ASYDE: An Argumentation-based System for classifYing Driving bEhaviors*

DISCUSSION PAPER

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Abstract

We introduce a framework for classifying the driving behaviors of motorists, where the readings collected by inertial sensors during the trip are first integrated with the available information on the characteristics of the road traveled by the vehicle, and then processed to obtain a driving-style certificate. The core of the approach is a reasoner based on *Abstract Argumentation Framework*, that is a well-known paradigm for modeling disputes between agents. Specifically, the decision on which driving-style class best describes the behavior exhibited at each time point is modeled as the "outcome" of a dispute involving different agents, where each agent proposes a class, that may be aligned or in conflict with the other agents' opinions and with what suggested by the sensors' readings on the assessment of the driver's behavior. A prototype implementing the framework was implemented and its experimental validation on real-life data is presented.

1. Introduction

Examining the influence of human behavior on road safety is a matter of considerable interest. As studies in this field over the past decades [1] have demonstrated a correlation between the drivers' behavior and road safety, there is an increasing demand for solutions supporting the analysis of the driving style of motorists. In this context, the objective of this research is the definition of a framework for recognizing and classifying the behavior exhibited by a motorist during a trip on the basis of the readings gathered by various devices monitoring the vehicle status, such as the readings of the inertial sensors of the driver's smartphone and those registered by the *Electronic Control Unit* (ECU) of the vehicle, which periodically records the speed, the engine rpm (rate per minute), etc.. In particular, the proposed framework returns a *driving certificate*, where the kinematic characteristics of the vehicle registered by the sensors during the trip and the available information on the road traveled by the vehicle (such as the speed limits) are taken into account. The core of the approach is a reasoner based on a well-known AI framework, namely Dung's *Abstract Argumentation Framework* (AAF), that has proved effective in supporting the reasoning over several situations [2, 3, 4], especially when different pieces of information provide a partial assessment of the situation. Specifically, AAFs can effectively handle the case where the pieces of information describing the characteristics of the examined situation are conflicting: this is a characteristics affecting the addressed scenario, since the various sensors monitoring the vehicle may provide different measures of the same physical dimension, due to noise or failures.

In the proposed framework, called ASYDE (*Argumentation-based System for classifYing Driving bEhaviors*), the reasoning over the driving style is modeled as a dispute (encoded as an AAF): the participants of the dispute are the sensors, that claim arguments encoding the measures read at time point t (such as "*I read the speed value* 60 *Km/h at* t*, so the motorist held a very high speed in the urban road at* t"), and virtual agents, whose "*assessment arguments*" assign one of the available classes of

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driving style (i.e. *calm*, *normal*, *aggressive*) to the motorist's behavior at t (an example of assessment argument is "*Based on the sensors' readings, it is fair to classify the motorist's driving style at* t *as* calm"). In the AAF built this way, also the contradictions holding between the claims are considered, and they are represented in terms of *attacks* between arguments: for instance, attacks are considered between assessment arguments suggesting different classifications at the same time point, or between sensors' arguments claiming significantly different measures. Starting from this, a well-known reasoner is run over the AAF, and, for each time point, we collect the assessment arguments that turn out to be *accepted* (which, under argumentation terminology, means that they consist of claims that are resilient to the attacks from other arguments, so they can be reasonably considered truthful). Then, the returned driving-style certificate contains, for each driving-style class $C \in \{$*calm*, *normal*, *aggressive*$\}$, the minimum and maximum percentage of time points (against the overall time points composing the time interval of the trip) where an assessment argument voting for C is accepted. Herein, the minimum percentage represents the percentage of time points where only the assessment argument at τ voting for class C is accepted (so the motorist's behavior is classified in C with no uncertainty), whereas the maximum percentage represents the time points where *also* assessment arguments voting for alternative classes are accepted (meaning that the classification in C is uncertain, as it is only one of the possible classes suggested by the sensor readings). This uncertainty is due to the fact that sensor readings can be affected by errors, so it may happen that alternative classifications for the same time point may be accepted, depending on which sensors are considered trustworthy.

