A Novel Agent Software Architecture Inspired by Psychology

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Abstract. Computer simulation of social phenomena is a promising field of research at the intersection between social, mathematical and computer sciences. Agent-based technologies have been used to simulate human society and aim to provide explanation for emerging behaviours. As software agents are encoded as executable program code, their structure and underlying architecture frame the way how the decision-making process is described. Current architectures mainly origin from computer science and do not make efficient attempts to describe human-like reasoning or consider the language of non-computing domains. This can create obstacles in communication between involved researchers; hence we propose here a new agent architecture based on the Theory of Interpersonal Behaviour. This theory originates from psychology, and therefore we consider it to be more suitable for the usage in interdisciplinary research, as it enables domain experts to encode better human-like decision making processes.

1 INTRODUCTION

A growing number of social scientists have begun to convert their theories into computer programs, in particular Multi-Agent Systems, to enable testing them in a controlled environment [5, 15], as well as to gain insight into patterns of the collective behaviour of agents [3, 10]. While encoding, it is necessary to keep a close connection to the domain in which the model origins from.

There are several architectures for agent-based reasoning available for research purposes. Two good examples are *Belief - Desire - Intention model (BDI)* [7] and *SOAR* [9]. These architectures however, have been motivated by technical developments from Computer Science, which ease the design and implementation of models, but hinder the communication with non-technical researchers since they often do not consider metaphors in the application domain.

Triandis' Theory of Interpersonal Behaviour (TIB) [13] states that behaviour is primarily a function of the intention to engage in the act, habit and facilitating conditions. It provides a large set of aspects that contributes to decision-making in psychology which can be incorporated inside an agent system. Therefore, we propose to use this model as a backbone to develop a new agent architecture incrementally from individual cognitive components.

2 METHODOLOGY

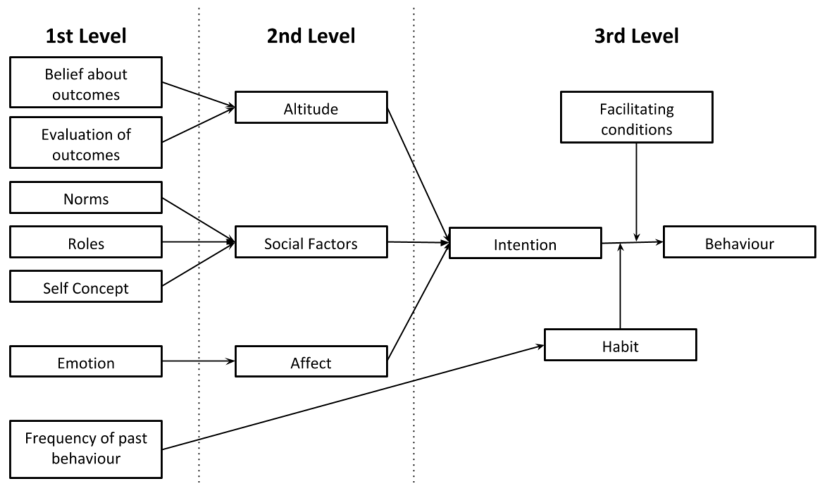

Fig. 1. Triandis' tri-level model. [13].

2.1 Towards Human Psychology

In psychology, Ajzen and Fishbein's Theory of Reasoned Action [6] and Ajzen's Theory of Planned Behaviour [2] stated that the key determinant of behaviour is an individual's intention to perform a specific act. In his tri-level TIB model (see Fig 1), Triandis added habits and the presence of facilitating conditions. The first level is concerned with the way personal characteristics and prior experiences shape personal attitudes, beliefs and social factors that contribute to behaviours. The second level explains how cognition, affect, social determinants and personal normative beliefs influence the formation of intentions with regards to a specific behaviour. Finally, the third level states that intentions regarding the behaviour, prior experience and situational conditions determine whether or not the person will perform the behaviour in question.

2.2 Agent Architecture

Our agent design (see Fig. 2) is based on a combination of horizontal and one-pass vertical layered architectures [14, chap. 5.2]. An agent first selects a single isolated decision-making task from a list that are sequentially executed. Its personal desire/goal is then combined with external means provided by the external environment to generate the list of possible actions. They are ranked (given a normalised value) according to specific psychological aspects which are organised into layers (or levels). The action' referenced value in one level can be combined (with an associated weight) to produce a new referenced value in the next level.

As an example, an agent is making a decision to use a transportation mode. There might be 3 options available: *walking*, *using car* or *taking train*. According to the *price*, they can be ranked as walk(1), train(2), car(3) - which are added to 6. According to *time*, they can be ranked as train(1), car(2), walk(3) - which are also added to 6. If weights of *price* and *time* are 7 and 3 respectively, the new referenced value of *walking* in next level list(*Attitude*) would be $1/6*7 + 3/6*3 = 2.08$ and referenced value of *car* would be $3/6*7+2/6*3 = 2.75$.

The result is a final actions list, where each referenced value can be interpreted as the chance that an agent will perform that action. For a single decision-making process, the agent can select one option based on the probabilities generated by the values. The structure of all decision-making aspects are mapped according to TIB, however their weights can either be adjusted by the agent from learning of its prior experience (through feedback loops) or be calibrated by the modeller to fit the purpose of the specific simulation at hand.

