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INTERMODALITÉ
DES TRANSPORTS

DYNAMIC PROGRAMMING APPROACHES FOR ESTIMATING AND APPLYING LARGE-SCALE DISCRETE CHOICE MODELS

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CONTENU

- ▶ Introduction
- ▶ Recursive logit
- ▶ Summary of contributions
- ▶ Recursive models (correlated random terms)
- ▶ Results and comparisons
- ▶ Ongoing work
- ▶ Conclusions

INTRODUCTION

- ▶ This presentation gives an overview of Tien Mai's dissertation (seven papers)
- ▶ Many transport related choice problems (e.g. location, activity, route, mode, departure time) share some characteristics
 - ▶ Network-based
 - ▶ Large number of alternatives
 - ▶ Dynamic
 - ▶ Alternatives are similar (can, in a RUM framework, be translated to correlated random terms)
- ▶ In this presentation we focus on route choice modelling

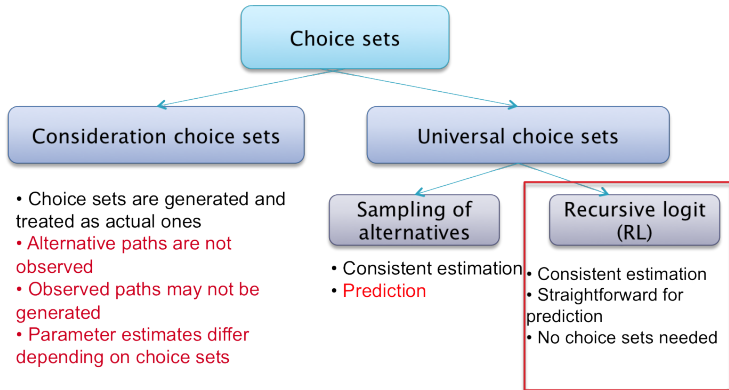
INTRODUCTION – ROUTE CHOICE

- ▶ Given an origin and destination in a transport network, which route does a traveller choose?
- ▶ Shortest path and/or recommended route
- ▶ Analyst has imperfect knowledge of travellers' generalized cost and perception of network
- ▶ Discrete choice models estimated based on RP data are used to define choice probability distributions over alternatives

INTRODUCTION – ROUTE CHOICE

- ▶ Objectives
 - ▶ Models that can be consistently estimated using maximum likelihood
 - ▶ Models that produce accurate predictions in short computational time
- ▶ Main challenges
 - ▶ Definition of choice sets
 - ▶ Modelling correlation

INTRODUCTION



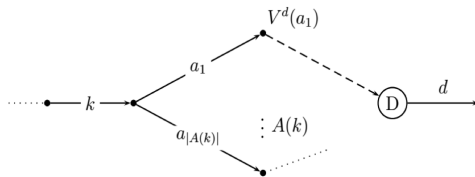
RECURSIVE LOGIT

- ▶ Proposed by Fosgerau, Frejinger and Karlstrom (2013)
- ▶ Shortest path problems are typically solved by dynamic programming (DP)
 - ▶ Deterministic problem: labelling correction methods and associated heuristics such as A^*
 - ▶ Stochastic problem: find an optimal stationary policy in an infinite horizon formulation with absorbing state
- ▶ How to formulate a discrete choice model defining path choice probabilities using the DP framework (i.e. network-based approach)?
Optimal policy is utility maximization and utilities are link-additive

RECURSIVE LOGIT

- ▶ Simple case: deterministic attributes and link choice model is logit which yields a logit model over all paths (no correlation)
- ▶ The recursive logit is based on results from Rust (1987)

RECURSIVE LOGIT



- ▶ Link additive instantaneous utilities $u(a|k) = v(a|k) + \mu\varepsilon(a)$
- ▶ $v(a|k) = v(x_{a|k}; \beta) < 0$, $v(d|k) = 0$
- ▶ $E[\varepsilon(a)] = 0$

