Argumentation-based Reasoning guided by Chunk Activation in ACT-R

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Abstract

Argumentation is a widely studied topic in philosophy, psychology, and AI. In this paper, we are particularly interested in its psychological implications. According to Mercier and Sperber argumentation is the means for human reasoning. Here, we will investigate how the context plays a role in the argumentation process and bridges to lower levels of cognition. For this purpose the relevant knowledge within a given context determines the choice of the arguments by applying the spreading activation theory of memory. Relevant knowledge can be factual, conditional or hypothetical and, when in conflict, might have different strengths in relation to each other. We propose three comparison mechanism for choosing the winning argument for a given position. Different than in computational argumentation, we are not interested in an exhaustive search for arguments, but a guided process determined by the given context. By using the cognitive architecture ACT-R we specify this process through the spreading activation of chunks. Finally, we implement two models of conditional reasoning within the cognitive architecture ACT-R and evaluate them with the results of a famous reasoning task.

Introduction

Cognitive theories of reasoning investigate how humans reason to understand, model, and eventually predict their decisions. The adequacy of these theories is usually assessed by comparing their predictions to the experimental results of typical reasoning tasks (e.g., Byrne (1989), Wason (1968)) and by developing new experiments. Most of these reasoning tasks are designed as follows: Given some (causal) information, for instance in form of conditional sentences, such as "if A, then B" together with a set of given premises, humans are asked what can be concluded from this information.

According to Newell's (1990) classification of human experience and information processing mechanisms into the four bands of cognition, conditional reasoning might best be classified between the cognitive and rational bands. To facilitate the different aspects of human behavior into various levels (or bands) of cognition, Newell suggested the development of cognitive architectures. This proposal implied that different fields in the area of cognition need to link their work to each other. Cognitive architectures provide a formal specification of the structure of the brain, the functions of the mind, and how the structure explains the function, guided by the findings from decades of research. Within these cognitive architectures, the cognitive processes are organized as modular entities coordinated within one environment thus simulating human cognition. Even though bridging the gap between Newell's bands of cognition is still an open problem, the developed cognitive architectures (e.g. ACT-R (Anderson, 2007), SOAR (Laird, 2012)) had a significant contribution on providing formal methodologies.

In this paper, we will investigate conditional reasoning, where we are mainly interested in three aspects: (i) how do humans understand conditionals in the given context, (ii) how do they infer new information from that context, and (iii) how can (i) and (ii) be implemented such that they account for existing theoretical findings of lower levels of cognition. For addressing (i) and (ii), cognitive argumentation is chosen as the theoretical foundation, where well-known cognitive phenomena are formalized as cognitive principles and conclusions are derived based on the dialectic argumentation process. Arguments are usually understood symbolically. Yet, the process of building and choosing them, and then deciding which argument wins seems to be heavily guided by biases or heuristics, influenced by the given context, which might partially be modeled statistically. By exploiting the probabilistic functions in the cognitive architecture ACT-R (Anderson, 1990; Anderson, Byrne, Douglass, Lebiere, & Qin, 2004), we implement argumentation-based reasoning guided by chunk activation.

Finally, two models of argumentation-based reasoning in ACT-R will be presented and evaluated to data from the well-known Byrne's (1989) suppression task.

Related Work

Various (non-classical) logic-based approaches for conditional reasoning have been proposed in the past (Braine, 1978; Johnson-Laird, 1983; Johnson-Laird & Byrne, 1991; Rips, 1994; Polk & Newell, 1995; Stenning & van Lambalgen, 2008; Dietz, Hölldobler, & Ragni, 2012). However, only a few of them (Braine, 1978; Rips, 1994; Johnson-Laird, 1983; Johnson-Laird & Byrne, 1991; Chater & Oaksford, 1999) proposed a theory on the (internal) reasoning process itself. Up to now, only the (mental) model theory (Johnson-Laird, 1983; Johnson-Laird & Byrne, 1991) and some reasoning tasks have been embedded into ACT-R (Khemlani & Trafton, 2012; Ragni & Brüssow, 2010; Ghosh, Meijering, & Verbrugge, 2014).

