Modeling of Individual Naturalistic Decision Making in a Cognitive Architecture

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Abstract

In the dynamic environment of train stations, managing passenger flow to prevent overcrowding and ensure safety is challenging, particularly with an increased passenger volume and less predictability of travel routes introduced by the 49-euro ticket. The aim of the overall research project is to allow for an effective passenger flow and an optimal distribution of individuals first in a simulation of a train station, later on in a real-world train station. Therefore, the passengers or agents are addressed through transparent and individualized messages. To achieve this overall goal, this work focuses on the modeling of the reactions to these messages. Human behavior in such settings is complex, driven by personal goals and influenced by intuitive and analytical decision-making processes. The Naturalistic Decision-Making (NDM) framework, which highlights the role of experience and intuition in decision-making under real-world constraints, forms the basis of our approach. To model these behaviors, we employ cognitive modeling, specifically the ACT-R (Adaptive Control of Thought—Rational) architecture, which simulates human cognitive processes and predicts behavior in dynamic situations. Our modelling approach integrates both intuitive and analytical decision-making processes, accommodating environmental changes and feedback. We represent individual personas with static and dynamic attributes, allowing for varied responses to information in a realistic manner. This cognitive model aims to predict passenger behavior in response to messages and guide their actions within the station. The paper outlines the technical implementation of the ACT-R model, detailing the representation of the station environment, individual goals, and decision criteria. By simulating human behavior, we can generate valuable data to inform decision-making processes without relying solely on empirical testing, ultimately contributing to safer and more efficient passenger flow management.

Keywords

Cognitive Modelling, Intuitive Decision Making, Naturalistic Decision Making, ACT-R

1. Introduction

Unpredictable upcoming crowds are a problem at larger train stations, not just because of security reasons. It is often not known how many people are in the station at the same time. The 49-euro ticket, allowing for free travel with regional trains without the need to book the journey in advance, increases this effect. Due to the dynamic nature of stations, there are often situations where localized crowds form or individual sections are overcrowded, even though there is sufficient space in the rest of the station.

The overall objective of the whole projects to develop a methodology for the efficient administration of passenger traffic within a train station in order to circumvent the formation of local crowds. Therefore, a multi-agent simulation of a train station is administered in the overall project with the objective to ensure an optimal distribution of individuals within the station, while simultaneously addressing their specific needs. It is of particular importance to ensure that individual needs are not overlooked or disregarded by persuading people to act against their will. Therefore it is essential to align the overarching goal with people's individual goals as much as possible by addressing their personal preferences. To this end, it is crucial to provide transparent and easily accessible information. This can be achieved by sending individualized messages to guide the actions of passengers at the station.

However, human behavior is inherently complex. Individuals act in accordance with their personal objectives and possess their own unique preferences. In the context of a train station, where the majority of individuals are pursuing a fixed goal, such as taking a specific train at a designated time or reaching a particular destination, it can be assumed that their actions are often driven by self-interest and the pursuit of their own goals, with the common good

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not being a primary consideration. The reality of a train station is also a dynamic situation in which a large number of different individuals act and spontaneous events, such as a train breakdown, constantly alter the overall situation.

The field of psychology has identified two distinct modes of thinking: intuitive and analytic. Intuition is a subconscious process that draws upon patterns from knowledge, experience, and emotion, allowing the brain to rapidly filter decision-making options based on past experiences. This intuitive process is influenced by emotional responses (Thomson et al., 2015, Hall, 2002). The theory of predictive processing posits that the brain is engaged in a continuous process of comparison between incoming information and stored knowledge, with the objective of reducing prediction errors. In the event of a discrepancy, the brain modifies its mental models to enhance the decision-making processes. However, when our experience or knowledge is limited, we are forced to rely on slow, logical, and rational analytic thinking, which requires time for testing, learning, and analysis (Wang & Ruhe, 2007)

This is consistent with the Naturalistic Decision-Making (NDM) framework, as described by (Klein, 2008). The NDM framework is concerned with the decision-making processes of individuals operating within real-world environments that are characterized by a number of factors, including uncertainty, dynamicity, the presence of competing or ill-defined goals, time pressure, action and feedback loops, and information sources of varying reliability. The framework underscores the significance of experience and intuition in expeditious decision-making, in accordance with the notion that intuition draws upon patterns derived from past knowledge, experience, situation awareness, and emotional responses to rapidly filter choices. Although this approach differs from traditional decision-making models that frequently assume that decision-makers have sufficient time and information to evaluate options in a systematic manner, the NDM framework recognizes the importance of these analytical processes. In circumstances where intuition is inadequate due to limited knowledge, uncertainty, or novel circumstances, decisions may be made through analytical, logical, and conscious processes. This integration of intuitive and analytic processes within NDM illustrates how mental models are continually refined to minimize prediction errors, thereby ensuring effective decision-making in dynamic contexts. It demonstrates the interplay between rapid, intuitive judgments and slower, analytic reasoning in optimizing decision outcomes.

