A Theory Repair Based Traffic Regulations Generalisation for Autonomous Vehicles

Yiwei Lu[1,2], Xue Li[3], Zhe Yu[1]⋆, Yuhui Lin[4], Burkhard Schafer[2], Alan Bundy[3], Andrew Ireland[4], and Zhe Lin[5]

[1] Institute of Logic and Cognition, Department of Philosophy, Sun Yat-sen University; `Y.Lu-104@sms.ed.ac.uk; yuzh28@mail.sysu.cn`

[2] School of Law, Old College, University of Edinburgh; `B.Schafer@ed.ac.uk`

[3] School of Informatics, University of Edinburgh; {`xue.shirley.li, A.Bundy`}`@ed.ac.uk`

[4] School of Mathematical & Computer Sciences, Heriot-Watt University; {`y.lin, ceeai`}`@hw.ac.uk`

[5] Department of Philosophy, Xiamen University; `pennyshaq@163.com`

Abstract. The development of AI products poses unique challenges to law reform, especially specific normative reform. In particular, some AI technologies like autonomous driving technologies blur the boundaries of these fundamental concepts of law, such as human beings, objects and behaviours. This gives rise to inconsistency and inapplicability of existing human-specific laws when turned to AI, such as irrational division of responsibility, conceptual ambiguities, conflicting guidance on behaviour, and conflicts with legislative intent. Considering the complexity and scale of the legal structure and how AI affects this structure, especially in a dynamic context, pure manual legal adjustments will naturally face difficulties in terms of accuracy and efficiency. This study therefore extended an automated theory repair system to design an intelligent legal aid system for the revision of driving rules in the context of automated driving and provided the code necessary to implement these functions.

Keywords: Abduction, Automated theory repair, Legal modification, Autonomous driving

1 Introduction

The continuous development of artificial intelligence technology has brought about entirely new pressures for fast legal change [7]. This is reflected, on the one hand, in the fact that pre-existing legal theories are challenged by ethical and fundamental assumptions, and, on the other hand, in the persistent difficulty of providing clear standards of conduct applicable to AI products [3]. For the development and manufacture of AI products, the impact of the second point may be even greater. This is because if avoiding the risk of additional violations is one of the most fundamental motivations for engineers and manufacturers to pursue legal compliance, then the lack of a clear code of conduct will make it difficult to continue product design. For example, if it is not clear whether an autonomous vehicle (AV) should perform the actions that a driver should

⋆ Corresponding author.

take while in motion, it will be difficult to design whether it should require children to fasten their seatbelts before starting, as human drivers do. In addition, without a clear code, producers would make different decisions and then end up with chaotic products that are potentially dangerous and harmful to users and society.

There are a number of difficulties common to the adaptation of any system of legal norms [24]. For one thing, the law is a multi-layered and complex structure. The relationships between legal norms are diverse, and changes to a single rule or norm are likely to have a knock-on effect on other norms, which places high demands on the precision of adjustment. For the other thing, the number of legal norms is extremely large, and the inconsistencies and uncertainties associated with any change are likely to be widespread. This makes even small-scale modifications of legal norms a costly exercise in checking and correcting.

Unfortunately, the characteristics of AI technology have an amplifying effect on the difficulties described above [10]. Serious incompatibilities arise when we try to apply existing human-specific legal norms to govern the behaviour of AI products, and we face additional challenges when we try to achieve consistency. At root, this is because AI products blur the law's basic assumptions about people, things, and behaviour. Whether we view them as subjects or instruments of behaviour, they trigger further inconsistencies. One immediate problem this creates is confusion between behaviour and the corresponding liability. For example, if we view an AV as a driving tool under current law, it would seem that it could be exempt from being fully responsible for the driving choices it controls and the passengers it affects. If we view it as a driver under current law, should it be the car's autonomous system that is responsible, or its designer or manufacturer, or the operator of some online platform?

In addition, current law presupposes that the subjects who read, understand, and practice it are human beings. This means that the expressions it adopts as well as the behaviours it prescribes are based on a common sense understanding of human beings, which includes but is not limited to human comprehension, human bodily and physical functions, and the behavioural ability and knowledge level of most people. When we apply such a legal system to the AI context, the first thing it brings is the difficulty of understanding and practicing. Artificial intelligence products may not have some of the common sense or associative abilities that humans need to understand legal concepts and rules, resulting in the inability to choose specific behaviours based on these norms. Just as a human can easily understand what it means to maintain an appropriate distance, an intelligent system may need more precise guidance on the concept of appropriateness. In response to this, a large body of research has attempted to address the problem in terms of changing the form of legal expression. For example, traffic laws are formally expressed and cut into the operating system of an AV to directly regulate its behaviour [2,23]. However, this would still face another problem, namely, that the characteristics of AI products change the original causal relationship between legal behaviours and outcomes. For example, for a human driver, the long-time use of video devices while driving can lead to distraction, resulting in danger. For an autonomous driving system, however, this may even be necessary to drive safely. Similarly, standards set against humans for a particular goal may not apply to AI like driving speed, driving time and so on.

