

Towards Convention-Based Game Strategies

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Abstract. For the effective development of cooperative multiagent systems, we introduce an architecture that facilitates the agents’ dynamic adoption of conventions. It expands an existing agent model’s action selection architecture with a component that uses Natural Language Processing techniques. This component embeds conventions into agent interaction strategies to improve the predictability of other agents’ actions if all agents adopt the same conventions in their strategies.

Keywords: Norm extraction · Multiagent systems · Cooperative AI.

1 Introduction

Conventions can be defined as recurrent behaviour patterns of human communities [2] that increase the predictability of interaction outcomes. In an AI context, conventions can coordinate agents’ actions in multiagent systems and simplify the agents’ decision-making machinery. In general, not all agents are necessarily willing or capable of adhering to the same conventions. However, in a cooperative multiagent system, we may assume that the agents will accept to adhere to the same conventions to improve their collective performance.

In the literature, different terms are used to refer to these patterns of agent behaviour, often used to determine whether a certain action is “correct”, and that sometimes represent customary behaviour in a society. The term *convention* is often related to patterns that result from an agreement among members of a given community or culture. The term *norm* is often related to legal aspects of behaviour and frequently contains rewards or sanctions. The general term *rule of behaviour* is also commonly used. In this paper, we will use the term *convention*, but our proposal could be applied to norms or rules, as they all share the same basic structure.

Previous research has demonstrated that conventions can considerably enhance a multiagent system’s overall performance. Conventions may have either an external or an internal origin. Machine learning methods, such as Reinforcement Learning, have been used to identify particular agents’ communication patterns as *intrinsic* conventions [13, 17, 19, 33]. *Extrinsic* human social conventions are quite often imposed over human communities or multiagent systems

[16, 20, 21, 36]³. Conventions are frequently hand-coded in those previous works, which represents a costly effort for engineers. Any modification to the system’s conventions often requires manual checks of their soundness. To our knowledge, no attempt has been made to develop automatic techniques to embed conventions into a system. In this paper, we introduce an architecture based upon [27] primarily concerned with processing natural language conventions. We believe it will facilitate the creation of convention-based multiagent systems and give users a degree of control over multiagent behaviour. To illustrate the components of the architecture, we will use the board game Hanabi. Nonetheless, we will also attempt to present the architecture, particularly the NLP component, in as general terms as possible. Our vision is to “program” agents by *declaring* in natural language the game rules and the strategic behaviour that the agent should show.

In short, the contributions of this paper are: 1) to propose a generalisation of the decision-making component of an existing architecture [27], 2) to discuss the use of an NLP pipeline for norm extraction, and 3) to explore the combination of ontologies and convention patterns to formally represent conventions. This paper is divided into four sections. Section 2 describes the research problem and our focus, Section 3 introduces the relevant background knowledge, Section 4 presents our preliminary proposal for the architecture, and Section 5 discusses future work. This paper is submitted as a short paper presenting ongoing work.

2 Problem

Our research objective is to study “how agents adapt their strategies to conventions in a cooperative multiagent system.” To achieve this objective we need to design an architecture with the following aspects/requirements.

2.1 Conventions

Conventions are normally expressed in natural language and can be represented in a logical formalism [9, 14, 15]. Although conventions often lack the sanctioning aspect of (legal) norms, their structure is similar: both impose constraints on human or agent behaviour [1]. Thus, in our architecture, we focus on using NLP techniques for *norm extraction* (see Section 3.1) to process the conventions. We aim at automatically translating natural language conventions into a machine-readable representation for our agent model. Section 4.1 will outline this mechanism.

³ Some of these works focus on *policies* rather than conventions. These two concepts are similar, although policies sometimes have a more probabilistic flavour: there is the option that an agent probabilistically chooses an alternative to the action recommended by the policy when *exploring* the space.

2.2 Knowledge Representation

Agents must have a *model of the environment* to observe the actions of others and their consequences. In order to achieve their common goal, agents must also be able to understand, that is, find explanations for, the actions made by other agents. Hence, our agent model must include some *Theory of Mind* (ToM) representation [27] (see Section 3.2).

