
Capturing Correlation in Route Choice Models using Subnetworks

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Outline

- Issues of route choice analysis
- Modelling correlation with subnetworks
 - Methodology
 - Example
- Empirical results
 - Borlänge GPS dataset
 - Estimation results
 - Forecasting results
- Conclusion and future work

Route Choice Problem

Given a transportation *network* composed of nodes, links, origin and destinations.

For a given transportation mode and *origin-destination pair*, which is the chosen *route*?

- Issues:
 - Universal choice set very large
 - Correlated alternatives due to overlapping paths
 - Data collection issues

Route Choice Modelling

- Deterministic utility maximisation e.g. **shortest path** assumption is behaviourally **unrealistic**
- Random utility models

Utility U_{in} an individual n associates with alternative i :

$$U_{in} = V_{in} + \varepsilon_{in}$$

where $V_{in} = \beta^T X_{in}$ is the deterministic part and ε_{in} is the random term

Route Choice Models

- Few models explicitly capturing correlation have been used on route choice problems of real size
 - C-Logit (Cascetta et al., 1996)
 - Path Size Logit (Ben-Akiva and Bierlaire, 1999)
 - Link-Nested Logit (Vovsha and Bekhor, 1998)
 - Logit Kernel model adapted to route choice situation (Bekhor et al., 2002)
- Probit model (Daganzo, 1977) permits an arbitrarily covariance structure specification but can rarely be applied in a real size route choice context

Subnetworks

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- Which are the behaviourally important decisions?
- Our hypothesis: choice of specific parts of the network (e.g. main roads, city centre)
- Concept: subnetwork

Subnetworks

- Subnetwork approach designed to be behaviourally realistic and convenient for the analyst
- Subnetwork component is a set of links corresponding to a part of the network which can be easily labelled
- Paths sharing a subnetwork component are assumed to be correlated even if they are not physically overlapping

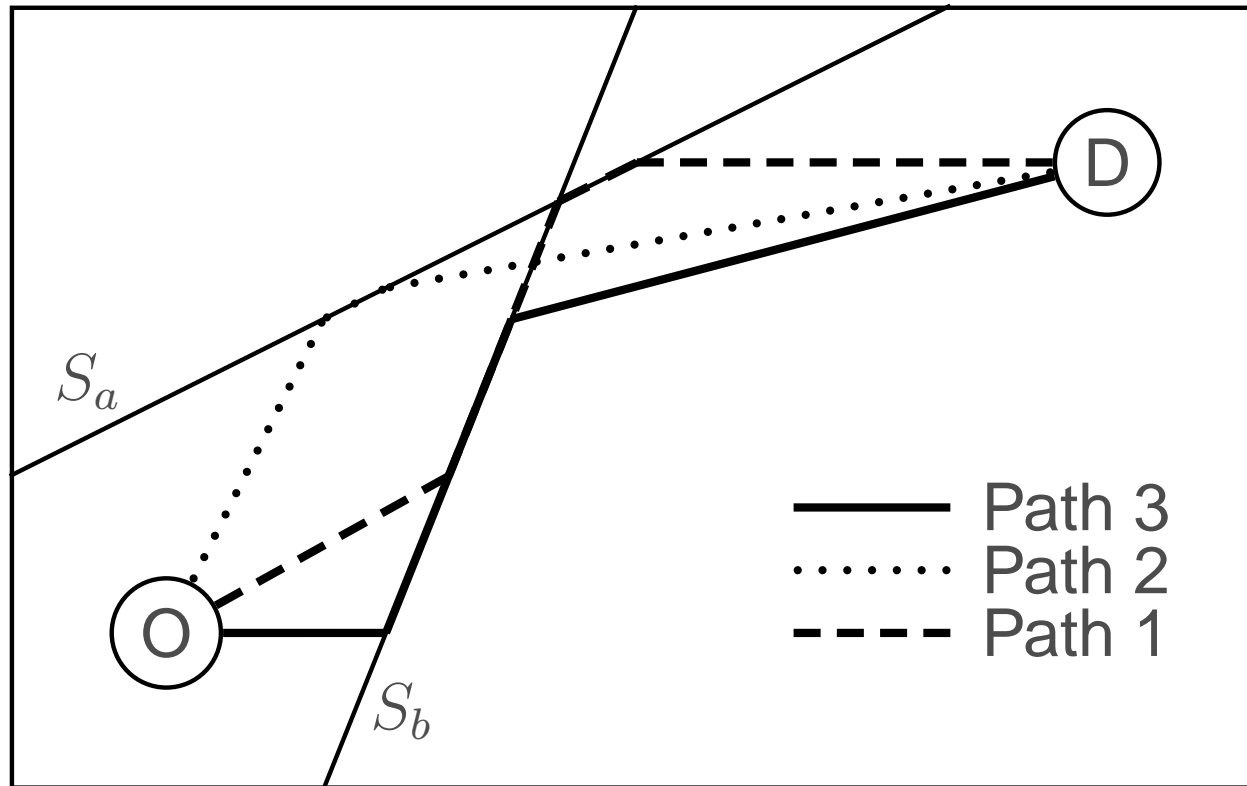
Subnetworks - Methodology

- Factor analytic specification of an error component model (based on model presented in Bekhor et al., 2002)

