



Stochastic Path Generation Algorithm for Route Choice Models

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Outline

- Introduction
- Stochastic path enumeration approach
- Sampling of alternatives
- Preliminary numerical results
- Conclusions

Introduction

- 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**?*

- Discrete choice modeling framework

- Issue

Universal choice set very large, individual specific choice set unknown

Introduction

- Choice sets need to be defined prior to the route choice modeling
- Path enumeration algorithms are used for this purpose, many heuristics have been proposed, for example:
 - Deterministic approaches: link elimination (Azevedo et al., 1993), labeled paths (Ben-Akiva et al., 1984)
 - Stochastic approaches: simulation (Ramming, 2001) and doubly stochastic (Bovy and Fiorenzo-Catalano, 2006)

Introduction

- Underlying assumption: the actual choice set is generated
- Empirical results suggest that this is not always true
- Our approach:
 - True choice set = universal set
 - Too large
 - Sampling of alternatives

Sampling of Alternatives

- Multinomial logit model (e.g. Ben-Akiva and Lerman, 1985):

$$P(i|\mathcal{C}_n) = \frac{q(\mathcal{C}_n|i)P(i)}{\sum_{j \in \mathcal{C}_n} q(\mathcal{C}_n|j)P(j)} = \frac{e^{V_{in} + \ln q(\mathcal{C}_n|i)}}{\sum_{j \in \mathcal{C}_n} e^{V_{jn} + \ln q(\mathcal{C}_n|j)}}$$

\mathcal{C}_n : set of sampled alternatives

$q(\mathcal{C}_n|j)$: probability of sampling \mathcal{C}_n given that j is the chosen alternative

Importance Sampling of Alternatives

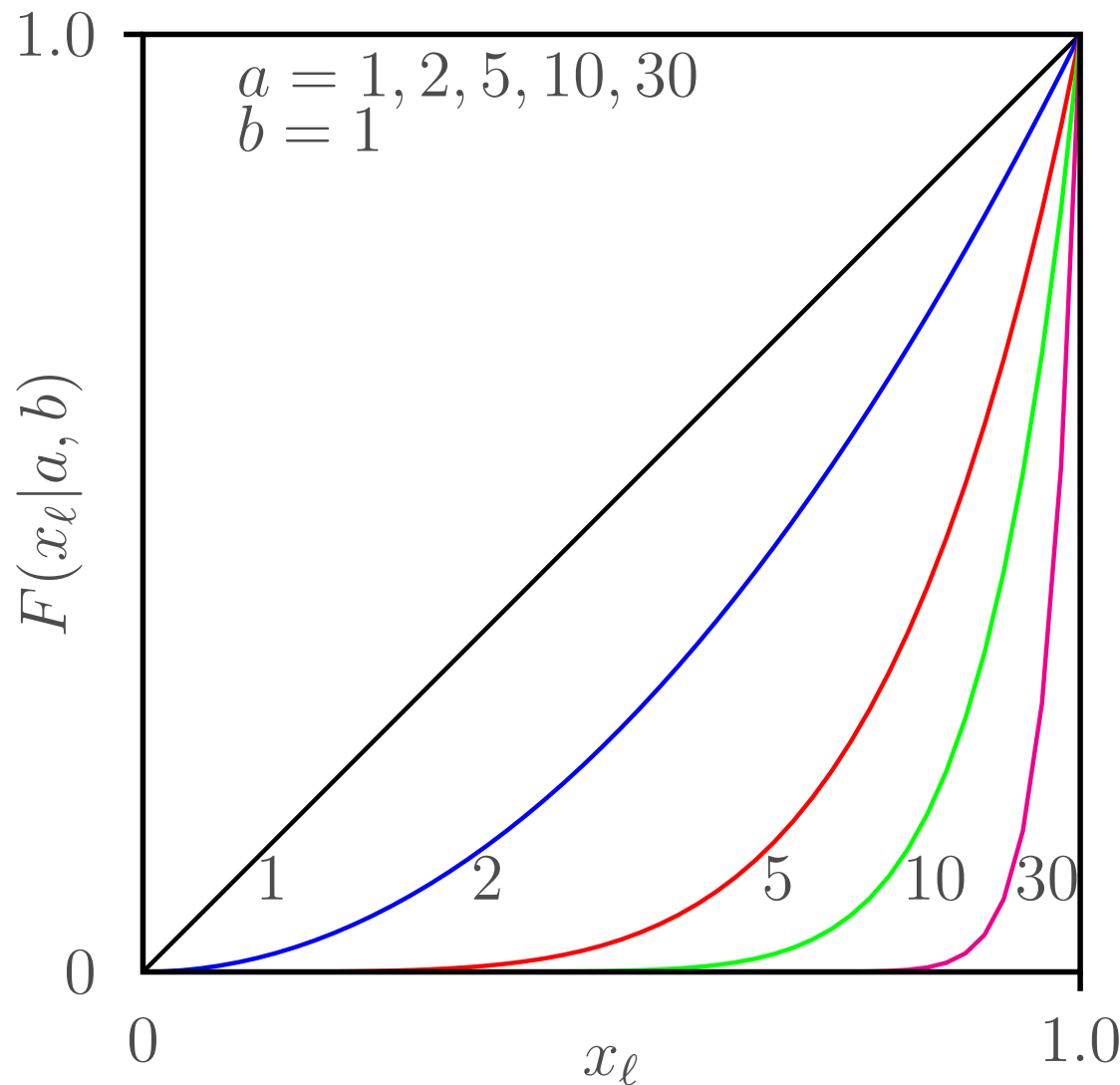
- Attractive paths have higher probability of being sampled than unattractive paths
- Path utilities must be corrected in order to obtain unbiased estimation results

