Methods to Harmonise Data on Human Driving Performance from Different Datasets

D1.1| 25.04.2023

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Project Acronym	Grant Agreement #	Project Title	Deliverable Reference #	Deliverable Title
i4Driving	101076165	Integrated 4D Driver Modelling under Uncertainty	D1.1	Methods to Harmonise Data on Human Driving Performance from Different Datasets

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DISSEMINATION LEVEL

X	P	PUBLIC
	C	CONFIDENTIAL

This project has received funding from the European Union's Horizon Europe programme, under grant agreement No 101076165.

Funded by the Horizon 2020 programme of the European Union

Grant Agreement No 101076165

Version History

Revision	Date	Authors	Organisation	Description
V0.1	01.02.2023	Florian Finkeldei	TUM	First draft
V0.2	24.02.2023	Florian Finkeldei	TUM	Revision according to feedback from TU Delft
V0.3	14.03.2023	Florian Finkeldei	TUM	Revision according to feedback from VTI
V0.4	19.04.2023	Florian Finkeldei	TUM	Revision according to feedback from Panteia
V1.0	25.04.2023	Lucia Schlemmer/ Maria Rodrigues	Panteia	Final review

Executive Summary

The availability of high-quality datasets is essential for the i4Driving project. These datasets are the basis for the human driver model identification process. To enable identifying suitable models over a wide range of traffic situations, driving data from various driving domains and situations must be available in a homogenous format. The CommonRoad framework, developed at the Cyber-Physical Systems group at TUM, offers an appropriate solution. Currently, seven trajectory-based datasets are available in the unified and harmonised CommonRoad data format. This report describes the methodology, gives an overview of the available datasets, and discusses the extensibility to human factors datasets.

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1 Introduction

The i4Driving research project aims to derive high-fidelity human driver behaviour models in challenging driving scenarios. This model identification process relies on the availability of records from numerous driving situations. As there are various datasets, focusing on, e.g., different driving domains, it is necessary to harmonise the different datasets beforehand. This facilitates the extensive and meaningful data analysis which will be necessary for deriving human driver models.

This report presents the work developed, and the results of Task 1.1 of the i4Driving project, which aims to provide ready-to-use datasets as a basis for other work packages (WP2, WP4). To this end, it is envisaged to harmonise traffic scenarios from various available datasets to a common data format. Moreover, the harmonised datasets are supposed to be unambiguous, plausible, platform-independent, open accessible, and they should cover a varying degree of scenario complexity. If the datasets would not be harmonised and kept in their as-recorded data-format, each of the work packages which use the datasets for their purposes would have to implement this pre-processing on their own. As verifying the quality of the harmonised datasets is an import, but sometimes neglected step, this could even impair the quality of the research results.

In general, it is distinguished between different levels of scenario abstraction [1]: Functional scenarios use a semantic scenario description. The vocabulary is use-case domain specific and can offer different levels of detail. Logical scenarios are a formal description of actors and their relations in the state space. For example, permissible parameter ranges of the actors are defined. Concrete scenarios define concrete values and trajectories respectively for each parameter. To represent and analyse recorded traffic scenarios, concrete traffic scenarios are best-suited, as they keep the highest level of detail.

In the autonomous driving development domain, there are multiple data-formats with varying degrees of adaptability [2]. While many of these focus on the description of logical scenarios (e.g., OpenScenario), the CommonRoad scenario offers a concrete traffic scenario description. The CommonRoad framework is a benchmarking suite for automated motion planners. Besides providing an unambiguous data format for the description of driving situations, it offers a conversion tool for multiple datasets into its own data format. As the access to diverse datasets is necessary for motion planners benchmarking, this dataset conversion tool is extendable to feature additional datasets. Furthermore, the CommonRoad scenario format offers the advantage of being platform-independent and openly accessible [2]. Due to these beneficial advantages, the CommonRoad scenario format is chosen as the target format of the converted traffic scenario datasets.

Within this report, the main aspects of the CommonRoad scenario format will be explained in section 2. The necessary steps for harmonising existing datasets by converting them into the CommonRoad scenarios are covered in section 3. An overview of the yet harmonised datasets is given in section 4. Finally, a summary, remarks on the current state of the data harmonisation and next steps are given in section 5.

