

# SEMANTIC TECHNOLOGIES FOR CONNECTED VEHICLES IN A WEB OF THINGS ENVIRONMENT



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**EURECOM**  
Sophia Antipolis

**BMW GROUP**  
THE NEXT 100 YEARS 

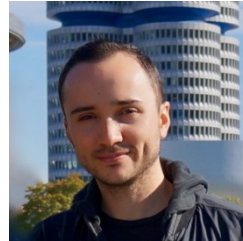


Rolls-Royce  
Motor Cars Limited

# CREDITS

– Dr. Benjamin Klotz (EURECOM / BMW)

– Daniel Alvarez Coello  
(PhD Candidate, Uni. Oldenburg)  
<https://www.linkedin.com/in/jdacoello/>



– Dr. Daniel Wilms (BMW researcher)  
<https://www.linkedin.com/in/danielwilms/>

## BENJAMIN KLOTZ

[Home](#) [Publications](#) [Contact](#)



Benjamin Klotz

PhD student

EURECOM and BMW Group



## Biography

Benjamin Klotz is a CIFRE PhD student in the Data Science Department of EURECOM and BMW Research, New Technologies, Innovation. His research focuses on applying best practices from the semantic web and Internet of Things to connected vehicles. He is also co-chair of the Data Tack force of the W3C Automotive Working Group.

## Interests

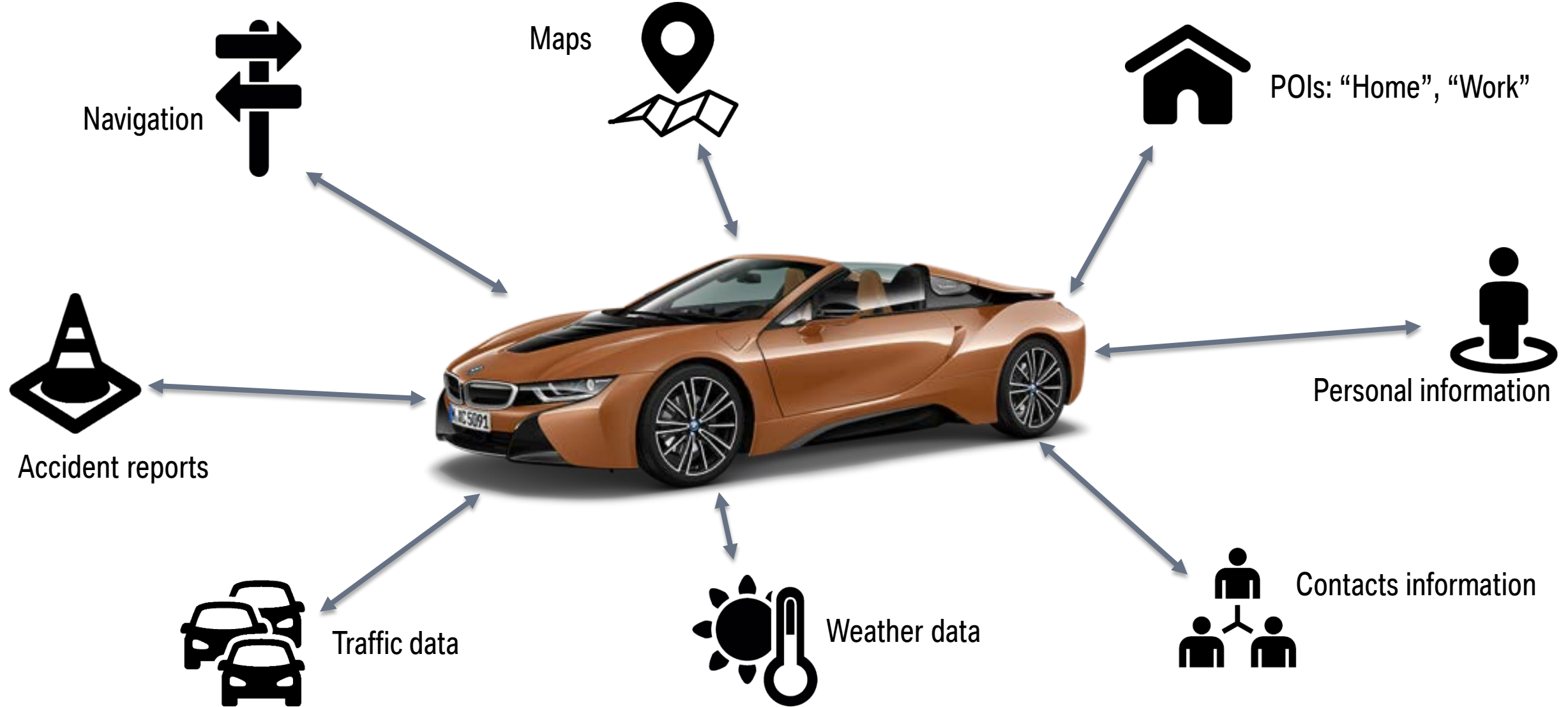
- Connected Vehicles
- Semantic Technologies
- Internet of Things

## Education

- 🎓 PhD: 'Semantic Technologies for Vehicles Data' [ongoing], 2019  
EURECOM
- 🎓 Engineering degree in Embedded systems and electrical networks, 2015  
Ecole Centrale de Nantes
- 🎓 MSc in Real-Time computing, 2015  
IRCCyN

<http://www.eurecom.fr/~klotz/>

# DATA AROUND THE AUTOMOTIVE DOMAIN





# SENSOR DATA IN THE AUTOMOTIVE DOMAIN

OpenXC

```
{"acceleratorPedal":{"position":"4095","ecoPosition":"3"},"brakeContact":"16","speedActual":"0"}, {"timestamp":"2018-01-10T17:01:27.297Z",}
```



```
{"name":"accelerator_pedal_position","value":0,"timestamp":1361454211.483000}  
{"name":"fuel_level","value":23.478279,"timestamp":1361454211.485000}  
{"name":"torque_at_transmission","value":1,"timestamp":1361454211.488000}
```

Temperature sensor

Adaptive cruise control

Front camera

Radar



Blind spot detection

Wheel speed sensor

Oil temperature sensor

Tire pressure sensor

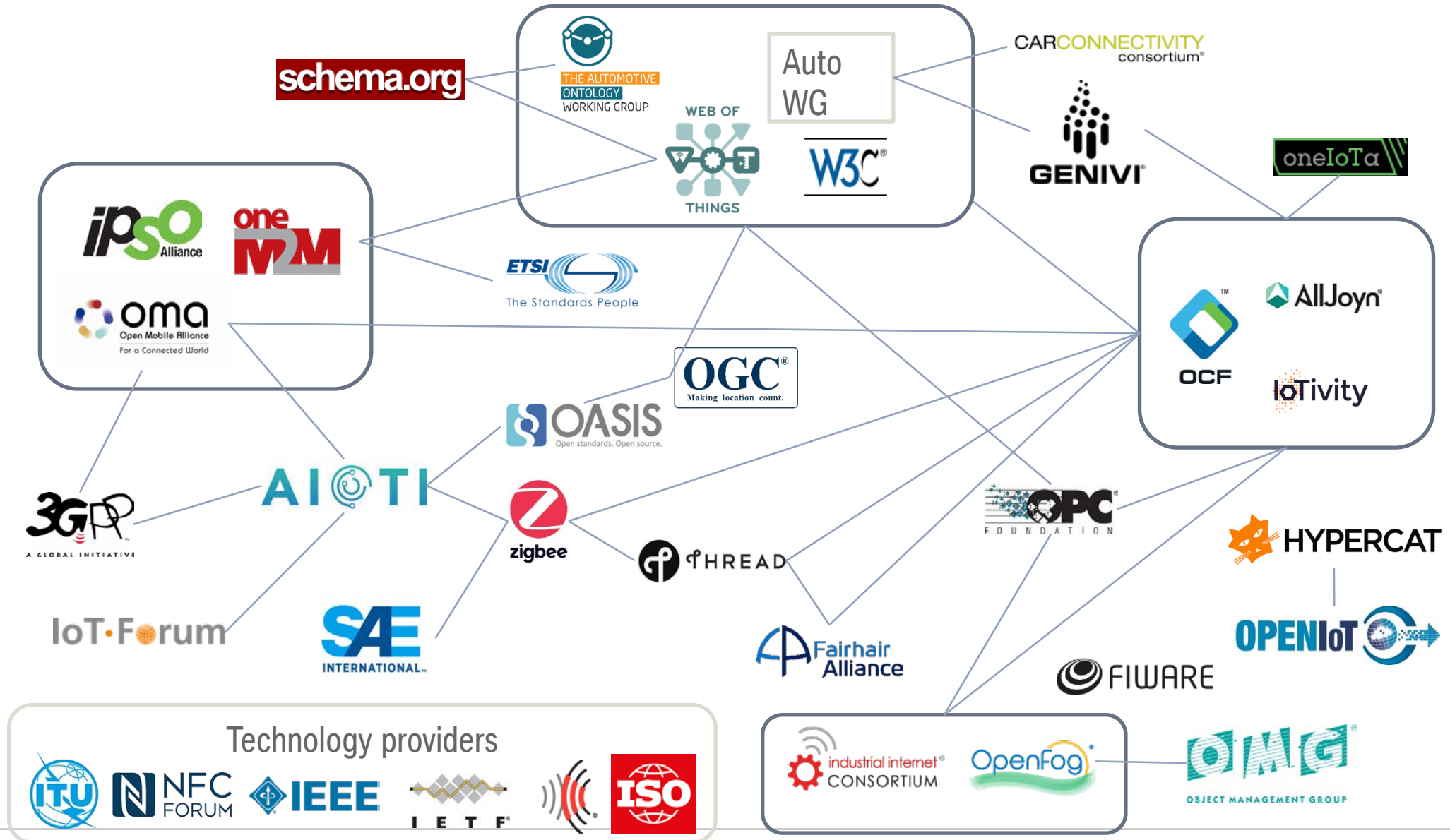
Steering angle sensor

Park assistant

Vehicle height sensor

Signal name?  
Units?  
Datetime?

# INTEROPERABILITY IN A FRAGMENTED IOT ECOSYSTEM



# HOW CAN PROVIDE INTEROPERABLE DESCRIPTION OF VEHICLE DATA?

## REQUIREMENTS: COMPETENCY QUESTIONS

Get information about attributes and signals on connected vehicles

### 32 competency questions...

#### Attributes

What type of fuel does this car need?

What is the model of this car?

How old is this car?

What type of transmission does this car have?

#### Signals and sensors

Is there a signal measuring the steering wheel angle?

How many different speedometers does this car contain?

#### Dynamic signals

What is the current gear?

What is the local temperature on the driver side?

... generated from domain needs  
on vehicle signals and attributes

Telematics



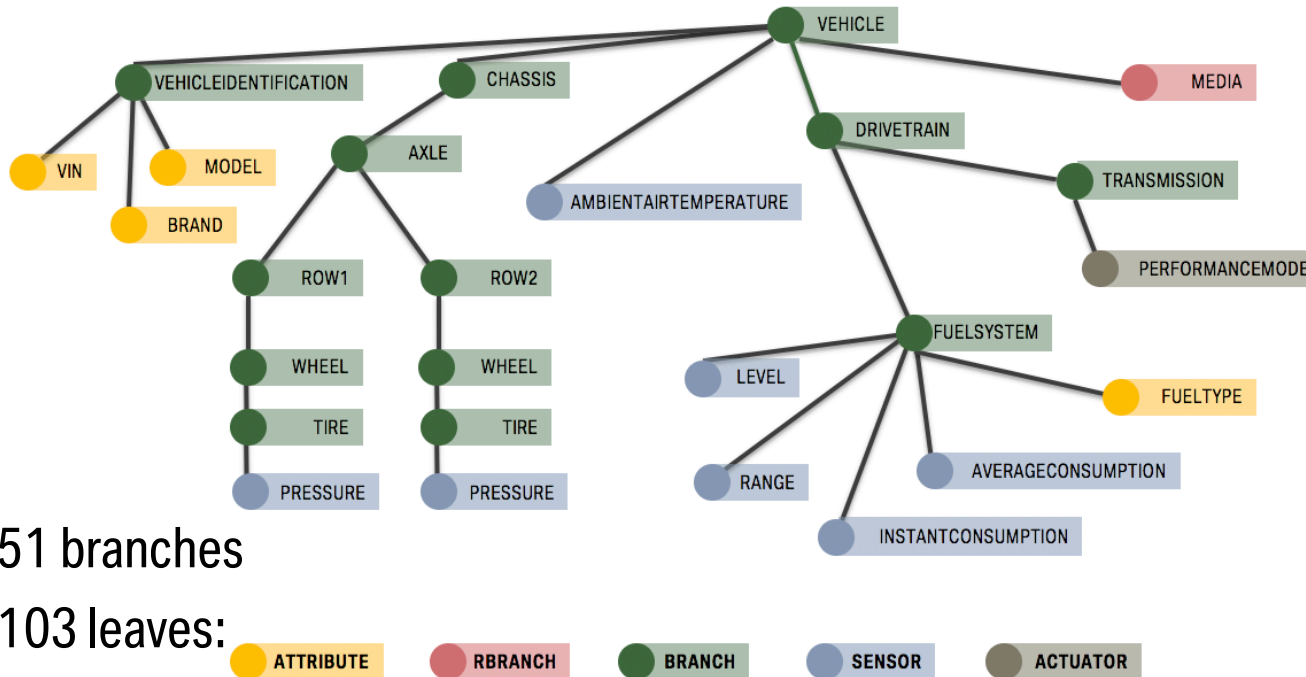
E-commerce



Garage/diagnosis

Seamless experience

# VSS IN A NUTSHELL



- 451 branches
- 1103 leaves:
  - 43 attributes
  - 1060 signals: including
    - (700 seat-related),
    - 268 with unit

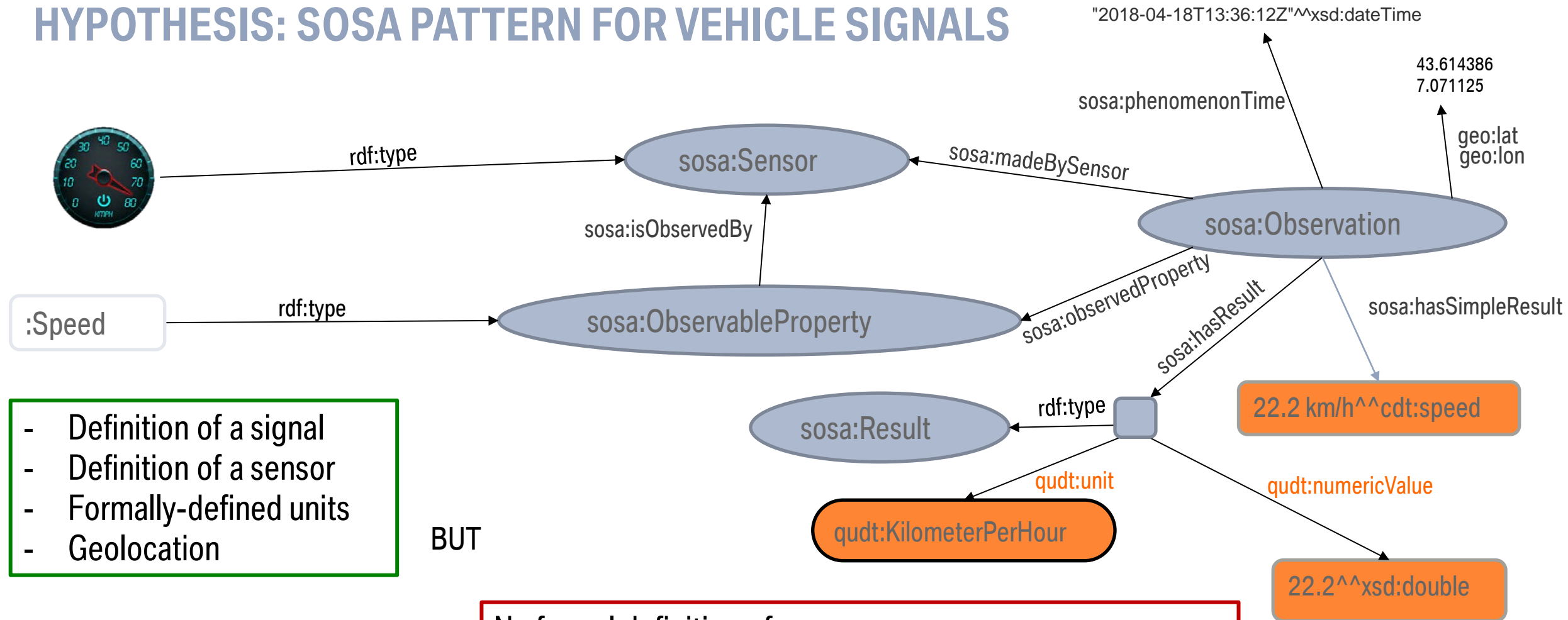
```
- Drivetrain.Transmission.Speed:  
  type: sensor  
  datatype: uint16  
  unit: km/h  
  min: 0  
  max: 300  
  description: The vehicle speed, as measured by the drivetrain.
```

