A Formal Account of Opportunism in Multi-agent Systems

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A Formal Account of Opportunism in Multi-agent Systems

Een formele benadering van opportunisme in multi-agent systemen

(met een samenvatting in het Nederlands)

PROEFSCHRIFT

ter verkrijging van de graad van doctor aan de Universiteit Utrecht op gezag van de rector magnificus, prof.dr. G.J. van der Zwaan, ingevolge het besluit van het college voor promoties in het openbaar te verdedigen op maandag 30 april 2018 des middags te 2.30 uur

door

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geboren op 21 april 1987 te Shunde, Guangdong, China

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Copromotor: Dr. M. Knobbout

Contents

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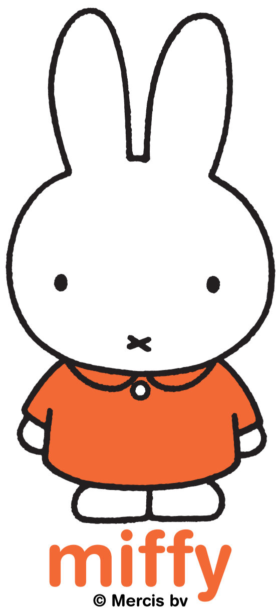
Luora
20.01.2018



1
Introduction

Opportunistic behavior (or opportunism) is a selfish behavior that intentionally takes advantage of relevant knowledge asymmetry to achieve own gain, regardless of other agents' value. In the context of multi-agent systems, knowledge is distributed among different agents, which creates the opportunity for agents to perform opportunistic behavior to other agents. Since opportunistic behavior has undesirable results for other agents in the system, the aim of this thesis is to eliminate such a selfish behavior from the system. In order to reach this goal, we will perform the investigation of opportunism with the notion of values for different issues.

1.1 Motivation

Consider a common social scenario. In a market a seller is trying to sell a cup to a buyer and it is known only by the seller beforehand that the cup is actually broken (e.g. there is a crack at the bottom of the cup). The buyer finally buys the cup for its good appearance, but immediately gets disappointed when he fills it with water. In this example, the seller earns money from the buyer by exploiting the opportunity of having more knowledge about the transaction than the buyer, while the buyer didn't know the quality of the cup before he buys it. Such a behavior intentionally performed by the seller is first named opportunistic behavior (or opportunism) by economist

Williamson [Williamson, 1975], which is a selfish behavior that takes advantage of knowledge asymmetry and results in promoting agents' own value but demoting other agents' value. Opportunistic behavior commonly exists in business transactions and other types of social interactions in various forms such as deceit, lying and betraying. This is because individuals working in different positions are capable to have access to different amounts of information, which provides the opportunity for them to gain personal advantage, regardless of the consequences to others. Since it has negative results for other individuals involved in the relationship and strongly affects the cooperative relationship once it is unveiled, it is prevented or eliminated by social laws and norms. In the next chapter we will give a brief review of opportunism in social science.

Is the investigation of opportunism of interest to AI? Social concepts are often used to construct artificial societies. Viewing individuals as agents, we might have similar phenomena in the context of multi-agent systems. Interacting agents were designed to behave in a human-like way with characteristics of self-interest. When such agents possess different amounts of relevant information about a specific transaction and try to maximize their own benefits, those who are more knowledgeable might perform opportunistic behavior to other agents in their own interest, which is against others' benefits. It is important to design mechanisms to eliminate opportunism in multi-agent systems, as it has undesirable results for other agents in the system.

In this thesis, we use logic-based formal approaches to investigate opportunism with the notion of values. Many logic-based formal approaches have been developed in the agent community, such as logics for knowledge and belief and logics for mental states (see [Van Ditmarsch et al., 2007] and [Cohen and Levesque, 1990]). With logic-based formal approaches we can specify and reason about multi-agent systems. Typically we can prove properties of systems that we are intended to have after implementing the system with respect to the specification. The first reason why we use logic-based formal approaches in this thesis is that they allow us to understand more clearly the elements that construct opportunism and how they relate to each other. Lots of work has been done on the logics of action and the logics for agents' mental states since last century (see [McCarthy and Hayes, 1969] and [Bratman, 1987]), which turn them into two mature research areas. Based on those logics we can have a formal definition of opportunism. The second reason for the use of logic-based formal approaches is that they allow us to specify our monitoring and eliminating mechanisms for opportunism. The interesting properties we prove based on the formal approaches show the characteristics of our mechanisms. The third reason why we use logic-based formal approaches in this thesis is that it is possible to combine it with other formal approaches and theories. For example, in order to reason about agents' opportunistic propensity, we combine logic with decision theory in the way that agents determine their preferences over different states by evaluating state properties. Logic-based formal approaches are commonly used in the research of Artificial Intelligence and can be seen as appropriate for the investigation of opportunism from different perspectives.

1.2 Research Questions

The aim of this thesis is to eliminate opportunism in multi-agent systems. In order to reach this goal, it is of great importance to understand opportunistic behavior in the context of multi-agent systems. Namely, what kind of actions can be categorized as opportunistic behavior? In the logic of action, people represent an action by specifying its pre- and post-condition: the precondition specifies the scenario where the action can be performed, whereas the postcondition specifies the corresponding scenario resulting from performing the action with the precondition. Besides, it is also important to interpret an action by considering its mental state when the action is performed, typically because intentionality is used to distinguish opportunistic behavior from other behaviors. Therefore, we need to define opportunism in a formal way to capture its pre- and post-condition and the mental state of opportunistic agents.

Research Question 1. *How can we formally define opportunistic behavior in the context of multi-agent systems?*

Norms have been commonly used to regulate and control the behavior of the agents or the system. As opportunistic behavior has undesirable results for other agents in the system, norms can be used to prescribe forbidden actions that are opportunistic, or forbidden states that opportunistic behavior results in. Typically we want to use enforcement norms, which are norms that can be violated and lead to sanctions once the violation is detected. But then there has to be a monitoring mechanism to detect norm violations. On the one hand, it is important to detect it, as it has undesirable results for the participating agents and we want to impose sanction to the agent who was opportunistic. On the other hand, since opportunism is always in the form of lying, deception and betrayal, meaning that the system does not know what the agent performs or even the motivation behind it (for example, in a distributed system), opportunistic behavior cannot be observed directly. Thus, there has to be a monitoring mechanism that can detect the performance of opportunistic behavior in the system.

Research Question 2. *How can we develop a mechanism for monitoring opportunism even though the system is not able to see its performance objectively?*

In the investigation of opportunism, it is also important to predict and specify when an agent will perform opportunistic behavior so that the appropriate amount of monitoring and eliminating mechanisms can be put in place. Evidently, not every agent is likely to be opportunistic. An agent will perform opportunistic behavior when he has the ability and the desire of doing that. Based on this assumption, can we design a framework to reason about agents' opportunistic propensity? Once we know when an agent is inclined to perform opportunistic behavior, we know when an agent will not perform opportunistic behavior by making the ability and the desire of being opportunistic unsatisfied. In other words, this framework can also be used to design a mechanism for eliminating opportunism.

Research Question 3. *How can we develop a framework that allows us not only to reason about agents' opportunistic propensity but also to design a mechanism for eliminating opportunism?*

The first question will be explored in Chapter 3, the second question will be explored in Chapter 4, and the third question will be explored in Chapter 5 and Chapter 6. Before we start our exploration, it is important to clarify that we have different definitions of opportunism in different chapters. We propose a formal definition of opportunism in Chapter 3, which forms a solid foundation for our future research. However, we find that it is difficult to apply this thorough definition to every research issue. For example, even though we do define the mental state of opportunistic agents in Chapter 3, it is impossible for monitors to detect any mental states. Thus, we remove all the references to mental states (knowledge, intention) for the definition of opportunism in Chapter 4. For Chapter 5 and Chapter 6, we define opportunistic propensity based on the definition of opportunism in Chapter 3. Moreover, even though in Chapter 3 we define opportunism that consists of multiple actions and is situated in a system with norms, in the later chapters we only tackle the kind of opportunism that contains only one action and happens between two agents for simplification, which influences the way we define norms, rational alternatives and so on. To summarize, we will look at opportunism from different perspectives to explore different research issues.

1.3 Thesis Outline

We will give a brief outline of the thesis:

- Chapter 2: We give a brief overview on the topics of opportunism, multi-agent systems, values and action theory.
- Chapter 3: We propose a formal definition of opportunism with the notion of values based on the situation calculus. This chapter is based on our paper [Luo and Meyer, 2017].
- Chapter 4: We propose a formal framework based on the specification of actions to specify monitoring approaches for opportunism. This chapter is based on our paper [Luo et al., 2016].
- Chapter 5: We introduce a formal framework to reason about agents' opportunistic propensity. This chapter is based on our paper [Luo et al., 2017].
- Chapter 6: We propose a formal framework that allow us to design two mechanisms for eliminating opportunism. This chapter is based on our paper [Luo et al., 2018].
- Chapter 7: We summarize this thesis.

2

Background

In this chapter, we will briefly review the concepts of opportunism, multi-agent systems and values, and the logic of action upon which we conduct this research.

2.1 Opportunism

Opportunism is a economic concept proposed by economist Williamson [Williamson, 1975]. In his theory of transaction cost economics, he has proposed that economic agents be described as opportunistic where this means self-interest seeking with guile [Williamson, 1993]. Even though it provides the original definition of opportunism, so far there is no general and agreed definition or theory of opportunism. The main reason is that sometimes opportunism is assessed against some norms and principles, and controversy about what that norm or principle should be makes a general definition difficult [Chen et al., 2002]. However, because of the word “guile”, it is commonly accepted that opportunism involves deliberate deceit, betrayal, or deliberately withholding, shirking or distorting important business information, which have been later referred to taking advantage of information asymmetry. Since it was proposed by economist Williamson, scholars have studied this typical social behavior of economic players from various perspectives i.e. transaction cost economics [Williamson and Mueller, 1986], resource-based view [Conner and Prahalad, 1996], game theory [Cabon-Dhersin and Ramani, 2007], agency theory [Jiraporn et al., 2008] and strategic management [Yaqub, 2011]. For example, transaction cost economics propose to expand the boundary of a firm such that both parties have common interests involved in the transaction.

The investigation of opportunism is new in Artificial Intelligence. Even though work about opportunism in social science is indeed all worthwhile, it is difficult to directly apply their conclusions to multi-agent systems for improving the system's behavior because most of them are informal, which makes reasoning about this behavior in multi-agent systems impossible, and also not commonly accepted even in their own area as we commented above. However, there is some work on logic of lying, deception and dishonesty [Sakama et al., 2010] [Sakama et al., 2015] [Van Ditmarsch et al., 2012], which are forms of opportunism. In their work, modalities for belief and intention are commonly used for formalizing different types of dishonest communication, which is similar to our work. However, Sakama's work [Sakama et al., 2010] [Sakama et al., 2015] only formalizes one agent's communication to another agent and his mental states, regardless of the effect on another agent, which means that we cannot reason about the state transition based on the approach. The primary goal of van Ditmarsch's work [Van Ditmarsch et al., 2012] is to model lying by modeling how agents' believes change from the communications. It analyses the effect of lying in public discourse, and explains how lying can be used as an optimal strategy through a game-theoretical analysis. For providing a formal model of opportunism, we not only need to formalize the mental states of interacting agents, but also need to reason about how the physical situations are changed by opportunistic behavior, both of which are related to the above work.

2.2 Multi-agent Systems

Multi-agent systems (MAS) are systems that consist of multiple interacting computing elements, known as *agents*, within an environment [Wooldridge, 2009]. Examples of multi-agent systems can be electronic markets where sellers and buyers can perform transactions, energy systems to supply energy-services to end-users and so on. Agents are computer systems that are capable of autonomous actions in an environment in order to meet their delegated objectives [Wooldridge, 2009]. Agents are reactive in the reveal that they are able to perceive their environment and respond timely to changes, proactive in the reveal that they take the initiative to satisfy their design objectives, and social in the reveal that they are capable of interacting with other agents. Since [Dennett, 1971] put forward the notion of *the intentional stance*, people started to study an agent's choice of action by considering its beliefs and desires. [Bratman, 1987] incorporates the notion of intention for describing agent behavior, building the foundation of the BDI (belief, desire and intention) approach to artificial agents. After Bratman's philosophy was published, researchers tried to formalize this theory using logical means. Three well-known approaches are [Cohen and Levesque, 1990], [Rao and Georgeff, 1991] and [Meyer et al., 1999]. An agent will have a set of actions available to it. This set of possible actions represent the agent's ability to modify its situated environment. Depending on the system, the environments where agents find themselves in might have different properties. The environments of the systems we will consider in this thesis have the following properties [Wooldridge, 2009]:

- Inaccessible: It is impossible for agents to gather complete and accurate information about the environment. Namely, agents have partial views about the environment.
- Deterministic: An action has a single definite effect and there is no uncertainty about the state that will result from performing an action.
- Dynamic: The environment can be changed beyond agents' control.
- Discrete: There are a fixed, finite number of actions in the environment.

In this thesis, we use transition systems to represent the underpinning semantics of multi-agent systems, which consist of agents, states, actions and transitions between states by actions. When an action is performed in a certain state, the system might progress to a different state in which different propositions might hold. A lot of work on logic formalism has been designed for representing and reasoning about the dynamic of the systems such as the situation calculus [McCarthy and Hayes, 1969], the event calculus [Kowalski and Sergot, 1989] and most commonly used modal logic [Blackburn et al., 2002]. As we will see, we use different logic-based frameworks in different chapters:

- We will use the situation calculus, which is dialect of first-order logic, to define opportunism in Chapter 3, typically because it is designed to represent and reason about actions.
- We will use modal logic in Chapter 4. In order to investigate the monitoring issue that the system cannot directly detect opportunistic behavior,

we will develop a framework where an action is specified through its precondition and its effect (postcondition), and where every state transition in the system is defined based on action specification.

- We will use modal logic in Chapter 5 and Chapter 6. Because these two chapters are closely related to opportunistic propensity, agents in the system will have their own preferences over states and actions.

To summarize, we use different logic-base frameworks for different purposes. Even though they are different, the definitions of opportunism we will use based on our frameworks are consistent in the reveal that the same properties can be proved. Another issue we would like to stress here is about the access to the internal architecture of agents. In this thesis, we will have various access to the internal architecture of agents, depending on from which perspective we study an issue: In Chapter 3, we will define opportunism with an agent's knowledge and intention from the internal perspective. In Chapter 4, we will remove all the references to mental states (knowledge, intention) for the definition of opportunism because monitors have no access to any mental states, but we assume that the system can reason whether an agent's value gets promoted or demoted along a state transition based on the corresponding value systems. In Chapter 5, the system will predict whether an agent will perform opportunistic behavior with an assumed value system; while in Chapter 6 agents' value systems are unknown to the mechanism system designer.

2.2.1 Norms

Norms have their origins in social science. Sociologist Gibbs defined norms in [Gibbs, 1965] as "a collective evaluation of behavior in terms of what it ought to be; a collective expectation as to what behavior will be; and/or particular reactions to behavior, including attempts to apply sanctions or otherwise induce a particular kind of conduct". In short, norms are the prescriptions of desirable/undesirable states of affairs with concepts such as obligations, permissions and prohibitions. An example can be that a seller shouldn't sell a broken cup to a buyer. Since last century norms have been commonly used to regulate and coordinate agents' behavior in order to achieve the overall objectives of multi-agent systems. [Therborn, 2002] distinguishes among three kinds of norms. *Constitutive norms* define a system of action and an agent's membership in it, *regulative norms* describe the expected contributions to the social system, and *distributive norms* defining how rewards, costs, and risks are allocated within a social system. All the norms we will use in this thesis are regulative norms and agents in the system are able to decide whether to comply with them. Norms can be explicitly represented, for example in deontic logic [McNamara, 2014]. Deontic logic studies logical relations among obligation, permission, and related concepts. Among various systems of deontic logic, *Standard Deontic Logic* (SDL) is the most cited and studied one, mainly because it builds upon propositional logic, and is a distinguished member of modal logics.

The investigation of opportunism cannot be done without norms. Agents in multi-agent systems are residing in a normative context which provides obligations, permissions and other types of norms for guiding agents' behaviors. In this thesis, those norms are enforcement norms that agents can obey or violate, and that lead to sanctions when they are violated. The setting of those norms reflect the values of the system. We can consider the system as an entity, agents can perform opportunistic behavior to the system through violating norms secretly. We will tackle this issue in Chapter 3 and Chapter 4. When we look for ways to eliminate opportunism in multi-agent systems, removing knowledge asymmetry between agents might contradict the privacy norms in the system, and norms with enforcement policies can be used to switch agents' opportunistic choices. We will tackle this issue in Chapter 6. Moreover, we will use the following types of norms in different chapters:

- State-based norms: State-based norms prescribe the state properties that should/shouldn't be achieved. An example is [Lomuscio and Sergot, 2002] which uses green and red to color allowed and disallowed states respectively. We will use state-based norms as our enforcement norms in Chapter 6 to simply the semantics of system update via norms.
- Action-based norms: Action-based norms prescribe the particular actions that should/shouldn't be executed rather than the state properties to be achieved. They are well studied in [Fiadeiro and Maibaum, 1991]. The norms we use in Chapter 3 and Chapter 4 are action-based norms, and we represent the ones in Chapter 3 in deontic logic, whereas the other ones in a tuple form.

Notice that in this thesis we will not study how norms are to be perceived by agents or to be implemented in the system. We simply assume that there are a set of norms that are enforced by the system designer and agents in the system are able to decide whether to comply with them.

2.3 Values

Values are the perspective from which we study opportunism in this thesis. Compared to values, goals are more commonly used in logical formalization (e.g. [Cohen and Levesque, 1990] and [Rao and Georgeff, 1991]), so are utilities in decision theory and game theory (e.g. [Steele and Stefánsson, 2016] and [Von Neumann and Morgenstern, 2007]), for expressing similar idea. However, the concept of value has been recently discussed in the logical literature, especially some work in the area of argumentation practical reasoning that reasons about agents' preferences and decision making by values (e.g. [Bench-Capon et al., 2012], [Van der Weide, 2011], [Pitt and Artikis, 2015], [Zurek, 2017] and [Lorini, 2014]). For example, [Zurek, 2017] discusses the issue of modeling of values and goals in reasoning and argumentation, and in [Lorini, 2014] a logical theory exploring the connections between the concepts of value, preference, knowledge and rationality is provided. Even though goals, utilities and values can be used to represent agents' preferences about situations, they have different features.

- Goals and Values: Goals are concrete and should be specified with time, place and objects. For example, to earn 1000 euro next month is a goal. If one agent's goal is achieved in one situation, then he has high evaluation on that situation. Value is described by Schwartz as trans-situational [Schwartz, 1992], which means that value is relatively stable and not limited to be applied in a specific situation. For instance, if honesty is a value of somebody, he will be honest for a long period of time. Since state transitions are caused by the performance of actions, we can evaluate actions by whether our value is promoted or demoted in the state transition, as what we do in this thesis.
- Utilities and Values: For representing agents' evaluation on states, Keeney and Raiffa proposed Multi-Attribute Utility Theory (MAUT) in which states are described in terms of a set of attributes and the utilities of the states are calculated by the sum of the scores on each attribute based on agents' value system [Keeney and Raiffa, 1993]. Apparently, not everything can be evaluated with numbers, which is one of the reasons why people consider using value systems as an alternative. A value system is like a box

that allows us to define its content as we need. In Chapter 3 and Chapter 4, situations/states are represented through propositions and agents refer to a specific proposition based on their value systems to evaluate a state transition. Starting from Chapter 5, we will open up the *black box* of value systems. A value is modeled as a formula in our language and a value system is constructed as a total order over a set of values. Instead of calculating the utility of states, agents specify their preferences over states by evaluating the value change that they most care about.

We will prove that the state preferences we define with value systems obey the standard properties we expect from a preference relation.

2.4 Logic of Action

In computer science, people realize that computers perform actions in the reveal that executing program statements change computer internals and outside world. Hence, a logic of action provides a means to verify programs [Segerberg et al., 2016]. Historically, different ways of program verification have been proposed. In Hoare logic [Hoare, 1969], the execution of a program is described through a Hoare triple $\{P\}C\{Q\}$, where C is a program, P is the precondition and Q is the postcondition, which is quite close to our approach of action specification $\langle \psi_p^a, \psi_e^a \rangle$ in Chapter 4.

Representing and reasoning about actions is one of the central topics in artificial intelligence, particularly in knowledge representation. One of the main problems that one encounters when reasoning about actions in AI is *frame problem* [McCarthy and Hayes, 1969], namely the challenge of representing the effects of action in logic without having to represent explicitly a large number of intuitively obvious non-effects. Reiter proposed a solution within a framework, which is called the *situation calculus* [Reiter, 2001]. The situation calculus is a dialect of first-order logic especially designed to reason about actions. Its idea is that we can represent any reachable states in terms of actions that are required to reach them, and that the reachable states are called situations. There are three elements: actions Act that can be performed by agents, situations S that represent a history of action occurrences, and fluents F that describe the properties of the situation. Situation S_0 represents the initial situation that no action can result in. The properties of situations are specified through relational and functional fluents taking a situation term as their last argument, which means their truth value may vary from situation to situation. Based on the situation calculus, Reiter's Basic Action Theory is defined as a set of axioms:

$$D = \Sigma \cup D_{ap} \cup D_{ss} \cup D_{so} \cup D_{una}$$

Σ: the set of foundational axioms,

- $\mathrm{do}(a_1, s_1) = \mathrm{do}(a_2, s_2) \rightarrow a_1 = a_2 \wedge s_1 = s_2$; Two situations are the same if and only if they are the same sequence of actions.
- $(\forall Q)Q(S_0) \wedge (\forall s, a)[Q(s) \rightarrow Q(\mathrm{do}(a, s))] \rightarrow (\forall s)Q(s)$; This is a second-order induction axiom saying that for any property Q, if $Q(S_0)$ and, for any situation s and action a, property Q remains the same, then we have $(\forall s)Q(s)$.
- $\neg s \sqsubset S_0$; The relation $\sqsubset$ provides an ordering relation on situations. $s \sqsubset s'$ means that the action sequence s is a sub-sequence of that of s'. Thus, s is a sub-sequence of $\mathrm{do}(a, s')$ if and only if s is a sub-sequence of s' or they have the same action sequence. And no situation is before initial situation S_0.
- $s \sqsubset \mathrm{do}(a, s') \equiv s \sqsubseteq s'$;

D_{ap}: the set of actions preconditions,

$$\mathrm{Poss}(a(x), s) \equiv \pi(x, s)$$

where $\pi(x, s)$ is a formula uniform in s and whose free variables are among x and s. Thus, whether $a(x)$ can be performed in situation s depends entirely on s.

D_{ss}: the set of successor state axioms,

$$F(\mathrm{do}(a, s)) \equiv \gamma_F^+(a, s) \vee (F(s) \wedge \neg\gamma_F^-(a, s))$$

Here $\gamma_F^+(a, s)$ and $\gamma_F^-(a, s)$ are two formulas expressing the conditions for the fluent F becoming true and false, respectively; the effect of action is specified through successor state axioms, which consist of positive consequences and negative consequences.

D_{so}: the sentences uniform in S_0 describing the initial situation;

D_{una}: the unique name axioms for actions.

The situation calculus is the technical framework of next chapter, where we will formally define opportunistic behavior based on our understanding of the concept from social science.

2.5 Possible-world Structure

Possible-world structure (or Kripke structure) is the model that people adopt to formalize knowledge, belief, intention and obligation in the situation calculus and modal logic. Therefore, we will briefly introduce this model before we use those modalities in our later chapters. A Kripke structure is proposed by Saul Kripke [Kripke, 1963] and has become the standard type of the models in modal logic and related non-classical logics. Basically it is a graph whose nodes represent the possible states of the system and whose edges represent accessibility relations. A valuation function maps each node to a set of properties hold in the corresponding state. Formally, let Φ be a set of atomic propositions. A Kripke structure over Φ is defined as a tuple $M = (S, \mathcal{R}, \pi)$, where

- S denotes a set of states (or situations);
- $\mathcal{R} \subseteq S \times S$ is a set of accessibility relations;
- $\pi : S \rightarrow 2^{\Phi}$ denotes a valuation function, meaning that for each state $s \in S$ the set $\pi(s)$ of atomic propositions hold in s. Therefore, $fluents$ in the situation calculus can be interpreted as: given a proposition p, fluent $p(s)$ holds iff $p \in \pi(s)$.

By means of a Kripke structure we can represent exactly an agent's mental state in a certain state (or situation). Figure 2.1 is an example of a Kripke structure. Suppose that our underlying logical framework is the situation calculus. The actual situation where p is true and q is false, represented by situation $s \in S$ for which it holds that $p(s)$ and $\neg q(s)$. Now the model can be represented by $S = \{s, s', s''\}$, where s is as above, s' is $p(s')$ and $q(s')$, and s'' is $\neg p(s'')$ and $q(s'')$. The accessibility relation $\mathcal{R}$ is illustrated as Figure 2.1.

Kripke structures are adopted by the situation calculus and modal logic to represent agents' mental states (knowledge, belief, intention and obligation) and transition systems . Taking knowledge as an example, we assume that there is an accessibility relation over states, where state s' is accessible from state s if an agent residing in state s thinks he might be in state s'. So something is known in state s if it holds in state s and every state s' accessible from s, and something is not known if it doesn't hold in at least one accessible state.

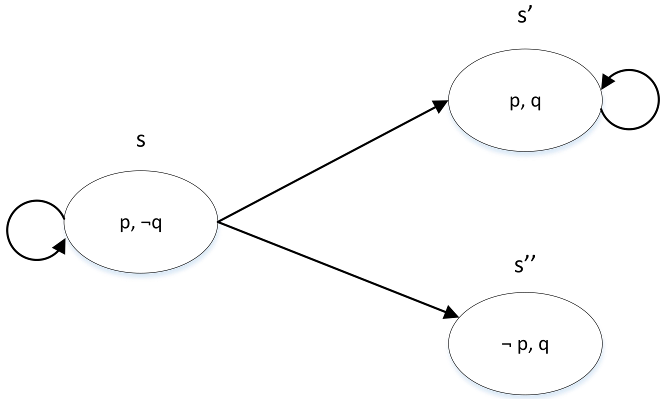


Figure 2.1. Example of a Kripke structure.

2.6 Neighborhood Semantics

Neighborhood semantics [Pacuit, 2007], also known as Scott-Montague semantics, is another formal semantics for modal logics compared to normal possible-world semantics. It is developed by Dana Scott and Richard Montague. The basic idea behind a neighborhood model is that: at each situation, list all the sets that are considered "necessary". That is, given a non-empty set of situations S, each situation s is assigned a set of subsets of S (these subsets are called neighborhoods). Formally, let Φ be a set of atomic propositions. A neighborhood model over Φ is defined as tuple $M = \{S, N, v\}$, where

- S denotes a set of situations;
- N is a neighborhood function $N : S \to 2^{2^S}$ which assigns a collection of sets of situations to each situation in S;
- $v : \Phi \to 2^S$ denotes a valuation function assigning a set of possible worlds to each atomic proposition. Therefore, *fluents* in the situation calculus can be interpreted as: given a proposition p, fluent $p(s)$ holds iff $s \in v(p)$.

Similar to Kripke structures, we can represent exactly an agent's mental state in a certain situation by neighborhood semantics. Fig. 2.2 is an example of a neighborhood model. Suppose that s is the actual situation and S consists of the following situations: $S = \{(p, q, r), (p, \neg q, r), (p, q, \neg r), (\neg p, \neg q, r)\}$. Neighborhood function $N(s)$ returns a set of subsets of S that are the neighborhoods in s. Set $\{(p, q, r), (p, \neg q, r), (p, q, \neg r)\}$ is called the truth set of p and it is a neighborhood in s. The same with $\neg q$ and r. The model is illustrated as below:

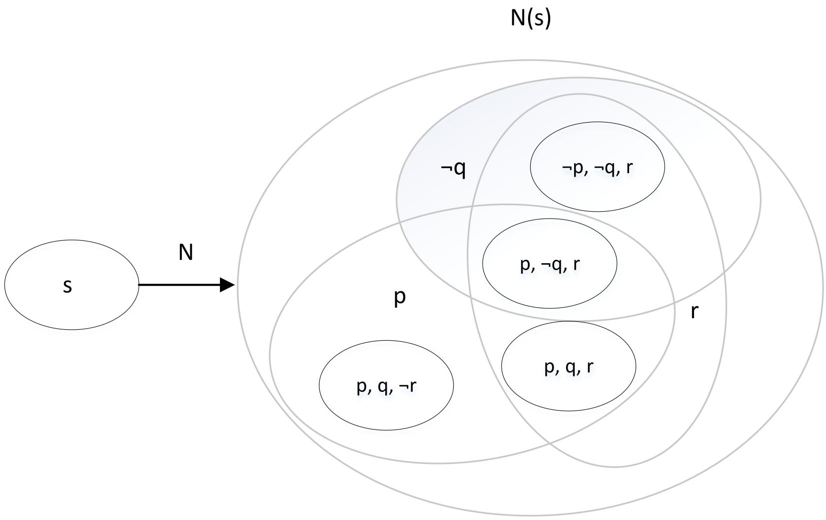


Figure 2.2. Example of a neighborhood model.

In Chapter 3, we adopt neighborhood semantics to define *Intention*. Suppose we have a set of situations labeled with propositions. Proposition p is intended to be in the actual situation s if and only if the truth set of p is an intentional neighborhood in s.

3

A Formal Definition of Opportunism

In this chapter, we introduce formal definitions of opportunism with the notion of value based on the situation calculus. We first propose a model of opportunism that only considers a single action between two agents, and then extend it to multiple actions and incorporate normative context in the model. A simple example of selling a broken cup is used to illustrate our models. Through our models, we can have a thorough understanding of opportunism, which provides a solid foundation for the investigation of predicting, monitoring and eliminating opportunism.

3.1 Introduction

In order to perform the investigation of opportunism, we first need to have a formal specification of opportunism with a widely applicable generalization. Through the specification, we can understand more clearly the elements in the definition, how they relate to each other, and derive interesting properties that are useful for our future research. We believe that such a research perspective can ease the debates about opportunism in social science (for instance, is the intention of opportunistic agents to harm other agents? What is the asymmetric knowledge that enable the performance of opportunistic behavior?). Moreover, future work on its emergence and constraint mechanism can be conducted based on our formal definition, rendering our study relevant for multi-agent system (MAS) research.

In this chapter, we take the initiative to propose formal models of opportunism. We integrate the notion of value in our models to represent agents' preference on different situations before and after the performance of opportunistic behavior. We then formalize opportunism using the situation calculus [McCarthy, 1963] and [Reiter, 2001] as our technical framework based on our extended definition. We first propose a model of opportunism that only considers a single action between two agents, indicating three basic concepts knowledge asymmetry, value opposition and intention in the model, and then extend it to multiple actions and incorporate a normative context in the model. A simple example of selling a broken cup is used to illustrate our models.

3.1.1 Chapter Outline

The rest of the chapter is organized as follows.

- In Section 3.2 we have an informal definition of opportunism extended from Williamson's, highlighting the key elements we need to model.
- In Section 3.3 our technical framework of the situation calculus is briefly introduced.
- In Section 3.4 we propose a preliminary model of opportunism, which serves as a basis for the following extensions.
- In Section 3.5 we extend our model to multiple actions
- In Section 3.6 we incorporate in our model a normative context.
- Section 3.7 illustrates our models by a simple example.
- Section 3.8 discusses this chapter.
- Section 3.9 summarizes the chapter.

3.2 Defining Opportunism with Value

In this section, we extend Williamson's definition of opportunism and suggest a more explicit one as a prelude and basis to proposing a formal model in the next section. The classical definition of opportunism is offered by Williamson as "self-interest seeking with guile" [Williamson, 1975], where guile means the use of clever but usually dishonest methods. While this definition has been used in a large amount of research, it only mentions two attributes, self-interest and guile, explicitly, leaving other attributes for researchers to interpret from different perspectives. For example, Das defined partner opportunism as "a behavior by a partner firm that is motivated to pursue its self-interest with deceit to achieve gains at the expense of the other alliance members" [Das and Rahman, 2010]. In a game-theoretical setting, Seabright defines opportunism as "the behavior of those who seek to benefit from the efforts of others without contributing anything themselves" [Seabright, 2010]. Even though those definitions are elaborated enough, they come from different theoretical settings.

The example about hiding important information from peers that we encountered in Chapter 1 is opportunistic behavior, since it is against others' benefits or not allowed by the system. However, if hiding is not forbidden by the system, the agent could not be said to have done anything wrong. Or if hiding is accepted by peers, it may not be against their interest. We can see that both the system and the agents' perspectives can influence the judgment of opportunism, and they are the representation of value systems at the collective level and individual level respectively, which might be different among systems and agents.

Value is something abstract that we think is important, and various types of values together with their orderings form a value system, which is the basis of our decision-making. By integrating the notion of value into our model, the result of performing opportunistic behavior is represented as promoting opportunistic agents' own value and demoting other agents' value. Furthermore, even though a value system is relatively stable within individuals, it may differ across different individuals and societies. For different societies, each has its own value system as part of the context and it serves as the basis for any judgment within the society. In this sense, some behaviors which are regarded as opportunistic in one society may not be considered as opportunistic in another society, if the two societies do not share the same value system. A similar idea, although more centering around opportunistic propensity, can be found in [Chen et al., 2002]. Given the value system of the society, opportunistic behavior promotes the self-interest which is in opposition with others' value.

In this thesis, based on the definition of Williamson, we compare opportunistic scenarios with non-opportunistic ones, and then redefine this behavior in a more explicit way with the notion of value:

Opportunism is a behavior that intentionally takes advantage of relevant knowledge asymmetry [1] *to achieve own gain, regardless of other agents' value.*

First of all, there has been reached consensus that opportunistic behavior is performed with self-interest intention [Das and Rahman, 2010]. We admit that self-interested pursuit is the natural property of human beings, but opportunism is more than that: agents with opportunistic behavior do not care about the negative effects on others. Secondly, relevant knowledge asymmetry provides the chance to agents to be opportunistic. Opportunistic agents may break the contracts or the relational norms using the relevant knowledge that others do not have. It is important for opportunistic agents to use lying, deceit or infidelity for hiding their self-interest motive. Therefore, agents with more relevant knowledge will have more potential for being opportunistic. Thirdly, principles are ignored by opportunistic agents. The reason to use "ignore" here is to distinguish opportunism from accidentally bringing harm to others. Opportunistic behavior is performed intentionally without any compensation to the victims. Other agents' value can be represented by the contract rules or the relational norms that are used for balancing various interests and already agreed to by a majority of the agents. Fourthly, even though we do not explicitly declare the result of performing opportunistic behavior in our extended definition, such a behavior must result in gains at the expense of others. Any self-interested behavior that does not end up in affecting other agents should not be considered as opportunism. Last but not least, Wathne and Heide [Wathne and Heide, 2013] clarify that situations where one agent receives compensation in some forms should not be considered as opportunism. Since we have to consider whether the agent who got harmed receives any compensation later on, we discuss the issue of compensation for opportunism for the case with multiple actions.