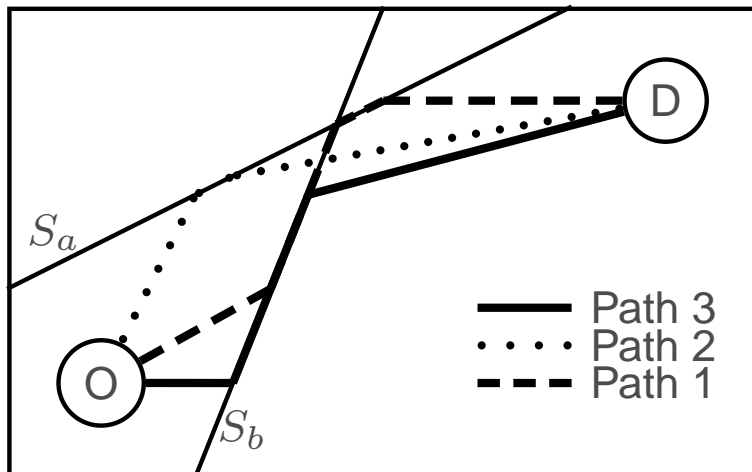
$$\mathbf{U}_n = \beta^T \mathbf{X}_n + \mathbf{F}_n \mathbf{T} \zeta_n + \nu_n$$

- $\mathbf{F}_n (J \times Q)$: factor loadings matrix
- $(f_n)_{iq} = \sqrt{l_{niq}}$
- $\mathbf{T}_{(Q \times Q)} = \text{diag}(\sigma_1, \sigma_2, \dots, \sigma_Q)$
- $\zeta_n (Q \times 1)$: vector of i.i.d. $N(0,1)$ variates
- $\nu_{(J \times 1)}$: vector of i.i.d. Extreme Value distributed variates

Subnetworks - Example



Subnetworks - Example



$$U_1 = \beta^T X_1 + \sqrt{l_{1a}}\sigma_a\zeta_a + \sqrt{l_{1b}}\sigma_b\zeta_b + \nu_1$$

$$U_2 = \beta^T X_2 + \sqrt{l_{2a}}\sigma_a\zeta_a + \nu_2$$

$$U_3 = \beta^T X_3 + \sqrt{l_{3b}}\sigma_b\zeta_b + \nu_3$$

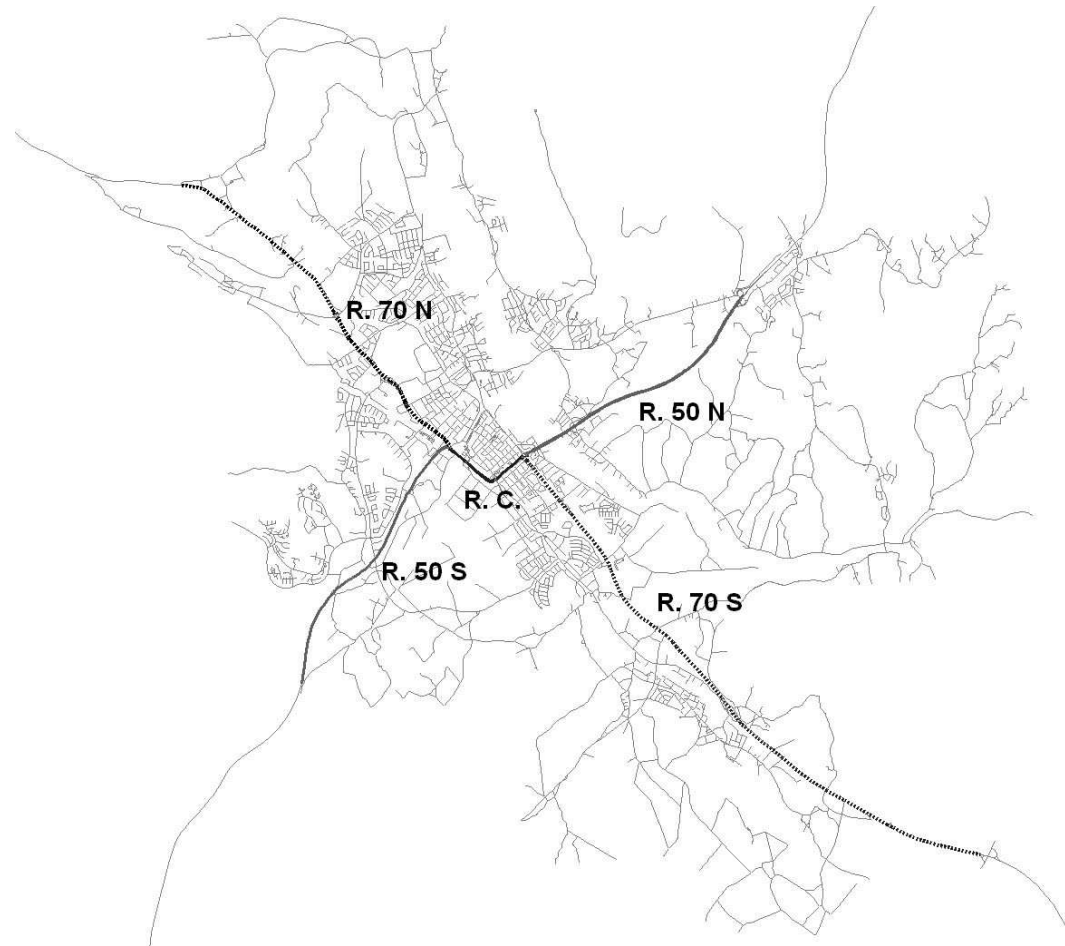
$$\mathbf{F}\mathbf{T}\mathbf{T}^T\mathbf{F}^T =$$