VSS

- Data model: data structure for attributes, sensors and actuators of vehicles
- Specifies uniform structure for data description
  - Path / name
  - (Data-)Type
  - Unit
  - Range
  - Description
- Extensible and suitable for multi user collaboration

[https://github.com/GENIVI/vehicle\\_signal\\_specification](https://github.com/GENIVI/vehicle_signal_specification)

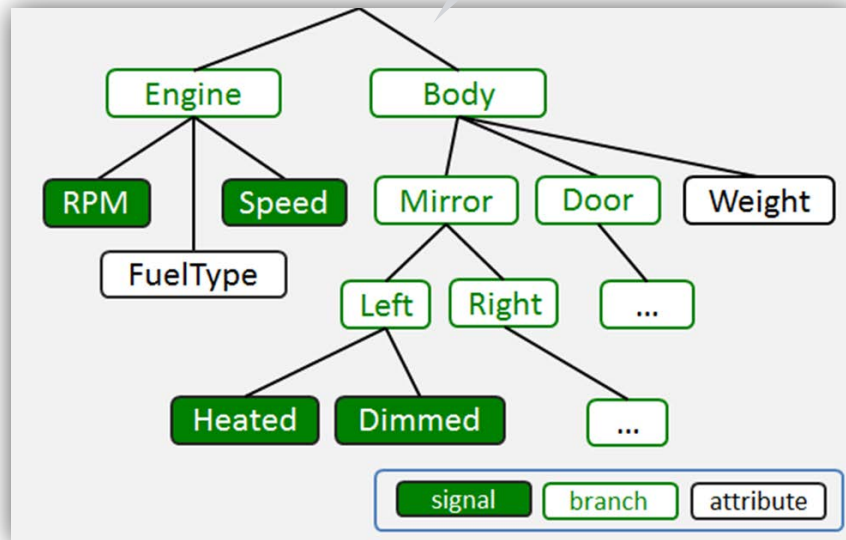
# HYPOTHESIS: SOSA PATTERN FOR VEHICLE SIGNALS





# VSSo DEVELOPMENT

VSS



Reuse design patterns  
- SSN/SOSA  
- QUDT (unit)

Generate definition of  
VSS concepts

Fixing problems

Manually validate and  
clean the generated  
ontology

VSS ontology (VSSo)

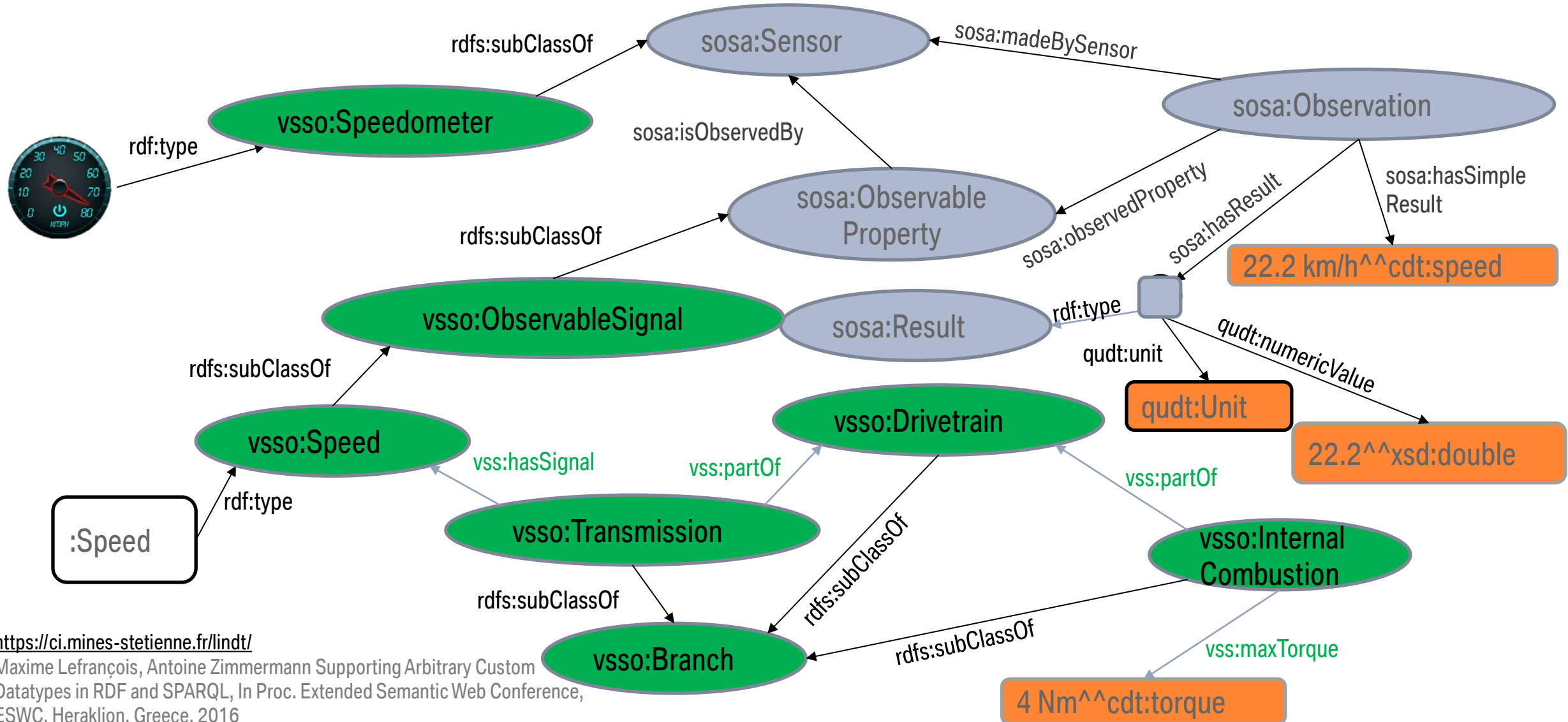
Add sensors and  
actuators

## Fixing problems

1. VSS concepts have unique names
2. All signals are either observable, actuatable or both
3. Different signals can yield the same phenomenon (e.g. speed)
4. All branches are part of the top “vss:Vehicle” branch
5. All position-dependent branches have a property “position”

Benjamin Klotz, Raphael Troncy, Daniel Wilms, and Christian Bonnet. VSSo: A Vehicle Signal and Attribute Ontology. In 9th International Semantic Sensor Networks Workshop (SSN), Monterey, California, October 2018.

# VSSo EXAMPLE



# VSSo SUMMARY

**VSSo: a Vehicle Signal and Attribute ontology** (<http://automotive.eurecom.fr/vsso>)

- OWL ontology of DL expressivity: ALUHOI+
- 483 classes (~300 signals); 63 properties (~50 attributes)
- Reuse SSN/SOSA modeling patterns

## Evaluation:

**Hypothesis:** VSSo data enables SPARQL queries answering the set of competency questions

**Dataset:** simulated (random) values for 19 signals and 23 fixed attributes on a sliding window of 3 seconds

**Experiment:** set 2 SPARQL endpoints with VSSo data (with 1 vehicle, with a fleet of 3 vehicles)

<http://automotive.eurecom.fr/simulator/query>

<http://automotive.eurecom.fr/simulator/fleetquery>

# VSSo USAGE

## VSSo expressivity: most requirements can be translated into SPARQL queries

What are the dimension of this car?

```
SELECT ?length ?width ?height
WHERE { ?branch vss:length ?length;
        vss:width ?width;
        vss:height ?height.}
```

**90%** of competency  
questions can be answered

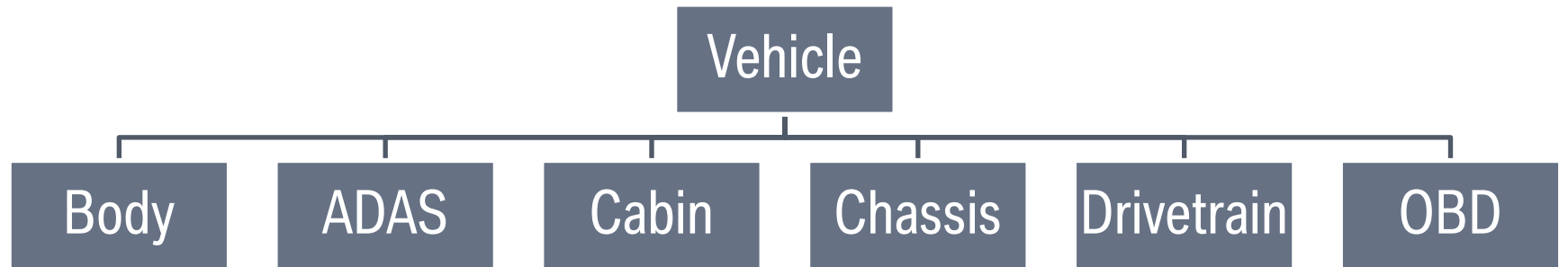
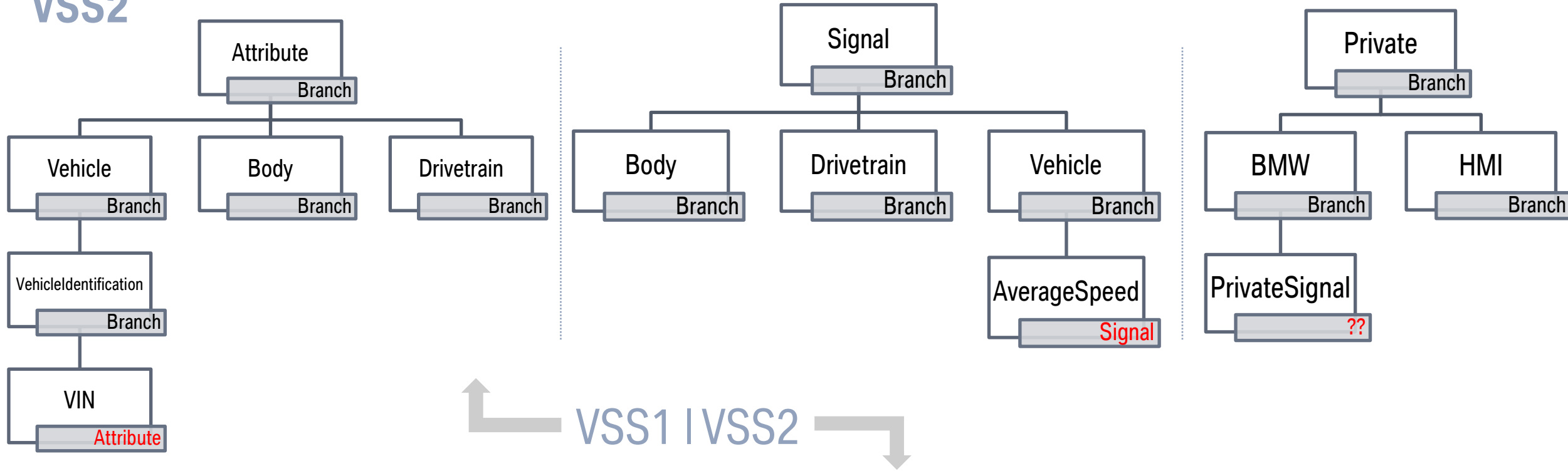
<http://automotive.eurecom.fr/simulator/query>  
<http://automotive.eurecom.fr/simulator/fleetquery>

What is the current temperature on the driver  
side?

```
SELECT DISTINCT ?localTemperature ?value ?position ?time
WHERE { ?wheel a vss:SteeringWheel;
        vss:steeringWheelSide ?steeringWheelSide.
        ?branch a vss:LocalHVAC;
        vss:position ?position;
        vss:hasSignal ?localTemperature.
        ?localTemperature a vss:LocalTemperature.
        FILTER regex(str(?steeringWheelSide),str(?position))
```

```
?obs a sosa:Observation;
        sosa:observedProperty ?localTemperature;
        sosa:hasSimpleResult ?value;
        sosa:phenomenonTime ?time.
}
ORDER BY DESC(?time)
LIMIT 1
```

# VSS2



Private branches and leaves should:

- Overwrite pre-existing concepts
- Extend the VSS tree

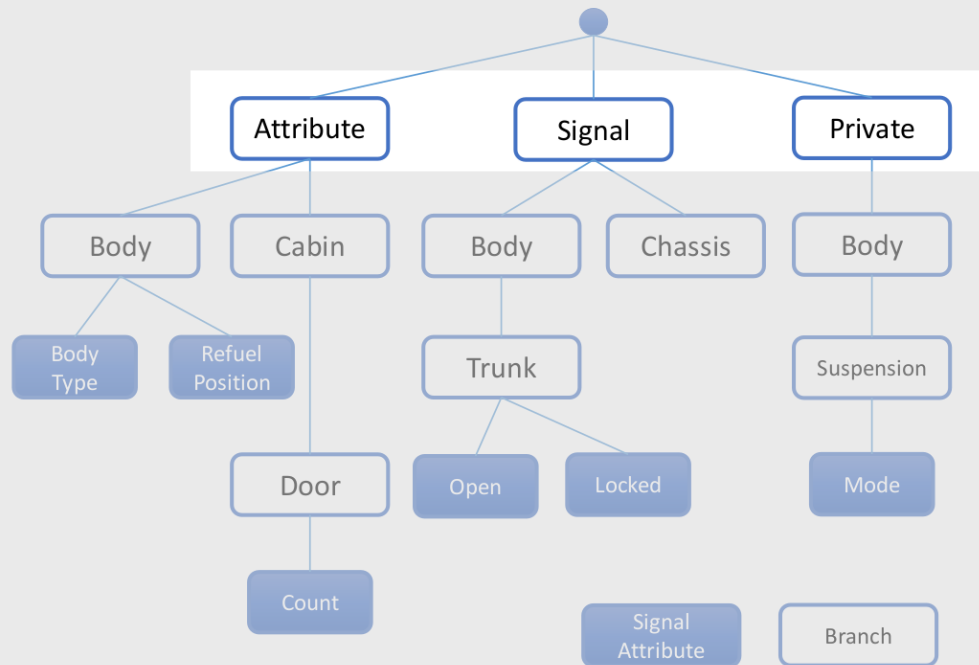
VSS needs consistent position patterns



# TYPES

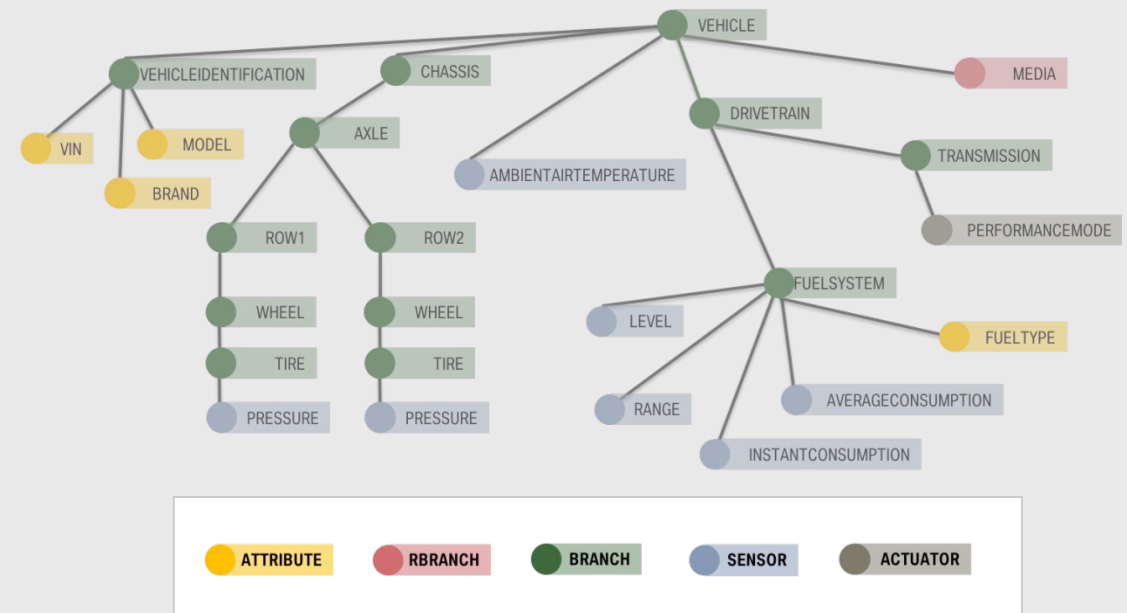
**VSS 1 - Attribute/Signal Branch:** Attributes and signals were handled as separate branches from the root node, which lead to:

