Norms, Institutions, and Robots
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Abstract—Interactions within human societies are usually regulated by social norms. If robots are to be accepted into human society, it is essential that they are aware of and capable of reasoning about social norms. In this paper, we focus on how to represent social norms in societies with humans and robots, and how artificial agents such as robots can reason about social norms in order to plan appropriate behavior. We use the notion of institution as a way to formally define and encapsulate norms, and we provide a formal framework for institutions. Our framework borrows ideas from the field of multi-agent systems to define abstract normative models, and ideas from the field of robotics to define physical executions as state-space trajectories. By bridging the two in a common model, our framework allows us to use the same abstract institution across physical domains and agent types. We then make our framework computational via a reduction to CSP and show experiments where this reduction is used for norm verification, planning, and plan execution in a domain including a mixture of humans and robots.

Index Terms—Norms, Institutions, Institutional robotics, Social robotics, Mixed human-robot society, Cognitive robotics

I. INTRODUCTION

Roby needs a new battery. He enters a hardware store, goes to the clerk, Sally, and they agree on the type of the battery and its price. Then Roby handles some cash to Sally, and she gives him the battery. Roby takes the battery and rolls out of the store.

Roby, of course, is a robot. Like most of us, both Roby and Sally follow social norms in their interactions. Social norms are a fundamental part of our society; they influence our behavior in shops, at work, on the road, when dining with friends, or when playing soccer. Norms create prescriptions for social behaviors, facilitate decision making and regulate how humans communicate, act and cooperate. By constraining our activities, norms make behavior more predictable. Failure to cope with social norms causes difficulties to account for the intentions behind one’s behavior and can easily be evaluated as odd, amusing, dumb, uncanny, or simply unlawful.

For robots to become part of our society, they will need to be aware of social norms, reason about these norms, and act according to the expectations that they create. A number of formal and computational models have been proposed in the field of Multi-Agent Systems (MAS) to do so [1, 2], and we review many of them in the next section. As we shall see, however, these models are not fully adequate to be used in physically embodied robotic systems, as they often lack a clear operational semantics [3] and are typically disconnected from physical execution [4].

In this paper, we propose a framework for normative reasoning that can be used by robots that operate in human society. Our framework contains formal elements to represent explicitly: (1) abstract norms, that we encapsulate in reusable structures called institutions; these describe social situations and include roles, actions, artifacts, as well as a set of norms that bind them; (2) a physical domain where these norms are to be applied; and (3) the relation between the abstract norms and the physical domain, that we call grounding. The vignette above shows an instance of an abstract ‘trading’ institution instantiated in a physical hardware store, where the roles of buyer and seller are grounded to Roby and Sally, and the artifacts are grounded to the cash and the battery.

A key point of our framework is that it combines insights from the fields of MAS and robotics. From MAS, we borrow the separation between abstract normative models and concrete realizations; from robotics, we borrow the notions of physical execution and state-space trajectories. Our framework thus includes: (A) A formal model of institutions which encodes the relation between abstract norms and their instantiation into a concrete robotic domain; (B) a full computational model which enables norm verification, planning, and plan execution by robots; and (C) support for artifacts, which is of high importance in robotics since robots and humans interact and coordinate via relevant objects in the environment.

Our framework defines institutions as abstractions that can be applied to different sets of heterogeneous agents, including robots and humans, which are not specifically built to work together. This feature is especially important in the case of robots, since it would not be sensible, or economical, for a manufacturer to design a robot to work within a particular institution or to cater to specific norms, as this would restrict the social contexts in which it can be used. Robots should be able to reason about the roles they play in a particular institution, the obligations that they have to fulfill, while using corresponding artifacts to do so. This spawns a need to create a correspondence between a robot’s domain (the concrete environment in which it operates) and an institution (the current social context of the robot).

This paper is organized as follows. Section II surveys related work. We introduce institutions and domains in Sections III and IV, respectively. In Section V we relate domains and institutions, and show how abstract norms can be given domain-specific semantics. In Section VI we discuss the reasoning problems associated with institutions, and in Section VII we define a computational model to address these problems. Section VIII illustrates the model on a simple trading example, and Section IX demonstrates it with real robots and humans.
II. RELATED WORK

Our analysis of the state of the art begins with an overview of the general concept of norms. An extensive overview of social norms in the literature is given by Boella et al. [1], who observe that research on norms is rooted in different areas, including philosophy [5] and sociology [6]. It is noted that concepts and theories from other disciplines should be used for normative specifications in Computer Science. In Computer Science, prominent work on norms was done by Meyer and Wieringa [7], which led to deontic logic becoming a dominant tool for modeling norms. The reason lies in the lack of other methods to define behaviors which are illegal but nevertheless possible, since illegal behavior is usually ruled out by problem specification. Alechina et al. [8] stress the importance of operational semantics for normative languages, which is essential for creating computational frameworks. The authors also discuss the lack of a ‘one-size-fits-all’ normative formalism. As we will see, many of the specific choices made in our framework stem from such general questions.

In our work, we use institutions as a way to encapsulate norms and their context. In MAS institutions are commonly described as a set of norms [2], or as “rules of the game in the society” [8]. Frameworks supporting this idea include: MOISE [9], OPERA [10], ISLANDER [11], AMELI [12], InstAL [13], and JaCaMo[14]. They all abstract from the pure agent representation to a social level, where the notion of roles is usually defined. Roles are associated with norms and agents can enact roles, and act depending on the specified norms. The Agents and Artifacts (A&A) framework [15] also models environmental artifacts to address objects in a working environment, as it is important for physical interactions. The social level is typically associated with the level on which agents operate (in the further text referred to as a domain). This is usually done via the count-as principle, which is related to our notion of grounding. It should be noted that the problem of operationalization of organizational rules and connecting them to concrete execution in a domain is not trivial task to achieve. Thus, most of frameworks concerned with abstraction cannot verify/enforce formal properties. Others do not offer full abstraction from a concrete (physical) domain in a level of details required for robot operations. Most also lack means to equip agents with planning and plan execution mechanisms. As we shall see, our framework addresses these issues.

A line of research focuses on the questions of how norms can be used operationally via reasoning. The groundwork addressing the operationalization of norms is done by Oren et al. [16]. They are able to track changing state of norm by extending its deontic representation. Authors introduce conditions for norms activation, violation, maintenance, etc. Frameworks that define operational semantics are typically based on these ideas. For example, Alvarez-Napagao et al. [17] use their framework for monitoring norm compliance. The norm operational semantics is realized by translating norm conditions to rules and then, by using a production system, they compile rules to structures that are used to describe the state of the norms. A similar approach is done by García-Camino et al. [18], where their production system is enhanced with constraint-satisfaction techniques, which leads to more expressiveness of norms, as claimed by the authors. Also, as they claim, one of the limitations of their language is the inability to plan. In general various other frameworks use operational semantics for monitoring norms compliance. For instance, Bolton and Bass [19] present experiments where the behavior of humans is observed and its adherence to norms is verified. However, since they do not explicitly address the planning problem and it is not clear how they can be extended to autonomous planning, they are omitted in this summary of related work.