The concept of dynamic decision-making becomes pertinent when multiple decisions must be made in a given situation. It is an ongoing process of learning, dependent on experience and feedback. Decisions are made in a sequential manner as potential alternatives become apparent over time, rather than all at once. This type of decision-making considers not only singular aspects, such as attentional influence, but also environmental factors that provide feedback, necessitating adaptation to new conditions. As Gonzalez (2017) notes, dynamic decisions are motivated by goals and external events and are influenced by previous choices and external conditions. Feedback from the environment shapes future choices and decision outcomes, making dynamic decision-making highly experience-based and dependent on immediate feedback.

To guarantee the effective management of passenger flows without having to depend on lengthy test runs in which individuals are provided with erroneous or unhelpful information, it is crucial to simulate the reactions of individuals to the messages in their entirety. It is essential that these decisions are modeled in a realistic and transparent manner, with the objective of ensuring that the decision-making process is as close as possible to reality.

2. Why cognitive modelling?

The method of cognitive modeling forces precision of vague theories. For scientific theories to be precise, these verbal theories should be formally modeled (Dimov et al., 2013).

Cognitive models provide an opportunity to predict how various aspects or variables interact to produce human behavior observed in empirical studies. In real-life situations, this behavior is shaped by multiple influences. Consequently, cognitive models are a valuable tool for understanding the interrelated cognitive processes that lead to observed behavioral outcomes. By simulating multiple ongoing cognitive processes, cognitive models are capable of performing the same tasks as human participants. This enables models to offer insights into tasks that are too complex to be analysed through controlled experiments (Wolff and Brechmann, 2015).

While cognitive architectures are not a definitive solution for studying decision-making, they are a valuable tool for exploring complex theories that traditional experimental methods are unable to address. In particular, the study of dynamic decision-making is challenging due to its inherent cognitive complexity and the limitations of introspection. By manipulating symbolic elements and their activation strengths, these models allow for the examination of processes within the model and the formulation of testable predictions about the cognitive mechanisms of decision making. This, in turn, supports the goal of modeling and understanding the processes underlying human decision-making.

In conclusion, cognitive modeling represents a falsifiable methodology for the study of cognition. In scientific practice, this signifies that exact hypotheses are implemented in executable cognitive models, with the principal objective of describing, predicting, and prescribing human behavior. The aim is to develop a generalizable cognitive model that can predict human behavior in diverse situations (Marewski and Link, 2014).

A model embedded in cognitive architectures has the capacity to simulate a multitude of parallel processes, effectively capturing complex psychological phenomena and even making predictions for tasks that are inherently complex. However, the construction of these models necessitates a systematic, step-by-step approach to clearly identify and separate the various influencing factors.

3. The cognitive Architecture ACT-R

The cognitive architecture ACT-R (Adaptive Control of Thought—Rational) has been effectively utilized to model various dynamic decision-making tasks (Anderson, 2007; Prezenski et al., 2017; Gonzalez, 2014). The following section provides a technical overview of the main structures of ACT-R that are relevant to our modelling approach.

The ACT-R cognitive architecture aims to model overall cognition by employing a modular approach, whereby different modules interact to simulate cognitive processes. These modules communicate via interfaces referred to as "buffers." As a hybrid architecture, ACT-R incorporates both symbolic and subsymbolic mechanisms within its modules.

Our model employs the declarative, imaginal, goal, and procedural modules. Figure 2 shows an overview of the whole ACT-R cognitive architecture. The declarative module serves as ACT-R's long-term memory, where all information units (chunks) are stored and subsequently retrieved. The imaginal module serves as ACT-R's working memory, maintaining and modifying the current problem state, which is an intermediate representation that is crucial for task performance. The goal module oversees the management of control states, which are subgoals that are essential for the attainment of the primary decision-making objective. The procedural module plays a crucial role in ACT-R, functioning as the interface for other processing units by selecting production rules based on the current state of the modules.

