-based) or a data-based process producing truthful knowledge

- ❑ Testing is a controlled experiment on the S (real or virtual) to assess the degree of validity of P.
  - is subject to observability and controllability constraints: distinction between system inputs (controllable) and outputs (observable)
  - is limited to properties P characterizing an I/O relation; properties involving universal quantification can be only falsified.
  - produces empirical knowledge - can fully validate only properties of combinatorial systems with finite input and output domains.
  - Can test methods be applied to AI systems?

# Validation of ADS – Test Methods

- Tests are used to validate experimentally that a system  $y=S(x)$  satisfies a property  $P(x,y)$ .
  - System S: the system under test e.g. an electric bulb, an autopilot or an AI component;
  - Property P: a predicate (hypothesis) characterizing the I/O behavior of S;
  - Oracle: is an agent that can decide logically or empirically whether  $P(x,y)$  holds producing verdicts *pass* or *fail*.



- Test method: How do you choose between possible test cases and decide whether the process is successful or not?
  - Coverage Function:  $coverage(X) \in [0,1]$  measures the extent to which the set of test cases X explores the characteristics of the system's behavior in relation to the property P
  - Score Function:  $score(X,Y)$  measures for a test set (X,Y) the likelihood that S meets P .

Reproducibility: If  $(X1,Y1)$ ,  $(X2,Y2)$  are two sets of tests then:

$$coverage(X1)=coverage(X2) \text{ implies } score(X1,Y1) \sim score(X2,Y2)$$

# Validation of ADS – When a Self-driving Car is Safe Enough?

## Waymo has now driven 10 billion autonomous miles in simulation

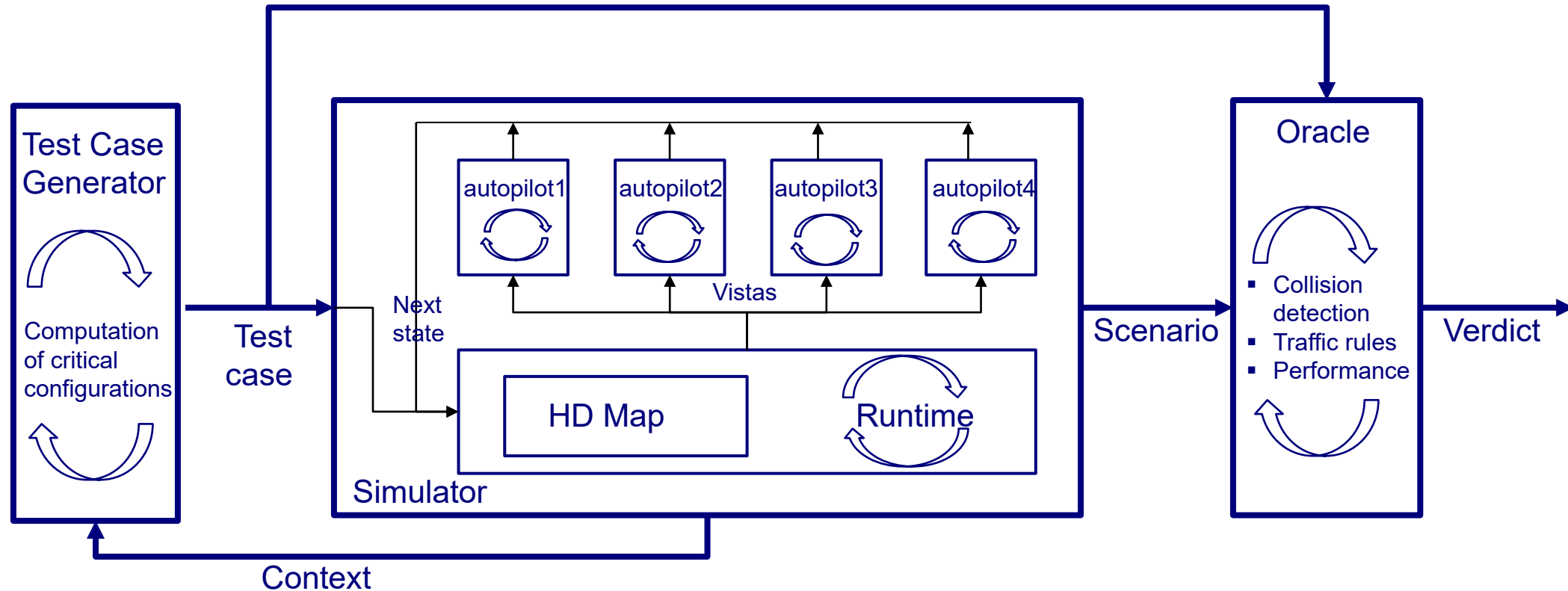
Darrell Etherington @etherington / 11:17 pm CEST • July 10, 2019

Comment



- ❑ The inability to build global system models limits system validation to simulation and testing.
  - Simple simulation is not enough - how a simulated mile is related to a “real mile” ?
  - We need evidence, based on coverage criteria, that the simulation deals fairly with the many different situations, e.g., different road types, traffic conditions, weather conditions, etc.
  
- ❑ Test methods to calculate, on the basis of statistical analysis, confidence levels for given properties.
  - Sampling theory: methods for building sample scenarios that adequately cover real-life situations
  - Repeatability: for two samples of scenarios with the same degree of coverage, the estimated confidence levels are approximately the same.

# Validation of ADS – Test Environment



- Validation of ADS
- Compositional Testing
- Test Methodology
- Experimental Results
- Discussion

# Compositional Testing – Principles

- The complexity of ADS can be tamed by applying a compositionality principle.
  - **Locality of context:** ADS safety is strongly dependent on the context in which vehicles operate
    - The traffic infrastructure can be seen as the composition of a finite number of patterns comprising different types of roads and intersections with their signalling equipment.
    - We can therefore imagine that a vehicle's safety policy is the composition of elementary policies, each of which is used to drive safely according to the corresponding basic road patterns.
  - **Locality of knowledge:** A vehicle's driving policy is based only on local knowledge of the ADS state due to limited visibility.
    - It must therefore drive safely, taking into account the obstacles closest to it, delimited by a visibility zone.
    - In this way, the collective behavior of vehicles in an ADS can be understood and analyzed as the composition of smaller sets of vehicles grouped according to proximity and visibility criteria.
  - **Rights-based responsibility:** ADS are a special kind of distributed systems where each agent is responsible for managing a space in its planned route defined by traffic rules.
    - Hence, there is no interaction between the vehicles.
    - Traffic rules guarantee that if each vehicle drives safely in the free space determined dynamically by its rights, then the whole system is safe.
    - This principle of rights-based responsibility greatly simplifies the validation problem as the interaction between vehicles is unidirectional (flow-oriented).  
It is enough to show that a reference vehicle, called the ego vehicle, drives safely in its own free space.



# Compositional Testing – Metric Graphs

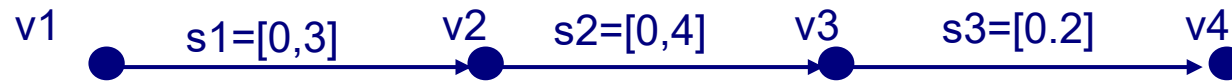
A Metric Graph is a triple  $G=(V,S, E)$  where

- $V$  : set of vertices
- $S$  : set of segments equipped with a partial composition operation  $\circ : S \times S \rightarrow S \cup \{\perp\}$  and a length norm  $\|\cdot\| : S \rightarrow \mathbb{R}_{\geq 0}$
- $E$  : set of edges  $E \subseteq V \times S \times V$

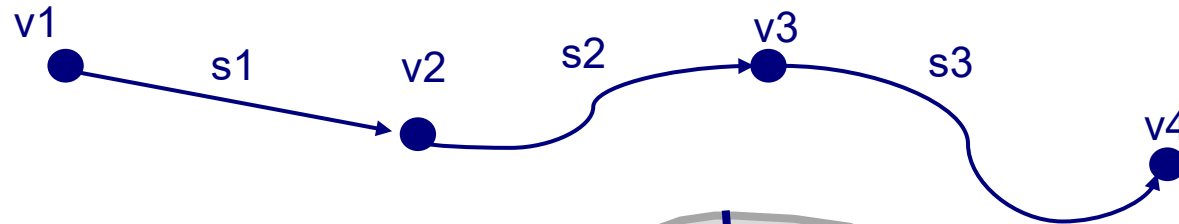
Properties of  $\circ$  :

- associativity;
- additivity:  $\|s_1 \circ s_2\| = \|s_1\| + \|s_2\|$ ;
- refinement:  $\|s\| = a = a_1 + a_2 \rightarrow \exists! s_1, s_2. s = s_1 \circ s_2$  and  $\|s_1\| = a_1, \|s_2\| = a_2$