Addressing the question of how humans integrate what is known and what is conjectured or observed to what is inferred to explain has been addressed by Weick (1995), who proposed the theory of Sensemaking. Sensemaking is about the process to search for contexts that make sense.

Lebiere et al. (2013) proposed computational models that specify how observed sensemaking behavior can be produced from elementary cognitive processes and modules. Among other aspects, they considered the process of information gathering and hypothesis updating. The authors' goal is to identify and understand the core mechanisms of cognitive biases generally. A sensemaking model for intuitive decision-making employing instance-based learning has been proposed by Thomson, Lebiere, Anderson, and Staszewski (2015). In the following section, we will briefly point to similarities between argumentation and sensemaking.

A generally observed problem in the field of Cognitive Science is that many ad-hoc formulations of domain-specific models exist and therefore Thomson et al. (2015) suggest driving the field of cognitive modeling to the generalizability of models. Salvucci (2013) has addressed this aspect by integrating models through cognitive skill acquisition. In the PRIMs architecture, cognitive processes can be reused such that they are applicable in many different combinations (Taatgen, 2013). Serving a similar purpose for the case of reasoning, in this paper we will introduce cognitive principles, which are formalized task-independent assumptions made by humans.

Cognitive Argumentation

Experiments by Mercier and Sperber (2011) have shown evidence that humans arriving at and justifying claims seems to be done through the construction of arguments. They state that arguments are the means for human reasoning. Without expanding on the formal details, we will here briefly introduce the theoretical foundation of our approach, Cognitive Argumentation (Dietz Saldanha & Kakas, 2019; Dietz & Kakas, 2020, 2021), where reasoning (or inference) is based on a dialectic argumentation process. In Cognitive Argumentation, argument construction is guided by cognitive principles. These arguments are built from argument schemes, which represent general links between information.

We will first introduce the relevant cognitive principles and then illustrate the dialectic argumentation process by an example.

Cognitive Principles

Cognitive principles are assumptions that humans make while reasoning. The specification of such principles helps us to explain why humans come to certain conclusions in particular when they diverge from valid conclusions in classical logic. Furthermore, the notion of a cognitive principle allows us to understand and distinguish between different types of reasoners.

The first two principles, **maxim of quality** and **maxim of relevance** are motivated by Grice's (1975) conversational implicature. The maxim of quality states that, if there is no reason to assume differently, humans believe that what they are told as factual information, is true (Δ^{fact}). The maxim of relevance states that humans believe what they are told is relevant (Δ_{hyp}). This maxim applies when humans perform some **hypothesis generation** to infer consequences, not based on facts, but based on what hypothetically could be true or false.

The principles of **necessary ($\overset{n}{\rightsquigarrow}$) and sufficient conditions** ($\overset{s}{\rightsquigarrow}$), are motivated by Byrne, Espino, and Santamaría (1999) and Byrne (2005): Consider the conditionals *If she meets a friend, then she will go to a play* and *If she has enough money, then she will go to a play*. In the first conditional, *she meets a friend* is sufficient support for *she will go to a play*. This is a sufficient condition. For the second conditional, *she has enough money* can be understood as a necessary condition, i.e. the negation, *she does not have enough money* is plausible support for the negation of the conclusion, *she will not go to the play*. Together with the cognitive principle of **hypothesis generation**, the hypothesis that *she does not have enough money* functions as a **disabling condition** to the modus ponens conclusion that *she will go to a play*. Similarly, given that *If she has free tickets, then she will go to the play*, the hypothesis of the sufficient condition *she has free tickets* functions as an **alternative condition** and discards the condition *she has enough money* as necessary for the conclusion *she will go to the play*. This classification of necessary and sufficient conditions is dynamic and strongly depends on the context.