From the above elaboration, we can derive something interesting and important about opportunism: opportunistic agents ignore the interest of others, which means that it is already known by them that the behavior will cause harm to others; as opportunistic agents intend to gain personal advantage, can we say that it is also their intention to cause harm to others? We will investigate this problem through our formal models of opportunism.

[1] Many papers in social science use information asymmetry to represent the situation where one party in a transaction knows more compared to another. We argue that once the information is stored in our mind and can be used appropriately it becomes our knowledge. For this reason, we would rather revise the term as knowledge asymmetry in the whole thesis, which is also consistent with our technical framework.

3.3 Technical Framework: Situation Calculus

The situation calculus provides a formal language for representing and reasoning about dynamical worlds based on first-order logic. Its idea is that we can represent any reachable states in terms of actions that are required to reach them, and that the reachable states are called situations. There are three elements: actions *Act* that can be performed by agents, situations S that represent a history of action occurrences, and fluents F that describe the properties of the situation. Situation S_0 represents the initial situation that no action can result in. The properties of situations are specified through relational and functional fluents taking a situation term as their last argument, which means their truth value may vary from situation to situation. The relational fluents can be true or false, while the functional fluents can take a range of values. For instance, $ontable(x, s)$ is a relational fluent which is true in situation s where object x is on the table, and $temperature(s)$ is a functional fluent whose value in situation s is an integer representing the temperature of the environment.

To represent how situations change, one has to specify in which situation an action can be performed and how to reason about the changes in the world by performing an action. In the situation calculus, we use predicate symbol $\mathrm{Poss}(a, s)$ to denote the set of preconditions that action a is executable in situation s, and a distinguished binary function $\mathrm{do}(a, s)$ to denote the unique successor situation that results from the performance of action a in situation s. For example, in order to pick up object x one must have an empty hand and object x must be on the table in situation s:

$$\mathrm{Poss}(pick(x), s) \equiv handempty(s) \wedge ontable(x, s).$$

And $\mathrm{do}(pick(x), s)$ represents the situation that results from the performance of action $pickup(x)$ in situation s. One more example: in order to repair object x in situation s, the object x must be broken and there must be a glue available in situation s:

$$\mathrm{Poss}(repair(x), s) \equiv broken(x, s) \wedge hasglue(s).$$

Other special predicates and functions can be introduced as needed. For instance, propositions P can be used as assertions from classical proposition logic instead of fluents, that is, their truth values are not dependent on the situation but consistent throughout all the situations.

With the situation calculus, we can reason about how the world changes as the result of the available actions. The effects of actions are specified through *successor state axioms*. For example, the effect on fluent *broken* of object x is:

$$broken(x, \mathrm{do}(a, s)) \equiv broken(x, s) \vee (\exists r) fragile(x, s) \wedge a = drop(r, x),$$

which is saying that object x will be broken in the successor situation $\mathrm{do}(a, s)$ if and only if x is fragile in s and the action that takes us to the successor situation is someone r dropping x, or x is already broken in s.

This is a brief overview of the situation calculus, which is the technical preliminary of our formalization. However, this language can only provide information about the history of a situation and there is no way to represent the future of a situation. For example, propositions like "I shall sell the cup now" cannot be represented by situation calculus. Since this representation is of great importance to our formalization, we extend the situation to one-step further in the future. An extended situation is a pair (s, s') such that s is a situation and s' is the next situation of s connected with an action, and *occur* is a relation between actions and situations. Here is the semantics of *occur*:

$(s, s') \models \mathrm{occur}(a, s)$ iff $s' = \mathrm{do}(a, s)$. That is, $\mathrm{occur}(a, s)$ holds if action a occurs in situation s.

From now on, the situation calculus we are using as our technical framework will be extended with the semantics above.

After John McCarthy's introduction of this theory, people made extensions capable of representing knowledge, belief, intention and obligation in order to better reason about actions and their effects on the world [Shapiro et al., 2000] [Scherl and Levesque, 2003] [Demolombe and Parra, 2009]. We will introduce and adopt those extensions in the following sections as appropriate. Since in the situation calculus the last argument is always a situation, we will follow this convention in this chapter for any definition of fluents and predicates.

3.4 Formalizing Opportunism

For better understanding, we first propose a preliminary model of opportunism that only considers a single action between two agents, without any legal or moral evaluation. It serves as a basis for the extensions of multiple actions and a normative context in the following sections. We will use normal possible-world semantics to define knowledge and neighborhood semantics to define intention. Ones who are unfamiliar with the two types of semantics can refer to [Chellas, 1980] and [Montague, 1970] [Scott, 1970] for their introductions.

3.4.1 Knowledge Asymmetry

We adopt the approach of Scherl to formalizing knowledge, which is to add an agents' possible-world model of knowledge to situation calculus [Scherl and Levesque, 2003]. To treat knowledge as a fluent, we have a binary relation $K(s', s)$, reading as situation s' is epistemically accessible from situation s. It is reflexive ($K(s, s)$ holds for all $s \in S$), transitive ($K(s, s') \wedge K(s', s'')$ implies $K(s, s'')$ for all $s, s', s'' \in S$) and symmetric ($K(s, s')$ implies $K(s', s)$ for all $s, s' \in S$).

Definition 3.4.1 (Knowledge).

$$\mathrm{Know}(i, \varphi, s) \overset{def}{=} (\forall s')K_i(s', s) \rightarrow \varphi[s']$$

This definition shows that agent i has knowledge about φ if and only if φ holds in all the epistemic possible situations of the agent. Then we can have the definition of knowledge asymmetry.

Definition 3.4.2 (Knowledge Asymmetry).

$$\begin{aligned}\mathrm{Knowasym}(i, j, \varphi, s) &\overset{def}{=} \\ &\mathrm{Know}(i, \varphi, s) \wedge \neg\,\mathrm{Know}(j, \varphi, s) \wedge \mathrm{Know}(i, \neg\,\mathrm{Know}(j, \varphi, s), s)\end{aligned}$$

Knowasym is a fluent in situation s where agent i has knowledge about φ while agent j does not have it and this is also known by agent i. The asymmetric situation can be the other way around with i and j. But for simplicity of our model, we limit this definition to one case.

3.4.2 Value Opposition

From the definition of opportunism, we know that agents have different evaluations on the same state transition. For agent i who performs opportunistic behavior, his value gets promoted, while the value of agent j gets demoted. We argue that this is because agents always have the evaluation from their perspective, which is part of their value system. This property of state transition is named value opposition in this study. In order to extend our technical framework with value theory, we define a symbol V to represent agents' value system and a binary relation $<$ over situations to represent agents' preference, where $s <_V s'$ denotes "s' is preferred to s based on value system V".

In the situation calculus, situations can be described in terms of fluents F, which are structured with objects and their properties. For having preferences on situations, we argue that agents evaluate the truth value of specific propositions, which are called perspectives in this study, based on their value systems. For instance, the buyer tries to see if the cup has good quality or not in order to have a preference on the situations before and after the transaction. In order to specify agents' preference on situations, we first define a function Evalref that represents agents' perspective for evaluation:

Definition 3.4.3 (Evaluation Reference).

$$\mathit{Evalref}\colon V \times S \times S \to F.$$

It returns a proposition that an agent refers to for specifying his preference on two situations based on his value system. It is worth noting that in real life agents' specification of preferences on situations is based on a set of fluents 2^F rather than a single fluent. For instance, both whether the cup has good quality and appearance are important to the buyer. For simplicity, here we restrict the return value to only one proposition without loss of generality.

We then specify agents' preferences on situations, where V is restricted to perspective-based value:

$$s <_{V_i} s' \equiv \neg p(s) \land p(s'),\ \mathit{where}\ p = \mathrm{Evalref}(V_i, s, s').$$

$$s >_{V_i} s' \equiv p(s) \land \neg p(s'),\ \mathit{where}\ p = \mathrm{Evalref}(V_i, s, s').$$

It means that agent i's value gets promoted/demoted from s to s' when the truth value of the proposition p that he refers to based on his value system V_i changes. As for the example about selling the broken cup, the seller's value gets promoted when he has earned money from the transaction, whereas the buyer's value gets demoted when the cup he bought is broken. Because of having different value systems, they refer to different propositions and thereby evaluate different propositions for specifying their preferences. Similar to knowledge asymmetry, we only limit the specification to one case in terms of the truth value of p.

Definition 3.4.4 (Value Opposition).

$$\text{Valueopp}(i, j, s, s') \stackrel{def}{=} s <_{V_i} s' \wedge s >_{V_j} s'$$

We define value opposition as a property of a state transition where a state transition from s to s' can promote the value of agent i but demote the value of agent j. In other words, agent i has positive effects from the state transition, while agent j has negative effects. Again, we only limit the definition to one case for simplicity.

3.4.3 Intention

Opportunistic behavior is performed by intent rather than by accident. In order to suggest this aspect in our formal model, we adopt the logic of *intention to do something for being something* in our framework. *Do something* refers to an action and *being something* refers to a state of affairs represented by propositional formula. The notion of *Intend* is defined through neighborhood semantics instead of Kripke semantics. This is because agents need not intend all the expected side-effects of their intentions as Bratman argued [Bratman, 1987]. For example, an agent has a toothache and is going to see the dentist with intention to get his tooth fixed. Although the agent believes that it will cause him much pain, we surely cannot say that he *intends* to get the pain. The formal definition of *Intend to be φ by doing a* is given as followed:

Definition 3.4.5 (Intention).

$$\text{Intend}(i, a, \varphi, s) \stackrel{def}{=} ||A|| \in N_I(i, s),$$

where

$$||A|| = \{s' \in S \mid \text{occur}(a, s') \wedge \varphi[s', \text{do}(a, s')]\}$$

$N_I(i, s)$ is an intentional neighborhood function of agent i that returns a set of subsets of S, meaning that what is the case in the neighborhood is intended to have in situation s. $\text{occur}(a, s')$ is true when action a is performed in situation s', and φ is true in the state transition. An intention of agent i $\text{Intend}(i, a, \varphi, s)$ holds if and only if the truth set of $\text{occur}(a, s')$ and

$\varphi[s', \text{do}(a, s')]$ is an intentional neighborhood in s. Notice that $\varphi[s', \text{do}(a, s')]$ means φ is true in the transition from s' to $\text{do}(a, s')$. Based on this definition of intention, we have two instances for value promotion $pro(j) = s' <_{V_j} \text{do}(a, s')$ and value demotion $de(j) = s' >_{V_j} \text{do}(a, s')$ by action a, which will be later used for providing the final definition and proving its properties

$$\text{Intend}(i, a, pro(j), s) \stackrel{def}{=} ||A|| \in N_I(i, s),$$

where

$$||A|| = \{s' \in S \mid \text{occur}(a, s') \wedge s' <_{V_j} \text{do}(a, s')\}$$

and

$$\text{Intend}(i, a, de(j), s) \stackrel{def}{=} ||A|| \in N_I(i, s),$$

where

$$||A|| = \{s' \in S \mid \text{occur}(a, s') \wedge s' >_{V_j} \text{do}(a, s')\}$$

$\text{Intend}(i, a, pro(j), s)$ denotes that agent i intends to promote the value of agent j by action a in situation s. Similar for $\text{Intend}(i, a, de(j), s)$. When $i = j$, agent i intends to promote/demote his own value by action a.

3.4.4 Opportunistic Behavior

The above definitions are basic ingredients that we need for having the formal model of opportunism: knowledge asymmetry as the precondition, value opposition as the effect, and intention as the mental state. Besides, based on the informal definition we gave in Section 3.2, there are two more aspects that should be suggested in the definition. Firstly, the knowledge that the performer has while others do not have should be relevant to the state transition. Secondly, the performer is aware of value opposition for the state transition beforehand but still ignores it. Opportunism is defined as follows:

Definition 3.4.6 (Opportunism). *Let D be a Situation Calculus BAT* [2]*, K and I be the axioms for knowledge and intention representation in the Situation Calculus respectively, V be the value system of agents, Evalref be the reference function representing the object for an agent's evaluation on situations, and*

[2] See Chapter 2 for an introduction of Reiter's Basic Action Theories.

$<_V$ *be a preference ordering on situations. Then* $(D \cup K \cup I, V, Evalref, <_V)$ *is a situation calculus BAT extended with knowledge, intention, value and preference. Within this system, we have*

$$\mathrm{Opportunism}(i, j, a, s) \stackrel{def}{=} \mathrm{Poss}(i, j, a, s) \wedge \mathrm{Intend}(i, a, pro(i), s) \wedge \varphi$$

where

$$\mathrm{Poss}(i, j, a, s) \equiv \mathrm{Knowasym}(i, j, \varphi, s)$$

$$\varphi = \mathrm{Valueopp}(i, j, s, \mathrm{do}(a, s)).$$

This formula defines a predicate *Opportunism* where action a is opportunistic behavior by agent i to agent j in the situation s. In this concise formula, the precondition of action a is knowledge asymmetry about the state transition from s to $\mathrm{do}(a, s)$, and action a is performed by intent and results in value opposition.

One observation from the model is about the subjectivity of opportunism. We can see through the functional fluent Evalref that agents always evaluate the situations and consequently the state transition from their own perspectives, which are part of their value systems. If the value systems upon which they have evaluation change to other ones, the property of value opposition may become false. Opportunism is presented as a "problem" in most social science work. However, the above formal model of opportunism implies that it depends on from which perspective, or more generally, value system, we evaluate the state transition. It is positive from the perspective of agent i, while it is negative from the perspective of agent j. In multi-agent systems, people usually take the established norms into consideration when they decide whether it should be prevented, and the result may be different from society to society and from system to system.

After having the formal model of opportunism, we show how the propositions we informally suggest in text at the beginning is captured by our formalization.

Proposition 3.4.1. *Given an opportunistic behavior a performed by agent i to agent j, each agent evaluates the behavior from a different perspective, which is formalized as:*

$$\vDash \mathrm{Opportunism}(i, j, a, s) \rightarrow \mathrm{Evalref}(V_i, s, \mathrm{do}(a, s)) \neq \mathrm{Evalref}(V_j, s, \mathrm{do}(a, s))$$

Proof. If $\mathrm{Opportunism}(i, j, a, s)$ *holds, the property* $\mathrm{Valueopp}(i, j, s, \mathrm{do}(a, s))$ *also holds. Following the definition of value opposition, we have*

$$s <_{V_i} \mathrm{do}(a, s) \wedge s >_{V_j} \mathrm{do}(a, s).$$

The specification of $s <_{V_i} \mathrm{do}(a, s)$ *is*

$$\neg p(s) \wedge p(\mathrm{do}(a, s)), \text{ where } p = \mathrm{Evalref}(V_i, s, \mathrm{do}(a, s)) \tag{3.1}$$

The specification of $s >_{V_j} \mathrm{do}(a, s)$ *is*

$$q(s) \wedge \neg q(\mathrm{do}(a, s)), \text{ where } q = \mathrm{Evalref}(V_j, s, \mathrm{do}(a, s)) \tag{3.2}$$

Sentence (1) and (2) hold together. Since any formula has only one truth value given a situation, we have $p \neq q$*, that is*

$$\mathrm{Evalref}(V_i, s, \mathrm{do}(a, s)) \neq \mathrm{Evalref}(V_j, s, \mathrm{do}(a, s)).$$

Proposition 3.4.2. *Given an opportunistic behavior a performed by agent i to agent j, agent i knows the performance of this behavior demotes agent j's value, but needs not intend to get this result for agent j, which is characterized by:*

$$\vDash \mathrm{Opportunism}(i, j, a, s) \to \mathit{Know}(i, s >_{V_j} \mathrm{do}(a, s), s)$$

$$\nvDash \mathrm{Opportunism}(i, j, a, s) \to \mathrm{Intend}(i, a, de(j), s)$$

Proof. The first formula is already in the definition of opportunism, so we are going to prove the second one. In our model, opportunistic behavior is performed with intention and $\mathrm{Opportunism}(i, j, a, s) \to de(j)$*, then definitely* $de(j)$ *holds in agent i's intentional neighborhood where* $\mathrm{Opportunism}(i, j, a, s)$ *holds (denoted as set* O*). In neighborhood semantics, if* $\mathrm{Intend}(i, a, de(j), s)$ *holds, then the truth set of* $de(j)$ *(denoted as set* D*) must be an intentional neighborhood of agent i. However, we only know that* O *is an intentional neighborhood of agent i and* D *might be bigger than* O *(*$O \subseteq D$*) so that* D *might not necessarily be an intentional neighborhood. Therefore, we can theoretically conclude that agent i might not intend to demote agent j's value.*

We can also give intuition to this proof. Free riding is one of the classic models about opportunism, and it occurs when someone benefits from resources, goods, or services but does not contribute to them, which results in either an under-provision of those goods or services, or in an overuse or degradation of a common property resource [Baumol, 2004]. Suppose agent i is a free rider, it is rather weird to say that agent i intends to reduce others' share of public goods.

The proposition shows that it is not the intention of opportunistic agents to harm others even though opportunism is deliberate with self-interest motive. The ignored principles are a specific kind of knowledge about the interest of others that cannot be considered as an intention to be opportunistic.

3.5 Opportunistic Behavior for Multiple Actions

In the previous section, we only consider one single action as opportunistic behavior. But in more realistic scenario one can imagine that opportunistic behavior consists of multiple actions. For instance, unlike the simple selling example at the beginning of this thesis, commerce transactions between businesses usually consist of a sequence of actions, each of which ends up in a situation. In this case, the whole sequence of actions could be regarded as opportunistic behavior instead of any single action individually. Of course, a sequence of actions can be seen as one action if we only look at the precondition of the first action and the effect of the last action, but we might also be interested in what properties we can derive from opportunistic behavior when considering multiple actions instead of a single action. For instance, is it necessary for the individual actions to be opportunistic behavior in order for the whole sequence of actions to be opportunistic behavior? How can we interpret the property of non-compensation for opportunism that we encountered in Section 3.2? We will study the above issues considering multiple actions for opportunism.

In situation calculus, a binary function $\mathrm{do}(a, s)$ is used to denote the situation resulting from performing action a in situation s, so for a finite sequence of actions $a_1, \ldots, a_n$, the situation resulting from performing the sequence of actions in situation s is denoted as $\mathrm{do}(a_n, \mathrm{do}(a_{n-1}, \ldots \mathrm{do}(a_1, s)))$. Each action within the sequence brings about a new situation that satisfies certain properties. Formally, based on Definition 3.4.6, opportunism for multiple actions is defined as below:

Definition 3.5.1 (Opportunism for Multiple Actions). *Let D be a Situation Calculus BAT, K and I be the axioms for knowledge and intention representation in the Situation Calculus respectively, V be the value system of* *agents, Evalref be the reference function representing the object for an agent's evaluation on situations, and* $<_V$ *be a preference ordering on situations. Then* $(D \cup K \cup I, V, Evalref, <_V)$ *is a situation calculus* BAT *extended with knowledge, intention, value and preference. Within this system, we have*

$$\text{Opportunism}(i, j, a_1, \ldots, a_n, s_1) \stackrel{def}{=} \bigwedge_{1 \le k \le n} \text{Poss}(i, j, a_k, s_k) \wedge \text{Intend}(i, a_k, pro(i), s_k) \wedge \varphi$$

where

$$\text{Poss}(i, j, a_k, s_k) \equiv \text{Knowasym}(i, j, \varphi, s_k),$$

$$\varphi = \text{Valueopp}(i, j, s_1, \text{do}(a_n, \text{do}(a_{n-1}, \ldots \text{do}(a_1, s_1)))),$$

$$s_k = \text{do}(a_{k-1}, \ldots \text{do}(a_1, s_1))(1 < k \le n).$$

Because each action in the sequence must be possible to be performed and it is the property of intention to be persistent along the whole sequence of actions [Bratman, 1987], knowledge asymmetry and intention is true in s_k for $1 \le k \le n$. Value opposition is the property of the state transition by the sequence of actions. A finite sequence of actions $a_1, \ldots, a_n$, which is performed by agent i to agent j in situation s_1, is opportunistic behavior if and only if each action is possible to be performed with the intention to promote agent i's value and the whole sequence results in value opposition for agent i and j.

Regarding the effects of opportunistic behavior, agent j's value gets demoted by the behavior, which can be permanent or repairable. In the former case, it is impossible to compensate the negative effect on agent j (e.g. somebody dies from it); while in the latter case it is possible in some forms (e.g. a broken cup can be returned). Since opportunistic behavior is performed by intent, we argue that agent i will not actively compensate agent j's loss, no matter whether it is permanent or repairable. For this reason, we introduce the following definition *non-compensation* for agent j, which is an essential property of opportunism:

Definition 3.5.2 (Non-compensation). *Given a sequence of actions* $Seq = a_1, \ldots, a_n$ *as opportunistic behavior* $\text{Opportunism}(i, j, Seq, s_1)$ *and* $q = \text{Evalref}(V_j, s, \text{do}(Seq, s))$*, we say that* Seq *is non-compensated for agent* j

iff $\exists k : a_k \in Seq$ *such that for the subsequence of actions* $Seq_B = a_1, \ldots, a_k$

$$q(s_1) \wedge \neg q(\mathrm{do}(Seq_B, s_1))$$

and for the subsequence of actions $Seq_R = a_{k+1}, \ldots, a_n$*,* $\forall m : a_m \in Seq_R$

$$q(\mathrm{do}(a_m, s_m)) \equiv q(s_m).$$

By this definition, we separate the sequence of actions into two parts: Seq_B that brings about $\neg q$, and Seq_R that retains $\neg q$. Note that Seq_R can be empty, which implies that the whole sequence brings about $\neg q$ and the situation transition is permanent and irreversible. Moreover, as the whole sequence of actions is performed by agent i, the compensation for agent j's loss comes from agent i rather than agent j itself or someone else.

Definition 3.5.1 together with its property of non-compensation captures some interesting properties, which cannot be derived from Definition 3.4.6. First of all,

Proposition 3.5.1. *For a sequence of actions* $Seq = a_1, \ldots, a_n$ *being opportunistic behavior* $\mathrm{Opportunism}(i, j, Seq, s)$*, we have*

$$\models \mathrm{Opportunism}(i, j, Seq, s) \rightarrow (\exists a \notin Seq_R)\neg(s >_{V_j} \mathrm{do}(Seq_B, \mathrm{do}(a, s)))$$

It implies that the negative effect of opportunistic behavior on agent j could have been compensated but is not done by agent i. Typically when Seq_R is empty, it is meaningless to talk about action a, because the negative effect is permanent.

Proposition 3.5.2. *Given a finite sequence of actions* $a_1, \ldots, a_n$ *as opportunistic behavior, we can prove that*

$$\begin{aligned}&\models \mathrm{Opportunism}(i, j, a_1, \ldots, a_n, s_1) \rightarrow \\ &\qquad \mathrm{Knowasym}(i, j, \varphi, s_k) \wedge \mathrm{Knowasym}(i, j, \varphi, \mathrm{do}(a_k, s_k))(1 < k < n)\end{aligned}$$

Proof. Each action in the sequence is possible to be performed and also

$$\mathrm{Poss}(i, j, a_k, s_k) \equiv \mathrm{Knowasym}(i, j, \varphi, s_k)(1 \leq k \leq n)$$

$$s_k = \mathrm{do}(a_{k-1}, \ldots, \mathrm{do}(a_1, s_1))(1 < k \leq n)$$

Combining these two formulas, we can easily get

$$\text{Knowasym}(i, j, \varphi, s_k) \wedge \text{Knowasym}(i, j, \varphi, \text{do}(a_k, s_k))(1 \leq k < n).$$

This proposition shows that, when opportunistic behavior consists of a sequence of actions, the property of knowledge asymmetry is preserved throughout the whole sequence.

Proposition 3.5.3. *Given a finite sequence of actions $a_1, \ldots, a_n$ as opportunistic behavior, we can prove action a_i needs not be opportunistic, which is characterized by*

$$\nvDash \text{Opportunism}(i, j, a_1, \ldots, a_n, s_1)(n > 1) \rightarrow \text{Opportunism}(i, j, a_k, s_k)(1 \leq k \leq n)$$

Proof. In order to prove this proposition, we are going to find a counter-example of opportunistic behavior which satisfies condition $n > 1$ but each action does not satisfy all the properties of opportunism.

Freeriding is still a suitable model to prove this property. Since freeriding is one form of opportunistic behavior, $\text{Opportunism}(i, others, freeride, s_1)$ *is true in our model. Now we are going to split it into a sequence of actions $a_1, \ldots, a_n$ and suppose a free rider exist in a society with a large population and benefits from the public goods without paying. Since the amount that the free rider is supposed to pay is shared by a large population, other agents do not notice (or even not care about) the small change of the current situation thus not getting their value demoted for little amount of freeriding. That is, for action a_k,*

$$\text{Evalref}(V_{others}, s_k, \text{do}(a_k, s_k)) = \top$$

so that $s <_{V_{others}} \text{do}(a, s)$ does not hold any more. Therefore, it is not true that

$$\text{Opportunism}(i, j, a_k, s_k)(1 \leq k \leq n).$$

However, once the amount that the free rider is supposed to pay accumulates to be large enough for getting other agents' value demoted (the whole sequence of actions is considered), it will be regarded as opportunistic behavior. By theoretical comparison, this example is quite similar to Sorites paradox, where grains are individually removed from a heap of sands and the heap stops being a heap when the process is repeated for enough times [Hyde, 2014]. So it is also interesting to think about when the behavior starts to be regarded as opportunistic. In next section, we start to assume a normative context for the study of opportunism. We consider a set of agents as a system with norms representing their collective value system. Opportunism is defined with respect to an agent and a system with norms.

3.6 Opportunistic Behavior with a Normative Context

In the previous sections, we made an assumption for the sake of simplicity that there is no legal or moral evaluation being made or implied to opportunistic behavior such that we cannot necessarily evaluate it as good or bad. However, agents in MAS are residing in a normative context which provides obligations, permissions and other types of norms for guiding agents' behaviors. The setting of those norms reflect the value system of a MAS. To have a formal model of opportunism with a normative context, we can of course replace the agent j in our previous models with a system (in this way, we see the whole system as an agent) and get similar properties as in last two sections, but now we are more interested in putting opportunism in a deontic-based normative context to see how it relates to norms. Thus, in this section, we are going to place opportunistic behavior into a normative context and propose a formal model of opportunism from this perspective.

For defining opportunistic behavior with a normative context, we adopt the definition of knowledge asymmetry and intention in previous sections but redefine value opposition. Firstly, we have three normative statuses, which are similar to deontic logic.

- it is obligatory that (OB)
- it is permissible that (PE)
- it is forbidden that (FO)

Secondly, we define the above deontic notions for specifying the normative propositions Π.

Definition 3.6.1 (Obligatory, Permissible and Forbidden).

$$\mathrm{OB}(i, a, s) \stackrel{def}{=} (\forall s')R_i(s', s) \rightarrow \mathrm{occur}(a, s')$$

$$\mathrm{PE}(i, a, s) \stackrel{def}{=} (\exists s')R_i(s', s) \wedge \mathrm{occur}(a, s')$$

$$\mathrm{FO}(i, a, s) \stackrel{def}{=} (\forall s')R_i(s', s) \rightarrow \neg\,\mathrm{occur}(a, s')$$

In the definition, $R_i(s', s)$ denotes the deontic accessibility relation of agent i, meaning that what is the case in situation s' is ideal for situation s, and $\mathrm{occur}(a, s')$ is true when action a is performed in situation s'. R-relation is serial, which means for all situations s there is at least one possible situation s' such that $R_i(s', s)$ holds. This property of R-relation ensures the validity $\vDash \mathrm{OB}(i, a, s) \rightarrow \mathrm{PE}(i, a, s)$ to be hold, which is also consistent with our intuition. Each modality can be taken as a basic to define the other two modalities.

We then specify the preference of the system on situations, where V is restricted to deontic-based social value.

$$s <_{V_A} s' \equiv (\exists a, i)s' = \mathrm{do}(a, s) \wedge \mathrm{OB}(i, a, s)$$

$$s >_{V_A} s' \equiv (\exists a, i)s' = \mathrm{do}(a, s) \wedge \mathrm{FO}(i, a, s)$$

Here symbol A represents the whole system, which is a set of agents. The first equivalence means that the social value gets promoted if there exists an action whose performance complies with the norm, while the second one means that the social value gets demoted if there exists an action whose performing violates the norm.

Together with the specification of agents' preferences on situations, we have the definition of value opposition between an agent and the whole system.

Definition 3.6.2 (Value Opposition with a Normative Context).

$$\mathrm{Valueopp}(i, A, s, s') \overset{def}{=} s <_{V_i} s' \wedge s >_{V_A} s'$$

For the state transition from s to s', the value of agent i gets promoted whereas the social value gets demoted. Again, we only limit the definition to one case excluding the other way around for simplicity.

Therefore, similar to Definition 3.4.6, we have the definition of opportunistic behavior with a normative context.

Definition 3.6.3 (Opportunism with a Normative Context). *Let D be a Situation Calculus BAT, K and I be the axioms for knowledge and intention representation in the Situation Calculus respectively, V be the value system of agents, Evalref be the reference function representing the object for an agent's evaluation on situations, Π be a finite set of normative propositions, and $<_V$ be a preference ordering on situations. Then $(D \cup K \cup I, V, Evalref, \Pi, <_V)$ is a situation calculus BAT extended with knowledge, intention, value, norms* *and preference. Within this system, we have*

$$\mathrm{Opportunism}(i, A, a, s) \overset{def}{=} \mathrm{Poss}(i, A, a, s) \wedge \mathrm{Intend}(i, a, pro(i), s) \wedge \varphi$$

where

$$\mathrm{Poss}(i, A, a, s) \equiv \mathrm{Knowasym}(i, A, \varphi, s)$$

$$\varphi = \mathrm{Valueopp}(i, A, s, \mathrm{do}(a, s)).$$

Action a performed by agent i is regarded as opportunistic behavior if and only if it is performed with the asymmetric knowledge φ about the state transition from s to $\mathrm{do}(a, s)$ and the intention of self-interest, and results in value opposition against the system A where agent i is.

The definition of opportunistic behavior with a normative context shows that, given the value system of a system, opportunistic behavior is considered to be bad since its performance results in demoting the social value. Further, it implies the moral dilemma concerning the conflict between desire and obligation. More precisely, an agent has the desire "to do what he wants", while the normative context where the agent is residing gives the obligation "to do what one ought to do". Opportunistic agents follow their desire but ignore the obligation. Hence, it is prohibited by laws or norms from the perspective of the whole system.

Since we assume a normative context in this section, it is worth investigating the relation between deontic notions and mental states. Our model governs Proposition 3.6.1 regarding opportunistic agents having knowledge about the relevant norms, and Proposition 3.6.2 and Proposition 3.6.3 about the intention of opportunistic behavior not being derived from the obligation.

Proposition 3.6.1. *Let action a be opportunistic behavior performed by agent i within system A in situation s, for the normative proposition associated with action a $\mathrm{FO}(i, a, s) \in \Pi$ we have*

$$\vDash \mathrm{Opportunism}(i, A, a, s) \rightarrow \mathrm{Know}(i, \mathrm{FO}(i, a, s), s)$$

Proof. Since $\mathrm{Opportunism}(i, A, a, s)$ *holds, by Definition 3.6.3, agent i must have knowledge about the effect of performing action a, that is,* $\mathrm{Know}(i, \varphi, s)$ *holds, where* $\varphi = \mathrm{Valueopp}(i, A, s, \mathrm{do}(a, s))$*. By Definition 3.6.2,* $\varphi = (s <_{V_i} \mathrm{do}(a, s) \wedge s >_{V_A} \mathrm{do}(a, s))$*. Therefore,* $\mathrm{Know}(i, s >_{V_A} \mathrm{do}(a, s), s)$ *holds. Because V is restricted to deontic-based social value in our model,*

$(s >_{V_A} \mathrm{do}(a, s)) \equiv \mathrm{FO}(i, a, s)$ *holds, thereby* $\mathrm{Know}(i, \mathrm{FO}(i, a, s), s)$ *holds as well.*

Agents have the knowledge about the relevant norms in the system and decide whether and which to comply with based on their own analysis. Typically, opportunistic agents behave in their interest, regardless of the norms they are supposed to follow.

Moreover, as Broersen and his colleagues indicate in their BOID architecture [Broersen et al., 2005], intention might be derived from obligation (e.g., I ought to go to work this morning, so I intend to go to work this morning), or might just come from agents' own desire (e.g., I feel thirsty, so I intend to get some water). In a given situation, agents intend to perform opportunistic behavior, which is motivated by self-interest. In order to prove this property rigorously, we first prove what opportunistic agents care about is not the norm they have to comply with.

Proposition 3.6.2. *Let action a be opportunistic behavior performed by agent i within system A in situation s, and V_i be agent i's value system, for the norm associated with action a* $\mathrm{FO}(i, a, s) \in \Pi$, *we have*

$$\vDash \mathrm{Opportunism}(i, A, a, s) \rightarrow (\mathrm{Evalref}(V_i, s, \mathrm{do}(a, s)) \neq \mathrm{FO}(i, a, s))$$

Proof. By contradiction, we assume that $\mathrm{Evalref}(V_i, s, \mathrm{do}(a, s)) = \mathrm{FO}(i, a, s)$, *which means that what agent i cares about is the norm he has to comply with. Because of that, he is not performing action a in order to promote his value, and if that is the case, the system value will not get demoted. That is, $s <_{V_i} s' \wedge s >_{V_A} s'$ does not hold. Consequently,* $\mathrm{Opportunism}(i, A, a, s)$ *does not hold, either. Therefore,* $\mathrm{Evalref}(V_i, s, \mathrm{do}(a, s)) = \mathrm{FO}(i, a, s)$ *is false for opportunistic behavior.*

Using Proposition 3.6.2, we are going to prove it is not the case for opportunistic behavior that the intention is derived from the obligation.