Stochastic Path Enumeration

- Flexible approach that can be combined with various algorithms, here a biased random walk approach
- The probability of a link ℓ with source node v and sink node w is modeled in a stochastic way based on its distance to the shortest path
- Kumaraswamy distribution, cumulative distribution function $F(x_\ell|a, b) = 1 - (1 - x_\ell^a)^b$ for $x_\ell \in [0, 1]$.

$$x_\ell = \frac{SP(v, d)}{C(\ell) + SP(w, d)}$$

Stochastic Path Enumeration



Stochastic Path Enumeration

- Probability for path j to be sampled

$$q(j) = \prod_{\ell=(v,w) \in \Gamma_j} q((v,w) | \mathcal{E}_v)$$

- Γ_j : ordered set of all links in j
- v : source node of j
- \mathcal{E}_v : set of all outgoing links from v
- Issue: in theory, the set of all paths \mathcal{U} is unbounded.
We treat it as bounded with size J .

Sampling of Alternatives

- Following Ben-Akiva (1993)
- Sampling protocol
 1. A set $\tilde{\mathcal{C}}_n$ is generated by drawing R paths with replacement from the universal set of paths \mathcal{U}
 2. Add chosen path to $\tilde{\mathcal{C}}_n$
- Outcome of sampling: $(\tilde{k}_1, \tilde{k}_2, \dots, \tilde{k}_J)$ and $\sum_{j=1}^J \tilde{k}_j = R$

$$P(\tilde{k}_1, \tilde{k}_2, \dots, \tilde{k}_J) = \frac{R!}{\prod_{j \in \mathcal{U}} \tilde{k}_j!} \prod_{j \in \mathcal{U}} q(j)^{\tilde{k}_j}$$

- Alternative j appears $k_j = \tilde{k}_j + \delta_{cj}$ in $\tilde{\mathcal{C}}_n$

Sampling of Alternatives

- Let $\mathcal{C}_n = \{j \in \mathcal{U} \mid k_j > 0\}$

$$q(\mathcal{C}_n|i) = q(\tilde{\mathcal{C}}_n|i) = \frac{R!}{(k_i - 1)! \prod_{\substack{j \in \mathcal{C}_n \\ j \neq i}} k_j!} q(i)^{k_i-1} \prod_{\substack{j \in \mathcal{C}_n \\ j \neq i}} q(j)^{k_j} = K_{\mathcal{C}_n} \frac{k_i}{q(i)}$$

