TOWARDS INTELLIGENT URBAN DECISION SUPPORT: COGNITIVE DUALITY AND DIGITAL TWINS

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Urban intelligence is an emerging research area focused on leveraging advanced technologies and data analysis techniques to enhance urban efficiency, sustainability, and livability. Decision support plays a crucial role within urban intelligence, utilizing automated reasoning to both plan activities on the urban landscape and react to its dynamic changes. Drawing inspiration from dual-process cognitive theories, this paper explores the integration of automated planning and rule-based systems to facilitate decision-making in urban management.

Keywords: *timeline-based planning, plan execution, urban intelligence, decision support system*

1. Introduction

Urban areas are intricate and ever-changing, demanding continuous management to uphold their efficiency, sustainability, and livability. With the expansion and diversity of urban populations, the complexities of urban management intensify [1, 2]. In recent times, there has been a growing interest in utilizing advanced technologies and data analysis techniques to bolster decision-making in urban management. Urban intelligence, an emerging and evolving research domain, aims to harness these advancements to enhance the effectiveness, sustainability, and livability of urban areas [3]. Urban intelligence encompasses decision support as a crucial element, enabling informed choices for urban development and management. A specific type of decision support system (DSS) called a cognitive decision support system (CDSS) incorporates cognitive theories and models of human decision-making to aid in complex decision-making tasks [4]. The dual processing theory [5], among the various cognitive theories available, has found widespread application in the development of CDSS [6, 7]. This theory proposes two distinct cognitive systems known as System 1 and System 2. System 1 entails fast, automatic, and intuitive thinking relying on heuristics, mental shortcuts, and past experiences to make judgments and decisions. It operates at an unconscious or intuitive level being involved in perception, pattern recognition, and emotional responses. On the other hand, System 2 involves slower, deliberate, and analytical thinking based on logic, reasoning, and conscious effort to make judgments and decisions. It operates at a conscious or rational level and is engaged in problem-solving, planning, and decision-making activities. Inspired by the dual processing theory, this paper presents COCO (COmbined deduction and abduCtiOn logic reasoner), a cognitive architecture that serves as a digital twin of urban decision makers. COCO integrates a rule-based system to replicate the characteristics of System 1 and a timeline-based planner, enhanced with semantic reasoning capabilities, to emulate the cognitive processes of System 2. By embodying the decision-making traits of urban decision makers, COCO aims to enhance decision-making in urban management, allowing the simulation and analysis of various scenarios, conducting what-if analyses, and even simulating suboptimal decision-making behaviors.

2. Thinking, Fast and Slow, Logically: COCO

Rule-based systems are a type of Artificial Intelligence (AI) systems that use predefined “if-then” rules to make fast and reliable decisions in various situations. For instance, a rule like “IF temperature is above 30 degrees Celsius AND humidity is above 70%, THEN activate the sprinkler system in the park” exemplifies a rule-based system. By introducing facts such as "current temperature is 35 degrees Celsius" and "current humidity is 75%", the system activates the corresponding rule and executes the action. These systems store rules and facts in a knowledge base, allowing quick assessment and response without extensive analysis. The transparency of rule-based systems enhances trust and accountability in decision-making. COCO adopts the CLIPS[1] rule-based system to recognize familiar patterns and make intuitive decisions, similar to System 1 processes.

Automated planning is another field of AI focused on creating computer programs that generate plans and strategies to accomplish specific goals or tasks [8]. One approach within automated planning is timeline-based planning [9, 10], in which activities are organized over timelines, considering temporal constraints and dependencies. Such activities are represented through tokens, consisting of a predicate symbol (denoted as n) and parameters (denoted as $x_0, \ldots, x_i$), which can include temporal details. The tokens can be classified as either facts or goals. Rules play a crucial role in achieving goals. They consist of a head (e.g., $n\left(x_0, \ldots, x_k\right)$) and a body ($\mathbf{r}$), defining the requirements (i.e., other tokens, token constraints, conjunctions or disjunctions of requirements) for reaching a specific goal. Tokens can also be associated with timelines, identified by a special object variable τ. Different tokens with the same τ value belong to the same timeline and may interact with each other based on the nature of the timeline. There are different types of timelines, such as state-variable timelines, where tokens on the same state-variable cannot overlap temporally, and reusable-resource timelines, where tokens representing resource usages can overlap as long as the concurrent usage remains within the resource's capacity. In timeline-based planning, the objective is to find a set of tokens that satisfy all the constraints, rules, and a requirement defined within the planning problem. This is typically achieved through a process of reasoning and decision-making, similar to the deliberate and intentional decision-making of System 2 thinking.