2.3 Reasoning

The architecture of [27] includes a component to determine the agent’s next action. This component contains a set of conventions to select an action from among several possibilities. We follow the same path in our architecture with some adaptations (see Section 4.4). For instance, decision rules in [27] contain priorities expressed with natural numbers. The higher the number the higher the priority. Since [27] only shows examples requiring a few simple conventions, it is enough to make them hand-coded. However, for larger sets of conventions, possibly more complex, we will require (semi-)automated approaches for priority determination.

2.4 Testbed: Hanabi

Hanabi is a cooperative board game for two to five players that will serve as an illustrative example for this paper. The goal of the game is to build card stacks in a specific order. There are five distinct colour stacks, each containing up to five cards that must be played in order from 1 to 5; the more cards correctly played, the better the final score. The players cannot view their own cards, only those of their fellow players. The game actions are: providing a hint on a card held by another player (so-called “clue a card”, saying its colour or number), discarding a card, and playing a card. There is a series of conventions that complement these rules. For instance, H-Group Conventions⁴ are conventions organised and published by Hanabi players, Table 1 shows some of them. This paper will mainly use the two conventions labelled as “Chop” in Table 1 as examples. See next an illustration of the use of a convention.

Example: Alice has no clued cards, while Bob has cards in the first, third and fifth slots clued. Considering only the game rules, players could play or discard any card. However, when following the “Chop” conventions, Alice *should* discard her *chop* card in her fifth slot, and Bob should discard the card in his fourth slot.

3 Background

3.1 Norm Extraction

This paper’s primary focus is on conventions. Hence, how to process conventions is the critical part of the architecture we want to discuss in detail in this paper.

⁴ <https://hanabi.github.io>

Table 1. Some conventions extracted from the H-Group Conventions.

Labels	Conventions
Chop	The right-most unclued card in a player’s hand is called their “chop” card. When a player needs to discard, they should discard their chop card.
Types of Clues	Players are only allowed to give two types of clues: a Play Clue (meaning to play the focused card) and a Save Clue (meaning to save the focused card for later).
Play Clues	Play Clues can be given with either a colour clue or a number clue.
Save Clues	Save Clues can only be given to chop cards.

We will adapt existing state-of-the-art norm extraction techniques. Norm extraction is a sub-task of natural language processing that involves recognising and extracting norm structures from natural language text using (semi-)automatic approaches. Most past research has been conducted in the context of norm extraction from legal documents. Even though the definitions of norms and conventions are slightly different, from an NLP perspective the differences are such that we can apply legal norm extraction techniques to conventions. However, we are well aware that certain procedures were developed to address specific concerns of legal norms that may not be needed to process conventions. Unlike legal texts, the structure and semantics of conventions, particularly those for Hanabi, can be pretty simple and limited.

The evaluation of recent norm extraction techniques and a general overview was provided in [12]. Norm extraction, like other NLP tasks, usually begins with text preprocessing. Several existing NLP toolkits and pipelines (e.g. NLTK⁵, or Stanza⁶) provide automated preprocessing techniques, including tokenisation, removal of stop words and punctuation, and lemmatisation. In addition, some particular syntactic structures of the input text need to be modified, such as lists of items with enumerations, colons and numerous references which contains punctuation and alpha-numeric characters (very common in legal texts), to avoid failure of the sentence processing [39]. After this preprocessing, subsequent steps consist of parsing and/or tagging, the standard techniques in NLP. Some studies applied pre-trained general parsers, such as the Stanford parser⁷ [10, 34, 39], or the Berkeley parser⁸ [34]. Based on various grammar systems, parsers generate the grammar tree structure of the sentence over words (dependency) or phrases (constituency). Tagging, on the other hand, is the annotation process that can attach syntactic, semantic, or logical features to words. The tagging and parsing processes can be performed simultaneously by the same tool or alternatively, by tagging before parsing. For instance, we can automatically annotate words with part-of-speech (POS) tags before the parsing process starts. Some specific anno-