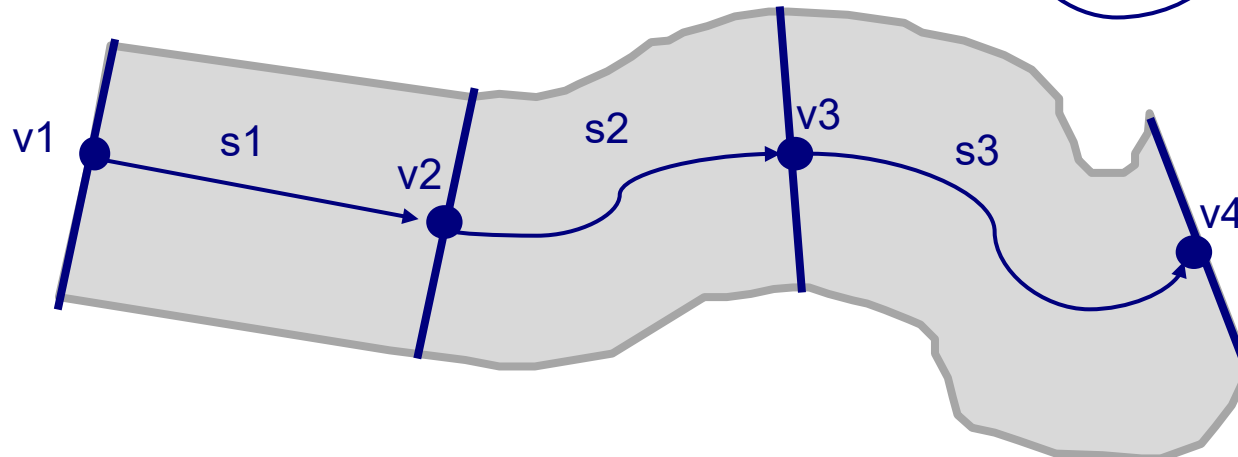
Segment  
Abstraction



Interval metric graph



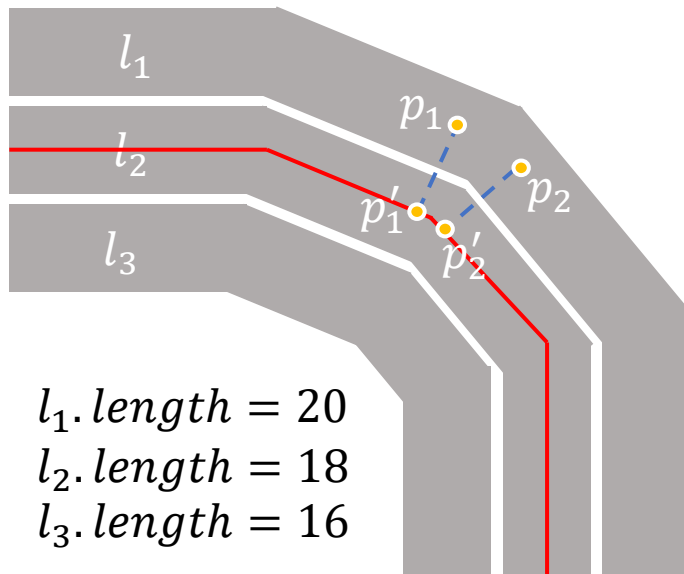
Curve metric graph



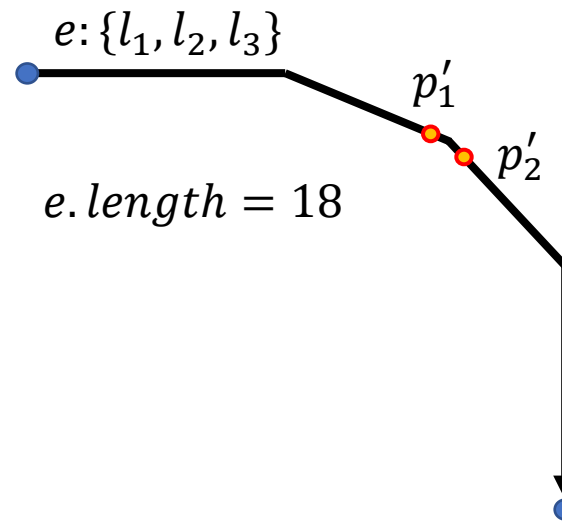
Region metric graph

# Compositional Testing – Map Compositionality

From HD maps to their abstract representation



Apollo Map



Metric Graph

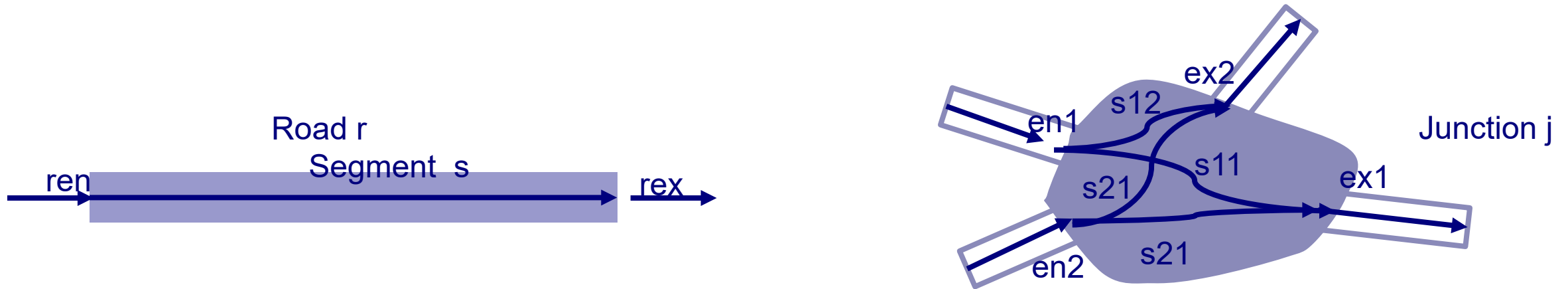
- $p_1$  on  $l_1$  is mapped to  $p'_1$  on  $e$ ;  
 $p_2$  on  $l_1$  is mapped to  $p'_2$  on  $e$ .
- The actual distance between  $p_1$  and  $p_2$  is larger than the distance between  $p'_1$  and  $p'_2$
- The difference may affect the checking of safe distance.

# Compositional Testing – Maps and ADS

□ A map  $G = \{Gr\}_{r \in R} \cup \{Gj\}_{j \in J}$  where R and J are respectively the sets of roads and junctions.

- A road r has a single entrance  $ren$  and a single exit  $rex$  connected by a segment  $rs$ .
- A junction j is a graph including a set of segments  $jS$  of the form  $sxy$  where  $x \in jEN$ ,  $y \in jEX$ .

G is obtained by gluing together exits of roads to entrances of junctions and entrances of roads to exits of junctions.



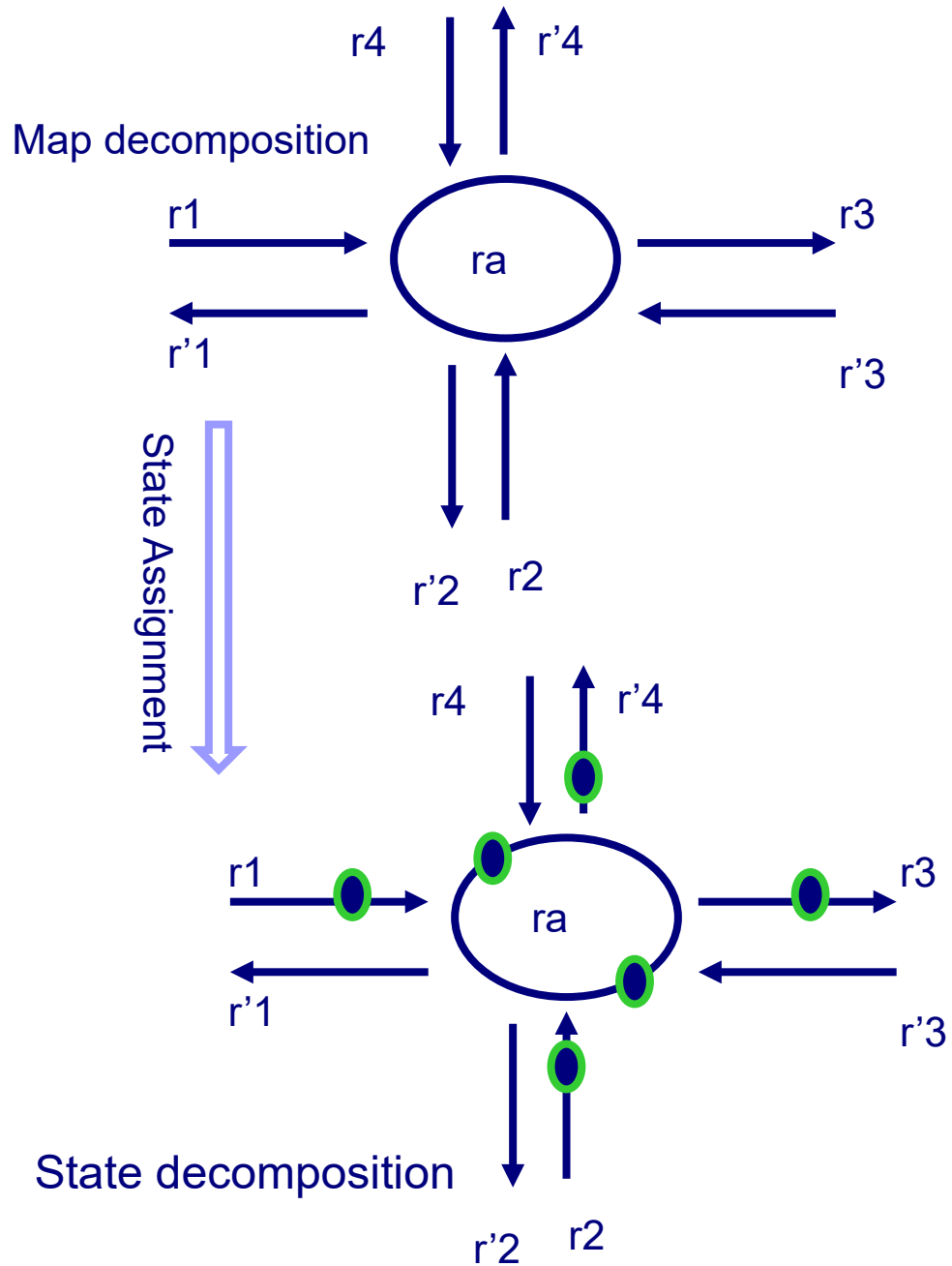
□ An ADS consists of 1) a map G; 2) a set of vehicles C and a set of objects O.

Its state is a set  $q = \{qc\}_{c \in C} \cup \{qo\}_{o \in O} = qC \cup qO$  where,

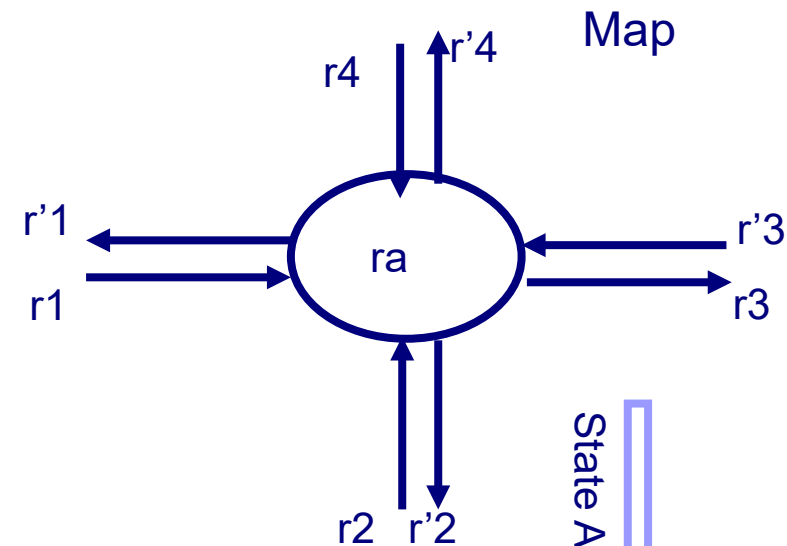
- $qc = \langle pc, vc, sc, \dots \rangle$ , where  $pc$ : position of c;  $vc$ : the speed of c;  $sc$ : a segment of the map describing the route of c
- $qo = \langle po, atto, \dots \rangle$ , where  $po$ : position of o;  $atto$  is an attribute of o e.g speed limit with  $vl$ , state of a traffic light

An ADS is a dynamic system evolving from an initial state  $q_0 = qC_0 \cup qO_0$  and through states  $q_i = qC_i \cup qO_i$  with  $q_i \xrightarrow{\Delta t} q_{i+1}$ .

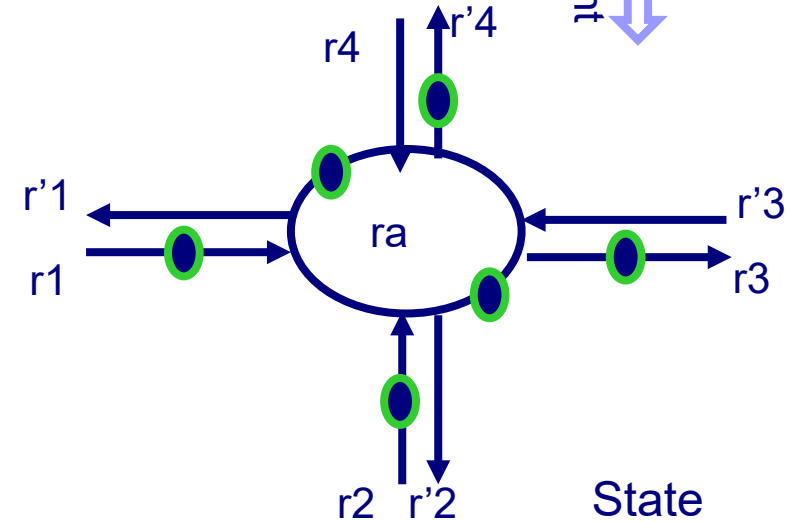
# Compositional Testing – Map and State Composition