$$\begin{bmatrix} l_{1a}\sigma_a^2 + l_{1b}\sigma_b^2 & \sqrt{l_{1a}}\sqrt{l_{2a}}\sigma_a^2 & \sqrt{l_{1b}}\sqrt{l_{3b}}\sigma_b^2 \\ \sqrt{l_{1a}}\sqrt{l_{2a}}\sigma_a^2 & l_{2a}\sigma_a^2 & 0 \\ \sqrt{l_{3b}}\sqrt{l_{1b}}\sigma_b^2 & 0 & l_{3b}\sigma_b^2 \end{bmatrix}$$

Empirical Results

- The approach has been tested on three datasets: Boston (Ramming, 2001), Switzerland, and **Borlänge**
- Deterministic choice set generation
Link elimination
- **GPS data** from 24 individuals
2978 observations, 2179 origin-destination pairs
- Borlänge network
3077 nodes and 7459 links
- **BIOGEME** (biogeme.epfl.ch, Bierlaire, 2003) has been used for all model estimations

Borlänge Road Network



Subnetwork Components

	R.50 S	R.50 N	R.70 S	R.70 N	R.C.
Component length [m]	5255	4966	11362	7028	1733
Nb. of Observations	173	153	261	366	209
Weighted Nb. of Observations (N_q)	36	88	65	73	116

$$N_q = \sum_{o \in O} \frac{l_{oq}}{L_q}$$

Model Specifications

- Six different models: MNL, PSL, EC_1 , EC'_1 , EC_2 and EC'_2
- EC_1 and EC'_1 have a simplified correlation structure
- EC'_1 and EC'_2 do not include a Path Size attribute
- Deterministic part of the utility

$$V_i = \beta_{PS} \ln(PS_i) + \beta_{EstimatedTime} EstimatedTime_i + \\ \beta_{NbSpeedBumps} NbSpeedBumps_i + \beta_{NbLeftTurns} NbLeftTurns_i + \\ \beta_{AvgLinkLength} AvgLinkLength_i$$

Estimation Results

- Parameter estimates for explanatory variables are stable across the different models
- Path size parameter estimates

Parameter	PSL	EC ₁	EC ₂
Path Size	-0.28	-0.49	-0.53
Scaled estimate	-0.33	-0.53	-0.56
Rob. T-test 0	-4.05	-5.61	-5.91

- All covariance parameters estimates in the different models are significant except the one associated with R.50 S

Estimation Results

Model	Nb. σ Estimates	Nb. Estimated Parameters	Final L-L	Adjusted Rho-Square
MNL	-	12	-4186.07	0.152
PSL	-	13	-4174.72	0.154
EC ₁ (with PS)	1	14	-4142.40	0.161
EC' ₁	1	13	-4165.59	0.156
EC ₂ (with PS)	5	18	-4136.92	0.161
EC' ₂	5	17	-4162.74	0.156

1000 pseudo-random draws for Maximum Simulated Likelihood estimation

2978 observations

Null log likelihood: -4951.11

BIOGEME (biogeme.epfl.ch) has been used for all model estimations.