Many approaches in the literature have been developed for classifying driving behavior. However, to the best of our knowledge no studies have been conducted applying Argumentation Framework to the task of classifying driving behavior. The power of Argumentation Frameworks lies in their ability to analyze and evaluate conflicting pieces of information, allowing for more accurate and reliable conclusions. In the addressed task, conflicting information arises when a certain sensor devoted to collect driving data, provides errors in the measurements. In this case, if several devices are monitoring the same quantity, we may be provided with different readings of the same physical measurement. Through the employment of argumentation, we are able to solve these conflicts and correct measurement errors by considering not only the readings at a specific time point but also taking into account the surrounding events. In cases where conflict resolution is not feasible, our framework considers alternative possible classifications.

In what follows, we will introduce the ASYDE framework, and show some results coming from a preliminary evaluation over real-life data.

2. Preliminaries

An *Abstract Argumentation Framework* (AAF) [5] is a pair $\langle A, D \rangle$, where A is a finite set, whose elements are called *arguments*, and $D \subseteq A \times A$ is a binary relation over A, whose elements are called *attacks*. Given a set of arguments S and an argument a, we say that "S *attacks* a" if there is an argument b in S such that b attacks a, and that "a *attacks* S" if there is an argument $b \in S$ such that a attacks b. Moreover, we say that a *is acceptable w.r.t.* S if every argument attacking a is attacked by S, and say that S is *conflict-free* if there is no attack between its arguments.

A dispute between agents presenting different claims can be easily represented via an AAF. Each claim is encoded as an argument, and any contradiction between two arguments a and b is encoded by the attack (a, b) or (b, a) or both, depending on which direction of attack best fits. For instance, given the three arguments:
a: "*As it will rain all day long, it is a bad idea to organize a picnic this afternoon*";
b: "*As it is certain that today it will not rain, it is a good idea to organize a picnic this afternoon*";
c: "*As we are in the middle of the rainy season, it is highly probable that this afternoon it will rain*";
a reasonable way to encode their relationships is via the attacks (a, b) and (b, a) (as the premises of the two arguments a and b contradict each other) and (c, b) (as the conclusion of c contradicts the premise of b).

The analysis of the dispute encoded via an AAF is typically done by locating its *extensions* and its *accepted arguments*. An *extension* is a set of arguments S that collectively represent a strong point of view, in the sense that S is coherent (i.e. its arguments do not contradict each other) and capable of counterattacking the attacks from arguments outside S. These general properties give rise to several semantics of the notion of extension, such as the admissible and the preferred: S is an *admissible extension* iff S is conflict-free and all its arguments are acceptable w.r.t. S; a *preferred extension* iff S is a maximal (w.r.t. $\subseteq$) admissible set of arguments.

The notion of *accepted argument* is based on that of extension and encodes the robustness of a single argument, that is assessed by verifying its membership in an extension. In particular, since multiple extensions can exist, the credulous and the skeptical perspectives of acceptance can be adopted: under a semantics, a is credulously (resp., skeptically) accepted if it belongs to at least one (resp., every) extension under the semantics.

In the example above regarding the reasonability of organizing a picnic, no set containing both a and b, or both c and b, is an extension (under any semantics), since it would not be conflict free. In this case, there are 4 admissible extensions (i.e. $\emptyset$, $\{c\}$, $\{a\}$, $\{a, c\}$), while under the preferred semantics there is only one extension, i.e. $\{a, c\}$. Correspondingly, a and c are credulously accepted under both the semantics, and are skeptically accepted under the preferred but not under the admissible.

3. Our strategy

In this section, we formalize our framework and illustrate our strategy.

The aim of our framework is that of providing the users with a driving certificate that characterizes the driver behavior during the time interval at hand on the basis of some predefined classes (also called assessments) of behaviors and of the predefined physical measures of interest.

We start by defining these concepts.

Let us denote as $\mathcal{M}$ the set of the **physical measures** we take into account, as $\mathcal{B} = \{calm, aggressive, ...\}$ the set of **assessments** concerning the driving behaviors, and as $[0..T]$ the time interval under analysis. Moreover, we denote as $\mathcal{D}$ the set of **devices** at hand, and as $\mathcal{D}(M)$ the set of devices measuring the physical measure M. Now, we define the concept of *Event*.