Alongside norm monitoring, the operational semantics of norms is also used to execute agents actions. An approach for specifying and executing normative protocols comes from Artikis et al. [20]. They make norms computational by producing transition systems via action language (C+), which can be used to execute agent actions. However, as shown, the approach is not practical for run-time agent execution due to its long compilation time for action descriptions. Work closely related to this paper is done by Álvaro Napagao [21]. While being focused on Service-Oriented Architectures, their framework is general with respect to the type of agent. The authors extend deontic logic to dyadic deontic logic (to support conditions) and to LTL (to support temporal reasoning). They reduce the operational semantics of norms to fluent-based semantics and further translate it into PDDL, therefore bringing norm monitoring close to a planning problem. LTL supports only qualitative temporal relations, while in our work, we are additionally interested in quantifiable temporal relations so we can provide a sufficient level of specification and reasoning in human-robot interactions.

For cyber-physical (social) systems in general or human-robot interaction in particular, it is important that norms semantics can be used for real-time reasoning about physical aspects of the environment. This requires, but is not limited to, qualitative and quantitative temporal and spatial reasoning for monitoring norm compliance and planing robotic action to adhere to norms. Furthermore, norms semantics should contain extended count-as principle to include objects in the environment and map them to a social level (as artifacts). Those are some of the issues we address in our approach. Several frameworks deal with sanctioning mechanisms. We do not address this aspect in our framework since its importance for robotics is not clear, but leave it for future work.

Some works in human-robot interaction, do not use the notion of norms explicitly, rather, ontologies that capture whole aspects of a situation. Quintas et al. [22] focus on overcoming uncertainty by probabilistic plans, however not providing a general formalism that can verify if execution adheres to the provided model. Wang et al. [23] deal with verification and the generic aspect of behavior, however, focus on behavior couplings and do not deal with context and dependence of behaviors on objects in the environment. All of these aspects are addressed in our work.

Regarding related work about norms for robots, Brinck et al. [24] post strong arguments about why we should provide social norms to robots. They argue that robots should behave in human-like fashion and this is only possible if robots...
can organize and coordinate their behaviors with the social expectations of others. Norms in automated planning have been studied by Panagiotidi et al. [25], who extended the STRIPS language to include norm semantics. A goal state is then a state of the world where the effects of all active norms are achieved. Cirillo et al. [26], Montreuil et al. [27], Pecora et al. [28] extend planning to support human activities. Köckemann et al. [29] have developed the notion of interaction constraints relating to robot actions and human activities, thus allowing for norm-aware plans to be generated. In our previous work [30], we have introduced Socially Aware Planner (SAP) that supports social norms. With social norms we were able to relate the current social context to concrete robots and humans activities. In general, while several authors have accounted for normative behavior in robots, none of them provide a means to represent norms in an abstract and reusable way that does not depend on a domain. A step in this direction was made by Carlucci et al. [31], and the work in this paper provides one further step.

Institutions have received much less attention in the field of Robotics than norms. An institutional framework for robots was developed by Pereira et al. [32]. Institutions are defined in terms of Petri Nets, which gives the framework a sound mathematical foundation but falls short of including task planning. “Institutional Robotics” is an important work by Silva et al. [33] in which they discuss and analyze to great extend the meaning, importance, and different ways of usage of institutions for robotics. Their experiments are based on Pereira et al. [32].

### III. Norms and Institutions

The ingredients that define our institutions at an abstract level are a set of artifacts, a set of roles, a set of actions, and a set of norms that link roles, actions, and artifacts. If we take as an example the game of football (soccer), artifacts include a ball, a field and two goals; roles include goalkeeper, player, referee and audience; actions include defending, scoring, and attacking; and norms regulate how actions are performed, e.g., “a player should attack the opposite goal”, or “a goalkeeper can handle the ball while in the penalty area”.

More formally, let these sets be:

- \( \text{Arts} = \{\text{art}_1, \text{art}_2, \ldots, \text{art}_n\} \)
- \( \text{Roles} = \{\text{role}_1, \text{role}_2, \ldots, \text{role}_m\} \)
- \( \text{Acts} = \{\text{act}_1, \text{act}_2, \ldots, \text{act}_k\} \)

We define a normative statement, or simply norm, to be a predicate over ground statements, where a ground statement is a triple including a subject, a predicate, and an object.

**Definition 1.** A norm has the form \( q(\text{stm}^*) \), where \( q \) is a qualifier and \( \text{stm}^* \) are triples of the form:

\[ \text{stm} \in \text{Roles} \times \text{Acts} \times (\text{Arts} \cup \text{Roles}) \]

Qualifiers are deontic verbs, like must or must-not, or relations, like inside or before. By talking about ground statements, qualifiers define the normative language of an institution. For example, a unary qualifier for necessity can be used to express an obligation like “a goal-keeper must defend its goal”. Qualifiers defined over pairs of statements can, for example, express temporal concepts such as ‘before’, ‘during’, etc. In Section V-B we shall see how these intuitive semantics are formalized. We distinguish between obligation norms, that impose obligatory actions, and modal norms, that describe other requirements on statements.

An obligation norm has a unary qualifier denoting that the action in the statement must be executed. The qualifier could indicate that it is necessary to execute the action at least once, or that it should be executed repeatedly. An obligation norm may express that for example that “a goal-keeper must defend its goal” as must \( ((\text{goal-keeper}, \text{defend}, \text{ownGoal})) \), or that “a buyer must pay a seller” as must \( ((\text{buyer}, \text{pay}, \text{seller})) \).

One can also define norms that state which actions are forbidden in an institution using a unary qualifier must not, e.g., mustNot \( ((\text{referee}, \text{play}, \text{footballField})) \).

A modal norm can encode where and when actions should be carried out, for instance, the fact that “a player plays inside a football-field” can be represented as inside \( ((\text{player}, \text{plays}, \text{footballField})) \). A modal norms can have an \( n \)-ary qualifier, which can be used to specify a relation between two or more statements, like in before \( ((\text{buyer}, \text{pays}, \text{money}), (\text{seller}, \text{gives}, \text{goods})) \), representing “the buyer pays before the seller gives the goods”.

Obligation norms and modal norms predicate over statements. We define a third type of norm that predicates over roles, namely, indicating the normative minimum and the maximum number of agents that can enact (play) a certain role, e.g., “there can be only one goalkeeper (per team)”.

**Definition 2.** A cardinality norm associates roles to the minimum and maximum cardinality:

\[ \text{card} : \text{Roles} \rightarrow \mathbb{N} \times \mathbb{N} \]

We can now define an institution as follows:

**Definition 3.** An institution is a tuple

\[ \mathcal{I} = (\text{Arts}, \text{Roles}, \text{Acts}, \text{Norms}) \]

where \( \text{Norms} = \text{OBN} \cup \text{MON} \cup \{\text{card}\} \) is a collection of obligation, modal and cardinality norms.

The above formalization is in line with the literature in social and economic sciences, where institutions are typically seen as mechanisms that regulate social action by defining and upholding norms [34]. It is also in agreement with North [8], who sees institutions as containers of the “rules of the game in a society”, and with Harré and Secord [35], who stress the importance of roles, seen as “normative concept[s], focusing on what is proper for a person in a particular category to do”.

### IV. Robots and Domains

An institution is an abstraction, which can be instantiated in different concrete systems that are physically different but have the same organizational structure. For instance, the same football institution can be used to regulate a game played by
a group of children and one played by a group of robots. We model such a concrete system through the notion of a domain.