Map composition



State composition

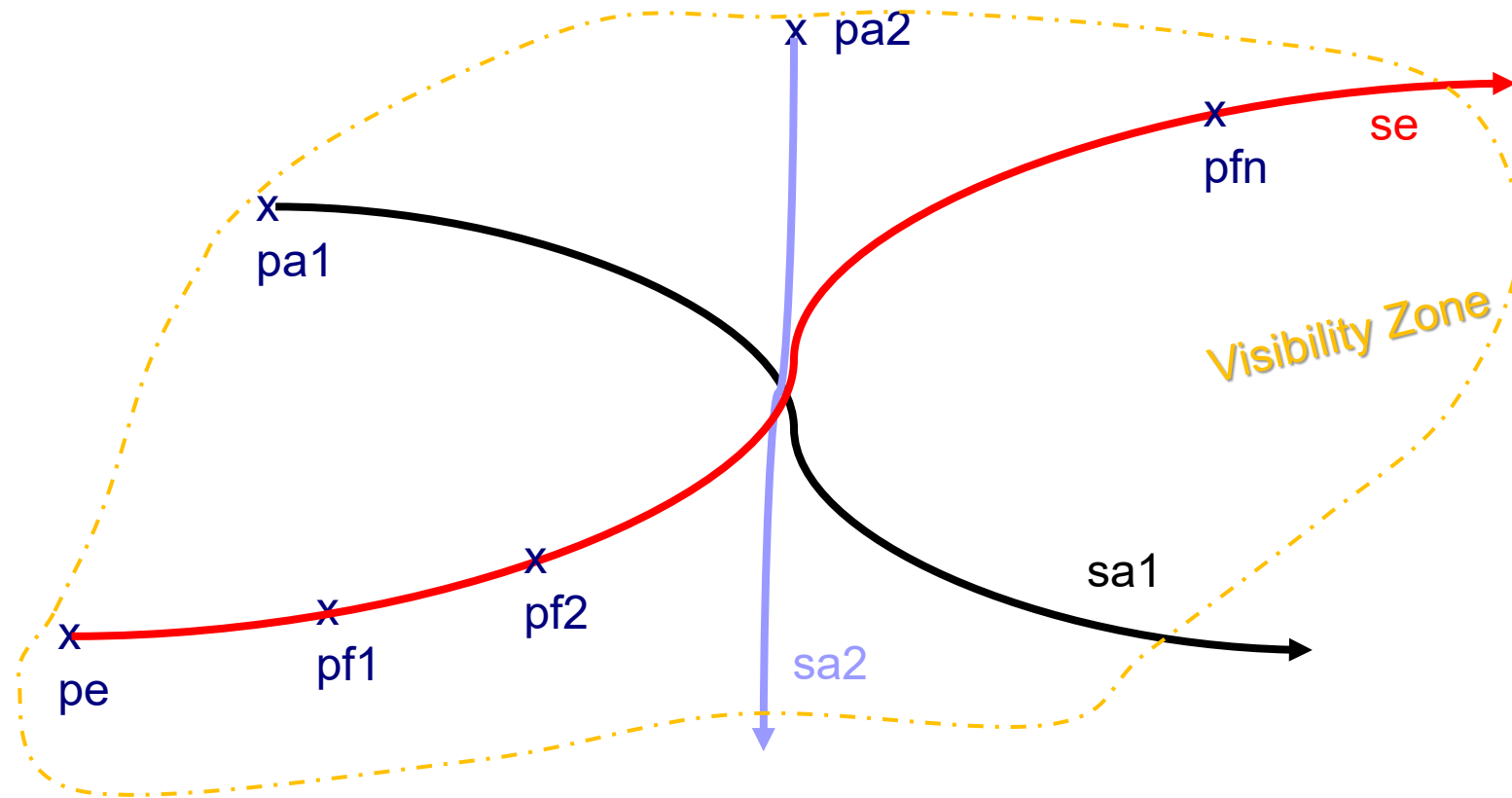


# Compositional Testing – The Concept of Vista

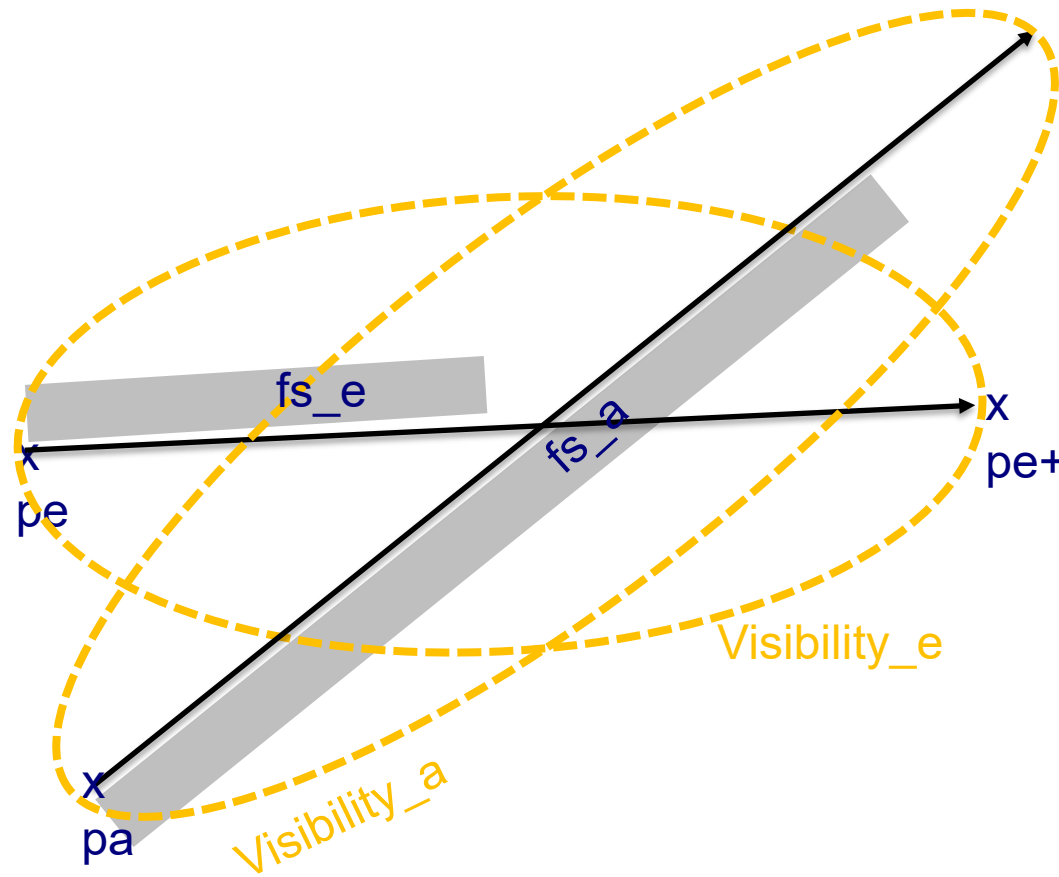
A vista is the view of the global state for an ego vehicle including all the relevant obstacles in its neighbourhood depending on its visibility.

For an ego vehicle its vista  $vse(q)$  is defined for a given state  $q$ : A vista is a set  $\{ \langle se, ve \rangle, qf1, \dots, qfn, qa1, \dots, qak \}$ , with

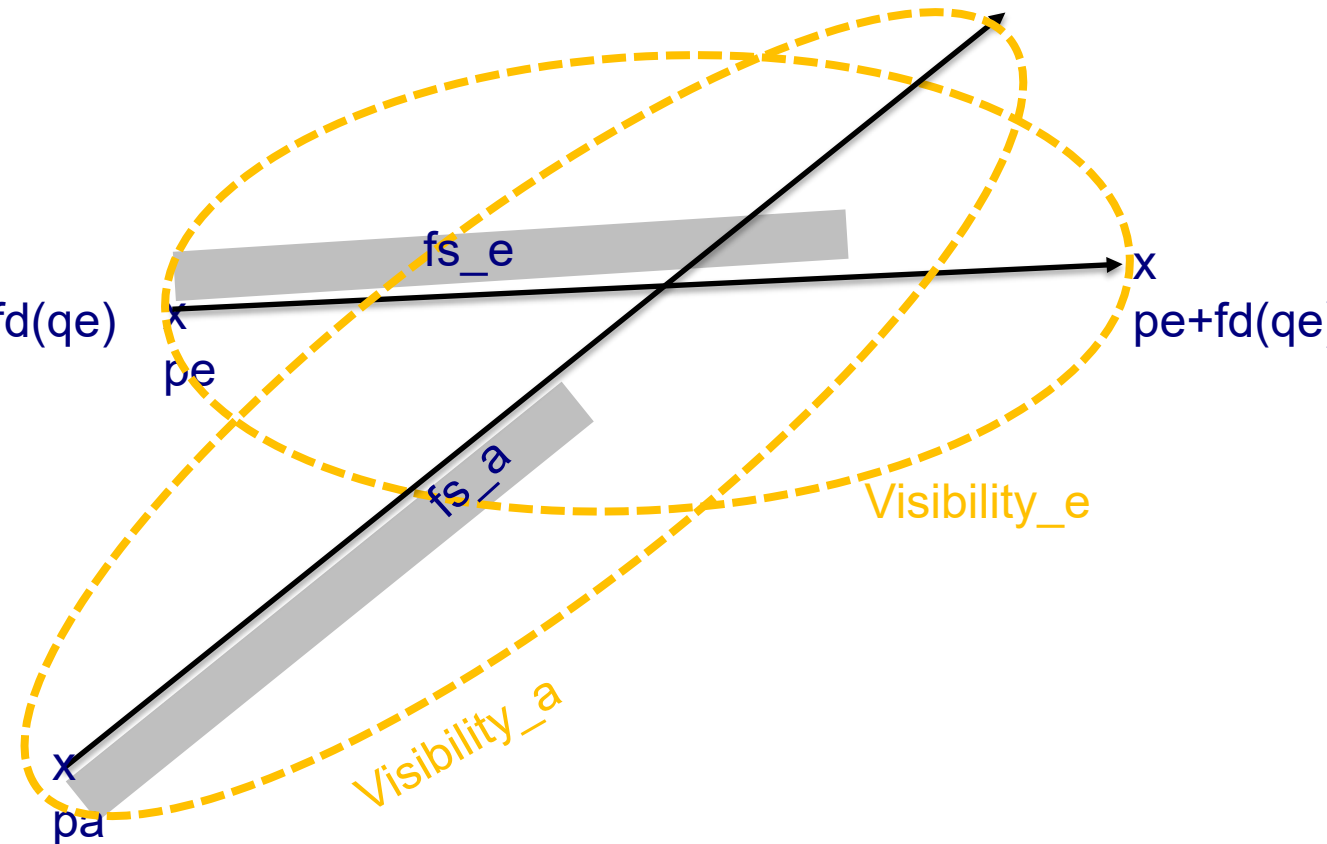
- 1) the set of the front obstacles  $F = \{f1, \dots, fn\} \subseteq C \cup O$  located in front of it (on its route segment  $se$ ) with their position and speed
- 2) the set of the arriving vehicles  $A = \{a1, \dots, ak\} \subseteq C$  whose route  $sa$  may intersect with  $se$  or merge into  $se$ .



# Compositional Testing – The Concept of Free Space

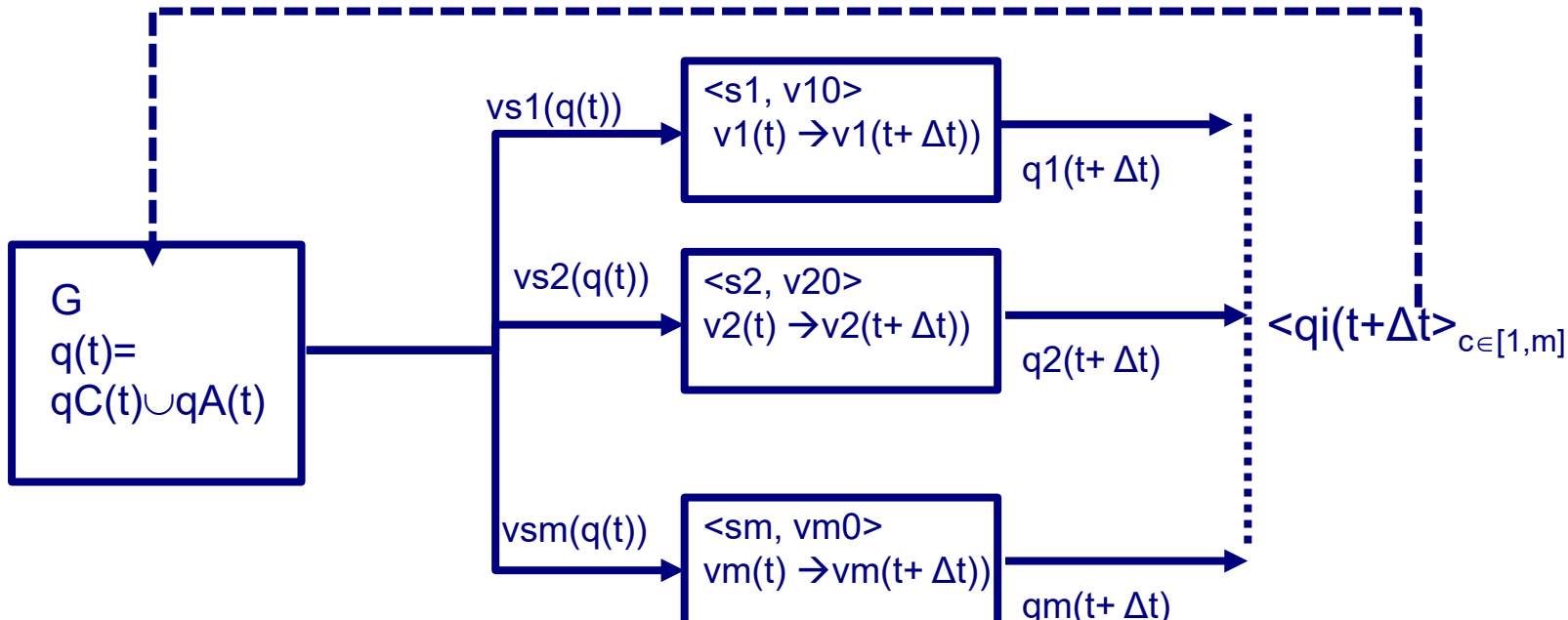
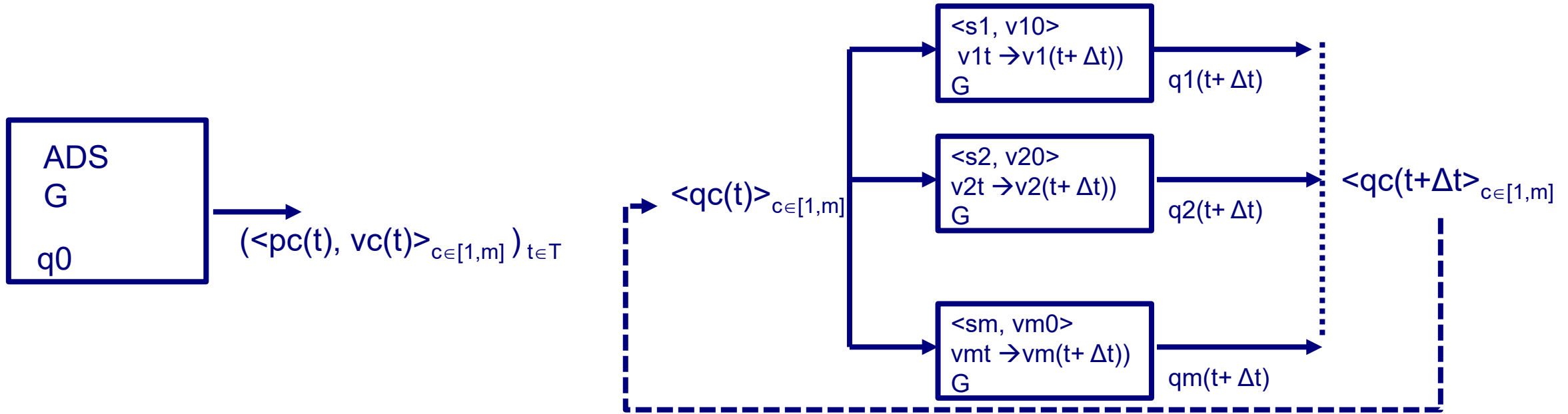