RECURSIVE LOGIT

- ▶ Bellman's equation: $V^d(k) = E [\max_{a \in A(k)} (v(a|k) + \mu \varepsilon(a) + V^d(a))]$
- ▶ Logsum

$$V^d(k) = \mu \ln \sum_{a \in A(k)} e^{\frac{1}{\mu}(v(a|k) + V^d(a))}$$

- ▶ System of linear equations

$$\mathbf{z} = \mathbf{M}\mathbf{z} + \mathbf{b} \Leftrightarrow (\mathbf{I} - \mathbf{M})\mathbf{z} = \mathbf{b}$$

- ▶ \mathbf{z} ($|\tilde{A}| \times 1$), $z_k = e^{\frac{1}{\mu}V^d(k)}$, \mathbf{b} ($|\tilde{A}| \times 1$), $b_k = 0 \forall k \in A$, $b_k = 1, k = d$
- ▶ \mathbf{M} ($|\tilde{A}| \times |\tilde{A}|$)

$$M_{ka} = \begin{cases} \delta(a|k) e^{\frac{1}{\mu}v(a|k)} & \forall a \in \tilde{A}, \forall k \in A \\ 0 & \text{otherwise} \end{cases}$$

RECURSIVE LOGIT

- ▶ Probability of choosing link a given state k

$$P(a|k) = \frac{e^{\frac{1}{\mu}(v(a|k)+V(a))}}{\sum_{a' \in A(k)} e^{\frac{1}{\mu}(v(a'|k)+V(a'))}}$$

- ▶ Path $\sigma = \{k_i\}_{i=0}^I$, k_0 is the origin and $k_I = d$, $P(\sigma) = \prod_{i=0}^{I-1} P(k_{i+1}|k_i)$

$$\begin{aligned} P(\sigma) &= \prod_{i=0}^{I-1} e^{\frac{1}{\mu}(v(k_{i+1}|k_i)+V(k_{i+1})-V(k_i))} \\ &= e^{-\frac{1}{\mu}V(k_0)} \prod_{i=0}^{I-1} e^{\frac{1}{\mu}v(k_{i+1}|k_i)} \end{aligned}$$

CONTRIBUTIONS

Route choice models and estimation methods

- No path choice sets are needed
- Consistent estimation
- Straightforward for prediction
- Allow path utilities to be **correlated** (IIA is relaxed)
 - ✓ Nested logit
 - ✓ General MEV
 - ✓ Mixed logit
 - ✓ Random regret decision rule

Methods for other related problems

- A model misspecification test
- Estimation of large-scale MEV models
- Optimization algorithms for maximum likelihood estimation (MLE)

CONTRIBUTIONS

Link attributes	Deterministic	Stochastic
Static	<ul style="list-style-type: none">• Uni-modal network (car)• Revealed preferences data	
Dynamic	<ul style="list-style-type: none">• State is defined by time and location• Ramos et al. (2012) and ongoing work	<ul style="list-style-type: none">• State is time, location and perceived real-time information (e.g. day to day travel time variability)• Challenges: a large number of states, and complicated dynamic programming problems• Ongoing work

RECURSIVE MODELS

- ▶ Mai T., Fosgerea M., Frejinger E. (2015). A nested recursive logit for route choice analysis, *Transportation Research Part B*, 75(1), p.100-112.
- ▶ Mai T., Recursive network MEV model for route choice analysis, submitted to *Transportation Research Part B*.
- ▶ Mai, T., Bastin, F., and Frejinger, E. A decomposition method for estimating recursive logit based route choice models, under revision *EURO Journal on Transportation and Logistics*.
- ▶ Mai, T., Bastin, F., and Frejinger, E. Comparing regret minimization and utility maximization for route choice using the recursive logit model, under revision *Journal of Choice Modeling*

RECURSIVE MODELS – NESTED

- ▶ Scale parameters of the random terms are assumed to be link specific
- ▶ Logit at each choice stage but IIA property does not hold

- ▶ Bellman's equation:

$$V^d(k) = E \left[\max_{a \in A(k)} (v(a|k) + \mu_k \varepsilon(a) + V^d(a)) \right], \varepsilon(a) \text{ are i.i.d. EV}$$

$$z_k^d = \sum_{a \in A(k)} M_{ka} (z_a^d)^{\frac{\mu_a}{\mu_k}} + b_k$$

- ▶ Large system of non-linear equations, can be solved by value iteration (we propose “dynamic accuracy”)