⁵ <https://www.nltk.org>⁶ <https://stanfordnlp.github.io/stanza/index.html>⁷ <https://nlp.stanford.edu/software/lex-parser.shtml>⁸ <https://github.com/slavpetrov/berkeleyparser>

tations, such as deontic information of legal norms can only be done manually. Additional knowledge sources, such as Word Net [10] and Wikipedia [22, 30], were explored to supplement the semantic representation. In [34], the method was more sophisticated, containing a task-specific dictionary and vectorisation of sentences. Once obtained a collection of annotated data, norms can be incorporated into an AI system through machine learning or symbolic methodologies. One example is using the tax code as training data for a complicated multi-layer convolutional neural network (CNN) to classify sentences into several deontic categories [26]. Symbolic applications include NL2KR [14], and the Candc and Boxer tool chain [10]. Although their processes are not identical, their primary goal is to produce formal representations of input sentences adopting Combinatory Categorical Grammar (CCG). However, neither tool is maintained, so users should anticipate compatibility issues when applying them. As for the evaluation, although [12] created the gold standard for semantic parsing in the legal domain, the size of this test set is limited. Like the other test sets for legal norm extraction, they have to be annotated by experts. For metrics, recall, precision, and accuracy were commonly used [6, 11, 29, 34].

3.2 Theory of Mind

Theory of Mind (ToM) is an ability acquired through social interaction. To comprehend the actions of others, humans need to create models of the beliefs of others. This ability can be further nested. For instance, not just the beliefs that agent i holds about the beliefs of j , but also the beliefs that agent i holds about the beliefs of j about the beliefs of k and so on. The former example is a first-order ToM statement, and the latter a second-order ToM statement. Although a higher order implies a deeper degree of comprehension, the rise in complexity will usually offset any gains [37, 38], so it is vital to consider and control the depth. [27] offers a thorough introduction to the previous research. Our agents require this capacity to predict the actions of others and act upon that prediction.

3.3 Hanabi

Hanabi has been proposed as a challenging game⁹ to explore the limits of machine learning or rule-based systems [7, 18, 24, 33, 35, 36]. For example, a new game-play setting named *other-play* [35] (implemented from [19]), or an adversarial mechanism to self-play [36]. In these works, the agents either followed *different* conventions or played with human players. We do not discuss them in this article since, as stated previously, we focus our work on agents that play together and adhere to the same conventions. Thus, there is no need to address potential convention conflicts.

⁹ A detailed literature review is provided by [4].

4 Architecture

The complete architecture we propose is illustrated in Figure 1. [27] serves as the inspiration. In our approach, a cooperative agent receives as input: information about the environment, messages from other agents, and a list of conventions to be followed when making decisions. A series of modules process the input so the action selection component can determine the action to take. These modules are divided into two blocks: “NLP” and “Agent Decision-making”. The next subsections describe the modules in detail.

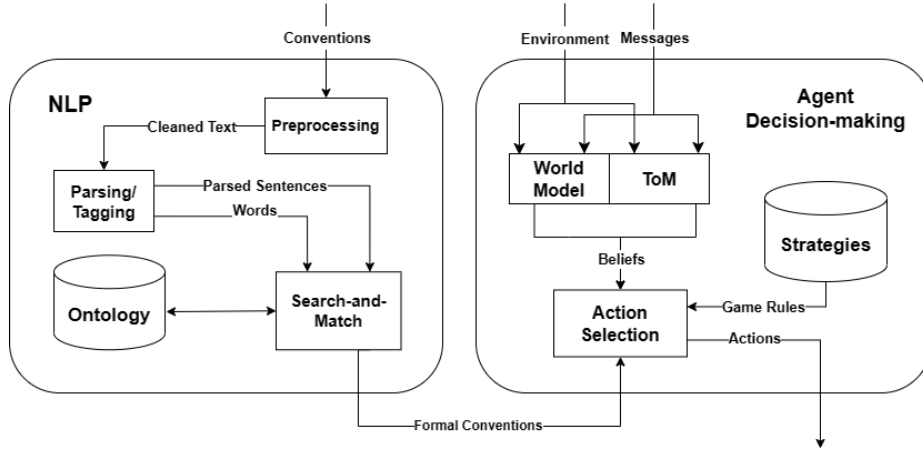


Fig. 1. The architecture for an agent in the convention-based cooperative multiagent system. Note that the “NLP” block works offline, which means that the processing will be done only once and before the agent decision-making process takes place.