The rapid evolution of AI technologies creates unprecedented pressure for legal adaptation, presenting a dual challenge: maintaining legal consistency while enabling efficient updates. Current approaches to rule generalization face significant limitations:

- Rule-based systems (e.g., LegalRuleML [19]) use static templates that lack flexibility for novel AI conflicts, requiring manual updates.
- Knowledge graph methods [1] effectively query existing norms but cannot generate new rules or resolve dynamic inconsistencies.
- LLM-based approaches often produce logically inconsistent outputs and lack verifiable reasoning chains for legal auditing [15].

Given these limitations, and the impracticality of relying solely on manual or fully automated methods, a hybrid approach is needed. Automated reasoning can generate logically consistent repair suggestions at scale, while human experts retain control over semantic validation and final decisions.

According to the previous analysis, this automated reasoning tool should have several characteristics: (1) It can express the characteristics of legal information and AI products. (2) The ability to detect problems between current legal systems and new features of AI products. (3) Able to give logical modification solutions while ensuring the legal intentions. Based on this, we chose to introduce and extend the ABC system [17,4]. And to better show how ABC works in this mission, we selected some British traffic rules (mainly from the Highway Code) as case studies. We analysed the types of adjustments needed to apply these rules to AVs and explored how the ABC method can be used to provide repair recommendations. The Highway Code is one of the legal guidance documents for obtaining a driving licence in the UK. If 'driving like a human' is considered the minimum requirement for legal compliance for AVs, then testing and adapting traffic rules for human drivers can serve as a good example.

Next, we review related work and compare several existing methods with ABC. In §3, we summarize the key adjustments required when applying current traffic rules to autonomous vehicles. Subsequently, in §4, we introduce ABC and demonstrate how it generates reasonable repair suggestions for diverse issues. To further clarify the repair process, we present a case study in §5. Finally, we conclude the paper in §6.

2 Related Work

How to detect problems in existing theoretical frameworks has always been an important issue in the field of knowledge representation and reasoning. In the fields of semantic web and knowledge graphs, there are many methods for detecting conflicts in existing knowledge bases. This is especially true in subfields such as entity embedding and quality assessment [12,20]. However, effective methods for fixing these problems have rarely been proposed.Some existing methods that focus on theoretical repair have excessive requirements for data formats [8], or only provide limited types of modifications [17]. In a legal context, it is difficult to deal with the combination of expression forms and reasoning patterns.Some research requires a large amount of manual intervention in the reasoning process, which fails to meet efficiency requirements. More importantly, these methods treat the formal detection and removal of inconsistencies as the main or sole goal of theory modification, while ignoring the environment in which the modified theory will be applied. Legal adjustments need to consider the legislative intention and the underlying application logic, and consistency repair is only meaningful within this framework.

Some machine learning methods have been used to mine logical features to generate rules [21,14]. They can 'create' concepts and predicates to a certain extent, but cannot modify logical relationships on demand. On the one hand, legal adjustments are relatively diverse, and creating independent concepts and rules for each new situation is not a way for law to self-repair. On the other hand, machine learning algorithms rely heavily on empirical data, but legal amendments are not a frequent occurrence, making it difficult to find a large amount of historical data for legal amendments in the same field. Moreover, past legal amendments have very limited reference value in terms of statistical probability regularity. Machine learning algorithms also find it difficult to break through the existing patterns in empirical data. Since laws are written in natural language, LLMs have some advantages in addressing this issue. However, they are not yet accurate in reasoning [11], and are therefore better at integrating and explaining existing legal information and structures than at making innovative changes. Furthermore, although LLMs can produce reasoning results that can be read directly, the reasoning process severely lacks the explainability valued by law. Current LLMs capable of providing so-called thought processes also focus on presenting the various factors that influence the reasoning results, rather than the complete logical process.

Based on the above discussion, the reason for introducing ABC in this research is primarily its ability to modify theories around a given goal. The ABC repair system can accept an input theory and a benchmark, and then repair the theory to make it consistent with the benchmark while satisfying the consistency requirement [17,4]. This satisfies the requirement for consistency in the legal adjustment process while protecting legal intention, and also enables the reasoning process to be interpreted from a legal perspective. Secondly, unlike machine learning-based systems, ABC is a logic-based automatic reasoning system. Therefore, it requires only a small amount of input data to function.Furthermore, symbolic reasoning based on formal representations is interpretable and strictly follows logical rules [13,18], which enables legal experts to reuse the reasoning results. ABC can provide repair solutions based on concept changes and logical relationship adjustments in more diverse ways[6] and can clearly trace the reasoning process and basis. All these features make ABC highly suitable for preliminary screening of legal adjustment solutions and significantly improve the efficiency of legal experts in considering logical consistency.

In previous research, ABC has been applied to model virtual bargaining in human coordination processes subject to communication constraints to generate repair solutions with better alternatives, thereby improving agreements [5]. In the field of software system maintenance, ABC has also been applied to root cause analysis [5]. It is used to detect missing information and provide repair solutions to address these root causes. Furthermore, ABC has been used to correct erroneous analogies [6]; and to explore students' misunderstandings of arithmetic processes using repair solutions [22]. In these

[6] ABC's conceptual change include splitting/merging predicates, increasing and decreasing the arity of a predicate and introducing new predicates and constants.

tasks, ABC demonstrates good performance in terms of reasoning accuracy, explainability, and adaptability to repair tasks.