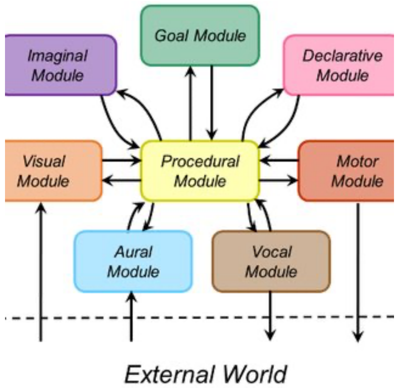

Figure 2. Overview of the modules of the ACT-R cognitive architecture

The creation of a model in ACT-R necessitates the specification of its symbolic components, namely production rules and chunks. In ACT-R, all data is stored in chunks, which are the basic units of information. A production rule, or production, is composed of two parts: a condition and an action. The selection of productions is conducted in a sequential manner, with only a single production being selected at any given time. A production is selected when its condition part is matched with the current state of the modules. Thereafter, the action part modifies the chunks within the modules. In the event that multiple productions satisfy the conditions, a subsymbolic selection process is employed to determine which production is selected.

4. Modelling in ACT-R

The objective is to develop an ACT-R modeling approach which still needs to be implemented in the future. The model should be applied to real-world decision-making situations and accordingly must be construct a cognitive representation of the situation of the train station in which it is required to cope with uncertainty. This should include both intuitive decision-making processes and analytical decision-making processes. In order to cope with the necessity of making multiple decisions, it is essential to incorporate changes in the environment that occur subsequent to previous decisions into the decision-making process.

The cognitive model should provide a transparent representation of the underlying cognitive processes associated with real-world decision-making. To ensure the model's generalizability across different experimental settings and data sets, it is essential to maintain its simplicity. Although the underlying cognitive processes are complex, the model only makes minimal and necessary assumptions. Therefore, the provided, individual messages draw on a limited selection of options, and similarly, the individuals' personal goals are also restricted. The aim of the decision process is to assess whether these two sets of goals can be aligned in any way, which may result in a decision either in favor of or against the message. Consequently, this modeling approach should be capable of predicting behavior in response to different stimulus materials and be transferable to other similar tasks, such as managing visitor flows in airports.

The following section presents a potential implementation of the model. Initially, the primary representations of the self and the situation are outlined. These are represented as chunks in ACT-R. Subsequently, the concept of the yet outstanding decision-making process is described, reflecting the underlying cognitive processes.

4.1 Chunks in the Model

The implemented chunks are illustrated in Figure 1. In order to process the data contained within the messages, it is essential to incorporate a fundamental understanding of the train station's operational characteristics into the model. This includes data regarding the distances between platforms, the necessity of navigating stairs, and other pertinent information. The extent to which this basic knowledge can be accessed should vary depending on the individual. This represents an opportunity to incorporate a certain degree of uncertainty into the model. In the event that the knowledge situation is unclear, the model can utilize intuitive decision-making mechanisms, given that a comprehensive assessment of the situation is not feasible. The implementation of the basic knowledge will be stored in the declarative memory, from which it will be retrieved.

The chunk representing of the individual is stored in the imaginal memory, due to its dynamic components. It contains the persona information defined by a series of attributes. On the one hand, these are static attributes, such as the need to avoid crowds, mobility, or knowledge about the train station. Conversely, the persona should also be characterized by dynamic attributes that evolve over the course of the individual's stay and navigation within the station. Frustration serves as an illustrative example. The objective is to incorporate a substantial number of personas into the model, which are then represented by a series of individuals. The initial stage of the process is to define the various personas, which are characterized by a range within static attribute values. For example, one might consider a commuter or an older person. Given that individuals within a given persona group exhibit a range of attributes, it is necessary to randomly select each individual from the specified range. This allows for the generation of different individuals, who may also exhibit distinct responses to a given message, within the same persona group.

The chunk representing the dynamic perceived situation is also stored in the imaginal buffer, functioning as an intermediate representation of the surrounding passenger situation. As the model is unable to perceive by itself, information from the station simulation is integrated . The chunk relates to the immediately perceived environment of the individual and includes surrounding crowds and whether the individual's potential path is blocked. The manner in which this situation is interpreted by the individual is also represented here. This is once more dependent on the attributes of the persona. In a further slot, the influence of a previous decision on the overall situation is evaluated.

The message chunk is also stored in the imaginal buffer. The message slots include the target and the reason for the message. Additionally, the message may contain incentives to achieve this target. To keep the model simple, both the goals and the reasons for the message are based on a limited set of alternatives. For example, this could involve temporarily switching to another track or moving to the waiting area due to a forecasted overcrowding at the current location.