Different from valid inferences in classical logic, humans have the ability to reason from observations to explanations, which is sometimes called abduction. Abductive reasoning is motivated by the **maxim of inference to the best explanation** (Peirce, 1903). Additionally, the plausibility of explanations increases or decreases by setting them in contrast to the alternative explanations. So might the support for one explanation discount the support for the alternative explanations (Kelley, 1973; Sloman, 1994).

If contradictory information is given, and if there is no obvious information that can be discarded, then, according to Wason (1964), humans might reconsider the given information, and a valid inference from some arbitrary or general assumption will be given up in favor of a fact (Johnson-Laird, Girotto, & Legrenzi, 2004). This observation will be called the **conflicts in reasoning** principle and motivates the following relative strength relation among the cognitive principles: hypotheses (Δ_{hyp}) are the weakest, whereas facts (Δ^{fact}) are the strongest. Derivations from necessary conditions ($\overset{n}{\rightsquigarrow}$) are stronger than derivations from sufficient conditions ($\overset{s}{\rightsquigarrow}$).

Dialectic Argumentation Process

We informally introduce the dialectic argumentation process (Baroni, Gabbay, Giacomin, & van der Torre, 2018): **Step 1.** Construct a root argument supporting the conclusion of interest, **Step 2.** Consider a counter-argument, **Step 3.** Find a defense argument, **Step 4.** Check if the defense argument is not in conflict with the root argument (in Step 1), **Step 5.** Add the defense argument to the root argument, **Repeat**

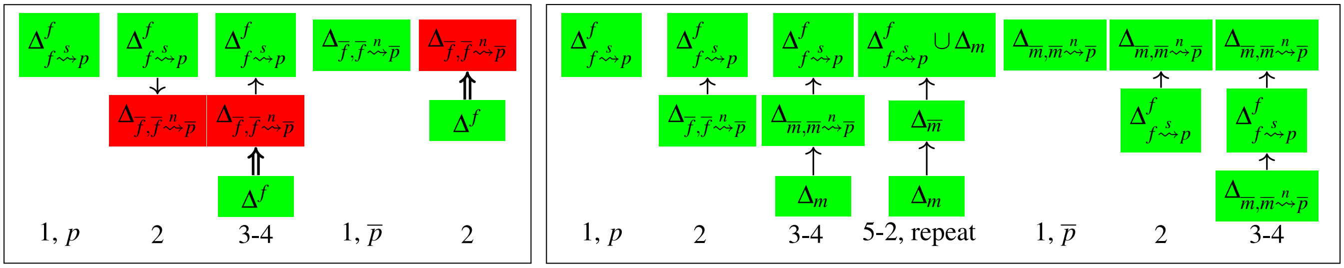

Figure 1: The dialectic argumentation process is guided by cognitive principles. Acceptable arguments are in green and non-acceptable arguments in red. $\uparrow$ shows attacks and/or weak defenses and $\Uparrow$ show strong attacks and/ or defenses.

from Step 2. This process is repeated until no other counter-arguments (step 2) can be found. The extended root argument is then the acceptable argument supporting the conclusion of interest. Informally, conclusions follow credulously when they are supported by acceptable arguments. They follow skeptically when they are acceptable and there are no acceptable counter-arguments.

