

Possibilities for internship and/or final project for AM student in OR or MDS track. Contact Jasper Goseling (j.goseling@utwente.nl) or the company.

VACANCY: Regularized reinforcement learning and the recursive logit model for route choice

INTRODUCTION

Transport model systems are decision tools to determine the impact of measures and to forecast the future usage of the mobility system. These model systems describe and connect the different behavioral choices of travelers (e.g. mode, destination, departure time) using a separate model for each choice type. The traffic assignment (TA) model describes the route choices of travelers on transport networks.

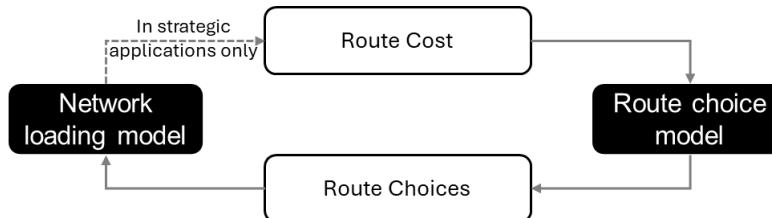


Figure 1: components of TA models (conceptually)

As depicted in Figure 1, conceptually, TA models consist of a route choice model (yielding route choices) and a network loading model (yielding route cost). For road traffic, the following TA model types are commonly used in practice:

1. Static capacity restrained network loading models (Beckmann et al., 1956), in which route choices are either based on deterministic user equilibrium (DUE) conditions (Wardrop, 1952) or stochastic user equilibrium (SUE) conditions (Fisk, 1980) on link level.
2. Static or semi-dynamic capacity constrained network loading models in which route choices are based on SUE conditions on route level (e.g.: Brederode, 2023).
3. Dynamic capacity and storage constrained network loading models, in which route choices are based on SUE conditions on route level (e.g.: Daganzo, 1995; Yperman, 2007).

PROBLEM DESCRIPTION

Key favorable properties for TA models for road traffic are:

- Stability: the extent to which the model converges to UE conditions
- Unconditionality on a prior routeset: application of a priorly generated routeset enables application of more advanced TA models 2) and 3), but also leads to less accuracy (as outcomes are also conditional to the prior routeset) and less scalability (as the prior routeset needs to be stored)
- Accuracy in congested conditions: the extent to which effects of active bottlenecks are accounted for.
- Availability of an endogenous parameter estimation method: the extent to which it is possible to estimate route choice parameters using observed network data (i.e. turn fractions and/or link flows), instead of adopting exogenous parameters from value of time surveys (Wardman et al., 2016)

Table 1 confronts these favorable properties with the three TA models types for road traffic.

	1) static capacity restrained	2) static or semi- dynamic capacity constrained	3) dynamic capacity and storage constrained
a) converges to UE conditions	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	
b) unconditional to prior route set	<input checked="" type="checkbox"/>		
c) accurate in congested conditions		<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/> <input checked="" type="checkbox"/>
d) endogenous parameter estimation method			

Table 1: key properties of most commonly used macroscopic TA models

DAT.Mobility believes that replacing the 'regular' logit route choice model (McFadden, 1972) used in TA model type 2 by the recursive logit model (Fosgerau et al., 2013) would result in a TA model that checks all the boxes.

During his internship at DAT.Mobility, (Hanskamp, 2025) deepened our understanding on the recursive logit model by defining conditions for the existence of its solution and applying it on a real sized transport model network. His internship also suggests a link between recursive logit and regularized reinforcement learning. For example, (Pitombeira-Neto et al., 2024) consider a

discounted version of recursive logit, which is referred to as Random Utility Inverse Reinforcement Learning.

RESULT / OBJECTIVE

The cornerstone of this assignment is to develop a mathematical formalization of the link between recursive logit and regularized reinforcement learning. With this cornerstone in place, (at least) the following opportunities around recursive logit as a route choice model arise:

- The regularized formulation does not involve exponentials of the value function and is therefore expected to remove the numerical problems encountered when solving recursive logit in the traditional way.
- The mathematical expression for the relative duality gap for recursive logit (to measure the extent to which a model instance has converged to SUE conditions) has not yet been derived. It is expected that it can be derived from a formal mathematical problem formulation for the recursive logit model, analogously to the derivation for (route based) multinomial logit in (Bliemer et al., 2013).
- Recursive logit models allow for endogenous parameter estimation using likelihood maximization (de Freitas, 2018; Van Oijen et al., 2020; Zimmermann et al., 2017). However, to our best knowledge, such methods have not yet been applied in the context of strategic transport model systems, which raises questions on practical value and data and computational requirements
- The recursive logit model might potentially be applicable as a replacement for public transport-specific TA models (e.g.: Spiess and Florian, 1989; Veitch and Cook, 2022) and bicycle specific TA models (see Vincent, 2024 and references therein), leading to a unified route choice model for all modes.

ASSIGNMENT

During the internship, the student is asked to formalize the mathematical description of recursive logit in the context of regularized reinforcement learning as a cornerstone and, if time allows, conduct research on one of the follow-up research directions mentioned above. The student is encouraged to define his/her own scope in collaboration with the university and DAT.Mobility.

INFORMATION

When interested in this internship assignment please contact: Luuk Brederode (lbrederode@dat.nl). More information on DAT.Mobility and Goudappel can be found via www.dat.nl and www.goudappel.nl.

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