2 CommonRoad Framework

The CommonRoad framework aims to provide a unified and unambiguous format for representing traffic scenarios, enabling the benchmarking of automated motion planners [3]. In this ecosystem, several applications and tools for different use-cases have evolved (see **Error! Reference source not found.**).

The core of the framework is CommonRoad scenarios. These offer a concrete description of traffic scenarios. As such, numeric vales are defined for all necessary parameters, making the description as precise as possible. It is a generic format for the description of traffic scenarios [4]. It is suited for the representation of the harmonised data. The key components of CommonRoad scenarios are described in the following sections. Additional information on the format which is outside the scope harmonising datasets is given in [3,4,5].

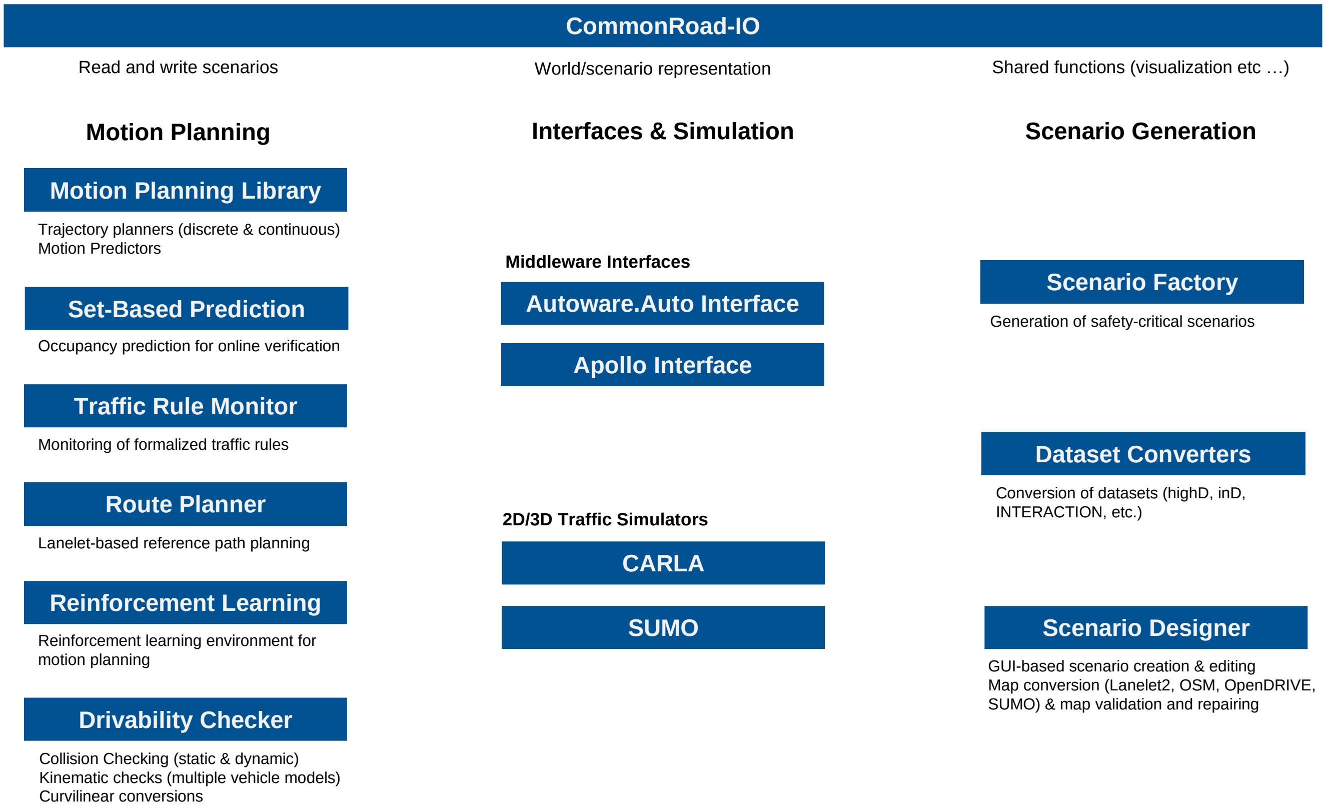

Figure 1: Overview of the CommonRoad framework.