3 Patterns of Conflicts

As mentioned above, in order to show more concretely how this system can give possible solutions for modifying existing legal norms to give clear guidance to autonomous vehicles, we select and analyse a series of traffic rules to summarise what types of problems and adjustments we need to handle. Firstly, we extract some main legal intentions from these rules, i.e., what effects these rules are essentially seeking. A list of legal intentions/responsibilities is shown below as a shown case:

1. Maintaining control of the vehicle;
2. Communicate necessary information to other road participants in a timely manner;
3. Protects public and private properties;
4. Keep oneself and other road participants moving properly and efficiently;
5. Protecting the lives of all other road participants;
6. Protecting the lives of drivers and passengers in special situations;
7. Prevention of possible accidents.

We consider legal intention as functions, i.e., taking target objects and scenarios to achieve certain properties. Problems arising when applying current legal rules to AVs could be understood as breaking/hampering the targeted functions. We manually extract 3 patterns of problems or needed adjustments surrounding the legal intentions as shown below. Conflicts between current traffic rules and autonomous could raise from one of or combinations of these 3 patterns:

Pattern 1. Prohibition from Legal intentions The original legal intention is to avoid specific situations by prohibiting some actions. But the AVs have to or are expected to do them.
Cases: Highway Code 149 and 150 (summarised): Drivers are prohibited from using handheld communication devices while driving. Hand-free communication devices should also be used on a limited basis without causing distraction. Viewing of any video device not related to driving is prohibited. Limited viewing of navigation and other related systems is permitted only if it does not cause distraction. This rule is to guarantee the driver focus on driving and road conditions. But for autonomous driving, communication devices, video sensors, and visualisation devices are the basis for safe driving. Prohibiting or partially prohibiting them could cause safety problems. And similar rules are but not limited to: Highway Code 148, 275.

Pattern 2. Instruction and suggestion from legal intentions To realise given legal intentions, the law instructs or requires the driver to take certain actions. But these actions are unnecessary, impossible or even harmful for AVs.
Cases: Highway Code 91 (summarised): Human drivers should take a break of at least 15 minutes every two hours when driving long distances. This instruction is to ensure the physical and mental state of human drivers and to avoid fatigue driving. But AVs don't get fatigued or need to take high-frequency breaks as humans

do. Following this instruction would instead defeat the purpose of people applying autonomous driving. Similar rules are but not limited to: Highway Code 97, 160, 271.

Pattern 3. Unification and partition of legal subject In current regulation, human drivers are considered as a unity of multiple legal subjects, while regulations assign multiple responsibilities to the single subject. However, in the case of AV, this is no longer the case. Part of the legal responsibilities, e.g. car control has been separated from the AI, while the others remain the legal subjects such as car owners or passengers. Moreover, we can further partition the legal subject in AI with subsystems, given that the main operation procedures of an AI is a loop of *sense*, *perceive*, *plan* and *act*.
Cases: Highway Code 99 (summarised): Drivers should ensure that eligible children are using the corresponding safety facilities, such as seat belts and child seats. In an autonomous driving situation, where the vehicle has no physical function to ensure this move is made, the duty to detect and alert may be more appropriate. The responsibility for ensuring that children use safety facilities should perhaps be separated from the legal subject of the driver and attributed to the adults travelling with the child. Similar rules are but not limited to: Highway Code 89, 97, 228, 229.

Now we know the legal intentions and patterns violating these intentions when applying current traffic rules to autonomous vehicles. In the next section, we introduce the ABC system and demonstrate how it gives legal modification suggestions for different patterns for given legal intentions.

4 A Theory Repair Approach to Suggest Legal Regulation Generalisation

4.1 Theory Repair by ABC

The ABC repair system (ABC) is designed to repair formal logical theories, whose core mechanism resembles elements in regulation generalisation. It effectively addresses faults like inconsistencies, insufficiencies, and incompatibilities within a logical theory, as defined below. In these definitions, C denotes a conclusion, with P1 and P2 representing logical reasoning processes leading to C under a given theory.

- *Inconsistency*: the theory is self-contradictory w.r.t. the truth value of C [9].
- *Insufficiency*: when C is wanted, but it cannot be derived from the theory [17].
- *Incompatibility*: when C is unwanted, but it is derivable from the theory [17].

Based on the definitions of the three problems, we can correspond them or their combinations to the previously discussed patterns. The exact correspondence depends on the way we understand and model the contradiction. For example, in the case of autonomous vehicles having to make heavy use of communication and video devices, we can understand it as an incompatibility, i.e., we do not want the vehicle to lose focus on the road, but prohibiting the use of communication and video devices leads to this. We can also read it as an insufficiency, i.e., we want the vehicle to be able to pay attention to the road, but prohibiting the use of communication and video devices will not get that result. This modelling flexibility is also one of the strengths of ABC. It allows legal experts to condition their reasoning with their own inputs on their needs. For example, whether something is to be treated as an observed objective situation or a result that the law must ensure. We will also illustrate this point in a subsequent case.