To enable effective decision-making in dynamic environments, the COCO system integrates a rule-based system as a sequencing (reactive) tier, and a timeline-based planner[2] as a deliberative tier, applying production rules to deduce new information or actions while reasoning backward to find action sequences that achieve goals. Notably, the sequencing tier has the capability to interact with both the environment and introspectively with higher-level reasoning. The intrinsic motivations and higher-level tasks generated during plan execution by the deliberative tier serve as suggestions rather than mandatory components for the system's autonomy, influencing the choice of actions made by the sequencing tier. By combining the reactivity and explainability of the rule-based system with the planning capabilities of the timeline-based planner, this integration harnesses the strengths of both components. The architecture, depicted in Figure 1, consists of a deliberative tier for plan generation and adaptation, a sequencing tier for executing actions, and sensing and controlling tiers for interpreting sensor data and actuator commands. By functioning as a digital twin of the urban decision makers, this integration provides a comprehensive support by addressing System 1 tasks such as abstraction and low-level command generation, as well as System 2 tasks including reasoning and high-level plan adaptation based on dynamic environmental information. This enables the system to facilitate what-if analysis and offers decision makers a powerful tool to simulate and evaluate different scenarios, thereby enhancing their decision-making capabilities in urban management.

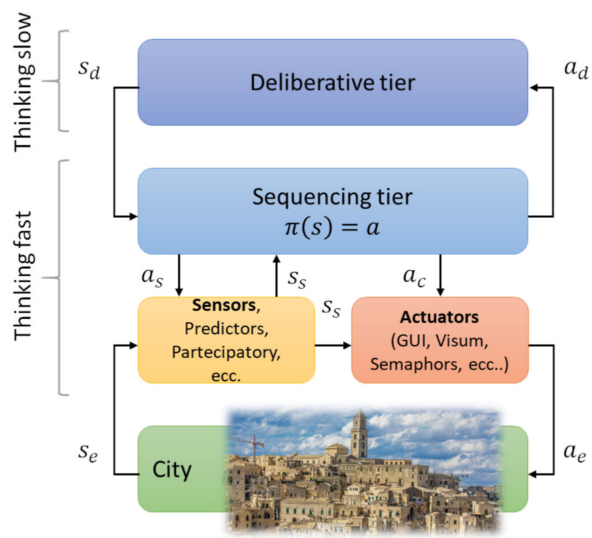

Figure 1: The COCO three-layer architecture.

[1]https://www.clipsrules.net

[2]https://github.com/ratioSolver/oRatio

3. Conclusions

The COCO system, introduced in this paper, combines a rule-based system and automated planning to support decision-making in urban management. Rule-based systems excel at responding to environmental changes, while automated planning generates task-oriented plans for achieving desired goals. By merging these two approaches, urban managers and decision-makers gain a comprehensive and efficient solution for managing diverse aspects of urban life. The rule-based system utilizes indexing techniques to generate reactive behaviors efficiently, while the deliberative component handles scenarios, plan adaptation during execution, and what-if analyses, despite its computational demands. The effectiveness of the COCO system has been initially evaluated by assessing the efficiency of the reasoners' resolution processes. This evaluation has involved benchmark problems of increasing complexity to estimate the resolution times as the problems grew in size. The goal was to measure how quickly COCO could respond when urban decision-makers used the system to analyze and modify generated solutions by adding additional constraints for what-if analyses. Impressively, even with the exponential complexity of the problem, the resolution times consistently remained within a few seconds, even with larger numbers of activities. It's important to note that both System 1 and System 2 heavily rely on defining rules, which can be a challenging and time-consuming task. To simplify and automate this process, future efforts will explore machine learning techniques such as induction and decision tree learning.

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