CommonRoad scenarios provide high-level, but detailed and concrete information on the road infrastructure. Moreover, there are multiple ways to represent traffic participants. It is therefore well suited for various applications [3], including the data analysis of existing datasets.

Each CommonRoad scenario consists of the four elements [4]:

- Meta information;
- Formal representation of the road network;
- Static and dynamic obstacles; and
- Planning problem for the ego vehicles.

An overview of the file structure of CommonRoad scenarios is attached to this report (see section 7).

2.1 Meta Information

The meta information includes values such as the unique benchmark ID of a scenario [3], the data source name, or the discretisation time-step size. Additional meta information such as scenario tags, environment details etc. can also be stored (see [4] for full list of possible meta information fields).

2.2 Road Network

The backbone of the formal representation of the road network are lanelets. The geometry of lanelets is defined by polylines representing their left and right boundaries (see Figure 2). Moreover, for both boundaries, the corresponding line marking type can be stored. This information is useful, e.g., when evaluating traffic rules. The information about preceding and succeeding lanelets are stored for each lanelet, as well as information about neighbouring lanelets on their adjacent left or right-hand side. Lanelets also contain references to traffic signs and traffic lights.

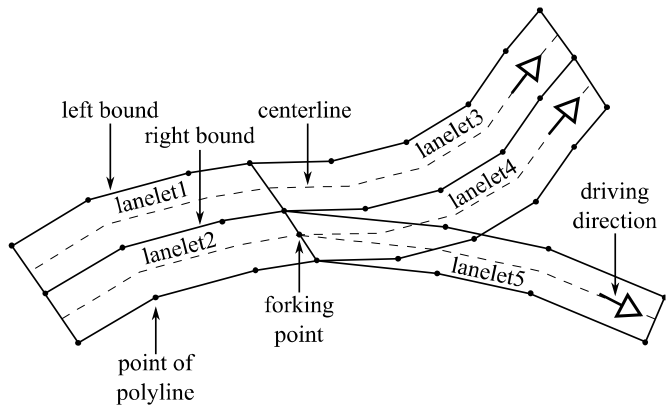

Figure 2: Lanelet network representation.

Traffic signs are composed of at least one traffic sign element, where each element corresponds to a defined traffic rule. The list of currently supported traffic sign elements is given in the CommonRoad format specification [4]. Traffic signs can also be virtual, e.g., if a speed limit has been previously set outside the captured road network [4].

Traffic lights have a cycle which consists of one or more cycle elements. Each cycle element is defined by its duration and traffic light colour.

To define intersections, adjacent lanelets with the same driving direction are grouped as incomings (see Figure 3). These incomings also have a reference to their neighbouring incoming in counterclockwise direction. This information enables to evaluate the right-before-left traffic rule.

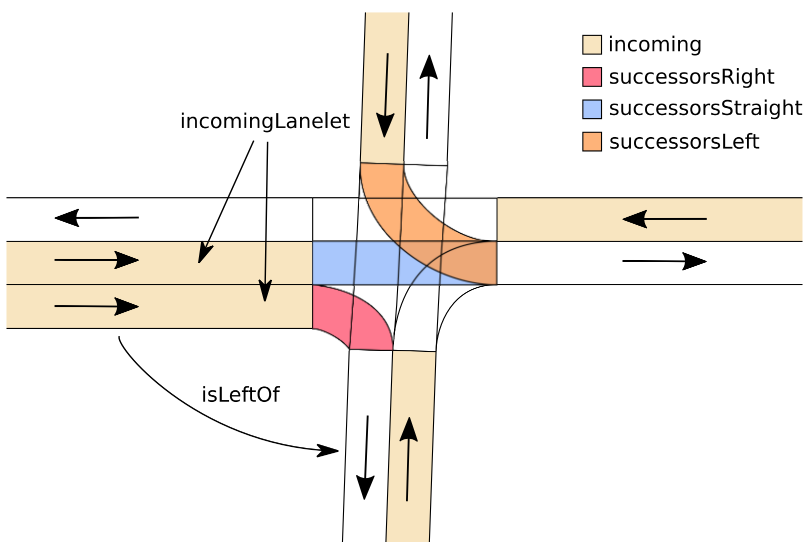

Figure 3. Example intersection. For better visibility, only one example lanelet is highlighted for each successors Right / Straight / Left element. [4]

2.3 Obstacles

Obstacles hinder the movement of traffic participants. They can be grouped into static and dynamic obstacles. Static obstacles can be e.g., parked vehicles, road work zones, or road boundaries [4]. Besides their type, they are defined by their geometric shape as well as their initial state (i.e., position), which remains unchanged over the course of time.