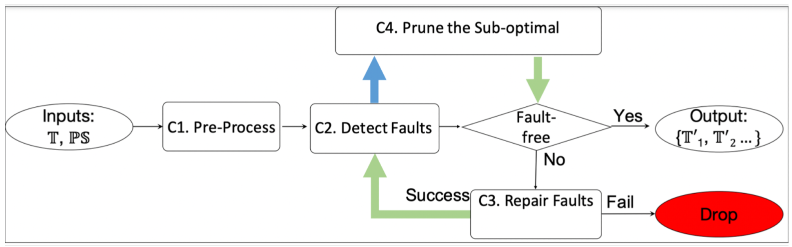

Fig. 1. Flowchart of ABC

The flowchart of ABC is presented in Fig.1. In this figure, green arrows indicate the sequential transfer of individual theories to the next process, while the blue arrow collects and transfers theories as a set. When a faulty theory is found to be irreparable, it is excluded from the repair process [16]. The inputs include the object theory $\mathbb{T}$ and a preferred structure $\mathbb{PS}$, where the former is subject to repair if faults are detected and the latter serves as the benchmark for evaluating the correctness of $\mathbb{T}$. When the theory is faulty,[7] ABC generates and outputs all possible repaired versions that meet the benchmark conditions. The code implementing the functionalities described in this research is available at: **ABC_Datalog**.

Table 1. Faults and their repair strategy in the ABC repair system.

Faults	Issue	Repair strategy
Inconsistency & Incompatibility	Exist the occurrences of proofs of C (P1s)	Break P1s
Insufficiency	Cannot find any proofs of C (P2s)	Build a P2

As we can see in Table 1, ABC has two main strategies for repair: breaking proofs for unwanted conclusions and constructing proofs for targeted ones. This supports repairing legal systems under given intentions like prohibition, instruction, requirement and so on. More importantly, ABC enables modifications that include adjustments to the internal structure of the legal regulations, in addition to the addition and deletion

[7] The original version of ABC addresses incompatibility and insufficiency and has since been extended to handle inconsistency. For simplicity, these aspects are uniformly referred to here as inconsistencies or faults, assuming that incompatibilities and insufficiencies represent inconsistencies between the theory and $\mathbb{PS}$.

of rules. Specifically, ABC has 11 operations that implement these two strategies for certain problems as shown in Fig. 2 and Fig. 3.

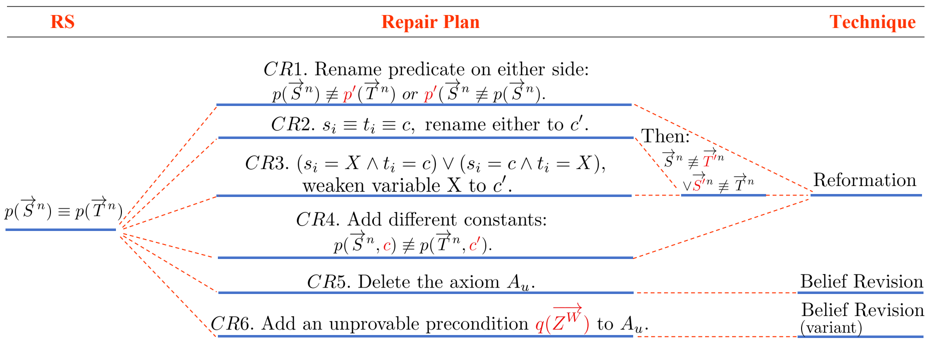

Fig. 2. Repairing operations for incompatibility and inconsistency

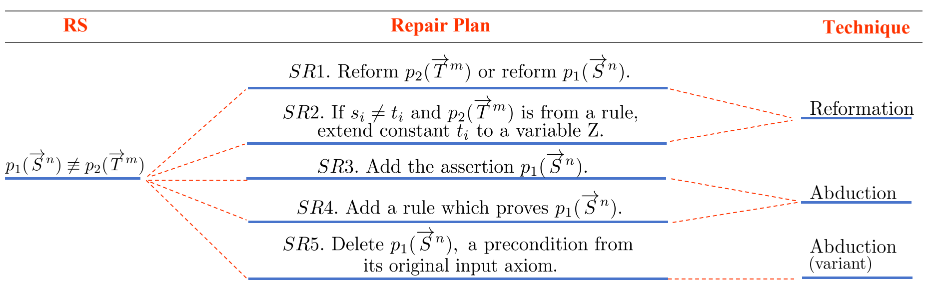

Fig. 3. Repairing operations for insufficiency

To better understand these 11 operations, we categorize them into four types based on their logical methods (following [16]), as shown in Table 2. RC1 modifies the subject, object, or behavior relationship in a rule. For example, changing 'a citizen may drive an automobile' to 'a citizen may sit in an automobile'. RC2 alters the conditions of a rule, such as modifying 'a citizen may drive a car' to 'a citizen of adult age may drive a car'. RC3 adjusts the semantic scope of concepts or conditions, for instance changing 'male citizens of adult age may drive an automobile' to 'all citizens of adult age may drive an automobile'. Finally, RC4 represents the simplest form of legal modification - adding or deleting complete rules, like prohibiting autonomous car usage by adding: 'citizens are forbidden to use autonomous cars'. A more detailed correspondence between repair operations in ABC and legal modification methods can be found in Fig. 4.