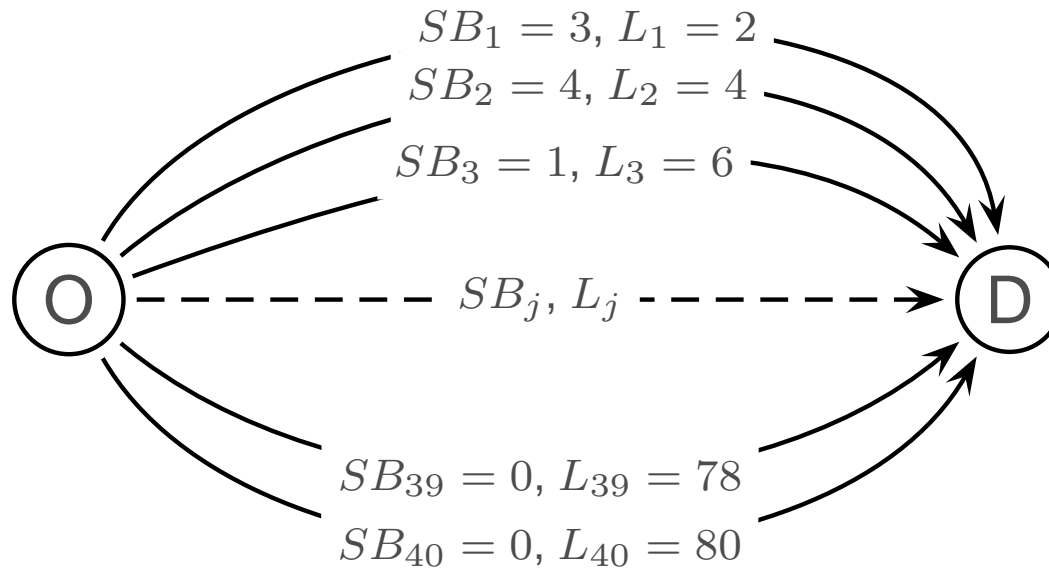
$$K_{\mathcal{C}_n} = \frac{R!}{\prod_{j \in \mathcal{C}_n} k_j!} \prod_{j \in \mathcal{C}_n} q(j)^{k_j}$$

$$P(i|\mathcal{C}_n) = \frac{e^{V_{in} + \ln\left(\frac{k_i}{q(i)}\right)}}{\sum_{j \in \mathcal{C}_n} e^{V_{jn} + \ln\left(\frac{k_j}{q(j)}\right)}}$$

Preliminary Numerical Results

- Estimation of models based on synthetic data generated with postulated models
 - Non-correlated paths
Postulated model same as estimated model (multinomial logit)
 - Correlated paths in a “grid-like” network
Postulated model is probit and estimated models are multinomial logit and path size logit
- True parameter values are compared to estimates

Preliminary Numerical Results



Preliminary Numerical Results

- True model: multinomial logit

$$U_j = \beta_L \text{length}_j + \beta_{SB} \text{nbspeedbumps}_j + \varepsilon_j$$

$$\beta_L = -0.6 \text{ and } \beta_{SB} = -0.3$$

ε_j is distributed Extreme Value with location parameter 0 and scale 1

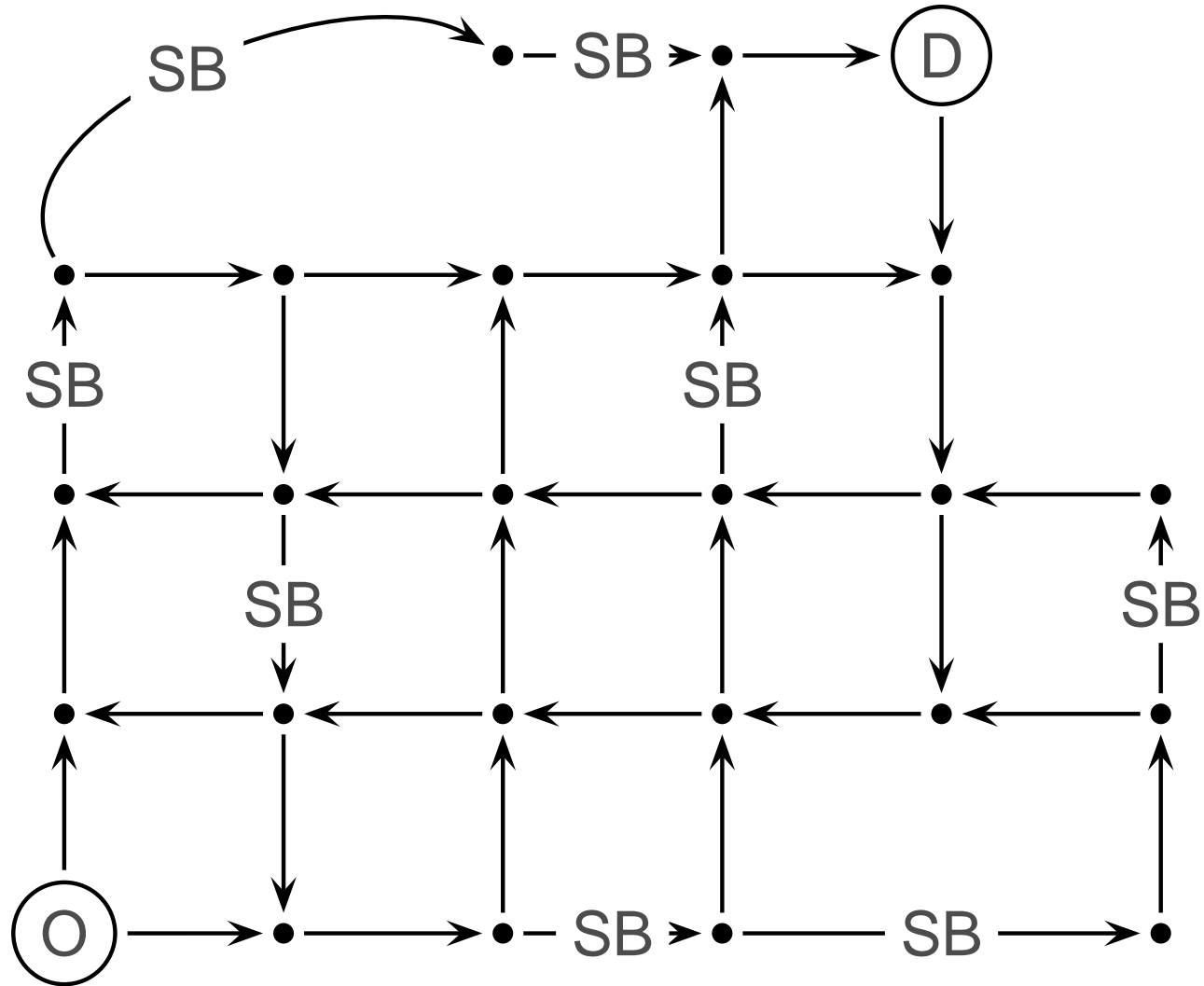
- 500 observations, therefore 500 choice sets are sampled
- Biased random walk using 40 draws with $a = 2$ and $b = 1$