Definition 1 (Event). *An event ϵ is a tuple $\langle M, D, v, t\rangle$, where $M \in \mathcal{M}$, D is a device belonging to $\mathcal{D}(M)$, $v \in \Re$ is the value collected by D, and t is a time point belonging to $[0..T]$.*

Each sensor reading produces an *Event*. Once the events have been collected on the basis of the measurements, we build an argumentation framework consisting of (i) arguments derived from the events, (ii) arguments derived from the assessment classes, (iii) several other arguments built to enable a reasoning mechanism that provides as a final result the **Driving Certificate**, that consists in, for each predefined classes (also called assessments), the number of time points where the driving style of the driver corresponds to it.

In brief, our strategy consists of the following steps:

1. Building the events by **collecting measurements**;
2. Building an **argumentation framework** incrementally starting from time point 0, that is augmenting it with more arguments and attacks for each time point, till the last time point;
3. Reasoning over the argumentation framework trying to establish the driving behavior at each time point, exploiting the arguments and attacks related to that time point and also the arguments and attacks related to the previous and subsequent time point. This way, the evaluation of each time point is done considering the time points in a non-independent way, so that possible measurement errors due to malfunctioning of some of the devices can be fixed in the reasoning;
4. Computing, at the end, the **Driving Certificate** that characterizes the driver behavior based on reasoning over the argumentation framework;

In the following subsection, we define all the arguments and attacks that we use to build the argumentation framework.

3.1. The ASYDE framework

We now introduce our argumentation framework, named *ASYDE*. The he crucial arguments in our framework are the **Low-level arguments** and the **Assessment arguments**. We formally define both of them as follows:

Definition 2 (Low-level argument). *A low-level argument is a tuple $\langle M, D, v, t\rangle$, where M is a physical measure belonging to $\mathcal{M}$, v is a value belonging to $\mathcal{R}$, t is a time point belonging to $[0..T]$., and $D \in \mathcal{D}(M)$ is a device/sensor that detects M's value v at time point t.*

Definition 3 (Assessment argument). *Given a set of driving behavior assessments $\mathcal{B}$, an assessment argument is a pair $\langle B, t\rangle$, where B belongs to $\mathcal{B}$, and t belongs to $[0..T]$.*

Basically, the **Low-level arguments** are directly derived from the events, while the **Assessment arguments** are directly derived from the pre-defined assessment classes. For each time point, we build an assessment argument for each class and a low-level argument for each device and each measure.

Our argumentation framework also includes the **High-level arguments**. These arguments represent a projection of the values collected by the devices into ranges, typically *High*, *Medium* and *Low*. We build an argument for each range, for each time point and for each measure.

Provided that (i) for each measure M, we denote as *levels*(M) the set of its levels, (ii) given a level $L \in$ *levels*(M), we denote as *values*(L, M) the set of numerical values associated to it, and (iii) we denote as *compatible*(L, M) the set of levels L' of *levels*(M) that are compatible with L in the sense that it is possible, for M, to change from L' to L in one time point, the **High-level arguments** are defined as follows:

Definition 4 (High-level argument). *A high-level argument is a tuple $\langle M, L, t\rangle$, where M is a physical measure belonging to $\mathcal{M}$, L is a level belonging to levels(M), and t belongs to $[0..T]$.*

We also have two types of *service* arguments, whose aim will be clearer in what follows. The first one is used to link the low-level arguments to the high-level arguments of the current time point and to link the arguments referring to the current time point with the arguments referring to the previous and the subsequent time point.

Definition 5 (Dummy argument). *A dummy argument is a tuple $\langle q, M, L, t\rangle$, where q belongs to $\{$past,present,future$\}$, M is a physical measure belonging to $\mathcal{M}$, L is a level belonging to levels(M), and t belongs to $[0..T]$.*

The second one is used to link high-level arguments to assessment arguments.

Definition 6 (Dummy Assessment argument). *A dummy assessment argument is a tuple $\langle b, M, t\rangle$, where b is a driving behavior assessment belonging to $\mathcal{B}$, M belongs to $\mathcal{M}$, and t belongs to $[0..T]$.*

The framework is incrementally built, starting from the initial time point 0, augmenting it by adding new arguments at each time point, until the final time point T. For each time point t, we add edges (attacks) between arguments referring to t, but also that correlate t with both the preceding and subsequent time point.

We finally define the ASYDE framework.