- Duplication in the tree structure
- Leaf properties handled as branches



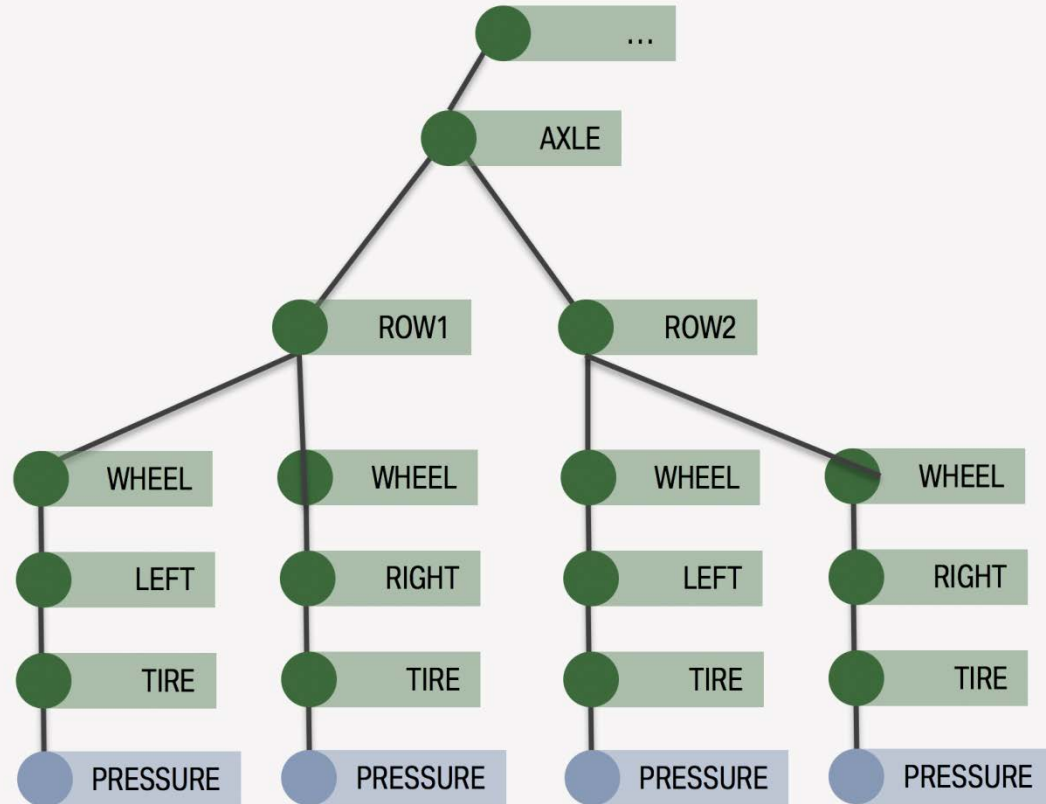
**VSS 2 - Introducing new types:** To avoid duplication and to add the properties to the leaf, new types were introduced and datatypes got their own property.

- Branch: Node in the tree, which has subnodes
- Sensor: Read-only, which updates in some interval x
- Actuator: sensor + write
- Attribute: read-only and static

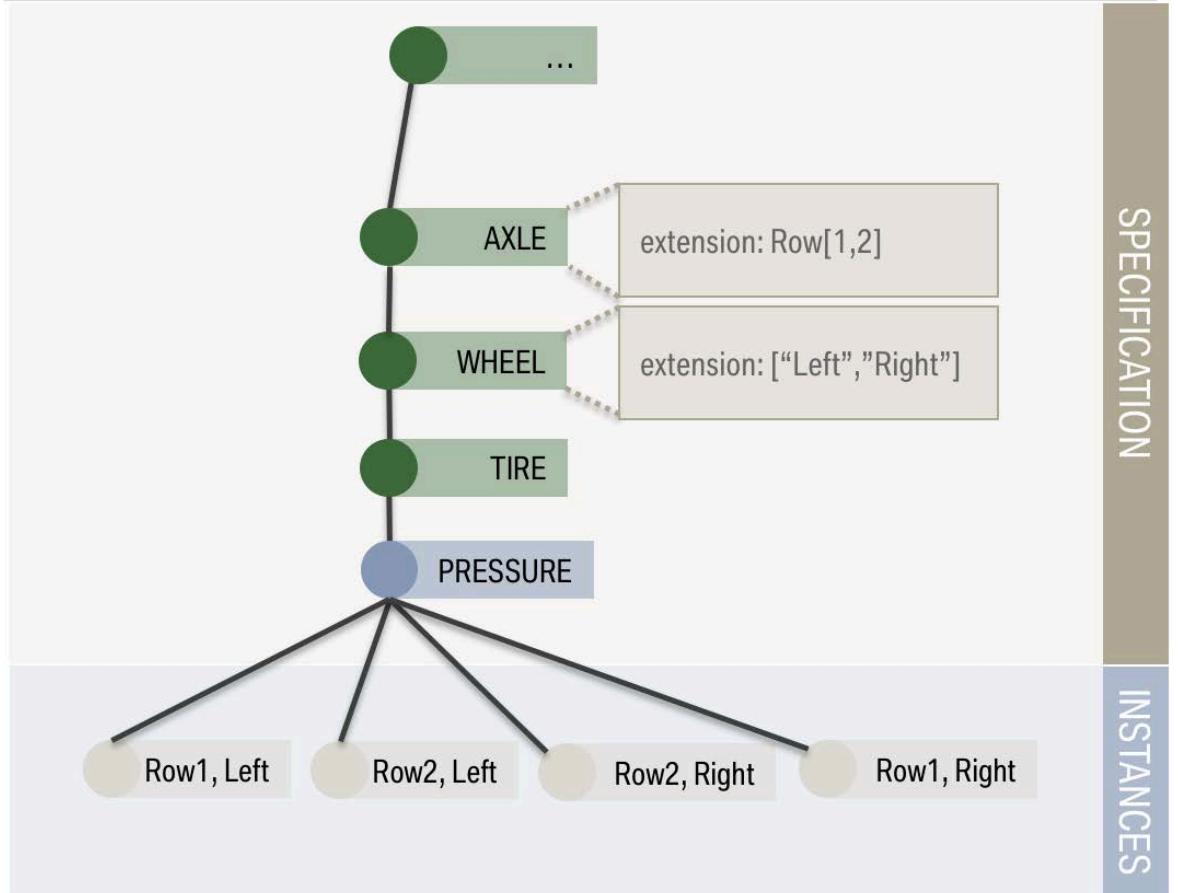


# EXTENSIONS

**VSS 1 – Extensions as branches:** Extensions, often used for positioning, are modeled in the path of the tree. This leads to duplication in the resulting tree (not in tooling), which makes the tree hard to read. Further it hardens filtering and zoning, e.g. like all left tire pressures.

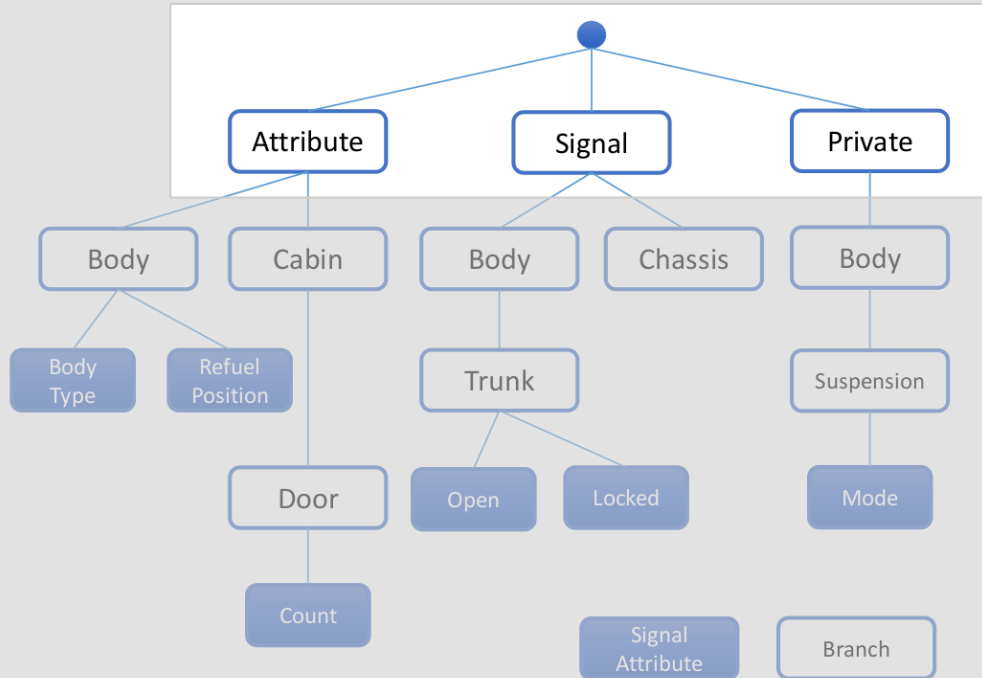


**VSS 2 – Extensions as attributes:** In VSS 2 extensions are modeled as attributes where they occur. The specification is a straight path to the sensor. The sensor description itself can be seen as “class” and the realization as its “instances”. This allows for more flexibility, a cleaner graph representation and zoning and filtering.



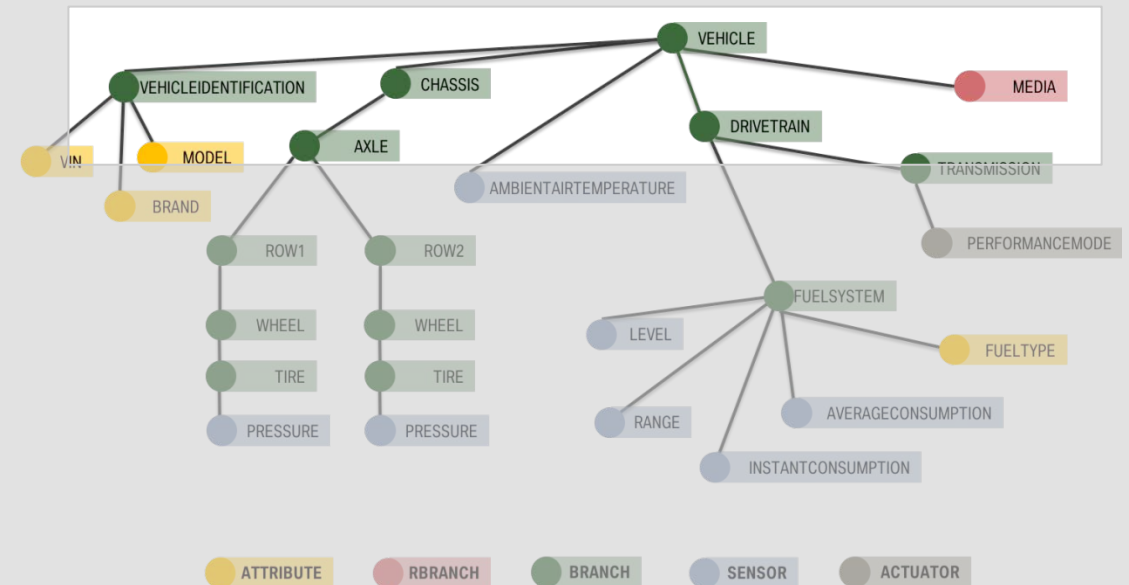
# ROOT NODE

- VSS 1 - Attribute/Signal Branch:** Attributes and signals were handled as separate branches from the root node, which lead to:
- Duplication in the tree structure
  - Leaf properties handled as branches



**VSS 2 - Introducing new types:** To avoid duplication and to add the properties to the leaf, new types were introduced and datatypes got their own property.