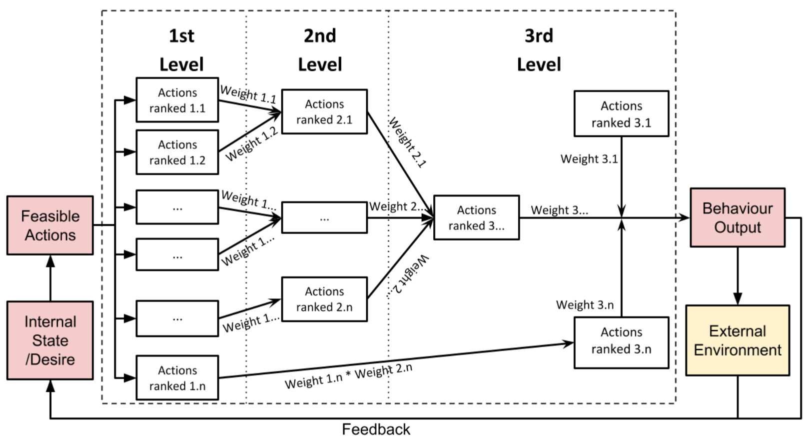

Fig. 2. New agent architecture with mapping to TIB elements.

2.3 Implementation

We are developing a framework implementing the outlined architecture, based on the Repast [11] library. In conjunction, this framework is also used to implement a standalone system (called BedDeM) to investigate the mobility demands by capturing the human decision-making in a dynamic environment. In the recent study, we tested BedDeM capability to mimic Neoclassical Economics (NCE)'s linear demand curves [4], which depicts the relationship between price and demand of a special good/service when consumers are assumed fully-rational.

The agent-based simulator is embedded in an experimentation set-up, which consists of three main components: controller, agents and environment. Each agent has a list of tasks (choosing a mode for mobility desire) to perform - the timetable. From input data, the controller generates a number of agents, then schedules them according to their timetables and starts the simulation. For each event, an agent considers all available transportation modes and evaluates them according to its decision making procedure (currently the first branch of TIB - *Attitude*, which was selected so that results are comparable with NCE's theory). The agent picks the option that has the minimum costs associated and allows it to reach destination in time, updates its budget and informs the environment about its action.

Using realistic data gained from Swiss Statistical Office's publications [1], we created a linear demand curve of private car usage through a point that represents current demand (average daily person km) and price (average cost per km) using formula of point elasticity of demand [8,12], which is represented as the blue line in Fig.3. Similarly, data points of private car demand with respect to varied price scales in the output of BedDeM and their linear regression line are illustrated on the same graph (as dots and red line respectively).

To evaluate how close the two lines are, we then applied R^2 and *Root Mean Square Error (RMSE)* tests. R^2 value is $\sim$96%, which means BedDem can explains most of the variability in neoclassical linear demand curve. RMSE value ($\sim$1.47) indicates the standard errors of the residuals. In addition, slopes of the linear regression line of the dots and neoclassical demand curve are close to each other (which are -0.06 and -0.05 respectively). These data show that BedDeM can mimic linear demand curve when its agents are set fully-rational.

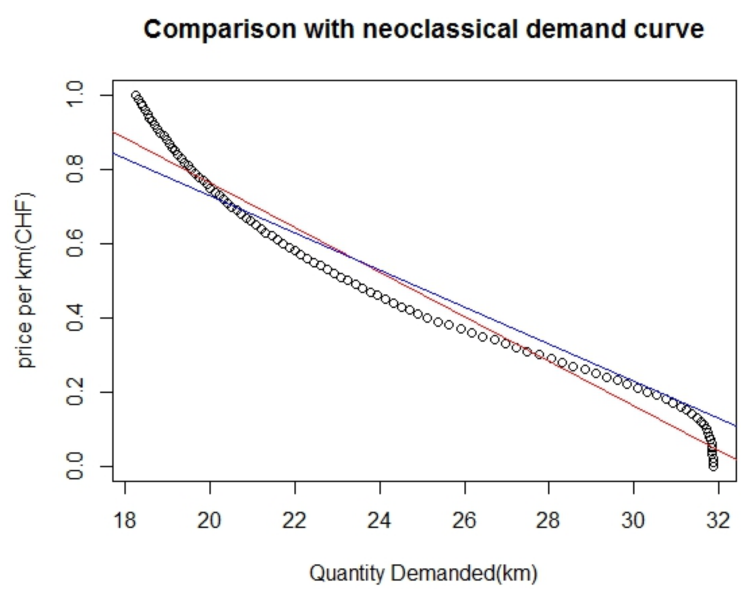

Fig. 3. Linear regression line (red) of the dots that BedDeM create and neoclassical demand curve (blue)

3 DISCUSSION

Our proposed agent architecture uses TIB to allow modellers to express implementing models in a language more suitable (i.e. domain specific) to the application's domain. In the recent case study [4], we were able to reproduce an economic linear demand curve for some transportation services using BedDeM. After further extending the framework to fully reflect the foundation of the cognitive model that influence agent's decision making process, we will apply it to other projects to show that it can allow modellers to simulate and reason about behaviour of individual agent from different research fields' perspectives.

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