In the “NLP” block, we find the modules that constitute the pipeline for processing natural language conventions and generating their formal representations. In the “Agent Decision-making” block, there are modules concerned with the knowledge the agent has of the world (World Model) and the module building explanations for the actions of others (Theory of Mind — ToM). These two modules contain the agent’s beliefs and methods to update them.

4.1 NLP

The “NLP” block’s goal is to translate natural language conventions into a machine-readable formalism so that the agent can adapt its strategies. As stated in Section 3.1, adapting an off-the-shelf translation system is not feasible as all previous systems we are aware of are not maintained anymore [10, 14]. Therefore, we must adapt some of the methods and ideas of these systems to develop our own processing pipeline. This pipeline includes a preprocessing step, a parser

(with a tagging/annotating step), a database for ontologies, and a novel algorithm that generates the formal representation of conventions.

The “Preprocessing” module, as discussed in 3.1, will contain the techniques that must be applied for a general norm extraction task. Note that, for instance, H-Group Conventions are published in HTML format, so for having those conventions as input, the text needs to be extracted from the HTML code. We can either manually extract them, or apply existing web content extraction tools such as GOOSE¹⁰, which was reported with the best performance for English newspaper text [3]¹¹.

In the “Parsing/Tagging” module, existing parsers like Stanford Parser can be used to retrieve the semantic and syntactic features from the conventions. We can assume that the parsing output will neither contain a vast vocabulary nor a complex sentence structure. The terms in the conventions will thus refer to the limited ontology of a particular domain, e.g. cards, colours, or numbers in Hanabi, so the vocabulary is naturally small. Similarly, conventions are relatively plain rules to be understandable by the public, e.g. conventions in Table 1. Differently from legal norms the conventions we aim at are thus very simple. Given this overall simplicity, we consider that first-order logic is expressive enough to formalise conventions. More concretely, [28] proposed a representation language called “Agent Situation Language” (ASL) used to represent the rules of games. We will explore the use of this language, or an extension of it, to represent conventions, as conventions have a similar expressive power to game rules. We might explore using Jason as the interpreter of ASL since ASL is similar to Agentspeak [31], a programming language used to represent some Hanabi conventions in [27].

“Ontology” is a ontology database, which works closely with the “Search-and-Match” module for formal conventions’ generation. A simpler mechanism of “Search-and-Match” would be to just analyse the frequent words from the input and their semantic and syntactic features, which need no ontology. For example, when considering the tokens extracted from a convention, the verb phrases (VP) are naturally mapped into predicates, and noun phrases (NP) are naturally mapped into predicate arguments. Therefore, a simple rule can be: from a sentence $S = NP\ V\ ADJ$ generate $V(NP, ADJ)$. For instance, from “The card colour is red” we obtain the predicate instance `is(card_colour, red)`. However, ontologies are much richer structures that allow to represent complex knowledge within a particular domain [5, 8, 25]. Thus, if there is an existing ontology in the particular domain of the conventions or a reference ontology, we can use it to determine the meaning of the words¹². Applying an existing ontology can also reduce the work of creating formal representations for conventions from scratch.

¹⁰ <https://github.com/goose3/goose3>

¹¹ Another tool with the best performance in [3] was Newspaper. Unlike GOOSE, it was designed mostly for newspaper texts and cannot extract structured text.

¹² If no ontology exists then we can generate one from text by means of parsing and concepts/relation extraction rules, which consider semantic and syntactic features of the words [23].

Back to the sentence “The card colour is red”, instead of creating a rule to capture the features, we can search the ontology for concepts like “card” and “colour”, and use the known relation between them, that is, cards have colours and red is a common colour for cards. With these concepts and relations, we can formalise this sentence more efficiently. The intuitive meaning behind the name “Search-and-Match” is that the algorithm will use the input (words and tags in parsed sentences) as keywords to search the same (or similar) concepts in the “Ontology” database, match the keywords with the concepts, decide which relations can be found between the keywords, and generate the formal representation of the convention based on these relations.