Proposition 3.6.3. *Let action a be opportunistic behavior performed by agent i within system A in situation s, for the norm associated with action a* $\mathrm{OB}(i, a, s) \in \Pi$, *we have*

$$\vDash \mathrm{Opportunism}(i, A, a, s) \rightarrow \neg(\mathrm{Intend}(i, a, pro(i), s) \rightarrow \mathrm{OB}(i, a, s))$$

Proof. Because formula $\neg(\mathrm{Intend}(i, a, pro(i), s) \rightarrow \mathrm{OB}(i, a, s))$ *is equivalent to* $\mathrm{Intend}(i, a, pro(i), s) \wedge \neg\mathrm{OB}(i, a, s)$, *we need to prove that it is always the* *case that* $\mathrm{Opportunism}(i, A, a, s) \rightarrow \mathrm{Intend}(i, a, pro(i), s) \wedge \neg\mathrm{OB}(i, a, s)$. *From Definition 3.6.3 we have* $\mathrm{Opportunism}(i, A, a, s) \rightarrow \mathrm{Intend}(i, a, pro(i), s) \wedge \mathrm{FO}(i, a, s)$. *Because* $\mathrm{FO}(i, a, s) \rightarrow \neg\mathrm{OB}(i, a, s)$, $\mathrm{Opportunism}(i, A, a, s) \rightarrow \mathrm{Intend}(i, a, pro(i), s) \wedge \neg\mathrm{OB}(i, a, s)$ *holds.*

3.7 Example: Selling a Broken Cup

Recall the example that we used to introduce opportunism at the beginning of the thesis. The scenario is simple but sufficient to illustrate our formal specification of opportunism. We label the seller and the buyer as s and b, who can be in one of the situations: S_0 (the initial situation, before the transaction) and $\mathrm{do}(a, S_0)$ (after the transaction). The seller can either sell the cup ($a = sell(x)$) or keep it. If the seller performs the action $sell(x)$ in S_0, then situation will go to $\mathrm{do}(sell(x), S_0)$.

In situation S_0, the asymmetric knowledge owned by the seller but not the buyer is not only about the broken cup, but also the state transition: once the transaction finishes, the situation will go from S_0 to $\mathrm{do}(sell(x), S_0)$, which gets the value of the seller promoted whereas the value of the buyer demoted. That is, the precondition $\mathrm{Knowasym}(s, b, \varphi, S_0)$ holds. Now consider the value for both parties. In this example we assume that both parties go for economic value. However, they have different and contradictory perspectives about the economic value. What the seller cares about is how much money he earns from the transaction. When the broken cup has already been sold, his value gets promoted ($S_0 <_{V_s} \mathrm{do}(sell(x), S_0)$ holds). Conversely, what the buyer cares about is whether the cup has good quality or not. So once the buyer knows the cup is broken, his value gets demoted ($S_0 >_{V_b} \mathrm{do}(sell(x), S_0)$ holds). The above two sentences ensure sentence $\mathrm{Valueopp}(s, b, S_0, \mathrm{do}(sell(x), S_0))$ holds. Further, since it is the seller's intention to sell the broken cup to the buyer for promoting his value, sentence $\mathrm{Intend}(s, sell(x), pro(s), S_0)$ also holds. With the above formalization, the formula for this example $\mathrm{Opportunism}(s, b, sell(x), S_0)$ holds.

We now discuss two interesting situations extended from the simple example. Firstly, if the buyer buys the cup only for decoration without using it, he will never know the cup is broken or even cares about it. That is, the buyer's perspective is revised to $\mathrm{Evalref}(V_b, S_0, \mathrm{do}(sell(x), S_0)) = appearance$ and then sentence $S_0 >_{V_b} \mathrm{do}(sell(x), S_0)$ does not hold any more. In this case, because the two perspectives are not contradictory, the seller's behavior is not opportunistic from the perspective of the buyer, if the norms are not taken into account. It is already proved in Proposition 3.4.1 that agents must have different perspectives about the same state transition if there is opportunistic behavior between those two agents. But the above discussion shows that having different perspectives does not necessarily lead to opportunistic behavior: they must be contradictory. The subjectivity of opportunism is reflected by the different judgments on the same action.

Secondly, if there is nothing the seller can do except selling the broken cup when being in state S_0, it will still be regarded as opportunistic behavior based on Definition 3.4.6, which might be allowed by the system. It is because there is no moral or legal evaluation in this definition thus no matter whether the behavior is good or bad. However, it will be different if we analyze it with Definition 3.6.3. Suppose it is allowed by the system (i.e., $\mathrm{PE}(i, a, S_0)$). Then $S_0 >_{V_A} \mathrm{do}(sell(x), S_0)$ does not hold, and then selling a broken cup is not opportunistic behavior from the perspective of the system. In our example, the options available to the buyer in state S_0 are $\{sell, keep\}$, which means it is not the only choice for the seller to sell the broken cup. Moreover, sometimes it is our intention to put ourselves in a situation where we only have one option to choose. In this case, the whole sequence of actions that illustrates how the situation arrives in one option available might be opportunistic.

Further, with the help of our model, we can gain practical insights into eliminating opportunism. In our case, one important reason why the seller's behavior is seen as opportunistic is that the seller and the buyer evaluate the state transition from two opposed perspectives based on their value systems. In other words, even though they both go for economic value, they evaluate the action from different perspectives. When applying this approach in collaborative relationships, it is much easier to understand how a relationship can end up in defection. Therefore, one way of eliminating opportunism is to avoid having contrasted value systems in the relationship. As for the precondition of opportunism, even though it is difficult to prevent knowledge asymmetry in business transactions, we still need to think about how much information we can provide to our collaborating agents, especially during negotiation, and how they are going to use the information.

3.8 Discussion

In this chapter we attempted to propose a simple but elegant model of opportunism for different context settings, our specification might not manage to capture every possible scenario. For instance, in Section 3.4 we only talk about the interaction between two agents and investigate the evaluation on the state transition based on the value system of the two agents who are involved in the transaction. But actually such evaluation can also be done by others. This is because in the specification of value promotion and demotion the proposition evaluated based on an agent's value system is not necessarily related to the transactions the agent is involved. Assume that a friend of the buyer knows the story about the broken cup. He may get angry with the seller for the unfair transaction and then the behavior performed by the seller is regarded as opportunistic from his perspective, even though he is not involved. In other words, the judgment of opportunism is subjective not only for the agents involved, but also for anybody who evaluate the action based on his or her own value system. Further, our models only consider intentional actions. However, opportunistic behavior can also be intentional inactions such as withholding information. In this case, the social value gets demoted for agent i's not performing an obligatory action instead of performing a forbidden action. Of course, our models can capture this scenario in a way that doing nothing can be seen as a particular way of doing something. Interesting insights can be gained from further study on this part.

We also propose that the asymmetric knowledge obtained by opportunistic agents is value opposition about the state transition, which is out of our intuition. The reason can be shown by the example in Section 3.7. Intuitively the asymmetric knowledge that the seller has is about the broken cup. Now we assume that both the seller and the buyer know the cup is broken and the seller sells it with a high price. Once the buyer knows that the broken cup is not worth that price, his value will get demoted. From that, we can conclude that it does not matter whether the fact about the broken cup is only known by one party beforehand, but whether value opposition about the transaction is only known by one party beforehand. In other words, the asymmetric knowledge is not about the objective fact, but about agents' evaluation on the state transition.

The definition of non-compensation is introduced for opportunism with multiple actions, based on the fact that the negative effect of opportunistic behavior can be repairable or permanent. Given a normative context, the norm that opportunistic behavior triggers (violates) can be repaired or not based on the same fact. In the former case, we can eliminate opportunistic behavior by imposing punishments or sanctions on the norm. For instance, in the case of free riding, reparation of opportunism can be handled through fine. Opportunistic agents may be forced to repair the norm by regimented norms after the opportunistic behavior is detected. When the norm cannot be repaired once being violated, such an opportunistic behavior is supposed to be prevented from happening. In other words, the norm should be implemented in the environment or by designing norm-abiding agents.

3.9 Chapter Summary

Agents with knowledge asymmetry might perform opportunistic behavior to others in their interest. Numerous works about such a selfish behavior have been done in social science due to its negative effect on the relationship between people. However, most conclusions are based on a given form of opportunism, making it hard to build a fundamental theory that can be applied in any context. This chapter took the initiative to propose a formal model of opportunism in the multi-agent system context based on the extended informal definition from Williamson. The modeling work was done based on the situation calculus integrating the notion of values. We first proposed a preliminary model that only considers a single action between two agents, and then extended it for multiple actions with a normative context. Each model captured interesting properties that were useful for our future research. It is important to keep in mind that the aim of this chapter is not to find out where opportunistic behavior comes from and how to eliminate it, but rather to have a thorough understanding of the nature of opportunism before exploring those issues. Therefore, the main strength of this chapter is defining such a behavior from our specific perspective in a formal way, so as to represent the elements in the definition and their relations and reason about the state transition by the behavior.

Based on our understanding of the concept of opportunism, we can study where and when opportunism arises in a social setting. Evaluation based on different value systems is the reason for value opposition of a state transition. So considerable insights can be achieved from the investigation of the compatibility of different value systems and the co-evolution of agents' value systems with a normative context or environmental changes. Further, as opportunism is a self-interested behavior that may conflict with norms, its emergence might come from the way in which agents resolve the conflicts between beliefs, obligations, intentions and desires. For instance, an agent whose desires always overrule obligations might behave opportunistically. Those conflicts and their resolutions corresponding to different agent types are investigated in the BOID architecture [Broersen et al., 2001] and [Broersen et al., 2005]. A well-designed monitoring mechanism can be used to automatically detect opportunism in (computer-based) human interactions, providing ways to protect agents' values from being demoted. Another important topic is designing mechanisms to eliminate opportunism in the system.

4

Monitoring Opportunism

Opportunism is a behavior that causes norm violation and promotes agents' own value. In the context of multi-agent systems, we want to eliminate such a selfish behavior through setting enforcement norms. Because opportunistic behavior cannot be observed directly, there has to be a monitoring mechanism that can detect the performance of opportunistic behavior in the system. This chapter provides a logical framework based on the specification of actions to specify monitoring approaches for opportunism. We investigate how to evaluate agents' actions to be opportunistic with respect to different forms of norms when those actions cannot be observed directly, and study how to reduce the monitoring cost for opportunism.

4.1 Introduction

Consider a common scenario. A seller sells a cup to a buyer and it is known by the seller beforehand that the cup is actually broken. The buyer buys the cup without knowing it is broken. The behavior results in promoting the seller's value but demoting the buyer's value. Such a selfish behavior intentionally performed by the seller is first named opportunistic behavior (or opportunism) by economist Williamson [Williamson, 1975]. It is a typical behavior that is motivated by self-interest and takes advantage of knowledge asymmetry about the behavior to promote an agent's own value, regardless of the other agent's value (Chapter 3). In the context of multi-agent systems, we want to constrain such a selfish behavior through setting enforcement norms, in the reveal that opportunistic agents receive a corresponding sanction when they violate the norm. On the one hand, it is important to detect it, as it has undesirable results for the participating agents and we want to impose sanction to the agent who was opportunistic. On the other hand, since opportunism is always in the form of cheating, deception and betrayal, meaning that the system does not know what the agent performs or even the motivation behind it (for example, in a distributed system), opportunistic behavior cannot be observed directly. Therefore, there has to be a monitoring mechanism that can detect the performance of opportunistic behavior in the system.

This chapter provides a logical framework based on the specification of actions to monitor opportunism. In particular, since monitors cannot read agents' mental states and it is demotivated to perform opportunistic behavior from the perspective of the system, we define opportunism as a behavior that causes norm violation and promotes agents' own value. Based on this definition, we investigate how to evaluate agents' actions to be opportunistic with respect to different forms of norms when those actions cannot be observed directly, and explore how to reduce the monitoring cost for opportunism based on the monitoring approaches we proposed. We study formal properties of our monitoring approaches in order to determine whether they are effective in the reveal that whenever an action is detected to be opportunistic, it was indeed opportunistic, and that whenever an action was opportunistic, it is indeed detected.

4.1.1 Chapter Outline

The rest of the chapter is organized as follows:

- Section 4.2 introduces the logical framework, which is a transition system specified based on the specification of actions;
- Section 4.3 defines opportunism from the perspective of monitors;
- Section 4.4 proposes our monitoring approaches for opportunism with respect to different forms of norms, each following a discussion of formal properties;
- Section 4.5 investigates monitoring cost for opportunism based on our monitoring approaches;
- Section 4.7 summarizes the chapter.

4.2 Framework

In this section we introduce the models and the logical language we use, and define the concept of norms by means of our language.

4.2.1 Monitoring Transition Systems

Monitors cannot observe the performance of opportunism directly. However, actions can be represented and identified through the information about the context where the action can be performed and the property change in the system. Those kinds of information is called *action specification* [Reiter, 2001] or *action description* [Fiadeiro and Maibaum, 1991]. Usually an action can be specified through its precondition and its effect (postcondition): the precondition specifies the scenario where the action can be performed whereas the postcondition specifies the scenario resulting from performing the action. For example, the action, dropping a glass to the ground, can be specified as holding a glass as its precondition and the glass getting broken as its effect. In this chapter, we assume that every action has a set of pairs of the form $\langle \psi_p^a, \psi_e^a \rangle$, where ψ_p^a is the precondition of action a and ψ_e^a is the effect of action a performed in the context of ψ_p^a, both of which are propositional formulas. Sometimes a particular action a can have different effects depending on the context in which it is performed. Based on this idea, we argue that action a can be represented through a set of pairs $D(a) = \{\langle \psi_p^a, \psi_e^a \rangle, ...\}$, each element indicating its precondition and its corresponding effect. The absence of a preconditioon means that the performance of the action is not context-dependent.

In this chapter, the models that we use are transition systems, which consist of agents Agt, states S, actions Act and transitions $\mathcal{R}$ between states by actions. When an action $a \in Act$ is performed in a certain state s, the system might progress to a different state s' in which different propositions might hold. Such a state transition is defined based on action specification. Namely, given a state transition from state s to state s' by action a, the precondition of action a is satisfied in state s and the effect of action a is satisfied in state s'. We also extend the standard framework with an observable accessibility relation $\mathcal{M}$. The restriction on the $\mathcal{R}$ and the extension of $\mathcal{M}$ make our models different from the standard ones in [Keller, 1976] [Baier et al., 2008]. Note that in this chapter we don't talk about concurrent actions for simplifying our model, meaning that we assume there is only one action to execute in every state. Moreover, actions are deterministic; the same action performed in the same state will always result in the same new state. Formally,

Definition 4.2.1. *Let $\Phi = \{p, q, ...\}$ be a finite set of atomic propositional variables. A monitoring transition system over Φ is a tuple $\mathcal{T} = (Agt, S, Act, \pi, \mathcal{M}, \mathcal{R}, s_0)$ where*

- *Agt is a finite set of agents;*
- *S is a finite set of states;*
- *Act is a finite set of actions;*
- *$\pi : S \to \mathcal{P}(\Phi)$ is a valuation function mapping a state to a set of propositions that are considered to hold in that state;*
- *$\mathcal{M} \subseteq S \times S$ is a reflexive, transitive and symmetric binary relation between states, that is, for all $s \in S$ we have $s\mathcal{M}s$; for all $s, t, u \in S$ $s\mathcal{M}t$ and $t\mathcal{M}u$ imply that $s\mathcal{M}u$; and for all $s, t \in S$ $s\mathcal{M}t$ implies $t\mathcal{M}s$; $s\mathcal{M}s'$ is interpreted as state s' is observably accessible from state s;*
- *$\mathcal{R} \subseteq S \times Act \times S$ is a relation between states with actions, which we refer to as the transition relation labeled with an action; since we have already introduced the notion of action specification, a state transition $(s, a, s') \in \mathcal{R}$ if there exists a pair $\langle \psi_p^a, \psi_e^a \rangle \in D(a)$ such that ψ_p^a is satisfied in state s and ψ_e^a is satisfied in state s', and both ψ_p^a and ψ_e^a are evaluated in the conventional way of classical propositional logic; since actions are deterministic, sometimes we also denote state s' as $s\langle a \rangle$ for which it holds that $(s, a, s\langle a \rangle) \in \mathcal{R}$; for convenience, we use $\mathcal{R}(\varphi, \psi) = \{(s, a, s') \in \mathcal{R} \mid \mathcal{M}, s \models \varphi \text{ and } \mathcal{M}, s' \models \psi\}$ to denote the transitions going from a φ-state to a ψ-state;*
- *$s_0 \in S$ denotes the initial state.*

Norms are regarded as a set of constraints on agents' behavior. More precisely, a norm defines whether a possible state transition by an action is considered to be demotivated or not. The same as [Agotnes et al., 2007], we simply consider a norm as a subset of $\mathcal{R}$ that is decided by the designers of the system. Formally,

Definition 4.2.2 (Norm). *A norm η is defined as a subset of $\mathcal{R}$, i.e. $\eta \subseteq \mathcal{R}$. Intuitively, given a state transition (s, a, s'), $(s, a, s') \in \eta$ means that transition (s, a, s') is forbidden by norm η. We say (s, a, s') is an η-violation if and only if $(s, a, s') \in \eta$. Otherwise, (s, a, s') is an η-compliant.*

From the way that we define a norm, we can realize two extreme cases: if norm η is an empty set, all the possible state transitions are η-compliant; and it is also possible that a norm leads to states with no legal successor, which means that agents can only violate the norm.

4.2.2 Logical Setting

The logical language we use in this chapter is propositional logic $\mathcal{L}_{prop}$ extended with action modality, denoted as $\mathcal{L}_{modal}$. The syntax of $\mathcal{L}_{modal}$ is defined by the following grammar:

$$\varphi ::= p \mid \neg\varphi \mid \varphi_1 \vee \varphi_2 \mid \langle a \rangle \varphi$$

where $p \in \Phi$ and $a \in Act$. The semantics of $\mathcal{L}_{modal}$ are given with respect to the satisfaction relation "$\models$". Given a monitoring transition system $\mathcal{T}$ and a state s in $\mathcal{T}$, a formula φ of the language can be evaluated in the following way:

- $\mathcal{T}, s \models p$ iff $p \in \pi(s)$;
- $\mathcal{T}, s \models \neg\varphi$ iff $\mathcal{T}, s \not\models \varphi$;
- $\mathcal{T}, s \models \varphi_1 \vee \varphi_2$ iff $\mathcal{T}, s \models \varphi_1$ or $\mathcal{T}, s \models \varphi_2$;
- $\mathcal{T}, s \models \langle a \rangle \varphi$ iff $\exists s'$ such that $(s, a, s') \in \mathcal{R}$ and $\mathcal{T}, s' \models \varphi$;

Other classical logic connectives (e.g.,"$\wedge$", "$\rightarrow$") are assumed to be defined as abbreviations by using $\neg$ and $\vee$ in the conventional manner. We write $\mathcal{T} \models \varphi$ if $\mathcal{T}, s \models \varphi$ for all $s \in S$, and $\models \varphi$ if $\mathcal{T} \models \varphi$ for all monitoring transition systems $\mathcal{T}$.

Given the language $\mathcal{L}_{modal}$, a norm η can be defined in a more specific way such that it contains all the state transitions that are forbidden by norm η. Norms are described in various ways so that they can represent the forbidden behaviors explicitly. Below we define three forms of norms: $\eta(\varphi, \psi)$, $\eta(\varphi, a)$ and $\eta(\varphi, a, \psi)$, each following an example for better understanding. Notice that it is only a choice in this chapter and more forms of norms can be described and constructed based on our logical framework.

- **Norm** $\eta(\varphi, \psi)$ Let φ and ψ be two propositional formulas and $\mathcal{T}$ be a monitoring transition system. A norm $\eta(\varphi, \psi)$ is defined as the set $\eta_{\mathcal{T}}(\varphi, \psi) = \{(s, a, s') \in \mathcal{R} \mid \mathcal{T}, s \models \varphi \wedge \langle a \rangle \psi\}$. In the rest of the chapter, we will write $\eta(\varphi, \psi)$ for short. This is the most simple form of norms. The interpreted meaning of a norm $\eta(\varphi, \psi)$ is simply that it is forbidden to achieve ψ in the states satisfying φ (φ-state) by any actions. The forbidden actions are implicitly indicated in this type of norms. For example, it is forbidden to keep the light on when everybody is sleeping, no matter you turn on the flashlight or the lamp or lighten the candle.

- **Norm** $\eta(\varphi, a)$ Let φ be a propositional formula, a be an action, and $\mathcal{T}$ be a monitoring transition system. A norm (φ, a) is defined as the set $\eta_{\mathcal{T}}(\varphi, a) = \{(s, a', s') \in \mathcal{R} \mid \mathcal{T}, s \vDash \varphi \textit{ and } a' = a\}$. In the rest of the chapter, we will write $\eta(\varphi, a)$ for short. The interpreted meaning of a norm $\eta(\varphi, a)$ is that it is forbidden to perform action a in a φ-state. This is the most common form in which the action and the context where the action is forbidden are explicitly represented, regardless of the effect that the action brings about. For example, it is forbidden to smoke in a non-smoking area.
- **Norm** $\eta(\varphi, a, \psi)$ Let φ and ψ be two propositional formulas, a be an action, and $\mathcal{T}$ be a monitoring transition system. A norm (φ, a, ψ) is defined as the set $\eta_{\mathcal{T}}(\varphi, a, \psi) = \{(s, a', s') \in \mathcal{R} \mid \mathcal{T}, s \vDash \varphi \wedge \langle a' \rangle \psi \textit{ and } a' = a\}$. In the rest of the chapter, we will write $\eta(\varphi, a, \psi)$ for short. The interpreted meaning of a norm $\eta(\varphi, a, \psi)$ is that it is forbidden to perform action a in φ-state to achieve ψ. In this type of norms, the action, the context where the action is forbidden and the effect that the action will bring about are all represented explicitly. For example, in China it is forbidden to buy a house based on mortgage when you already own one.

Sometime propositional formula φ, which is indicated in three types of norms above, is called the precondition of an action for action prescription [Fiadeiro and Maibaum, 1991]. It should be distinguished from the precondition ψ_p^a we introduced in action specification. Formula φ is used to characterize the context where the action(s) is forbidden to perform by the system, whereas ψ_p^a is used to represent in which situation the action can be physically performed. Certainly there are relationships between φ and ψ_p^a. For instance, $\varphi \wedge \psi_p^a$ should be satisfied for the validity of norm $\eta(\varphi, a)$. We will take it into consideration when investigating monitoring approach for opportunism.

4.3 Defining Opportunism

Before we propose our monitoring approach for opportunism, we should formally define opportunism from the perspective of the system so that the system knows what to detect for monitoring opportunism. In our previous chapter 3 we emphasize opportunistic behavior is performed by intent rather than by accident. However, monitors cannot read agents' mental states, so for the issue of monitoring we assume that agents violate the norms always by intention from a pragmatic perspective. For example, we always assume that speeding is performed with intention. In this paper we remove all the references to the mental states from the formal definition of opportunism in our previous chapter 3, and also assume that the system can tell whether a state transition can promote or demote an agent's value through the facts that have been detected. In a sentence, from the perspective of the system, since it is demotivated to perform opportunistic behavior, opportunistic behavior performed by an agent in a normative context can be simply defined as a behavior that causes norm violations and promotes his own value.

Opportunistic behavior results in promoting agents' own value, which can be interpreted as that opportunistic agents prefer the state that results from opportunistic behavior rather than the initial state. As what we did in Chapter 3, we argue that agents always have preferences over two different states through evaluating the truth value of specific propositions in those states based on their value systems. For instance, the seller tries to see whether he gets the money from selling a broken cup in order to have a preference over the states before and after the transaction. After the transaction, the seller's value gets promoted, because the proposition he verifies (whether he gets the money) based on his value system becomes true. Based on this interpretation, we first define a function Evalref that points to the proposition an agent cares about:

Definition 4.3.1 (Evaluation Reference). *Let V be a set of agents' value systems, S be a finite set of states, and Φ be a finite set of atomic propositions, $EvalRef : V \times S \times S \to \Phi$ is a function named Evaluation Reference that returns a proposition an agent refers to for specifying his preference over two states.*

This function means that the proposition that an agent cares about is dependent on his value system and the two differnt states. Note that it is an abstract way to have what agents care about in a state transition through function Evalref. For a more concrete way, one can refer to function Mpreferred in Chapter 5 where we define a value system as a linear order over a set of formulas. For simplicity, we assume that for value promotion the truth value of the proposition that agents refer to changes from false to true in the state transition. For example, assuming that proposition p represents the seller earns money, the seller promotes his value in the way of bringing about p through selling a broken cup. Based on this assumption, we define *Value Promotion*, which is an important element of opportunistic behavior.

Definition 4.3.2 (Value Promotion). *Given two states s and s', and an agent's value system V_i, his value gets promoted from state s to s', denoted as $s <_{V_i} s'$, iff $s \vDash \neg p$ and $s' \vDash p$, where $p = \mathrm{Evalref}(V, s, s')$.*

As we already introduced the notion of value for defining opportunism, we extend our logical setting with value systems. We define a tuple of the form $V = (V_1, V_2, ..., V_{|Agt|})$ as agents' value systems. A multi-agent system is a combination of a monitoring transition system and value systems, one for each agent, representing the evaluation basis of the agents in the system. Formally, a multi-agent system, $\mathfrak{M}$, is a tuple:

$$\mathfrak{M} = (\mathcal{T}, V)$$

where $\mathcal{T}$ is a monitoring transition system and V is a set of value systems for the agents in Agt. Now the syntax of $\mathcal{L}_{modal}$ still follows the one we defined above, and the semantics with respect to the satisfaction relation become of the form $\mathfrak{M}, s \vDash \varphi$ but is still defined in the same way as above.

Now we are ready to formalize opportunism from the perspective of the system. Again, comparing to the definition of opportunism in our previous work, we remove all the references to mental states (knowledge, intention) because it is impossible for monitors to detect any mental states, but we assume that the system can reason whether an agent's value gets promoted or demoted along a state transition based on the corresponding value systems. Firstly, we extend our language to also include $\mathrm{Opportunism}(\eta, a)$, and then we extend the satisfaction relation such that the following definition holds.

Definition 4.3.3 (Opportunism). *Given a multi-agent system $\mathfrak{M}$ and a norm η, an action a performed by agent i in state s being opportunistic behavior is defined as follows: $\mathfrak{M}, s \vDash \mathrm{Opportunism}(\eta, a)$ iff state transition $(s, a, s\langle a \rangle) \in \eta$ and $s <_{V_i} s\langle a \rangle$.*

Intuitively, opportunism is a state transition which is an η-violation. Besides, the state transition also promotes the value of the agent who performs action a (agent i) by bringing about p, which is the proposition that the agent refers to for having preference over state s and $s\langle a \rangle$. Action a performed in state s, more essentially state transition $(s, a, s\langle a\rangle)$, is opportunistic behavior from the perspective of the system. We illustrate this definition through the following example.

Example 4.1 (Selling a Broken Cup). *Consider the example of selling a broken cup in Figure 4.1. A seller sells a cup to a buyer. It is known only by the seller beforehand that the cup is actually broken. The buyer buys the cup, but of course gets disappointed when he uses it. Here the state transition is denoted as* $(s, sell(brokencup), s')$. *Given a norm* $\eta(\top, sell(brokencup))$ *interpreted as it is forbidden to sell broken cups in any circumstance, the seller's behavior violates norm* η. *Moreover, based on the value system of the seller, his value gets promoted after he earns money from the transition (*$\text{Evalref}(V_s, s, s') = hasmoney(seller)$, $\mathfrak{M}, s \vDash \neg hasmoney(seller)$, $\mathfrak{M}, s' \vDash hasmoney(seller)$*). Therefore, the seller performed opportunistic behavior to the buyer from the perspective of the system.*

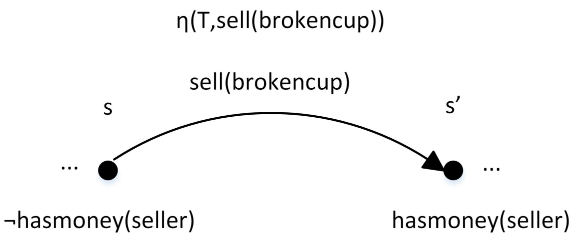


Figure 4.1. Opportunistic behavior of selling a broken cup.

4.4 Monitoring Opportunism

We propose monitoring approaches for opportunism in this section. A monitor in this chapter is considered as an external observer that can evaluate a state transition with respect to a given norm. However, a monitor can only verify state properties instead of observing the performance of actions directly. Our approach to solve this problem is to check how things change along a given state transition and reason about the action taking place in between. Here we assume that our monitors are always correct, which means that the verification for state properties can always be done perfectly. One who doubts that this assumption is too ideal can refer to [Bulling et al., 2013] for the investigation of correctness of monitors, and we don't discuss this issue in this chapter. In general, we consider monitoring as a matter of observing the system with an operator m such that $m(\varphi)$ is read as "φ is detected" for an arbitrary property φ. Multiple monitors can be combined together in order to deal with a monitoring issue.

We first define a state monitor m_{state}, which can evaluate the validity of a given property in a given state. We define state monitors in this chapter in a similar way to we define knowledge in epistemic logic. This is because a monitor can be seen as an external observer that observe the behavior of the system objectively. Sentence "φ is detected to be true" can be interpreted in the way "φ is known" by the monitor; "φ is not detected to be true" can be interpreted in the way "φ is unknown" by the monitor in the reveal that the monitor cannot distinguish φ and $\neg\varphi$. We extend our logical language to also include $m_{state}(\varphi)$ and the satisfaction relation such that the following definition holds.

Definition 4.4.1 (State Monitors). *Given a propositional formula φ, a multi-agent system $\mathfrak{M}$, a state monitor m_{state} over φ is defined as follows: $\mathfrak{M}, s \vDash m_{state}(\varphi)$ iff for all s' $s\mathcal{M}s'$ implies $\mathfrak{M}, s' \vDash \varphi$. Sometimes we will write $m_{state}(\varphi)$ for short if clear from the context.*

Because state monitors are defined in a similar way to knowledge in epistemic logic, they correspondingly adopt the S5 properties of knowledge.

Proposition 4.4.1 (Properties of State Monitors). *Given a multi-agent system $\mathfrak{M}$, and a state monitor m_{state} over φ, m_{state} is*

- $\mathfrak{M} \vDash m_{state}(\varphi) \rightarrow \varphi$, *meaning that what the state monitor detects is always considered to be true;*
- $\mathfrak{M} \vDash m_{state}(\varphi) \rightarrow m_{state}(m_{state}(\varphi))$, *meaning that the fact that something is detected to be true is always detected to be true;*
- $\mathfrak{M} \vDash \neg m_{state}(\varphi) \rightarrow m_{state}(\neg m_{state}(\varphi))$, *meaning that the fact that something is not detected to be true is always detected to be true.*

This proposition holds since our binary relation $\mathcal{R}$ is equivalence relation (reflexive, transitive and symmetric). We omit the proof for the space limitation.

State monitors are the basic units in our monitoring mechanism. We can combine state monitors to check how things change in a given state transition and evaluate it with respect to a given set of norms. In Section 4.2, we introduced three forms of norms through which certain agents' behaviors are forbidden by the system. As we defined in Section 4.3, opportunistic behavior performed by an agent is a behavior that causes norm violations and promotes his own value, that is, opportunism is monitored with respect to a given norm and a given value system of an agent. Based on this definition, we design different monitoring opportunism approaches with respect to different forms of norms and discuss in which condition opportunism can be perfectly monitored. It is worth stressing that one important issue of this chapter is to have an effective monitoring mechanism for opportunism in the reveal that

- whenever an action is detected to be opportunistic, it was indeed opportunistic;
- whenever an action was opportunistic, it is indeed detected.

We will discuss these two issues every time we propose a monitoring approach.

Definition 4.4.2 (Monitoring Opportunism with Norm $\eta(\varphi, \psi)$). *Given a .. multi-agent system $\mathfrak{M}$ and a norm $\eta(\varphi, \psi)$, whether an action a' performed by agent i in state s is opportunistic behavior can be monitored through a combination of state monitors as follows:*

$$m_{opp}((\varphi, \psi), a') := m_{state}(\varphi) \wedge \langle a' \rangle m_{state}(\psi)$$

where

$$\mathfrak{M} \models \varphi \to \neg p,\ \mathfrak{M} \models \psi \to p,\ \textit{and}\ p = \mathrm{Evalref}(V_i, s, s\langle a' \rangle)$$

In order to check whether action a' is opportunistic behavior in state s, we check if the state transition $(s, a', s\langle a' \rangle)$ is forbidden by norm $\eta(\varphi, \psi)$: because the interpreted meaning of norm $\eta(\varphi, \psi)$ is that it is forbidden to achieve ψ in φ-state by any actions, we check whether propositional formulas φ and ψ are successively satisfied in a state transition. Moreover, we assume the following implications in our model that φ implies $\neg p$ and ψ implies p, where proposition p is the proposition that agent i cares about along the transition. Since state s and $s\langle a' \rangle$ are not given and our monitors can only have partial information about the two states, we have a candidate set of states for state s and a candidate set of states for state $s\langle a' \rangle$ and any two states from them satisfy the resulting property of function Evalref, which means that given the partial information the execution of action a' in state s brings about p thus promoting agent i's value. The forbidden actions are not explicitly stated in the norm. Therefore, although the monitors cannot observe the performance of opportunistic behavior, it still can be perfectly detected with respect to norm $\eta(\varphi, \psi)$, which can be expressed by the following proposition:

Proposition 4.4.2. *Given a multi-agent system $\mathfrak{M}$ and a norm $\eta(\varphi, \psi)$, an action a' performed by agent i is detected to be opportunistic with respect to $\eta(\varphi, \psi)$ over $\mathcal{M}$ if and only if action a' was indeed opportunistic:*

$$\mathfrak{M} \vDash \text{Opportunism}((\varphi, \psi), a') \leftrightarrow m_{opp}((\varphi, \psi), a')$$

Proof. It trivially holds because the monitors detect exactly what the norm indicates and they are assumed to be correct.