Definition 7 (ASYDE Framework). *An ASYDE framework is a tuple $Y = \langle A, R\rangle$, where A is the set of arguments and $R \subseteq A \times A$ is the set of attacks. The set A of arguments is composed by $\langle LA, HA, DA, ADA, AA, R\rangle$, where LA is a set of low-level arguments, HA is a set of high-level arguments, DA is a set of dummy arguments, ADA is a set of dummy assessment arguments, and AA is a set of assessment arguments.*

For a generic time point t, the ASYDE framework is composed of:

1. a low-level argument $la = \langle M, D, v, t \rangle$ from each event $\langle M, D, v, t \rangle$;
2. a high-level argument $ha = \langle M, L, t \rangle$ for each measure and for each of its levels;
3. three dummy arguments $\langle \textit{present}, M, L, t \rangle$, $\langle \textit{past}, M, L, t \rangle$, and $\langle \textit{future}, M, L, t \rangle$ for each measure and for each of its levels;
4. two mutual attacks for every pair of high-level arguments $ha = \langle M, L, t \rangle$ and $ha' = \langle M, L', t \rangle$;
5. (i) a self-attack to every dummy argument, (ii) an attack from every $da = \langle \textit{present}, M, L, t \rangle$ to every $ha = \langle M, L, t \rangle$, (iii) an attack from every $la = \langle M, D, v, t \rangle$ to every $da = \langle \textit{present}, M, L, t \rangle$ such that value v belongs to level L for M, (iv) an attack from every $da = \langle \textit{past}, M, L, t \rangle$ to every $ha = \langle M, L, t \rangle$, (v) an attack from every $ha = \langle M, L, t-1 \rangle$ to every $da = \langle \textit{past}, M, L', t \rangle$ such that $L' \in \textit{compatible}(L, M)$, (vi) an attack from every $da = \langle \textit{future}, M, L, t \rangle$ to every $ha = \langle M, L, t \rangle$, (vii) an attack from every $ha = \langle M, L, t+1 \rangle$ to every $da = \langle \textit{future}, M, L', t \rangle$ such that $L' \in \textit{compatible}(L, M)$;
6. an assessment argument for each class in $\mathcal{B}$;
7. a dummy assessment argument $\langle b, M, t \rangle$ for each class in $\mathcal{B}$;
8. two mutual attacks for every pair of assessment arguments $\langle b, t \rangle$ and $\langle b', t \rangle$;
9. (i) a self-attack to every dummy assessment argument, an attack from every $\langle b, M, t \rangle$ to every $\langle b, t \rangle$, and an attack from every $ha = \langle M, L, t \rangle$ to every $\langle b, t \rangle$ such that L for M is judged compatible with the driving behavior b: for example, speed's level low is compatible with the *CalmDriving* behavior assessment.

In a nutshell, our aim is that of enabling a mechanisms that allows to have at least one preferred extension containing exactly one assessment argument per time point, or possibly multiple preferred extensions such that each preferred extension contains at most one of the assessment arguments for each time point. This way, we can compute, for each assessment class B, the percentage of time points t where the assessment argument $\langle B, t \rangle$ is skeptical accepted (resp. credulous accepted) in a preferred extension. Then, we compute the final result of our technique, that is the *Driving Certificate*, as follows:

Definition 8 (Driving Certificate). *A* Driving Certificate DC *is a set of pairs of the form* $\langle b, [psk..pcr] \rangle$*, where* b *is a driving behavior class belonging to* $\mathcal{B}$*,* psk *(resp.,* pcr*) is a percentage representing the number of time points an assessment argument* aa *of the form* $aa = \langle b, t \rangle$ *has been skeptical (resp., credulous) accepted in the time interval* $[0..T]$.

Example 1. *Consider the case where we have a single physical measure, namely speed (denoted by* S*), monitored by two devices, GPS and OBDII and a time interval* $[0..2]$*. For each time point* $t \in [0..2]$*, we have two low-level arguments, corresponding to each speed measurement. Figure 1 shows an excerpt of the structure of our framework focused on time point* 1*. For the sake of space, we show all the arguments and attacks built at* $t = 1$*, but only the arguments and attacks built at* $t = 0$ *and* $t = 2$ *that are linked to arguments built at* $t = 1$*. The two low-level arguments for time point* 1 *are depicted in green with dashed lines.*

In this example we define $levels(S) = \{L, M, H\}$*, where* L *stands for* Low*,* M *and* H *for* Medium *and* High*, respectively. Then, for each level and for each time point, we have a high-level argument, depicted in yellow. Assuming that drivers' behavior is classifiable in three categories (*CalmDriving *(*CD*),* NormalDriving *(*ND*), and* AggressiveDriving *(*CD*)), we have the three assessment arguments depicted in white.*

The dummy arguments that attack the high-level arguments and are attacked by low-level arguments are depicted as orange circles. The dummy arguments that link the current time point to the previous (resp. subsequent) one depicted as blue squares (resp. pink stars). The dummy assessment arguments are depicted as brown diamonds.

