



# A Heuristic-Primed Decision-Making Model under the Assumption of Bounded Resources <sup>†</sup>

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<sup>†</sup> Presented at the 2023 Summit of the International Society for the Study of Information (IS4SI 2023), Beijing, China, 14–16 August 2023.

**Abstract:** Existing decision-making models are generally based on the classical normative paradigm, which seldom considers the limited cognitive and environmental resources of humans when making decisions in real environments. We draw on the theory of Artificial General Intelligence technology, Non-Axiomatic Reasoning System and heuristic-primed decision-making processes of psychology to propose a heuristic-primed decision-making model under the assumption of bounded resources. Firstly, we propose a spreading activation belief network based on experience-grounded semantics, which takes concepts as nodes and semantic relevance as edges, and changes the weights of logical reasoning links according to the evidence presented using multiple inferences rules so as to achieve the self-organization of its network topology. Next, multiple dynamically changing and conflicting goals are represented by a Non-Axiomatic Logic statement with two-dimensional desire-values. Finally, a controlled concurrent heuristic algorithm that can dynamically allocate limited computational resources and perform multiple inferences is proposed.

**Keywords:** decision-making; bounded rationality; Artificial General Intelligence; Non-Axiomatic Reasoning System; heuristics; belief revision; multiple-goal



**Citation:** Slam, N.; Li, X.; Feng, B. A Heuristic-Primed Decision-Making Model under the Assumption of Bounded Resources. *Comput. Sci. Math. Forum* **2023**, *8*, 42. <https://doi.org/10.3390/cmsf2023008042>

Academic Editors: Zhongzhi Shi and Wolfgang Hofkirchner

Published: 11 August 2023



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## 1. Introduction

Building an intelligent decision-making model based on the cognitive process of human decision making in a real environment is a challenging task.

Psychological and philosophical studies have shown that human beings often use heuristics to make concise decisions under insufficient cognitive and environmental resources [1,2]. However, existing decision-making models are generally based on the classical normative paradigm, which seldom considers the limited cognitive and environmental resources of humans when making decisions in real environments.

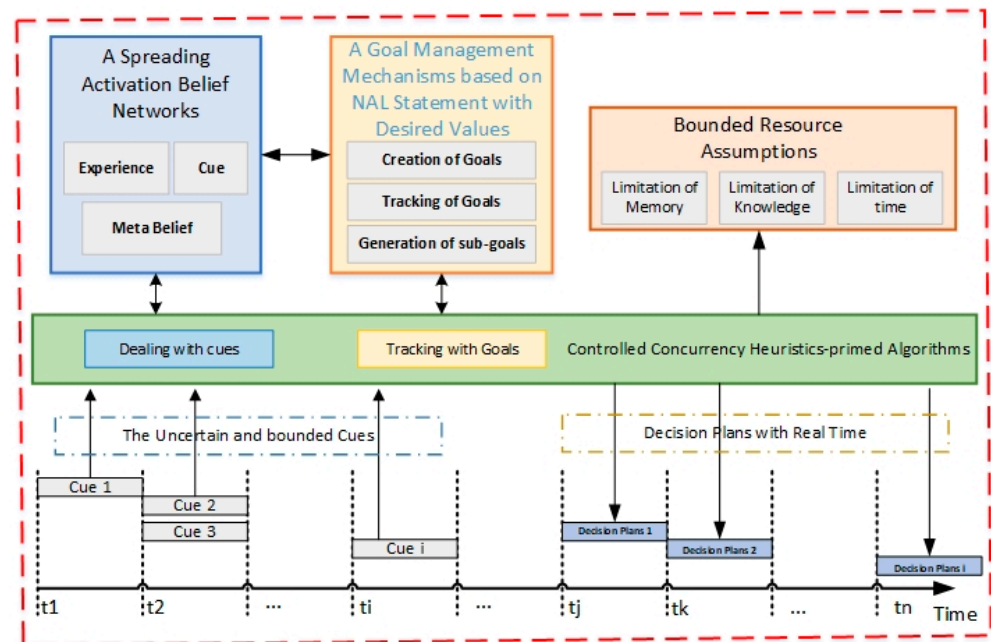
Classical decision-making theory [3] (choosing one action) and Markov decision processes (choosing a sequence of actions) are still the theoretical basis of constructing computational models of decision-making in AI. On the other hand, the existing heuristic-primed decision-making models [4,5] proposed by naturalistic decision-making and its computational methods [6–8] have not reflected the principle of the heuristics-primed decision-making process described in cognitive science.