Definition 4.4.3 (Monitoring Opportunism with Norm $\eta(\varphi, a)$). *Given a .. multi-agent system $\mathfrak{M}$, a norm $\eta(\varphi, a)$, and a pair $\langle \psi_p^a, \psi_e^a \rangle$ of action a ($\langle \psi_p^a, \psi_e^a \rangle \in D(a)$ and $\varphi \wedge \psi_p^a$ is satisfiable on $\mathfrak{M}$), whether action a' performed by agent i in state s is opportunistic behavior can be monitored through a combination of state monitors as follows:*

$$m_{opp}((\varphi, a), \langle \psi_p^a, \psi_e^a \rangle, a') := m_{state}(\varphi \wedge \psi_p^a) \wedge \langle a' \rangle m_{state}(\psi_e^a)$$

where

$$\mathfrak{M} \vDash \varphi \wedge \psi_p^a \rightarrow \neg p,\ \mathfrak{M} \vDash \psi_e^a \rightarrow p,\ \textit{and } p = \text{Evalref}(V_i, s, s\langle a' \rangle)$$

In order to check whether action a' is opportunistic behavior (violates norm $\eta(\varphi, a)$ and promotes own value), we verify if action a' is performed in a φ-state. Besides, we check if action a' is the action that the norm explicitly states. Since the monitors cannot observe the performance of action a', we only can identify action a' to be possibly action a by checking if formulas ψ_p^a and ψ_e^a are successively satisfied in the state transition by action a', where ψ_p^a is action a's precondition and ψ_e^a is the corresponding effect. Similar to norm $\eta(\varphi, \psi)$, we assume that $\varphi \wedge \psi_p^a$ implies $\neg p$ and ψ_e^a implies p, where p is the proposition that agent i cares about along the transition. Again, with this approach we have a candidate set of states for state s and a candidate set of states for state $s\langle a' \rangle$ and any two states from them satisfy the resulting property of function Evalref, which means that given the partial information the execution of action a' in state s brings about p thus promoting agent i's value.

Given a norm and an agent's value system, we can evaluate whether a state transition by an action is opportunistic behavior. However, since the monitors can only verify state properties instead of observing the performance of the action directly, we cannot guarantee that an action that is detected to be opportunistic was indeed opportunistic, which is given by the following proposition:

Proposition 4.4.3. *Given a multi-agent system $\mathfrak{M}$, a norm $\eta(\varphi, a)$, a pair $\langle \psi_p^a, \psi_e^a \rangle$ of action a ($\langle \psi_p^a, \psi_e^a \rangle \in D(a)$ and $\varphi \wedge \psi_p^a$ is satisfiable on $\mathfrak{M}$), let a' be an action performed by agent i, action a' that is detected to be opportunistic was possibly opportunistic, which is characterized as*

$$\mathfrak{M} \nvDash m_{opp}((\varphi, a), \langle \psi_p^a, \psi_e^a \rangle, a') \rightarrow \text{Opportunism}((\varphi, a), a')$$

Proof. *This is because pair $\langle \psi_p^a, \psi_e^a \rangle$ might not be unique for action a within the actions that are available in a φ-state. That is, we have a set of actions $Act' = \{a' \in Act \mid \mathfrak{M}, s \vDash m_{state}(\varphi \wedge \psi_p^a) \wedge \langle a' \rangle m_{state}(\psi_e^a)\}$, and both action a and action a' are in Act'.*

Given this problem, we want to investigate in which case or with what requirement the action that is detected by the opportunism monitor was indeed opportunistic behavior. From the proof of Proposition 4.4.3 we see that $\langle \psi_p^a, \psi_e^a \rangle$ in $D(a)$ has to be unique for action a. However, such a requirement is quite hard to satisfied in reality. For example, we can design multiple (probably infinite) computer programs with the same input and output. One possible way to solve this problem is to limit the set of actions that might have occurred through the context where the action is performed and the result that the action brings about. Recalling that we have defined $\mathcal{R}(\varphi, \psi)$ for the transitions going from a φ-state to a ψ-state, we have the following proposition:

Proposition 4.4.4. *Given a multi-agent system $\mathfrak{M}$, a norm $\eta(\varphi, a)$, a pair $\langle \psi_p^a, \psi_e^a \rangle$ of action a ($\langle \psi_p^a, \psi_e^a \rangle \in D(a)$ and $\varphi \wedge \psi_p^a$ is satisfiable on $\mathfrak{M}$), let a' be an action performed by agent i, the following statements are equivalent:*

1. *$\mathfrak{M} \vDash m_{opp}((\varphi, a), \langle \psi_p^a, \psi_e^a \rangle, a') \leftrightarrow \text{Opportunism}((\varphi, a), a')$;*
2. *there exists only one action a that has pair $\langle \psi_p^a, \psi_e^a \rangle$ within the set of transitions $\mathcal{R}(\varphi, \top)$.*

Proof. *$1 \Rightarrow 2$: Statement 1 implies that action a' that is detected to be opportunistic was indeed opportunistic. If it holds, then $a' = a$. Because we identify action a with pair $\langle \psi_p^a, \psi_e^a \rangle$, $a' = a$ implies that pair $\langle \psi_p^a, \psi_e^a \rangle$ is unique for* *action a within the set of transitions $\mathcal{R}(\varphi, \top)$. In other words, we cannot find one more action in transitions $\mathcal{R}(\varphi, \top)$ that also has a pair $\langle \psi_p^a, \psi_e^a \rangle$. 2 $\Rightarrow$ 1: If action pair $\langle \psi_p^a, \psi_e^a \rangle$ is unique for action a within transitions $\mathcal{R}(\varphi, \top)$, then once the pair is detected in the state transition we can deduce that $a' = a$. Hence, action a' is indeed opportunistic behavior. And from the proof of proposition 4.4.3 we can see that action a is within the set of actions that are detected to be opportunistic, so if action a' was opportunistic behavior then it is indeed detected.*

We can also derive a practical implication from this proposition: in order to better monitor opportunistic behavior, we should appropriately find an action pair $\langle \psi_p^a, \psi_e^a \rangle$ such that the possible actions that took place can be strongly restricted and minimized. Assuming that we use monitoring approach $m_{opp}((\varphi, a), \langle \top, \top \rangle, a')$, the possibility that the opportunism monitor makes an error is extremely high, because every action that is available in φ-state will be detected to be opportunistic behavior given the action pair $\langle \top, \top \rangle$.

Definition 4.4.4 (Monitoring Opportunism with Norm $\eta(\varphi, a, \psi)$). *Given a multi-agent system $\mathfrak{M}$, a norm $\eta(\varphi, a, \psi)$, and a pair $\langle \psi_p^a, \psi_e^a \rangle$ of action a ($\langle \psi_p^a, \psi_e^a \rangle \in D(a)$ and $\varphi \wedge \psi_p^a$ and $\psi \wedge \psi_e^a$ are satisfiable on $\mathfrak{M}$), let a' be an action performed by agent i in state s, whether action a' is opportunistic behavior can be monitored through a combination of state monitors as follows:*

$$m_{opp}((\varphi, a, \psi), \langle \psi_p^a, \psi_e^a \rangle, a') := \\ m_{state}(\varphi) \wedge \langle a' \rangle m_{state}(\psi) \wedge m_{state}(\psi_p^a) \wedge \langle a' \rangle m_{state}(\psi_e^a)$$

where

$$\mathfrak{M} \vDash \varphi \wedge \psi_p^a \to \neg p, \ \mathfrak{M} \vDash \psi \wedge \psi_e^a \to p, \ \textit{and } p = \mathrm{Evalref}(V_i, s, s\langle a' \rangle)$$

In order to check whether action a' is opportunistic behavior (violates norm $\eta(\varphi, a, \psi)$ and promotes own value), we verify if action a' is performed in a φ-state and secondly verify if action a' brings about ψ. Besides, as the forbidden action a is explicitly stated in norm η, we only can identify action a' to be possibly action a by checking if formulas ψ_p^a and ψ_e^a are successively satisfied in the state transition by action a', where ψ_p^a is action a's precondition and ψ_e^a is the corresponding effect. Similar to norm $\eta(\varphi, \psi)$ and $\eta(\varphi, a)$, we assume that $\varphi \wedge \psi_p^a$ implies $\neg p$ and $\psi \wedge \psi_e^a$ implies p, where p is the proposition that agent i cares about along the transition. Again, with the partial information our monitors have detected we have a candidate set of states for state s and a candidate set of states for state $s\langle a'\rangle$ and any two states from them satisfy the resulting property of function Evalref, which means that given the partial information the execution of action a' in state s brings about p thus promoting agent i's value.

The same as we do with $\eta(\varphi, a)$, we cannot guarantee that an action that is detected to be opportunistic was indeed opportunistic, which is given by the following proposition:

Proposition 4.4.5. *Given a multi-agent system $\mathfrak{M}$, a norm $\eta(\varphi, a, \psi)$, a pair $\langle\psi_p^a, \psi_e^a\rangle$ of action a ($\langle\psi_p^a, \psi_e^a\rangle \in D(a)$ and $\varphi \wedge \psi_p^a$ and $\psi \wedge \psi_e^a$ are satisfiable on $\mathfrak{M}$), let a' be an action performed by agent i, action a' that is detected to be opportunistic was possibly opportunistic, which is characterized as*

$$\mathfrak{M} \nvDash m_{opp}((\varphi, a, \psi), \langle\psi_p^a, \psi_e^a\rangle, a') \rightarrow \text{Opportunism}((\varphi, a, \psi), a')$$

Proof. *Similar to proposition 4.4.3, it is because pair $\langle\psi_p^a, \psi_e^a\rangle$ might not be unique for action a within the actions that can be performed in φ-state to achieve ψ, and action a indicated in norm η is one of those actions.*

Because the set of state transitions is finite in our framework, we can assume that all the possible state transitions are known beforehand. As all the state transitions in our framework are labelled with an action, we introduce a function called $Al(a)$, which maps each action to a non-empty subset of state transitions, denoting all the transitions labelled with action a. Thus we have $Al(a) \in \mathcal{P}(\mathcal{R})$. And then we have the following proposition:

Proposition 4.4.6. *Given a multi-agent system $\mathfrak{M}$, a value system set V, a norm $\eta(\varphi, a, \psi)$, a pair $\langle\psi_p^a, \psi_e^a\rangle$ of action a ($\langle\psi_p^a, \psi_e^a\rangle \in D(a)$ and $\varphi \wedge \psi_p^a$ and $\psi \wedge \psi_e^a$ are satisfiable on $\mathfrak{M}$), let a' be an action performed by agent i, the following statements are equivalent:*

1. $\mathfrak{M} \vDash m_{opp}((\varphi, a, \psi), \langle\psi_p^a, \psi_e^a\rangle, a') \leftrightarrow \text{Opportunism}((\varphi, a, \psi), a')$;
2. *there exists only one action a that has a pair $\langle\psi_p^a, \psi_e^a\rangle$ within the set of transitions $\mathcal{R}(\varphi, \psi)$;*
3. $\mathcal{R}(\varphi \wedge \psi_p^a, \psi \wedge \psi_e^a) \subseteq Al(a)$.

Proof. *The proof for $1 \Rightarrow 2$ is the same as the proof of proposition 4.4.4, so we are going to prove $2 \Rightarrow 3$ and $3 \Rightarrow 1$. We can consider ψ_p^a and ψ_e^a as two normal propositional formulas. From statement 2 it is clear that $\varphi \wedge \psi_p^a$ and*

$\psi \wedge \psi_e^a$ are successively satisfied in the state transition. From this we can divide the transitions into two classes: one for the transitions that $\varphi \wedge \psi_p^a$ and $\psi \wedge \psi_e^a$ are successively satisfied (denoted as $\mathcal{R}(\varphi \wedge \psi_p^a, \psi \wedge \psi_e^a)$), and the other do not. Since pair $\langle \psi_p^a, \psi_e^a \rangle$ is unique to action a within $\mathcal{R}(\varphi \wedge \psi_p^a, \psi \wedge \psi_e^a)$, all the transitions in $\mathcal{R}(\varphi \wedge \psi_p^a, \psi \wedge \psi_e^a)$ are labeled with action a. Therefore, $\mathcal{R}(\varphi \wedge \psi_p^a, \psi \wedge \psi_e^a)$ is a subset of $Al(a)$. From 2 $\Rightarrow$ 3 is concluded. From 3 $\Rightarrow$ 1, if all the transitions in $\mathcal{R}(\varphi \wedge \psi_p^a, \psi \wedge \psi_e^a)$ are labeled with action a, then $a' = a$ and we can guarantee that action a' is indeed opportunistic behavior.

Example 4.1 (continued). *We still use the example of selling a broken cup Figure 4.2 to illustrate our monitoring approach. Here the state transition is denoted as (s, a', s') instead of $(s, sell(brokencup), s')$ because the monitor cannot observe the action directly. Given a norm $\eta(\top, sell(brokencup))$ and the seller's value system V_s, the system checks whether the seller performed opportunistic behavior. Firstly, the monitor doesn't need to check the context where action a' is performed because action $sell(brokencup)$ is forbidden in any context as norm η says. Secondly, the monitor tries to identify if action a' is indeed $sell(brokencup)$ as norm η indicates: assuming that $\langle hascup(seller) \wedge \neg hasmoney(seller), hascup(buyer) \wedge hasmoney(seller) \rangle$ is the pair we find for action $sell(brokencup)$, we check if both $\mathfrak{M}, s \vDash m_{state}(hascup(seller)) \wedge \neg hasmoney(seller)$ and $\mathfrak{M}, s' \vDash m_{state}(hascup(buyer) \wedge hasmoney(seller))$ hold. Moreover, the information we had for state s and s' implies that the seller's value gets promoted, as* $\mathrm{Evalref}(V_s, s, s') = hasmoney(seller)$. *If they all hold, action a' is detected to be opportunistic behavior. As the action pair we find is unique to action $sell(brokencup)$, action a' is indeed $sell(brokencup)$ thus being opportunistic.*

However, if $\langle hascup(seller), hascup(buyer) \rangle$ is the pair that we find for action $sell(brokencup)$, then action a' is not necessarily $sell(brokencup)$ because possibly $a' = give(brokencup)$, meaning that $\langle hascup(seller), hascup(buyer) \rangle$ is not unique to action $sell(brokencup)$.

We proposed three approaches to monitor opportunistic behavior with respect to three different forms of norms. Based on the definitions of three approaches, the following validities hold: given a multi-agent system $\mathfrak{M}$ and an action a',

$$\mathfrak{M} \vDash m_{opp}((\varphi, a, \psi), \langle \psi_p^a, \psi_e^a \rangle, a') \rightarrow m_{opp}((\varphi, \psi), a')$$
$$\mathfrak{M} \vDash m_{opp}((\varphi, a, \psi), \langle \psi_p^a, \psi_e^a \rangle, a') \rightarrow m_{opp}((\varphi, a), \langle \psi_p^a, \psi_e^a \rangle, a')$$

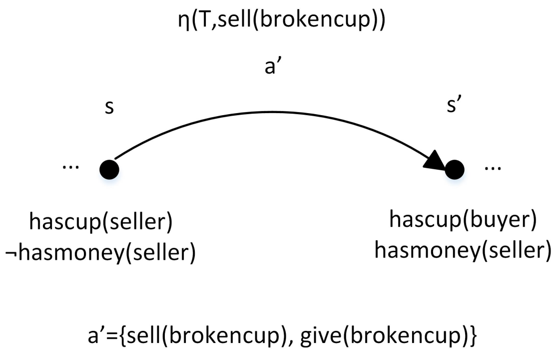


Figure 4.2. Monitoring opportunism of selling a broken cup.

The interpreted meaning of the first validity is that, if action a' is detected to be opportunistic behavior with respect to norm $\eta(\varphi, a, \psi)$, then it will be also detected to be opportunistic behavior with respect to norm $\eta(\varphi, \psi)$. Similar with the second validity. This is simply because, the less information the norm gives, the more actions are forbidden to perform. The state transitions that violate norm $\eta(\varphi, a, \psi)$ is the subset of the state transitions that violate norm $\eta(\varphi, \psi)$ or $\eta(\varphi, a)$. This gives us an implication that the approach to monitor opportunistic behavior with respect to $\eta(\varphi, a, \psi)$ can be used to monitor the other two ones, because $\eta(\varphi, a)$ can be represented as $\eta(\varphi, a, \top)$ and $\eta(\varphi, \psi)$ can be represented as $\eta(\varphi, a, \psi)(\forall a \in Act)$. However, we have to consider monitoring cost when choosing a monitoring approach. Apparently the approach with respect to $\eta(\varphi, a, \psi)$ is the most costly one because we need to verify more things compared to the other two ones. We will study our monitoring mechanism with cost in the next section.

4.5 Monitoring Cost for Opportunism

We investigate monitoring cost for opportunism in this section based on the monitoring approaches we proposed in the previous section. For designing a monitoring mechanism, we not only think about whether it can perfectly detect agents' activities, but also consider if it is possible to decrease the cost involved in the monitoring process. We first propose several ideas about how to reduce monitoring cost in general, and then discuss them with our monitoring approaches for opportunism.

4.5.1 Monitoring Cost

There is always cost involved when we monitor something, and the cost depends on what we want to check and how accurate the result we want to get. For example, recording a video is more expensive than taking a photo. We would like to use a monitoring approach which can accomplish our task and is cost-saving as well. Our basic idea in this chapter is that a monitor is considered as an external observer to verify state properties, and that given a set of propositional formulas X as state properties, we verify the conjunction of all the formulas from X through combining state monitors. We first define the monitoring cost of a state property through a function $c : \mathcal{L}_{prop} \to \mathbb{R}^+$. Intuitively, given a state property denoted by a propositional formula φ, function $c(\varphi)$ returns a positive real number representing the cost that it takes to verify φ. Such costs can be deduced from expert knowledge and are assumed to be given.

Definition 4.5.1 (Monitoring Cost for State Properties). *Cost c over state properties $\mathcal{L}_{prop}$ is a function $c : \mathcal{L}_{prop} \to \mathbb{R}^+$ that maps a propositional formula to a positive real number. Given a set of propositional formulas X, we also define $c(X) := \sum_{\varphi \in X} c(\varphi)$ for having the cost of monitoring a set X.*

Given a set of propositional formulas X, the cost of monitoring X is the sum of the monitoring cost for each element in X. However, those elements in X might have some properties that can help us save the monitoring cost. The first property we investigate is inference relation. Basically, if it holds for $\varphi, \varphi' \in X$ that $\varphi \neq \varphi'$ and $\varphi \to \varphi'$, then monitoring $X \backslash \{\varphi'\}$ is actually the same as monitoring X: when φ is detected to be true, φ' is also true; when φ is detected to be false, φ' is also false. But $c(X \backslash \{\varphi'\})$ is less than $c(X)$ if we logically assume that there is no inference cost [1]. This leads us to have the following definition *Largest Non-inferential Subset*:

Definition 4.5.2 (Largest Non-inferential Subset). *Given a monitoring transition system $\mathfrak{M}$ and a set of formulas X, let $X_{\mathfrak{M}}$ be the largest non-inferential subset such that for all $\varphi \in X_{\mathfrak{M}}$ there is no $\varphi' \in X_{\mathfrak{M}}$ with $\varphi \neq \varphi'$ such that $\mathfrak{M} \models \varphi \to \varphi'$.*

Proposition 4.5.1. *Given a monitoring transition system $\mathfrak{M}$, a set of formulas X and its largest non-inferential subset $X_{\mathfrak{M}}$, it holds that $c(X_{\mathfrak{M}}) \leq c(X)$.*

[1] It is logical to assume that inference cost is lower than monitoring cost, as we only need to compute the inference relation among formulas in the machine while monitoring usually requires setting up costly hardwares (such as cameras).

Proof. It holds obviously because $X_{\mathfrak{M}}$ is a subset of X.

Therefore, given a set of propositional formulas we want to verify, we always look for its largest non-inferential subset before checking anything in order to reduce the monitoring cost. Certainly, there are more properties among those formulas but we leave them for future study.

For reducing monitoring cost, it is also important to verify a set of propositional formulas $X = \{\varphi_1, ..., \varphi_n\}$ in a certain order instead of checking each formula $\varphi_i (1 \leq i \leq n)$ randomly. Besides, given the truth property of a conjunction that a conjunction of propositions returns false if and only if there exists at least one false proposition, we can stop monitoring X once a proposition is detected to be false because it has already made the conjunction false, regardless of the truth value of the rest of the propositions. Therefore, it is sensible to sort the propositions in X in ascending order by cost before checking anything, when the sorting cost is much lower than the monitoring cost. In order to introduce this idea, we first define the function of monitoring cost for a sequence and the notion of cost ordered sequence. In total, we have $n!$ sequences over X. A sequence over X is denoted as $\lambda(X)$ and the set of all the sequences over X is denoted as $L(X)$. The function of monitoring cost for a sequence and the notion of cost ordered sequence are defined as follows:

Definition 4.5.3 (Monitoring Cost for Sequences). *Given a set of propositional formulas $X = \{\varphi_1, ..., \varphi_n\}$ and a sequence $\lambda(X)$, the monitoring cost of $\lambda(X)$ is defined as follows:*

$$c(\lambda(X)) := \sum_{i=1}^{n} c(\varphi_i) d_i,$$

where

$$d_i = \begin{cases} 0 & \textit{if } m(\varphi_{i-1}) = \textit{ false or } d_{i-1} = 0 \ (i > 1); \\ 1 & \textit{otherwise.} \end{cases}$$

With this function of monitoring cost for a sequence, the monitoring process will stop and no more monitoring cost will arise after a false proposition is detected. Given a random sequence $\lambda(X)$ for monitoring, each proposition formula in X is likely to be true or false. We call each combination about the truth value of the formulas a scenario. Since there are $|X| = n$ propositions in X, there are in total 2^n scenarios about the truth value of the propositions in X. If the probability of each scenario to present is $p_i (i = 1, ..., 2^n)$, the expected value of the monitoring cost of $\lambda(X)$ can be computed in the following way:

$$E(c(\lambda(X))) = p_1 \sum_{i=1}^{n} c(\lambda(X)[i]) + p_2 \sum_{i=1}^{n} c(\lambda(X)[i]) + ... + p_{2^n} c(\lambda(X)[1])$$

Formula $\sum_{i=1}^{n} c(\lambda(X)[i])$ represents the monitoring cost for the scenario where all the propositions are detected to be true, and formula $\sum_{i=1}^{n} c(\lambda(X)[i])$ represents the monitoring cost for the scenario where all the propositions are detected to be true except the last one,..., $c(\lambda(X)[1])$ represents the monitoring cost for one scenario where the first proposition is detected to be false. The expected value of the monitoring cost of $\lambda(X)$ is the finite sum of the probability of each scenario to present timing the monitoring cost for the scenario.

Typically, when the priori probability for each formula $\varphi \in X$ to be true is the same and all the formulas are independent to each other, it is more cost-saving to first verify the formulas with low monitoring cost from the perspective of statistic. In order to propose this idea, we first introduce the notion *Cost Ordered Sequence*.

Definition 4.5.4 (Cost Ordered Sequence). *Given a set of propositional formulas X, a cost ordered sequence $\lambda(X)_c$ is a sequence over X ordered by the monitoring cost of each element in X such that $X_c \in L(X)$ and for $0 \leq i \leq j$ we have $c(\lambda(X)_c[i]) \leq c(\lambda(X)_c[j])$. In general, such a sequence is not unique because it is possible for two propositions to have the same monitoring cost; in this case we choose one arbitrarily.*

A cost ordered sequence $\lambda(X)_c$ represents the monitoring order over X: we follow the order in $\lambda(X)_c$ to check the elements in X one by one. Statistically speaking, we can reduce the monitoring cost if we follow the cost ordered sequence, which is represented by the following proposition:

Proposition 4.5.2. *Given a set of propositional formulas X and a cost ordered sequence $\lambda(X)_c$ over X, if the priori probability that each formula $\varphi \in X$ is true is 1/2, the expected value of the monitoring cost of X_c is the lowest in that of any sequence over X, that is, $E(c(\lambda(X)_c)) \leq E(c(\lambda(X)))$, where $\lambda(X) \in L(X)$.*

Proof. Because the priori probability that each formula $\varphi \in X$ is true is 1/2, the probability of each scenario to present is $1/2^n$. As we discussed above, since there are $|X| = n$ propositions in X and each proposition can be detected to be true or false, there are in total 2^n scenarios about the truth value of the propositions in X, and the monitoring cost for each scenario can be calculated according to Definition 4.5.3. Let us use $Scen(X)$ to denote the set of all the scenarios about the truth value of the propositions in X, and each scenario from $Scen(X)$, denoted as $\widehat{\varphi}$, contains for each proposition $\varphi \in X$ either true or false. Therefore, the expected value of the monitoring cost of any $\lambda(X)$ is formalized as

$$\begin{aligned} E(c(\lambda(X))) &= \frac{1}{2^n} \sum_{\widehat{\varphi} \in Scen(X)} \sum_{i=1}^{n} c(\varphi_i) d_i \\ &= \frac{1}{2^n} \left(\sum_{i=1}^{n} c(\lambda(X)[i]) + \sum_{j=1}^{n} \sum_{i=1}^{j} 2^{n-j} c(\lambda(X)[i]) \right) \\ &= \frac{1}{2^n} \left(\sum_{i=1}^{n} c(\lambda(X)[i]) + \sum_{i=1}^{n} 2^{n-n} c(\lambda(X)[i]) + ... + 2^{n-1} c(\lambda(X)[1]) \right), \end{aligned}$$

where $\sum_{i=1}^{n} c(\lambda(X)[i])$ represents the monitoring cost for the scenario where all the propositions are detected to be true, and $\sum_{i=1}^{n} c(\lambda(X)[i])$ represents the monitoring cost for the scenario where all the propositions are detected to be true except the last one, ..., and $c(\lambda(X)[1])$ represents the monitoring cost for the scenarios where the first proposition is detected to be false. From this equation we can see that the monitoring cost of the propositions at the front of the sequence strongly influence the value of $E(c(\lambda(X)))$: the lower monitoring cost the propositions at the front have, the less value $E(c(\lambda(X)))$ returns. Thus, the expected value of the monitoring cost of $\lambda(X)_c$, where all the formulas are sorted in ascending order by monitoring cost, is the lowest in all the sequences over X.

4.5.2 Reducing Monitoring Cost for Opportunism

Until now we investigated how to reduce monitoring cost for any given finite set of formulas generally. In this subsection we will apply the above ideas to monitoring opportunism. Recall that opportunism is monitored with respect to a norm and a value system. Given a norm $\eta(\varphi, a, \psi)$ and a value system V_i, we evaluate a state transition (s, a', s') by checking whether set $X_1 = \{\varphi, \psi_p^a, p\}$ hold in state s, and whether $X_2 = \{\varphi, \psi_e^a, p\}$ hold in state s', where $\langle \psi_p^a, \psi_e^a \rangle \in D(a)$ and $p = \text{Evalref}(V_i, s, s')$. Note that we cannot combine set X_1 and X_2 into one set because we verify the two sets of formulas in different states. The inference relation among the formulas give rise to the relation between different monitoring approaches.

Proposition 4.5.3. *Given a multi-agent system $\mathfrak{M}$, a norm $\eta(\varphi, a, \psi)$, a pair $\langle \psi_p^a, \psi_e^a \rangle$ of action a ($\langle \psi_p^a, \psi_e^a \rangle \in D(a)$ and $\varphi \wedge \psi_p^a$ and $\psi \wedge \psi_e^a$ are satisfiable on $\mathfrak{M}$), and an action a', if*

$$\mathfrak{M} \vDash (\varphi \to \psi_p^a) \wedge (\psi \to \psi_e^a),$$

then

$$\mathfrak{M} \vDash m_{opp}((\varphi, \psi), a') \leftrightarrow m_{opp}((\varphi, a, \psi), \langle \psi_p^a, \psi_e^a \rangle, a');$$

if

$$\mathfrak{M} \vDash \psi_e^a \to \psi,$$

then

$$\mathfrak{M} \vDash m_{opp}((\varphi, a), \langle \psi_p^a, \psi_e^a \rangle, a') \leftrightarrow m_{opp}((\varphi, a, \psi), \langle \psi_p^a, \psi_e^a \rangle, a').$$

Proof. If $\mathfrak{M} \vDash (\varphi \to \psi_p^a) \wedge (\psi \to \psi_e^a)$ holds, we have the largest non-inferential subset of X_1, $(X_1)_{\mathfrak{M}} = \{\varphi\}$, and the largest non-inferential subset of X_2, $(X_2)_{\mathfrak{M}} = \{\psi\}$, which means that we only need to verify φ in the initial state and ψ in the final state of any state transition. Thus, monitoring approach $m_{opp}((\varphi, \psi), a')$ has the same result as monitoring approach $m_{opp}((\varphi, a, \psi), \langle \psi_p^a, \psi_e^a \rangle, a')$. We can prove the second statement similarly.

This proposition implies that when the above inference holds we can monitor opportunism with the approach $m_{opp}((\varphi, \psi), a')$ (or $m_{opp}((\varphi, a), \langle \psi_p^a, \psi_e^a \rangle, a')$) rather than $m_{opp}((\varphi, a, \psi), \langle \psi_p^a, \psi_e^a \rangle, a')$ for saving monitoring cost.

Together with our general ideas about monitoring cost, we propose the following steps to monitor opportunism: given a multi-agent system $\mathfrak{M}$, a norm $\eta(\varphi, (a), (\psi))$, a pair $\langle \psi_p^a, \psi_e^a \rangle$ for action a and an action a' performed by agent i in state s, in order to check whether action a' is opportunistic behavior,

1. Check if there is any inference relation in $\mathfrak{M}$ among the formulas we need to verify in state s $X_1 = \{\varphi, \psi_p^a, p\}$ and $s\langle a' \rangle$ $X_2 = \{\varphi, \psi_e^a, p\}$, find out the largest non-inferential subsets $(X_1)_{\mathfrak{M}}$ and $(X_2)_{\mathfrak{M}}$, and choose the corresponding monitoring approach;
2. Sort all the formulas from $(X_1)_{\mathfrak{M}}$ and $(X_2)_{\mathfrak{M}}$ in a sequence ordered by monitoring cost $\lambda((X_1)_{\mathfrak{M}} \cup (X_2)_{\mathfrak{M}})_c$;
3. Verify all the formulas from $((X_1)_{\mathfrak{M}} \cup (X_2)_{\mathfrak{M}})_c$ one by one; when one formula is detected to be false, the monitoring process stops and action a' is detected not to be opportunistic behavior; otherwise, it is detected to be opportunistic behavior.

With the above steps, the monitoring cost for opportunism can be reduced statistically when the monitoring is performed for lots of times. For a single time of monitoring, we still cannot guarantee that the monitoring cost is reduced with the above steps. This is because possibly (only) we unfortunately come across the situation where the last formula in the cost ordered sequence is detected to be false, for which the monitoring cost is the Mpreferred compared to any sequence ordered at random.

4.6 Related Work

Apart from related work we introduce in Section 2, this chapter is also related to norm violation monitoring. Norms have been used as a successful approach to regulate and organize agents' behaviors [Shoham and Tennenholtz, 1992]. There are various ways of the specification of norms and norm violations such as [Anderson, 1958]. Similar to [Agotnes et al., 2007], we only consider a norm as a subset of all possible system behaviors. About norm violation monitoring, [Bulling et al., 2013] proposes a general monitoring mechanism for the situation where agents' behaviors cannot be perfectly monitored. It studies different types of monitors and provides a logical analysis of the relations between monitors and norms to be monitored. Our work is strongly inspired by them, but we focus on the situation where agents' actions cannot be observed directly but can be reasoned about through checking how things change, assuming state properties can be perfectly verified. Our monitoring approaches are similar to Artikis' methods of complex event recognition in norm-governed multi-agent systems [Artikis et al., 2015], which take as input streams of low-level events, such as a change in temperature, and combine them to infer complex high-level events of interest, such as the start of a fire incident.

4.7 Chapter Summary

For the issue of monitoring, opportunism is a behavior that causes norm violation and promotes agents' own value. In order to monitor its invisible performance in the system, we developed a logical framework based on the specification of actions. In particular, we investigated how to evaluate agents' actions to be opportunistic with respect to different forms of norms when those actions cannot be observed directly, and studied how to reduce the monitoring cost for opportunism. We proved formal properties aiming at having an effective and cost-saving monitoring mechanism for opportunism. Future work can be done on value: in our monitoring approaches it is assumed that we can reason whether an action promotes or demotes the value with a value system and how things change by the action, but a value system is still like a black box that we still don't know how the propositions we detect relate to a value system. Moreover, in our framework every state transition is labeled with an action and a hypothetical agent. We can improve the effectiveness of our monitoring mechanism by attaching *capability* to agents. In this way, given an agent with its capability, the possible actions that were performed by the agent can be eliminated. About reducing monitoring cost, apart from inference more properties among formulas can be studied concerning about the relations among the formulas we detect for monitoring opportunism.

5

Reasoning about Opportunistic Propensity

Opportunism is a behavior that takes advantage of knowledge asymmetry and results in promoting agents' own value and demoting others' value. We want to eliminate such selfish behavior in multi-agent systems, as it has undesirable results for the participating agents. In order for monitoring and eliminating mechanisms to be put in place, it is needed to know in which context agents will or are likely to perform opportunistic behavior. In this chapter, we develop a framework to reason about agents' opportunistic propensity. Opportunistic propensity refers to the potential for an agent to perform opportunistic behavior. In particular, agents in the system are assumed to have their own value systems and knowledge. With value systems, we define agents' state preferences. Based on their value systems and incomplete knowledge about the state, they choose one of their rational alternatives, which might be opportunistic behavior. We then characterize the situation where agents will perform opportunistic behavior and the contexts where opportunism is impossible to occur.

5.1 Introduction

Opportunism is a selfish behavior that takes advantage of relevant knowledge asymmetry and which results in promoting one's own value and demoting others' value (Chapter 3). In the context of multi-agent systems, it is normal that knowledge is distributed among participating agents in the system, which creates the ability for the agents to behave opportunistically. We want to eliminate such a selfish behavior, as it has undesirable results for other agents in the system. Evidently, not every agent is likely to be opportunistic. In social science, ever since the theory about opportunism was proposed by Williamson in economics, it has gained a large amount of criticism due to over-assuming that all economic players are opportunistic. [Chen et al., 2002] highlights the challenge on how to predict opportunism *ex ante* and introduces a cultural perspective to better specify the assumptions of opportunism. In multi-agent systems, we also need to investigate the interesting issues about opportunistic propensity so that the appropriate amount of monitoring [Luo et al., 2016] and eliminating mechanisms can be put in place.

Based on decision theory, an agent's decision on what to do depends on the agent's ability and preferences. If we apply it to opportunistic behavior, an agent will perform opportunistic behavior when he can do it and he prefers doing it. Those are the two issues that we consider in this chapter without discussing any normative issues. Based on this assumption, we develop a model of transition systems in which agents are assumed to have their own knowledge and value systems, which are related to the ability and the desire of being opportunistic respectively. Our framework can be used to predict and specify when an agent will perform opportunistic behavior, such as which kinds of agents are likely to perform opportunistic behavior and under what circumstances. A monitoring mechanism for opportunism benefits from this result as monitoring devices may be set up in the occasions where opportunism will potentially occur. We can also design eliminating mechanisms for opportunism based on the understanding of how agents decide to behave opportunistically. Besides, our framework can be used by autonomous agents to decide whether to participate in the system, as their actions might potentially be regarded as opportunistic behavior given their knowledge and value systems.