Examples of dynamic obstacles which can be handled in CommonRoad scenarios are cars, trucks, buses, motorcycles, bicycles, pedestrians, priority vehicles, or trains. Like static obstacles, they contain information about their shape and initial state. Their behaviour over time can be given either as a trajectory, an occupancy set, or a probability distribution (see Figure 4). In the case of converting recorded datasets, as it will be conducted in the scope of this report, their precise trajectory is known for all traffic participants. Therefore, a sequence of states is suitable for representing the trajectory of each traffic participant.

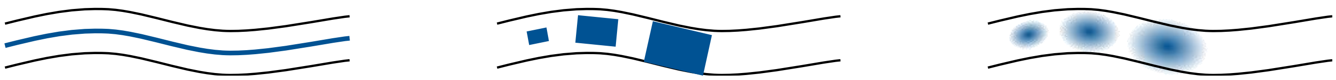

Figure 4: Options to model the temporal behaviour of dynamic obstacles: Trajectory (left); reachable set prediction (middle); probability distribution (right)

To harmonise the different, available driving datasets, these are converted to fit the CommonRoad scenario format. That process is described in the subsequent section.

3 Software Tool for Harmonising the Data

For converting datasets into the CommonRoad scenarios, the CommonRoad framework includes a dataset converter. Crucial for the successful conversion of datasets into CommonRoad scenarios is the correct representation of the road network and the modelling of all traffic participants as dynamic obstacles.

3.1 Road Network

As not all datasets provide details about their road networks, these can be created, e.g., with the CommonRoad scenario designer [5]. This tool offers the functionality to convert Open Street Map data into the CommonRoad road network format. However, as the CommonRoad road network format contains additional information compared to the Open Street Map data, some values need to be heuristically approximated during the map conversion performed by the CommonRoad scenario designer. For example, the information about lanelet widths is not included in the Open Street Map database. Therefore, after automatically generating road networks with the CommonRoad scenario designer, these must be manually reviewed and edited such that they become as close as possible to the reality. This is a major challenge of the dataset harmonisation process. As an example, the “west” camera perspective and its corresponding CommonRoad lanelet network are shown in Figure 5.

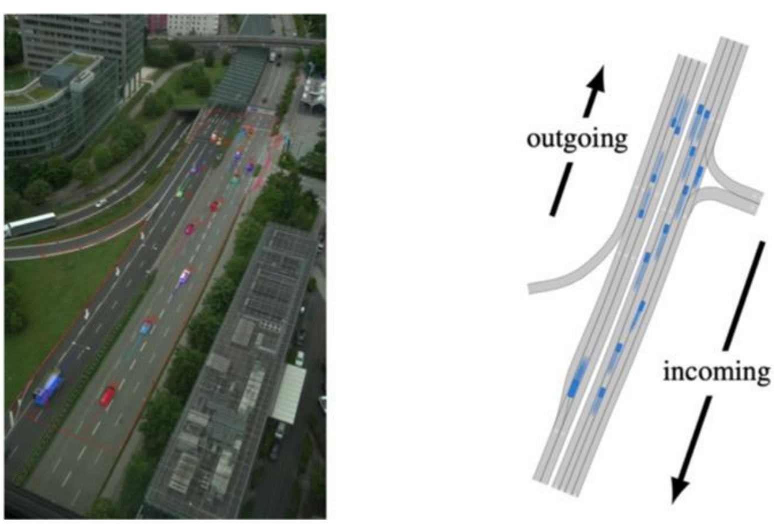

Figure 5: “West” camera perspective of MONA dataset (left) and its CommonRoad lanelet network (right).