**Definition 4.** A domain is a tuple $D = (A, O, B, F, R)$, where
- $A$ is a set of agents,
- $O$ is a set of physical entities,
- $B$ is a set of behaviors,
- $F \subseteq A \times B \times (O \cup A)$ is a set of affordances,
- $R$ is a finite set of state variables.

The agents $A$ could be a mix of humans and robots, e.g.,

$\{\text{Tom, Sally, Ann, Nao3, Roomba1, Turtlebot4}\}$.

$B$ is the set of all behaviors that agents can execute, e.g.,

$\{\text{walk, play, talk, dance, run}\}$.

Physical entities $O$ are ordinary objects in the domain, e.g.,

$\{\text{whiteboard, ball, floor, chair, meadow, brush}\}$.

Agents can be heterogeneous and have different capabilities. The affordance relation $F$ indicates which agents can execute which behaviors with which object, e.g.,

$\{(\text{Sally}, \text{walk, floor})$, $(\text{Nao3}, \text{play, ball})$, $(\text{Roomba1}, \text{clean, brush})\}$.

The state variables $R$ define properties of the entities in the domain. They may indicate the position of an object, the size of an agent, the status of activation of a behavior, etc. For instance, $\rho = \text{active(walk, Nao3)}$ is a state variable that indicates whether the walk behavior is active on the agent Nao3. We denote with $\text{vals}(\rho)$ the set of possible values of state variable $\rho$, e.g., $\text{vals}(\text{active(walk, Nao3)}) = \{\top, \bot\}$.

Some other state variable $\text{pos(ball1)}$, for instance, can indicate the qualitative position of an object:

$\text{vals}(\text{pos(ball1)}) = \{\text{back-half, front-half, goal-area, . . .}\}$.

In a different domain, the $\text{pos}$ state variable may hold continuous values in a given coordinate system.

**Definition 5.** Given a domain $D = (A, O, B, F, R)$, the state space of $D$ is $S = \prod_{s \in R} \text{vals}(s)$. The value of $\rho$ in state $s \in S$ is denoted $\rho(s)$.

In a dynamic environment, the values of most properties change over time. In our formalization, we represent time points by natural numbers in $\mathbb{N}$, and time intervals by intervals $I = [t_1, t_2]$ of $\mathbb{N}$. We denote by $I$ the set of all such time intervals. We then represent the evolution of properties over time by trajectories of states.

**Definition 6.** A trajectory is a pair $(I, \tau)$, where $I \in \mathbb{N}$ is a time interval and $\tau : I \to S$ maps time to states.

Figure 1 shows an example of a trajectory in the space defined by three state variables: $\text{position(ball1)}$, $\text{active(moveTo, Nao)}$ and $\text{active(shoot, Nao)}$. The agent Nao engages in behaviors $\text{moveTo}$ and $\text{shoot}$ until the ball is in the goal. At time $t_1$ the ball is at goal1Area. At $t_2$ and $t_3$ the ball is in the same goal, and the agent’s behavior $\text{moveTo}$ is active: $\text{active(moveTo, Nao)}(\tau(t_3)) = \top$. At $t_4$ $\text{moveTo}$ finishes and Nao shoots the ball: $\text{active(shoot, Nao)}(\tau(t_4)) = \top$. At $t_5$ the ball is in a new position: $\text{position(ball1)}(\tau(t_5)) = \text{goal2Area}$. A similar sequence repeats until the ball’s position is Goal2.

V. RELATING INSTITUTIONS AND DOMAINS

The above formalization separates all aspects of the institution abstraction from the physical domain. This separation provides the key to reuse the same abstract institution to describe or regulate different systems of robots and humans. We now study how to bind an institution to a given domain.

A. Grounding Institutions

Consider the above football institution, and imagine a domain consisting of a group of children in a meadow. If the children want to play football, they need to map physical objects and agents to the entities in the football institution. In other words, they need to ground the institution.

**Definition 7.** Given an institution $I$ and a domain $D$, a grounding of $I$ into $D$ is a tuple $\mathcal{G} = (\mathcal{G}_A, \mathcal{G}_B, \mathcal{G}_O)$, where:
- $\mathcal{G}_A \subseteq \text{Roles} \times A$ is a role grounding,
- $\mathcal{G}_B \subseteq \text{Acts} \times B$ is an action grounding,
- $\mathcal{G}_O \subseteq \text{Arts} \times O$ is an artifact grounding.

We denote by $A_{\text{role}} = \{a | a \in A \land (\text{role, } a) \in \mathcal{G}_A\}$ the set of all agents to which a specific role is grounded. We define $B_{\text{act}}$ and $O_{\text{art}}$ in a similar way.

In our example, the children may decide to use two trees to ground the two goal posts, and the meadow to ground the football field. This corresponds to artifact grounding, $\mathcal{G}_O$. Institutional artifacts, like the football field, are related to concrete objects in the real world, like the meadow: $(\text{meadow, footballField}) \in \mathcal{G}_O$. The children also decide which role each child is going to play. This corresponds to role grounding, $\mathcal{G}_A$, where, e.g., the role of goal-keeper is assigned to a child named Tom: $(\text{goalkeeper, Tom}) \in \mathcal{G}_A$. If children can dynamically join or leave the game, then $\mathcal{G}_A$ needs to be changed dynamically. Finally, specific behaviors of children,
that correspond to executions that comply with that norm. In important philosophical connotations. The grounding domain, and grounding.

Figure 2 graphically represents the relation between institution, semantics of a certain institutional meaning (a status) to domain elements. This fact is known as the principle \[36\]. Searle \[37\] explain this principle as assigning ‘status functions’ to elements, so that \(X\) counts as \(Y\) in context \(C\). For example, a specific piece of paper counts as money in a trading institution, while putting a paper in the box could count as voting in an election institution. Behaviors that are in the ‘count as’ relationship with institutional actions are also referred to as having institutional power \[36\].

B. Giving Semantics to Norm

Once we have decided a domain and a grounding, the syntactic elements (roles, actions, and artifacts) of an institution acquire meaning in the physical world. However, this is not yet the case for norms: what is the meaning of “must ((buyer, pay, goods))” in a particular domain?

We give semantics to norms in terms of trajectories in the state space. For instance, the semantics of the above norm can be defined as all trajectories where the action pay is executed at least once. The semantics of the norm before ((buyer, pays, money), (buyer, takes, goods)) can be defined as all trajectories where the behavior that is grounded to the pay action happens before the behavior that is grounded to the takes action. Formally, let \(\mathcal{T}\) be the set of all possible trajectories \((I, \tau)\) over the state-variables in domain \(D\). Let \(q(stm*)\) be any norm, as per Definition \[1\]. We define the semantics of \(q(stm*)\), written \(\llbracket q(stm*) \rrbracket\), as:

\[
\llbracket q(stm*) \rrbracket \subseteq \mathcal{T}
\]

Intuitively, a norm identifies a set of trajectories, namely, those that correspond to executions that comply with that norm. In other words, norms express constraints on the possible values that state variables take over time.

In general, whenever we ground an institution \(I\) to a domain \(D\), we must make sure that all of the qualifiers used to define norms in \(I\) are given semantics in terms of acceptable executions in \(D\). To illustrate this concept, below, we provide examples of semantics for a selection of qualifiers. It is important to note that these examples are not an exhaustive list of the qualifiers and norms that can be encoded in our framework: they only serve to illustrate the kinds of semantics that one can define over state variables in the domain.