- Branch: Node in the tree, which has subnodes
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- Attribute: read-only and static



# Vehicle machine learning

In-car learning

Fleet learning

Behavior

Mental State

Environment

Trajectory patterns

- Aggressiveness
- Drowsiness
- Driving style
- Diagnosis

- Emotions
- Stress
- Mental load
- Frustration
- Distraction

- Topology
- Marks
- Potholes
- Obstacles
- Weather

- Maneuvers
- Intents

Data sources:

- Car sensors
- Smartphones/cameras
- Physiological sensors



## Introduction

## Approach

## Implementation & Results

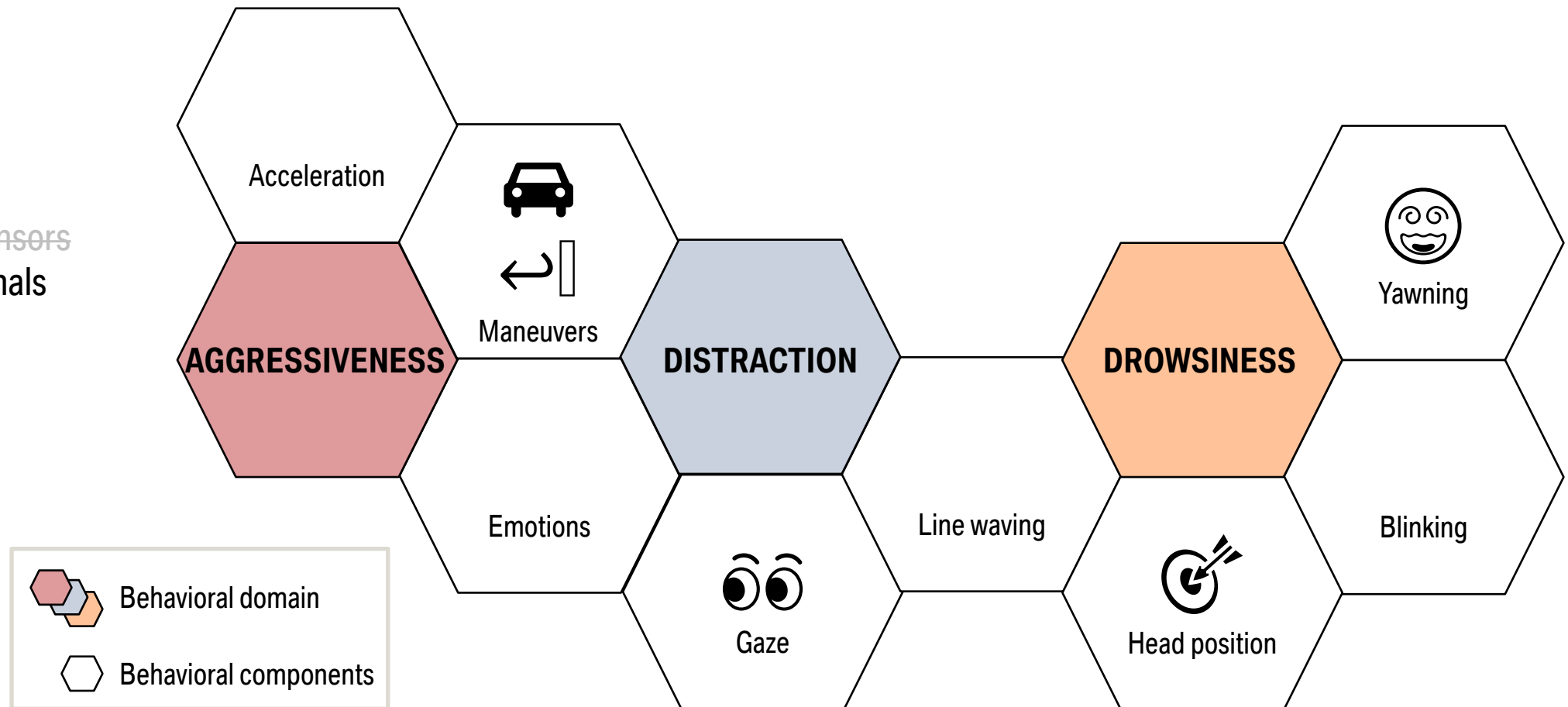
## Conclusion

### Sources:

Cameras

External sensors

Vehicle signals





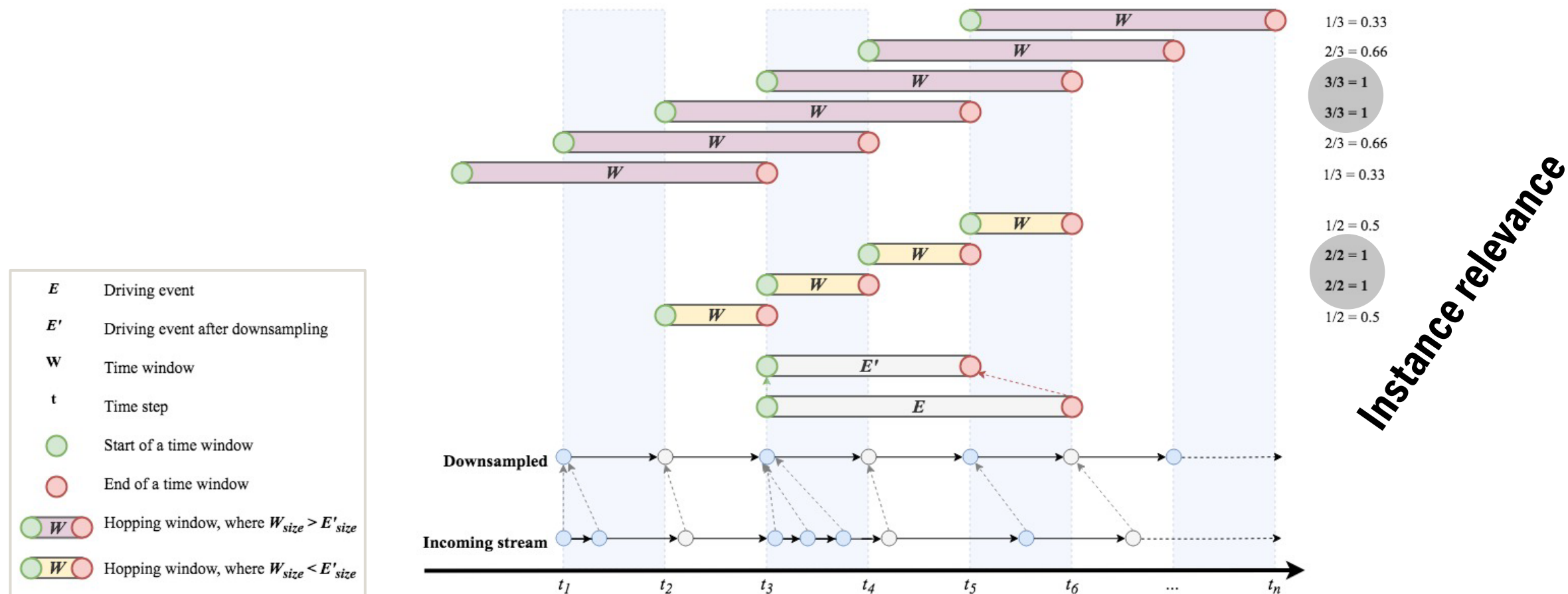


Introduction

Approach

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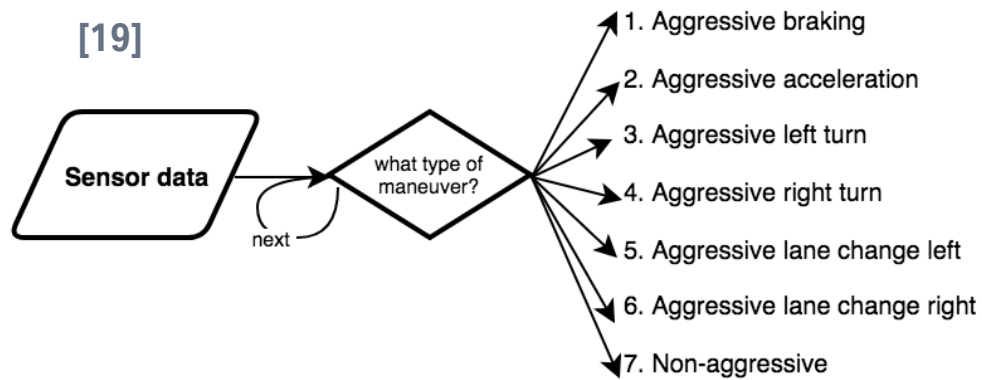
Conclusion



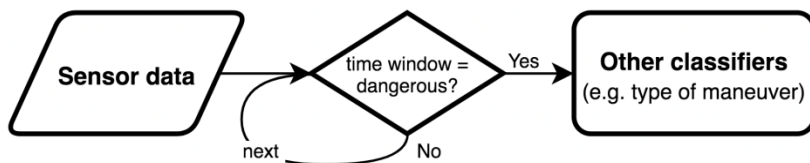


## Reference

[19]



## Base classifier



[26], [30]

Random Forest

RNN

[20]

Features	
Continuous signals	Categorical signals
Lateral acceleration	Acceleration efficiency
Longitudinal acceleration	Gear *
Accelerator pedal position	Brake pressed
Actual speed	Brake Dynamic Stability Control (DSC) state *
Speed displayed *	
Engine consumption	
Engine RPM speed	
Engine torque	
Custom parameters	
Window size [frames]	{2, 3, 4, ..., 10}
Minimum instance relevance	{0.1, 0.2, ..., 1.0}
Random Forest	
Number of estimators	{10, 11, 12, ..., 25}
Maximum features	{10, 15, "log2"}
Maximum depth	{5, 10, 15}
Recurrent Neural Network	
Number of hidden layers	{1, 2}
Number of recurrent units in the hidden layer	{10, 15, 16, 32, 64, 128}
Recurrent unit type	{LSTM, GRU}
Dropout	{0.1, 0.2}
Recurrent dropout	{0.1, 0.2}



### Dataset:

- Manually labeled
- Drivers → 2
- Driving events → 183 (maneuvers)
- Classes → 6
  - Aggressive Turns (L & R)
  - Aggressive Lane change (~~L & R~~)
  - Aggressive Brake
  - Aggressive Acceleration
  - Normal
- Down sample and aggregate data to 0.5s
- ~13 hours of recorded data
- ~3,5 hours of aggressive driving

### Training considerations:

- Evaluation metric → Area Under the ROC Curve (AUC)
- Loss function:
  - Binary classification → Binary cross-entropy
  - Maneuver classification → Categorical cross-entropy
- Input data:
  - Random Forest → Statistical features extracted
    - Mean, median, std. deviation, trend
  - RNN → Min-Max normalization (w.r.t., sensor specs.)



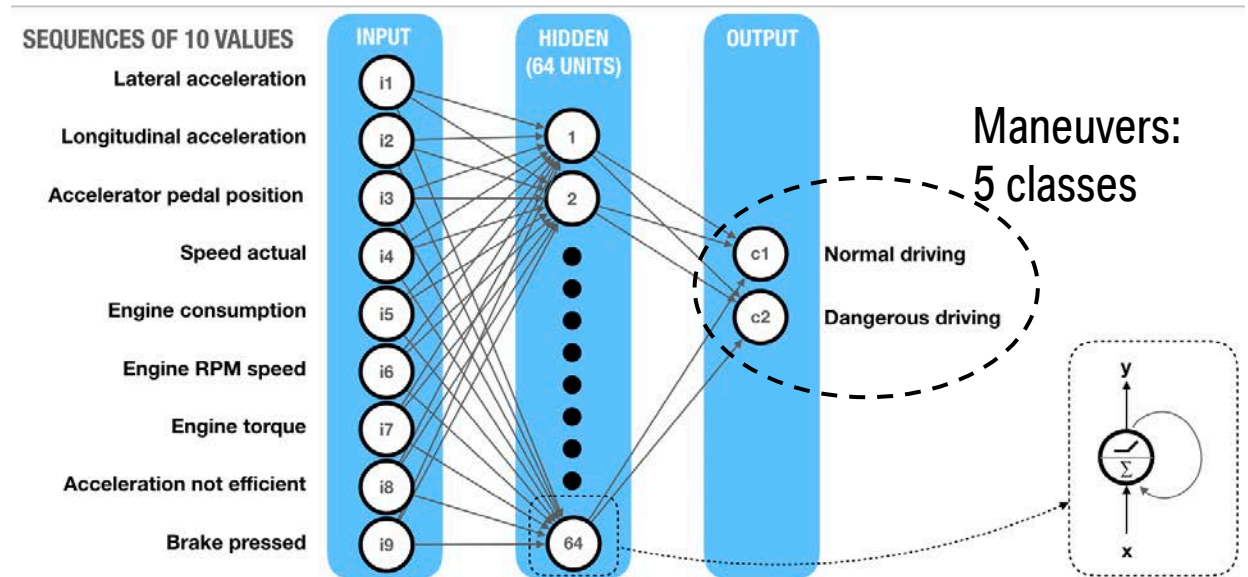
## Best found parameters

Random Forest

Parameter \ Classifier	Base	Maneuver
Window size [frames]	10	10
Minimum instance relevance	0.9	0.8
Number of estimators	15	24
Maximum features	5	"log2"
Maximum depth	10	15

RNN

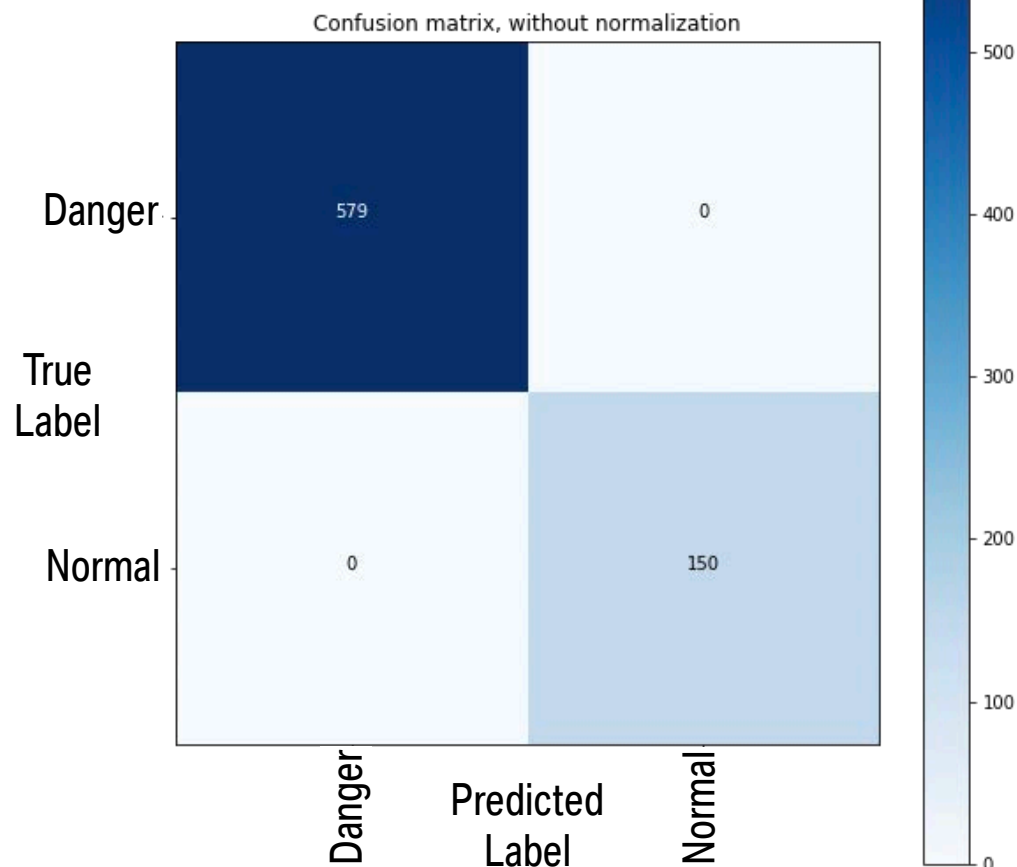
- LSTM cells
- Input  $\rightarrow$  9 features
- Hidden layer  $\rightarrow$  x1 (64 units)
- Output  $\rightarrow$  2 and 5 respectively



