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Cognitive Logics – Features, Formalisms, and Challenges

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Abstract. Logic is responsible for scientific progress in many disciplines. In particular, computer science and AI would be impossible without it. Classical logics have long been accepted as a normative framework for human reasoning to capture correct reasoning. However, many psychological findings such as the Wason Selection Task have demonstrated that classical logic cannot serve as a possible descriptive language for the human inference process, which is the aim of what we call a *cognitive logic*. Recently, some nonmonotonic logics have been employed to explain human inferences for some well-known examples. In this paper, we discuss possible features of cognitive logics, present first results, and highlight new challenges.

1 Specifics of the cognitive logics approach

Reasoning is part of our everyday life and relevant in many disciplines in AI. Systems of tomorrow will more closely interact with humans and demonstrate some features of human information processing. The human reasoning process is *exception tolerant*, robust, flexible enough to change in the light of new information, and it includes *common sense reasoning*.

We propose the *cognitive system reverse-engineering problem*: Given problems consisting of premises (the input) and conclusions (the output), what is an appropriate inference system that generates the respective output for the given input? The objective here goes beyond cognitive modeling that aims to develop a white-box model of the human mind; the challenge is to develop formal systems that are built on general human reasoning principles and can demonstrate the cognitive features mentioned above. Its ultimate goal is to build a cognitive logic that can be a relevant part of an artificial mind that in its nature demonstrates cognitive features.

A *cognitive logic* is a logic-based formalism that is *cognitively adequate*, incorporates principles of human rationality and specifics of human inference processes, and is *empirically validated*. An advantage over existing mechanisms in machine learning is its formal analysis and its explainability, i.e., its diagnostic power that can explain the contribution of each of the employed principles.

A formalism is cognitively-adequate if it demonstrates at least two features: First, if the system draws the same inferences as humans then we call a system *inferentially cognitive-adequate*. Second, if the system knowledge base contains the same beliefs represented mentally in the humans' representation, we call the system *conceptually cognitive-adequate* [20].

Applications of cognitive logics are in common sense reasoning, human-machine interaction (especially for assistance systems that can adapt to humans), cognitive modeling, knowledge representation and reasoning, computational intelligence, foundations of AI, AI systems for rationality, and whenever an AI system needs to specifically adapt to the information processing of a human interaction partner.

Research on cognitive logics has its own specific goals and methods.

Goals. For developing cognitive logics, we set up four core goals: First, a common language (including a specification of the concepts and formalizations) to bridge the gap between the fields of psychology, cognitive science, symbolic AI and logics is necessary. Second, a working concept for principles of human rationality needs to be developed. Third, demonstrative examples from psychology and cognitive science on reasoning need to be collected. Fourth, existing formal logics, especially from nonmonotonic reasoning, and other formalisms on the demonstrative examples need to be evaluated.

Methods. Cognitive logics is transdisciplinary and injects the human into the formal inference systems. Three methods need to be applied: *Data side*: Psychological experiments identify and support features/phenomena of cognitive adequacy. The phenomena need to be extracted and compiled, and made (easily) available for formal modelers. *Formal side:* A common ground language to compare formalisms with each other and to evaluate them on empirical data and derived cognitive principles. *Evaluation measure:* Different measures (beyond inferential adequacy, e.g., intermediate step correspondence) can be analyzed to allow a systematic improvement of theories [21].

2 Benchmark problems for cognitive logics

The idea of benchmark sets in the sense of a repository of important reasoning problems have been not yet realized. However, the quality of robust phenomena in human reasoning can be decided based on the following conservative criteria: (i) There have been meta-analyses or the phenomena has been repeatedly reported in (in top journals) articles, (ii) distinct cognitive theories/models have been proposed to explain the phenomena, (iii) the phenomena demonstrate a deviation from the predictions of classical first-order logic and cannot be explained by a lack of concentration, a misunderstanding, or anything else.