In this chapter, we introduce a framework to reason about agents' opportunistic propensity. Opportunistic propensity refers to the potential for an agent to perform opportunistic behavior. More precisely, agents in the system are assumed to have their own value systems and knowledge. We specify an agent's value system as a strict total order over a set of values, which are encoded within our logical language. Using value systems, we define agents' state preferences. Moreover, agents have partial knowledge about the true state where they are residing. Based on their value systems and incomplete knowledge, they choose one of their rational alternatives, which might be opportunistic. We thus provide a natural bridge between logical reasoning and decision making, which is used for reasoning about opportunistic propensity. We then characterize the situation where agents will perform opportunistic behavior and the contexts where opportunism is impossible to happen.

5.1.1 Chapter Outline

The rest of the chapter is organized as follows:

- Section 5.2 introduces the logical framework, which is a transition system extended with agents' epistemic relations;
- Section 5.3 introduces how agents form their rational alternatives for decision making with their value systems and limited knowledge about the system;
- Section 5.4 defines opportunism for making prediction;
- Section 5.5 characterizes the situation where agents will perform opportunistic behavior and the contexts where opportunism is impossible to happen;
- Section 5.7 summarizes the chapter.

5.2 Framework

We use Kripke structures as our basic semantic models of multi-agent systems. A Kripke structure is a directed graph whose nodes represent the possible states of the system and whose edges represent accessibility relations. Within those edges, equivalence relation $\mathcal{K}(\cdot) \subseteq S \times S$ represents agents' epistemic relation, while relation $\mathcal{R} \subseteq S \times Act \times S$ captures the possible transitions of the system that are caused by agents' actions. We use s_0 to denote the initial state of the system. It is important to note that, because in this chapter we only consider opportunistic behavior as an action performed by an agent, we do not model concurrent actions so that every possible transition of the system is caused by an action instead of joint actions. We use $\Phi = \{p, q, ...\}$ of atomic propositional variables to express the properties of states S. A valuation function π maps each state to a set of properties that hold in the corresponding state. Formally,

Definition 5.2.1. *Let $\Phi = \{p, q, ...\}$ be a finite set of atomic propositional variables. A Kripke structure over Φ is a tuple $\mathcal{T} = (Agt, S, Act, \pi, \mathcal{K}, \mathcal{R}, s_0)$ where*

- *$Agt = \{1, ..., n\}$ is a finite set of agents;*
- *S is a finite set of states;*
- *Act is a finite set of actions;*
- *$\pi : S \to \mathcal{P}(\Phi)$ is a valuation function mapping a state to a set of propositions that are considered to hold in that state;*
- *$\mathcal{K} : Agt \to 2^{S \times S}$ is a function mapping an agent in Agt to a reflexive, transitive and symmetric binary relation between states; that is, given an agent i, for all $s \in S$ we have $s\mathcal{K}(i)s$; for all $s, t, u \in S$ $s\mathcal{K}(i)t$ and $t\mathcal{K}(i)u$ imply that $s\mathcal{K}(i)u$; and for all $s, t \in S$ $s\mathcal{K}(i)t$ implies $t\mathcal{K}(i)s$; $s\mathcal{K}(i)s'$ is interpreted as state s' is epistemically accessible from state s for agent i. For convenience, we use $\mathcal{K}(i, s) = \{s' \mid s\mathcal{K}(i)s'\}$ to denote the set of epistemically accessible states from state s;*
- *$\mathcal{R} \subseteq S \times Act \times S$ is a relation between states with actions, which we refer to as the transition relation labeled with an action; we require that for all $s \in S$ there exists an action $a \in Act$ and one state $s' \in S$ such that $(s, a, s') \in \mathcal{R}$, and we ensure this by including a stuttering action sta that does not change the state, that is, $(s, sta, s) \in \mathcal{R}$; we restrict actions to be deterministic, that is, if $(s, a, s') \in \mathcal{R}$ and $(s, a, s'') \in \mathcal{R}$, then $s' = s''$; since actions are deterministic, sometimes we denote state s' as $s\langle a \rangle$ for which it holds that $(s, a, s\langle a \rangle) \in \mathcal{R}$. For convenience, we use $Ac(s) = \{a \mid \exists s' \in S : (s, a, s') \in \mathcal{R}\}$ to denote the available actions in state s.*
- *$s_0 \in S$ denotes the initial state.*

Now we define the language we use. The language $\mathcal{L}_{\text{KA}}$, propositional logic extended with knowledge and action modalities, is generated by the following grammar:

$$\varphi ::= p \mid \neg\varphi \mid \varphi_1 \vee \varphi_2 \mid K_i\varphi \mid \langle a \rangle \varphi \qquad (i \in Agt, a \in Act)$$

The semantics of $\mathcal{L}_{\text{KA}}$ are defined with respect to the satisfaction relation $\models$. Given a Kripke structure $\mathcal{T}$ and a state s in $\mathcal{T}$, a formula φ of the language can be evaluated as follows:

- $\mathcal{T}, s \models p$ iff $p \in \pi(s)$;

- $\mathcal{T}, s \models \neg\varphi$ iff $\mathcal{T}, s \not\models \varphi$;
- $\mathcal{T}, s \models \varphi_1 \vee \varphi_2$ iff $\mathcal{T}, s \models \varphi_1$ or $\mathcal{T}, s \vDash \varphi_2$;
- $\mathcal{T}, s \models K_i\varphi$ iff for all t such that $s\mathcal{K}(i)t$, $\mathcal{T}, t \models \varphi$;
- $\mathcal{T}, s \models \langle a\rangle\varphi$ iff there exists s' such that $(s, a, s') \in \mathcal{R}$ and $\mathcal{T}, s' \models \varphi$;

Other classical logic connectives (e.g.,"$\wedge$", "$\rightarrow$") are assumed to be defined as abbreviations by using $\neg$ and $\vee$ in the conventional manner. As is standard, we write $\mathcal{T} \models \varphi$ if $\mathcal{T}, s \models \varphi$ for all $s \in S$, and $\models \varphi$ if $\mathcal{T} \models \varphi$ for all Kripke structures $\mathcal{T}$.

In this chapter, in addition of the $\mathcal{K}$-relation being S5, we also place restrictions of *no-forgetting* and *no-learning* based on Moore's work [Moore, 1980] [Moore, 1984] to simplify our model. It is specified as follows: given a state s in S, if there exists s' such that $s\langle a\rangle\mathcal{K}(i)s'$ holds, then there is a s'' such that $s\mathcal{K}(i)s''$ and $s' = s''\langle a\rangle$ hold; if there exists s' and s'' such that $s\mathcal{K}(i)s'$ and $s'' = s'\langle a\rangle$ hold, then $s\langle a\rangle\mathcal{K}(i)s''$. Following this restriction, we have

$$\models K_i(\langle a\rangle\varphi) \leftrightarrow \langle a\rangle K_i\varphi.$$

The *no-forgetting* principle says that if after performing action a agent i considers a state s' possible, then before performing action a agent i already considered possible that action a would lead to this state. In other words, if an agent has knowledge about the effect of an action, he will not forget about it after performing the action. The *no-learning* principle says that all the possible states resulting from the performance of action a in agent i's possible states before action a are indeed his possible states after action a. In other words, the agent will not gain extra knowledge about the effect of an action after performing the action. We will illustrate our framework through the following example:

Example 5.1. *Consider the following example: Figure 5.1 shows a Kripke structure $\mathcal{T}$ for agent i. In state s, agent i considers state s and s' as his epistemic alternatives. Formula u, $\neg v$ and $\neg w$ hold in both state s and s', meaning that agent i knows u, $\neg v$ and $\neg w$ in state s. By the performance of action a_1, state s and s' result in state $s\langle a_1\rangle$ and $s'\langle a_1\rangle$ respectively, where formula $\neg u$, $\neg v$ and w hold.*

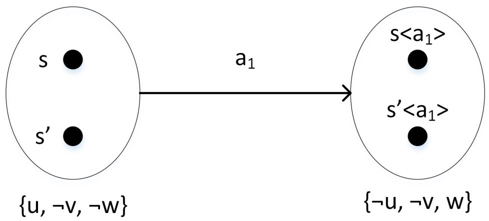


Figure 5.1. A Kripke structure $\mathcal{T}$ for agent i.

5.3 Value System and Rational Alternative

Agents in the system are assumed to have their own value systems and knowledge. Based on their value systems and incomplete knowledge about the system, agents form their rational alternatives for the action they are going to perform.

5.3.1 Value system

Given several (possibly opportunistic) actions available to an agent, it is the agent's decision to perform opportunistic behavior. Basic decision theory applied to intelligent agents relies on three things: agents know what actions they can carry out, the effects of each action and agents' preference over the effects [Poole and Mackworth, 2010]. In this chapter, the effects of each action are expressed by our logical language, and we will specify agents' abilities and preferences in this section. It is worth noting that we only study a single action being opportunistic in this chapter, so we will apply basic decision theory for one-shot (one-time) decision problems, which concern the situations where a decision is experienced only once.

One important feature of opportunism is that it promotes agents' own value but demotes others' value, and agents' value systems work as the basis of agents' consideration about performing opportunistic behavior. A value can be seen as an abstract basis according to which agents define their preferences over states. For instance, if we have a value denoting *equality*, we prefer the states where equal sharing or equal rewarding hold. Related work about values can be found in [Pitt and Artikis, 2015] and [Van der Weide, 2011]. Because of the abstract feature of a value, it is usually interpreted in more detail as a state property, which is represented as an $\mathcal{L}_{\mathrm{KA}}$ formula. The most basic value we can construct is simply a proposition p, which represents the value of achieving p. More complex values can be interpreted such as of the form $\langle a\rangle\varphi \wedge \langle a'\rangle\neg\varphi$, which represents the value that there is an option in the future to either achieve φ or $\neg\varphi$. Such a value corresponds to *freedom of choice*. A formula of a value can also be in the form of $K\varphi$, meaning that it is valuable to *achieve knowledge*. In this chapter, we denote values with v, and it is important to remember that v is an element from the language $\mathcal{L}_{\mathrm{KA}}$. However, not every formula from $\mathcal{L}_{\mathrm{KA}}$ can be intuitively classified as a value.

We argue that agents can always compare any two values. The rationale for this argument is that, when two values are equivalent (or simply incomparable) to us, we can consider them as one value. In other words, every element in the set of values is comparable to each other and none of them is logically equivalent to each other. Therefore, we define a value system as a strict total order over a set of values, representing the degree of importance of something, which are inspired by the preference lists in [Bulling and Dastani, 2016] the goal structure in [Ågotnes et al., 2007].

Definition 5.3.1 (Value System). *A value system* $V = (\mathrm{Val}, \prec)$ *is a tuple consisting of a finite set* $\mathrm{Val} = \{v, ..., v'\} \subseteq \mathcal{L}_{\mathrm{KA}}$ *of values together with a strict total ordering* $\prec$ *over* Val. *When* $v \prec v'$*, we say that value* v' *is more important than value* v *as interpreted by value system* V*.*

We also use a natural number indexing notation to extract the value of a value system, so if V gives rise to the ordering $v \prec v' \prec \ldots$, then $V[0] = v$, $V[1] = v'$, and so on. Since a value is interpreted as an $\mathcal{L}_{\mathrm{KA}}$ formula and it can be promoted or demoted by an action, value promotion and demotion along a state transition can be defined as follows:

Definition 5.3.2 (Value Promotion and Demotion). *Given a value* v *and an action* a*, we define the following shorthand formulas:*

$$\begin{aligned}\mathrm{promoted}(v,a) &:= \neg v \wedge \langle a\rangle v\\ \mathrm{demoted}(v,a) &:= v \wedge \langle a\rangle\neg v\end{aligned}$$

We say that a value v *is promoted along the state transition* (s, a, s') *if and only if* $s \models \mathrm{promoted}(v, a)$*, and we say that* v *is demoted along this transition if and only if* $s \models \mathrm{demoted}(v, a)$*.*

An agent's value v gets promoted along the state transition (s, a, s') if and only if v doesn't hold in state s and holds in state s'; an agent's value v

gets demoted along the state transition (s, a, s') if and only if v holds in state s and doesn't hold in state s'. Note that in principle an agent is not always aware that his or her value gets demoted or promoted, i.e. it might be the case where $s \models \text{promoted}(v, a)$ but agent i does not know this, i.e. $s \models \neg(K_i \, \text{promoted}(v, a))$.

Now we can define a multi-agent system as a Kripke structure together with agents' value systems, representing their basis of practical reasoning. We also assume that value systems are common knowledge in the system. Formally, a multi-agent system $\mathcal{M}$ is an $(n+1)$-tuple:

$$\mathcal{M} = (\mathcal{T}, V_1, ..., V_n)$$

where $\mathcal{T}$ is a Kripke structure, and for each agent i in $\mathcal{T}$, V_i is a value system.

We now define agents' preferences over two states in terms of values, which will be used for modelling the effect of opportunism. We first define a function $\mathrm{Mpreferred(i, s, s')}$ that maps a value system and two different states to the most preferred value that changes when going from state s to s' from the perspective of agent i. In other words, it returns the value that the agent most cares about, i.e. the most important change between these states for the agent.

Definition 5.3.3 (Most Preferred Value). *Given a multi-agent system $\mathcal{M}$, an agent i and two states s and s', function* $\mathrm{Mpreferred} : Agt \times S \times S \to \mathrm{Val}$ *is defined as follows:*

$$\mathrm{Mpreferred(i, s, s')}_{\mathcal{M}} := V_i[min\{j \mid \forall k > j : \mathcal{M}, s \models V_i[k] \Leftrightarrow \mathcal{M}, s' \models V_i[k]\}]$$

We write $\mathrm{Mpreferred(i, s, s')}$ *for short if $\mathcal{M}$ is clear from context.*

Note that if no values change between s and s', we have that $\mathrm{Mpreferred(i, s, s')} = V_i[0]$, i.e. the function returns the agent's least preferred value. Moreover, it is not hard to see that $\mathrm{Mpreferred(i, s, s')} = \mathrm{Mpreferred(i, s', s)}$, meaning that the function is symmetric for the two state arguments.

With this function we can easily define agents' preference over two states. We use a binary relation "$\precsim$" over states to represent agents' preferences.

Definition 5.3.4 (State Preferences). *Given a multi-agent system $\mathcal{M}$, an agent i and two states s and s', agent i weakly prefers state s' to state s, denoted as $s \precsim_i^{\mathcal{M}} s'$, iff*

$$\mathcal{M}, s \models \mathrm{Mpreferred(i, s, s')} \Rightarrow \mathcal{M}, s' \models \mathrm{Mpreferred(i, s, s')}$$

We write $s \precsim_i s'$ for short if $\mathcal{M}$ is clear from context. Moreover, we write $S \precsim_i S'$ for sets of states S and S' whenever $\forall s \in S, \forall s' \in S' : s \precsim s'$.

As standard, we also define $s \sim_i s'$ to mean $s \precsim_i s'$ and $s' \precsim_i s$, and $s \prec_i s'$ to mean $s \precsim_i s'$ and $s \not\sim_i s'$. The intuitive meaning of the definition of $s \precsim_i s'$ is that agent i weakly prefers state s' to s if and only if the agent's most preferred value does not get demoted (either stays the same or gets promoted). In other words, agent i weakly prefers state s' to s: if $\mathrm{Mpreferred(i, s, s')}$ holds in state s, then it must also hold in state s', and if $\mathrm{Mpreferred(i, s, s')}$ does not hold in state s, then it does matter whether it holds in state s' or not. Furthermore, the interpreted meaning of $s \sim_i s'$ is that state s and s' are subjectively equivalent to agent i, not necessarily that they objectively refer to the same state. Thus, given an agent's state preference, a set of states can be classified into different groups with an ordering in between. Clearly there is a correspondence between state preferences and promotion or demotion of values, which we can make formal with the following proposition.

Proposition 5.3.1. *Given a model $\mathcal{M}$ with agent i, state s and available action a in s, and let $v^* = \mathrm{Mpreferred(i, s, s\langle a\rangle)}$. We have:*

$$s \prec_i s\langle a\rangle \Leftrightarrow \mathcal{M}, s \models \mathrm{promoted}(v^*, a)$$
$$s \succ_i s\langle a\rangle \Leftrightarrow \mathcal{M}, s \models \mathrm{demoted}(v^*, a)$$
$$s \sim_i s\langle a\rangle \Leftrightarrow \mathcal{M}, s \models \neg(\mathrm{demoted}(v^*, a) \vee \mathrm{promoted}(v^*, a))$$

Proof. Firstly we prove the third one. We define $s \sim_i s\langle a\rangle$ to mean $s \precsim_i s\langle a\rangle$ and $s\langle a\rangle \precsim_i s$. $s \precsim_i s\langle a\rangle$ means that value v^* doesn't get demoted when going from s to $s\langle a\rangle$, and $s\langle a\rangle \precsim_i s$ means that value v^* doesn't get demoted when going from $s\langle a\rangle$ to s. Hence, value v^* doesn't get promoted or demoted (stays the same) by action a. Secondly we prove the first one. We define $s \prec_i s\langle a\rangle$ to mean $s \precsim_i s\langle a\rangle$ and $s \not\sim_i s\langle a\rangle$. $s \precsim_i s\langle a\rangle$ means that value v^* doesn't get demoted when going from s to $s\langle a\rangle$, and $s \not\sim_i s'$ means that either value v^* gets promoted or demoted by action a. Hence, value v^* gets promoted by action a. We can prove the second one in a similar way.

Additionally, apart from the fact that $s \prec_i s\langle a\rangle$ implies that the Mpreferred changed value gets promoted, we also have that no other value which is more preferred gets demoted or promoted. We have the result that the $\precsim_i$ relation obeys the standard properties we expect from a preference relation.

Proposition 5.3.2 (Properties of State Preferences). *Given an agent i, his preferences over states "$\precsim_i$" are*

- *Reflexive:* $\forall s \in S : s \precsim_i s$*;*
- *Transitive:* $\forall s, s', s'' \in S$ *: if* $s \precsim_i s'$ *and* $s' \precsim_i s''$*, then* $s \precsim_i s''$*;*
- *Total:* $\forall s, s' \in S$*:* $s \precsim_i s'$ *or* $s' \precsim_i s$*.*

Proof. *The proof follows Definition 5.3.4 directly. In order to prove $\precsim_i$ is reflexive, we have to prove that for any arbitrary state s we have $s \precsim_i s$. From Definition 5.3.3 and Definition 5.3.4 we know* $\mathrm{Mpreferred(i, s, s')} = V_i[0]$ *when $s = s'$, and for any arbitrary state s we always have $\mathcal{M}, s \models V_i[0]$ implies $\mathcal{M}, s \models V_i[0]$. Therefore, $s \precsim_i s$ and we can conclude that $\precsim_i$ is reflexive.*

In order to prove transitivity, we have to prove $\mathcal{M}, s \models v^*$ implies $\mathcal{M}, s'' \models v^*$, where $v^* = \mathrm{Mpreferred(i, s, s'')}$*. It can be the case where v^* stays the same in state s and s'' or the case where $\mathcal{M}, s \models \neg v^*$ and $\mathcal{M}, s'' \models \neg v^*$. For the first case, when $s \sim s'$ and $s' \sim s''$, meaning that all the values stay the same when going from s to s' and from s' to s'', it is also the case when going from s to s''. We now consider the case where $\mathcal{M}, s \models \neg v^*$ and $\mathcal{M}, s'' \models \neg v^*$. Firstly, we denote* $\mathrm{Mpreferred(i, s, s')}$ *as u^* and* $\mathrm{Mpreferred(i, s', s'')}$ *as w^*. It can either be that $u^* \sim_i w^*$, $u^* \prec_i w^*$ or $u^* \succ_i w^*$. If $u^* \sim_i w^*$, we can conclude that $u^* \sim_i w^* \sim_i v^*$, hence the implication holds. We now distinguish between the cases where $u^* \prec_i w^*$ or $u^* \succ_i w^*$.*

- *If $u^* \prec_i w^*$, we know that w^* is the most preferred value that changes and gets promoted when going from s' to s'', but stays the same between s and s'. Hence, we can conclude that $\mathcal{M}, s \models \neg w^*$ and $\mathcal{M}, s'' \models w^*$, and that $w^* = v^*$ (i.e., w^* is the most preferred value that changes between s and s''). Hence we have $\mathcal{M}, s \models v^*$ implies $\mathcal{M}, s'' \models v^*$.*
- *If $u^* \succ_i w^*$, we know that u^* is the most preferred value that changes and gets promoted when going from s to s', but stays the same between s' and s''. Hence, we can conclude that $\mathcal{M}, s \models \neg u^*$ and $\mathcal{M}, s'' \models u^*$, and that $u^* = v^*$ (i.e. v^* is the most preferred value that changes between s and s''). Hence, we have $\mathcal{M}, s \models v^*$ implies $\mathcal{M}, s'' \models v^*$.*

In order to prove totality by contradiction, we assume that we can find a witness that $\exists s, s' : s \not\precsim_i s'$ and $s' \not\precsim_i s$, that is, $\exists s,' : s \succ_i s'$ and $s \prec_i s'$. If $s \succ_i s'$, we know that $v^* = \mathrm{Mpreferred(i, s, s')}$ *gets demoted when going from* *state s to s'; if $s \prec_i s'$, we know that $v^* = \mathrm{Mpreferred(i, s, s')}$ gets promoted when going from state s to s'. Contradiction!*

In our system, we only look at the value change that is most cared about to deduce state preferences. Certainly, there are other ways of deriving these preferences from a value system. Instead of only considering the value change that is most cared about in the state transition, it is also possible to take into account all the value changes in the state transition. For example, we can define a function that tells whether and to what extent a state transition promotes or demotes an agent's overall value by attaching weights to values, and the weights can be the indexes of values in a value system. Then we sum all the weights for the state transition. The summation can tell whether and to what extent a state transition promotes or demotes an agent's overall value. With this approach, an agent considers all the values that are either promoted or demoted in the state transition. The higher index the value has, the more the agent values it. For opportunism, what we want to stress is that opportunistic agents ignore (rather than consider less) other agents' interest, which has a lower index in the agent's value system. In order to align with this aspect, we use the most preferred value approach in this chapter.

5.3.2 Rational Alternatives

Since we have already defined values and value systems as agents' basis for decision making, we can start to apply decision theory to reason about agents' decision-making. Given a state in the system, there are several actions available to an agent, and he has to choose one in order to go to the next state. We can see the consideration here as a one-shot decision making. In decision theory, if agents only act for one step, a rational agent should choose an action with the Mpreferred (expected) utility without reference to the utility of other agents [Poole and Mackworth, 2010]. Within our framework, this means that a rational agent will always choose a rational alternative based on his value system. We will introduce the notion of rational alternatives below.

Before choosing an action to perform, an agent must think about which actions are available to him. We have already seen that, for a given state s, the set of available actions is $Ac(s)$. However, since an agent only has partial knowledge about the state, we argue that the actions that an agent knows to be available is only part of the actions that are physically available to him in a state. For example, an agent can call a person if he knows the phone number of the person; without this knowledge, he is not able to do it, even though he is holding a phone. Recall that the set of states that agent i considers as being the actual state in state s is the set $\mathcal{K}(i,s)$. Given an agent's partial knowledge about a state as a precondition, he knows what actions he can perform in that state, which is the intersection of the sets of actions physically available in the states in this knowledge set.

Definition 5.3.5 (Subjectively Available Actions). *Given an agent i and a state s, agent i's subjectively available actions are the set:*

$$Ac(i,s) = \bigcap_{s' \in \mathcal{K}(i,s)} Ac(s').$$

Because a stuttering action sta is always included in $Ac(s)$ for any state s, we have that $sta \in Ac(i,s)$ for any agent i. When only sta is in $Ac(i,s)$, we say that the agent cannot do anything because of his limited knowledge. Obviously an agent's subjectively available actions are always part of his physically available actions ($Ac(i,s) \subseteq Ac(s)$). Based on agents' rationality assumptions, he will choose an action based on his partial knowledge of the current state and the next state. Given a state s and an action a, an agent considers the next possible states as the set $\mathcal{K}(i, s\langle a\rangle)$. For another action a', the set of possible states is $\mathcal{K}(i, s\langle a'\rangle)$. The question now becomes: How do we compare these two possible set of states? Clearly, when we have $\mathcal{K}(i, s\langle a\rangle) \prec_i \mathcal{K}(i, s\langle a'\rangle)$, meaning that all alternatives of performing action a' are more desirable than all alternatives of choosing action a, it is always better to choose action a'. However, in some cases it might be that some alternatives of action a are better than some alternatives of action a' and vice-versa. In this case, an agent cannot decisively conclude which of the actions is optimal, which implies that the preferences over actions (namely sets of states) is not total. This leads us to the following definition:

Definition 5.3.6 (Rational Alternatives). *Given a state s, an agent i and two actions $a, a' \in Ac(i,s)$, we say that action a is* dominated *by action a' for agent i in state s iff $\mathcal{K}(i, s\langle a\rangle) \prec_i \mathcal{K}(i, s\langle a'\rangle)$. The set of* rational alternatives *for agent i in state s is given by the function $a_i^* : S \to 2^{Act}$, which is defined as follows:*

$$\begin{aligned} a_i^*(s) = \{a \in Ac(i,s) \mid \neg\exists a' \in Ac(i,s) : a \neq a' \ \textit{and} \\ a' \ \textit{dominates } a \textit{ for agent } i \textit{ in state } s\}. \end{aligned}$$

The set $a_i^*(s)$ are all the actions for agent i in state s which are available to him and are not dominated by another action which is available to him. In other words, it contains all the actions which are rational alternatives for agent i. Since it is always the case that $Ac(i,s)$ is non-empty because of the stuttering action sta, and since it is always the case that there is one action which is non-dominated by another action, we conclude that $a_i^*(s)$ is non-empty. We can see that the actions that are available to an agent not only depend on the physical state, but also depend on his knowledge about the current state. The more he knows, the better he can judge what his rational alternative is. In other words, an agent tries to make a best choice based on his value system and incomplete knowledge. The following proposition shows how an agent removes an action with our approach.

Proposition 5.3.3. *Given a state s, an agent i and two actions $a, a' \in Ac(i,s)$, action a is dominated by action a' iff*

$$\neg\exists s', s'' \in \mathcal{K}(i,s) : s'\langle a\rangle \succ s''\langle a'\rangle.$$

Proof.

$$\begin{aligned}
&\exists s', s'' \in \mathcal{K}(i,s) : s'\langle a\rangle \succ s''\langle a'\rangle \\
\Leftrightarrow\ &\mathcal{K}(i, s\langle a\rangle) \not\prec \mathcal{K}(i, s\langle a'\rangle), \\
&\textit{because } s'\langle a\rangle \in \mathcal{K}(i, s\langle a\rangle) \textit{ and } s''\langle a'\rangle \in \mathcal{K}(i, s\langle a'\rangle) \\
\Leftrightarrow\ &\textit{ Action } a \textit{ is non-dominated by action } a'.
\end{aligned}$$

Agents remove all the options (actions) that are always bad to do, and there is no possibility to be better off by choosing a dominated action. The following proposition connects Definition 5.3.6 with stuttering action and state preferences.

Proposition 5.3.4. *Given a multi-agent system $\mathcal{M}$, a state s and an agent i,*

$$sta \notin a^*(s) \Rightarrow \forall a \in a^*(s) : s \prec_i s\langle a\rangle.$$

Proof. We prove it by contradiction. Statement $\neg(\forall a \in a^*(s) : s \prec_i s\langle a\rangle)$ is equivalent to statement $\exists a \in a^*(s) : s \succsim_i s\langle a\rangle$. We will make the proof with the situations where $\exists a \in a^*(s) : s \succ_i s\langle a\rangle$ and $\exists a \in a^*(s) : s \sim_i s\langle a\rangle$. If there exists an action $a \in a^*(s)$ such that agent i's value will get demoted by *performing it ($\exists a \in a^*(s) : s \succ_i s\langle a\rangle$), it will be dominated by the stuttering action sta. Sincw sta is not in $a^*(s)$, action a is not in $a^*(s)$ as well. If there exists an action $a \in a^*(s)$ such that agent i's value will keep agent i's values neutral ($\exists a \in a^*(s) : s \sim_i s\langle a\rangle$), sta will also be in $a^*(s)$, because all the actions in agent i's rational alternatives are equivalent to agent i and sta has the same effect as action a. Contradiction!*

If the stuttering action *sta* is not in the set of rational alternatives for agent i, meaning that it is dominated by an action (not necessarily in the set of rational alternatives), agent i can always promote his value by performing any action in his rational alternatives.

Our approach to comparing two sets of states resulting from two different actions is proposed with the assumption that an agent knows what he knows and what he doesn't know, which are the properties of positive introspection and negative introspection of agents' epistemic relations. Certainly, there are multiple ways of doing it. For instance, instead of removing all the options that are always bad to do, we can also do it merely with our limited knowledge about the actions. As we know, given a state s' from agent i's knowledge set $\mathcal{K}(i,s)$, it results in $s'\langle a\rangle$ and $s'\langle a'\rangle$ by action a and action a' respectively. Action a is dominated by action a' if and only if for all the states s' from $\mathcal{K}(i,s)$ we have $s'\langle a\rangle \prec_i s'\langle a'\rangle$. In this pairwise comparison approach, agent i compares two states resulting from the same state, which means that he only takes into account what he knows and ignores what he doesn't know for removing dominated actions. In this chapter, we remove the actions by which agents are impossible to be better off, because it has natural ties to game theory in the context of (non-)dominated strategies [Dixit and Nalebuff, 2008]. We will illustrate the above definitions and our approach through the following example.

Example 5.1 (continued). *We extend Example 5.1 as follows: Figure 5.2 shows a transition system $\mathcal{M}$ for agent i. State s and s' are agent i's epistemic alternatives, that is, $\mathcal{K}(i,s) = \{s, s'\}$. Now consider the actions that are physically available and subjectively available to agent i. $Ac_i(s) = \{a_1, a_2, a_3, sta\}$, $Ac_i(s') = \{a_1, a_2, sta\}$. Because $Ac(i,s) = Ac_i(s) \cap Ac_i(s')$, agent i knows that only sta, a_1 and a_2 are available to him in state s .*

Next we talk about agent i's rational alternatives in state s. Given agent i's value system $V_i = (u \prec v \prec w)$, and the following valuation: u, $\neg v$ and $\neg w$ hold in $\mathcal{K}(i,s)$, $\neg u$, $\neg v$ and w hold in $\mathcal{K}(i, s\langle a_1\rangle)$, and u, v and $\neg w$ hold in

$\mathcal{K}(i, s\langle a_2\rangle)$, we then have the following state preferences: $\mathcal{K}(i, s) \prec \mathcal{K}(i, s\langle a_1\rangle)$, $\mathcal{K}(i, s) \prec \mathcal{K}(i, s\langle a_2\rangle)$ and $\mathcal{K}(i, s\langle a_2\rangle) \prec \mathcal{K}(i, s\langle a_1\rangle)$, meaning that action a_2 and the stuttering action sta are dominated by action a_1. Thus, we have $a_i^*(s) = \{a_1\}$.

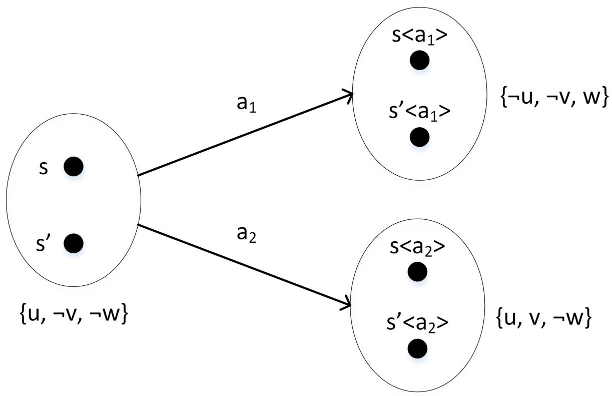


Figure 5.2. A transition system $\mathcal{M}$ for agent i.

5.4 Opportunism Propensity

Before reasoning about opportunistic propensity, we should first formally know what opportunistic propensity actually is. Opportunism is a selfish behavior that takes advantage of relevant knowledge asymmetry and results in promoting one's own value and demoting others' value (Chapter 3). It means that it is performed with the precondition of relevant knowledge asymmetry and the effect of promoting agents' own value and demoting others' value. Firstly, knowledge asymmetry is defined as follows.

Definition 5.4.1 (Knowledge Asymmetry). *Given two agents i and j, and an $\mathcal{L}_{\mathrm{KA}}$ formula φ, knowledge asymmetry about φ between agent i and j is the abbreviation:*

$$\text{Knowasym}(i, j, \varphi) := K_i\varphi \wedge \neg K_j\varphi \wedge K_i(\neg K_j\varphi).$$

It holds in a state where agent i knows φ while agent j does not know φ and this is also known by agent i. It can be the other way around for agent i and agent j. But we limit the definition to one case and omit the opposite case for simplicity. Now we can define opportunism:

Definition 5.4.2 (Opportunism Propensity). *Given a multi-agent system $\mathcal{M}$, a state s and two agents i and j, the assertion* $\text{Opportunism}(i, j, a)$ *that action a performed by agent i is opportunistic behavior is defined as:*

$$\text{Opportunism}(i, j, a) := \text{Knowasym}(i, j, \text{promoted}(v^*, a) \\ \wedge \text{demoted}(w^*, a))$$

where $v^* = \text{Mpreferred}(\text{i}, \text{s}, \text{s}\langle\text{a}\rangle)$ *and* $w^* = \text{Mpreferred}(\text{j}, \text{s}, \text{s}\langle\text{a}\rangle)$.

This definition shows that if the precondition Knowasym is satisfied in state s then the performance of action a will be opportunistic behavior. The asymmetric knowledge that agent i has is about promoting value v^* and demoting value w^* along the transition by action a, where v^* and w^* are the values that agent i and agent j most care about along the transition respectively. It follows that agent j is partially or completely not aware of it. Definition 5.4.2 about opportunistic propensity is aligned with the definition of opportunism in Chapter 3 in the reveal that the precondition of performing opportunistic behavior is modeled in an explicit way. As is stressed in Chapter 3, opportunistic behavior is performed by intent rather than by accident. In this chapter, instead of explicitly modeling intention, we interpret it from agents' rationality that they always intentionally promote their own values. We can derive three propositions from the definition, which are useful in our next section.