C. Examples of Semantics

In these examples, we assume that a domain \(D = \langle A, O, B, F, R \rangle\) and a grounding \(G = \langle G_A, G_B, G_O \rangle\) are given. We also assume that the set of state variables \(R\) in \(D\) contains state variable active\((b, ag)\) for every pair of \((b, ag) \in B \times A\), with values \(vals(\text{active}(b, ag)) = \{\top, \bot\}\), and agent \(ag\) executes behavior \(b\) in state \(s\) iff \(\text{active}(b, ag)(s) = \top\).

**Must.** The semantics of a ‘must’ norm makes sure that certain behavior is active at least once in the given trajectory:

\[
\llbracket \text{must}\((\text{role}, \text{act}, \text{art})\)\rrbracket \equiv \{(I, \tau) | \forall a \in A_{\text{role}}, \exists b(t) \in B_{\text{act}} \times I : \text{active}(b, a)(\tau(t)) = \top\}.
\]

The semantics of this norm is defined as all trajectories \((I, \tau)\), where for each agent playing a role, there is at least one behavior in the grounding of act that is active for that agent at some time \(t\). Variants of this semantics are possible, e.g., a persistent version, where the behavior should be enacted at all times (not just once), or a version imposing that the artifact art should be used.

**At.** This is an example of a norm with a spatial semantics:

\[
\llbracket \text{at}\((\text{role}, \text{act}, \text{art})\)\rrbracket \equiv \{(I, \tau) | \forall b, a, t \in B_{\text{act}} \times A_{\text{role}} \times I, \exists o \in O_{\text{art}} : \text{active}(b, a)(\tau(t)) = \top \implies \text{pos}(b, a)(\tau(t)) = \text{pos}(o)(\tau(t))\}.
\]

All agents in the role grounding for which behaviors grounded by the action are active should have the same position as the position of at least one artifact in the artifact grounding. This simple semantic model can, of course, be changed to encode more sophisticated spatial relations, e.g., the object has to be within certain boundaries of another object.

**Use.** This norm regulates the usage of artifacts:

\[
\llbracket \text{use}\((\text{role}, \text{act}, \text{art})\)\rrbracket \equiv \{(I, \tau) | \forall b, a, t \in B_{\text{act}} \times A_{\text{role}} \times I, \exists o \in O_{\text{art}} : \text{active}(b, a)(\tau(t)) = \top \implies \text{using}(b, a)(\tau(t)) = o\}.
\]

Similarly to the semantics of at, this states that all agents in the role grounding with behaviors in the action grounding that are active should use an object in the artifact grounding.

**Before.** This is an example of a norm that relates two statements, and that has a temporal semantics:

\[
\llbracket \text{before}\((\text{role}_1, \text{act}_1, \text{art}_1), (\text{role}_2, \text{act}_2, \text{art}_2)\)\rrbracket \equiv \{(I, \tau) | \forall (a_1 \in A_{\text{role}_1}, a_2 \in A_{\text{role}_2}, b_1 \in B_{\text{act}_1}, b_2 \in B_{\text{act}_2}) : \text{active}(b_1, a_1)(\tau(t_1)) = \top \land \text{active}(b_2, a_2)(\tau(t_2)) = \top \implies t_1 < t_2\}
\]
This states that all behaviors in the action grounding, if active, have to be in a certain order: the first should precede the second. The semantic model could be even more specific, addressing exact objects with which actions are performed. In a similar way, it is also possible to model the other qualitative temporal relations in Allen's Interval Algebra [38].

VI. REASONING ABOUT INSTITUTIONS

Together, grounding and semantics provide the connection between the abstract elements in an institution and the physical entities in a domain. In our opening example of a trading institution, grounding is what binds Roby to the “buyer” role and Sally to the “seller” role; and the norm before “(buyer, pays, money), (seller, gives, goods)” induces, through its semantics, a temporal relation between the behaviors executed by Roby and those executed by Sally. Since the institution, the domain, and their connection are all formal elements in our framework, a robot can reason about them. We now define two properties that are crucial in such reasoning.

A. Admissibility

There are a few things we expect from an intuitively ‘good’ grounding. First, if an institution includes an obligation norm for some role, then the agents to which that role is grounded should be capable of executing the actions required by the norm. More precisely, each such agent should be capable of executing at least one behavior grounded to that action using an object grounded to the relevant artifact. Consider for example a football institution I that includes a (persistent) obligation norm must (Goalkeeper, Defend, OwnGoal). Let G be a grounding for I such that (Goalkeeper, nao) ∈ GA, (Defend, block) ∈ GB and (OwnGoal, net1) ∈ GO. We expect that nao can use block behavior on net1. If this is not the case, then G should not be used as a grounding. The following definition formalizes this intuition:

Definition 8. Let G be a grounding of I into D. An obligation norm q(role, act, art) in I is executable under G iff

\[ \forall a \in A_{role}, \exists (b, o) \in B_{act} \times O_{art} : (a, b, o) \in F. \]

A similar condition can be stated for obligation norms that refer to actions whose object is another role: for example, an escort institution might include an obligation norm like “the follower must follow the leader”.

Definition 9. Let G be a grounding of I into D. An obligation norm q(role, act, role_a) in I is executable under G iff

\[ \forall a \in A_{role}, \exists (b, a_0) \in B_{act} \times A_{role_a} : (a, b, a_0) \in F. \]

Finally, a grounding should respect the cardinality of norms.

Definition 10. Let G be a grounding of I into D. A cardinality norm card in I is satisfied for role \( \text{role} \in \text{Role} \) iff

\[ \min (\text{card}(\text{role})) \leq |A_{role}| \leq \max (\text{card}(\text{role})). \]

Putting these conditions together:

Definition 11. Let G be a grounding of I into D. G is admissible iff all its obligation norms are executable and its cardinality norm is satisfied for all roles.

B. Adherence

The admissibility property of grounding is not concerned with semantics, nor with the dynamic aspects of the domain: with this property alone, we cannot tell whether or not a given execution satisfies the norms in an institution. Consider the trading institution in our opening example: the grounding of the roles and artifacts to our agents (Roby and Sally) and to our objects (the cash and the battery) is admissible, which means for instance that Sally has the capability to give a battery to Roby. But admissibility alone does not discriminate an execution where Sally does give the battery to Roby after she has got the cash, from an execution where she does not.

In our framework, dynamic aspects are captured by trajectories. Given an institution, admissible grounding and norm semantics, a trajectory may or may not adhere to the institution’s norms. The fact that a given trajectory satisfies these norms depends on the specific semantics of the norms. The following definition captures this intuition:

Definition 12. Let \( I = (\text{Arts, Roles, Acts, Norms}) \) be an institution and D a domain. Let G be an admissible grounding of I into D, and let \( \llbracket \cdot \rrbracket \) be a semantic function. A trajectory (I, \( \tau \)) in D adheres to I under G and \( \llbracket \cdot \rrbracket \) if

\[ (I, \tau) \in \llbracket \text{norm} \rrbracket, \forall \text{norm} \in \text{Norms}. \]

In other words, a trajectory (I, \( \tau \)) adheres to the institution I if it does not violate any of the constraints induced by the institution’s norms through the semantic function \( \llbracket \cdot \rrbracket \) during the time interval I on which the trajectory is defined.