It is easy to see that each high-level argument must be defended against the dummy-argument attack to be included in a preferred extension by at least one low-level argument. In this example, at time point 1*, we have one low-level argument defending the high-level argument* $\langle S, M, 1 \rangle$*, representing the level* Medium*,* *and the other one defending the high-level argument representing the level* Low*. The high-level argument representing the level* High *is instead not defended, and therefore, can not be accepted in any preferred extension. In practice, this means that assuming that the driver was driving at a high-level speed is not reasonable for time point* 1*.*

By correlating the current time point with both preceding and subsequent ones, we can eliminate certain possibilities that we would not be able to rule out by considering only the current time point. Specifically, to be accepted in a preferred extension, each high-level argument must be defended by both the attack from the blue square dummy argument and the pink star dummy argument. This defense is implemented by the high-level arguments of the previous and subsequent time point, respectively, that represent a compatible range. In other words, if, for instance, at time point 0 *we accepted the high-level argument representing the level* High*, at time point* 1 *the high-level arguments associated with levels* High *and* Medium *are defended, while the one related to level* Low *is not. Consequently,* $\langle S, L, 1\rangle$ *can not be accepted in any preferred extension.*

Assuming that, at time point 0 *(resp.,* 2*), there are the two arguments* $\langle S, OBDII, 80, 0\rangle$*,* $\langle S, GPS, 85, 0\rangle$ *(resp.,* $\langle S, OBDII, 65, 2\rangle$*,* $\langle S, GPS, 95, 2\rangle$*), defending* $\langle S, H, 0\rangle$ *(resp.,* $\langle S, M, 2\rangle$ *and* $\langle S, H, 2\rangle$*) from the attacks by the dummy arguments, we have that* $\langle AD, 0\rangle$ *(resp.,* $\langle ND, 2\rangle$ *and* $\langle AD, 2\rangle$*) is defended by them from the attacks by the dummy assessment arguments. Furthermore, we have that the arguments* $\langle S, M, 1\rangle$ *and* $\langle S, H, 1\rangle$ *(resp.* $\langle S, L, 1\rangle$*,* $\langle S, M, 1\rangle$ *and* $\langle S, H, 1\rangle$*) are defended by* $\langle S, H, 0\rangle$ *(resp.,* $\langle S, M, 2\rangle$ *and* $\langle S, H, 2\rangle$*) from the attacks by the blue-square (resp. pink-star) dummy arguments. On the contrary,* $\langle S, L, 1\rangle$ *is not defended by the blue-square dummy argument attack, and therefore, is not accepted in any preferred extension. In other word, we assume that the reading of the speed that supports the level* Low *at time point* 1 *is due to a failure of the device which collected it. Therefore, we exclude the possibility of classifying the driving style as Calm at time point* 1*.*

Then, we have two preferred extensions:

- $\{\langle S, OBDII, 80, 0\rangle, \langle S, GPS, 95, 0\rangle, \langle S, H, 0\rangle, \langle AD, 0\rangle,$
  $\langle S, OBDII, 60, 1\rangle, \langle S, GPS, 30, 1\rangle\langle S, M, 1\rangle, \langle ND, 1\rangle,$
  $\langle S, OBDII, 65, 2\rangle, \langle S, GPS, 95, 2\rangle, \langle S, M, 2\rangle, \langle ND, 2\rangle\}$
- $\{\langle S, OBDII, 80, 0\rangle, \langle S, GPS, 95, 0\rangle, \langle S, H, 0\rangle, \langle AD, 0\rangle,$
  $\langle S, OBDII, 60, 1\rangle, \langle S, GPS, 30, 1\rangle\langle S, M, 1\rangle, \langle ND, 1\rangle,$
  $\langle S, OBDII, 65, 2\rangle, \langle S, GPS, 95, 2\rangle, \langle S, H, 2\rangle, \langle AD, 2\rangle\}$

The produced driving certificate is:

- $\{\langle CD, [0.0\% - 0.0\%]\rangle, \langle ND, [33.3\% - 66.7\%]\rangle, \langle AD, [33.3\% - 66.7\%]\rangle\}$

In conclusion, in this example, according to the certificate, the driving style can be classified as both Normal and Aggressive over the entire time interval considered.