Generated choice sets include at least 7, maximum 18 and on average 11.9 paths

Preliminary Numerical Results

	MNL without	MNL with
Sampling correction		
$\hat{\beta}_L$ (-0.6)	-0.203	-0.286
Scaled estimate	-0.600	-0.600
Robust std.	0.0193	0.019
Robust t-test	-10.53	-15.01
$\hat{\beta}_{SB}$ (-0.3)	-0.0194	-0.143
Scaled estimate	-0.0573	-0.300
Robust std.	0.0662	0.0661
Robust t-test	-0.29	-2.17
Null log-likelihood	-1069.453	-1633.501
Final log-likelihood	-788.42	-759.848
Adjusted $\bar{\rho}^2$	0.261	0.288
BIOGEME has been used for all model estimations.		

Preliminary Numerical Results



Preliminary Numerical Results

- True model: probit (Burrell, 1968)

$$U_\ell = \beta_L \text{length}_\ell + \beta_{SB} \text{nbspeedbumps}_\ell + \sigma \sqrt{L_\ell} \nu_\ell$$

$$\beta_L = -0.6 \text{ and } \beta_{SB} = -0.4$$

ν_ℓ is distributed standard Normal

Link utility variance assumed proportional to length
with parameter $\sigma = 0.8$

- Path utilities are link additive
- 382 observations are generated after 500 realizations of the link utilities

Preliminary Numerical Results

- Biased random walk using 30 draws with $a = 2$ and $b = 1$ (382 choice sets)

Generated choice sets include at least 7, maximum 19 and on average 13.5 paths

Preliminary Numerical Results

	MNL	MNL	PSL	PSL
Sampling correction	without	with	without	with
$\hat{\beta}_L$ (-0.6)	-0.627	-0.978	-0.619	-0.969
Scaled estimate	-0.600	-0.600	-0.600	-0.600
Robust std.	0.0397	0.032	0.0407	0.0358
Robust t-test	-15.79	-30.57	-15.22	-27.04
$\hat{\beta}_{SB}$ (-0.4)	-0.0822	-0.0801	-0.347	-0.461
Scaled estimate	-0.0787	-0.0491	-0.336	-0.285
Robust std.	0.052	0.0559	0.182	0.158
Robust t-test	-1.58	-1.43	-1.90	-2.92
$\hat{\beta}_{PS}$			1.17	1.74
Scaled estimate			1.13	1.08
Robust std.			0.788	0.705
Robust t-test			1.49	2.47

Preliminary Numerical Results

Sampling correction	MNL without	MNL with	PSL without	PSL with
Null log-likelihood	-988.63	-2769.959	-988.63	-2769.959
Final log-likelihood	-676.111	-653.396	-674.481	-649.268
Adjusted $\bar{\rho}^2$	0.314	0.337	0.315	0.340
BIOGEME has been used for all model estimations.				

Conclusions and Future Work

- Stochastic path enumeration algorithms are viewed as an approach for importance sampling of alternatives
- We propose an algorithm that allows for computation of path selection probabilities and correction for sampling
- Ongoing research, further work will be dedicated, for example, to empirical results on real data and correction in prediction