However, some utterances, words or phrases represent features that require strong domain-dependent knowledge to be formalised. This knowledge can be expressed as logical formulae patterns that include ontological elements, from “Ontology”, and some of the features extracted from the text of the convention. The “Search-and-Match” module will first consult the “Ontology” with those utterances, words or phrases from its input, and try to match them with ontology concepts based on their semantic similarity (e.g. the semantic features they share or the similarity between their semantic features). If the existing ontology in the database does not contain these (domain-specific) concepts, this module should be capable to update or enrich the ontology. For instance, consider the expression “right-most card” in Table 1. It is a relative concept: its meaning may refer to either a physical position (e.g. 5th slot in Hanabi), or a “chop” (see the example in Section 2.4). The ontology should be able to help select the second (logical) meaning as the actual meaning of the expression “right-most card”. Here is the example for *discard chop (right-most unclued) card* code that the ontology should provide:

```

if    convention_concept(right_most_card) and
      next_option([discard(_,_,X),discard(_,_,Y),discard(_,_,Z)]) and
      clued(_,_,Z) and ~clued(_,_,Y) and ~clued(_,_,X) and X < Y
then next_action(discard(_,_,Y))

```

That in English would read like “if the convention text mentions the word `right_most_card`, the strategic component doubts about discarding one of three cards, and only one of them is clued, then the card to discard will be the one of the non-clued two that is in the right-most position.”

Such schemes can be grouped into structures representing the semantic similarity of the concepts. For instance, the code patterns for “right-most” and “left-most” concepts can be placed close to each other, possibly both hanging from “position”, even if “position” does not appear in the conventions. For example, see the pattern associated with the concept of “position”. It contains a variable `OP` as a placeholder for an operator that can be later instantiated, once we determine univocally the concrete position expressed in the convention:

```

[position(OP) for convention([position, place, location])] :=
if    next_option([discard(_,_,X),discard(_,_,Y),discard(_,_,Z)]) and
      clued(_,_,Z) and ~clued(_,_,Y) and ~clued(_,_,X) and X OP Y

```



```
then next_action(discard(.,.,Y))
```

If a word in the convention (e.g. “right_most” or “right_place”) is found by the ontology as related with the concept “right_most_card” the ontology can then provide the instance **position(<)**, or **position(>)** instead if the concept “left_most_card” is found. Such structure can be expressed in the language for formal conventions as:

```
[right_most_card(<) is_a position(OP)
  for convention([right_most, on_the_right, right_place])]
```

A complex ontology structure might have programming patterns for some of its concepts but not necessarily for all of them. If no programming patterns can be obtained from the ontology, a request for ontology update may be issued.

When importing an existing domain-independent ontology we will need to particularise it to the context of an application, e.g. Hanabi, adding programming patterns. For instance, from a node in an ontology like “position,” we can add as leaves more domain-specific concepts (“left_most_card” and “right_most_card”) and associate them with the rules shown above.

In short, the “Search-and-Match” module performs two operations. On the one hand, it updates ontologies by adding concepts appearing in the conventions under analysis and associating formal convention programming patterns with them. This ontology can be enriched (e.g. by training a long short-term memory neural network for updating ontologies when new concepts are introduced [32]). On the other hand, it instantiates the parameters of existing formal convention programming schemes with particular values coming from the annotated words from the NLP conventions analysis.

4.2 World Model

The “World Model” is the module that represents knowledge about the environment. It contains Precepts, Domain-related Clauses, and Impossibility Clauses, all representing different kinds of information.

Factual information (facts) about the environment is represented as literals. The initialisation of an agent’s set of beliefs can thus be obtained from the observation of the environment. In our running example, these facts include the colour and number of cards other players hold. Though each agent does not have explicit knowledge of its cards, they can make inferences about the cards’ colour or number. The system’s possible states and actions are limited since there are just two types of clauses (about colour and number). “Domain-related” clauses indicate relationships among literals and specify more sophisticated characteristics; for example, a “playable” card must have a number which is one unit above the number on the card of the same colour that is on the stack on the table (e.g. red 3 is a “playable” card when there is a red 2 on the top of the red stack). “Impossibility clauses” express the circumstances where two literals cannot both be true. For example, the impossibility clause for “two different cards cannot occupy the same slot” will have its condition become true when more than one card is assigned to the same slot.

4.3 ToM

The “ToM” module represents the beliefs that one agent has about the beliefs of others. It combines Theory of Mind clauses and Abducible Clauses. Theory of Mind clauses explicitly represent the beliefs that agents have about facts of the environment, while Abducible clauses represent the possible beliefs that they might have about facts of the environment.