We draw on the theory of Artificial General Intelligence (AGI) technology, Non-Axiomatic Reasoning System (NARS) [9,10] and heuristic-primed decision-making processes in the descriptive decision-making paradigm of psychology to propose a heuristic-primed decision-making model under the assumption of bounded resources. Firstly, we

propose a spreading activation belief network based on experience-grounded semantics, which takes concepts as nodes and semantic relevance as edges, and organizes semantically similar or related concepts through different levels. The network can change the weights of specific reasoning links according to the evidence presented using multiple inferences rules, so as to achieve the self-organization of its network topology. Next, multiple dynamically changing and conflicting goals are represented by a non-axiomatic logic statement with two-dimensional desire-values. Finally, a controlled concurrent heuristic algorithm that can dynamically allocate limited computational resources and perform multiple inferences is proposed.

## 2. The Architecture of Proposed Decision-Making Model

We propose an architecture of the heuristic-primed decision-making model under the assumption of bounded resources, which can inference decision-making plans (course of actions) based on its own beliefs and desires, using limited cognitive and environmental resources with some heuristic-primed strategies. The details of the representation and updating methods of belief networks, management mechanisms of dynamic multi-objective components, and heuristics-primed algorithm of the proposed model are shown as Figure 1.



**Figure 1.** The Architecture of proposed decision-making model.

According to above Figure, at different moments in time,  $t_1, t_2, \dots, t_i$  ( $i = 1, 2, \dots, n$ ), the intelligent agent designed according to the above architecture perceives different amounts of cues ( $\text{cue}_1, \text{cue}_2, \dots, \text{cue}_i$  ( $i = 1, 2, \dots, n$ )) containing multiple uncertainties (randomness, fuzziness, ignorance, etc.) from the external environment. The controlled concurrent heuristic-primed decision algorithm in the architecture will pre-process the obtained cue information, transmit it to the belief module, and activate the fragment in the network that has semantic relevance to the cue through multiple inference rules defined by the established meta-belief. The nodes in the activated network will then activate the semantically-related nodes to other connected nodes. At the same time, the algorithm will consider the creation of goals, the change of its desire values, and the derivation of subgoals, in order to infer a decision plan based on the activated network and its tracked goals.

As the intelligent agent accumulates more cues from the environment over time, the architecture activates the relevant cue-related network, continuously adjusts the desire value of the goal, and re-determines the context of the decision. In a working cycle, the intelligent agent will infer a “rational” decision plan that is adapted to the situation.

Since the proposed model assumes bounded resources, it will take into account the limited cognitive and environmental resources, and the controlled concurrent mechanism will inference a decision plan characterized by “satisfying” through a heuristic algorithm. “Satisfiability” is reflected in the fact that the system does not reason further to try to obtain the “optimal plan”; as soon as it obtains a satisfactory decision plan under time and resource constrain.

### 2.1. A Spreading Activation Belief Network Based on Experience-Grounded Semantics

**Definition 1.** A spreading activation belief network is a semantic network with concepts as nodes and semantic relevance as edges. Where the form of the concepts can be words, compound words, simple or compound statements and implication with independent variables, the strength of the semantic relation between nodes is expressed by a pair of numbers,  $f$  and  $c$ .

$$f = w^+ / w \qquad c = w / (w + k) \qquad (1)$$

The frequency “ $f$ ” indicates the proportion of positive evidence and that the value of “ $f$ ” is a real number  $[0, 1]$ . Confidence “ $c$ ” is a measure of the stability of the frequency against future evidence. In the above formula, “ $w^+$ ” is the number corresponding to the amount of positive evidence, while “ $w$ ” corresponds to the total amount of evidence.