The intuition of this process will now be illustrated with the help of the previously introduced examples and Figure 1: Given *If she meets a friend (f), then she will go to a play (p)*, assume that the condition is both sufficient ($f \overset{s}{\rightsquigarrow} p$) and necessary ($\overline{f} \overset{n}{\rightsquigarrow} \overline{p}$). Further, assume that we are given the factual information that *She meets a friend* (Figure 1, left). Let us start with the position that *She will go to a play*: 1. We build the (strong) argument $\Delta^f_{f \overset{s}{\rightsquigarrow} p}$ for p, from the fact that f and that f is a sufficient condition for p (1, p). 2. We build the counter argument $\Delta_{\overline{f},\overline{f} \overset{n}{\rightsquigarrow} \overline{p}}$ from the hypothesis that *She does not meet a friend* ($\overline{f}$) and that f is (also) a necessary condition for p. 3.-4. However, Δ^f is a defense argument against $\Delta_{\overline{f},\overline{f} \overset{n}{\rightsquigarrow} \overline{p}}$, as f is a (strong) fact. 5. The new argument for p stays $\Delta^f_{f \overset{s}{\rightsquigarrow} p}$ as f is already part of the root argument. The only counter-argument left is $\overline{f}$ against which Δ^f is trivially a strong defense (repeat). Finally, the root argument $\Delta^f_{f \overset{s}{\rightsquigarrow} p}$ is an acceptable argument for the conclusion p.

Next, let us consider the arguments for $\overline{p}$, which can only be built from the hypothesis $\overline{p}$, $\Delta_{\overline{p}}$, or $\Delta_{\overline{f},\overline{f} \overset{n}{\rightsquigarrow} \overline{p}}$ (1, $\overline{p}$). $\Delta^f_{f \overset{s}{\rightsquigarrow} p}$ and Δ^f are (strong) attacks against which $\Delta_{\overline{p}}$ and $\Delta_{\overline{f},\overline{f} \overset{n}{\rightsquigarrow} \overline{p}}$ cannot defend against. There is no acceptable argument for $\overline{p}$, thus p is a skeptical conclusion.

Let us consider the argumentation processes when we additionally receive the information that *If she has enough money (m), she will go to a play (p)*, where *she has enough money* is a necessary condition for *she will go to the play* ($m \overset{n}{\rightsquigarrow} p$). (Figure 1, right): 1. Starting with, (1, p) $\Delta^f_{f \overset{s}{\rightsquigarrow} p}$ is a strong argument for p. 2. The attack $\Delta_{\overline{m},\overline{m} \overset{n}{\rightsquigarrow} \overline{p}}$ is built from the new conditional $m \overset{n}{\rightsquigarrow} p$ and the hypothesis that *she does not have enough money* 3.-4. which can be defended against with the hypothesis that *She has enough money* (Δ_m). 5. This defense argument is added to the root argument, and defends against all its attacks ($\Delta^f_{f \overset{s}{\rightsquigarrow} p} \cup \Delta_m$): This is an acceptable argument for p.

Consider now the process for the opposing position: 1. The (strong) argument for $\overline{p}$ is $\Delta_{\overline{m},\overline{m} \overset{n}{\rightsquigarrow} \overline{p}}$. 2. $\Delta^f_{f \overset{s}{\rightsquigarrow} p}$ attacks $\Delta_{\overline{m},\overline{m} \overset{n}{\rightsquigarrow} \overline{p}}$, however 3.-4. $\Delta_{\overline{m},\overline{m} \overset{n}{\rightsquigarrow} \overline{p}}$ can defend itself against $\Delta^f_{f \overset{s}{\rightsquigarrow} p}$, as necessary conditions ($\overline{m} \overset{n}{\rightsquigarrow} \overline{p}$) are stronger than sufficient conditions ($f \overset{s}{\rightsquigarrow} p$). $\Delta_{\overline{m},\overline{m} \overset{n}{\rightsquigarrow} \overline{p}}$ is also an acceptable argument for $\overline{p}$: Both p and $\overline{p}$ are credulous conclusions.

Sensemaking We can draw parallels between the theory of sensemaking (Klein, Moon, & Hoffman, 2006) and the argumentation process, where sensemaking models can be analogously understood as arguments considering the description given by Klein, Phillips, Rall, and Peluso (2007)[115]. Initially, humans generate just-in-time mental models (i.e. local cause-effect connections) to explain events (Step 1). They then elaborate and question that model with inconsistencies (Step 2), fixate on the initial model, eventually discover inadequacies and compare alternative(s) (Step 3), reframe the initial model, and (if applicable) replace the model with another one (Step 4 and 5).