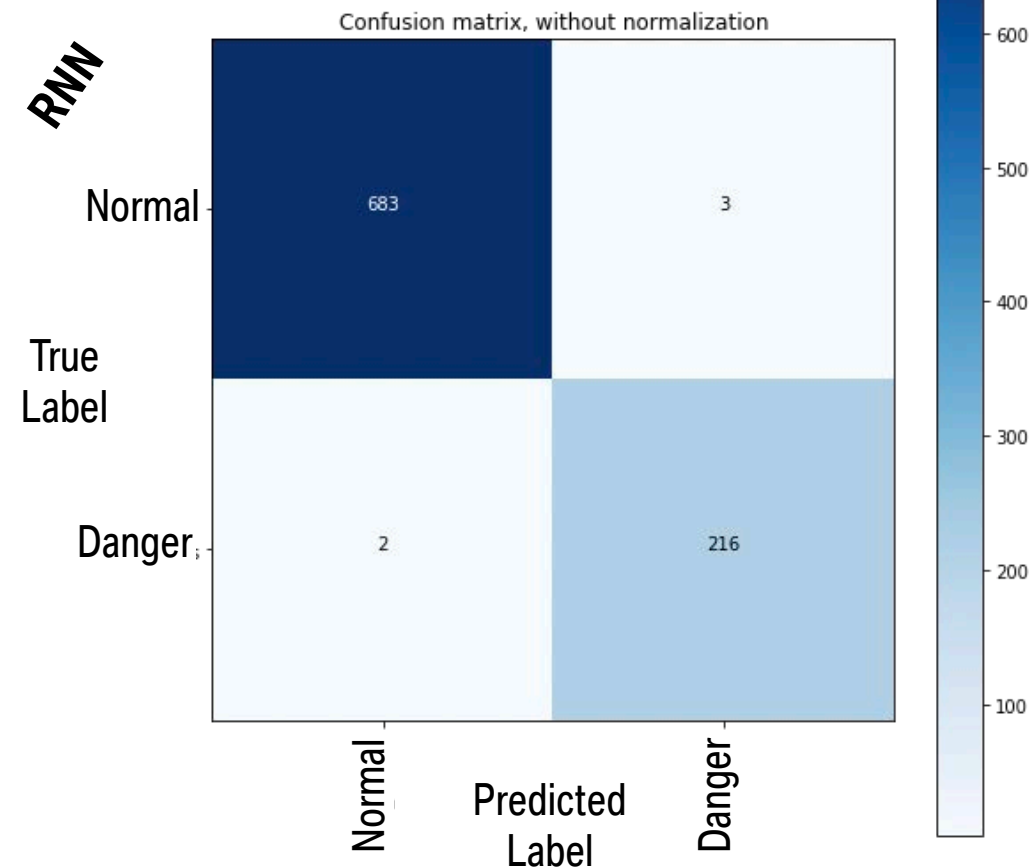


## Base classifier (Danger vs. Normal)

**Random Forest**



**RNN**







Introduction

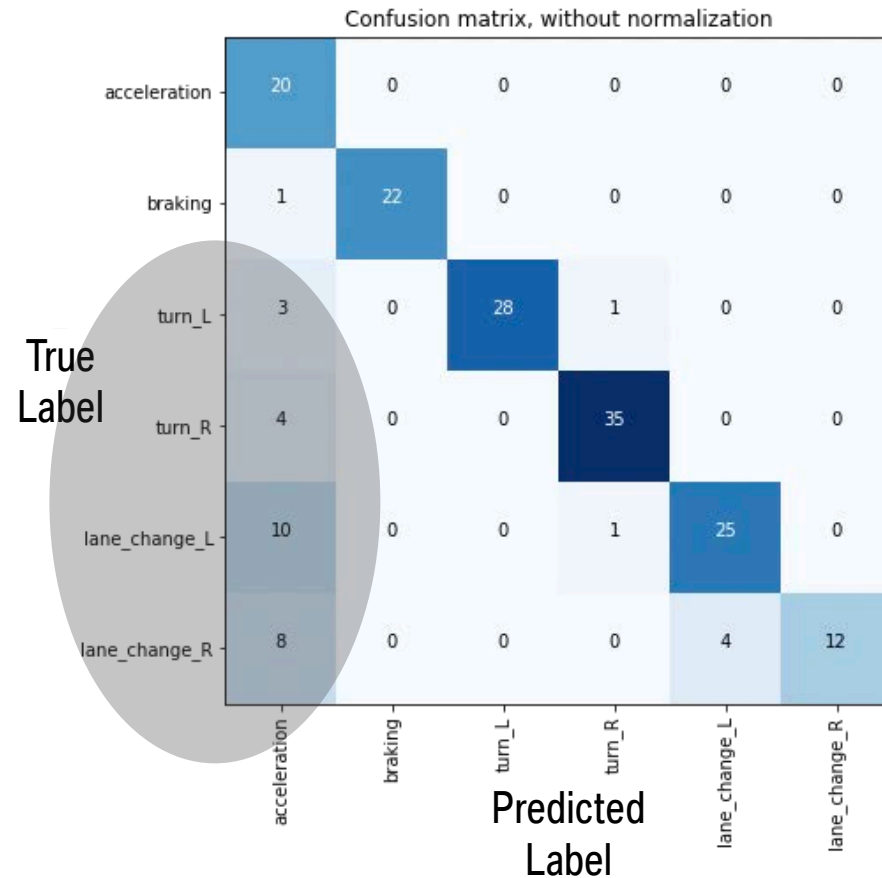
Approach

Implementation & Results

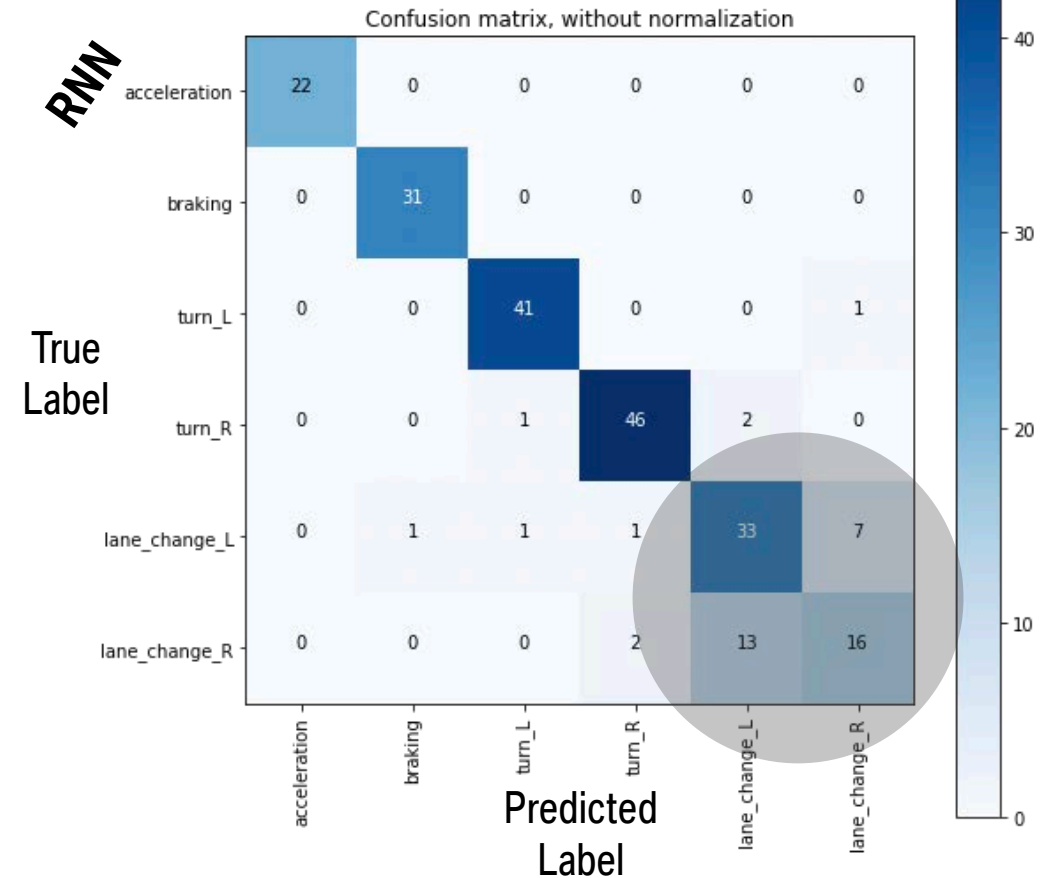
Conclusion

## Maneuver classification (6 classes)

Random Forest



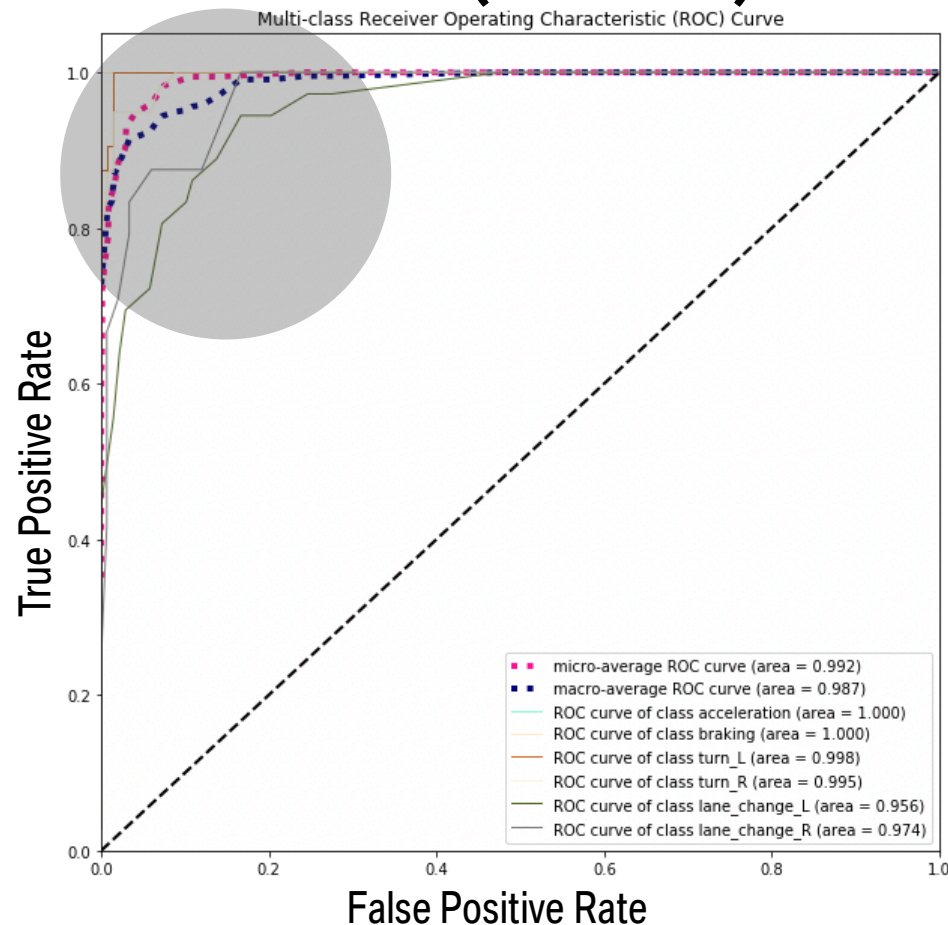
RNN



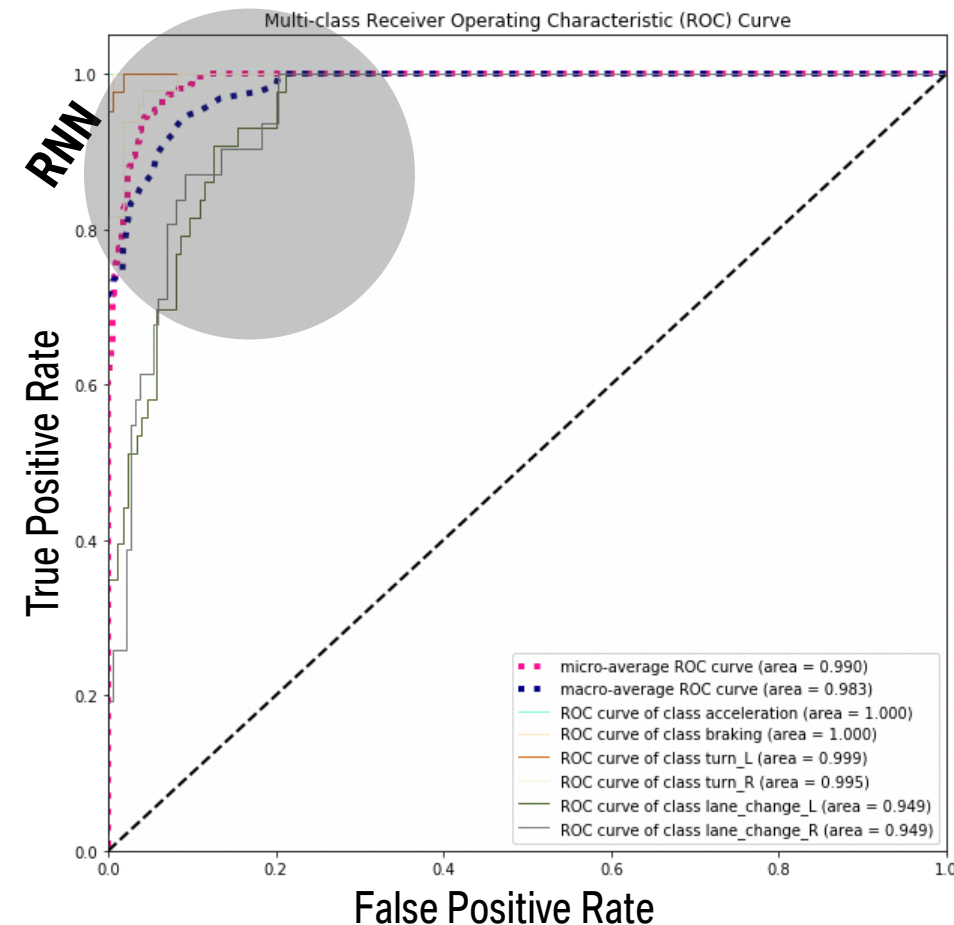
## Maneuver classification (6 classes)