C. Reasoning Problems

An institution, grounding, trajectory, domain, and semantics could be known (given); or some or all of these elements may have to be inferred or calculated. Different combinations of what is given in a particular situation lead to different kinds of reasoning problems. Table I helps us identify and classify interesting problems in a systematic way.

a) Verification: Ensure that the given trajectory adheres to the given institution with grounding, domain, and semantics. For example, a trajectory representing our initial trading vignette would pass the verification test, whereas one where Sally runs away with the money would not.

b) Grounding: Find an admissible grounding for a given I and D. For instance, a football player must be able to grab a ball in order to be assigned to the role of a goalkeeper.

c) Planning: Generate a trajectory in domain D that is adherent to institution I, with a given grounding and semantics. For Roby in our scenario, this is the problem of regulating its give and take behaviors so that the norms of the trading institution are satisfied. Sometimes the Grounding and Planning problem may be combined, that is, the planner has to choose agents, behaviors, and objects, and to generate an adherent trajectory with them.

d) Recognition: The task here is to recognize which agents, behaviors, and objects are bound to which institutional elements. For example, what is the role of a person standing in front of a goal during a football game? Or what action is being executed by kicking a ball into a net?
TABLE I: Overview of reasoning problems with institutions. Legend: \( \top \) = given, \( x \) = to be found, \( - \) = not of interest.

| Problem                      | \( I \) | \( G \) | \( (\tau, I) \) | \( D \) | \( \emptyset \) |
|------------------------------|---------|--------|----------------|-------|------------|
| Verification                | \( \top \) | \( \top \) | \( (\tau, I) \) | \( D \) | \( \emptyset \) |
| Grounding                   | \( \top \) | \( x \) | \( \top \) | \( x \) | \( \top \) |
| Planning                    | \( \top \) | \( x \) | \( \top \) | \( x \) | \( \top \) |
| Recognition                 | \( \top \) | \( \top \) | \( \top \) | \( x \) | \( \top \) |
| Relational learning         | \( x \) | \( \top \) | \( \top \) | \( x \) | \( \top \) |
| Institution learning/recognition | \( x \) | \( \top \) | \( \top \) | \( x \) | \( \top \) |

VII. COMPUTATION

We address the question of how to effectively compute a solution to the reasoning problems presented in Table I. We focus our attention on the verification problem (row I) since this is a basic step needed in all other problems. We show that the verification problem can be reduced to a known decision problem by introducing a specific assumption. We then discuss how verification can be used to enable planning.

A. Formulation as Constraint Satisfaction Problem (CSP)

We show that an institution grounded in a specific domain can be naturally expressed as a collection of constraints over suitably chosen state variables. Specifically, given an institution \( I \), domain \( D \), grounding \( G \), and semantic function \([\cdot]\), we can construct a constraint network \((W, C)\) where \( W \) is a set of variables and \( C \) is a set of constraints over \( W \) defined as follows. For each state variable \( \rho \in R \), we introduce a variable \( w_\rho \in W \) whose domain consists of all possible bounded trajectories for \( \rho \). Formally, \( \text{dom}(w_\rho) = \{ (I, \tau) \mid I \in I, \tau : I \rightarrow \text{vals}(\rho) \} \). As for the constraints \( C \), we note that there is a one-to-one correspondence between these constraints and the norm semantics as defined in Section VII.B since those semantics limit the possible trajectories in the state space. Norm semantics are defined over state variables \( R \), while the constraints \( C \) are defined over the corresponding variables in \( W \). For instance, the obligation norm \( n = \text{must} ((\text{role, act}, \text{art})) \) with the semantics given in [1] above induces the following constraint in \( C \):

\[
C_n = \bigwedge_{a \in A, \text{role}} \bigvee_{b \in B, \text{act}} (w_{\text{active}(b,a)} \circ \top).
\]

where we use the notation \( w_\rho \circ v \) to indicate that the value of \( w_\rho \) is a trajectory such that \( \rho \) assumes the value \( v \) at some point of it. Formally:

\[
w_\rho \circ v \equiv (w_\rho = (I, \tau) \land \exists t \in I : \tau(t) = v).
\]

An assignment of values to the variables \( W \) that satisfies all constraints in \( C \) thus represents a particular trajectory that adheres to the institution. Thus, the problem of finding an adherent trajectory in an institution is reduced to the Constraint Satisfaction Problem (CSP) [39].

A trajectory defines values for all state-variables. It is, therefore, possible to represent a trajectory as a collection of unary constraints over variables. Given trajectory \((I, \tau)\) in the state space defined by \( R \), we can obtain a set of unary constraints \( C_{(I, \tau)} = \{ w_\rho(t) = \rho(\tau(t)) \mid \forall t \in I \} \).

The constraint network \((W, C)\) represents the institution, grounding, and semantics, while \((W, C_{(I, \tau)})\) represents a given trajectory \((I, \tau)\). Thus, the constraint network \((W, C \cup C_{(I, \tau)})\) has a solution if and only if trajectory \((I, \tau)\) adheres to the institution with given grounding and semantics. This addresses the verification problem listed in Table I.

This computational model is clearly too complex to be practical, as variables may take on values representing any trajectory in state space. In the next section, we put several assumptions in place which make the verification problem feasible.

B. Solving the Verification Problem

Constraints in the above representation have to be checked at each time point in the interval \( I \) of a given trajectory. To keep the computational problem feasible, it is reasonable to make some assumptions on how state variable values can evolve. Henceforth, we assume a piece-wise constant temporal function for trajectories. Hence, constraint checking need not consider each time point in \( I \), rather each contiguous interval for which state variables have constant values. This assumption is commonly made in temporal planning as well as scheduling, as it allows to reason about the temporal sub-problem via temporal constraint reasoning methods like Simple Temporal Problems [40]. Timeline-based planning approaches use this assumption to reduce the planning problem to that of constructing trajectories in state space [41, 42]. A similar assumption is made for integrating planning and scheduling [43], and hybrid-reasoning for robots [44]. In all these approaches, the variables in the underlying CSP represent flexible intervals of time within which a state variable assumes a constant value.

In a verification problem the trajectory is given, that is, the values of state variables over time are known. We can use this to construct a trajectory-specific constraint network as follows. Let \( I \) be an institution linked to a domain \( D \) via grounding \( G \) and semantics \([\cdot]\), and let \((I, \tau)\) be a trajectory for the state variables \( R \) in \( D \). Assume that \((I, \tau)\) is such that each state variable \( \rho \in R \) takes on at least one of a finite set of values.
in \( \text{vals}(\rho) \), that is, for all \( t \in I \), \( \rho(t) \in \{ \tilde{v}_1, \ldots, \tilde{v}_d \} \). Let \( I_\rho = \{ \tilde{i}_1, \ldots, \tilde{i}_k \} \) be the set of maximal sub-intervals \( \tilde{i} \) of \( I \) such that \( \rho \) is constant over \( \tilde{i} \), that is, \( \forall t \in \tilde{i}, \rho(t) = \tilde{v}_k \) for some \( k \). We construct a constraint network \((\mathcal{W}, \mathcal{C})\) where the variables are all the constant segments in the given trajectory, that is, \( \mathcal{W} = \{ w_{\rho,i} | \rho \in I, i \in I_\rho \} \).