Table 2. ABC's Repair categories and the corresponding practice in regulation generalisation.

Repair Categories	Example (old → new))	Regulation Generalisation Practice.
RC1. Rename constant or predicate (CR1, CR2, SR1).	driver(D, C) → driver_dummy(D, C)	Change subject, object or relation.
RC2. Add/delete an argument of a predicate or a precondition of a rule (CR4, CR6, SR5).	driver(D, C) → driver(D, C, dummy)	Change applicable conditions or restrictions.
RC3. Generalise to broader individuals or restrict to specific individuals (SR2, CR3).	driver(D, C, dummy) → driver(D, C, X)	Extend to wider or restrict to narrower applicable range.
RC4. Delete or add an axiom (CR5, SR3, SR4).		Abandon or create a fact or a rule of regulation.

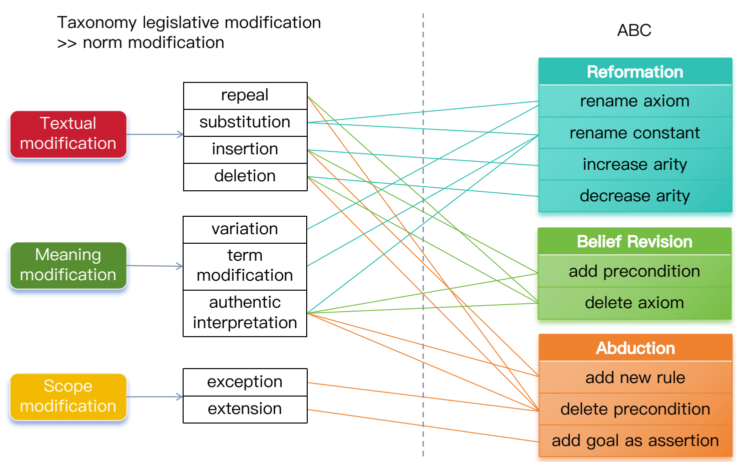

Fig. 4. A mapping of ABC repair operations with a legal modification account

It is important to highlight that ABC's approach to repair is based on logical symbols rather than legal semantics. Therefore, it is entirely up to the legal experts to decide which logical solution is ultimately chosen and what legal semantics should be used for that logical solution. ABC merely provides suggestions to satisfy the logical targets, which are part and basis of requirements of legal modification.

To summarise, the workflow of ABC to give legal modification suggestions is shown in Fig. 5. The underlying strategy of applying ABC will be introduced with simplified examples for demonstration[8].

[8] In this section, all examples are simplified for demonstration without directly citing laws.

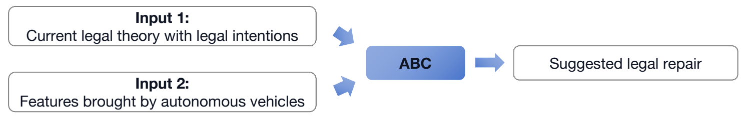

Fig. 5. Workflow of legal modification from ABC

4.2 Automating Law for AV Formalisation

For formalising law for AVs, current laws (CLs) provide the main source of necessary information. The relationship between CL and future AV-specific regulations is shown in Fig. 6, where L_1 denotes parts of current laws (black) that are irrelevant for AVs, L_2 covers provisions that are relevant (blue) and may be directly retained or modified to suit AV contexts, and L_3 represents entirely new content that current laws do not address but that is required for AVs.

This paper uses Example 1 to clarify this structure. E-L1, which regulates driver fatigue, becomes irrelevant for fully autonomous vehicles and thus belongs to L_1. E-L2 illustrates how an existing rule—prohibiting drunk driving—could still apply if passengers in AVs are treated as drivers under certain conditions, requiring only modification to reflect AV-specific requirements (marked in red). E-L3 adds a new provision that autonomous vehicles must not perform system updates while driving, to prevent delays or malfunctions. Such a rule has no meaning for conventional vehicles but is essential for AVs, thus falling under L_3.

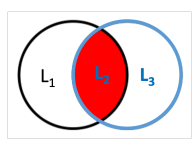

Fig. 6. Relationship between Current Laws and law for AVs

Example 1

E-L1. You must not drive for more than 10 hours in a day.
E-L2. Current drink-drive limit is 22 microgrammes of alcohol in 100 ml of breath.
E-L3. No operating system update while the vehicle is driving.

Accordingly, key tasks of formalising law for AV include reasoning about:

T1 what laws need to be added to deal with scenarios that only AVs experience?
T2 which parts of the current laws are to be revised due to their relevance but that they are inappropriate to AVs?
T3 what to remove when it is irrelevant to AVs?

Automating the law for AV formalisation can be understood as the task of automatically repairing current laws to meet a benchmark derived from expert decisions or simulation results of AV behaviour. Since the aim of this research is to support human legal experts in decision-making and ease their workload, the benchmark for ABC is assumed to rely primarily on characteristics observed during the AV design stage and in simulation tests.