The arriving vehicle has priority over the ego vehicle that is giving way



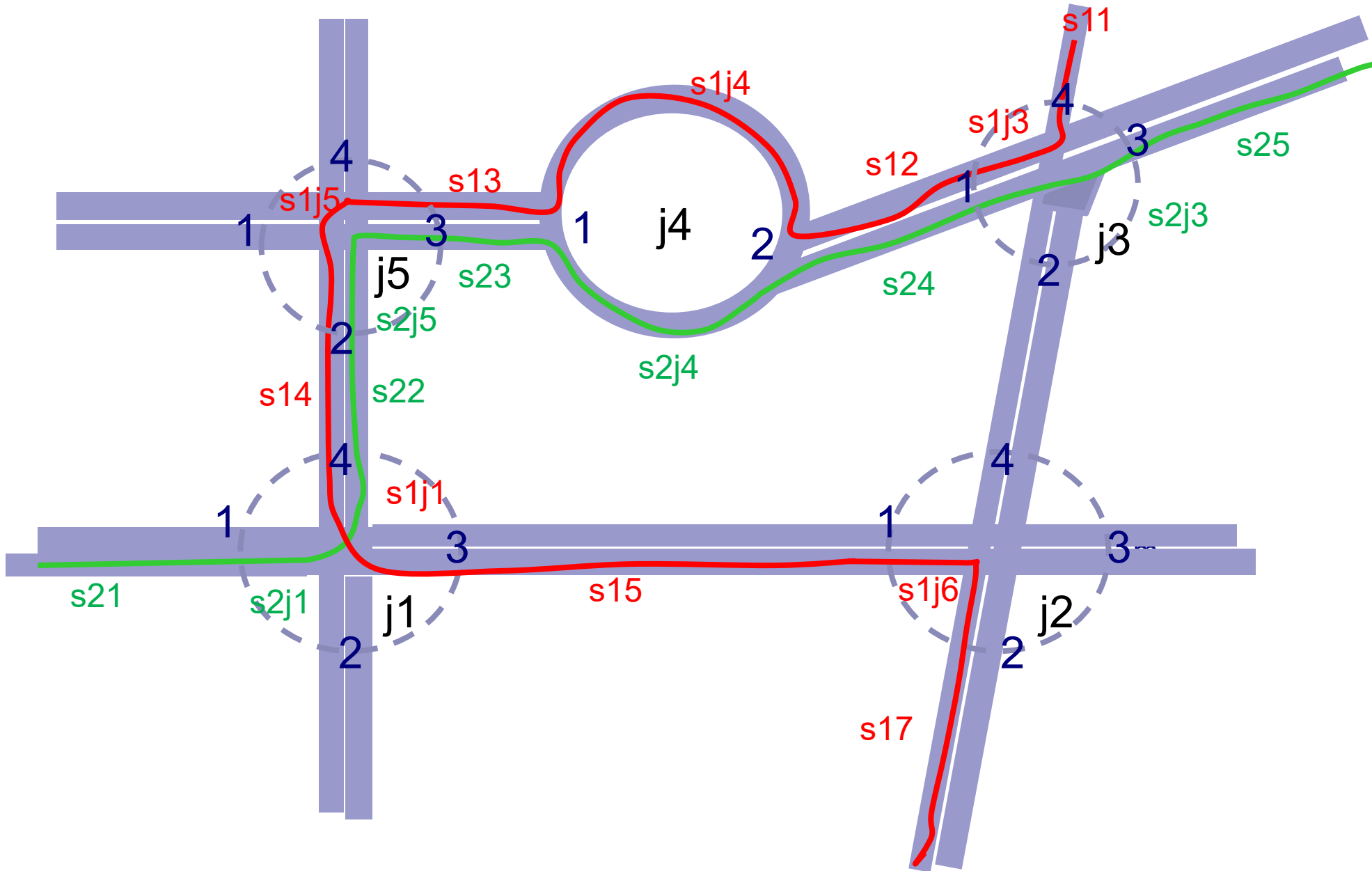
The ego vehicle decides to cross based on the distance of the arriving vehicle and the enforced speed limit

# Compositional Testing – Locality of Interaction



The vista of each vehicle is an abstraction of the relevant system state. So instead of receiving all the state  $q(t)$  it receives only vistas.

# Compositional Testing – Composition of Vistas



The route is a sequence of segments from roads, crossings and mergers that define corresponding types of vistas

For  $s1$  we have

- $s1 = s11 \ s1j3 \ (s41@j3)$
- $s12 \ s1j4 \ (s21@j4)$
- $s13 \ s1j5 \ (s32@j5)$
- $s14 \ s1j1 \ (s43@j1)$
- $s15 \ s1j6 \ (s12@j2)$
- $s17$



# Compositional Testing – The Tree Basic Vista Types

A simple analysis shows that, as a vehicle moves, its autopilot reacts to inputs that are changes in the state of its environment, characterized by three different types of vistas.

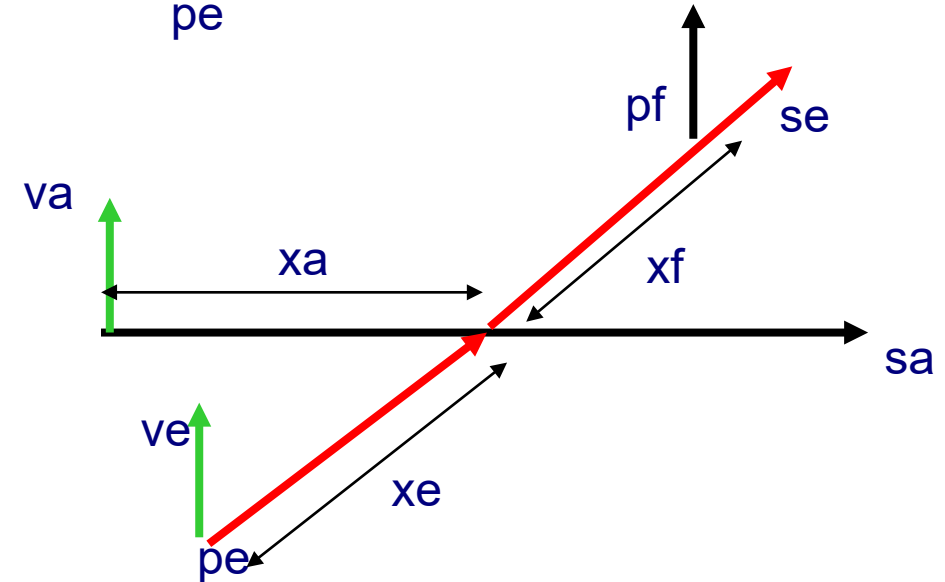
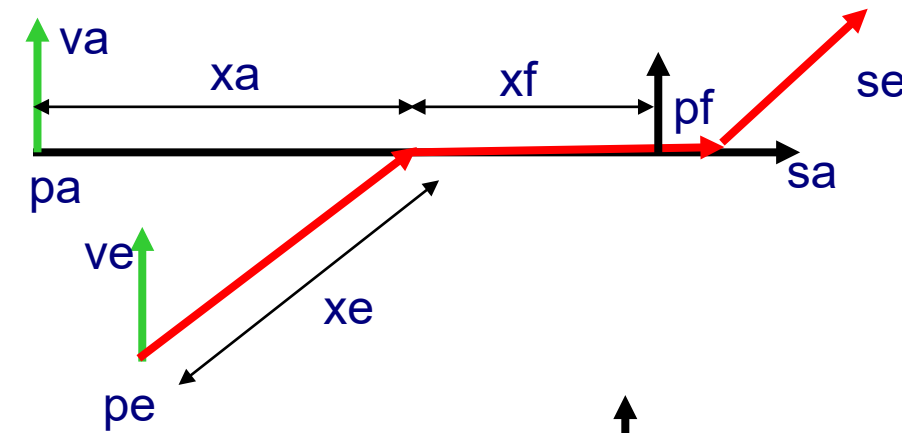
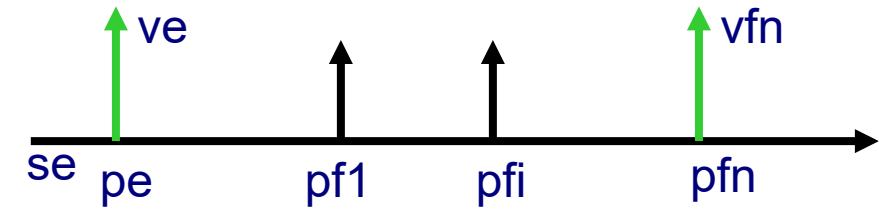
1. road vistas: where there are no crossroads in the vehicle's area of visibility, and the autopilot is tasked with taking into account the obstacles in its route ahead;

2. merging vistas: when the vehicle's route joins a road or a lane where oncoming vehicles have a higher priority and it must therefore give way to these vehicles;

3. crossing vistas: where the vehicle's route crosses a junction accessible to other vehicles, and therefore, the vehicle must comply with the traffic rules applicable in this context.