Proposition 5.4.1 (Value Opposition). *Given a multi-agent system $\mathcal{M}$ and an opportunistic behavior a performed by agent i to agent j in state s, action a will promote agent i's value but demote agent j's value, which can be formalized as*

$$\mathcal{M}, s \models \text{Opportunism}(i, j, a) \quad \Rightarrow \quad s \prec_i s\langle a \rangle \textit{ and } s \succ_j s\langle a \rangle$$

Proof. From $\mathcal{M}, s \models \text{Opportunism}(i, j, a)$ *we have:*

$$\mathcal{M}, s \models K_i(\text{promoted}(v^*, a) \wedge \text{demoted}(w^*, a))$$

And thus since all knowledge is true, we have that $\mathcal{M}, s \models \text{promoted}(v^*, a)$ *and*

$\mathcal{M}, s \models \text{demoted}(w^*, a)$. *Using the correspondence found in Proposition 5.3.1, we can conclude* $s \prec_i s\langle a\rangle$ *and* $s \succ_j s\langle a\rangle$.

We *objectively* say that agent i's value gets promoted and agent j's value gets demoted by opportunistic behavior a, but agent j is not aware of it even after opportunistic behavior a is performed due to the *no-learning* restriction on agents' epistemic relations. That is, if $\mathcal{M}, s \models \neg K_j(\langle a\rangle\neg w^*)$ for $\mathcal{M}, s \models \neg K_j\,\text{demoted}(w^*, a)$, then $\mathcal{M}, s \models \langle a\rangle\neg K_j(\neg w^*)$.

Proposition 5.4.2 (Different Value Systems). *Given a multi-agent system* $\mathcal{M}$ *and opportunistic behavior* a *performed by agent* i *to agent* j *in state* s, *agent* i *and agent* j *have different value systems, which can be formalized as*

$$\mathcal{M}, s \models \text{Opportunism}(i, j, a) \quad \Rightarrow \quad V_i \neq V_j.$$

Proof. We prove it by contradiction. We denote $v^* = \text{Mpreferred(i, s, s}\langle\text{a}\rangle)$ *and* $w^* = \text{Mpreferred(j, s, s}\langle\text{a}\rangle)$, *for which* v^* *and* w^* *are the property changes that agent* i *and agent* j *most care about in the state transition. If* $V_i = V_j$, *then* $v^* = w^*$. *However, because* $\mathcal{M}, s \models K_i(\text{promoted}(v^*, i) \wedge \text{demoted}(w^*, j))$, *and thus* $\mathcal{M}, s \models K_i(\neg v^* \wedge w^*)$, *and because knowledge is true, we have* $\mathcal{M}, s \models \neg v^* \wedge w^*$. *But, since* $v^* = w^*$, *we have* $\mathcal{M}, s \models \neg v^* \wedge v^*$. *Contradiction!*

From this proposition we can see that agent i and agent j care about different things based on their value systems about the transition.

Proposition 5.4.3 (Inclusion). *Given a multi-agent system* $\mathcal{M}$ *and opportunistic behavior* a *performed by agent* i *to agent* j *in state* s, *agent* j*'s knowledge set in state* s *is not a subset of agent* i*'s and action* a *is available in agent* i*'s knowledge set:*

$$\mathcal{M}, s \models \text{Opportunism}(i, j, a) \quad \Rightarrow \mathcal{K}(j, s) \not\subseteq \mathcal{K}(i, s) \textit{ and } a \in Ac(i, s).$$

Proof. We can prove it by contradiction. Knowledge set is the set of states that an agent considers as possible in a given actual state. $\forall t \in \mathcal{K}(i, s)$, *agent* i *considers state* t *as a possible state where he is residing. The same with* $\mathcal{K}(j, s)$ *for agent* j. *If* $\mathcal{K}(j, s) \not\subseteq \mathcal{K}(i, s)$ *is false, we have* $\mathcal{K}(j, s) \subseteq \mathcal{K}(i, s)$ *holds, which means that agent* j *knows more than or exactly the same as agent* i. *However, Definition 5.4.2 tells that agent* i *knows more about the transition by action* a *than agent* j. *So* $\mathcal{K}(j, s) \subseteq \mathcal{K}(i, s)$ *is false, meaning that*

$\mathcal{K}(j,s) \nsubseteq \mathcal{K}(i,s)$ holds. Further, because from $\mathcal{M}, s \models \mathrm{Opportunism}(i,j,a)$ we have $\mathcal{M}, s \models K_i(\langle a\rangle v^* \wedge \langle a\rangle \neg w^*)$, by the semantics of $\langle a\rangle v^*$ and $\langle a\rangle \neg w^*$, for all $t \in \mathcal{K}(i,s)$ there exists $(t,a,s') \in R$. Thus, we have $a \in Ac(i,s)$.

These three propositions are three properties that we can derive based on Definition 5.4.2. The first one shows that opportunistic behavior results in value opposition for the agents involved; the second one tells that the two agents involved in the relationship evaluate the transition based on different value systems; the third one indicates the asymmetric knowledge that agent i has for behaving opportunistically.

Example 5.2. *Figure 5.3 shows the example of selling a broken cup: The action selling a cup is denoted as sell and we use two value systems V_s and V_b for the seller and the buyer respectively. State s_1 is the seller's epistemic alternative, while state s_1 and s_2 are the buyer's epistemic alternatives. We also use a dash line circle to represent the buyer's knowledge $\mathcal{K}(b,s_1)$ (not the seller's). In this example, $\mathcal{K}(s,s_1) \subset \mathcal{K}(b,s_1)$. Moreover,*

$$hm = \mathrm{Mpreferred}(\mathrm{s}, \mathrm{s}_1, \mathrm{s}_1\langle \mathrm{sell}\rangle),$$

$$\neg hb = \mathrm{Mpreferred}(\mathrm{b}, \mathrm{s}_1, \mathrm{s}_1\langle \mathrm{sell}\rangle),$$

meaning that the seller only cares about if he gets money from the transition, while the buyer only cares about if he has a broken cup from the transition. We also have

$$\mathcal{M}, s_1 \models K_s(\mathrm{promoted}(hm, sell) \wedge \mathrm{demoted}(\neg hb, sell)),$$

meaning that the seller knows the transition will promote his own value while demote the buyer's value in state s_1. For the buyer, action sell is available in both state s_1 and s_2. However, hb doesn't hold in both $s_1\langle sell\rangle$ and $s_2\langle sell\rangle$, so he doesn't know whether he will have a broken cup or not after action sell is performed. Therefore, there is knowledge asymmetry between the seller and the buyer about the value changes from s_1 to $s_1\langle sell\rangle$. Action sell is potentially opportunistic behavior in state s_1.

5.5 Reasoning about Opportunistic Propensity

In this section, we will characterize the situation where agents will perform opportunistic behavior and the contexts where opportunism is impossible to

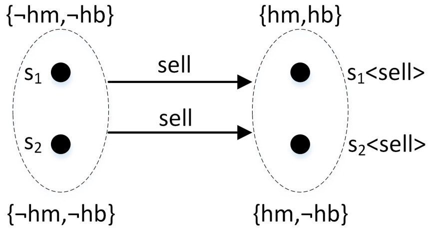


Figure 5.3. Selling a broken cup.

happen.

5.5.1 Having Opportunism

Agents will perform opportunistic behavior when they have the ability and the desire of doing it. The ability of performing opportunistic behavior can be interpreted by its precondition: it can be performed whenever its precondition is fulfilled. Agents have the desire to perform opportunistic behavior whenever it is a rational alternative.

There are also relations between agents' ability and desire of performing an action. As rational agents, firstly we think about what actions we can perform given the limited knowledge we have about the state, and secondly we choose the action that may maximize our utilities based on our partial knowledge. This practical reasoning in decision theory can also be applied to reasoning about opportunistic propensity. Given the asymmetric knowledge an agent has, there are several (possibly opportunistic) actions available to him, and he may choose to perform the action which is a rational alternative to him, regardless of the result for the other agents. Based on this understanding, we have the following theorem, which implies agents' opportunistic propensity:

Theorem 5.5.1. *Given a multi-agent system $\mathcal{M}$, a state s, two agents i and j and an action a, agent i will perform action a to agent j as opportunistic behavior in state s:*

$$\exists a \in a_i^*(s) : \mathcal{M}, s \models \text{Opportunism}(i, j, a)$$

iff

1. $\forall t \in \mathcal{K}(i,s) : \mathcal{M}, t \models \text{promoted}(v^*, a) \wedge \text{demoted}(w^*, a), \ \exists t \in$

$\mathcal{K}(j, s)$: $\mathcal{M}, t \models \neg(\text{promoted}(v^*, a) \wedge \text{demoted}(w^*, a))$, *where* $v^* = \text{Mpreferred(i, s, s}\langle\text{a}\rangle)$ *and* $w^* = \text{Mpreferred(j, s, s}\langle\text{a}\rangle)$*;*

2. $s \prec_i s\langle a \rangle$ *and* $s \succ_j s\langle a \rangle$*.*

3. $\neg\exists a' \in Ac(i, s) : a \neq a'$ *and* a' *dominates* a*.*

Proof. ***Forwards:*** *If action* a *is opportunistic behavior, we can immediately have statement 1 by the definition of Knowledge Set. Because action* a *is in agent* i*'s rational alternatives in state* s *(*$a \in a_i^*(s)$*), by Definition 5.3.6, action* a *is not dominated by any action in* $Ac(i, s)$*. Also because action* a *is opportunistic, by Proposition 5.4.1 it results in promoting agent* i*'s value but demoting agent* j*'s value (*$s \prec_i s\langle a \rangle$ *and* $s \succ_j s\langle a \rangle$*).* ***Backwards:*** *Statement 1 means that there is knowledge asymmetry between agent* i *and agent* j *about the formula* $\text{promoted}(v^*, a) \wedge \text{demoted}(w^*, a)$*. From this we can see the knowledge asymmetry is the precondition of action* a*. If this precondition is satisfied, agent* i *can perform action* a*. Moreover, by statement 2, because action* a *promotes agent* i*'s value but demotes agent* j*'s value, we can conclude that action* a *is opportunistic behavior. By statement 3, because action* a *is not dominated by any action in* $Ac(i, s)$*, it is a rational alternative for agent* i *in state* s *to perform action* a*.*

Given an opportunistic behavior a, in order to predict its performance, we should first check the asymmetric knowledge that agent i has for enabling its performance. Based on agent i's and agent j's value systems, we also check if it is not dominated by any actions in $Ac(i, s)$ and its performance can promote agent i's value but demote agent j's value. It is important to stress that Theorem 5.5.1 never states that an agent will for sure perform opportunistic behavior if the three statements are satisfied. Instead, it shows opportunism is likely to happen because it is in the agent's rational alternatives.

5.5.2 Not Having Opportunism

As Theorem 5.5.1 shows, we need much information about the system to predict opportunism, and it might be difficult to achieve all of them. Fortunately, in some cases it is already sufficient to know that opportunism is impossible to occur. An example might be detecting opportunism: if we already know in which context agents cannot perform opportunistic behavior, there is no need to set up any monitoring mechanisms for opportunism in those contexts. The following propositions characterize the contexts where there is no opportunism:

Proposition 5.5.1. *Given a multi-agent system $\mathcal{M}$, a state s, two agents i and j and an action a,*

$$\mathcal{K}(i,s) = \mathcal{K}(j,s) \Rightarrow \mathcal{M}, s \models \neg\, \mathrm{Opportunism}(i,j,a).$$

Proof. *When $\mathcal{K}(i,s) = \mathcal{K}(j,s)$ holds, which means that both agent i and agent j have the same knowledge. In this context, Statement 1 in Theorem 5.5.1 is not satisfied, so action a is not opportunistic behavior.*

Proposition 5.5.2. *Given a multi-agent system $\mathcal{M}$, a state s, two agents i and j and an action a,*

$$V_i = V_j \Rightarrow \mathcal{M}, s \models \neg\, \mathrm{Opportunism}(i,j,a).$$

Proof. *When $V_i = V_j$ holds, which means that both agent i and agent j have the same value system. In this case, the values of both agents don't go opposite, that is, Statement 2 in Theorem 5.5.1 is not satisfied. So action a is not opportunistic behavior.*

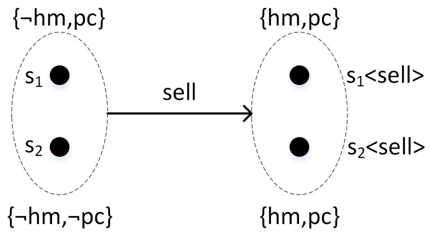


Figure 5.4. Variation of selling a broken cup.

The above two propositions show that opportunism is impossible to occur when there is no knowledge asymmetry between agents and they share the same value systems. After we defined opportunism, we had Proposition 5.4.2 showing that two agents have different value systems as a property of opportunism. Together with Proposition 5.5.1 and Proposition 5.5.2, it looks like once having two different value systems and knowledge asymmetry about the value changes are satisfied one agent will perform opportunistic behavior to the other agent. Now let us go back to the example of selling a broken cup, the buyer's value gets demoted along the state transition, because he wants to have a good cup for use, which he finally doesn't have. Suppose the buyer only cares about appearance in the deal: as we show in Figure 5.4, the buyer knows it is a pretty cup before he buys it, denoted as *pc*, and he gets a pretty cup (probably not for use) after the seller sells it. In this case, the behavior performed by the seller will not be seen as opportunistic behavior. From this variation, we notice that sometimes an action might not be seen as opportunistic behavior even though the agents involved have different value systems, because the two value systems are compatible rather than conflicting. This brings us to the notion of *compatibility*. Intuitively, compatibility describes a state in which two or more things are able to exist or work together in combination without problems or conflict. We then propose the notion of *compatibility of value systems* with respect to a state transition.

Definition 5.5.1 (Compatibility of Value Systems). *Given a multi-agent system $\mathcal{M}$, a state transition (s, a, s') and two value systems V_i and V_j ($V_i \neq V_j$), the two value systems are compatible with respect to transition (s, a, s') if and only if $\mathcal{M}, s \models \neg(\text{promoted}(v^*, a) \wedge \text{demoted}(w^*, a))$, where $v^* = \text{Mpreferred}(\text{i}, \text{s}, \text{s}')$ and $w^* = \text{Mpreferred}(\text{j}, \text{s}, \text{s}')$.*

From this definition we have $s \prec_i s'$ and $s \succ_j s'$ don't hold at the same time, which means that the values of two agents don't go opposite (one gets promoted and the other one gets demoted) along a transition if their value systems are compatible with respect to the transition. Now we can relate the notion of *compatibility of value systems* to predicting opportunism. The following proposition characterize another context where opportunistic behavior will not occur:

Proposition 5.5.3. *Given a multi-agent system $\mathcal{M}$ with a state s, two agents i and j and an action a, if value system V_i and V_j are compatible with respect to (s, a, s'), then*

$$\mathcal{M}, s \models \neg\, \text{Opportunism}(i, j, a).$$

Proof. This proposition holds because two compatible value systems with respect to transition (s, a, s') will not lead to the result that one agent's value get promoted and the other agent's value get demoted ($s \prec_i s'$ and $s \succ_j s'$). By Theorem 5.5.1, it implies that action a will not be opportunistic behavior.

In this section, we specified the situation where agents will perform opportunistic behavior and characterized the contexts where opportunism is impossible to happen. This information is essential not only for the system designers to identify opportunistic propensity, but also for an agent to decide whether to participate in the system given his knowledge about the system and his value system, as his behavior might be regarded as opportunistic.

5.5.3 Computational Complexity

Theorem 5.5.1 shows that whether a given action will be performed by an agent as opportunistic behavior, which gives an insight into checking opportunism in the system. From the perspective of system designers, given a multi-agent system we design, it is important to know whether there exists opportunistic behavior between agents and how difficult it is to check it. In this subsection, we will investigate this issue through proposing an algorithm. The decision problem associated with predicting opportunistic behavior is as follows:

PREDICTING OPPORTUNISM

Given: Multi-agent system $\mathcal{M}$.

Question: Does there exist opportunistic behavior between agents for $\mathcal{M}$?

Theorem 5.5.2. *Given a multi-agent system $\mathcal{M}$, the problem that whether there exists opportunistic behavior between agents for $\mathcal{M}$ can be solved in time $O(nmk^2)$, where n is the number of transitions, m is the maximal number of available actions to a given agent in a given state, and k is the maximal size of S5 class.*

Proof. In order to prove the problem can be solved in time $O(nmk^2)$, we need to find an algorithm that allows us to solve the decision problem with the same computational complexity. We design Algorithm 5.1 for verifying opportunistic behavior in a multi-agent system $\mathcal{M}$ based on Theorem 5.5.1. The algorithm loops through all the possible transitions in the system, which has complexity $O(n)$, where $n = |\mathcal{R}|$. Notice that transitions are executed by hypothetical agents, meaning that the value systems we consider for the transition is assumed to be known once the transition is given. For each transition, it verifies the statements listed in Theorem 5.5.1 one by one. Line 21-24 is to verify whether there is no action a' that dominates action a. Based on the definition of dominance between actions, the algorithm has to perform the comparison $\mathcal{K}(i, s\langle a\rangle)$ with $\mathcal{K}(i, s\langle a'\rangle)$ for all a' in $Ac(i, s)$. If for all $s' \in \mathcal{K}(i, s\langle a\rangle)$ and for all $s'' \in \mathcal{K}(i, s\langle a'\rangle)$ we have $s' \prec s''$, then action a is dominated by action a'. Hence, the complexity of executing line

Algorithm 5.1. Predicting Opportunism.

1: **procedure** HasKnowAsym(S_1, S_2, π, φ) **returns** *true* or *false*
2: set $g_1 \leftarrow true$
3: set $g_2 \leftarrow false$
4: **for** each $s \in S_1$ **do**
5: **if** $\varphi \notin \pi(s)$ **then**
6: set $g_1 \leftarrow false$
7: **break**
8: **for** each $s \in S_2$ **do**
9: **if** $\neg\varphi \in \pi(s)$ **then**
10: set $g_2 \leftarrow true$
11: **break**
12: **return** $g_1 \wedge g_2$
13:
14: **procedure** Predicting($\mathcal{M}$) **returns** *true* or *false*
15: set $flag \leftarrow false$
16: **for** each $(s, a, s\langle a\rangle) \in \mathcal{R}$ **do**
17: set $v^* \leftarrow \mathrm{Mpreferred(i, s, s\langle a\rangle)}$
18: set $w^* \leftarrow \mathrm{Mpreferred(j, s, s\langle a\rangle)}$
19: **if** HasKnowAsym($\mathcal{K}(i, s), \mathcal{K}(j, s), \pi, \mathrm{promoted}(v^*, a) \wedge \mathrm{demoted}(w^*, a)$) **then**
20: **if** $\mathrm{promoted}(v^*, a) \wedge \mathrm{demoted}(w^*, a) \in \pi(s)$ **then**
21: set $h \leftarrow 0$
22: **for** each $a' \in Ac(i, s)$ **do**
23: **if** $a \neq a'$ and $\mathcal{K}(i, s\langle a\rangle) \preceq \mathcal{K}(i, s\langle a'\rangle)$ **then**
24: $h{+}{+}$
25: **if** $h == 0$ **then**
26: set $flag \leftarrow true$
27: **break**
28: **return** $flag$

21-24 is $O(mk^2)$, where $m = |Ac(i, s)|$ and $k = |\mathcal{K}(i, s)|$. The computational complexity of the whole algorithm is $O(nmk^2)$, which implies that Algorithm 5.1 can check whether there exists opportunistic behavior between agents for a given multi-agent system in polynomial-time.

5.6 Discussion

We reason about agents' opportunistic propensity based on decision theory extended with knowledge and value systems, which correspond to some concepts from game theory. In game theory, agents can be situated in a game which is not fully observable, and the notion of information sets is introduced to represent the states that the agent cannot distinguish. In this chapter, we use a similar concept *knowledge set* to represent the set of states that the agent considers as possible. Based on the representation of uncertainty, we use the notion of dominance to compare two different actions: a dominated action is an action that is always bad to perform regardless of the uncertainty about the system, which is an approach bridging to (non-)dominated strategies in game theory. It is thus already seen that we can apply techniques from game theory based on the concept similarities to enrich the existing decision theory and enhance the reasoning capabilities on agents' opportunistic propensity. Further, [Bench-Capon et al., 2012] already pointed out that utility-based decision-mechainsms in game theory cannot represent agents' decision theory in a real way. In this chapter, we follow its idea using values and value systems as the basis for agents' choice, which allows us to better predict opportunism.

Given Definition 5.3.3, agent i only cares about the value change that he most prefers and ignores other value changes for defining his state preference. Hence, if we interprete value promotion as happiness and value demotion as sadness, this approach can be seen as the weight between the agent's happiness and sadness from the states: he prefers state s' rather than state s because his most preferred value gets promoted thus the happiness he gets is more than the sadness for being in state s' instead of state s. When talking about actions, $s \prec_i s\langle a\rangle$ for instance, because among all the value changes agent i's most preferred value gets promoted when going from state s to state $s\langle a\rangle$, we can say that he feels more happy than sad by performing action a (apparently $a \neq sta$) instead of doing nothing. This interpretation is of importance for the design of eliminating mechanism for opportunism: if we want to make it not optimal for an agent to be opportunistic, the sadness he will get from it must be higher than the happiness, which implies that the value change that is most cared about by the agent must be demotion.

Moreover, our approach can be used in practice. For instance, in the electronic market place, only the seller knows that the product is not good for the buyer before he ships it, and he can earn more money if he still claims that the product is good. In this context, if earning money is most important to the seller, he can and wants to perform opportunistic behavior, selling the product, to the buyer according to Theorem 5.5.1. Monitoring and eliminating mechanisms should be put there in order to demotivated such a behavior. However, if we can ensure that both the seller and the buyer are aware of the quality of the product before the seller ships it, meaning that knowledge asymmetry about the transaction is removed, it is impossible for the seller to get benefits from the buyer.

5.7 Chapter Summary

The investigation of opportunism is still new in the area of multi-agent systems. We ultimately aim at designing mechanisms to eliminate such selfish behavior in the system. In order to avoid over-assuming the performance of opportunism so that monitoring and eliminating mechanisms can be put in place, we need to know in which context agents will or are likely to perform opportunistic behavior. In this chapter, we argue that agents will behave opportunistically when they have the ability and the desire of doing it. With this idea, we developed a framework of multi-agent systems to reason about agents' opportunistic propensity without considering normative issues. Agents in the system were assumed to have their own value systems. Based on their value systems and incomplete knowledge about the state, agents chose one of their rational alternatives, which might be opportunistic behavior. With our framework and our definition of opportunism, we characterized the situation where agents will perform opportunistic behavior and the contexts where opportunism is impossible to occur and prove the computational complexity of predicting opportunism. Certainly there are multiple ways to extend our work. One interesting way is to enrich our formalization of value system over different sets of values, and the enrichment might lead to a different notion of the compatibility of value systems and different results about opportunistic propensity. Another way is to consider normative issues in our framework in addition to the ability and the desire of being opportunistic. Most importantly, this chapter set up a basic framework to design eliminating mechanisms for opportunism, which can be seen in the next chapter.

6

Eliminating Opportunism

Opportunism is a behavior that takes advantage of knowledge asymmetry and results in promoting agents' own value and demoting others agents' value. We want to eliminate such a selfish behavior in multi-agent systems, as it has undesirable results for the participating agents. However, as the context we study here is multi-agent systems, system designers actually might not be aware of the value system for each agent thus they have no idea whether an agent will perform opportunistic behavior. Given this fact, this chapter designs two mechanisms for eliminating opportunism given a set of possible value systems for the participating agents: in the epistemic approach an agent's knowledge gets updated so that the other agent is not able to perform opportunistic behavior, and in the normative approach the system is updated with a norm so that it is not optimal for an agent to perform opportunistic behavior.

6.1 Introduction

Opportunistic behavior (or opportunism) is a behavior that takes advantage of relevant knowledge asymmetry and results in promoting an agent's own value and demoting another agent's value. On the one hand, it is common in distributed multi-agent systems that agents possess different knowledge, which enables the performance of opportunism; on the other hand, opportunistic behavior has undesirable results for other agents who participate in the system. Thus, we want to design mechanisms to eliminate opportunism. This chapter investigates two different mechanisms, which allow us to eliminate the performance of opportunism in the system from different perspectives. In our previous chapters, we monitor and predict opportunism given a value system for an agent, i.e., an agent performed and will perform opportunistic behavior if he has the value system as we assume. However, as the context we study here is open multi-agent systems, system designers might not be aware of the value system for each agent before designing any mechanism to eliminate opportunism in the system. The goal of this chapter is thus to design mechanisms to eliminate opportunism given a set of possible value systems of agents, which contains the value systems with opportunistic propensity.

In mechanism design, a mechanism is an institute, procedure, or game for determining outcomes [Maskin, 2008] [Nisan, 2007]. Differently, we in this chapter consider an operation to the system as an indirect mechanism: a revealing update that can eliminate opportunism through updating the knowledge of the agent, and a norm that can eliminate opportunism through changing the environment of the system. More precisely, we argue that agents will perform opportunistic behavior when they have the ability and the desire of doing it in Chapter 5. Based on the idea, the first mechanism we propose is to remove the precondition of opportunism (knowledge asymmetry) by revealing knowledge to agents such that agents will not be able to perform opportunistic behavior, which is called an epistemic approach in this chapter; the second approach we propose is to update the state properties (typically normative properties) such that it is not optimal for agents to perform it, which is called a normative approach in this chapter. For the epistemic approach, since agents' value systems are unknown to the system designer, there might exist privacy norms that prevent agents from having the knowledge for eliminating opportunism. We prove formal properties that allow us to check whether we can eliminate opportunism and respect agents' privacy as well. For the normative approach, we show that the design of the sanction needs to consider all the agents' possible value system profiles in order to demotivate the choice of performing opportunistic behavior.

6.1.1 Chapter Outline

The rest of the chapter is organized as follows:

- Section 6.2 introduces our logical framework, which is a transition system extended with agents' epistemic relations and value systems;
- Section 6.3 defines opportunistic propensity;
- Section 6.4 introduces the types of norms we use in this chapter;
- Section 6.5 and Section 6.6 propose two different mechanisms (epistemic one and normative one) to eliminate opportunism;
- Section 6.7 relates our mechanisms to the theory of mechanism design;
- Section 6.8 compares two mechanisms, highlighting their advantages and disadvantages;
- Section 6.9 summarizes the chapter.

6.2 Framework

In this section, we introduce the model we use for multi-agent systems. A transition system consists of agents, states of the world, actions, agents' epistemic accessibility relations, transitions which go from one state to another by an action, and a valuation function that returns for each state the properties of the environment.

Definition 6.2.1. *Let $\Phi = \{p, q, ...\}$ be a finite set of atomic propositional variables. A transition system over Φ is a tuple $\mathcal{T} = (Agt, S, Act, \pi, \mathcal{K}, \mathcal{R}, s_0)$ where*

- *$Agt = \{1, ..., n\}$ is a finite set of agents;*
- *S is a finite set of states;*
- *Act is a finite set of actions;*
- *$\pi : S \to 2^{\Phi}$ is a valuation function mapping a state to a set of propositions that are considered to hold in that state;*
- *$\mathcal{K} : Agt \to 2^{S \times S}$ is a function mapping an agent in Agt to a reflexive, transitive and symmetric binary relation between states; that is, given an agent i, for all $s \in S$ we have $s\mathcal{K}(i)s$; for all $s, t, u \in S$ $s\mathcal{K}(i)t$ and $t\mathcal{K}(i)u$ imply that $s\mathcal{K}(i)u$; and for all $s, t \in S$ $s\mathcal{K}(i)t$ implies $t\mathcal{K}(i)s$; $s\mathcal{K}(i)s'$ is interpreted as state s' is epistemically accessible from state s for agent i; we also use $\mathcal{K}(i, s) = \{s' \mid s\mathcal{K}(i)s'\}$ to denote the set of agent i's epistemically accessible states from state s;*
- *$\mathcal{R} \subseteq S \times Act \times S$ is a relation between states with actions, which we refer to as the transition relation labeled with an action; we require that for all $s \in S$ there exists an action $a \in Act$ and one state $s' \in S$ such*

that $(s, a, s') \in \mathcal{R}$*, and we ensure this by including a stuttering action* sta *that does not change the state, that is,* $(s, sta, s) \in \mathcal{R}$*; we restrict actions to be deterministic, that is, if* $(s, a, s') \in \mathcal{R}$ *and* $(s, a, s'') \in \mathcal{R}$*, then* $s' = s''$*; since actions are deterministic, sometimes we denote state* s' *as* $s\langle a\rangle$ *for which it holds that* $(s, a, s\langle a\rangle) \in \mathcal{R}$*; we use* $Ac(s) = \{a \mid \exists s' \in S : (s, a, s') \in \mathcal{R}\}$ *to denote the available actions in state* s*;*

- $s_0 \in S$ *denotes the initial state.*

In the interest of simplicity, we only consider one action that takes place at a transition, thus the model is not concurrent.

Now we define the language we use. The language $\mathcal{L}_{\mathrm{KA}}$, propositional logic extended with knowledge and action modalities, is generated by the following grammar:

$$\varphi ::= p \mid \neg\varphi \mid \varphi_1 \vee \varphi_2 \mid K_i\varphi \mid \langle a\rangle\varphi \qquad (i \in Agt, a \in Act)$$

The semantics of $\mathcal{L}_{\mathrm{KA}}$ are defined with respect to the satisfaction relation $\models$. Given a transition system $\mathcal{T}$ and a state s in $\mathcal{T}$, a formula φ of the language can be evaluated as follows:

- $\mathcal{T}, s \models p$ iff $p \in \pi(s)$;
- $\mathcal{T}, s \models \neg\varphi$ iff $\mathcal{T}, s \not\models \varphi$;
- $\mathcal{T}, s \models \varphi_1 \vee \varphi_2$ iff $\mathcal{T}, s \models \varphi_1$ or $\mathcal{T}, s \models \varphi_2$;
- $\mathcal{T}, s \models K_i\varphi$ iff for all t such that $s\mathcal{K}(i)t$, $\mathcal{T}, t \models \varphi$;
- $\mathcal{T}, s \models \langle a\rangle\varphi$ iff there exists s' such that $(s, a, s') \in \mathcal{R}$ and $\mathcal{T}, s' \models \varphi$;

Other classical logic connectives (e.g.,"$\wedge$", "$\rightarrow$") are assumed to be defined as abbreviations by using $\neg$ and $\vee$ in the conventional manner. As standard, we write $\mathcal{T} \models \varphi$ if $\mathcal{T}, s \models \varphi$ for all $s \in S$, and $\models \varphi$ if $\mathcal{T} \models \varphi$ for all multi-agent systems $\mathcal{T}$. Notice that we can also interpret $\langle a\rangle\varphi$ as the ability to achieve φ by action a. Hence, we write $\neg\langle a\rangle\varphi$ to mean not being able to achieve φ by action a. In addition of the $\mathcal{K}$-relation being S5, we also place restrictions of *no-forgetting* and *no-learning* based on Moore's work [Moore, 1980] [Moore, 1984] to simplify our model. It is specified as follows: given a state s in S, if there exists s' such that $s\langle a\rangle\mathcal{K}(i)s'$ holds, then there is a s'' such that $s\mathcal{K}(i)s''$ and $s' = s''\langle a\rangle$ hold; if there exists s' and s'' such that $s\mathcal{K}(i)s'$ and $s'' = s'\langle a\rangle$ hold, then $s\langle a\rangle\mathcal{K}(i)s''$. Following this restriction, we have

$$\models K_i(\langle a\rangle\varphi) \leftrightarrow \langle a\rangle K_i\varphi.$$

In other words, if an agent has knowledge about the effect of an action, he will not forget about it after performing the action; and the agent will not gain extra knowledge about the effect of an action after performing the action.

Apart from the above elements, we need to provide an extension to enable the representation of values from the concept of opportunism. As we did in the previous chapter, we define a value as a $\mathcal{L}_{\mathrm{KA}}$ formula and then a value system as a total order (representing the degree of importance) over a set of values, which means that agents can always compare any two values. In other words, every element in the set of values is comparable to each other and none of them is logically equivalent to each other. One can see similar approaches in [Bulling and Dastani, 2016] and [Ågotnes et al., 2007].

Definition 6.2.2 (Value System). *A value system $V = (\mathrm{Val}, \prec)$ is a tuple consisting of a finite set $\mathrm{Val} = \{v, ..., v'\} \subseteq \mathcal{L}_{\mathrm{KA}}$ of values together with a strict total ordering $\prec$ over* Val. *When $v \prec v'$, we say that value v' is more important than value v as interpreted by value system V. A value system profile $(V_1, V_2, ..., V_{Agt})$ is a tuple containing a value system V_i for each agent i.*

We also use a natural number indexing notation to extract the value of a value system, so if we have the ordering $v \prec v' \prec \dots$ for a value system V, then $V[0] = v$, $V[1] = v'$, and so on. Note that different agents may or may not have different value systems. We now define a multi-agent system as a transition system together with agents' value systems. Formally, a multi-agent system $\mathcal{M}$ is an $(n+1)$-tuple:

$$\mathcal{M} = (\mathcal{T}, V_1, ..., V_n)$$

where $\mathcal{T}$ is a transition system, and for each agent i in $\mathcal{T}$, V_i is a value system.

We now define agents' preferences over two states in terms of values, which will be used for modeling agents' decision making and the effect of opportunism. We first define how a value gets promoted and demoted along a state transition:

Definition 6.2.3 (Value Promotion and Demotion). *Given a value v and an action a, we define the following shorthand formulas:*

$$\begin{aligned} \mathrm{promoted}(v, a) &:= \neg v \wedge \langle a \rangle v \\ \mathrm{demoted}(v, a) &:= v \wedge \langle a \rangle \neg v \end{aligned}$$

We say that a value v is promoted along the state transition (s, a, s') if and only if $s \models \mathrm{promoted}(v, a)$, and we say that v is demoted along this transition if and only if $s \models \mathrm{demoted}(v, a)$.

An agent's value v gets promoted along the state transition (s, a, s') if and only if v doesn't hold in state s and holds in state s'; an agent's value v gets demoted along the state transition (s, a, s') if and only if v holds in state s and doesn't hold in state s'.

We secondly define a function $\mathrm{Mpreferred(i, s, s')}$ that maps a value system and two different states to the most preferred value that changes when going from state s to s' from the perspective of agent i. In other words, it returns the value that the agent most cares about, i.e. the most important change between these states for the agent.