Cognitive psychology divides the field into three domains. In the following, we report a subset of the most relevant phenomena that have been accepted in these three domains: For *syllogistic reasoning*, i.e., reasoning about quantified statements of sets, we propose two data sets (i) a meta-analysis of all 64 syllogisms consisting of two premises and the four quantifiers *All, Some, Some ... not, None* [8], and (ii) reasoning about generalized quantifiers *Most, Few* [13]. Some statistical robust phenomena are: logically valid problems are easier than invalid ones, and the belief bias [9], i.e., a believable conclusion is accepted even if it cannot be derived from the premises. For *conditional reasoning*, i.e., reasoning about conditional statements,

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if.. then.., we propose two data sets (i) a meta-analysis of the Wason Selection Task [18] and classical conditional inferences [14]. Two robust effects are that modus tollens is less applied and modus ponens can be suppressed [1]. For *relational reasoning*, i.e., reasoning about relations such as *left of, north of, etc.* we propose three data sets (can be downloaded with CCOBRA[5]): (i) two premise inference problems about cardinal directions, (ii) small-large scale relations, i.e., differences in responses between left/east etc., (iii) continuity effect, i.e., if information is presented continuously or discontinuously and its impact on reasoning. There are three robust effects: The preference effect [17], in indeterminate problems participants give a specific answer, pseudo-transitive relations [5], the misinterpretation of relations as blood-related as transitive, and that complex relations are decomposed in smaller relations [4]. Additional benchmarks are from nonmonotonic [3, 12] or common sense reasoning.[6] We developed a testing framework CCOBRA that interfaces, for any implemented algorithm, data from real experiments.

3 Examples for research on cognitive logics

In [16], the authors investigate the cognitive adequacy of well-known formal systems of knowledge representation for the Suppression task [1], focussing on system P [10], Reiter's default logic [19], logic programming under the weak completion semantics [6], system Z [15], and c-representations [7]. Similar investigations have also been done in the work [22]. In the paper [2] it is shown how basic nonmonotonic reasoning in terms of preferential relations is able to resolve paradoxes that have been observed in studies of human reasoning. Moreover, also with the help of c-representations, it is possible to reverse-engineer the most plausible beliefs and the background conditional beliefs of the reasoners in the considered tasks. The paper [11] shows how formal approaches to reasoning that embody basic cognitive features may also help making machine learning more effective: the authors improve deep learning results for recognizing analogies by using symbolic structures expressing human understanding of analogies.

4 Challenges

This section comprises theoretical questions and challenges:

- Which formal principles and features from rationality formalized in the AI fields of knowledge representation and reasoning and reasoning under uncertainty (e.g., rational monotonicity) are grounded in human reasoning, i.e., are cognitively-adequate?
- Can existing domain-specific cognitive logics (e.g., for conditional reasoning) be extended to domain-general theories (e.g., relational reasoning, syllogistic reasoning)?
- How can predictions of cognitive logics be best evaluated on empirical data?
- What normative aspects beyond classical logic and probabilities are required? What are suitable norms for rational reasoners?
- Is it possible to axiomatize plausible reasoning?
- Which theories in the existing variety of nonmonotonic formalisms are cognitively-adequate?
- How can we systematically justify and validate nonclassical logics? Which cognitive principles does a logic have to satisfy?
- Which benchmarks problems are necessary?
- How can we formalize psychological theories as baseline theories to compare with cognitive logics?

We have set up a website[7], with more extensive information, the description of challenges, and publications.