The constraints \( \mathcal{C} \) are still derived directly from norm semantics, however, the scope of the constraints now includes all of the sub-variables \( w_{\rho,i} \) of a given state variable. For instance, the semantics of the norms \( n_1 = \text{must}((\text{role}, \text{act}, \text{art}), n_2 = \text{at}((\text{role}, \text{act}, \text{art})) \) and \( n_3 = \text{use}((\text{role}, \text{act}, \text{art}) \) may lead, respectively, to the following constraints:

\[
\begin{align*}
C_1 &\equiv \bigwedge_{a \in A, \rho \in B} \bigvee b \in B_{\text{act}} \forall \tilde{i} : w_{\text{active}(b,a),\tilde{i}} = \mathcal{T}, \\
C_2 &\equiv \bigwedge_{a \in A, \rho \in B} \bigwedge b \in B_{\text{act}} \bigwedge o \in O_{\text{act}} \forall \tilde{i} : w_{\text{active}(b,a),\tilde{i}} \rightarrow (\tilde{3}\tilde{i} : \tilde{i} \subseteq \tilde{i}' \wedge \tilde{w}_{\text{pos}(b,a),\tilde{i}} = \tilde{w}_{\text{pos}(b,a),\tilde{i}'}), \\
C_3 &\equiv \bigwedge_{a \in A, \rho \in B} \bigwedge b \in B_{\text{act}} \bigwedge o \in O_{\text{act}} \forall \tilde{i} : w_{\text{active}(b,a),\tilde{i}} \rightarrow (\tilde{3}\tilde{i} : \tilde{i} \subseteq \tilde{i}' \wedge (\tilde{w}_{\text{using}(b,a),\tilde{i}'} = o))
\end{align*}
\]

where \( \subseteq \) denotes interval inclusion.

\[\text{C. Planning via Verification}\]

Planning requires to compute a trajectory that adheres to an institution’s norms under given semantics. The CSP reduction shown above is appropriate for verifying candidate plans such as those considered by timeline-based planning approaches, which search the space of possible ‘timelines’ of state variables. The collection of these timelines is typically represented exactly as we have done above, in the form of a constraint network with as many variables as there are constant-valued intervals of time. These planners employ constraint reasoning techniques to verify that a candidate set of timelines (i.e., a candidate plan) adheres to constraints given in a domain specification. Some approaches, such as the one we use in Section \( \text{X} \) below, provide very expressive domain specification languages, which include temporal, spatial, resource and other constructs \( \text{[55]} \). This will allow us to express the semantics of norms directly in the domain specification, and to leverage the planner’s ability to search in the space of possible timelines to find an adherent trajectory \((I, \tau)\).

\[\text{VIII. Reasoning Example}\]

In this section, we unfold the concepts described so far on a trading institution inspired by the vignette of Roby and Sally seen in the Introduction. The institution consists of two roles, a buyer and a seller. The buyer pays with some form of payment and receives the purchased goods. The seller receives the payment and gives the goods to the buyer. In our framework, these concepts are specified as follows.

\[\begin{align*}
\text{Roles} &\equiv \{ \text{Buyer}, \text{Seller} \} \\
\text{Acts} &\equiv \{ \text{Pay}, \text{ReceiveGoods}, \text{ReceivePayment}, \text{GiveGoods} \} \\
\text{Arts} &\equiv \{ \text{PayForm}, \text{Goods} \}
\end{align*}\]

A set of obligations norms enforce that buyers pay and sellers give goods, respectively:

\[
N_1 = \text{must}((\text{Buyer}, \text{Pay}, \text{PayForm})), \\
N_2 = \text{must}((\text{Buyer}, \text{ReceiveGoods}, \text{Goods})), \\
N_3 = \text{must}((\text{Seller}, \text{ReceivePayment}, \text{PayForm})), \\
N_4 = \text{must}((\text{Seller}, \text{GiveGoods}, \text{Goods})).
\]

Other norms regulate the transaction in time and usage of artifacts:

\[
N_5 = \text{use}((\text{Buyer}, \text{Pay}, \text{PayForm})), \\
N_6 = \text{use}((\text{Buyer}, \text{ReceiveGoods}, \text{Goods})), \\
N_7 = \text{use}((\text{Seller}, \text{ReceivePayment}, \text{PayForm})), \\
N_8 = \text{use}((\text{Seller}, \text{GiveGoods}, \text{Goods})), \\
N_9 = \text{before}((\text{Buyer}, \text{Pay}, \text{PayForm}), \\
(\text{Buyer}, \text{ReceiveGoods}, \text{Goods})).
\]

A cardinality norm ensures that there is exactly one buyer and one seller in any trading instance:

\[
\text{card(Buyer)} = (1,1), \text{card(Seller)} = (1,1).
\]

Let us now consider a concrete realization by providing a specific domain \( \mathcal{D} = \{ \text{A}, \text{B}, \text{O}, \text{F}, \text{R} \} \):

\[
\begin{align*}
\text{A} &\equiv \{ \text{Roby}, \text{Sally} \} \\
\text{B} &\equiv \{ \text{give}, \text{take}, \ldots \} \\
\text{O} &\equiv \{ \text{cash}, \text{battery}, \ldots \} \\
\text{F} &\equiv \{ (\text{Roby}, \text{give}, \text{cash}), (\text{Roby}, \text{give}, \text{battery}), \\
(\text{Roby}, \text{take}, \text{cash}), (\text{Roby}, \text{take}, \text{battery}), \\
(\text{Sally}, \text{give}, \text{cash}), (\text{Sally}, \text{give}, \text{battery}), \\
(\text{Sally}, \text{take}, \text{cash}), (\text{Sally}, \text{take}, \text{battery}), \ldots \} \\
\text{R} &\equiv \{ \text{active(take, Roby), active(give, Roby),} \\
\text{active(take, Sally), active(give, Sally),} \\
\text{using(take, Roby), using(give, Roby),} \\
\text{using(take, Sally), using(give, Sally)} \}
\end{align*}
\]

\( \mathcal{D} \) may also include additional elements that are not relevant to our story, e.g., an object ‘motor’ and the fact that Sally has the affordance “(Sally, give, motor)”. The state variable active indicates whether a given agent is executing a given behavior (value = \( \mathcal{T} \)) or not (value = \( \mathcal{F} \), while the value of the variable using is the name of the object being used.

Finally, let’s consider the following grounding \( \mathcal{G} \):

\[
\begin{align*}
\mathcal{G}_A &\equiv \{ (\text{Buyer, Roby}, \text{Seller, Sally}) \} \\
\mathcal{G}_B &\equiv \{ (\text{Pay, give}, \text{ReceiveGoods, take}), \\
(\text{ReceivePayment, take}, \text{GiveGoods, give}) \} \\
\mathcal{G}_O &\equiv \{ (\text{PayForm, cash}, \text{Goods, battery}) \}
\end{align*}
\]

A. Admissibility

Recall that if a grounding \( \mathcal{G} \) is admissible it comply to the obligation norms. That is, each agent grounded to a role mentioned in an obligation norm should have an affordance with behavior and object which are grounded to the action and artifact of that norm – see Definition \( \text{[8]} \). This condition is checked by Algorithm \( \text{[1]} \).
Algorithm 1: Executable

Input: must ((role, act, art)) ∈ I, D, G
Output: true iff r is executable
1 Procedure Executable (r((role, act, art)), D, G)
2   for (role, ag) ∈ G_1 do
3     if ¬ Capable (ag, act, art, D, G) then
4       return false
5     return true
6 Procedure Capable (ag, act, art, D, G)
7   for (act, b) ∈ G_2 do
8     for (art, o) ∈ G_3 do
9       if (ag, b, o) ∈ D then
10      return true
11 return false;

Procedure Executable checks if an obligation norm is executable by checking if all grounded agents are capable of executing the required act with the corresponding art. The Capable procedure ensures that the object part of the statements can be used by required actions grounded to corresponding behaviors. The procedure is run for all obligation norms to ensure overall admissibility (Definition 1). For norm n1, since (Buyer, Roby) ∈ G_1 (line 2), the procedure checks if Roby is capable of executing action Pay with the artifact PayForm. Since (Pay, give) ∈ G_2 (line 7), (PayForm, cash) ∈ G_3 (line 8), the procedure verifies that (Roby, give, cash) ∈ F (line 9). This is the case, so norm n1 is deemed executable. All other obligation norms are verified in such a manner, and all are found executable given the domain and grounding in this example. Also, the number of grounded agents is in the limits of the cardinality norm (not shown in the algorithm), thus the grounding G is admissible.