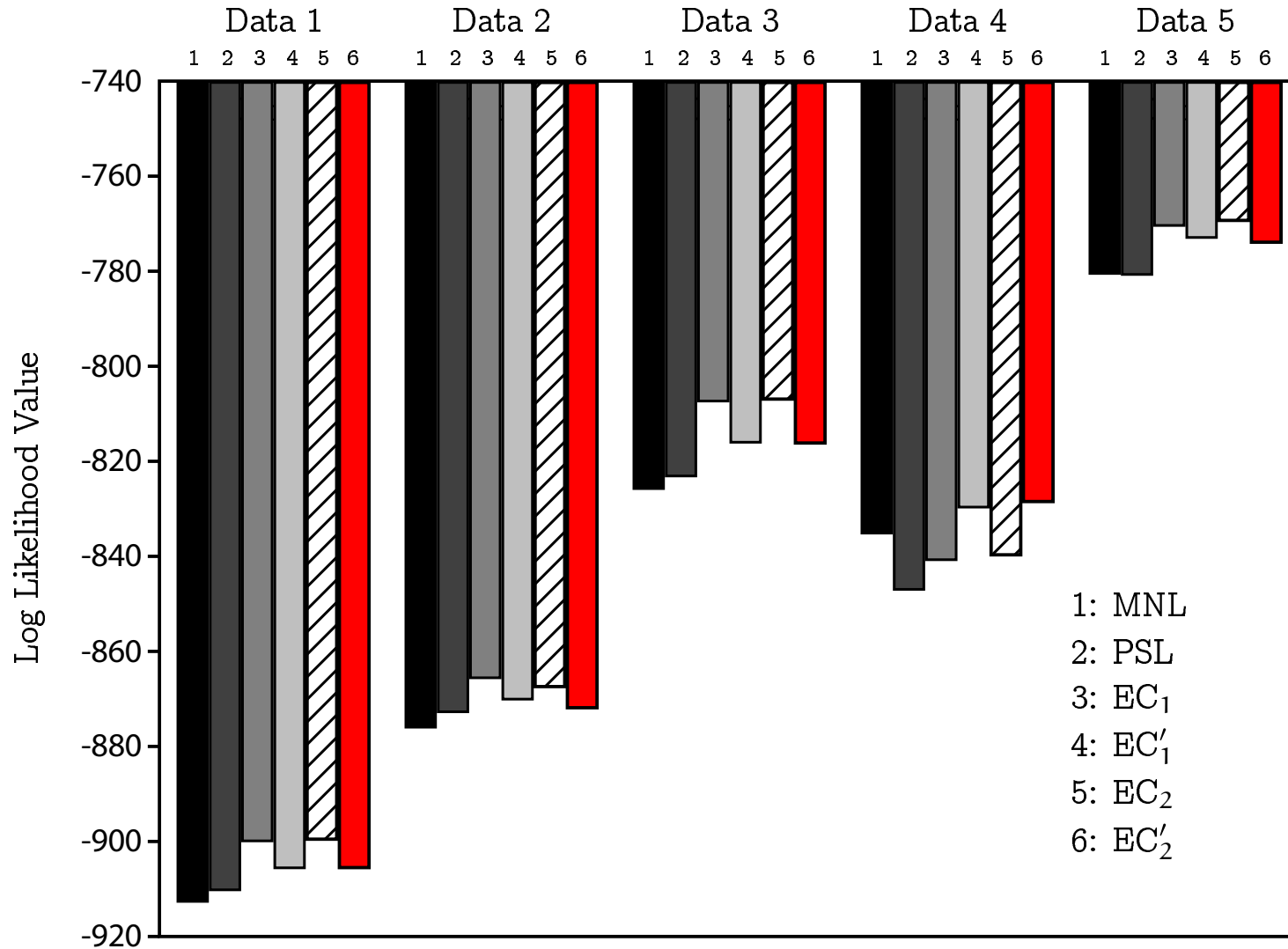
Forecasting Results

- Comparison of the different models in terms of their performance of predicting choice probabilities
- Five subsamples of the dataset
 - Observations corresponding to 80% of the origin destination pairs (randomly chosen) are used for estimating the models
 - The models are applied on the observations corresponding to the other 20% of the origin destination pairs
- Comparison of final log-likelihood values

Forecasting Results

- Same specification of deterministic utility function for all models
- Same interpretation of these models as for those estimated on the complete dataset
- Coefficient and covariance parameter values are stable across models

Forecasting Results



Conclusion

- Models based on subnetworks are designed for route choice modelling of realistic size
- Correlation on subnetwork is explicitly captured within a factor analytic specification of an Error Component model
- Estimation and prediction results clearly shows the superiority of the Error Component models compared to PSL and MNL

Conclusion

- The subnetwork approach is flexible and the trade-off between complexity and behavioural realism can be controlled by the analyst
- Paper to appear in Transportation Research Part B
- Future work
 - Analysis of the sensitivity of the results regarding the definition of the subnetwork
 - Influence of choice set generation algorithm