3.2 Obstacles

In the case of converting datasets, all traffic participants are modelled as obstacles in CommonRoad scenarios. Therefore, the trajectories are analysed: If a traffic participant moves less than one meter over the relevant course of time, and if it is not a pedestrian, it is classified and stored as a static obstacle. This ensures that a static obstacle is not misinterpreted as a dynamic one due to numerical issues. Otherwise, it is classified as a dynamic obstacle and its trajectory is stored together with the obstacle ID, type, shape, and initial state. Moreover, the state of the blinker indicator lights is derived based on the trajectory of the traffic participant. This is an information which typically cannot be recorded with sufficient accuracy. Therefore, it makes sense to add this information during the conversion.

The datasets which have been harmonised applying this methodology are presented in the next section.

4 Overview of Harmonised Datasets

In recent years, data from multiple different driving field experiments has been collected and published as datasets. Besides varying driving environments (e.g., highway or urban traffic), the situations differ e.g., in the types of intersections, number of vulnerable road users (VRUs), country of collection, road and weather conditions. Thus, datasets for a wide range of driving situations are available. The harmonisation thus far has been carried out for seven extensive datasets (see Table 1).

Table 1. Overview of harmonised datasets.

Name	Country	Driving environment	Focus on	Reference
highD	Germany	Highway	Highway traffic	[6]
exiD	Germany	Highway	Exits and entries	[7]
inD	Germany	Urban	Intersections	[8]
roundD	Germany	Urban	Roundabouts	[9]
MONA	Germany	Highway + urban	Multiple	[10]
INTERACTION	Multiple	Highway + urban	Multiple	[11]
SinD	China	Urban	Signalised intersection	[12]

The first four datasets (highD, exiD, inD, rounD) have been collected by the Institute for Automotive Engineering at RWTH Aachen University. By using drones to collect the footage, they developed a flexible approach for the dataset recording. Since the infrastructure requirements are low, it is possible to record data at locations of particular interest. Therefore, datasets focussing on highway traffic, highway exits and entries, intersections, and roundabouts have been collected. In addition, the uniD dataset [13], which has been collected at the campus of RWTH Aachen University, includes a high number of interactions with VRUs. This could possibly be included in the data basis.

The MONA dataset has been collected in a cooperation between the cyber-physical systems group at TU Munich, and fortiss. The data has been recorded by cameras on a tall building in Munich. They cover different perspectives; one of them is shown in Figure 5.

The INTERACTION dataset combines data from China, the US, Germany, and Bulgaria. It is also diverse in the types of traffic situations, e.g., roundabouts, signalized and unsignalized intersections, lane-changing and merging. Moreover, it claims to offer a high level of aggressive behaviour compared to other datasets.

The SinD dataset has been collected at a signalized intersection in Tianjin, China. Its footage has been captured by a drone. In addition, the collected data is enriched with the information about the traffic light status. This could be relevant to identifying driver models which describe the driving behaviour for approaching traffic lights.

However, the harmonised datasets include mainly trajectory data. This provides no information on human factors. Therefore, the acquisition or cooperation with additional human factors datasets such as UDrive [14] or Shrp2 [15] is currently being evaluated within the consortium. While trajectory datasets which are collected from a bird's-eye perspective do not offer information about the human drivers, these human factors datasets include such. This includes personal information like age, gender, visual impairment, sleep-related factors, medicines, driving knowledge, etc. Furthermore, the vehicles are equipped with additional sensors, inside and outside the vehicle. The outside ones collect data of the surrounding traffic situation, e.g., with radar sensors and cameras. Inside the vehicle, cameras are used to track the driver, and some information from the vehicle's data bus is collected, e.g., actuating of the pedals, steering wheel, or turn signals. The UDrive dataset has been collected as part of an EU research project, containing data from five EU countries. Besides data from cars, also data from trucks and powered two-wheelers are included. The author of the Sharp2 dataset is the Transportation Research Board of the National Academies of the US. Accordingly, the data has been collected in the US.

A disadvantage of these human factors datasets is that the information content is limited to the ego vehicle, meaning the vehicle which collects the data. Especially if the ego vehicle has impaired field of view, this reduces the completeness of a traffic scenario. However, for human driver modelling, these datasets can play an important role. The applicability of the developed harmonisation approach for these datasets is discussed in the following section.

5 Remarks and Next steps

At the time of writing this report, the harmonisation of datasets has been successfully applied for seven trajectory-based datasets. If necessary, additional trajectory-based datasets can be converted applying the same methodology. Moreover, the consortium aims to get access to datasets focusing on human factors. Namely, these are the UDrive [14] and Shrp2 [15] datasets, as mentioned above.