B. Adherence

Two similar trajectories are graphically summarized in Figure 3, where each picture shows a state. These states can be described as follows, where we omit the values of inactive behaviors:

- \( s_1 = \{\text{active(give, Roby)}(t_2) \mid \overline{\rho}, \text{using(give, Roby)}(t_2) = \text{cash}\} \)
- \( s_2 = \{\text{active(give, Roby)}(t_3) \mid \overline{\rho}, \text{using(give, Roby)}(t_3) = \text{cash}, \text{active(take, Sally)}(t_3) = \overline{\rho}, \text{using(take, Sally)}(t_3) = \text{cash}\} \)
- \( s_3 = \{\text{active(take, Roby)}(t_4) \mid \overline{\rho}, \text{using(take, Roby)}(t_4) = \text{battery}, \text{active(give, Sally)}(t_4) = \overline{\rho}, \text{using(give, Sally)}(t_4) = \text{battery}\} \)
- \( s'_3 = \{\text{active(take, Roby)}(t_4) \mid \overline{\rho}, \text{using(take, Roby)}(t_4) = \text{cash}, \text{active(give, Sally)}(t_4) = \overline{\rho}, \text{using(give, Sally)}(t_4) = \text{cash}\} \)

![Fig. 3: Pictorial representation of two stories (trajectories). The left one adheres to a trading institution, the right one doesn’t.](image-url)

The stories in the figure correspond to two trajectories, \( (I, \tau_a) \) and \( (I, \tau_b) \), where \( I = [t_1, t_4] \). States \( s_1, s_2 \) are shared between the two trajectories, whereas \( s_3 = \tau_a(t_4) \) and \( s'_3 = \tau_b(t_4) \) differ in the values of using(take, Roby) and using(give, Sally). The interesting question here is: **do these trajectories represent instances of a trading institution?** To answer this, we construct a CSP representing each story and verify whether or not it admits a solution.

C. Adherence and the CSP

Given the above I, D, and G, the sets \( A_{\text{role}}, B_{\text{act}} \) and \( O_{\text{art}} \) are as follows:

- \( A_{\text{Buyer}} = \{\text{Roby}\} \), \( A_{\text{Seller}} = \{\text{Sally}\} \),
- \( B_{\text{Pay}} = \{\text{give}\} \), \( B_{\text{ReceiveGoods}} = \{\text{take}\} \),
- \( B_{\text{ReceivePayment}} = \{\text{take}\} \), \( B_{\text{GiveGoods}} = \{\text{give}\} \),
- \( O_{\text{PayForm}} = \{\text{cash}\} \), \( O_{\text{Goods}} = \{\text{battery}\} \).

The variables of the constraint network \((\overline{\mathbb{W}}, \mathcal{C})\) obtained from I, D, G and the trajectory \((I, \tau_a)\) are shown in Table II.

| \( \rho \) | \( i \) | \( w_{\rho,i} \) |
|-----------|--------|----------------|
| active(give, Roby) | 1,1 | + |
| active(give, Roby) | 2,3 | + |
| active(give, Roby) | 4,4 | + |
| using(give, Roby) | 2,3 | cash |
| active(take, Roby) | 1,1 | + |
| active(take, Roby) | 4,4 | + |
| using(take, Roby) | 4,4 | battery |
| active(give, Sally) | 1,3 | + |
| active(give, Sally) | 4,4 | + |
| using(give, Sally) | 4,4 | battery |
| active(take, Sally) | 1,2 | + |
| active(take, Sally) | 3,3 | + |
| active(take, Sally) | 4,4 | + |
| using(take, Sally) | 3,3 | cash |

TABLE II: Variables \( w_{\rho,i} \) in \( \overline{\mathbb{W}} \) and their values.
The constraints reflecting the norms $N_1 - N_9$ in our example are constructed as follows. For the first obligation norm $N_1$, and recalling equation (5) above, we have:

$$C_{N1} \equiv \bigwedge_{a \in A_{buyer}} \bigvee_{b \in B_{pay}} \bigwedge_{c \in O_{pay}} \exists t : w_{active}(b,a), t = \top$$

$$\equiv \exists t : (w_{active}(give, Roby), t = \top)$$

Intuitively, there must be a segment in the execution trajectory during which Roby performs the 'give' behavior. Similarly, other obligation norms induce the following constraints:

$$C_{N2} \equiv \exists t : (w_{active}(take, Roby), t = \top),$$

$$C_{N3} \equiv \exists t : (w_{active}(take, Sally), t = \top),$$

$$C_{N4} \equiv \exists t : (w_{active}(give, Sally), t = \top).$$

As can be seen from Table II all obligation norms are satisfied by trajectory $(I, \tau_2)$ in our example. For instance, constraint $C_{N1}$ relative to norm $N_1$ is satisfied thanks to the fact that $w_{active}(give, Roby)[2,3] = \top$ (second line in Table II).

The constraint $C_{N5}$, induced by the usage norm $N_5$, is constructed (recall equation (7)) as follows:

$$C_{N5} \equiv \bigwedge_{a \in A_{buyer}} \bigwedge_{b \in B_{pay}} \bigwedge_{c \in O_{pay, form}} \forall t : w_{active}(b,a), t \rightarrow (\exists t' : i \subseteq i' \wedge (w_{using}(b,a), t' = o))$$

$$\quad \equiv \forall t : w_{active}(give, Roby), t \rightarrow (\exists t' : i \subseteq i' \wedge (w_{using}(give, Roby), t' = \text{cash})).$$

Intuitively, the execution trajectory must be such that whenever Roby performs the ‘give’ behavior, it does so using ‘cash’. The constraints for the other usage norms are constructed similarly:

$$C_{N6} \equiv \forall t : w_{active}(take, Roby), t$$

$$\rightarrow (\exists t' : i \subseteq i' \wedge (w_{using}(take, Roby), t' = \text{battery})),$$

$$C_{N7} \equiv \forall t : w_{active}(take, Sally), t$$

$$\rightarrow (\exists t' : i \subseteq i' \wedge (w_{using}(take, Sally), t' = \text{cash})),$$

$$C_{N8} \equiv \forall t : w_{active}(give, Sally), t$$

$$\rightarrow (\exists t' : i \subseteq i' \wedge (w_{using}(give, Sally), t' = \text{battery})).$$