4. Experimental Evaluation

We conducted a series of experiments to validate the capability of our prototype in distinguishing various driving styles. As also done in [6], we assumed that drivers' behavior is classifiable in the three categories: *CalmDriving* (CD), *NormalDriving* (ND), and *AggressiveDriving* (CD). The driving data were collected during two different trips performed by different drivers. Both the trips were taken on a rural road, under favorable weather conditions and without traffic, ensuring that traffic did not influence the test results.

4.1. Physical Measures Set and Devices Set

The devices used to collect data were:

- **OBDII device** - It enables access the vehicle's internal information connecting via Bluetooth to your phone.

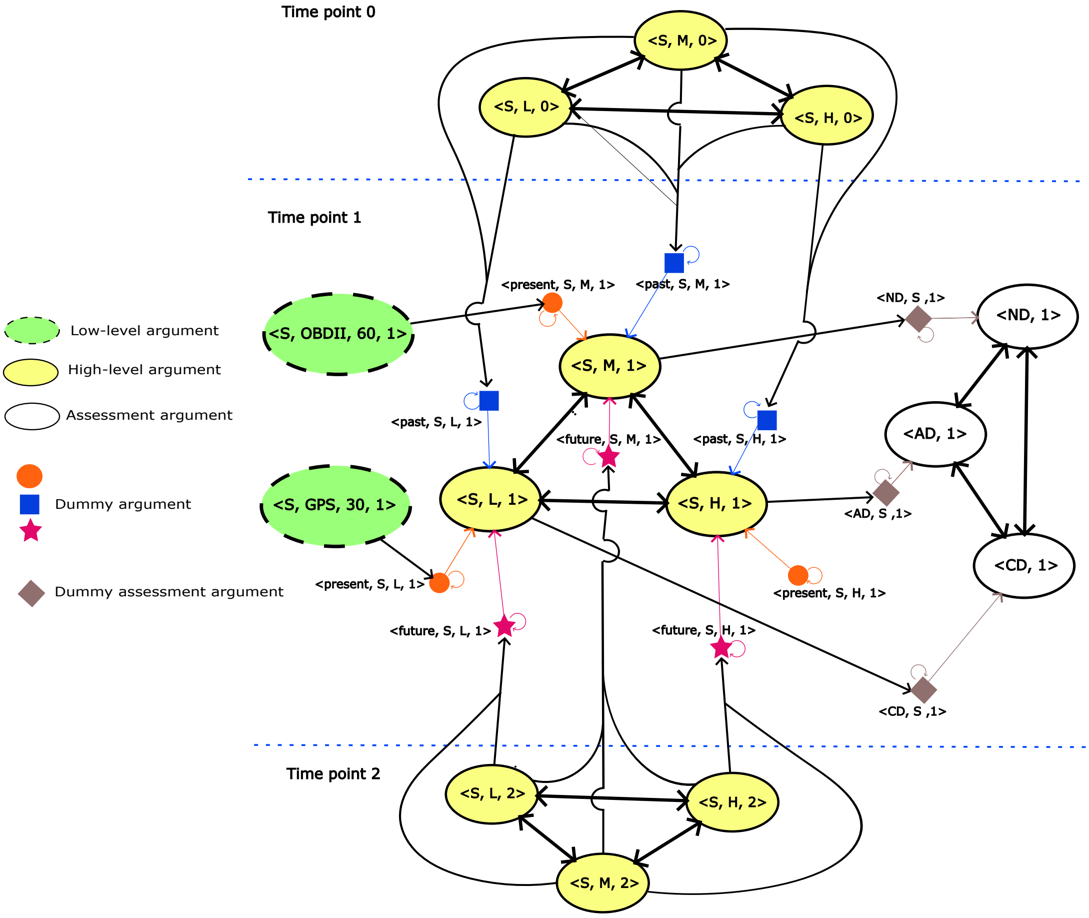

Figure 1: An example of ASYDE framework

- **Smartphone** - Smartphones are equipped with 3-axial accelerometers and 3-axial gyroscopes. The smartphone must be positioned inside the car so that its y-axis is oriented toward the vehicle's front and it's screen (z-axis) is oriented upward.
- **GPS device** - It is used to collect vehicle speed data.