The Theory of Mind Clauses are based on belief chains (see Section 3.2). Beliefs are encoded as literals of the type **believes**(**Ag**, **F**) in [27], which are true when the observer believes that an observee **Ag** is aware of a fact **F**. In our context, the concept of *fact* is equivalent to *belief* in the general definition of ToM, because the observation of actions and the state of the environment are the only things we plan to use. As the environment is not fully observable (e.g. player’s cards are hidden from them), beliefs do not necessarily correspond to reality. This is so because agents will update beliefs via querying specific ToM clauses based on abduction, and abduction does not necessarily provide truthful consequences. A relevant source of belief updates is those abductive consequences that an agent *i* derives from the beliefs it holds about the beliefs of another agent *j* on *i*, that is, on itself. In that case, an agent becomes an observer of itself through the eyes of another agent, observer and observee simultaneously.

Example: Alice clues one of Bob’s cards telling him that its colour is red. When doing so, Alice can infer how Bob might interpret that piece of knowledge in terms of Bob’s beliefs about Alice’s beliefs leading to her telling Bob the colour of the card. For instance, Bob may infer that Alice is giving him a save clue (see Table 1) to not discard the card, since this card is his current chop card.

Similarly to [27], we will leave out of our architecture any mechanism to determine beliefs about actions to be taken by other agents. We do so because of the high complexity of this kind of reasoning. However, We think that a ToM representation with such capability would be an important improvement of our agent architecture. We will consider it as future work.

Abducible Clauses complement the Theory of Mind Clauses. They add *potential* beliefs to the knowledge base as long as they do not contradict any preexisting beliefs. Note that these clauses are domain-specific.

Example: Alice is currently holding the belief *I have a red or blue card in the third slot*. If Alice’s abduction mechanism produces *I have a red card in the third slot* which is not contradictory to the current belief, she may (defeasibly) infer that the colour of the card is actually red and act accordingly.

4.4 Action Selection

The **SelectAction** function in [27] relies on *Action Selection Clauses* written in AgentSpeak. These clauses represent the actions the agents might take and the beliefs they need to hold to take these actions. All the clauses also contain priority information encoded as a natural number. In [27], the game rules were manually coded as an environment in Java, while some conventions were manually programmed as Action Selection clauses. In that work, the **SelectAction**

function implements hard-coded strategies and takes Action Selection Clauses as input. After ranking the Action Selection Clauses based on their priorities, the function checks the clauses in order starting from the highest priority ones. If the clause’s body is true according to the beliefs the agent is holding and the potentially abducible beliefs, then the action suggested by the clause is selected; the remaining clauses are not considered. The game rules further verify the feasibility of this selected action. If the verification fails, the agent will take a default action (can be defined by the developer).

Our architecture will modify the hard-coded strategies just described and implemented in the `SelectAction` function by a customisable component. Our “Action Selection” module will receive three kinds of input: the rules of the game from the “Strategies” database written in ASL, the Action Selection Clauses in [27] rewritten in ASL, and the other formal conventions, also written in ASL, from the “Search-and-Match” module.

5 Discussion and Future Work

This short paper presents the initial ideas for an NLP-based agent architecture capable of processing conventions expressed in natural language. We have illustrated the architecture using examples from the card game Hanabi. Our next objective is to implement an agent following this architecture and put it to work playing with other agents. We will check if our NLP correctly interprets the conventions when our agent plays with other agents that have the conventions hardwired in their strategy.

First, We will adapt and extend the model in [27] with additional modules for NLP. There will likely be some modifications to the original model, such as for the `SelectAction` function. The game rules and some conventions were manually coded in the original architecture. Thus, that implementation will be our testbed against which we will test the correct workings of our NLP component. We will also consider implementing modifications to the language ASL proposed in [28]. For instance, as discussed in Section 2.3, manual annotation of rule priorities may not be the best solution. We will work with real-world conventions to determine whether an alternative approach for ranking is required. In addition, apart from the already mentioned H-Group Conventions, other sources of conventions might be used. An example can be conventions generated from non-natural language data (e.g. records of game playing [16, 20]).

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