We focus on test cases for merging and crossing vistas trying to determine critical configurations of between the states of the ego vehicle the state of an arriving vehicle and the state of a front vehicle where

- The arriving vehicle moves at the maximal allowed speed limit  $v_l$
- The front vehicle is stopped



- Validation of ADS
- Compositional Testing
- Test Methodology
- Experimental Results
- Discussion

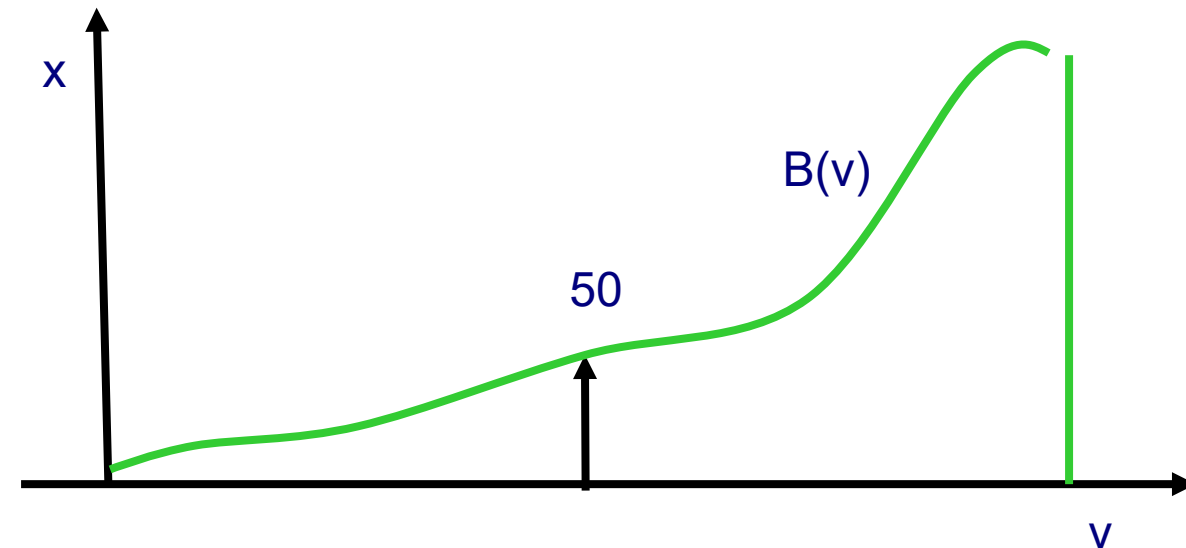
# Test Methodology – Assumptions about Policies and Vehicle Dynamics

- ❑ The test should allow detecting failures under the following assumptions:
  - The vehicles in the environment of the ego vehicle drive responsibly i.e. respect traffic rules such as speed limits, traffic lights etc.
  - Test cases should be realistic: the initial values of the states of the vehicles involved in a vista should be such that
    - The free space of each involved vehicle is large enough to be able to drive safely.
    - If there is violation of a traffic rule or an accident, it should be possible to identify responsibilities i.e. this is due to the fact that some vehicles have not applied a feasible safety control policy.
  - The test cases correspond to worst case situations (to be explained).

❑ To estimate feasible safe control policies we need to know the following A/D functions characterizing vehicle dynamics:

- The braking function  $B(v)$  that gives the required distance to brake from speed  $v$  to speed 0.
- The acceleration time function  $TA(v_0, x)$  that gives the time taken to accelerate from speed  $v_0$  traveling a distance  $x$ .
- The acceleration speed function  $VA(v_0, x)$  that gives the speed reached from  $v_0$  by accelerating for distance  $x$ .

We assume that the A/D functions are strict and monotonic.



# Test Methodology – Caution vs. Progress

A vista describes a relationship between the ego vehicle and other objects that the ego vehicle can eventually change by acting adequately. We distinguish two possible attitudes of the ego vehicle:

- Caution where the ego vehicle acts safely without changing this relationship e.g. following a vehicle, approaching a merge, approaching a crossing.
- Progress where the ego vehicle acts to change this relationship e.g. overtaking a vehicle, merging into a main road, crossing an intersection

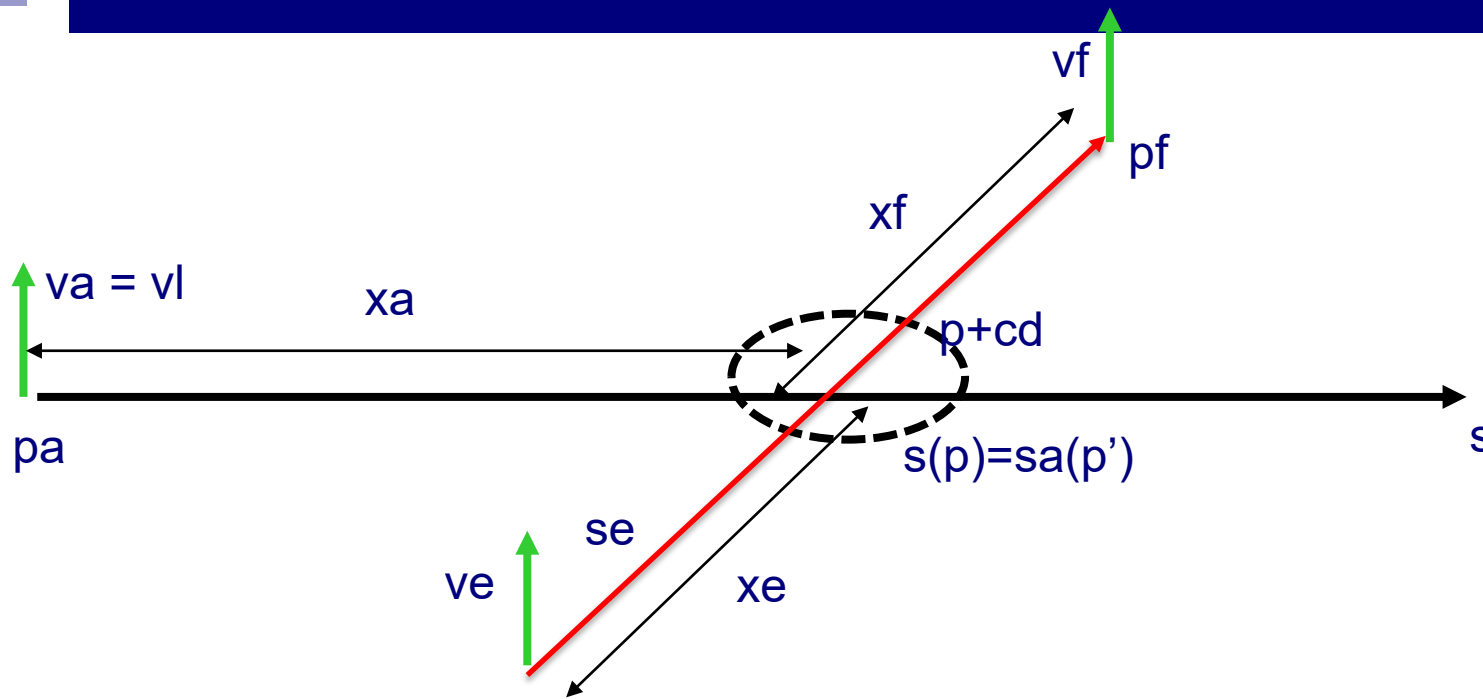
❑ Testing for caution: For each vista, determine the safe conditions for moving the ego vehicle while preserving its initial relationship with the other objects in the vista. Note that caution does not imply the obligation to move - an immobile vehicle remains cautious.

❑ Testing for progress: For each vista, determine the safe conditions for the ego vehicle to change the initial relationship with the other objects in the vista. Note that progress implies the obligation to move.

- Progress implies the ability to perform maneuvers and this allows optimizing road occupancy and avoiding bottlenecks;
- A vehicle can be cautious by applying very conservative control policies, for instance
  - move at low speed in a highway;
  - stop before a yield sign even if the priority road is clear;
  - not overtaking a slow vehicle in front, e.g. a truck, while this is permitted by the performance of the ego vehicle and the external lane is clear;
  - stop before a green light.

Note: The negation of a progress condition is an implicit caution condition that should be tested separately.

# Test Methodology – Caution vs. Progress



## Caution condition:

- As long as the ego vehicle cannot cross (not C1 or not C2), it can brake safely before reaching the critical region:  $B(ve) \leq xe$

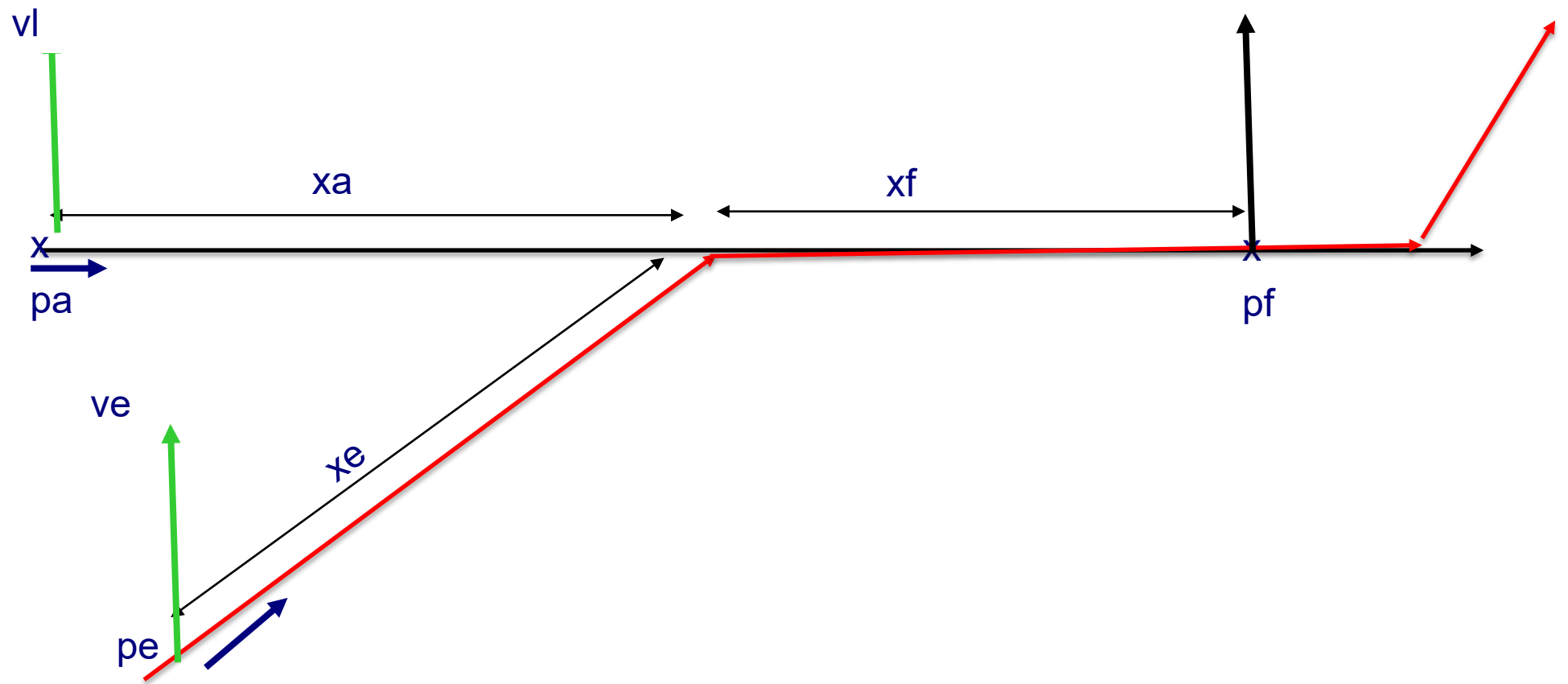
## Progress condition: The ego vehicle will cross if the following conditions hold

- **C1=  $xac \leq xa$** , where  $xac$  is a condition depending on  $xe, ve$ : an arriving vehicle has enough space to avoid collision traveling at the maximal allowed speed  $vl, d$
- **C2=  $xfc \leq xf$** , where  $xfc$  is a condition depending on  $xe, ve$ : the ego vehicle can keep a safe distance with respect to the first front vehicle

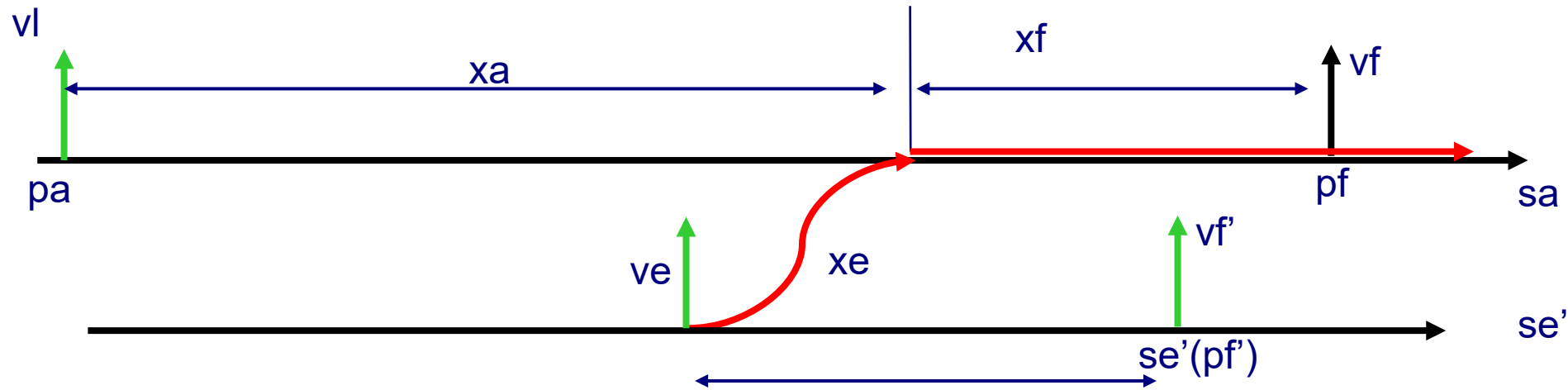
# Test Methodology – Testing Merging Maneuver

$TA(v_e, x_e)$  is the time to travel  $x_e$  from  $v_e$  by accelerating to reach speed  $v_e' = VA(v_e, x_e)$

- $C1 = v_l \cdot TA(v_e, x_e) + B(v_l) \leq x_a$        $C1 = v_e \leq a [x_a/v_l - v_l/2b] \left( \frac{a+b}{b} \right)^{1/2} - 1$ .
- $C2 = B(VA(v_e, x_e)) \leq x_f$        $C2 = v_e \leq b \left[ 2 x_f / (a+b) \right]^{1/2}$
- Worst case: both C1 and C2 are applicable: for a given  $v_e$  it determines a unique pair of critical values  $x_{ac}$  and  $x_{fc}$ .