Still using Example 1, when examining E-L1, one possible test is to simulate AV operation for $X,\ 0 < X \leq 24$ hours per day, combined with safety tests designed to determine whether continuous driving remains acceptable. If all safety tests are passed when $X = 24$, it can be reasonably inferred that autonomous vehicles do not require restrictions on daily driving time, provided the hardware operates correctly and sufficient energy is available. Thus, E-L1 can be categorised under L_1. In a similar way, E-L2 can be verified by simulating scenarios that test the operator's blood alcohol limit. For E-L3, accident data from AV simulations can serve as evidence to inductively develop new legal provisions that prevent similar incidents.

Based on the above information and Fig. 5, the initial input in ABC comprises laws originally designed for human drivers and the specific characteristics of autonomous vehicles. The reasoning logic encoded as rules within both sources serves as the preliminary basis for deriving AV-specific legal provisions. Accordingly, these elements are first classified into one of the categories L_1, L_2, or L_3. The fundamental approach for this classification is outlined as follows:

- C-L1. If corresponding rules are *not* involved in deriving any theorems from the theory representing simulations tests of the AV, those rules are probably not applicable to the AV so will be a candidate member of L_1.
- C-L2. If corresponding rules are involved in deriving any theorems from the theory representing simulations tests of the AV, the laws represented by those rules are probably applicable to the AV so will be a candidate member of L_2.
- C-L3. If some predicates from the theory representing system simulations never occur in rules representing laws, probably new rules need to be constructed, which is in class L_3, e.g., the new concept of operating system.

Note that using laws in L_1 and constructing laws for L_3 are more straightforward than operations for L_2 where a rule in L_2 is either directly taken or revised for AVs. The operation needed for a rule in L_2 depends on whether its conclusion violates legal principles, as discussed in Example 1.

Example for Revising the current law into law for AV. In this example, ABC detects the need to reform E-L2 based on simulation results. The input theory contains four axioms describing one should not drive when it is bigger than 0.22 in Scotland; $p1$ is allowed to drive in Scotland because of passing driving exams, although $p1$'s level of alcohol in the breath is 0.4. Here (A1) represents the current law corresponding to (E-L2). Then a simulation experiment is whether human operators of a certain alcohol level can pass driving exams under a certain level of alcohol[9]. The evidence from this simulation, highlighted in a purple background, is that $p1$'s alcohol in the breath is 0.4 and $p1$ passed driving exams, given by A3. The $\mathscr{T}(\mathbb{PS})$ is the benchmark of the correctness of the law for the current simulation[10]: the conclusion of the rule should

[9] The definition of driving in AVs is not discussed here, i.e., the main user in the AV is assumed to be the "driver".

[10] This is an extension of ABC that allows rules in the $\mathbb{PS}$ rather than just ground propositions.

be a theorem from the input theory when its precondition is satisfied by the theory. In this example, it requires that one is allowed to drive in Scotland if passing the driving exams.

$$\boxed{alcohol(X,Y,breath) \wedge Y > 0.22 \implies not(allow(driving,X,scotland))} \tag{A1}$$
$$\implies alcohol(p1,0.4,breath) \tag{A2}$$
$$\implies pass(p1,driving\_exams) \tag{A3}$$
$$\mathscr{T}(\mathbb{PS}) = \{pass(X,driving\_exams) \implies allow(driving,X,scotland)\} \tag{PS1}$$

The above theory is inconsistent because $p1$ is not permitted to drive according to (A1) and (A2), yet should be permitted under (A3) and $\mathscr{T}(\mathbb{PS})$. ABC can resolve this inconsistency in multiple ways. One possible repair is to adjust the precondition in A1 using the threshold specified in A2, as shown in (A1'), which is appropriate when a higher alcohol limit for autonomous vehicle users is desired. This revision implies that the law permits greater alcohol consumption for individuals using AVs, provided they do not become excessively intoxicated. Another repair option is to delete A1 entirely, which is suitable if the legal intention is to remove any alcohol concentration requirement for AV operation.

$$alcohol(X,Y,breath) \wedge Y > 0.4 \implies not(allow(driving(X,scotland))) \tag{A1'}$$

It can be observed that ABC may generate numerous modification options within the confines of logical consistency. Heuristic algorithms could therefore play an important role in avoiding undesirable modifications. In the example above, protecting A2–A3 from alteration by ABC serves as a desirable heuristic, since they represent objective facts that are not intended to be revised.

In summary, the underlying idea of applying ABC to the task of legal revision is as follows: designers and developers of autonomous vehicles provide descriptive product characteristics derived from simulation tests, which are then input into ABC as benchmarks because they constitute objective facts about AVs. ABC subsequently tests these features with the aim of aligning existing laws with the realities of autonomous vehicles. When elements incompatible with AV operation are identified, ABC proposes modifications that maintain logical coherence. Legal experts then determine whether these proposals are appropriate and how they should be integrated into the broader legal framework.