The personal goal of the individual is stored in the declarative memory, as are the sub-goals associated with it. Additionally, the interpretation of the goal presented by the message is represented. Several slots are provided to represent the various decision criteria.

4.2 Decision Process

The modeling of the decision-making process should be capable of representing both intuitive and analytical decision-making methods. It is important to note that the model's decisions are limited to choosing either for or against the content of the message. This manifests in a change of the personal goal, a description of the reason for the decision, and potentially a change in movement speed. First, the extent to which the individual goal can be aligned with the goal of the message should be modeled. Factors such as the necessity of detours, the presence of additional stairs, and the potential for avoiding crowds are of significant consequence in this regard. It is equally important to consider the personal attributes of the individual, such as their mobility, knowledge of the station, and level of frustration. In order to facilitate computational processing of the entire process, the slots of the decision criteria are calculated. In order to achieve this, the individual components of the different chunks are offset against each other in order to collect evidence for or against the decision in these decision criteria. To illustrate, the temporal feasibility decision criterion is employed, wherein the persona attributes of mobility and knowledge about the station are contrasted with the distance to the individual's intended destination and the surrounding crowd from the perceived situation chunk, as well as the distance to the destination of the message from the message chunk. In cases where central decision criteria can be evaluated with relative ease, such as when a course of action is deemed to be "hardly feasible in terms of time," clear and rapid decisions should be made that can be considered intuitive. The attributes of frustration and knowledge about the station also exert a significant influence on intuitive decision-making, and are designed to affect the extent to which decisions are rational. There are often situations in which no clear decision can be made. In the event that the model is unable to resolve the circumstances in an intuitive manner due to uncertainty or the presence of partially overlapping objectives, it would be beneficial to implement a mechanism for evidence accumulation. This entails the calculation of additional decision criteria, from which a trade-off is derived that ultimately informs an analytical decision. The outcome of preceding decisions should be integrated into the intuitive decision-making process and serve as a valuable source of information for evidence accumulation.

The decision process thus constitutes a reaction to the message at the conclusion of the decision-making process. Based on the decision chunk, the feedback provided to the simulation contains a greater degree of information than a purely binary decision. The feedback from the model should provide the message predictor with an opportunity to learn more effectively. To include the reaction to single messages in the simulation, they could be implemented as a distribution of reactions within a group of individuals. If an agent appears in the simulation, it will react to certain messages according to the distribution. By implementing the individual decisions in the learning of the predictor, these can also be incorporated into the simulation in a further step.

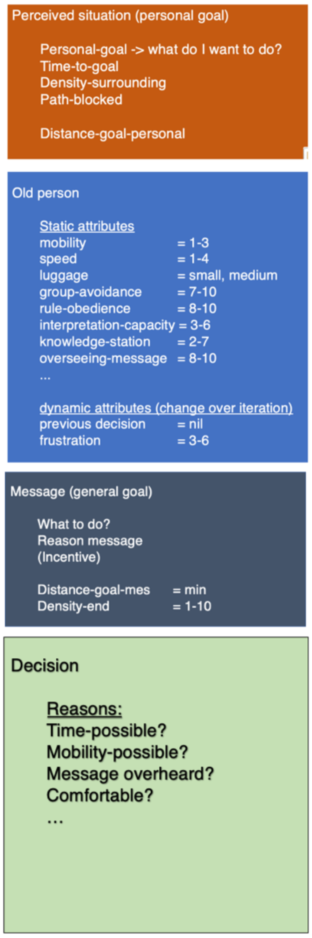

Figure 1. ACT-R Chunks used in modelling approach

5. Outlook

The modelling approach is of significant importance as it plays a crucial role in solving the passenger traffic problem in the whole multi-agent simulation. All decisions of the single individuals will form part of the training phase of the message predictor with the objective to improve to production of adequate messages. These messages should achieve the overall goal but are still likely to be followed by the individuals. With modeling the reactions, the generation of a substantial amount of data pertaining to human reactions in a time-efficient manner is enabled, thus avoiding the potential stress and inconvenience associated with direct observation of test participants. The models' decisions contain a greater quantity of information than that which can be derived from purely observed behavior. The subsequent phase of the process requires the involvement of human subjects to substantiate the potentially transparent and plausible predictions of the model. To this end, an experiment should be conducted to ascertain how individual groups of people respond to messages, thereby enabling the model's predictions to be refined. Subsequently, the validated model may be transferred to other decision-making processes. The simulation of human behavior in real-world settings will become increasingly crucial in the future, underscoring the need for further research in the domain of cognitive modelling with the aim to more realistic simulations.

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