Human factors datasets are typically not trajectory-based or require further processing steps like map-matching. Therefore, a conversion of these datasets into the CommonRoad format will only be possible, if e.g., their radar recordings offer a high accuracy and reliability. This can only be evaluated once the datasets are available. If the data quality is sufficient, this data can be utilised to localise surrounding vehicles reliably and automatically. Otherwise, it might be more appropriate to stick to the original data format of the UDrive or Shrp2 datasets – especially, as there will probably be one human factors dataset at most. Moreover, the tasks for which the different types of datasets are useful to differ, reducing the need to harmonise the different types. Also, it is imaginable to use human factors datasets as training datasets for the human driver model identification, whereas the trajectory-based datasets are better suited for validation purposes.

In addition to the data harmonisation, partners are currently working on integrating the software tools of other consortium partners into the CommonRoad framework. For example, traffic simulations with the Open Traffic Simulator [16] are planned to be triggered from within the CommonRoad framework. This will further enhance the collaboration among the partners. In a first step, the Open Traffic Simulator is supposed to generate random traffic situations for road networks provided by CommonRoad scenarios. Subsequently, the trajectory data of traffic participants in CommonRoad scenarios will be abstracted to match the Open Traffic Simulator traffic generator specifications [16]. Eventually, the preciseness of the derived human driver models can be assessed by comparing the traffic scenarios, synthesised with the Open Traffic Simulator, to the original datasets.

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7 Appendix

```
[1] commonRoad (commonRoadVersion, ...)
├── [1] tags
│   └── [1..N] tag: urban/interstate/.../intersection/
├── [1] location
│   ├── [1] geoNameId
│   ├── [1] gpsLatitude
│   ├── [1] gpsLongitude
│   ├── [0..1] geoTransformation
│   │   ├── [0..1] geoReference
│   │   └── [0..1] additionalTransformation
│   └── [0..1] environment
├── [1..N] lanelet (id)
│   ├── [1] leftBound
│   │   ├── [2..N] point
│   │   └── [0..1] lineMarking
│   ├── [1] rightBound
│   │   ├── [2..N] point
│   │   └── [0..1] lineMarking
│   ├── [0..N] predecessor (ref to lanelet)
│   ├── [0..N] successor (ref to lanelet)
│   ├── [0..1] adjacentLeft (ref to lanelet, drivingDir=same/opposite)
│   ├── [0..1] adjacentRight (ref to lanelet, drivingDir=same/opposite)
│   ├── [0..1] stopLine
│   ├── [1..N] laneletType: highway/urban/busStop/.../crosswalk
│   ├── [0..N] userOneWay: vehicle/car/truck/bicycle/.../pedestrian
│   ├── [0..N] userBidirectional: vehicle/car/truck/bicycle/.../pedestrian
│   ├── [0..N] trafficSignRef (ref to trafficSign)
│   └── [0..N] trafficLightRef (ref to trafficLight)
├── [0..N] trafficSign (id)
├── [0..N] trafficLight (id)
├── [0..N] intersection (id)
│   └── [1..N] incoming
├── [0..N] staticObstacle (id)
│   ├── [1] type: parkedVehicle/.../unknown
│   ├── [1] shape
│   └── [1] initialState
├── [0..N] dynamicObstacle (id)   (with either of the three below
│      behaviors)
│   ├── [1] type: car/truck/.../unknown
│   ├── [1] shape
│   ├── [0..1] initialSignalState
│   ├── [0..1] signalSeries
│   │   └── [1..N] signalState
│   ├── [1] initialState
│   ├── [0..1] trajectory   # dynamic with known behavior
│   │   └── [1..N] state
│   OR
│   ├── [0..1] occupancySet   # dynamic with unknown behavior
│   │   └── [1..N] occupancy
│   OR
│   └── [0..1] probabilityDistribution   # dynamic with unknown
│      stochastic behavior
├── [0..N] environmentObstacle (id)
│   ├── [1] type: building/median_strip/pillar/unknown
│   └── [1] shape
└── [1..N] planningProblem (id)
    ├── [1] initialState
    └── [1..N] goalState
```

Figure 6. Structure of the XML files encoding each CommonRoad scenario. [4]