5 Running Case

To better demonstrate the legal repair process of ABC, we formalise the situation below as a running case.

According to GB Domestic Rules: Drivers' hours,in order to avoid fatigued driving, drivers must not drive for more than 10 hours in a single day for passenger vehicles and lorries that are not required to comply with EU rules. At the same time, a rest period of at least 10 hours is to be taken between every two working days. Now we assume that autonomous vehicles can work continuously and don't need to take breaks, which only refers to working status excluding maintaining or charging.

For simplicity, we formalise the illustrative example by giving all information as the input theory without a preferred structure, which allows ABC to detect and repair faults in the theory as inconsistencies[11]. To understand the formalised expressions below definitions could be referred to:

driver(X): X is a driver.
driving_time(X, Y, Z): Driver X has drived Y hours during Z hours.
fatigue_driving(X, Y, Z): Driver X is fatigue after driving Y hours during Z hours.
rest_time(X, Y, Z): Driver X is required to rest at lease Y hours after Z working hours.

The running case in ABC is formalised and performed as shown in Example 2 and Example 3.

Example 2 is the current legal system with new features brought by autonomous vehicles. Proposition(1) to (2) is the current rules for human drivers. (5) to (7) is the instantiation of new features, meaning a driver called av is driving without rest. (3) to (4) in blue is the new but inconsistent theory we want to add, i.e. the driver av won't get fatigue and don't need to rest.

Example 2 ***Repaired fatigue driving theory.***

$$driver(X) \wedge driving\_time(X,Y,24) \wedge Y > 10 \implies fatigue\_driving(X,Y,24) \quad (1)$$
$$driver(X) \wedge rest\_time(X,Y,24) \wedge Y < 10 \implies rest\_required(X,Y,24) \quad (2)$$
$$driving\_time(av,Y,Z) \wedge fatigue\_driving(av,Y,Z) \implies \quad (3)$$
$$driver(av) \wedge rest\_time(av,Y,Z) \wedge rest\_required(av,Y,Z) \implies \quad (4)$$
$$\implies driving\_time(av,24,24) \quad (5)$$
$$\implies rest\_time(av,0,24) \quad (6)$$
$$\implies driver(av) \quad (7)$$

Example 3 ***Repaired fatigue driving theory.***

$$driver(X,human) \wedge driving\_time(X,Y,24) \wedge Y > 10 \implies fatigue\_driving(X,Y,24) \quad (8)$$
$$driver(X,human) \wedge rest\_time(X,Y,24) \wedge Y < 10 \implies rest\_required(X,Y,24) \quad (9)$$
$$driving\_time(av,Y,Z) \wedge fatigue\_driving(av,Y,Z) \implies \quad (10)$$
$$driver(X,system) \wedge rest\_time(av,Y,Z) \wedge rest\_required(av,Y,Z) \implies \quad (11)$$
$$\implies driving\_time(av,24,24) \quad (12)$$
$$\implies rest\_time(av,0,24) \quad (13)$$
$$\implies driver(av,system) \quad (14)$$

Example 3 is the repaired legal system. We can see in proposition (8), (9), (11) and (14) that the original predicate driver(X) has been added new conditions. The new predicate is driver(X, human) and driver(X,system) meaning driver X is human or a system. Now, if the driver is human, he has to follow the past rules, i.e. drive for limited

[11] Alternatively, certain observations can be given as positive examples and negative examples in the preferred structure for which the corresponding faults will be insufficiencies and incompatibilities.

times and take enough rest. But if the driver is an autonomous system, it can drive 24 hours a day without rest.

We need to note that the semantics or names of human and system should be given by legal experts. ABC will give new predicate in format of driver(X,dummy1) and driver(X,dummy2). We have modelled the results of this process directly in the case. And, only one of the repair solutions that ABC will give is shown here. It could give all the options available that meet the requirements based on the filtering criteria. For example: increase the amount of continuous driving time allowed by law, add a direct rule to allow autonomous cars to drive for extended periods of time, etc. We have chosen to show one of the most common sense options here.

As we mentioned earlier, one of the strengths of ABC is its flexible modelling approach. In this example, we view the autonomous vehicle situation as an objective situation that conflicts with current regulations. From a legal perspective, it is possible that there is a legal intention desired to be artificially avoided or guaranteed. For example, legal experts believe that even autonomous vehicles should not be driven for more than 18 continuous hours for safety reasons. Alternatively, the law does not consider it acceptable to have autonomous vehicles on the road at this time. In this case, ABC users can add their intentions to the positive and negative examples in preferred structure and receive corresponding repair suggestions.

6 Conclusion and Future Work

In this paper, we summarise the types of inapplicability of existing traffic regulations to autonomous driving scenarios. We then introduce and expand the ABC system to help the law make modifications to these inapplications. Our findings demonstrate that ABC can automate suggestions for logical modifications while maintaining the intention of the law, with selection and semantic embedding by legal experts. This would certainly be helpful in adapting the law in the face of AI developments. Additionally, we have provided code to realize the functionalities described in this paper (ABC_Datalog).