Random Forest



RNN

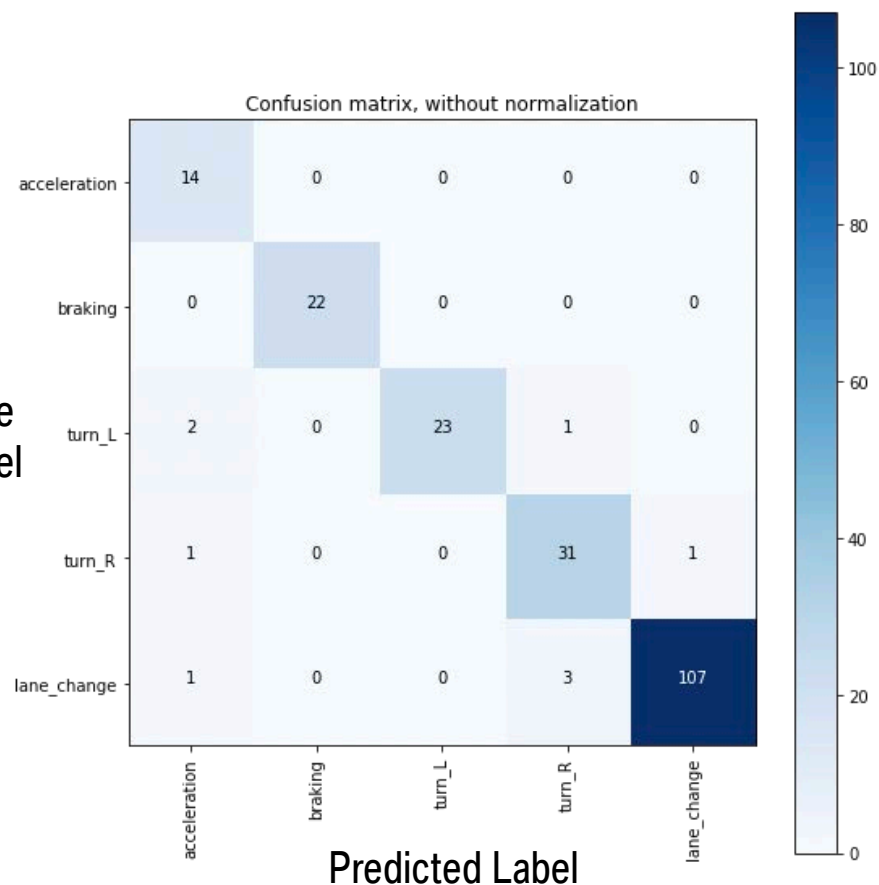




## Maneuver classification (5 classes)

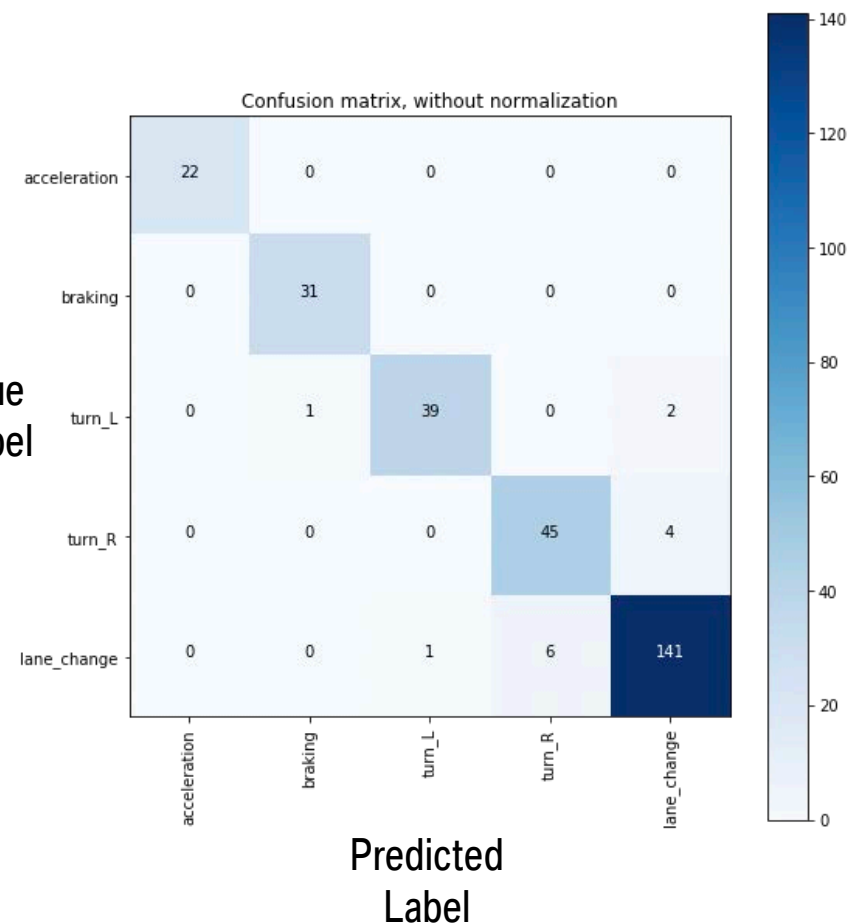
Random Forest

True  
Label



RNN

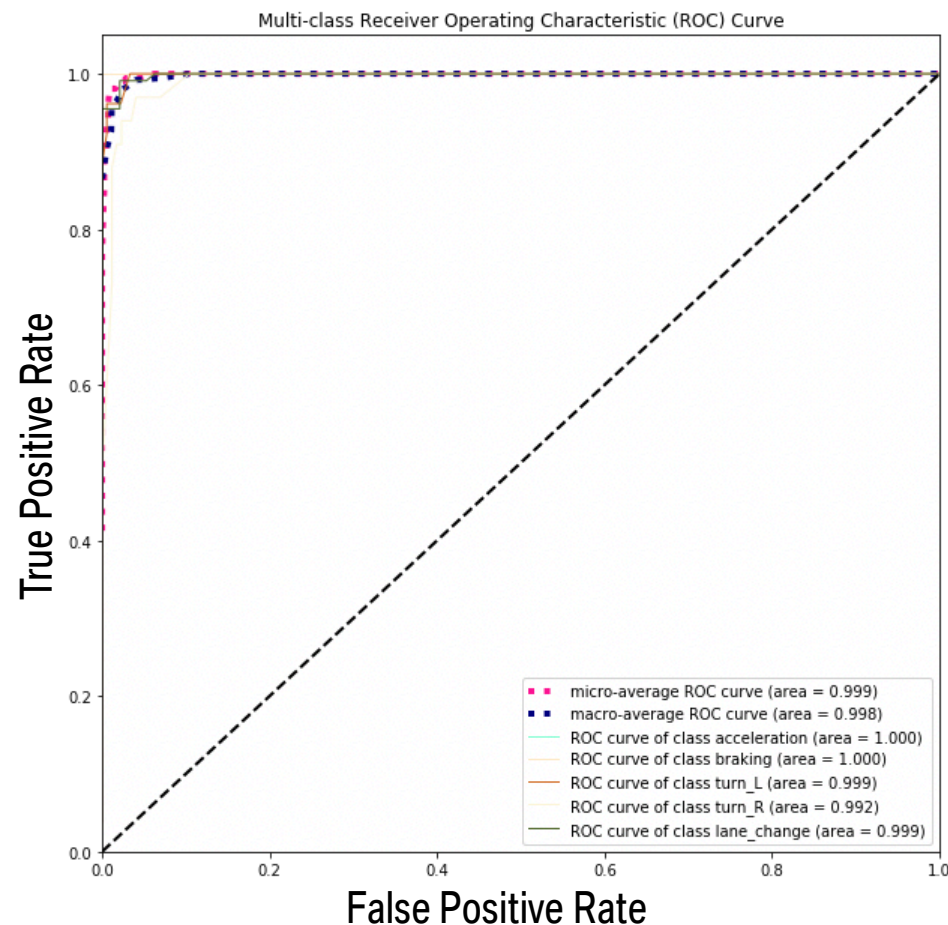
True  
Label



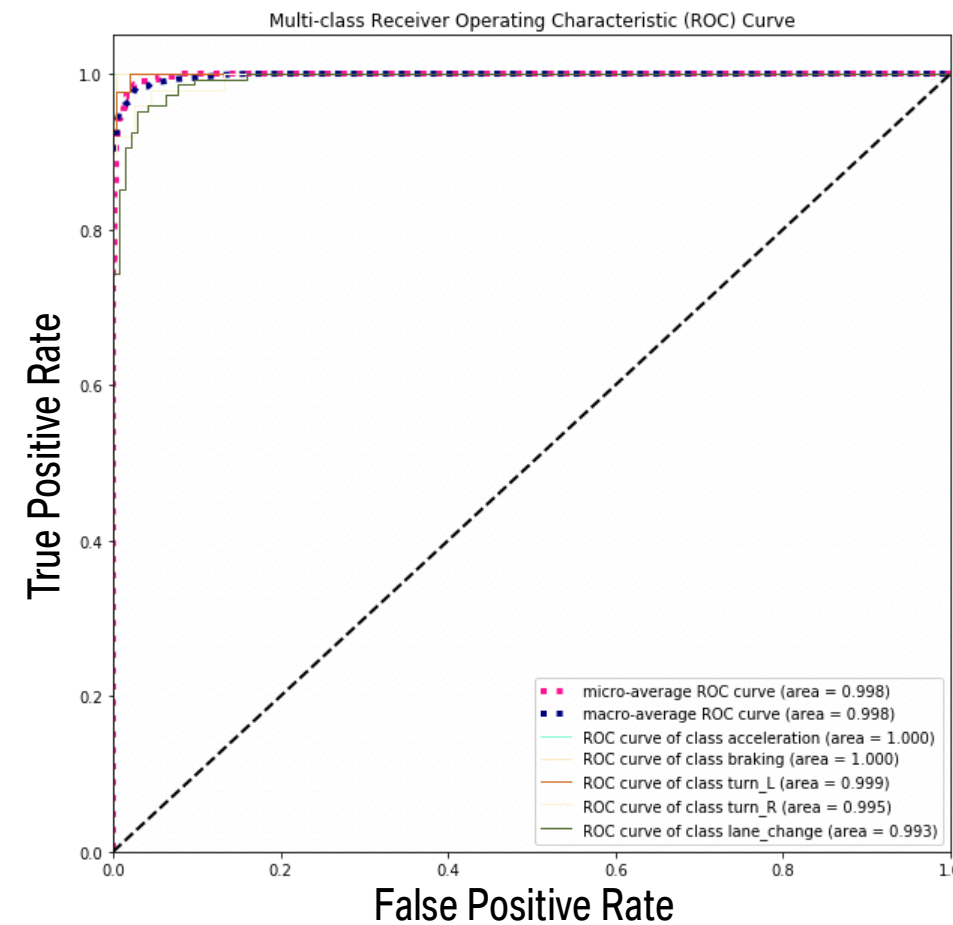


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Random Forest



RNN





Introduction

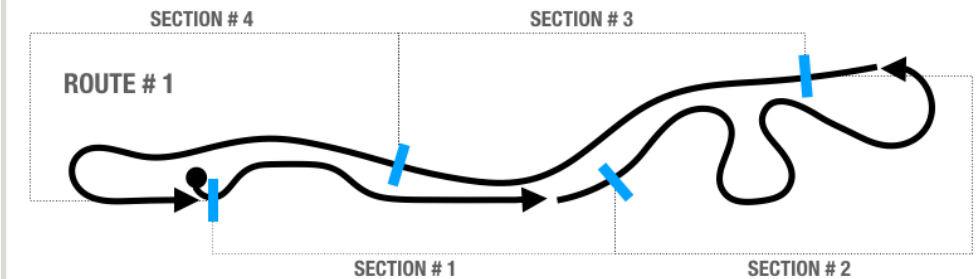
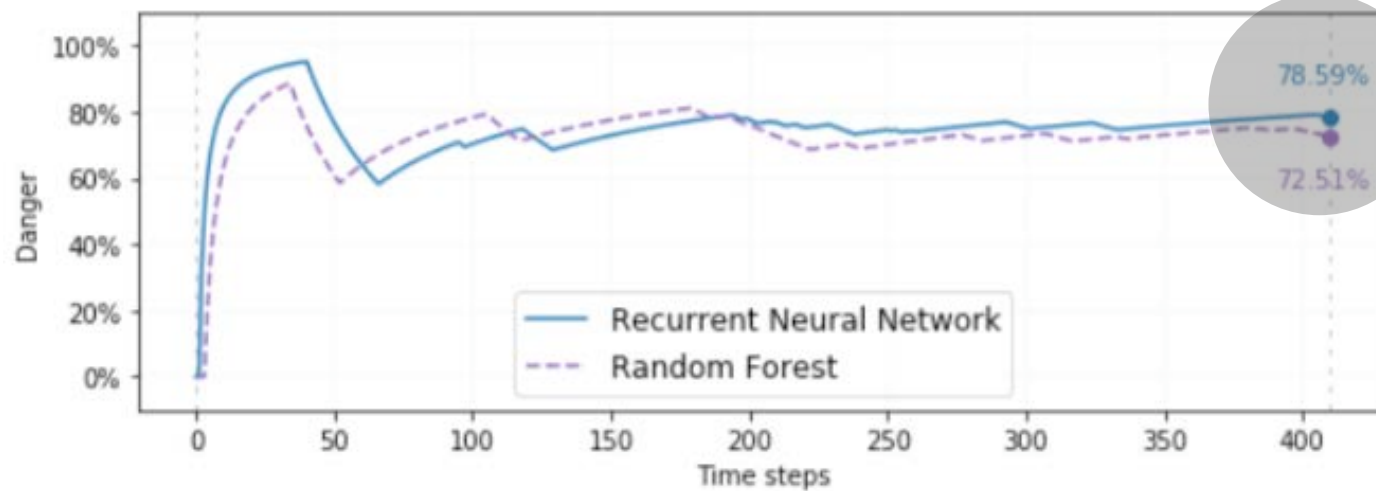
Approach

Implementation & Results

Conclusion

## Instructions

Route	Driver	Instruction
1	A	3 driving styles
1	B	3 driving styles
1	B	2 laps of free driving
2	A	3 driving styles



	Section	Co-pilot C	Co-pilot D
Lap 1	1	4	4
	2	2	2
	3	3	2
	4	3	3
Lap 2	1	1	2
	2	2	1
	3	4	3
	4	4	3
Danger perceived	23		20
Maximum possible danger (4 sections x 2 laps x 4)	32		32
Danger perceived [%]	71,875 %		62,5 %
Average danger perceived	67,1875 %		





Introduction

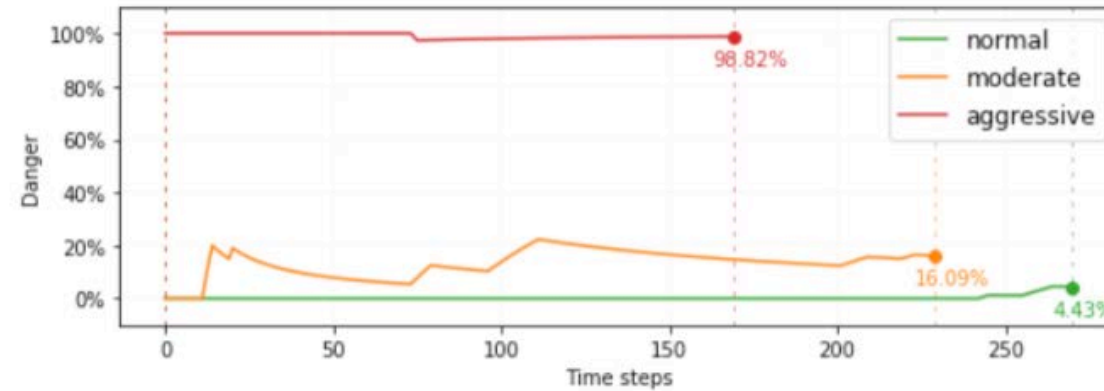
Approach

Implementation & Results

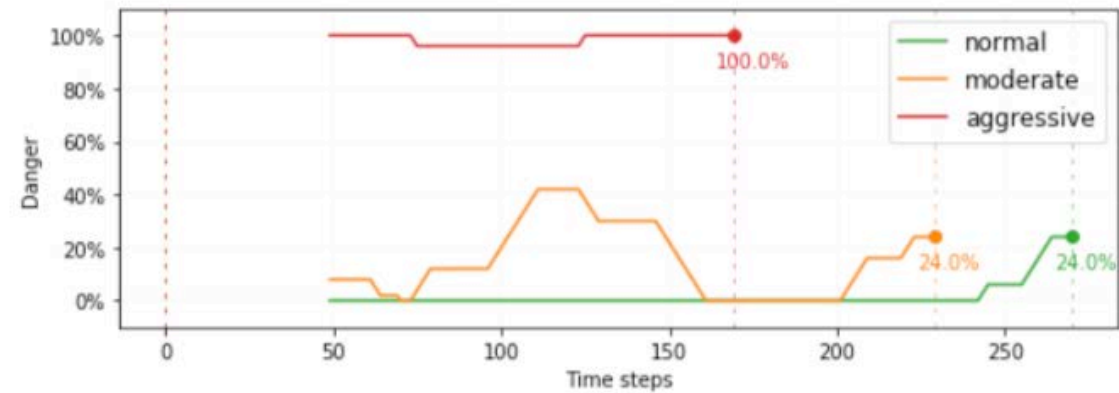
Conclusion

## Instructions

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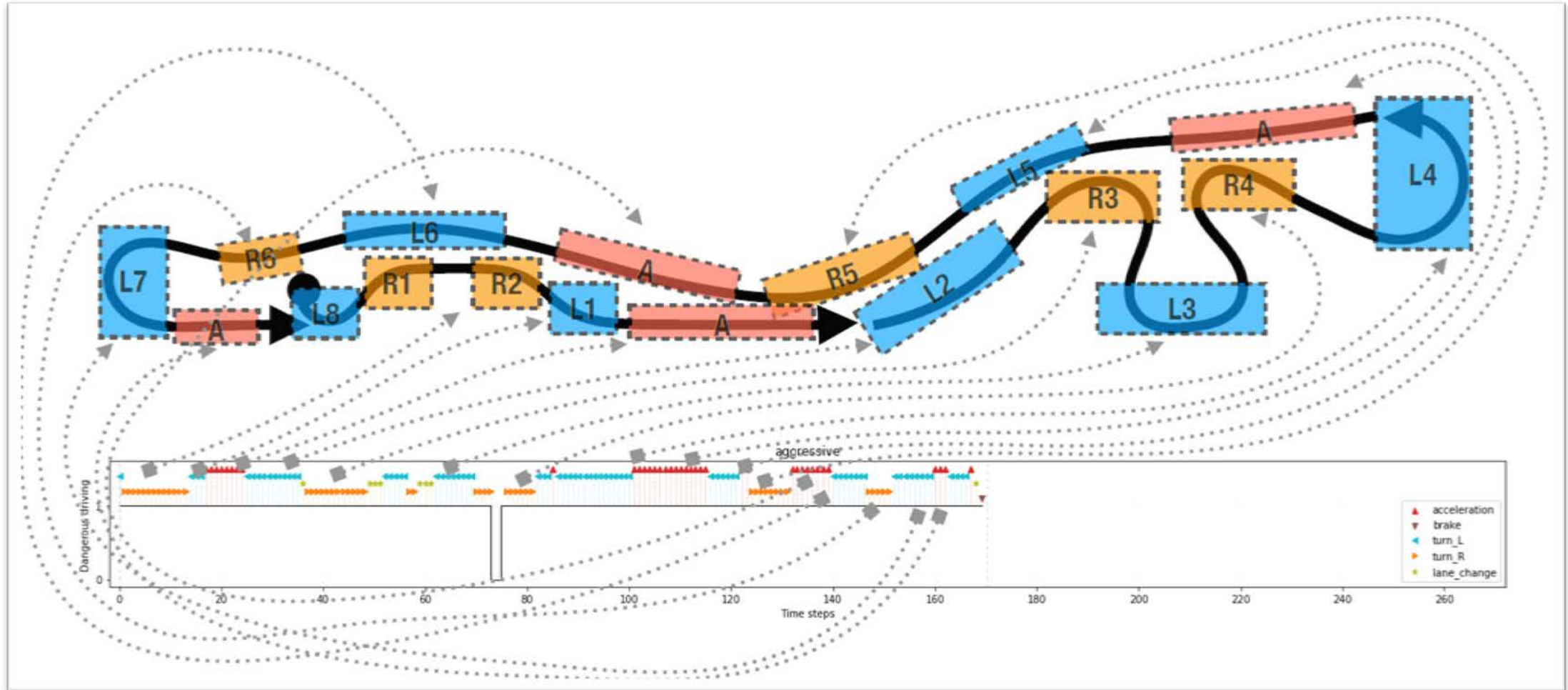