Guided Argumentation Process

It does not seem plausible, that humans rigorously follow such a step-wise procedure as described above but it is more likely that they are guided by some heuristics, which might depend on e.g. their simplicity, their strength, and their relevance in the context. In the following, we address this aspect by realizing a guided dialectic argumentation process in ACT-R.

Argumentation in ACT-R

Two ACT-R models based on the theory of Cognitive Argumentation are presented in this section. The structure of both models is shown in Figure 2.

Tasks

The proposed models implement three tasks, *read*, *argue* and *respond*, where the last two is each specified with one control state. Model I follows sequentially the tasks, whereas the *read* and *argue* tasks in model II are intertwined.

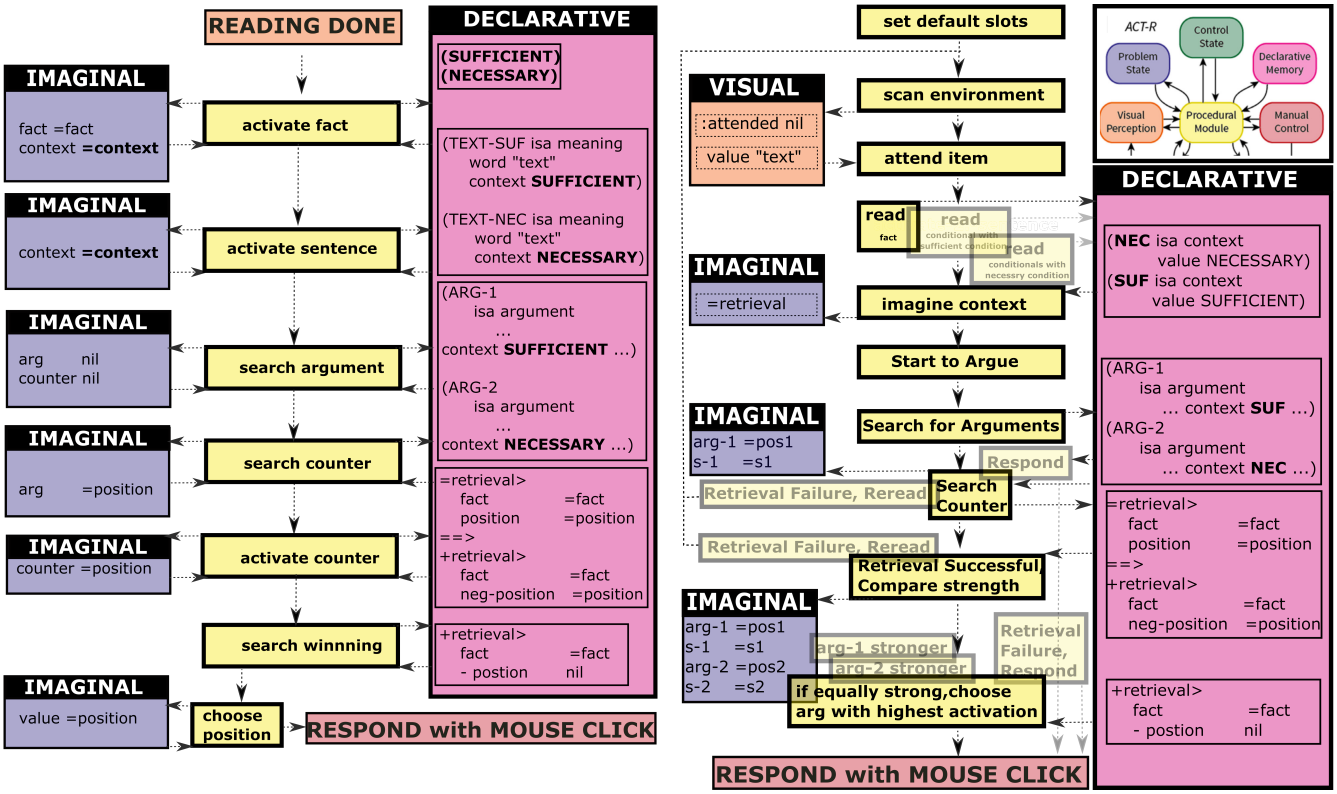

Figure 2: Model I (left) and model II (right), where each (yellow) block in the middle (between the imaginal buffer and the declarative memory) represents a production rule. The background colors in the models correspond to the ACT-R modules on the right to top of the right model.

Background Knowledge

Model I (Figure 2, left) stores the conditions as either necessary or sufficient in the declarative memory whereas in model II (Figure 2, right) this information is derived from the production rules. This classification determines which arguments are going to be considered relevant in the *argue* task.

Model I The production rules `activate fact` and `activate sentence` contain the following structure:

```
=imaginal>                    =imaginal>
 fact    =fact                 sentence    =sentence
 ==>                           ==>
+retrieval>                   +retrieval>
 word    =fact                 word    =sentence
```

A chunk will be retrieved having a slot `context` containing either the chunk `SUFFICIENT` or `NECESSARY`. Figure 2, left, DECLARATIVE, gives two examples of such chunks (`TEXT-SUF` or `TEXT-NEC`). In the next step, this `SUFFICIENT` or `NECESSARY` chunk is placed in the imaginal buffer (Figure 2, left, IMAGINAL). This activation spreads to the chunk arguments (e.g. `ARG-1` or `ARG-2`) which either contain the chunk `SUFFICIENT` or `NECESSARY` in their `context` slot.

Model II The `read` production rules in Figure 2, right, (e.g. read fact) all contain either the elements on the left or on the right:

```
=visual>                      =visual>
 value   ...                   value   ...
 ==>                           ==>
+retrieval>                   +retrieval>
 value   NECESSARY             value   SUFFICIENT
```

where ... is a placeholder for a string value that is different for each production rule (e.g. "She will meet a friend"). After reading, the model interprets (or contextualizes) the sentence: Depending on which production rule matches and fires, a context chunk where either value `NECESSARY` or `SUFFICIENT` is retrieved and this retrieved chunk, either `NEC` or `SUF` (Figure 2, right, DECLARATIVE), is placed in the imaginal buffer. After that, the respective hypothesis chunk (either with value `DISABLER` or `ALTERNATIVE`) is retrieved and placed into the imaginal buffer.

Argumentation Task

The *argue* task can only start after the models have accomplished the *read* task (or at least once for model II).

Arguments as Chunks The chunks of type `argument` contains the slots `fact, hypo` and `context` which contain other chunks, respectively. Additionally, `arguments` contain the slots `pos` and `neg-pos` having string values, representing the position and the opposite position, and the slot `str` having a float value, denoting the argument's strength. Consider two strong arguments from the example in the previous section:

```
(arg1 isa argument hypo NONE fact FRIEND
pos "YES" context SUF neg-pos "UNKNOWN" str 1)
(arg2 isa argument hypo DISABLER fact FRIEND
pos "UNKNOWN" context NEC neg-pos "YES" str 1)
```

`arg1` represents the modus ponens argument, stating that *She will meet a friend* (`fact FRIEND`), together with the conditional being understood as sufficient (`context SUF`), being an argument for *She will go to play* (`pos "YES"`). `arg2` represents the attacking argument including the final position: stating that, a disabling hypothesis (`hypo DISABLER`, e.g. *She does not have enough money*) and the conditional understood as necessary (`context NEC`), forms an argument for the position *She will not go to a play*. `arg1` and `arg2` are equally strong (`str` 1). As slot `hypo` in `arg2` has a disabling hypothesis (`DISABLER`), it defends against `arg1`, and makes both arguments acceptable (thus we cannot conclude skeptically that *She will go to the play* and therefore the position is `pos "UNKOWN`).