In future work, we will extend this research in four key directions: (1) conducting quantitative benchmarking against existing methods (e.g., LegalRuleML, LLMs) to evaluate response time and logical consistency; (2) expanding the test case set to include domains such as data protection and financial regulation; (3) developing expert-in-the-loop interfaces with explainable reasoning outputs; and (4) integrating legal ontologies to support large-scale automated rule repair, validated through real-world regulatory case studies.

References

1. Aparicio, J.T., Arsenio, E., Santos, F., Henriques, R.: Using dynamic knowledge graphs to detect emerging communities of knowledge. Knowledge-Based Systems **294** (2024)
2. Borgesa, G., Wüsta, C., Sasdellia, D., Margvelashvilia, S., Klier-Ringlea, S.: Making the implicit explicit: The potential of case law analysis for the formalization of legal. In: Proceedings of LN2FR 2022, pp. 66–75 (2022)

3. Brodsky, J.S.: Autonomous vehicle regulation: How an uncertain legal landscape may hit the brakes on self-driving cars. Berkeley Technology Law Journal **31**(2), 851–878 (2016)
4. Bundy, A., Li, X.: Representational change is integral to reasoning. Philosophical Transactions of the Royal Society A **381**(2251), 20220,052 (2023)
5. Bundy, A., Philalithis, E., Li, X.: Modelling virtual bargaining using logical representation change. Human-like machine intelligence pp. 68–89 (2021)
6. Cai, C.H., Bundy, A.: Repairing numerical equations in analogically blended theories using reformation. In: Proceedings of HLC 2022, pp. 18–23 (2022)
7. Carr, N.: As the role of the driver changes with autonomous vehicle technology, so, too, must the law change. St. Mary's Law Journal **51**, 817–843 (2020)
8. Dimou, A., Kontokostas, D., Freudenberg, M., Verborgh, R., Lehmann, J., Mannens, E., Hellmann, S., Van de Walle, R.: Assessing and refining mappingsto rdf to improve dataset quality. In: The Semantic Web - ISWC 2015, pp. 133–149. Springer, Cham (2015)
9. Gärdenfors, P.: Belief revision. Cambridge University Press (2003)
10. Hoffmann-Riem, W.: Artificial intelligence as a challenge for law and regulation. Regulating artificial intelligence pp. 1–29 (2020)
11. Huang, J., Chen, X., Mishra, S., Zheng, H.S., Yu, A.W., Song, X., Zhou, D.: Large language models cannot self-correct reasoning yet. arXiv preprint arXiv:2310.01798 (2023)
12. Idrissou, A., Van Harmelen, F., Van Den Besselaar, P.: Network metrics for assessing the quality of entity resolution between multiple datasets. Semantic Web **12**(1), 21–40 (2021)
13. Ilkou, E., Koutraki, M.: Symbolic vs sub-symbolic ai methods: Friends or enemies? In: CIKM (Workshops), vol. 2699 (2020)
14. Jarvis, M.P., Nuzzo-Jones, G., Heffernan, N.T.: Applying machine learning techniques to rule generation in intelligent tutoring systems. In: International Conference on Intelligent Tutoring Systems, pp. 541–553. Springer (2004)
15. Ji, Z., Lee, N., Frieske, R., Yu, T., Su, D., Xu, Y., Ishii, E., Bang, Y.J., Madotto, A., Fung, P.: Survey of hallucination in natural language generation. ACM Comput. Surv. **55**(12), 1 – 38 (2023)
16. Li, X.: Automating the repair of faulty logical theories. Ph.D. thesis, The University of Edinburgh (2021)
17. Li, X., Bundy, A., Smaill, A.: ABC repair system for datalog-like theories. In: Proceedings of IC3K 2018 - Volume 2: KEOD, pp. 333–340 (2018)
18. Linardatos, P., Papastefanopoulos, V., Kotsiantis, S.: Explainable ai: A review of machine learning interpretability methods. Entropy **23**(1), 18 (2020)
19. Palmirani, M., Governatori, G., Rotolo, A., Tabet, S., Boley, H., Paschke, A.: Legalruleml: Xml-based rules and norms. In: F. Olken, M. Palmirani, D. Sottara (eds.) Rule-Based Modeling and Computing on the Semantic Web, pp. 298–312. Springer, Berlin, Heidelberg (2011)
20. Raad, J., Beek, W., Van Harmelen, F., Pernelle, N., Saïs, F.: Detecting erroneous identity links on the web using network metrics. In: The Semantic Web–ISWC 2018, pp. 391–407. Springer (2018)
21. Schindler, C., Rausch, A.: Formal software architecture rule learning: A comparative investigation between large language models and inductive techniques. Electronics **13**(5) (2024)
22. Tang, J.: Arithmetic errors revisited: diagnosis and remediation of erroneous arithmetic performance as repair of faulty representations. Ph.D. thesis, School of Informatics, University of Edinburgh (2016)
23. Westhofen, L., Stierand, I., Becker, J.S., Möhlmann, E., Hagemann, W.: Towards a congruent interpretation of traffic rules for automated driving-experiences and challenges. In: Proceedings of LN2FR 2022, pp. 8–21 (2022)
24. Zander, M.: The law-making process. Bloomsbury Publishing (2015)