(a) Overall danger score



(b) Score of the past 50 frames

# RECONSTRUCTION OF DANGEROUS SITUATIONS



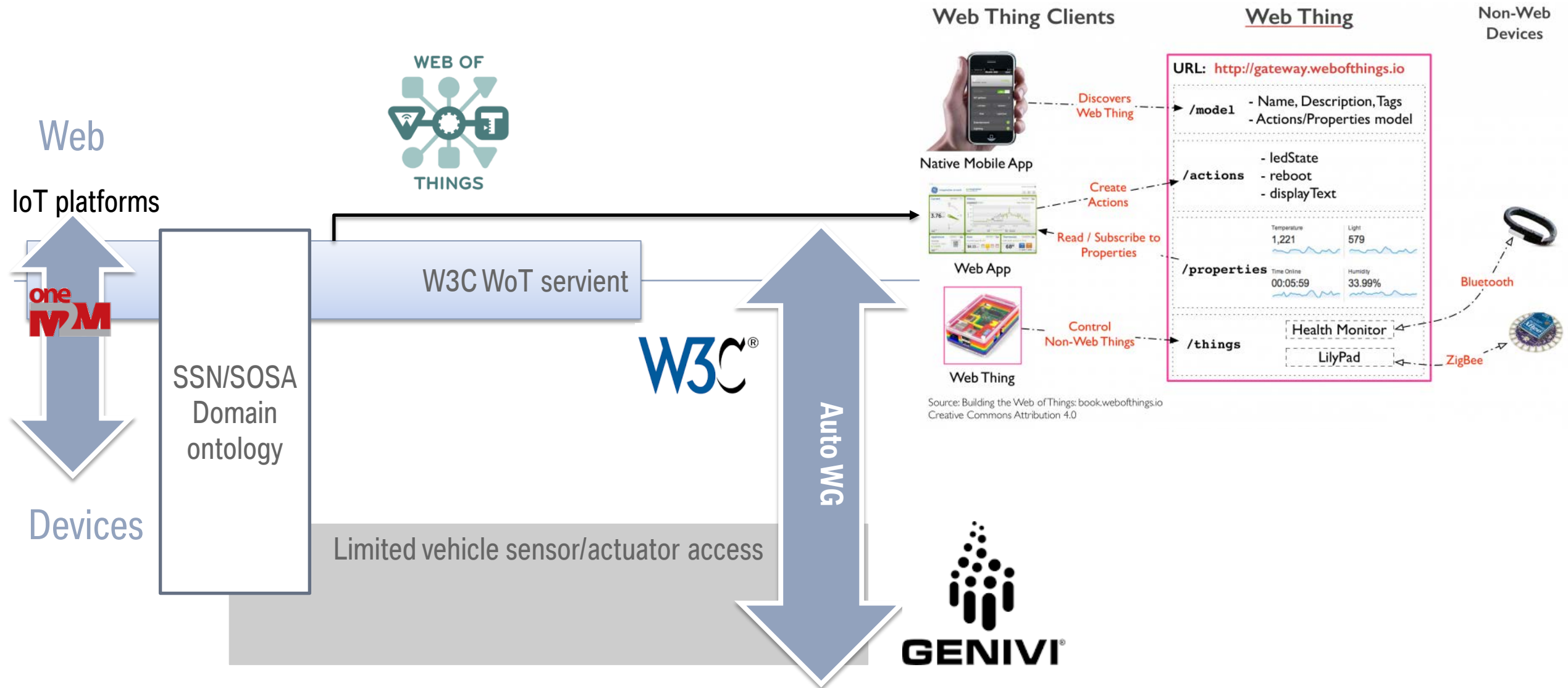
**2 biases**

Important difference between safe and aggressive



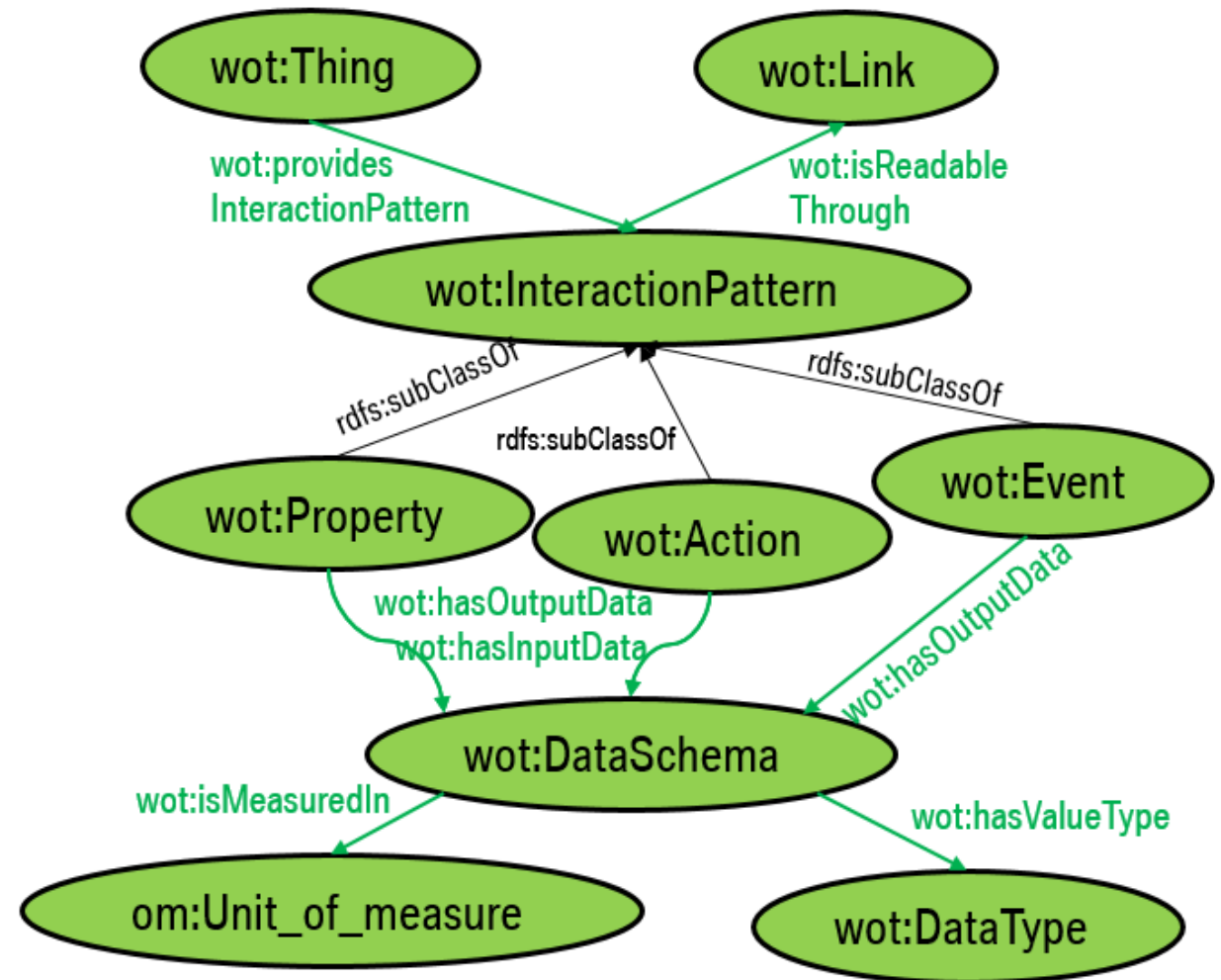
Track shape and speed far from public roads

# WEB OF THINGS DEVELOPMENT



# WOT ONTOLOGY

- Define a wot:Thing
- Centered on wot:interactionPattern
  - Properties
  - Actions
  - Events
- Use dataSchema
  - Literal value
  - wot:DataType
  - om:Unit of measure



<http://iot.linkeddata.es/def/wot/index-en.html>

# AUTOMOTIVE WEB THINGS: CHALLENGES

## Domain vs Nature of

- Things
- Interactions

```
"@id": "property/acceleration",  
"@type": ["Property", "vsso:LongitudinalAcceleration", "iot:Property"],
```

## Complexity of vehicles

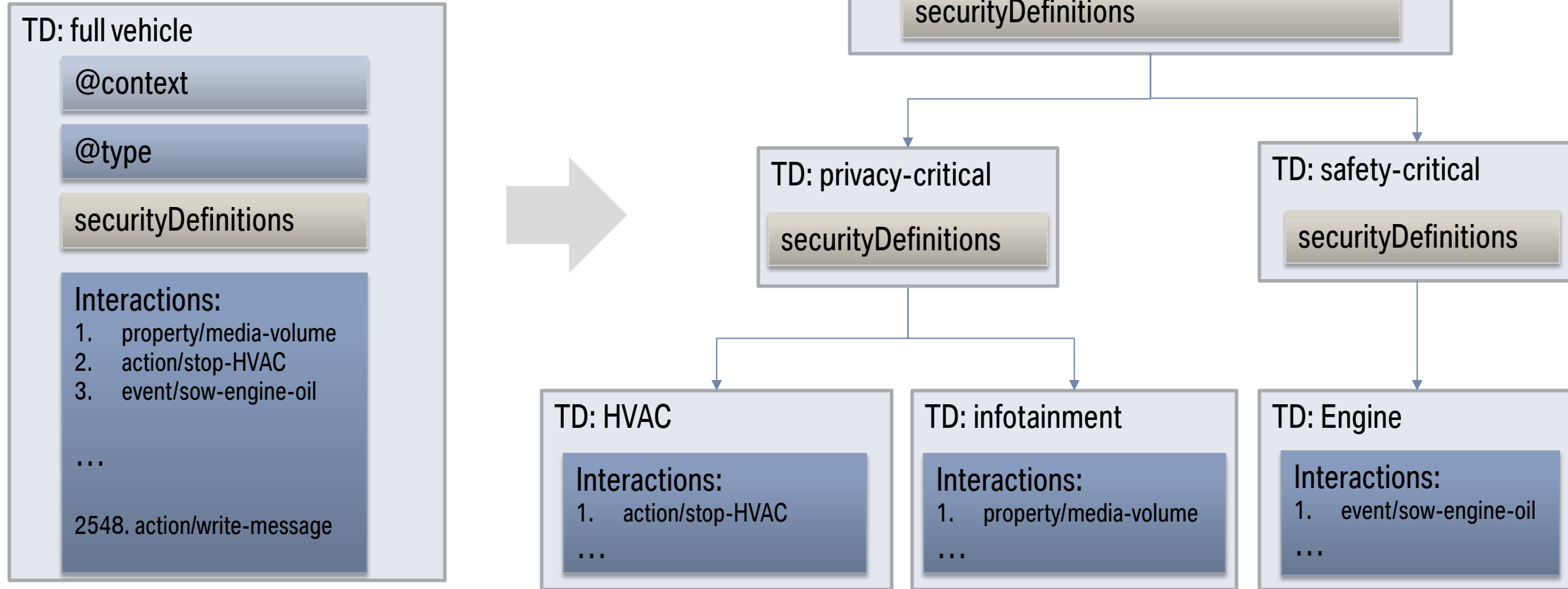
- Different access control and security
- Different expertise

## Data access

- External hardware
- Legacy solutions

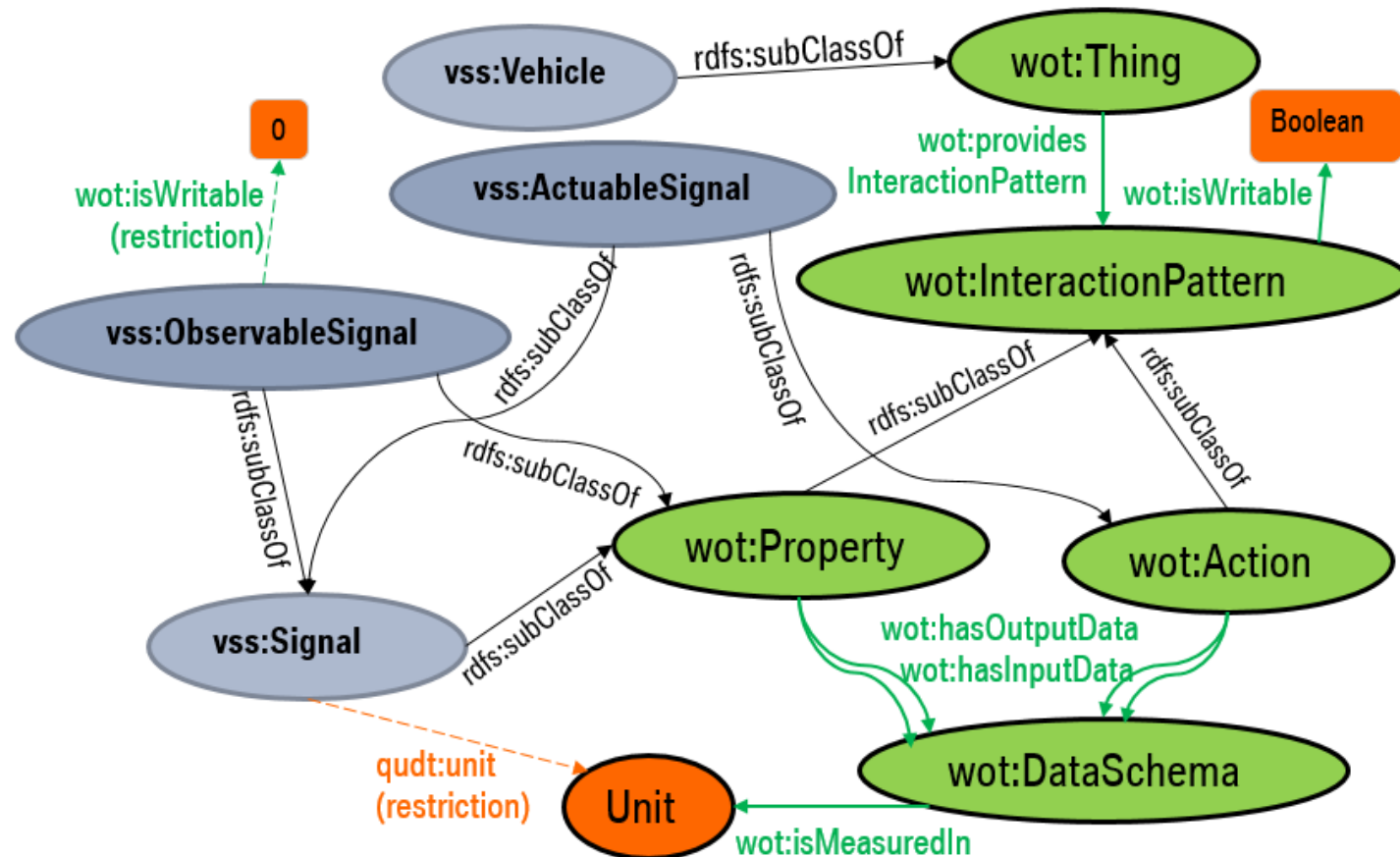
# DESCRIBING COMPLEX THINGS IN THE WOT

## Differing Safety, Security and Privacy ?





# ALIGNING WOT – SOSA FOR THE AUTOMOTIVE DOMAIN



Modeling pattern:

- i. Vehicles are Things
- ii. Signals are properties  
Read-write depending on the signal type
- iii. Actuatable signals are actions
- iv. DataSchema use the domain Units

Benjamin Klotz, Soumya Kanti Datta, Daniel Wilms, Raphael Troncy, and Christian Bonnet. A car as a semantic web thing: Motivation and demonstration. In 2nd Global Internet of Things Summit (GloTS'18), Bilbao, Spain, June 2018.