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REFERENCES

[1] R. M. J. Byrne, 'Suppressing valid inferences with conditionals', *Cognition*, **31**, 61–83, (1989).
[2] C. Eichhorn, G. Kern-Isberner, and M. Ragni, 'Rational inference patterns based on conditional logic', in *Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence, (AAAI-18)*, eds., S.A. McIlraith and K.Q. Weinberger. AAAI Press, (2018).
[3] R. Elio and F. J. Pelletier, 'Human benchmarks on AI's benchmark problems', in *Proceedings of the fifteenth annual conference of the cognitive science society*, pp. 406–411, (1993).
[4] G. P. Goodwin and P. N. Johnson-Laird, 'Reasoning about relations', *Psychological Review*, **112**, 468–493, (2005).
[5] G. P. Goodwin and P. N. Johnson-Laird, 'Transitive and pseudo-transitive inferences', *Cognition*, **108**, 320–352, (2008).
[6] S. Hölldobler and C. D. Kencana Ramli, 'Logic programs under three-valued Łukasiewicz semantics', in *Logic Programming, 25th International Conference, ICLP 2009*, eds., P. M. Hill and D. S. Warren, volume 5649, pp. 464–478, Heidelberg, (2009).
[7] G. Kern-Isberner, *Conditionals in Nonmonotonic Reasoning and Belief Revision*, number 2087 in LNCS, Springer, Berlin, DE, 2001.
[8] S. Khemlani and P. N. Johnson-Laird, 'Theories of the syllogism: A meta-analysis', *Psychological Bulletin*, (2012).
[9] K. C. Klauer, J. Musch, and B. Naumer, 'On belief bias in syllogistic reasoning', *Psychological Review*, **107**(4), 852–884, (2000).
[10] S. Kraus, D. Lehmann, and M. Magidor, 'Nonmonotonic reasoning, preferential models and cumulative logics', *Artificial Intelligence Journal*, **44**, 167–207, (1990).
[11] S. Lim, H. Prade, and G. Richard, 'Solving word analogies: A machine learning perspective', in *Proceedings of the 15th European Conference on Symbolic and Quantitative Approaches to Reasoning with Uncertainty, ECSQARU 2019*, eds., G. Kern-Isberner and Z. Ognjanović, volume 11726 of *LNCS*, pp. 238–250. Springer, (2019).
[12] V. Marek and M. Truszczynski, *Nonmonotonic logics - context-dependent reasoning*, Springer, 1993.
[13] M. Oaksford and N. Chater, *Bayesian rationality: The probabilistic approach to human reasoning*, Oxford University Press, Oxford, 2007.
[14] K. Oberauer, 'Reasoning with conditionals: A test of formal models of four theories', *Cognitive Psychology*, **53**, 238–283, (2006).
[15] J. Pearl, 'System Z: A natural ordering of defaults with tractable applications to nonmonotonic reasoning', in *Proc. of the 3rd Conference on Theoretical Aspects of Reasoning about Knowledge TARK '90*, ed., R. Parikh, pp. 121–135, Los Altos, CA, (1990). Morgan Kaufmann.
[16] M. Ragni, C. Eichhorn, and G. Kern-Isberner, 'Simulating human inferences in the light of new information: a formal analysis', in *Proceedings of the 25th International Joint Conference on Artificial Intelligence, IJCAI 2016*, ed., S. Kambhampati, pp. 2604–2610, Palo Alto, CA, USA, (2016). AAAI Press.
[17] M. Ragni and M. Knauff, 'A theory and a computational model of spatial reasoning with preferred mental models.', *Psychological Review*, **120**(3), 561–588, (2013).
[18] M. Ragni, I. Kola, and P. N. Johnson-Laird, 'On selecting evidence to test hypotheses: a theory of selection tasks', *Psychological Bulletin*, **144**(8), 779–796, (2018).
[19] R. Reiter, 'A logic for default reasoning', *Artificial Intelligence*, **13**(1-2), 81–132, (1980).
[20] J. Renz, R. Rauh, and M. Knauff, 'Towards cognitive adequacy of topological spatial relations', in *Spatial Cognition II*, 184–197, Springer, (2000).
[21] Herbert A. Simon and Dieter Wallach, 'Cognitive modeling in perspective', *Kognitionswissenschaft*, **8**(1), 1–4, (1999).
[22] K. Stenning and M. Lambalgen, *Human reasoning and cognitive science*, Bradford Books, MIT Press, Cambridge, MA, 2008.

[5] https://github.com/CognitiveComputationLab/ccobra
[6] http://commonsensereasoning.org/
[7] http://cognitive-logics.org/