Fixed point solution exists if $\sum_{a \in A(k)} M_{ka} < 1 \quad \forall k$

RECURSIVE MODELS – GENERALIZED

- ▶ Model at each choice stage can be any network MEV model (Daly and Bierlaire, 2006)
- ▶ Bellman's equation $V^d(k) = E [\max_{a \in A(k)} (v(a|k) + \varepsilon(a|k) + V^d(a))]$ where $\varepsilon(a|k) \forall a \in A(k)$ follow a MEV distribution with CPGF G_k
- ▶ Challenge: compute G_k and $\partial G_k \forall k$
- ▶ Trick: change the graph to include correlation structure at each stage (state augmentation), then use the same way to compute value function as the nested recursive model

RECURSIVE MODELS – MIXED

- ▶ Error component model combined with subnetwork (Frejinger and Bierlaire, 2007)
- ▶ Challenge: solve a very large number of linear systems
- ▶ Decomposition method that allows to solve *one* system of linear equations to obtain the value functions for all observations (useful also for RL model)

RECURSIVE MODELS – RANDOM REGRET

- ▶ Random regret minimization instead of random utility maximization
- ▶ Three different link regret functions (GRRM, ERRM, ARRM)

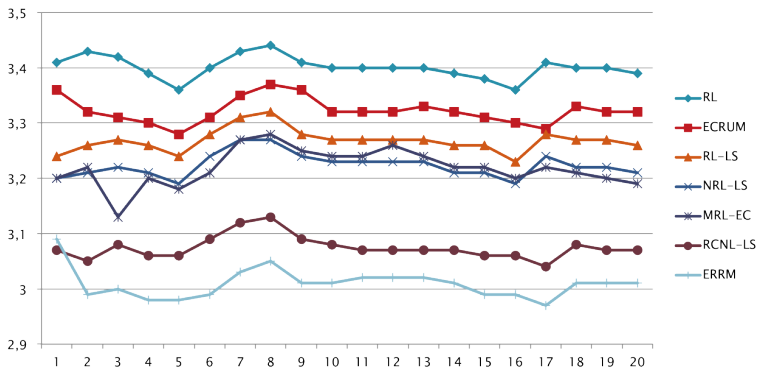
$$r^{ERRM}(a|k) = \sum_{a' \in A(k)} \sum_t \ln \left(\lambda_t + e^{\beta_t (x(a'|k)_t - x(a|k)_t) + \delta_t x(a'|k)_t} \right)$$

- ▶ “Competitive RUM” models

RESULTS – COMPARISON

- ▶ Borlänge data (some of the models have also been estimated and applied to Delft and Eugene networks but they are not presented here)
- ▶ Static and deterministic network
- ▶ 1832 observations, 466 destinations
- ▶ 5 attributes and all parameters have expected signs, are significant and have plausible relative magnitudes
- ▶ In-sample model fit cannot be compared across all models

RESULTS – COMPARISON



RESULTS – COMPARISON

- ▶ Non parallelized MATLAB code running under an Intel(R) 3.20GHz machine with a x64-based processor
- ▶ Estimation cost
 - RL: 4 minutes (with the DeC), 2 hours (without the DeC method)
 - RL-LS : 8 hours
 - NRL-LS: 30 hours
 - RCNL-LS: 3 days
 - MRL-LS (500 draws): 5-7 days
 - RRM, CRUM models: 10 hours (with the DeC method)
- ▶ For all the recursive models
 - Less than 1 minute to solve Bellman's equation
 - Few seconds to compute link flows, simulate a path

ONGOING WORK

Link attributes	Deterministic	Stochastic
Static	<ol style="list-style-type: none">1. NFXP for recursive models2. Discount factors in recursive models3. Bike route choice modeling	
Dynamic	<ol style="list-style-type: none">4. Recursive models for dynamic and deterministic networks	<ol style="list-style-type: none">5. A recursive routing policy choice model for stochastic time-dependent networks

CONCLUSIONS

- ▶ Different ways to analyze route choices (estimation and prediction) using discrete choice models
 - ▶ No generation of choice sets of paths
 - ▶ Correlated utilities
 - ▶ Prediction
- ▶ MATLAB code distributed on GitHub
<https://github.com/maitien86/RecursiveLogitCode>