Variations in Argumentation Process Humans differ in reasoning (c.f., (Khemlani & Johnson-Laird, 2016)): Some draw conclusions already based on one argument that supports a position, whereas others try to generate hypotheses to build (strong) counter arguments. The dialectic argumentation processes in model II (Figure 2, right) subsumes the one in model I and is as follows: In case an argument was successfully retrieved by `search for argument`, two production rules might apply, either (1) `Respond` with the position of that argument or (2) `Search Counter` argument. In the second case, three production rules might apply: (2a) there is a `Retrieval Failure` and the model `Responds` with the position of the current argument, (2b) there is a `Retrieval Failure` and the model `Rereads` the premises (which will increase either the activation of `NEC` or `SUF`) or (2c) `Retrieval` is `Successful` and both arguments are compared. The arguments can be compared in either one of the following ways: (2c,i) through their strengths (which argument is stronger?), (2c,ii) through their activation (which argument has the higher activation), or (2c,iii) based on their hypothesis (which argument has a disabling or alternative hypothesis?). Figure 2 only shows (2c,i), where depending on whether argument 1 or argument 2 is stronger, either one of the following production rules applies:

```
(p  arg-1-stronger
 =goal>
  state   argue
 =imaginal>
  strength-1   =val
  < strength-2   =val
  arg-1   =pos
  ==>
 =imaginal>
  value   =pos
 =goal>
  state   respond )
```

```
(p  arg-2-stronger
 =goal>
  state   argue
 =imaginal>
  strength-1   =val
  > strength-2   =val
  arg-2   =pos
  ==>
 =imaginal>
  value   =pos
 =goal>
  state   respond )
```

When the argument taking the disabling or alternative hypothesis into account is chosen (2c,iii) then one of the following production rules applies:

```
(p  arg-1-hypo
 =goal>
  state   argue
 =imaginal>
  - arg-1   nil
  - arg-2   nil
  arg-1   =pos
  - hypo-1   None
  ==>
 =imaginal>
  value   =pos
 =goal>
  state   respond )
```

```
(p  arg-2-hypo
 =goal>
  state   argue
 =imaginal>
  - arg-1   nil
  - arg-2   nil
  arg-2   =pos
  -hypo-2   None
  ==>
 =imaginal>
  value   =pos
 =goal>
  state   respond )
```

In the current implementation, model II includes all options, except (2c,ii). Further, the utility to respond with the position of the firstly retrieved argument (thus not searching for a counter argument) is higher than for the other production rules.

Evaluation

We first show how the models perform with respect to a cognitive reasoning task and then discuss their results.[1]

Application: Byrne's Suppression Task

The application of Cognitive Argumentation in ACT-R is shown by means of a typical reasoning task. In the suppression task (Byrne, 1989) participants were asked whether they could derive conclusions given variations of a set of premises. The task consists of two parts, where in both parts, the conditionals are the same, but the factual information changes.

Part I Group I was given the following two premises: *If she has an essay to finish, then she will study late in the library.* and *She has an essay to finish.* (*essay*) The participants were asked what of the following answer possibilities follows assuming that the above premises were true: *She will study late in the library, She will not study late in the library* or *She may or may not study late in the library.* 96% of the participants in this group concluded that *She will study late in the library* (*library*). Group II of participants additionally received the following premise: *If she has a textbook to finish, then she will study late in the library.* which yield to the same result: 96% of the participants in this group concluded that *She will study late in the library*. Group III of participants instead additionally received the following premise: *If the library is open then she will study late in the library.* In this case, only 38% concluded that *She will study late in the library*. If instead *She does not have an essay to finish* was given as a fact, only 4% of Group II concluded *She will not study late in the library*, whereas for Group I and Group III, the percentage was 46% and 63%, respectively.

[1] The models can be found here: https://github.com/eadietz/bst2actr.