All these constraints are also satisfied by trajectory $(I, \tau_2)$ in our example. For instance, $C_{N5}$ is satisfied because Roby activates the give behavior only in the interval [2,3], and the used object in that interval is cash. From lines 2 and 4 in Table II $w_{active}(give, Roby)[2,3] = \top$ and $w_{using}(give, Roby)[2,3] = \text{cash}$. Finally, paying and receiving actions are subject to the temporal norm $N_9$, for which we construct the following constraint:

$$C_{N9} \equiv \bigwedge_{a \in A_{buyer}} \bigwedge_{b \in B_{pay}} \bigwedge_{c \in O_{pay, goods}} \forall t_1, t_2 : w_{active}(b,a), t_1 = \top \wedge w_{active}(b,2, t_2 = \top)$$

$$\rightarrow t_1 < t_2$$

$$\equiv \forall t_1, t_2 : (w_{active}(give, Sally), t_1 = \top \wedge w_{active}(take, Roby), t_2 = \top)$$

$$\rightarrow t_1 < t_2$$

where $t_1 = [t_1', t_1''], t_2 = [t_2', t_2'']$ and $t_1 < t_2$ means $t_1' < t_2'$. This constraint is satisfied in our example, since active(give, Roby) is $\top$ in [2,3], and active(take, Roby) is $\top$ in [4,5] (see Table II).

Since all constraints $C_{N1} - C_{N9}$ are satisfied, we conclude that trajectory $(I, \tau_2)$ adheres to our trading institution under the given grounding. On the other hand, trajectory $(I, \tau_2)$ is not adherent, since it includes constraints $w_{active}(give, Sally), [4,5] = \top$ and $w_{using}(give, Sally), [4,5] = \text{cash}$, which violate constraint $C_{N8}$. In other words, the story on the right of Figure 3 does not represent a sound execution of a trading institution.

### IX. AN EXPERIMENT WITH ROBOTS AND HUMANS

In this section, we report a proof of concept experiment that illustrates the ability of our framework to verify and regulate norm adherence in mixed human-robot interactions. The experiment includes three scenarios that stress different aspects of our framework. The first scenario (A) focuses on the verification problem, and features a robot observing two humans; the second (B) and third (C) scenarios focus on the planning problem, and respectively involve a robot and a human (B) and two robots (C).

#### A. Experimental Setup

The scenarios are realized in a smart apartment named the PEIS Home [45] using two pepper robots [47]. Robot’s behaviors have been implemented via NAOqi, and the environment has been customized to simplify perception and manipulation: in particular, the objects exchanged are sponges of different colors rather than banknotes or batteries. For the planning parts, we have used an off-the-shelf timeline-based planning solution [39] which allows us to express norm semantics in the planner’s domain definition language.

For the experiments, we have developed a simple Institution Manager (IM) which encapsulates and implements all concepts discussed so far. The IM is responsible for several tasks: (1) It realizes our institution model, allowing users to define their own specification of institutions, domains, and groundings. (2) It checks the admissibility of grounding by implementing the algorithm [7] (3) It automatically translates an institution specification into requirements and operators in the planning domain, to be used for verification and planning; the semantics of norms are encoded directly into the domain definition, thus allowing the planner to directly generate adherent plans (see Section VII-C). (4) It controls plan execution by dispatching behaviors to the robots. (5) It uses feedback from the robots to verify the adherence of plan execution to norms. The code of the IM, together with the complete domain specification used by the planner are available at http://aiss.oru.se/~snte/TradeExperiment and videos of the scenario executions at https://youtu.be/OIMy4UYjFws.

#### B. Institution and Domain

The used institution specification is the same as the one in section VIII. The domain, however, is different. The following domain models the relevant parts of the physical setup used in our tests:

$$A = \{ \text{pepper}_1, \text{pepper}_2, \text{human}_1, \text{human}_2, \ldots \}$$

$$B = \{ \text{pick}, \text{give}, \ldots \}$$

$$O = \{ \text{sponge}_\text{yellow}, \text{sponge}_\text{blue}, \text{sponge}_\text{red}, \ldots \}$$

$$F = \{ \text{pepper}_x, \text{give}, \text{sponge}_\text{color}, \}$$

$$\quad \{ \text{pepper}_x, \text{pick}, \text{sponge}_\text{color}, \ldots \}$$

$$R = \{ \text{active(\text{pepper}_x, \text{give})}, \text{active(\text{pepper}_x, \text{pick})}, \text{active(\text{human}_x, \text{give})}, \text{active(\text{human}_x, \text{pick})}, \ldots \}. $$

We use $x$ and color subscripts as a compact way to indicate that some affordances or state-variables apply to several agents or objects. As specified by the affordance relation $F$, any robot can pick and give any sponge color. We have omitted from $F$ the affordances of humans, who are assumed to be capable of all behaviors.

The value of the active($a, b$) state variable is the object used by agent $a$ to run behavior $b$, or $\bot$ if $a$ is not running $b$. This variable conglomerates the two separate variables active($a, b$) and use($a, b$) that we used in VIII above. Thus, we can now simultaneously check the satisfaction of the ‘must’ and the ‘use’ norms.

#### C. Scenario A

The task is to check whether an observed execution adheres to an institution or not. We placed one Pepper robot in front of a table where two humans interact, and we developed a simple ad-hoc
The institution specification is translated by $\text{IM}$ into the set of operators and requirements for the planning domain used by the robots. An adherent trajectory is synthesized by the timeline-based planner whose domain contains the semantic models of all norms. The resulting plan was dispatched to $\text{pepper}_1$.

### E. Scenario C

In the final scenario, we used two robots instead of a robot and a human. This is achieved by simply replacing the roles grounding in $\mathcal{G}$ by the following:

$$G'_A = \{(\text{Buyer}, \text{pepper}_1), (\text{Seller}, \text{pepper}_2)\}$$

In this case, the resulting plan was dispatched to both robots: $\text{pepper}_1$ and $\text{pepper}_2$.

The grounding in all scenarios is admissible because it grounds the roles of traders to robots that are capable of executing the appropriate give and pick behaviors.

### X. Conclusion and Future Work

In this work, we have introduced a theoretical framework for modeling and reasoning about norms in robotics. The framework is grounded on the notion of institution, which provides a way to model how agents should behave in a given social context. The framework distinguishes between abstract norms and their instantiation into a concrete domain, and it combines insights from the fields of multi-agent systems and of robotics. It enables the definition of relevant computational tasks, such as verification and planning. Notably, the framework provides support for artifacts, which is of high importance in robotics, since robots and humans interact and coordinate via relevant objects in the environment. We have shown how the verification problem can be cast to a CSP, and how this enables the use of constraint-based planning and plan execution technology to control a robot system. Finally, we have demonstrated our framework in a physical system comprising both humans and robots. Additional experiments using different institutions and mixed human-robot interactions can be found in [48].

Institutions encapsulate all norms, roles, and artifacts that are relevant in a given social context. However, it is often the case in human societies that several institutions are relevant simultaneously, e.g., children who participate in a game playing institution still adhere to the norms of the surrounding school institution. Relating different institutions and exploiting these relations in verification and planning is the topic of ongoing work. Also, we plan to study how to use institutions for goal reasoning — e.g., if a robot realizes it needs a new battery, it may decide that the best way to obtain it is to engage in a trading institution.

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