

# Investigating Travel Choice Behaviour: a New Approach Using Interactive Experiments with Driving Simulators

## (Doctoral Consortium)

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### ABSTRACT

Transport models adopt simplified descriptions of travel behaviour and are used to make forecasts when evaluating transport policy measures (e.g. road pricing, traffic management, and traffic information). This research investigates travel choice behaviour on roads and aims to (i) improve our fundamental understanding of decision processes between interacting agents (drivers), with a final goal to (ii) make better forecasts for improved decision-making regarding transport policies. Specifically, the aim is to develop a novel methodology for describing travel choices in multi-agent systems using concepts from discrete choice theory, experimental economics and game theory.

### Keywords

Behavioural game theory; discrete choice theory; experimental economics; interactive experiments; driving simulators; learning and beliefs; quantal response equilibrium.

### 1. INTRODUCTION

Transport related projects typically are costly and impacts are difficult to predict. Policy makers make decisions based on project appraisal and cost-benefit analyses that are informed by outputs from forecasting models. All these forecasting models rely on simplified descriptions of travel choice behaviour of an agent, for example, maximisation of expected utility of an agent in situations where there is no other agent making choices that would affect the decision, including route choice, lane choice, speed choice, etc. Nevertheless, every agent's (in our case a driver) choice is not made in isolation, but rather is influenced by choices of other agents. Furthermore, [1] argued that the assumptions made in travel behavioural models using expected utility theory not fully associated with cognitive psychology, which considers how agents actually make decisions. There is significant scope for improvement in the forecasting abilities of these models by better describing interactions between agents that influence the system as a whole, for example in the cases of road pricing, traffic management and traffic information. Examples of interesting research questions are:

- What are the interaction dynamics between agents on a road section when considering lane changing behaviour?
- What is the agents' collective behaviour at a merging section of a construction zone?
- How is parking choice behaviour impacted by other agents searching for a parking spot?
- How is driving speed influenced by other agents?
- How do agents respond to information regarding accidents and delays?

The above examples are cases of how an agent's behaviour both influences and is influenced by the behaviour of other agents. This research will first investigate the route choice behaviour described in Section 3, and then will be applied to most of the above questions. Equilibria occur when agents make the same decision repeatedly based on prevailing conditions (i.e., the collective result of all individual choices), in which they keep adjusting their decision until no more gains can be obtained. However, in many cases, an agent makes a decision incidentally and makes assumptions (i.e., has beliefs) about the behaviour of other agents. For example, when an accident has happened on a route, does the agent decide to take a detour, or does the agent think that most other agents will do this and that it is better to stay on the current route? Such decisions are influenced by prior experience of the agent, which is often referred to as learning effects.

### 2. Quantal Response Equilibrium

One of the solution concepts for strategic interaction among agents, in laboratory experiments or field data, is Quantal Response Equilibrium (QRE) [2]. The name, QRE, is taken from *quantal response* problems (cases when outcomes/choices are countable and discrete). A key notion in QRE is that it substitutes perfect rational expectations of a Nash equilibrium with imperfect expectations. As such, QRE can be seen as a combination of random utility discrete choice models (DCM), in particular, multinomial logit models [3], and game theory. According to [4] "*the QRE notion of McKelvey and Palfrey (1995) can be viewed as an extension of standard random utility models of discrete ("quantal") choice to strategic settings, or as a generalization of Nash equilibrium that allows noisy optimizing behavior while maintaining the internal consistency of rational expectations*" (p. 1).

In a Nash equilibrium, every player chooses the best response to other players' strategies (with probability one), in other words,

*Appears in: Proc. of the 16th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2017), S. Das, E. Durfee, K. Larson, M. Winikoff (eds.), May 8–12, 2017, São Paulo, Brazil.*

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players' decisions are optimal. In contrast, QRE relaxes this optimality assumption by incorporating a random "noise" element, hence, decisions of players might be suboptimal. Equilibrium occurs when the beliefs of a player become consistent with responses of other players. Moreover, QRE can account for experience and learning of a player when playing a game. In transportation, QRE is a relatively new concept, although it has similarities to a stochastic user equilibrium (which include a random term that accounts for errors in agent's perception), which states that no agent can reduce his/her *perceived* travel time by unilaterally changing their route [5].