# Test Methodology – Lane Change Vista



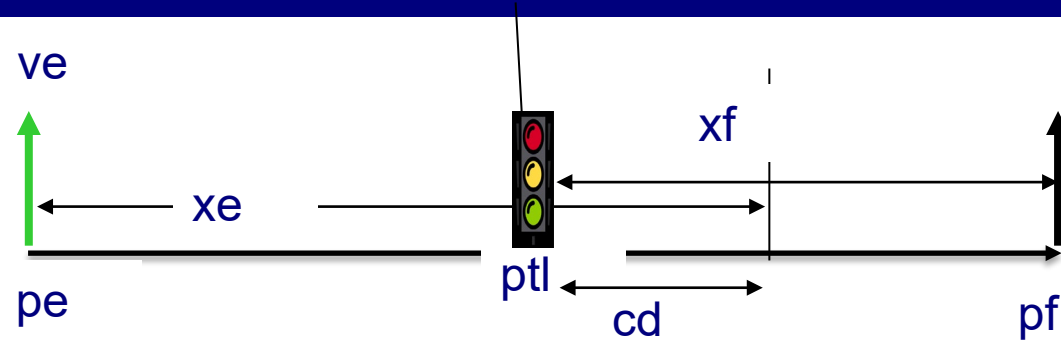
## Caution condition :

- As long as the ego vehicle does not perform a lane change (not C1 or not C2), it is in a safe braking distance with respect to the front vehicle  $f'$  i.e.  $B(v_e) \leq pf' - pe$ .
- The speed of the ego vehicle  $v_e$  is such that  $v_e \geq v_{f'}$ .

Progress condition: The ego vehicle will move to merge by accelerating if the following conditions hold:

- $C1 = v_l \cdot v_e / x_e + B(v_l) \leq x_a$  i.e. an arriving vehicle has enough space to avoid collision traveling at the maximal allowed speed  $v_l$ ,
- $C2 = B(v_e) \leq x_f$  i.e., the ego vehicle can keep a safe distance with respect to the first front vehicle on the external lane ,

# Test Methodology – Traffic Lights Vista



□ We consider a crossing with

- a critical section of length  $cd$ , guarded by traffic lights
- $t_y$  is the duration of the yellow light and  $t_{ar}$  the duration of the “all red” phase.

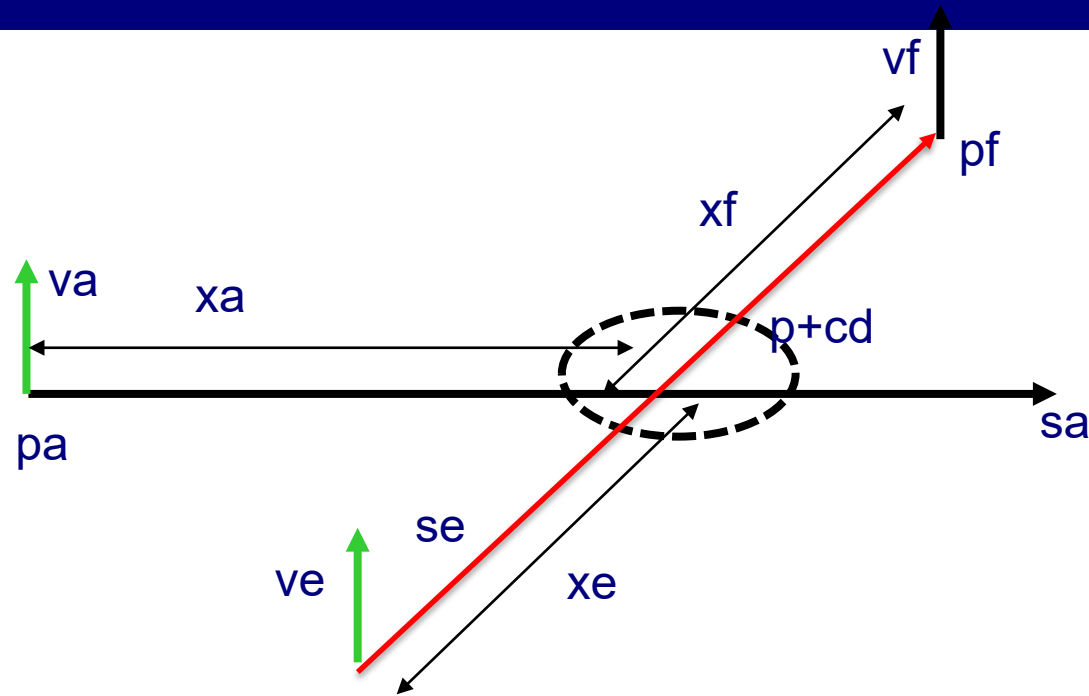
Caution condition : The ego vehicle has a speed  $v_e$  such that  $B(v_e) \leq x_e$ .

Progress condition:

- C1: The ego vehicle will cross by accelerating from distance  $d_r$  to reach a speed  $v_e'$  satisfying the conditions
  - $TA(v_e, x_e) \leq t_y$  guarantees no running a red light
  - $TA(v_e, x_e+cd) \leq t_y+t_{ar}$  guarantees exiting before the end of the all red phase
- C2:  $B(VA(v_e, x_e+cd)) \leq x_f$  guarantees no collision with the front vehicle



# Test Methodology – Crossing Vista

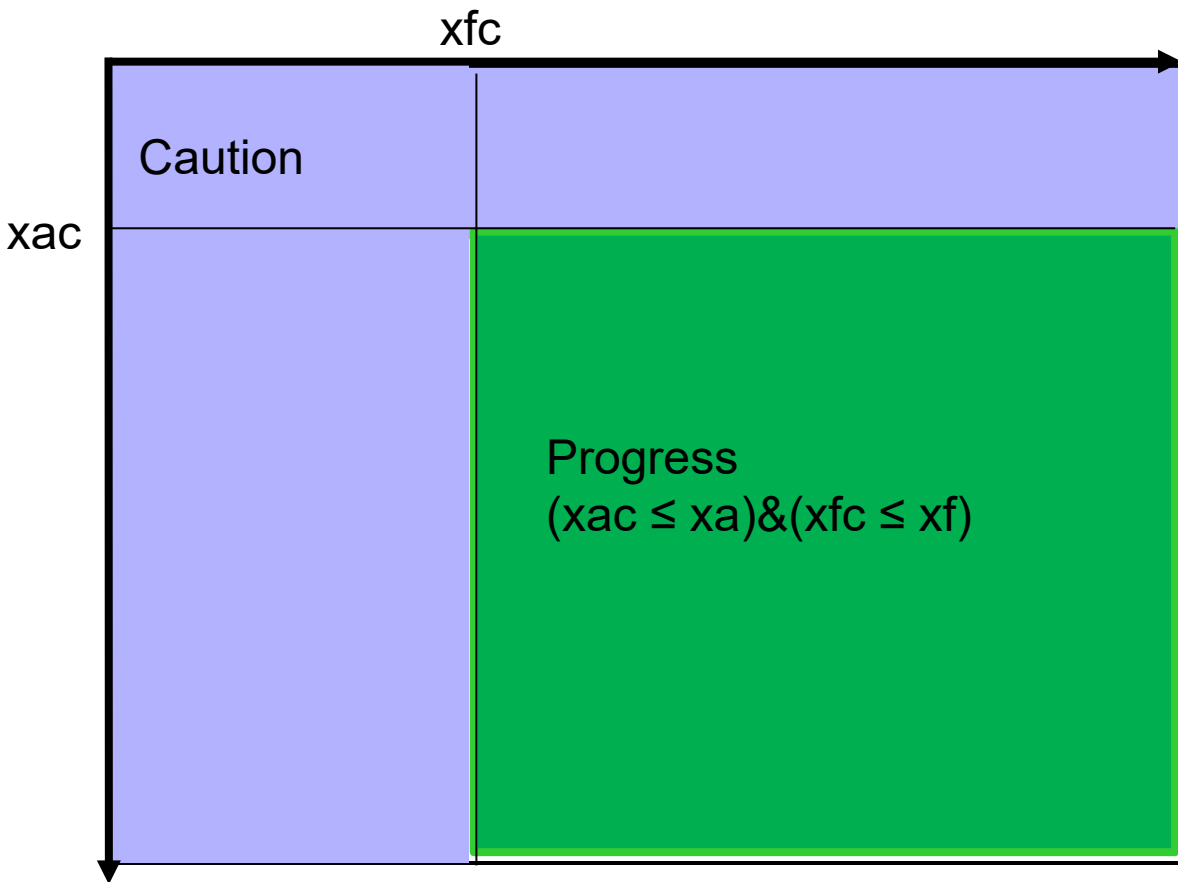


Safety condition for crossing: the vehicle can brake safely before the crossing point:  $x_e \leq B(v_e)$ .

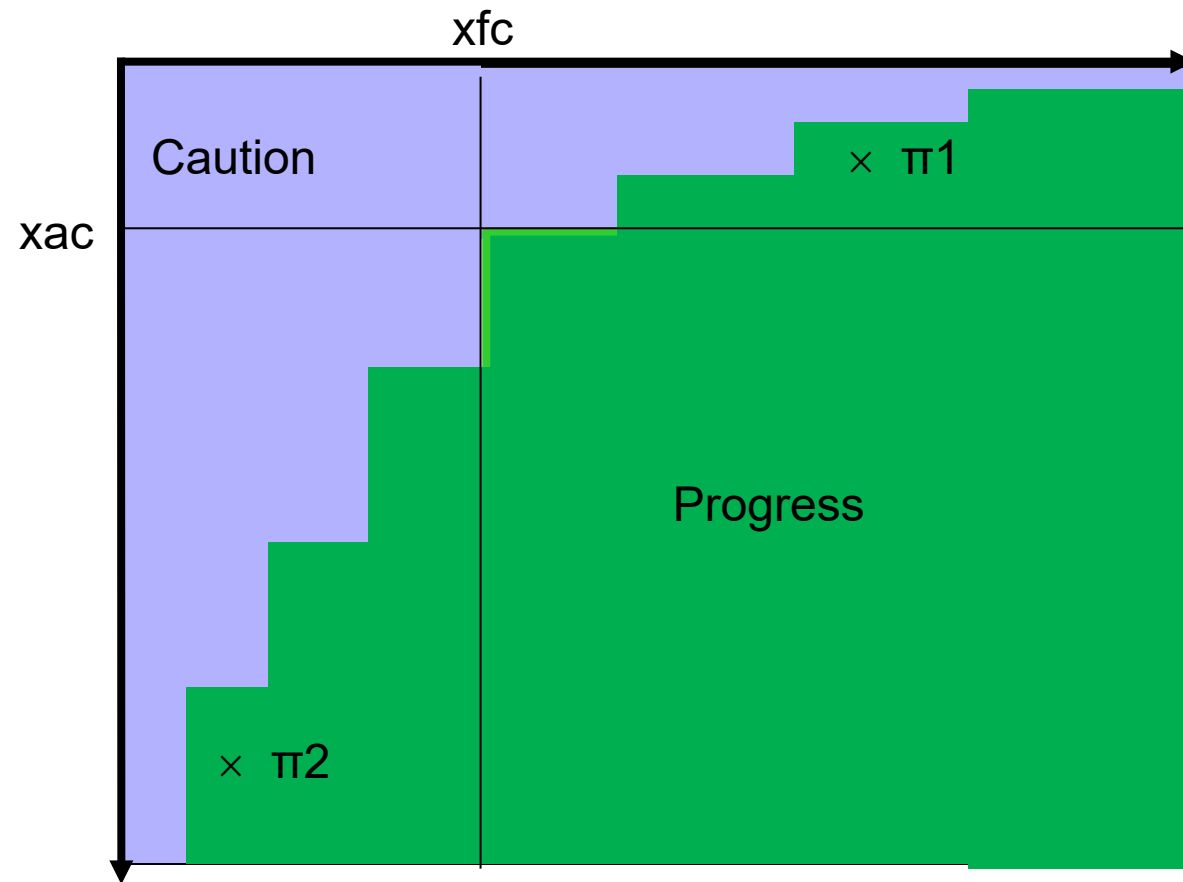
Progress condition: The ego vehicle will cross if the following conditions hold:

- $C1 = v_l \cdot TA(v_e, x_e) + B(v_l) \leq x_a$  i.e., an arriving vehicle has enough space to avoid collision traveling at the maximal allowed speed  $v_l$ .
- $C2 = : B(VA(v_e, x_e + cd)) \leq x_{ft}$  the ego vehicle can keep a safe distance with respect to the first front vehicle

# Decomposition of the Test Space



Caution/progress partition for worst case safe policies



Caution/progress partition for feasible safe policies

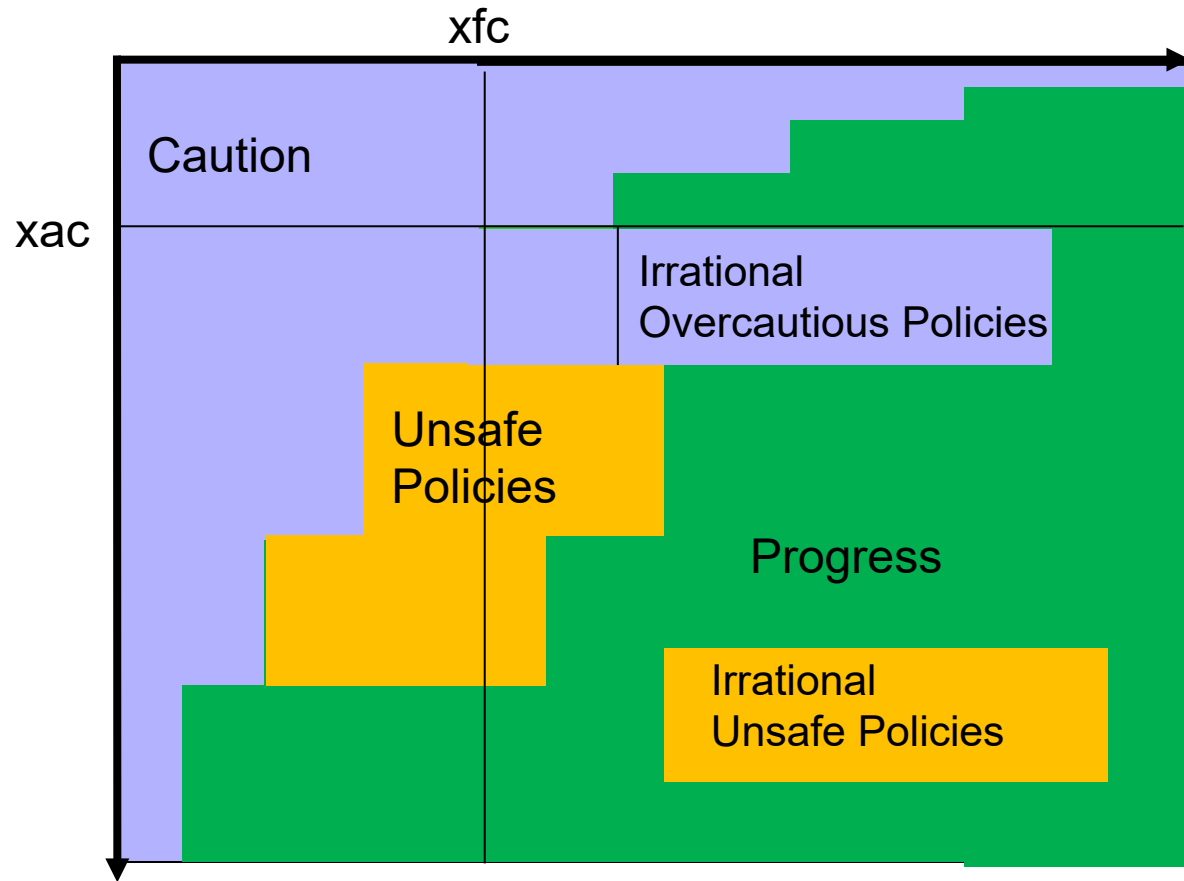
Note: The test space

- defines for given initial system state the function: Test Cases  $\rightarrow$  Verdicts for the considered scenarios (end of the caution or progress phase)
- is different from the decision space that involves also the controllable variables

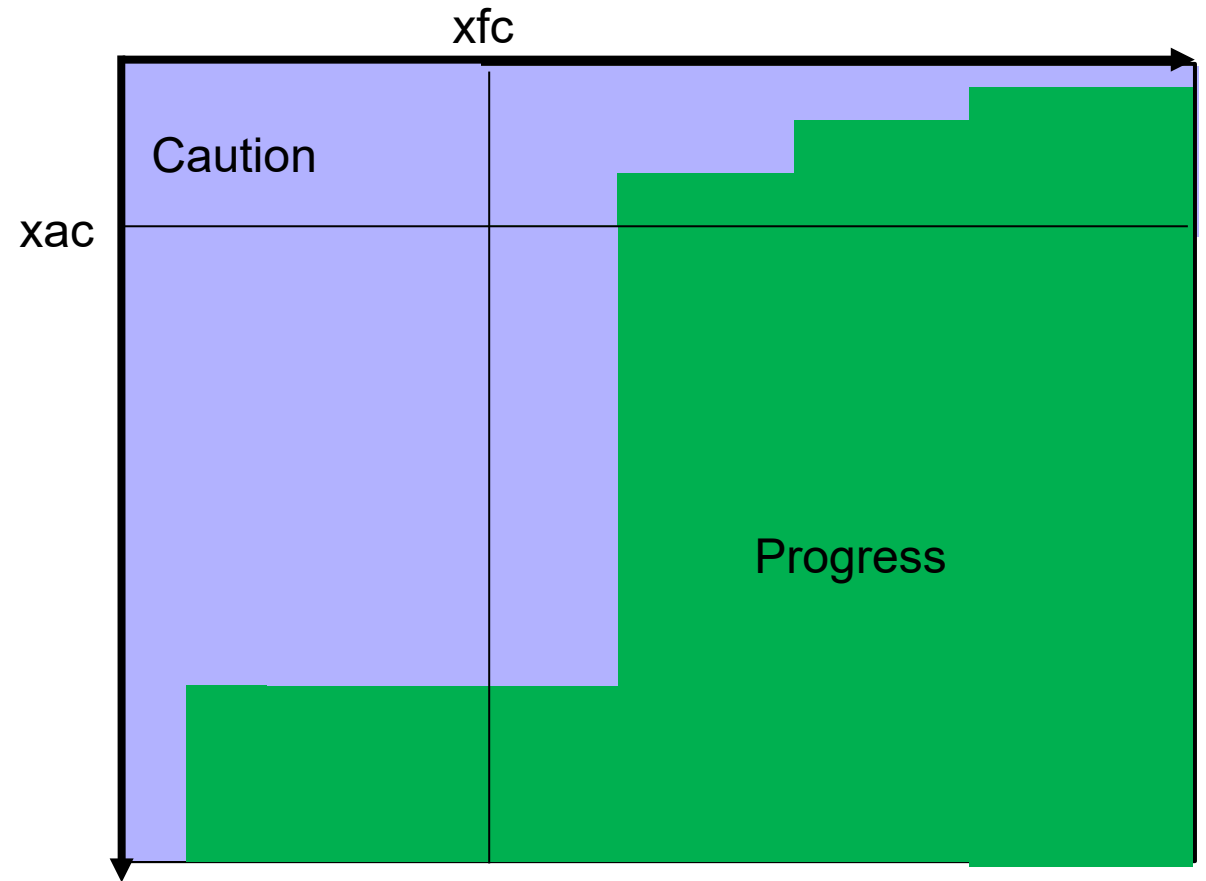
$\pi_1$ : the arriving vehicle decelerates in anticipation of the maneuver

$\pi_2$ : the ego vehicle does not fully accelerate to have enough space to stop before the front vehicle.

# Decomposition of the Test Space (2)



Undesirable situations revealed by testing



Corresponding feasible safe behavior of a rational controller

- Validation of ADS
- Compositional Testing
- Test Methodology
- Experimental Results
- Discussion