**Definition 2.** A cue is a piece of information about the current environment obtained at a certain moment, set as  $C = \{C_1, C_2, \dots, C_i, \dots, C_n\}$ , where  $C_i$  can be represented by an inheritance statement of non-axiomatic logic, in a logical form “ $\langle S \rightarrow P \rangle (f, c)$ ”, where  $S$  is the subject,  $P$  is the predicate, “ $\rightarrow$ ” represents the inheritance relation, and  $(f, c)$  is the measurement of uncertainty of the proposition.

**Definition 3.** The Meta-beliefs consist of syllogistic inference rules of Non-Axiomatic Logic and are constant throughout the life cycle of the system.

The syllogistic inference rules in meta-beliefs are mainly composed of six rules: deduction, induction, attribution, comparison, analogy, and similarity. In addition to the above inference rules, meta-beliefs also include two ‘local’ inference rules, revision and choice, to facilitate the merging of evidence from different sources.

When the acquired cues activate specific semantically-related nodes in the network, the related schema in that network can be activated. The activation spreads along each edge of that node, while simultaneously spread in all directions, first to the node directly connected to it, and then to other nodes. The higher the value of “ $f$ ” between nodes in the network, the faster the information spreads when the network is activated. The activity of the network will diminish with time and disturbances.

In addition, the longer a node is subjected to processing, the longer it will be active, however, this activity will gradually diminish in the network. On the other hand, the network continuously inference new evidence related to the cues in order to self-organize its topology according to the inference rules defined in its meta-beliefs to achieve the necessary revision and update its beliefs. The properties of the representation semantics of the proposed network facilitate a considerable degree of interpretability of its operational processes, such that it can form a certain memory capacity and accumulate decision-making experience, which can realize the improvement of the function of the empirical network itself while in operation.

### 2.2. A Goal Management Mechanism Based on Non-Axiomatic Logic statement with Desire Values

In this paper, we proposed a goal management mechanism based on Non-axiomatic Logic statement with desire values. An intelligent agent with this mechanism can continuously take relevant goals into consideration in order to enable the system to determine and track multiple dynamic goals based on the changed desired value of the goals under the constraints of limited resources.

**Definition 4.** Multiple goals are in the of the form “( $\mid$ ,  $g_1, g_2, \dots, g_i$ )”, where  $g_i$  is a goal that can be characterized by inherited statements based on Non-axiomatic Logic, and the desired value is represented by ( $f, c$ ) in the following form:

$$\langle \text{goal} \rangle :: = \langle \text{statement} \rangle ! \langle \text{desired value} \rangle \quad (2)$$

Based on such an approach, the overall expectations of the system can be constructed according to the way the system interacts with the external environment, rather than as a fixed function that needs to be predefined.

As time changes, the intelligent agent may generate multiple conflicts goals and dynamically change its goals, which can be in the state of “input”, “derived”, “adopted” or “dropped” in the goal detection mechanism.

The initial goal is generated by external input or by the system deriving sub-goals from parent goals. The system adopts goals and sorts them into the “alternative goal set” and “tracking goal set”, respectively, according to whether the goals’ attached desire values reach a certain threshold. In addition, in this paper we solve the problem of deriving sub-goals from the original parent goal in a backward inference manner so that the system can achieve autonomy by guiding the judgment and decision-making behavior of the system through its autonomously generated goals.

### 2.3. Controlled Concurrent Heuristic-Primed Inference Algorithm

In this study, we explore a controlled concurrent heuristic-primed inference algorithm with dynamic allocation of limited resources to infer some decision plans with “satisficing” characteristics based on multiple goals with different desired values to maximize the utility of the decision-making at the macro level.