According to [1], a payoff function (also referred to as utility) for an agent  $i$  for selecting a strategy  $j$  can be written as

$$\tilde{u}_{ij} = u_{ij} + \varepsilon_{ij}, \quad (1)$$

where  $\varepsilon_i$  is a random error/noise term for player  $i$ .

If the error terms are assumed to be independent and identically (i.i. d.) extreme value distributed, it leads to well-known logit response function (see [2]), i.e.

$$\sigma_{ij} = \frac{e^{\lambda u_{ij}}}{\sum_{k=1}^{J_i} e^{\lambda u_{ik}}} \quad (2)$$

where  $\lambda$  is a precision parameter and inversely proportional to the levels of error/noise.

### 3. QRE in Route Choice Game

The aim of this research is to apply QRE to travel choice behaviour of agents, integrate concepts from experimental design and experiments economics in the design of laboratory experiments, and to integrate concepts from advanced discrete choice theory to analyse the data. To this end, a series of experiments (driving simulator studies) in the Travel Choice Simulation Laboratory (TRACSLab) will be conducted. This world-first facility allows complete control of the environment (this includes the road system, traffic signals and controls, as well as computer-simulated cars as background traffic) and allows capturing all decisions made by a maximum of 10 human drivers in the same virtual environment. Our first experiment is related to route choice, although we will consider also other application contexts such as parking choice. The participants selected for these simulation experiments will be Uber drivers. In each, 10 agents will be simultaneously making choices, with multiple repetitions. Figure 1 shows the proposed route choice experiment.

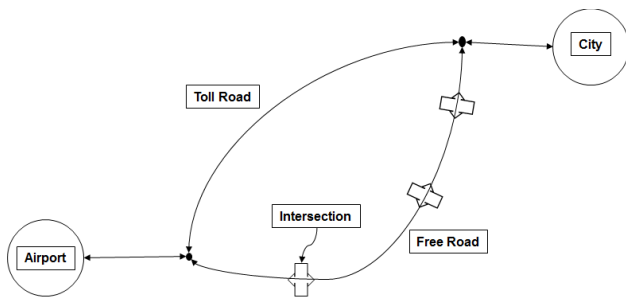


Figure 1: Proposed game for route choice experiment

In this experiment, the agents will be making trips from the airport to the city and vice versa. The purpose is to transport passengers assuming a fixed fee, and hence drivers will want to minimise their travel time. In other words, the faster they go the more people they can pick up, the more money they can make. Drivers can choose between two routes: the toll road and the free road. The toll road guarantees a congestion free trip, whereas the free road may become congested depending on the number of drivers on the road. The level of congestion can be varied by the analyst by setting traffic controls at three signalised intersections. Each driver, therefore, will make a decision based on their trade-off between time and money, as well as their expectations with respect to congestion and travel time unreliability.

Since agents may have different preferences towards travel times and costs, and may have different skill levels, beliefs, and learning speeds, it is possible that the parameters in the payoff functions as well as the precision parameter  $\lambda$  could be different for each agent. Therefore, we will test for heterogeneity in QRE, which extends the equilibrium definition in traditional QRE.

For these experiments, different scenarios will be developed using simulator software, traffic simulation software, and 3D scenario building software. Data collected in these experiments will be used to estimate behavioural models using novel statistical methods that combine maximum likelihood (borrowed from RUM/DCM) as well as game theoretical techniques (borrowed from experimental economics).

To conclude, our research will develop models which explicitly account for interactions and dynamics between agents under uncertainty and imperfect information. This will enrich and improve existing travel behaviour models and will improve fundamental understanding of these interactive decision processes that may also extend to other decision-making contexts.

### 4. ACKNOWLEDGMENTS

This research is funded by the Australian Research Council grant DP150103299, and is in collaboration with Vinayak Dixit at the University of New South Wales, Stephane Hess at the University of Leeds, Hans van Lint at Delft University of Technology, and Elisabet Rutström at Georgia State University.

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