# Experimental Results – Detailed Analysis of Apollo

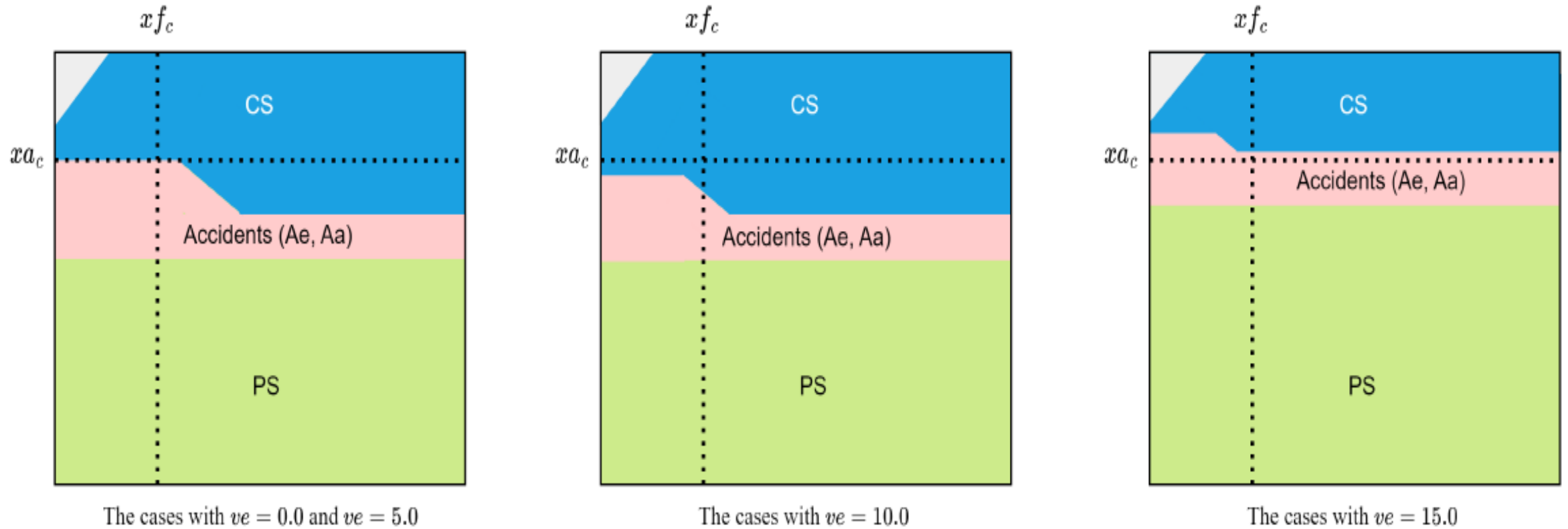


Fig. 1: Merging test cases for Apollo Autopilot

# Experimental Results – Detailed Analysis of Apollo

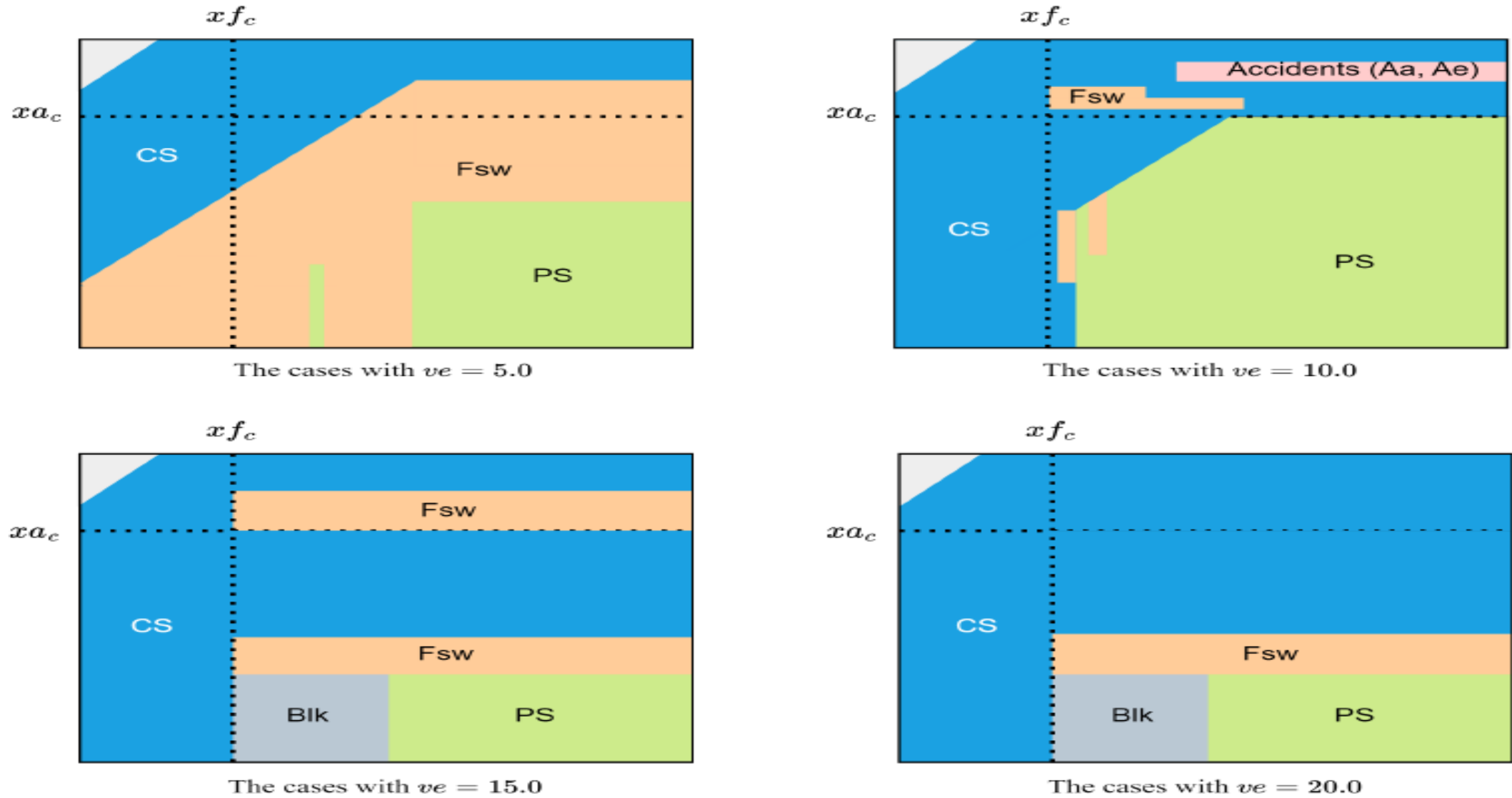


Fig. 2: Lane change test cases for Apollo Autopilot

# Experimental Results – Detailed Analysis of Apollo

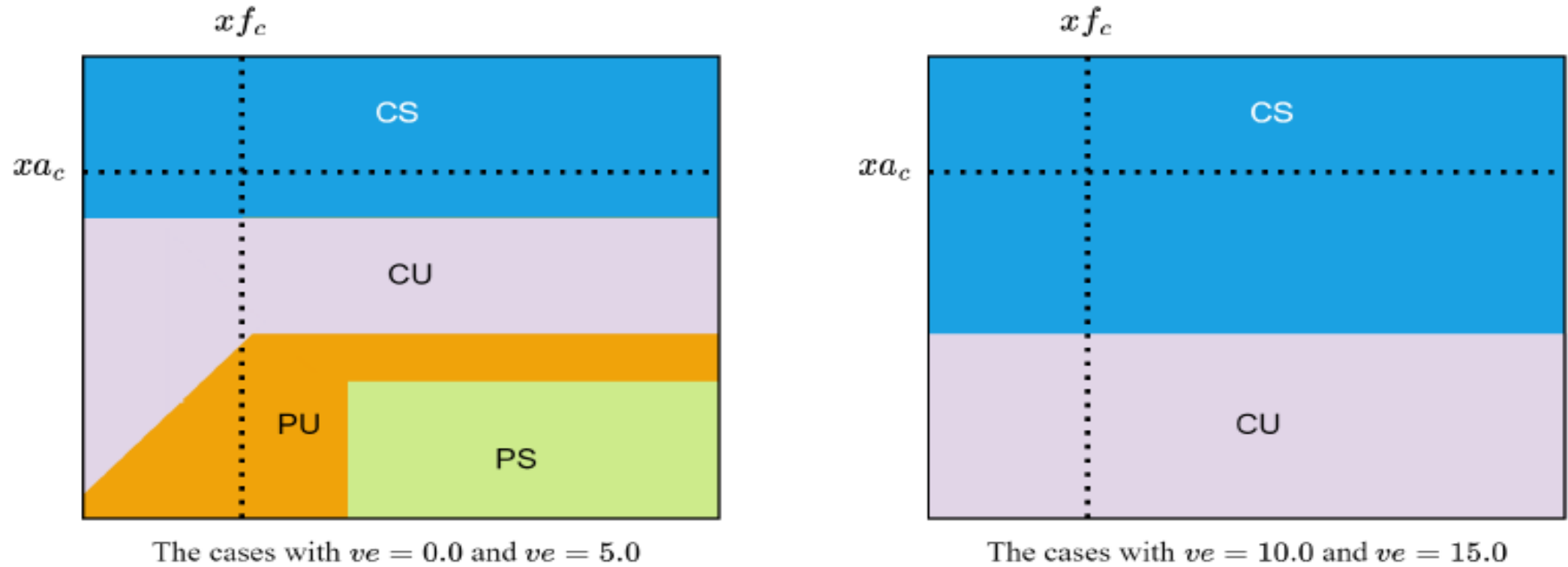


Fig. 3: Yield-sign crossing test cases for Apollo Autopilot

# Experimental Results – Effectiveness of the Method

- The method reveals safety problems for all autopilots and all vista types, with the exception of the Autoware autopilot when changing lanes and the Carla autopilot when crossing traffic lights.
- For a total of 14506 test cases, 3962 various types of defects detected, which corresponds to 27.31 % of the test cases.

**Table 26. Statistics on verdicts for merging scenarios**

Verdict	Autopilot			
	Apollo	Autoware	Carla	LGSVL
CS	432 (43.11%)	364 (37.18%)	304 (26.74%)	313 (19.95%)
PS	562 (56.09%)	439 (44.84%)	731 (64.29%)	761 (48.50%)
Ae	8 (0.80%)	12 (1.23%)	42 (3.69%)	126 (8.03%)
Aa	0 (0.00%)	164 (16.75%)	60 (5.28%)	369 (23.52%)
<b>Total</b>	1002	979	1137	1569

**Table 29. Statistics on verdicts for crossing with traffic light scenarios**

Verdict	Autopilot			
	Apollo	Autoware	Carla	LGSVL
CS	12 (19.67%)	9 (15.00%)	32 (57.14%)	0 (0.00%)
PS	32 (52.46%)	41 (68.33%)	24 (42.86%)	0 (0.00%)
CU <sub>p<sub>1</sub>p<sub>2</sub></sub>	0 (0.00%)	0 (0.00%)	0 (0.00%)	40 (75.47%)
PU <sub>p<sub>2</sub></sub>	0 (0.00%)	0 (0.00%)	0 (0.00%)	10 (18.87%)
PU <sub>p<sub>3</sub></sub>	1 (1.64%)	0 (0.00%)	0 (0.00%)	0 (0.00%)
PU <sub>p<sub>4</sub></sub>	13 (21.31%)	8 (13.33%)	0 (0.00%)	0 (0.00%)
PU <sub>p<sub>2</sub>p<sub>4</sub></sub>	0 (0.00%)	0 (0.00%)	0 (0.00%)	3 (5.66%)
PU <sub>p<sub>3</sub>p<sub>4</sub></sub>	3 (4.92%)	2 (3.33%)	0 (0.00%)	0 (0.00%)
<b>Total</b>	61	60	56	53

**Table 27. Statistics on verdicts for lane change scenarios**

Verdict	Autopilot			
	Apollo	Autoware	Carla	LGSVL
CS	1067 (39.69%)	381 (100.00%)	371 (31.15%)	887 (51.96%)
PS	727 (27.05%)	0 (0.00%)	611 (51.30%)	641 (37.55%)
Blk	212 (7.89%)	0 (0.00%)	0 (0.00%)	0 (0.00%)
Ae	0 (0.00%)	0 (0.00%)	76 (6.38%)	92 (5.39%)
Aa	15 (0.56%)	0 (0.00%)	133 (11.17%)	87 (5.10%)
Fsw	667 (24.81%)	0 (0.00%)	0 (0.00%)	0 (0.00%)
<b>Total</b>	2688	381	1191	1707

**Table 28. Statistics on verdicts for crossing with yield sign scenarios**

Verdict	Autopilot			
	Apollo	Autoware	Carla	LGSVL
CS	232 (25.69%)	63 (7.42%)	70 (7.69%)	0 (0.00%)
PS	171 (18.94%)	457 (53.83%)	408 (44.84%)	402 (41.88%)
CU <sub>p<sub>1</sub></sub>	176 (19.49%)	110 (12.96%)	60 (6.59%)	270 (28.12%)
CU <sub>p<sub>2</sub></sub>	0 (0.00%)	3 (0.35%)	12 (1.32%)	0 (0.00%)
CU <sub>p<sub>1</sub>p<sub>2</sub></sub>	161 (17.83%)	173 (20.38%)	96 (10.55%)	0 (0.00%)
PU <sub>p<sub>1</sub></sub>	2 (0.22%)	30 (3.53%)	72 (7.91%)	159 (16.56%)
PU <sub>p<sub>2</sub></sub>	8 (0.89%)	3 (0.35%)	10 (1.10%)	0 (0.00%)
PU <sub>p<sub>1</sub>p<sub>2</sub></sub>	153 (16.94%)	2 (0.24%)	98 (10.77%)	0 (0.00%)
Ae	0 (0.00%)	0 (0.00%)	48 (5.27%)	53 (5.52%)
Aa	0 (0.00%)	8 (0.94%)	36 (3.96%)	76 (7.92%)
<b>Total</b>	903	849	910	960



- Validation of ADS
- Compositional Testing
- Test Methodology
- Experimental Results
- Discussion

# Discussion – Key Findings

- ❑ The complexity of the test problem can be controlled by decomposing complex scenarios into sequences of simple types of scenarios for a limited number of traffic patterns and configurations of a small number of vehicles.
  - Simulating billions of miles without specifying how they relate to and cover real-life situations is not a convincing argument for safety.
  - Safety critical scenarios are rare and the probability of discovering such situations may be low for a car in simulation, but may become non-negligible for very large number of cars in real-life situations.
  
- ❑ The test method
  - enables detection of defects by means of a detailed analysis of vehicle dynamics, which determines critical situations when the autopilot switches from a cautious control to progress characterized by finely-tuned parameter combinations that are difficult to generate by random simulation.
  - differs from most work which focuses on simple scenarios, typically freeway driving. What's more, most simulators only allow you to control the ego vehicle, which limits the possibility of creating dangerous situations by controlling several vehicles.

## Discussion – Key Findings (2)

- The analysis of the dynamic behavior of the autopilots reveals some surprising non realistic features including the following
  - Limited maximal speed limited even on a free road e.g. 25 Km/h for MILE,
  - Non-realistic acceleration and deceleration rates e.g. 12 m/s<sup>2</sup>
  - Non rational and non monotonic policies make systematic testing impossible as they do not allow the application of the worst case principle “Who can do more can do less”
    - This is fundamental in risk management wherein the planner, in planning for potential disasters, considers the most severe possible outcome that can reasonably be projected to occur in a given situation.
    - Unlike model-based autopilots, which can be made monotonic and rational by design, these properties are difficult to guarantee for data-driven autopilots, in particular because of non reproducibility of their behavior and adversarial examples.



**THANK YOU**