We used the following measures, that, according to the recent literature ([7, 8, 9, 10, 11, 12, 13, 14, 15]), are deemed to be the most suitable set of physical measures for recognizing driving styles:

- **Longitudinal acceleration** - acceleration in the direction of the vehicle's motion, detecting acceleration and braking events (gathered by y-axis smartphone's accelerometer and OBDII device).
- **Lateral acceleration** - acceleration in the transverse direction of the vehicle's motion, detecting turning events (gathered by x-axis smartphone's accelerometer).
- **Angular velocity** - rate of rotation of the vehicle, detecting turning events (gathered by z-axis smartphone's gyroscope).
- **Speed** - identifying any exceeding of speed limits (gathered by GPS and OBDII devices).
- **Longitudinal jerk** - variation in acceleration in the direction of the vehicle's motion (calculated as derivatives of longitudinal acceleration).
- **Lateral jerk** - variation in acceleration in the transverse direction of the vehicle's motion (calculated as derivatives of lateral acceleration).

4.2. Measure Level set

Given a physical measure M, the values of M read by the sensors are mapped to specific levels $L \in levels(M)$. The categorization of levels and their respective threshold values for each physical measure are determined based on the comfort level of passengers, which is correlated with ride quality. Although the sense of comfort is subjective and varies among passengers, attempts have been made in literature to establish general measurement criteria. Various studies have identified threshold values for discomfort concerning different physical factors such as acceleration, lateral acceleration, and jerk. In our experiments, the threshold values for each physical measure were evaluated based on [16, 17, 18, 19]. The only exception is for speed threshold values, which refer to road signs to identify any exceeding of the limits. However, all the threshold values of the intervals are documented in a properties file, allowing for easy adjustment based on the user's specific requirements.

4.3. Results

We implemented the prototype described in Sec. 3 using μ-*toksia* argumentation reasoning system. This solver provides several reasoning tasks over AFs, such as credulous and skeptical acceptance of arguments [20].

The implemented prototype of the ASYDE framework processed the real-life data collected during the trips, obtaining the driving certificates reported in table 1. For each trip, we report the percentage of time points where the behavior of the driver who took the trip falls in each of the predefined assessment classes (*i.e. CalmDriving* (CD), *NormalDriving* (ND), and *AggressiveDriving* (CD)).

As shown in table 1, the prototype appears to be capable of distinguishing various driving styles. In fact, the class that represents the actual driving style with which the trip was conducted was recognized by the framework for a rather significant percentage of time compared to other classes.

Table 1
Certificates of driving style

Actual Driver Style	Our results on TEST 1	Our results on TEST 2
Calm Driver	$CD : [71.01\% - 80.25\%]$[1] $ND : [11.41\% - 20.65\%]$ $AD : [0.0\% - 0.0\%]$	$CD : [60.08\% - 72.19\%]$ $ND : [25.48\% - 37.79\%]$ $AD : [1.7\% - 2.76\%]$
Normal Driver	$CD : [24.28\% - 34.23\%]$ $ND : [63.67\% - 74.19\%]$ $AD : [1.34\% - 2.29\%]$	$CD : [22.84\% - 35.65\%]$ $ND : [60.7\% - 74.65\%]$ $AD : [1.95\% - 3.06\%]$
Normal-Aggressive Driver	$CD : [9.15\% - 16.16\%]$ $ND : [42.38\% - 51.22\%]$ $AD : [30.49\% - 34.15\%]$	$CD : [12.20\% - 16.61\%]$ $ND : [24.41\% - 33.22\%]$ $AD : [51.86\% - 57.97\%]$

[1] The minimum (resp., maximum) percentage corresponds to the percentage of time points where an assessment argument corresponding to the assessment class has been skeptical (credulous) accepted under preferred semantics.

5. Conclusions

We have discussed the ASYDE framework, whose aim is that of classifying driver behaviors by resorting to the abstract argumentation framework. We have also shown some prominent results coming from a preliminary experimental evaluation.

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