Firstly, the mental architecture extracts situational cues from the environment and determines whether the acquired cues are semantically relevant to its own experience. If there is semantic relevance, then the architecture analyzes the semantic similarity between the acquired cues and its own experience. If no semantic relevance is found, the situation is re-diagnosed, and further situational cues are obtained. Secondly, based on the diagnosis in the previous step, the architecture will derive decision-making plans based on multiple goals with attached desired values based on the activated experience network. If the parent goal cannot generate a decision solution, then the system derives sub-goals based on the parent goal. If the sub-goal is actionable, then the sub-goal will be executed by the intelligence as an action instruction. Before execution, the mental architecture still constantly observes whether the environment has changed. If there is a change in the environment, the goal is immediately adjusted, and the sub-goals associated with that goal are projected once again. If time permits, the mental architecture is able to continuously take cues from the environment and continuously modify the decision plans through multiple interactions.

### 3. Conclusions

We are dedicated to solving some bottleneck problems in the field of multi-stage and multi-objective (goals) decision making in the current uncertain environment, and providing new ideas and methods for the application of Artificial General Intelligence technology in the field of intelligent decision-making. Our research results will improve the efficiency of real-time decision-making and promote the use of intelligent decision-making models that can play an important role in practical application areas. The proposed model can provide a new concept for the computation of bounded rational decision-making and render the decision process interpretable.

**Author Contributions:** Conceptualization, N.S.; methodology, N.S.; validation, X.L. and Bojie Feng.; formal analysis, X.L. and B.F.; investigation, N.S.; writing—original draft preparation, N.S.; writing—review and editing, N.S.; visualization, N.S.; project administration, N.S.; funding acquisition, N.S. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by the Northwest Minzu University Project for Introduced Talents grant number Z20062 and Fundamental Scientific Research Expenses for Central Colleges and Universities grant number 31920210133.

**Institutional Review Board Statement:** Not Applicable.

**Informed Consent Statement:** Not Applicable.

**Data Availability Statement:** Not Applicable.

**Acknowledgments:** We are very grateful to Pei Wang for his comments and suggestions on the paper.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

1. Kahneman, D.; Slovic, P.; Tversky, A. Judgement Under Uncertainty Heuristics and Biases. *Science* **1974**, *185*, 1124–1131.
2. Gigerenzer, G. Reasoning the fast and frugal way: Models of bounded rationality. *Psychol. Rev.* **1996**, *103*, 650–669. [[CrossRef](#)] [[PubMed](#)]
3. Russell, S.; Norvig, P. *Artificial Intelligence: A Modern Approach*; Prentice Hall: Hoboken, NJ, USA, 2011.
4. Klein, G.; Moon, B.; Hoffman, R. Making Sense of Sensemaking 1: Alternative Perspectives. *Intell. Syst. IEEE* **2006**, *21*, 7073. [[CrossRef](#)]
5. Klein, G.; Moon, B.; Hoffman, R. Making Sense of Sensemaking 2: A Macro cognitive Model. *Intell. Syst. IEEE* **2006**, *21*, 8892.
6. Ji, Y.; Masanori, R.M.; Ager, J.; Yen, J.; Miller, R.E.; Ying, H. A fuzzy logic-based computational recognition-primed decision model. *Inf. Sci.* **2007**, *177*, 43384353. [[CrossRef](#)]
7. Mueller, S.T. A Bayesian recognitional decision model. *J. Cogn. Eng. Decis. Mak.* **2009**, *3*, 111130. [[CrossRef](#)]
8. Nowroozi, A.; Shiri, M.E.; Aslanian, A.; Lucas, C. A general computational recognition primed decision model with multi-agent rescue simulation benchmark. *Inf. Sci.* **2012**, *187*, 5271. [[CrossRef](#)]
9. Wang, P. *Non-Axiomatic Logic: A Model of Intelligent Reasoning*; World Scientific: Singapore, 2013.
10. Wang, P. Experience-grounded semantics: A theory for intelligent systems. *Cogn. Syst. Res.* **2005**, *6*, 282–302. [[CrossRef](#)]

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