# VEHICLE THING DESCRIPTION

```
"@context": ["https://www.w3.org/2019/wot/td/v1",
  {"auto": "https://auto.schema.org/" ,
   "iot": "https://iotschema.org/" ,
   "vsso": "https://automotive.eurecom.fr/vsso#" ,
   "qudt": "http://www.qudt.org/1.1/vocab/unit#"}
],
"@type": ["Thing", "auto:Car", "vsso:Vehicle"],
"id": "http://10.159.160.74:5001/WBY8P61020VD33272/",
"title": "MyCarThing",
"name": "MyCarThing",
"auto:brand": "BMW",
"auto:model": "i3",
"vsso:vin": "WBY8P61020VD33272",
```

Thing

```
"properties": {
  "secured": {
    "@type": ["iot:Property", "vsso:DoorLock"],
    "description": "Shows the current lock status of the car",
    "type": "string",
    "forms": [{
      "href": "property/secured",
      "contentType": "application/json",
      "op": "readproperty"
    }]
  }
}
```

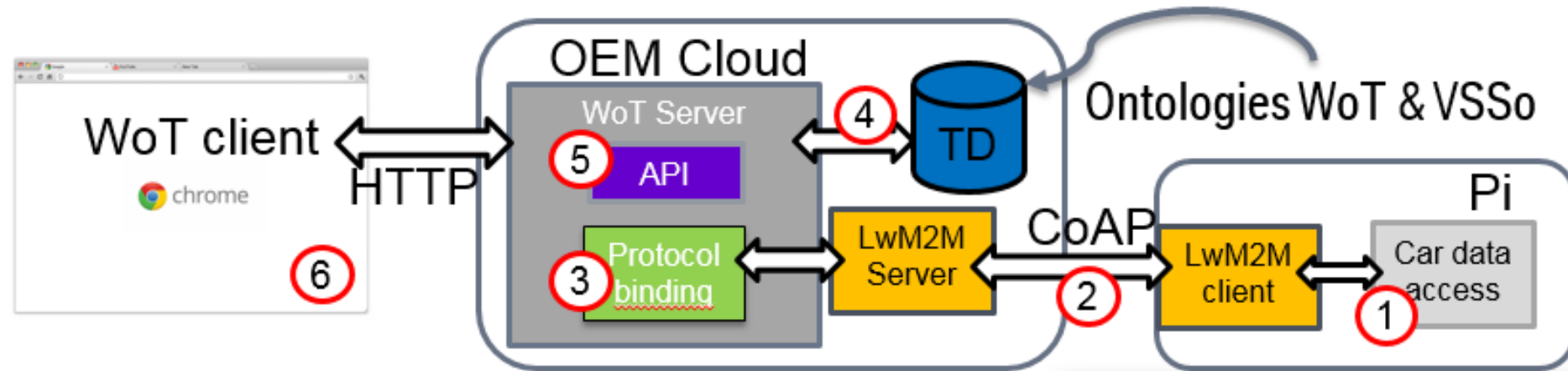
Properties

Actions

```
"actions": {
  "write-message": {
    "@type": ["Action", "iot:ChangePropertyAction"],
    "description": "Send message to the vehicle HMI",
    "safe": false,
    "idempotent": false,
    "input": {
      "type": "object",
      "properties": {
        "subject": {
          "type": "string"
        },
        "message": {
          "type": "string"
        }
      },
      "required": ["subject", "message"]
    },
    "forms": [{
      "href": "action/message",
      "contentType": "application/json",
      "op": "invokeaction"
    }]
  },
}
```

Semantics | Communication | Access

# DEMONSTRATION: CONTROLLING YOUR CAR WITH YOUR WEB BROWSER (2017)

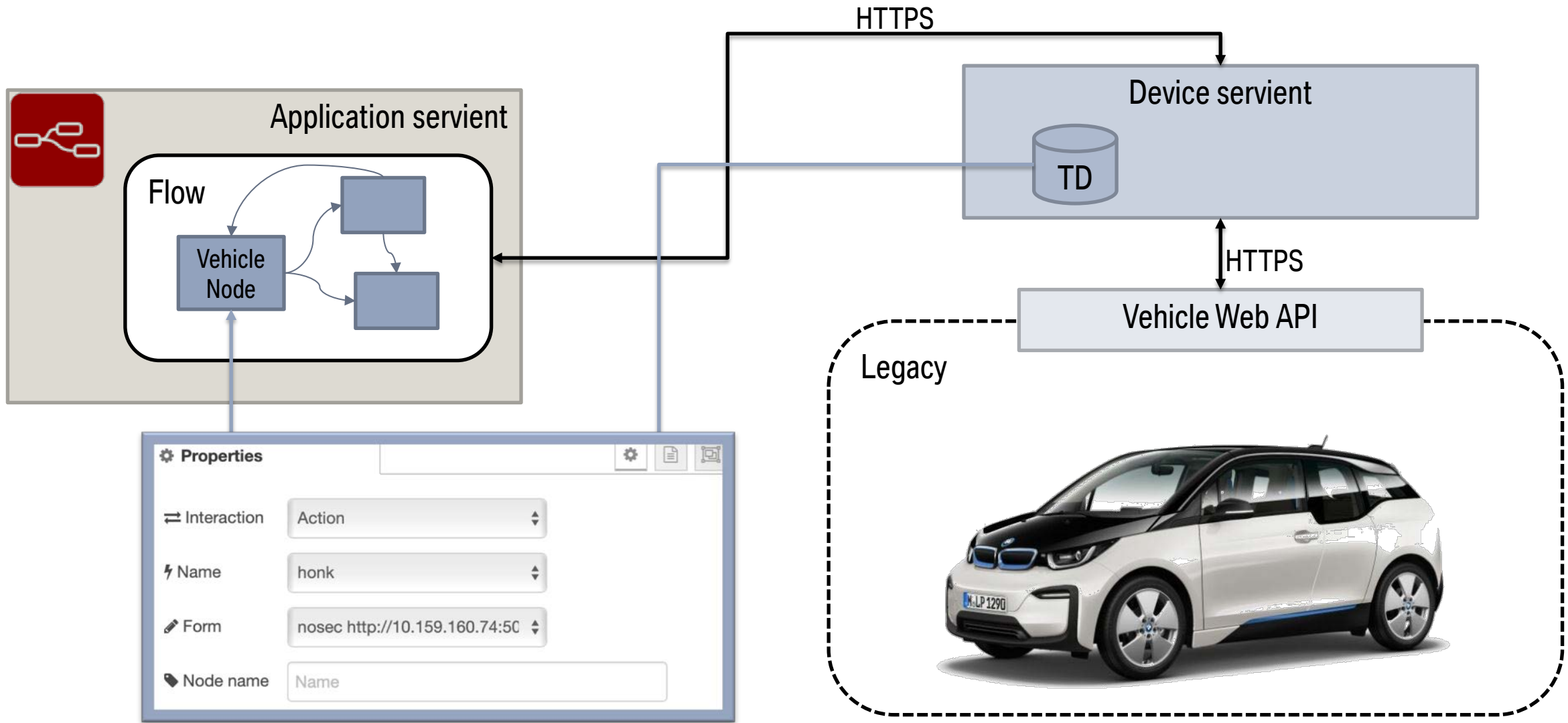


## Usage:

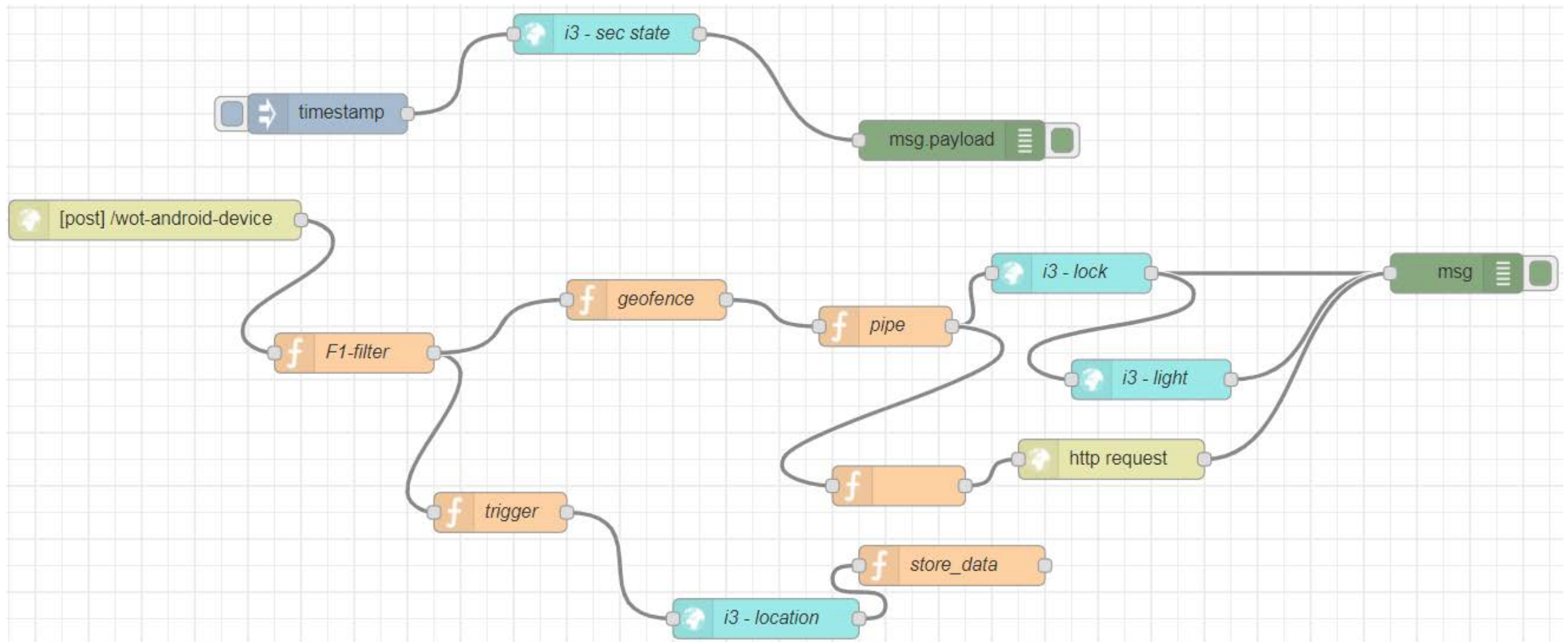
Behind a web browser, we can control the windows, doors and honk



# DEMONSTRATION: INTUITIVE INTERFACE ON LEGACY VEHICLES



# FLOW EXAMPLE (OPEN DAY)

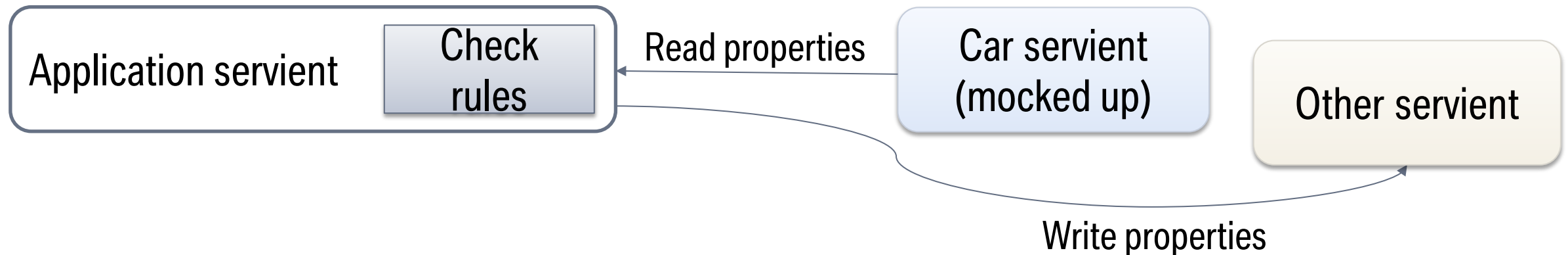


When the user is far from the unlocked vehicle, the vehicle lock is activated

# DEMONSTRATION: CAR INTERACTION IN THE WEB OF THINGS

## Triggering actions based on rules:

- If a door is open while speed > 0 then trigger a warning
- If longitudinal and lateral acceleration are high (dangerous driving), then turn on a red LED
- If the coordinates of the car are close to a fixed destination, control a garage door and light



<https://www.youtube.com/watch?v=pjgTLPIAsKQ>

<https://www.youtube.com/watch?v=zkL8Cdgy8PE>



# OUTLOOK AND PERSPECTIVES

## **Outlook: a step to make connected vehicles more interoperable**

- **Ontology for the Automotive domain / alignment with the Web of Things**
  - VSSo (<http://automotive.eurecom.fr/vsso>) ... being further developed in the W3C Automotive Business Group
  - Alignment VSSo/VDC/WoT (axioms to publish)
- **Datasets: semantic trajectories**
  - VSSo data: 5 trajectories, 8 signals, 16k observations (<http://automotive.eurecom.fr/trajectory>)
  - VDC data: 2 trajectories, 16 states, 16k observations, 130 events
- **Classifiers (Internal BMW)**
  - Aggressive driving prediction / Maneuvers prediction
- **WoT vehicles:** <https://www.youtube.com/watch?v=zKL8Cdgy8PE>

## **Many remaining challenges:**

- **Next generation vehicle server: VISS server ([implementations](#), [w3c recommendation](#)), RSI (or Gen2)**
- **In-vehicle machine learning**
- **Scalability of graph-based data representation (vehicle shadow data access using GraphQL)**
- **How much your vehicle should remember your driving patterns?**
- **Security / Privacy / Ethics / add yours ...**