Part II The second part of the experiment was similar, except that the given facts were different. The participants were given the fact that *She will study late in the library* (*library*) or *She will not study late in the library* (*not library*) and asked what of the following answer possibilities follows assuming that the given premises were true: *She has an essay to finish, She does not have an essay to finish* or *She may or may not have an essay to finish.*

Fact	Group	Model I	Model II	Byrne	Dieussaert^{+}
essay	I	98	90	96	88
	II	98	90	96	93
	III	52	37	38	60
	$\leadsto$ concluded *She will study late in the library*				
		Model I	Model II	Byrne	Dieussaert^{+}
not essay	I	47	31	46	49
	II	5	10	4	22
	III	73	65	63	49
	$\leadsto$ concluded *She will not study late in the library*				
		Model I	Model II	Byrne	Dieussaert^{+}
library	I	46	31	71	53
	II	4	10	13	16
	III	72	64	54	55
	$\leadsto$ concluded *She has an essay to finish*				
		Model I	Model II	Byrne	Dieussaert^{+}
not library	I	95	90	92	69
	II	99	89	96	69
	III	54	37	33	44
	$\leadsto$ concluded *She does not have an essay to finish*				

Table 1: The percentages of model I and II after 100 simulations compared to the experimental results by Byrne (1989) and Dieussaert et al. (2000), abbreviated by Byrne and Dieussaert^{+}, respectively. The first two columns are the cases and the groups. The highlighted rows show the suppression effects.

Results The results in Table 1 show that both, model I and model II account for the suppression effect in all four cases. The results that diverge most from the experimental data, are for cases II (*essay*) and III (*not essay*) for group I in model II. Model I fits better the data than model II, however which of the model's underlying mechanisms are more plausible?

Discussion

Model I fits better the data than model II, but model II's implementation of background knowledge, divisions of tasks and individual differences, might better account for the underlying cognitive process. Through optimization via meta parameters or the utility modules, an eventual perfect fit of the models to the data seems feasible, however, maybe less interesting.

Background knowledge In model I, background knowledge is stored in the declarative memory (where chunks differ in their base-level activation), whereas in model II, the knowledge is in the production rules.

Division of Tasks Model I's tasks of *read*, *argue* and *respond* are strictly ordered. This might be plausible for the *respond* task, however the *read* and *argue* tasks seem intertwined, which makes model II more plausible: participants might re-read the sentences while they argue for or against some response.

Argument Selection Chunks that are retrieved last have a higher activation than other chunks. Yet, for argumentative reasoning the strength or the attacking character (e.g. through disabling/ alternative hypotheses) might have stronger effects.

Individual Differences Competing production rules in model II represent the different individual's responses. Another modeling approach could have been the implementation of a set of models.

Learning Reasoning tasks usually do not consider learning, even though this is a relevant aspect for which cognitive architectures are well suited for.

Conclusions

This paper shows how cognitive argumentation can be implemented into a cognitive architecture. In cognitive argumentation, cognitive principles specify task-independent assumptions humans might make while reasoning. A variation of the original dialectic argumentation process is formalized in ACT-R. Most importantly, an exhaustive search for arguments is avoided, and instead, the argumentation process is guided through chunk activation. Two argumentation-based reasoning models are evaluated to the experimental results of a famous reasoning task. The approach provides an ACT-R implementation of two models that solves a (conditional) reasoning task through cognitive principles where reasoning is a guided dialectic argumentation process. Still, a lot needs to be done to refine this approach. The current implementation takes the existence of arguments as granted and does not provide a mechanism of argument construction. Furthermore, we need to consider other reasoning tasks such as tasks that investigate learning. With the help of new experiments, we could evaluate and refine the dialectic argumentation process as currently implemented. Finally, the automation of the conditions' classification and the problem of prior knowledge is still an open problem. Natural language processing and argument mining (Lawrence & Reed, 2020) might be helpful for this purpose.

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