Definition 6.2.4 (Most Preferred Value). *Given a multi-agent system $\mathcal{M}$, an agent i and two states s and s', function $\mathrm{Mpreferred} : Agt \times S \times S \rightarrow \mathrm{Val}$ is defined as follows:*

$$\mathrm{Mpreferred(i, s, s')}_{\mathcal{M}} := \\ V_i[min\{j \mid \forall k > j : \mathcal{M}, s \models V_i[k] \Leftrightarrow \mathcal{M}, s' \models V_i[k]\}]$$

We write $\mathrm{Mpreferred(i, s, s')}$ for short if $\mathcal{M}$ is clear from context.

For example, given agent i's value system $u \prec v \prec w$, if formula $u, \neg v$ and $\neg w$ hold in state s and formula u, v, and $\neg w$ hold in state s', function $\mathrm{Mpreferred(i, s, s')}$ will return v because the most preferred value w remains the same in both states. With this function we can define agents' preference over two states. We use a binary relation "$\precsim$" over states to represent agents' preferences.

Definition 6.2.5 (State Preferences). *Given a multi-agent system $\mathcal{M}$, an agent i and two states s and s', agent i weakly prefers state s' to state s, denoted as $s \precsim_i^{\mathcal{M}} s'$, iff*

$$\mathcal{M}, s \models \mathrm{Mpreferred(i, s, s')} \Rightarrow \mathcal{M}, s' \models \mathrm{Mpreferred(i, s, s')}$$

We write $s \precsim_i s'$ for short if $\mathcal{M}$ is clear from context. As standard, we also define $s \sim_i s'$ to mean $s \precsim_i s'$ and $s' \precsim_i s$, and $s \prec_i s'$ to mean $s \precsim_i s'$ and $s \not\sim_i s'$. Moreover, we write $S \precsim_i S'$ for sets of states S and S' whenever $\forall s \in S, \forall s' \in S' : s \precsim s'$.

The intuitive meaning is that agent i weakly prefers state s' to s if and only if the agent's most preferred value does not get demoted (either stays the same or gets promoted). Using the same example for function *Mpreferred*, given agent i's value system $u \prec v \prec w$, if formula $u, \neg v,$ and $\neg w$ hold in state s and formula $u, v,$ and $\neg w$ hold in state s', what the agent cares about is value u. Since it doesn't hold in state s but holds in state s', agent i will prefer state s' to state s. One can refer to Chapter 5 for further discussion about the definition. Clearly there is a correspondence between state preferences and value promotion or demotion by an action: given a model $\mathcal{M}$ with agent i, state s and available action a in s, and let $v^* = \mathrm{Mpreferred(i, s, s\langle a \rangle)}$,

$$s \prec_i s\langle a \rangle \Leftrightarrow \mathcal{M}, s \models \text{promoted}(v^*, a)$$
$$s \succ_i s\langle a \rangle \Leftrightarrow \mathcal{M}, s \models \text{demoted}(v^*, a)$$
$$s \sim_i s\langle a \rangle \Leftrightarrow \mathcal{M}, s \models \neg(\text{demoted}(v^*, a) \vee \text{promoted}(v^*, a))$$

One can refer to Chapter 5 for the proof. Moreover, the $\precsim_i$ relation is reflexive, transitive and total, which have been proved in our previous chapter. It is possible that agents have different preferences over states, since they may not share the same value system.

Since we have already defined values and value systems as agents' basis for decision making, we can start to apply decision theory to reason about agents' decision-making. Given a state in the system, there are several actions available to an agent, and he has to choose one in order to go to the next state. Before choosing an action to perform, an agent must think about which actions are available to him. We have already seen that, for a given state s, the set of available actions is $Ac(s)$. However, since an agent only has partial knowledge about the state, we argue that the actions that an agent knows to be available is only part of the actions that are physically available to him in a state. For example, an agent can call a person if he knows the phone number of the person; without this knowledge, he is not able to do it, even though he is holding a phone. Recall that the set of states that agent i considers as being the actual state in state s is the set $\mathcal{K}(i, s)$. Given an agent's partial knowledge about a state as a precondition, he knows what actions he can perform in that state, which is the intersection of the sets of actions physically available in the states in this knowledge set.

Definition 6.2.6 (Subjectively Available Actions). *Given an agent i and a state s, agent i's subjectively available actions are the set:*

$$Ac(i, s) = \bigcap_{s' \in \mathcal{K}(i,s)} Ac(s').$$

Because a stuttering action sta is always included in $Ac(s)$ for any state s, we have that $sta \in Ac(i, s)$ for any agent i. When only sta is in $Ac(i, s)$, we say that the agent cannot do anything because of his limited knowledge. Obviously an agent's subjectively available actions are always part of his physically available actions ($Ac(i, s) \subseteq Ac(s)$). Based on agents' rationality assumptions, he will choose an action based on his partial knowledge of the current state and the next state. Given a state s and an action a, an agent considers the next possible states as the set $\mathcal{K}(i, s\langle a\rangle)$. For another action a', the set of possible states is $\mathcal{K}(i, s\langle a'\rangle)$. The question now becomes: How do we compare these two possible set of states? Clearly, when we have $\mathcal{K}(i, s\langle a\rangle) \prec_i \mathcal{K}(i, s\langle a'\rangle)$, meaning that all alternatives of performing action a' are more desirable than all alternatives of choosing action a, it is always better to choose action a'. However, in some cases it might be that some alternatives of action a are better than some alternatives of action a' and vice-versa. In this case, an agent cannot decisively conclude which of the actions is optimal, which implies that the preferences over actions (namely sets of states) is not total. This leads us to the following definition:

Definition 6.2.7 (Rational Alternatives). *Given a state s, an agent i and two actions $a, a' \in Ac(i, s)$, we say that action a is* dominated *by action a' for agent i in state s iff $\mathcal{K}(i, s\langle a\rangle) \prec_i \mathcal{K}(i, s\langle a'\rangle)$. The set of* rational alternatives *for agent i in state s is given by the function $a_i^* : S \to 2^{Act}$, which is defined as follows:*

$$a_i^*(s) = \{a \in Ac(i, s) \mid \neg\exists a' \in Ac(i, s) : a \neq a' \textit{ and } a' \textit{ dominates } a \textit{ for agent } i \textit{ in state } s\}.$$

The set $a_i^*(s)$ are all the actions for agent i in state s which are available to him and are not dominated by another action which is available to him. In other words, it contains all the actions which are rational alternatives for agent i. More discussion can be found in Chapter 5 We can see that the actions that are available to an agent not only depend on the physical state, but also depend on his knowledge about the state and the next state. The more he knows, the better he can judge what his rational alternative is. In other words, an agent tries to make a best choice based on his value system and incomplete knowledge.

6.3 Defining Opportunistic Propensity

An agent will perform opportunistic behavior when he has the ability and the desire of doing it, which is called opportunistic propensity in [Luo et al., 2017]. By intuition, we can eliminate opportunism in the system by removing the ability or the desire. In this section, we will provide the definition of opportunistic propensity. Opportunism is a selfish behavior that takes advantage of relevant knowledge asymmetry and results in promoting one agent's own value and demoting another agent's value. It means that it is performed with the precondition of relevant knowledge asymmetry and the effect of value opposition. Firstly, knowledge asymmetry is defined as follows:

Definition 6.3.1 (Knowledge Asymmetry). *Given two agents i and j, and a formula φ, knowledge asymmetry about φ between agent i and j is the abbreviation:*

$$\text{Knowasym}(i, j, \varphi) := K_i\varphi \wedge \neg K_j\varphi \wedge K_i(\neg K_j\varphi).$$

It holds in a state where agent i knows φ while agent j does not know φ and this is also known by agent i. It can be the other way around for agent i and agent j. But we limit the definition to one case and omit the opposite case for simplicity. Now we can define opportunism as follows:

Definition 6.3.2 (Opportunism Propensity). *Given two agents i and j, the assertion* Opportunism(i, j, a) *that action a performed by agent i is opportunistic behavior is defined as:*

$$\text{Opportunism}(i, j, a) := \\ \text{Knowasym}(i, j, \text{promoted}(v^*, a) \wedge \text{demoted}(w^*, a))$$

where $v^* = \mathrm{Mpreferred(i, s, s\langle a\rangle)}$ *and* $w^* = \mathrm{Mpreferred(j, s, s\langle a\rangle)}$*. We use* OPP$(i, j, s)$ *to denote the set of opportunistic behavior performed by agent i to agent j in state s. That is,*

$$\text{OPP}(i, j, s) = \{a \in Ac(i, s) \mid \mathcal{M}, s \models \text{Opportunism}(i, j, a)\}.$$

This definition shows that if the precondition, Knowasym, is satisfied in a given state then the performance of action a will be opportunistic behavior. As the definition is given with the value systems of agent i and agent j, a value system profile (V_i, V_j) corresponds to one type of opportunistic behavior. The asymmetric knowledge that agent i has is about the change of the truth value of v^* and w^* along the transition by action a, where v^* and w^* are the propositions that agent i and agent j most prefer along the transition respectively. It follows that agent j is partially or completely not aware of it. Definition 6.3.2 follows our definition of opportunism for reasoning about opportunistic propensity of an agent in a state. As is stressed in Chapter 3, opportunistic behavior is performed by intent rather than by accident. In this chapter, instead of explicitly modeling intention, we interpret it from agents' rationality that they always intentionally promote their own values. We can derive a proposition from the definition, which is the effect of opportunism.

Proposition 6.3.1 (Value Opposition). *Given a multi-agent system $\mathcal{M}$ and an opportunistic behavior a performed by agent i to agent j in state s, action a will promote agent i's value but demote agent j's value, which can be formalized as*

$$\mathcal{M}, s \models \text{Opportunism}(i, j, a) \quad \textit{implies} \quad s \prec_i s\langle a\rangle \textit{ and } s \succ_j s\langle a\rangle.$$

Proof. $\mathcal{M}, s \models \text{Opportunism}(i, j, a)$ *implies* $\mathcal{M}, s \models K_i(\text{promoted}(v^*, a) \wedge \text{demoted}(w^*, a))$. *And thus, since all knowledge is true, we have that* $\mathcal{M}, s \models \text{promoted}(v^*, a) \wedge \text{demoted}(w^*, a)$. *Since* $v^* = \text{Mpreferred}(\text{i}, \text{s}, \text{s}\langle\text{a}\rangle)$ *and* $w^* = \text{Mpreferred}(\text{j}, \text{s}, \text{s}\langle\text{a}\rangle)$, *using Definition 6.2.5, we can conclude* $s \prec_i s\langle a\rangle$ *and* $s \succ_j s\langle a\rangle$.

Example 6.1. *We reuse the example in our previous chapters. Figure 6.1 shows the example of selling a broken cup: The action selling a cup is denoted as sell and we use two value systems V_s and V_b for the seller and the buyer respectively. State s_1 is the seller's epistemic alternative, while state s_1 and s_2 are the buyer's epistemic alternatives. We also use a dashed circle to represent the buyer's knowledge $\mathcal{K}(b, s_1)$ (not the seller's). In this example, $\mathcal{K}(s, s_1) \subset \mathcal{K}(b, s_1)$. Moreover,*

$$hm = \text{Mpreferred}(\text{s}, \text{s}_1, \text{s}_1\langle\text{sell}\rangle),$$

$$\neg hb = \text{Mpreferred}(\text{b}, \text{s}_1, \text{s}_1\langle\text{sell}\rangle),$$

meaning that the seller only cares if he gets money from the transition, while the buyer only cares about if he doesn't have a broken cup from the transition. Note that having a broken cup (hb) is not the same as the cup is broken. We also have

$$\mathcal{M}, s_1 \models K_s(\text{promoted}(hm, sell) \wedge \text{demoted}(\neg hb, sell)),$$

meaning that the seller knows the transition will promote his own value while demote the buyer's value in state s_1. For the buyer, action sell is available in both state s_1 and s_2. However, hb doesn't hold in both $s_1\langle sell\rangle$ and $s_2\langle sell\rangle$, so he doesn't know whether he has a broken cup or not after action sell is performed. Therefore, there is knowledge asymmetry between the seller and the buyer about the value changes from s_1 to $s_1\langle sell\rangle$. Action sell is potentially opportunistic behavior in state s_1.

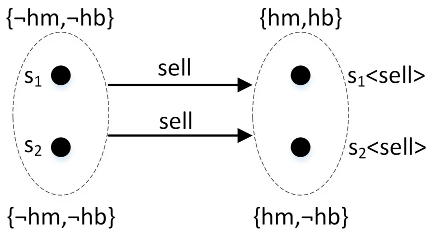


Figure 6.1. Selling a broken cup.

6.4 Norms

Research has shown that we can regulate and eliminate agents' behavior through setting norms in the system [Moses and Tennenholtz, 1995] [Shoham and Tennenholtz, 1992]. Due to the undesirable result of opportunistic behavior, it is valuable to study mechanisms for eliminating opportunism with norms. In Gibbs's influential article, norms are defined as a collective evaluation of behavior in terms of what it ought to be and/or particular reactions to behavior such as sanctions and a particular kind of conduct [Gibbs, 1965]. It means that norms should prescript desirable or undesirable states or actions, and that the enforcement policies can be separated from the specification of norms. We will follow this definition to formalize norms in this chapter.

There are two types of norms we will consider in the following sections. One is called privacy norms that are implemented for respecting agents' privacy. For instance, we wouldn't require the seller to share the original price of the cup to the buyer. Hence, it is about knowledge asymmetry between different agents. It is formalized as follows:

Definition 6.4.1 (Privacy Norms). *Let i and j be two agents, and γ be a formula in $\mathcal{L}_{\text{KA}}$, a privacy norm is in the form of* $\text{Knowasym}(i, j, \gamma)$*, stating that agent i should have privacy about the fact γ from agent j. Given a multi-agent system $\mathcal{M}$ with a state s, we say that privacy norm* $\text{Knowasym}(i, j, \gamma)$ *in state s is respected if $\mathcal{M}, s \models \text{Knowasym}(i, j, \gamma)$, and we use $\Pi(s)_{\mathcal{M}}$ to denote the set of privacy norms that are implemented in state s. We will write $\Pi(s)$ for short if it is clear from context.*

In this chapter, we assume that there are some privacy norms that are supposed to be respected in the system. For instance, privacy norm $\text{Knowasym}(s, b, oprice)$ is interpreted as the seller should have privacy about the original price from the buyer. Privacy norms are state-sensitive in the reveal that a privacy norm can be active in a state while dis-active in another state.

The other type of norms we consider is enforcement norms, which are associated with appropriate sanction to motivate or demotivate a state. We will give a language to construct norms. We first use $\Gamma \subseteq \Phi$ to denote a set of sanction propositions. Given a multi-agent system, we construct the language of norms in the following way:

$$\nu ::= (\varphi, SA) \qquad \text{where } \varphi \in \mathcal{L}_{\text{prop}}, SA \in \mathcal{P}(\Gamma).$$

The intuitive meaning of norms in this form is that whenever the system ends up in a φ-state, it will be updated with set SA that consists of sanction propositions, regardless the action that brings about the φ-state. Note that a sanction not only can be negative for demotivating φ-states, but also can be positive for encouraging φ-states, depending on an agent's preferences with his value system. For example, we can construct a negative norm $(money_s \wedge broken_b, \{fine\})$ to demotivate the state where the seller has money and the buyer has a broken cup with a fine to the seller. This is the only form of norms we consider in this chapter. The reason why we use it in this chapter is because it simplifies our semantics of update logic so that we can focus on the investigation of how to eliminate opportunism with a norm. One can refer to Chapter 4 for the specification of more forms of norms, and [Knobbout et al., 2016b] for the update semantics when actions are explicitly stated in the norm.

There are relationships between the two types of norms. Both of norms prescribe the desirable state of affairs. However, we use them in this chapter for different purposes: the enforcement policies are not stated in the privacy norms, as the issue we want to tackle with privacy norms is whether our revealing update might reveal the information that we want to keep secret through privacy norms, which is irrelevant to enforcement policies (Section 6.5); for enforcement norms, we simplify the prescription of a desirable state of affairs as a formula and state sanctions in the language as enforcement policies, since we want to study how agents' decision to be opportunistic is affected by sanctioning (Section 6.6). Note that, according to the basic schemes of normative implementation, both norms belong to soft constraints that it is possible to violate. The two sections below will investigate mechanisms for eliminating opportunism with the two types of norms in detail.

6.5 Eliminating Opportunism Using an Epistemic Approach

One possible way to eliminate opportunism in the system is to remove the possibility of being opportunistic for agents. Since the precondition of opportunistic behavior is knowledge asymmetry, we can simply prevent the satisfaction of knowledge asymmetry in all states so that it is impossible for agents to perform opportunistic behavior. If we are interested in how the system will behave after updating agents' knowledge, we enter the field of dynamic epistemic logic. Dynamic Epistemic Logic is the study of modal logics of model change by epistemic and doxastic consequences of actions such as public announcements and epistemic actions [Baltag and Renne, 2016] [Van Ditmarsch et al., 2007]. Opportunism can be eliminated through announcing certain information to the agent involved, such that knowledge asymmetry is removed. This requires the system or someone else in the system to be aware of the information that needs to be announced. Since the system is not aware of the value system of each agent but has a finite set of possible value systems for each agent, we argue that it is still practical for the system to reveal the important facts to the agent involved. For example, given two possible value systems of the buyer, namely one that cares about the usage of the cup and the other one that cares about the outlook of the cup, the system can make a 3D scan of the cup and then send it to the buyer, so that the buyer gets valuable information about the transaction to decide whether to buy the cup. The event or the procedure is called a revealing update that is performed by the system and results in updating agents' knowledge, and we want to study how to eliminate opportunism by revealing updates in this section. In this chapter, we denote a revealing update as $\mathrm{reveal}(\varphi)$ that reveals whether or not formula φ is true. Given a multi-agent system, our logical language $\mathcal{L}_{\mathrm{KA}[]}$ is an extension of $\mathcal{L}_{\mathrm{KA}}$ as follows:

$$\varphi ::= p \mid \neg\varphi \mid \varphi_1 \vee \varphi_2 \mid K_i\varphi \mid \langle a\rangle\varphi \mid [\mathrm{reveal}(\varphi)_i]\psi \qquad (i \in Agt, a \in Act)$$

As is standard, formulas with revealing updates are evaluated as follows: given a multi-agent system $\mathcal{M}$ and a state s in $\mathcal{M}$,

- $\mathcal{M}, s \models [\mathrm{reveal}(\varphi)_i]\psi$ iff $\mathcal{M}|\,\mathrm{reveal}(\varphi)_i, s \models \psi$

where $\mathcal{M}|\,\mathrm{reveal}(\varphi)_i = (Agt, S, Act, \pi, \mathcal{K}', \mathcal{R}, s_0, V_1, ..., V_n)$ and $\mathcal{K}'$ is defined as follows:

$$s\mathcal{K}'(i)s' \text{ iff } (s\mathcal{K}(i)s' \text{ and } (\mathcal{M}, s \models \varphi \text{ iff } \mathcal{M}, s' \models \varphi)).$$

The above semantics shows that, after the system performs the revealing update $\mathrm{reveal}(\varphi)$ to agent i, agent i's knowledge about φ gets updated, in the way that the access regarding to the indistinguishability of the truth value of φ is removed while the rest of the model remains unchanged. In other words, if φ is true in state s, the epistemic access of agent i that connects state s with the states where φ is false will be removed; if φ is false in state s, the epistemic access of agent i that connects state s with the states where φ is true will be removed. Notice that, after performing a revealing update, it is always possible to make the system consistent with our *no-learning* and *no-forgetting* restriction by repeatedly removing corresponding epistemic access. As this part of making consistent is not what we want to study in this chapter, we skip its formal definition. We can also see update $\mathrm{reveal}(\varphi)$ as a process of monitoring φ performed by the system for the given agent, distinguishing states which satisfy φ from those which do not satisfy φ. Note that this monitor returns a value from the set $\{\varphi, \neg\varphi\}$, while the monitor we defined in 4 returns a truth value from the set $\{true, false\}$ indicating whether an given formula is detected. Hence, in the rest of the chapter we always discuss two cases where φ holds and doesn't hold in the actual state for any definition and proof. We have the following validity, given a multi-agent system $\mathcal{M}$, a revealing update $\text{reveal}(\varphi)_i$,

$$\mathcal{M} \models \varphi \to [\text{reveal}(\varphi)_i]K_i\varphi,$$

which means that if φ holds then agent i knows φ after φ is revealed. Further, if the system reveals something to an agent that he already knew, the model will remain the same. We formalize it as

$$\text{if } \mathcal{M} \models K_i\varphi, \text{ then } \mathcal{M}|\,\text{reveal}(\varphi)_i = \mathcal{M}.$$

This is because the revealing update will not cause any epistemic access removal from the model.

In this chapter, we want to investigate how to eliminate the performance of opportunism, typically through removing knowledge asymmetry in the system in this section. In order to do that, we firstly introduce the notion *Eliminating Opportunism by a Revealing Update*: we say that a revealing update can eliminate opportunism if and only if the revealing update disables its performance, namely precondition *Knowledge Asymmetry* is removed by the revealing update. Formally,

Definition 6.5.1 (Eliminating Opportunism by a Revealing Update). *Given a multi-agent system $\mathcal{M}$, an opportunistic behavior a performed by agent i to agent j in state s, and a revealing update* $\text{reveal}(\xi)_j$*, we say the revealing update can eliminate opportunistic behavior a iff*

$$\mathcal{M}, s \models [\text{reveal}(\xi)_j]\neg\,\text{Knowasym}(i, j, \text{promoted}(v^*, a) \wedge \text{demoted}(w^*, a)),$$

where $v^* = \text{Mpreferred(i, s, s}\langle\text{a}\rangle)$ *and* $w^* = \text{Mpreferred(j, s, s}\langle\text{a}\rangle)$.

This definition shows how a revealing update eliminates opportunistic behavior: revealing update $\text{reveal}(\xi)_j$ disables the performance of opportunistic behavior a by making knowledge asymmetry false in the new system. Notice that based on the semantics of our framework, action a, which was opportunistic, is still not removed. However, since there is no knowledge asymmetry between agent i and agent j, agent j can prevent agent i from performing opportunistic behavior a, or can still accept it. In the latter case, action a is no longer opportunistic as knowledge asymmetry is false. For instance, *sell* and *buy* are synchronized to be one action. After the system reveals to the buyer that the cup is broken, the buyer will not buy the cup so that the deal cannot be done, or the buyer will still buy the broken cup as it is his only choice, but the latter case is not opportunistic behavior since there is no knowledge asymmetry about the deal. We can immediately have the following proposition, which shows the relationship between revealing updates and asymmetric knowledge:

Proposition 6.5.1. *Given a multi-agent system $\mathcal{M}$, an opportunistic behavior a performed by agent i to agent j in state s and a revealing update* $\mathrm{reveal}(\xi)_j$*, the revealing update can eliminate opportunistic behavior a if*

- *in the case $\mathcal{M}, s \models \xi$, $\mathcal{M} \models K_j(\xi \rightarrow (\mathrm{promoted}(v^*, a) \wedge \mathrm{demoted}(w^*, a)))$,*
- *in the case $\mathcal{M}, s \models \neg\xi$, $\mathcal{M} \models K_j(\neg\xi \rightarrow (\mathrm{promoted}(v^*, a) \wedge \mathrm{demoted}(w^*, a)))$,*

where $v^* = \mathrm{Mpreferred(i, s, s\langle a\rangle)}$ and $w^* = \mathrm{Mpreferred(j, s, s\langle a\rangle)}$.

Proof. In the case where ξ holds in state s, we have $\mathcal{M}, s \models K_j\xi$ after $\mathrm{reveal}(\xi)_j$ *is performed. Because $\mathcal{M} \models K_j(\xi \rightarrow (\mathrm{promoted}(v^*, a) \wedge \mathrm{demoted}(w^*, a)))$ implies $\mathcal{M} \models K_j\xi \rightarrow K_j(\mathrm{promoted}(v^*, a) \wedge \mathrm{demoted}(w^*, a))$, we have $\mathcal{M}, s \models K_j(\mathrm{promoted}(v^*, a) \wedge \mathrm{demoted}(w^*, a))$. Thus, there is no knowledge asymmetry between agent i and agent j about formula* $\mathrm{promoted}(v^*, a) \wedge \mathrm{demoted}(w^*, a)$*. Therefore, according to Definition 6.5.1, revealing update* $\mathrm{reveal}(\xi)_j$ *eliminate opportunistic behavior a. We can prove it in a similar way when $\neg\xi$ holds in state s.*

That is what we can directly derive from the definition of opportunism: to eliminate opportunism by removing the precondition of knowledge asymmetry between different agents. Notice that agent j is not aware of the whole formula $\mathrm{promoted}(v^*, a) \wedge \mathrm{demoted}(w^*, a)$ but might know part of the formula, for example $\mathrm{demoted}(w^*, a)$. In that case, the system needs to reveal ξ to agent j and agent j knows $\xi \rightarrow \mathrm{promoted}(v^*, a)$ or $\neg\xi \rightarrow \mathrm{promoted}(v^*, a)$.

Ideally we can let every agent have exactly the same knowledge such that there is no knowledge asymmetry thus opportunism will never occur. However, it is difficult to implement such an extreme case in reality, because sometimes we would like to design a system that can respect agents' privacy, which is realized through the implementation of privacy norms. However, since the system designer is not aware of agents' value systems thus doesn't know to reveal to agents for eliminating opportunistic behavior, there might exist privacy norms that prevent the system from revealing to agents the information that can eliminate opportunism. Namely, the revealing update performed by the system might reveal the information that the system wants to keep secret through setting a privacy norm. One simple example is that the system wants to reveal φ to an agent for eliminating opportunistic behavior but as is stated in a privacy norm the agent should not be aware of the information about φ. Hence, there exists a balance between respecting of agents' privacy and eliminating of opportunism. In other words, the system can perform revealing updates to agents for eliminating opportunistic behavior but also lower the privacy level in the system. In principle, given a set of possible value system profiles and a privacy norm, the system has to consider every possible value system profile in order to identify an action to be opportunistic, and then think about whether there exists a revealing update that can eliminate opportunistic behavior and respect the privacy norm as well. Since the identification of opportunism has closer relationship with the normative approach we will discuss next section, in this section we assume that opportunistic behavior is given and we will focus on the study about the trade-off between eliminating opportunistic behavior and respecting the privacy norm. Namely, suppose we already identified an action to be opportunistic behavior with a possible value system profile, a question arises:

Research Problem 1. *Given opportunistic behavior and a privacy norm, does there exist a revealing update that can eliminate opportunistic behavior and respect the privacy norm as well?*

Intuitively, an agent gets to know something after something was revealed to the agent, but the revealing update might disrespect another agent's privacy, which is stated by our privacy norms in the system. The following proposition shows that in which case a revealing update respects a privacy norm:

Proposition 6.5.2. *Given a multi-agent system* $\mathcal{M}$ *in a state* s*, a privacy norm* $\mathrm{Knowasym}(i, j, \gamma) \in \Pi(s)$ *with respect to formula* γ*, and a revealing update* $\mathrm{reveal}(\xi)_j$*, the revealing update respects privacy norm* $\mathrm{Knowasym}(i, j, \gamma)$ *if:*

- *in the case* $\mathcal{M}, s \models \xi$, $\mathcal{M}, s \models \neg K_j(\xi \to \gamma)$,
- *in the case* $\mathcal{M}, s \models \neg\xi$, $\mathcal{M}, s \models \neg K_j(\neg\xi \to \gamma)$,

Proof. In order to respect privacy norm $\mathrm{Knowasym}(i, j, \gamma)$*, we have to ensure* $\mathcal{M}, s \models [\mathrm{reveal}(\xi)_j]\neg K_j\gamma$ *so that* $\mathcal{M}, s \models [\mathrm{reveal}(\xi)_j]\,\mathrm{Knowasym}(i, j, \gamma)$

(Definition 6.3.1). In the case where ξ holds, $\mathcal{M}, s \models [\text{reveal}(\xi)_j]K_j\xi$ after the revealing update is performed to agent j. Furthermore, $\mathcal{M}, s \models \neg K_j(\xi \to \gamma)$ implies that there exists $s' \in \mathcal{K}(j,s) : \mathcal{M}, s' \models \neg(\xi \to \gamma)$, which is equivalent to $\mathcal{M}, s' \models \xi \wedge \neg\gamma$. Since agent j's epistemic access which connects $\neg\xi$-state to state s gets removed after the revealing update is performed, state s' where $\xi \wedge \neg\gamma$ holds is still in agent j's knowledge set. In other words, there exists $s' \in \mathcal{K}(j,s) : \mathcal{M}|\,\text{reveal}(\xi)_j, s' \models \xi \wedge \neg\gamma$. Therefore, we can conclude that $\mathcal{M}, s \models [\text{reveal}(\xi)_j]\neg K_j\gamma$ and it leads to $\mathcal{M}, s \models [\text{reveal}(\xi)_j]\,\text{Knowasym}(i,j,\gamma)$. We can prove it in a similar way when $\neg\xi$ holds in state s.

The proposition shows that privacy norm $\text{Knowasym}(i,j,\gamma)$ is respected if agent j is not aware of the inference. Reversely, if the above statement doesn't hold, the revealing update will reveal the information that the system wants to keep in private between agents. From Proposition 6.5.1 and Proposition 6.5.2, we can see our research problem is equivalent to the problem whether there exists a formula ξ such that the formulas from both propositions hold. Therefore,

Proposition 6.5.3. *Given a multi-agent system $\mathcal{M}$ in state s, an opportunistic behavior a performed by agent i to agent j, a privacy norm* $\text{Knowasym}(i,j,\gamma) \in \Pi(s)$ *and a revealing update* $\text{reveal}(\xi)_j$, $\text{reveal}(\xi)_j$ *can eliminate opportunistic behavior a and respect privacy norm* $\text{Knowasym}(i,j,\gamma)$ *if:*

- *in the case $\mathcal{M}, s \models \xi$, $\mathcal{M}, s \models K_j(\xi \to (\text{promoted}(v^*, a) \wedge \text{demoted}(w^*, a))) \wedge \neg K_j(\xi \to \gamma)$,*
- *in the case $\mathcal{M}, s \models \neg\xi$, $\mathcal{M}, s \models K_j(\neg\xi \to (\text{promoted}(v^*, a) \wedge \text{demoted}(w^*, a))) \wedge \neg K_j(\neg\xi \to \gamma)$,*

where $v^* = \text{Mpreferred}(\text{i}, \text{s}, \text{s}\langle\text{a}\rangle)$ and $w^* = \text{Mpreferred}(\text{j}, \text{s}, \text{s}\langle\text{a}\rangle)$.

Proof. The statement is the combination of the statements from Proposition 6.5.1 and Proposition 6.5.2. When agent j is aware of $\xi \to \text{promoted}(v^*, a) \wedge \text{demoted}(w^*, a)$, $\text{reveal}(\xi)_j$ can eliminate opportunistic behavior a; when agent j is not aware of $\xi \to \gamma$, revealing update $\text{reveal}(\xi)_j$ respects privacy norms $\text{Knowasym}(i,j,\gamma)$. Again, we can prove it in a similar way when $\neg\xi$ holds in state s.

Essentially, the above proposition shows the relation among a revealing update, agents' value systems and a privacy norm: if what an agent cares about, which his value system reflects, is not respected by the system through setting corresponding privacy norms in the system, such a revealing update to the agent doesn't exist. In other words, it is dependent on the compatibility between agents' value systems and the privacy norms in the system. For example, for the case where ξ holds, in order to eliminate opportunistic behavior a, the system has to reveal (verify) ξ to agent j, who knows that ξ implies value opposition along the transition. However, if he is also aware of the formula $\xi \to \gamma$, such a revealing update will reveal to agent j the information about γ, which is against the privacy norm. Hence, there is no revealing update that can eliminate opportunistic behavior a and respect the privacy norm with respect to γ as well. Further, sometimes formula $\xi \to \gamma$ is valid in $\mathcal{M}$ thus it becomes universal knowledge in the system. In that case, revealing update $\mathrm{reveal}(\xi)$ will always reveal the information about γ we want to keep in private. Thus, we have to remove privacy norm $\mathrm{Knowasym}(i, j, \gamma)$ so that it is allowed to perform revealing update $\mathrm{reveal}(\xi)$ to eliminate opportunistic behavior a, which can be seen as an alternative normative approach apart from using enforcement policies as in Section 6.6.

Example 6.2. *We again consider the scenario shown in Example 6.1. There is knowledge asymmetry between the seller and the buyer,*

$$\mathrm{Knowasym}(s, b, \mathrm{promoted}(hm, sell) \wedge \mathrm{demoted}(\neg hb, sell)),$$

which is equivalent to

$$\mathrm{Knowasym}(s, b, \neg hm \wedge \langle sell \rangle hm \wedge \neg hb \wedge \langle sell \rangle hb).$$

In this scenario the seller knows the transition will promote his own value while demote the value of the buyer, but the buyer is not aware of the demotion part, as $\langle sell \rangle hb$ doesn't hold in both state s_1 and state s_2. Now the buyer performs revealing update $\mathrm{reveal}(broken)_b$ to check whether the cup is broken or not, and he also knows that his value will get demoted while the buyer's value will get promoted if the cup is broken, that is,

$$\mathcal{M}, s \models K_b(broken \to (\mathrm{promoted}(hm, sell) \wedge \mathrm{demoted}(\neg hb, sell))),$$

which implies

$$\mathcal{M}, s \models K_b broken \to K_b(\mathrm{promoted}(hm, sell) \wedge \mathrm{demoted}(\neg hb, sell)).$$

Since the cup is actually broken ($\mathcal{M}, s \models broken$), the buyer knows the cup is broken after the system performs revealing update $\text{reveal}(broken)_b$ *to him ($\mathcal{M}, s \models K_b broken$) and thus he knows his value will get demoted while the buyer's value will get promoted,*

$$\mathcal{M}, s \models K_b(\text{promoted}(hm, sell) \wedge \text{demoted}(\neg hb, sell)).$$

Therefore, there is no knowledge asymmetry about the transition between the seller and the buyer (shown in Fig. 6.2), which prevents the seller from selling the broken cup to the buyer, according to Definition 6.3.2. Next we suppose a privacy norm $\text{Knowasym}(s, b, oprice)$ *in the system, which means that the seller should keep the original price in private. Since inference $broken \rightarrow oprice$ is not valid in $\mathcal{M}$ intuitively, the buyer is not aware of it,*

$$\mathcal{M}, s \models \neg K_b(broken \rightarrow oprice).$$

Therefore, revealing update $\text{reveal}(broken)_b$ *won't reveal the original price to the buyer and privacy norm* $\text{Knowasym}(s, b, oprice)$ *is still respected in the updated system.*

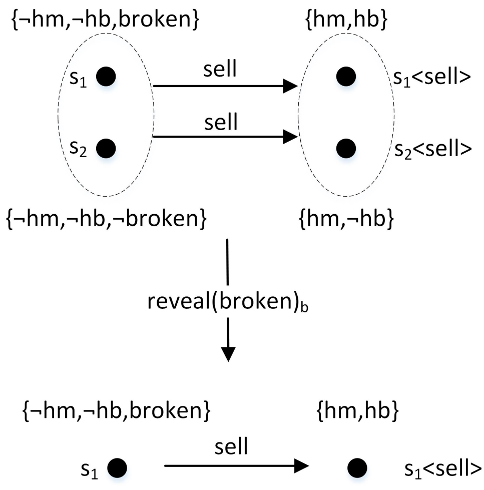


Figure 6.2. Update by revealing update $reveal(broken)_b$.

6.6 Eliminating Opportunism Using a Normative Approach

The first approach we discussed in the previous section is to remove knowledge asymmetry so that it is impossible for agents to perform opportunistic behavior in the system. However, as we mentioned before, sometimes we are supposed to respect agents' privacy in the sense that agents are allowed not to share certain information with other agents, which creates the possibility of opportunism. Instead of finding a balance between respecting of agents' privacy and eliminating opportunism, we may consider another approach that makes it not optimal for agents to perform opportunistic behavior. Namely, the pain or sadness of being opportunistic is more than the happiness or benefits of being opportunistic in order to deter agents from choosing to perform opportunistic behavior.

In Chapter 5, an agent forms his rational alternatives based on his limited knowledge about the current state and his value system without considering any norm. The approach we propose in this section is to eliminate opportunism through adding a norm to the system such that it will direct agents not to be opportunistic. Given the language in which we construct a norm in Section 6.4, we show how to update a multi-agent system using this form of norms, which is inspired by [Knobbout et al., 2016b]. We use $(\mathcal{M}, s)[\nu]$ to denote the updated system. Given a multi-agent system $\mathcal{M}$ in state s and a norm $\nu = (\varphi, SA)$, $(\mathcal{M}, s)[\nu] = (\mathcal{M}[\nu], s[\nu])$ such that:

- $\mathcal{M}[\nu] = (Agt, S, Act, \pi', \mathcal{K}, \mathcal{R}, s_0, V_1, ..., V_n)$, where for every $s \in S$:

$$\pi'(s) = \begin{cases} \pi(s) \cup SA & \text{if } \exists i \in Agt : s \in \mathcal{K}(i, s') \text{ and } \mathcal{M}, s' \models \varphi; \\ \pi(s) & \text{otherwise.} \end{cases}$$

- $s[\nu] = s$.

The semantics show that we only update the state properties while the frame of the system still remains unchanged. In order to implement the norm in the system, we not only update the state where φ is satisfied (the norm is applicable), but also update all the possible states for all the agents in that state. In this way, agents are aware of the norm, which influences their decision making in the new system. That is, if $\mathcal{M}, s \models \varphi$, then for all $i \in Agt, p \in SA$,

$(\mathcal{M}, s)[\nu] \models K_i p.$

Based on our update logic with norms and agents' decision making, we will investigate how norms can eliminate opportunism. Firstly, we need to consider whether an update with norms can change agents' decision making. Regarding the subjectively available actions, since agents' epistemic accessibility structures and the physically available actions in each state remain the same after we update the system with a norm, agents' subjective available actions are not changed by the update. That is, $Ac(i, s) = Ac(i, s[\nu])$. However, agents' rational alternatives are not necessarily the same as before the update. This is because state properties are updated with sanctions, which might lead to the change of agents' state preferences. For example, if $\mathcal{K}(i, s\langle a\rangle[\nu]) \prec_i \mathcal{K}(i, s\langle a'\rangle[\nu])$ doesn't hold after the update, action a is not dominated by action a'. We will eliminate opportunism based on this idea. Like what we did with our epistemic approach, we firstly introduce the notion *Normative Elimination*: we say that a norm can eliminate opportunism if and only if the opportunistic behavior is not in an agent's rational alternatives after the system is updated with the norm. Formally,

Definition 6.6.1 (Eliminating Opportunism by a Norm). *Given an opportunistic behavior a performed by agent i to agent j in state s, and a norm ν, we say that norm ν can eliminate opportunistic behavior a iff*

$$a \notin a_i^*(s[\nu]).$$

It is no longer optimal to perform opportunistic behavior a after the system is updated with norm ν. Following Definition 6.2.7, opportunistic behavior a is not in agent i's rational alternatives whenever it is dominated by another action a'. Notice that the dominating action is not necessarily an rational alternative. Additionally, if norm ν can eliminate opportunistic behavior a, the agent knows that there are at least two different actions available to him, i.e. $|Ac(i, s[\nu])| \geq 2$.

In our previous work, we monitor and predict the performance of opportunism with the given agents' value systems as an assumption. However, since the context we consider here is multi-agent systems, the system designers might not be aware of the preferences of the participating agents. For example, what the seller most cares about in the transaction might be his reputation, not necessarily money. This information must slowly be generated as the

Table 6.1. Eliminating opportunism by norm ν. We use O and N to denote being opportunistic and non-opportunistic respectively with respect to an action and a value system profile. Notation O or N with an underline means that the corresponding action is in agent i's rational alternatives..

	a	a'
(V_i, V_j)	$\underline{\text{O}}$	N
(V_i', V_j')	N	$\underline{\text{O}}$

$\xrightarrow{\nu}$

	a	a'
(V_i, V_j)	O	$\underline{\text{N}}$
(V_i', V_j')	$\underline{\text{N}}$	O

system is executed. The system designer is to design a mechanism given a set of possible an agent's preferences; the agent cannot do better by trying to manipulate the mechanism for its own gain. As we mentioned before, given a set of possible value system profiles, the system has to consider every possible value system profile in order to identify an action to be opportunistic. Once the precondition of knowledge asymmetry is satisfied, an agent is capable to be opportunistic to another agent; but the system designer has no idea which action the agent prefers and whether a given action is opportunistic behavior, as the value systems of both agents are unknown to the system designer (according to Definition 6.3.2). Therefore, the problem becomes:

Research Problem 2. *Given a set of possible value system profiles $\widehat{V}$, can we design a norm ν with appropriate sanction such that for every value system profile $(V_i, V_{-i}) \in \widehat{V}$ norm ν can eliminate opportunistic behavior?*

Based on Definition 6.6.1, norm ν can eliminate an agent's opportunistic behavior if and only if for every value system profile sanction SA removes an action, which was opportunistic behavior in the original system, from the agent's rational alternatives. For example, given two possible value system profiles for agent i and agent j $\{(V_i, V_j), (V_i', V_j')\}$ and two actions a and a' that are subjectively available to agent i, agent i will perform action a, which is opportunistic, with value system profile (V_i, V_j); while agent i will perform action a', which is opportunistic, with value system profile (V_i', V_j'). We need to design a norm ν such that agent i will perform action a', which is non-opportunistic, with value system profile (V_i, V_j), and agent i will perform action a, which is non-opportunistic, with value system profile (V_i', V_j'), as illustrated the table below.

Based on Definition 6.6.1, we can characterize our research problem as follows: given a multi-agent system M with two agents i and j in state s, a set of possible value system profiles $\widehat{V}$, and a norm ν, whether

$$\forall (V_i, V_j) \in \widehat{V} : a \notin a_i^*(s[\nu]).$$

We will use an example to show how a norm with sanction can or cannot eliminate opportunistic behavior.

Example 6.3. *We again discuss the scenario shown in Example 6.1, where the seller only considers state s as possible for simplification. Apart from the notations that were used, we use hr to denote having good reputation from the deal and hp to denote having a pretty cup. The seller knows that he can either sell the broken cup with a normal price (*sell*) or keep it (*keep*). Note that action* keep *is actually stuttering action sta. Suppose the seller has two possible value systems: V_s where $hr \prec hm$, and V_s' where $hm \prec hr$, and the buyer has one possible value system V_b where $hp \prec \neg hb$. Thus, we have the set $\widehat{V} = \{(V_s, V_b), (V_s', V_b)\}$ containing two value system profiles for the seller and the buyer. The problem is that we have no idea which value system the seller has, thus we can only say that it is possible for the seller to sell the broken cup to the buyer without letting him know the cup is broken, which is possibly opportunistic behavior.*

For value system profile (V_s, V_b), the seller will sell the broken cup to the buyer with a normal price and it is regarded as opportunistic behavior, because it most promotes the seller's value (bringing about hm) but demotes the buyer's value (bringing about $\neg hb$). For value system profile (V_s', V_b), the seller will keep the broken cup, because selling a broken cup to the buyer will demote his most preferred value (bringing about $\neg hr$). However, it is interesting to see that the seller will never be opportunistic no matter whether he will perform sell *or* keep*, because action* sell *will bring about $\neg hr$ thus demoting his most preferred value and action* keep *will not lead to value opposition. The above analysis is illustrated through the following figure and table.*

Table 6.2. Buyer's decision-making with different value systems.

	sell	*keep*
(V_s, V_b)	$\underline{\text{O}}$	N
(V_s', V_b)	N	$\underline{\text{N}}$

Next we are going to update the system with norm ν such that action sell

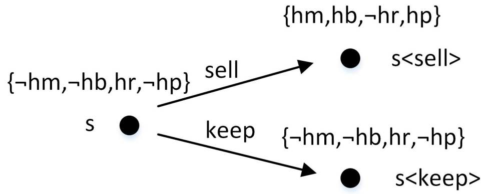


Figure 6.3. System before update.

will be dominated by action keep*, where* $\nu = (hm \wedge hb, \{sanction\})$*, illustrated through the following table:*

Table 6.3. System updated with norm ν. We use O and N to denote being opportunistic and non-opportunistic respectively with respect to an action and a value system profile. Notation O or N with an underline means that the corresponding action is in agent i's rational alternatives..

	sell	*keep*
(V_s, V_b)	$\underline{\text{O}}$	N
(V_s', V_b)	N	$\underline{\text{N}}$

$\xrightarrow{\nu}$

	sell	*keep*
(V_s, V_b)	N	$\underline{\text{N}}$
(V_s', V_b)	N	$\underline{\text{N}}$

Let us first consider value system profile (V_s, V_b)*. Because* $\mathcal{M}, s\langle sell\rangle \models hm \wedge hb$ *and the seller only considers state* $s\langle sell\rangle$ *as possible, state* $s\langle sell\rangle$ *gets updated with set* $\{sanction\}$*. If the seller has value system* V_s*, action* keep *will be dominated by action* sell*, because action* sell *will promote his most preferred value hm. In order to enforce action* keep *in the new system, we can either motivate action* keep *or demotivate action* sell *by norm* ν*. Since we have the restriction that norm* ν *functions directly on opportunistic behavior, we will not consider the latter case. In other words, sanction has to be negative for the seller and thus value* $\neg sanction$ *has to be more preferred by the seller than value hm in all cases, that is, for all* $t \in \mathcal{K}(s, s\langle sell\rangle[\nu])$ *and* $t' \in \mathcal{K}(s, s\langle keep\rangle[\nu]) : \mathcal{M}, t \models \neg sanction$ *and* $\mathcal{M}, t' \models sanction$*, where* $\neg sanction = Mpreferred(s, t, t')$*. Note that in the new system action* sell *is not opportunistic behavior any more, as it will demote the seller's most preferred value if he performs it.*

We now consider value system profile (V_s', V_b)*. If the seller has value sytem* V_s'*, it really doesn't matter whether the seller cares about the sanction or not, because: if* $\neg sanction \prec hr$*, then for all* $t \in \mathcal{K}(s, s\langle sell\rangle[\nu])$

and $t' \in \mathcal{K}(s, s\langle keep\rangle[\nu])$: $\mathcal{M}, t \models hr$ *and* $\mathcal{M}, t' \models \neg hr$*, where* $hr = Mpreferred(s, t, t')$*, which means that the seller still perfers action* keep*. If* $hr \prec \neg sanction$*, then* $\neg sanction = Mpreferred(s, t, t')$*, which is the same as the case where the seller has value system* V_s*. Thus, no matter how big the sanction is for the seller with value system* V_s'*, he will always choose action* keep*, which is not opportunistic behavior before the update.*

In summary, given a set of possible value system profiles, in order to remove action sell *from the seller's rational alternatives, we have to consider the sanction for every possible value system profile.*

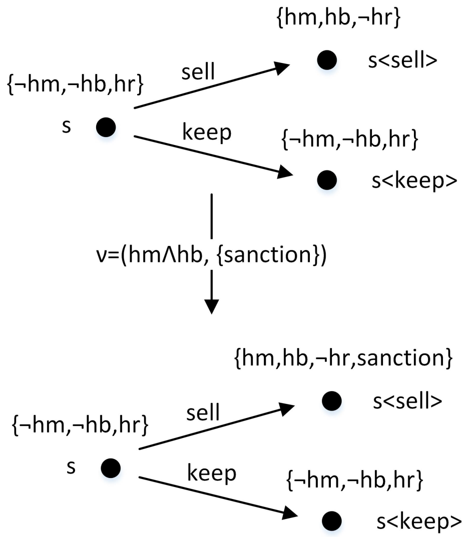


Figure 6.4. Update by norm ν.

6.7 Relation to Mechanism Design

Mechanism design is a field to design a game with desirable properties (outcomes) for various agents to play [Maskin, 2008] [Nisan, 2007]. Given agents' preferences $\precsim$ and an assumed solution concept g that defines agents' way of finding optimal outcomes, we can make a prediction of the outcomes that will be achieved, which is represented as $g(\precsim)$. Given agents' preferences $\precsim$ and a social choice rule f that specifies the criteria of the desirable outcomes, we say that $f(\precsim)$ are the set of social optimal outcome, which are the outcomes we want to have occur. Since agents' preference might be unknown to us, our goal is to design mechanisms such that for all the possible preference $\precsim$ the predicted outcomes $g(\precsim)$ coincide with (or is a subset of) the desirable outcomes $f(\precsim)$ (more elaboration can be found in [Knobbout et al., 2016a]). In this chapter, we take a slightly different view of mechanism design from the traditional one above: we consider a mechanism as an operation or an update to the system, which can be a revealing update or an enforcement norm.When applying the theory of mechanism design to eliminating opportunism, we see agents' rational alternatives as predicted outcomes, opportunistic behaviors as undesirable outcomes, and our goal is to design updates (revealing updates or a norms) to the system such that for all the possible value system profiles the intersection of an agent's *rational alternatives* (using our decision theory) and *opportunistic behaviors* in the new system is empty. In this section, we will discuss how revealing updates and enforcement norms implement non-opportunism respectively.

Given an opportunistic behavior, we know what kind of information the system needs to reveal to an agent for eliminating it. However, if we take into account an agent's decision-making, it can be the case where it is not optimal for the agent to perform such an opportunistic behavior thus it is not necessary to eliminate it. In that sense, we connect revealing updates with rational alternatives as what we did with enforcement norms previously. Hence, the goal of this chapter is to find out an update (a revealing update or an enforcement norm) such that it is not optimal for the agent to behave opportunistically after it is implemented. Given a value system for agent i, we know the set of agent i's rational alternatives $a_i^*(s)$. Given a value system profile for agent i and j, we can identify the set of opportunistic behaviors $\mathrm{OPP}(i,j,s)$ that agent i and j are involved in. We use $a_i^*(s)|\,\mathrm{reveal}(\xi)_j$ ($a_i^*(s)|\nu$) and $\mathrm{OPP}(i,j,s)|\,\mathrm{reveal}(\xi)_j$ ($\mathrm{OPP}(i,j,s)|\nu$) to denote the set of rational alternatives and the set of opportunistic behaviors after $\mathrm{reveal}(\xi)_j$ is performed in state s (norm ν is implemented) respectively. Because opportunistic behavior is undesirable from the perspective of the system and agents form their rational alternatives (possibly opportunistic) based on their value systems, it is important to know whether a revealing update removes opportunistic behavior from the system and whether an normative update removes opportunistic behavior from the rational alternatives. Formally, we define *non-opportunistic implementation* as follows:

Definition 6.7.1 (Non-opportunistic Implementation). *Given a multi-agent system $\mathcal{M}$ with two agents i and j in state s, a revealing update* $\mathrm{reveal}(\xi)_j$ *and a norm ν, we say that revealing update* $\mathrm{reveal}(\xi)_j$ *implements non-opportunism iff* $a_i^*(s)|\,\mathrm{reveal}(\xi)_j \cap \mathrm{OPP}(i,j,s)|\,\mathrm{reveal}(\xi)_j = \varnothing$*, and that norm ν implements non-opportunism iff* $a_i^*(s)|\nu \cap \mathrm{OPP}(i,j,s)|\nu = \varnothing$.

A revealing update or a norm implements non-opportunism if and only if the intersection between rational alternatives and opportunistic behaviors becomes empty after the revealing update is performed or the norm is implemented. Clearly, this concerns the update that they bring to the system. With our update logic of revealing updates and enforcement norms, we can discuss how a revealing update and an enforcement norm influence an agent's decision-making and the identification of opportunistic behavior.

Proposition 6.7.1. *Given a multi-agent system $\mathcal{M}$ with two different agents i and j in state s, and a revealing update* $\mathrm{reveal}(\xi)_j$*, agent i's rational alternatives will remain the same after* $\mathrm{reveal}(\xi)_j$ *is performed in state s, which is formalized as*

$$a_i^*(s) = a_i^*(s)|\,\mathrm{reveal}(\xi)_j.$$

Proof. *Since revealing update* $\mathrm{reveal}(\xi)_j$ *is performed by the system to agent j, agent i's epistemic structure will remain the same after* $\mathrm{reveal}(\xi)_j$ *is performed. Hence, according to Definition 6.2.6 and 6.2.7, agent i's subjectively available actions and rational alternatives will remain the same after* $\mathrm{reveal}(\xi)_j$ *is performed.*

Proposition 6.7.2. *Given a multi-agent system $\mathcal{M}$ with two different agents i and j in state s, and a revealing update* $\mathrm{reveal}(\xi)_j$*, opportunistic behaviors performed by agent i to agent j will not become more after* $\mathrm{reveal}(\xi)_j$ *is performed, which is formalized as*

$$\mathrm{OPP}(i,j,s) \supseteq \mathrm{OPP}(i,j,s)|\,\mathrm{reveal}(\xi)_j.$$

Proof. *Given a value system profile for agent i and j, we can identify the set of opportunistic behaviors* $\mathrm{OPP}(i,j,s)$ *in a state. Because* $\mathrm{reveal}(\xi)_j$ *causes update of agent j' knowledge, knowledge asymmetry will become false after* $\mathrm{reveal}(\xi)_j$*, and thus some actions will become non-opportunistic. Because the system might reveal the information that is not relevant to any opportunistic behavior, it is possible that all the opportunistic behaviors remain unchanged.*

If we limit a revealing update to the one that is performed to agent j, agent i's rational alternatives will remain the same while opportunistic behaviors performed by agent i to agent j will remain the same or become less, after reveal$(\xi)_j$ is performed. Therefore, if a revealing update can eliminate all the actions in the intersection of rational alternatives and opportunistic behavior, it implements non-opportunism. Notice that action a, which was opportunistic behavior, is still in agent i's rational alternatives, but it is not opportunistic any more because knowledge asymmetry regarding opportunistic behavior a is already removed. As for example 6.2, we see that reveal$(broken)_b$ can eliminate opportunistic behavior *sell*. Even though the seller can still sell the broken cup to the buyer, it is not opportunistic behavior any more because the buyer already know that he will have a broken cup. Therefore, we can conclude that given a set of value system profiles $\widehat{V} = \{(V_s, V_b)\}$ sensing action reveal$(broken)_b$ implements non-opportunism. For enforcement norms, they alter both rational alternatives and opportunistic behavior. Since agents' value systems are unknown to us, we need to examine those updates for every possible value system profile in $\widehat{V}$.

6.8 Discussion

We propose two distinct mechanisms, namely epistemic approach and normative approach, to eliminate opportunism in multi-agent systems, which are consistent with our assumption that agents will not perform opportunistic behavior if they don't have the ability or the desire of doing that. Both of them can be considered as updates to the system, and have their own advantages and disadvantages. For the epistemic approach, in order to reveal useful information to agents, the system has to first identify if a given action is opportunistic behavior with a set of value system profiles for the agents involved, and then reveal appropriate information to the agents to eliminate opportunism. Those revealing updates should not be demotivated by the system through setting privacy norms. This indeed puts a burden on the designer before implementing any privacy norms, as agents' value systems are initially unknown to the system designer. For the normative approach, we discussed in Section 6.6 how an enforcement norm with appropriate sanction demotivates the performance of opportunistic behavior for all the value system profiles, ignoring the possibility that such sanction can also make non-opportunism to opportunism. In other words, in order to eliminate opportunistic behavior, it is needed to guarantee the rational alternatives in the updated system are non-opportunistic behavior.

6.9 Chapter Summary

Opportunism is a behavior that takes advantage of relevant knowledge asymmetry and results in promoting an agent's own value and demoting another agent's value. As opportunistic behavior has undesirable results for other agents who participate in the system, we want to design mechanisms to eliminate opportunism. In this chapter we developed two approaches to eliminate opportunism in multi-agent systems. In this first approach, we eliminated opportunism by removing the precondition of opportunism *knowledge asymmetry*, which made the performance of opportunism impossible; in the second approach, we eliminated opportunism by enforcing normative facts, which made the choice of performing opportunistic behavior not optimal. Although both of these approaches involved norms, they are used for different purposes: *knowledge asymmetry* is removed by agents' revealing updates, which might reveal the information that the system wanted to keep private between agents through setting privacy norms. So we investigated the balance between eliminating opportunism and respecting agents' privacy. Enforcement norms with sanction are used to demotivate the choice of performing opportunistic behavior. Since agents' value systems are unknown to us, we investigate the design of sanction given all the possible value system profiles. Finally, we relate our approaches to the theory of mechanism design. An agent performs opportunistic behavior when he has the ability and the desire of doing. We eliminated opportunism by removing the ability in this paper, future work can be done by removing the desire, namely making the choice of being opportunistic not optimal. As there exists trade-off between eliminating opportunism and respecting agents' privacy, it will be interesting to eliminate opportunism through removing privacy norms.

7

Concluding Remarks

In this chapter, we will summarize our work for this thesis, highlighting our contributions from both theoretical and practical perspectives. Besides, we will explore possible venues for future work based on what we have done in this thesis.

7.1 Conclusions

At the beginning of this thesis, we stated our research questions that we needed to answer through the thesis. This section summarizes how our work answers those questions. We investigate opportunistic behavior, which is a concept from social science, with the notion of value in the context of multi-agent systems for different issues. In order to simplify our specification, most of the time we assume that opportunistic behavior contains only one action and happens between two agents. The norms we use for the study of opportunism are enforcement norms that agents in the system are able to obey or violate, and that lead to sanction once they are violated.

Research Question 1 asked whether we could formally define opportunistic behavior in the context of multi-agent systems. We answered this question through Chapter 3. Opportunistic behavior is a selfish behavior that takes advantage of knowledge asymmetry and results in value opposition. We formally defined opportunism using the situation calculus as our technical basis, capturing the features of opportunism: knowledge asymmetry as the precondition, value opposition as the postcondition and intention as the mental state. We then extended the definition to the case with multiple actions and a normative context. Such a formal definition laid a solid foundation for any work we performed in the following chapters.

Research Question 2 asked whether we could develop a mechanism for monitoring opportunism even though the system is not able to see its performance. We answered this question through Chapter 4. We developed a logical framework based on action specification, which allowed us to detect opportunistic behavior with respect to different forms of norms off-line. In this chapter, the system cannot see the performance of opportunistic behavior directly but can detect it through verifying its pre- and post-condition. Moreover, we studied how to reduce the monitoring cost for opportunism.

Research Question 3 asked whether we could develop a framework that allowed us not only to reason about agents' opportunistic propensity but also to design a mechanism for eliminating opportunism. We answered this question through Chapter 5 and Chapter 6. We developed a logical framework where agents were assumed to have their own value systems and incomplete knowledge about the system. In Chapter 5, agents form their rational alternatives, which might be opportunistic, based on their own value systems and incomplete knowledge. We characterized the situation where agents will perform opportunistic behavior and the contexts where opportunism is impossible to occur. Based on the same logical framework, in Chapter 6 we designed two mechanisms to eliminate opportunism in the system. In the epistemic approach, an agent's knowledge got updated so that the other agent was not able to perform opportunistic behavior, and in the normative approach the system was updated with a norm so that it was not optimal for an agent to perform opportunistic behavior. Both mechanisms corresponded to agents' ability and desire of being opportunistic respectively.

This thesis has both theoretical and practical contributions. Theoretically, the topic of opportunism in multi-agent systems is new. We take the initiative to build a formal theory of opportunism in the context of multi-agent systems, setting a foundation of any future work associated with this topic. Besides, we investigate different issues about opportunism. We develop a logical framework to study each issue, which can be seen as a formal specification of multi-agent systems. Practically, using our logical frameworks, we have consistent formal definitions of opportunism and the corresponding properties for the issues we investigate, which allows us to answer the research questions by checking the satisfaction of some formulas in the system. Further, our thesis has applications in real multi-agent systems such as e-commerce systems. The situation of knowledge asymmetry between customers and sellers about transactions leads to the risk of fraud, which bring undesirable results to the customers. Our thesis gives insights into the ways of monitoring, predicting and eliminating them.

7.2 Future Work

This thesis has opportunities for future research that should be noted. Firstly, while most of the time we study opportunistic behavior that contains one action, it is possible that opportunistic behavior contains multiple actions as we defined in Chapter 3. For monitoring opportunistic behavior with multiple actions, since we have already proved that a sequence of actions is opportunistic while an action within might not be opportunistic, it is important for the system to decide how many actions we evaluate as a whole to be opportunistic. For predicting opportunistic behavior with multiple actions, agents' decision making is done for a sequence of actions. In other words, agents maximize total reward over a finite number of steps, which altogether are considered as opportunistic behavior.

Secondly, it might be interesting to study opportunism with responsibility since there is a strong connection between these two notions. Intuitively, opportunistic agents are responsible for the undesirable result that they bring to other agents, because they are the ones who are aware of the situation of knowledge asymmetry. In this thesis, atomic actions are not labeled with agents. In order to reason about responsibility for opportunism, we need to know whether an action is actually performed by agent i in order to know whether this is opportunistic behavior of agent i. Therefore, our framework can be extended with responsibility to identify which agent is responsible for which action.

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Summary

Opportunistic behavior (or opportunism) is a selfish behavior that intentionally takes advantage of relevant knowledge asymmetry to achieve own gain, regardless of other agents' value. It is commonly existing in business transactions and social interactions in the form of cheating, lying, betrayal, etc, thereby gaining much attention and investigation from social science. In multi-agent systems, it is normal that knowledge is distributed among different agents, which creates the opportunity for agents to perform opportunistic behavior to other agents. Since opportunistic behavior has undesirable results for other agents in the system, the aim of this thesis is to eliminate such a selfish behavior from the system. In order to reach this goal, we perform the investigation of opportunism with the notion of values for different issues in the context of multi-agent systems. Logical specification is used for our investigation in order to prove useful properties with respect to the issue.

Based on our understanding of the concept of opportunism in social science, we first provide a formal definition of opportunism using the situation calculus, capturing the features of opportunism: knowledge asymmetry as the precondition, intention as the mental state and value opposition as the postcondition. We then extend the definition to the case where opportunistic behavior contains multiple actions and is situated in a context with norms. Such a formal definition of opportunism sets a theoretical foundation for any later research about opportunism. Because opportunistic behavior has undesirable results for other agents in the system but cannot be observed directly, there has to be a monitoring mechanism that can detect the performance of opportunistic behavior. We secondly provide a logical framework to specify monitoring approaches for opportunism. We investigate how to evaluate agents' actions to be opportunistic with respect to different forms of norms when those actions cannot be observed directly, and study how to reduce the monitoring cost for opportunism. In order for monitoring and eliminating mechanisms to be put in place, it is important to know in which context agents will or are likely to

perform opportunistic behavior. Therefore, we develop a logical framework to reason about agents' opportunistic propensity. Opportunistic propensity refers to the potential for an agent to perform opportunistic behavior. We argue that agents will perform opportunistic behavior when they have the ability and the desire of doing that. With this premise, agents in the system are assumed to have their own value systems and knowledge. Based on their value systems and incomplete knowledge about the state, they choose one of their rational alternatives, which might be opportunistic behavior. We then characterize the situation where agents will perform opportunistic behavior and the contexts where opportunism is impossible to occur. Finally, we reach our goal through designing two mechanisms for eliminating opportunism: in the epistemic approach an agent's knowledge gets updated so that the other agent is not able to perform opportunistic behavior, and in the normative approach the system is updated with a norm so that it is not optimal for an agent to perform opportunistic behavior. Both approaches corresponding to agents' ability and desire of being opportunistic respectively.

We take the initiative to build a formal theory of opportunism in the context of multi-agent systems, setting a foundation of any future work associated with this topic. Our research also has applications in real multi-agent systems such as e-commerce systems, giving insights into the ways of monitoring, predicting and eliminating opportunistic behavior in real life. Future work can be done for opportunism with multiple actions and responsibility.

Samenvatting

Opportunistisch gedrag (oftewel opportunisme) is egoïstisch gedrag waarmee intentioneel geprofiteerd wordt van kennis asymmetrie voor eigen gewin, ongeacht de waardes van andere agenten. Omdat het voorkomt in bedrijfstransacties en sociale interacties in de vorm van bedriegen, liegen, misleiden en andere vormen, krijgt dit onderwerp veel aandacht in onderzoek binnen de sociale wetenschappen. In multi-agent systemen is het normaal dat kennis gedistribueerd is onder de verschillende agenten, wat de mogelijkheid creëert voor agenten om opportunistisch gedrag te verrichten jegens andere agenten. Omdat opportunisme ongewenste resultaten oplevert voor de andere agenten in het systeem, is het hoofddoel van deze thesis om zulk egoïstisch gedrag te elimineren uit het systeem. Om dit doel te bereiken onderzoeken we opportunisme aan de hand van waardesystemen in de context van een multi-agent systeem. Om nuttige eigenschappen te bewijzen met betrekking tot opportunisme gebruiken we in ons onderzoek logica.

Op basis van het sociaalwetenschappelijke begrip van opportuinisme leveren we eerst een formele definitie van opportunisme door gebruik te maken van het formalisme dat bekend staat als de 'situation calculus'. Dit stelt ons in staat om verscheidende facetten van opportunisme te vangen: kennis asymmetrie als de pre-conditie, intentie als de mentale toestand en waardetegenstelling als de post-conditie. Vervolgens breiden we deze definitie uit naar gevallen waarbij opportunistisch gedrag bestaat uit verschillende handelingen en gevallen waarbij het gedrag plaatsvindt in de context van bepaalde normen. Deze formele definitie van opportunisme zet het theoretische fundament voor later onderzoek naar opportunisme. Omdat opportunistisch gedrag ongewenste resultaten oplevert voor andere agenten in het systeem maar niet rechtstreeks geobserveerd kan worden, moet er een monitorend mechanisme ingezet worden dat opportunistisch gedrag kan waarnemen. We ontwikkelen een logisch raamwerk voor dit soort monitorende aanpakken van opportunisme. We onderzoeken hoe we de handelingen van agenten kunnen evalueren als zijnde opportunistisch met betrekking tot verschillende vormen van normen wanneer deze handelingen niet rechtstreeks geobserveerd kunnen worden, en we bestuderen hoe we de kosten van monitoren kunnen beperken. Om monitorende mechanismen in te zetten is het belangrijk om te weten in welke contexten agenten vermoedelijk opportunistisch gedrag zullen uitvoeren. Om dit voor elkaar te krijgen ontwikkelen we een logisch raamwerk om te redeneren over de neiging tot opportunisme bij agenten. De neiging tot opportunisme hangt samen met het vermogen van een agent om opportunistisch gedrag uit te voeren. We betogen dat agenten opportunistisch gedrag zullen vertonen wanneer ze de mogelijkheid en het verlangen hebben om dit te doen. Voor dit uitgangspunt is het van belang dat agenten in het systeem ieders een onafhankelijk en persoonlijk systeem van waarden en kennis hebben. Gebaseerd op hun systeem van waardes en incomplete kennis over een toestand kiezen ze een van hun rationele alternatieven, wat mogelijk opportunistisch gedrag kan zijn. Vervolgens karakteriseren we de situatie waarin agenten opportunistisch gedrag zullen uitvoeren en de contexten waarin opportunisme uitgesloten is. Tenslotte bereiken we ons eerder gestelde doel door twee mechanismen te ontwikkelen die opportunisme elimineren: in de Epistemische aanpak wordt de kennis van een agent geüpdatet op een manier zodat de andere agenten niet in staat zijn om opportunistisch gedrag uit te voeren, en in de normatieve aanpak wordt het systeem geüpdatet met een norm zodanig dat het niet meer optimaal is voor een agent om opportunistisch gedrag uit te voeren. Deze aanpakken corresponderen respectievelijk met het vermogen en verlangen van de agent om opportunistisch te zijn.

Wij nemen het initiatief om een formeel raamwerk voor opportunisme te ontwikkelen in de context van multi-agent systemen. Hiermee zetten we het fundament voor toekomstig onderzoek naar dit onderwerp. Ons onderzoek heeft ook toepassingen in alledaagse multi-agent systemen, zoals e-commerce systemen, en levert daarmee inzicht in manieren om opportunisme in de werkelijkheid te monitoren, voorspellen en te elimineren. In opvolgend onderzoek kan er gekeken worden naar opportunisme met meerdere handelingen en verantwoordelijkheid.

Curriculum Vitae

Work Experience

2017 - Current	Post-doc researcher at CWI
	(Group: Intelligent and Autonomous Systems)
	I am currently working on a project which investigates the complex interplay between the dynamics and the network topology of complex systems. Typically for Boolean networks, I would like to develop a logical model that allows us to reason about update functions when they are uncertain without actually running the whole network.
2013 - 2018	PhD researcher at Utrecht University
	(Group: Intelligent Systems)
	My PhD project investigates opportunistic behavior in multi-agent systems using formal logic-based approaches. Since opportunistic behavior has undesirable results for other agents in the system, this project aims to design mechanisms to eliminate opportunism.

Education

2010 - 2013	Msc. Degree at Jinan University, China
	Major: Management Science and Engineering
2006 - 2010	Bsc. Degree at Jinan University, China
	Major: Information Management and Information Systems

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