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Routing Policy Choice Models in Stochastic Time-Dependent Networks: The Stockholm Case Study

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1 Background

Transportation networks are frequently subject to random disruptions such as incidents and bad weather, resulting in variable and unpredictable traffic conditions. According to the 2015 Urban Mobility Scorecard, traffic congestion in the United States cost 160 billion dollars in 2014. Meanwhile, with the fast development of sensor and telecommunication technologies, real-time in- formation is increasingly available for travelers and system operators to make better decisions in such an uncertain network, which includes radios, websites, smartphone applications, in-vehicle navigation systems, and connected vehicles. A crucial component in designing and evaluating real-time travel information systems is understanding travelers' route choice behavior in response to a wide range of traveler information situations in a network with dynamic and random traffic conditions.

A traveler makes decisions based on his or her knowledge of the available alternatives and their attributes. This knowledge is periodically updated by both personal experience and exogenous information, and as a result the decisions might be revisited and revised. In other words, a traveler "adapts" to the decision environment. The time scale at which route choice adaption happens can be broadly divided into two types: day-to-day and within-day. In a day-to-day context, a traveler's route choice today might be different from yesterday due to information collected yesterday during the trip. In a within-day context, route choice could be revised en route, e.g., taking a detour upon receiving information on a crash along the original route. This research focuses on within-day adaptive route choice, where the real-time information reflects travel conditions at or close to the decision time. The scope of our study is within-day route choice, which is arguably the most researched area of traveler response to real-time traveler information system.

2 Modeling Framework and Methodologies

2.1 Network, Information, Route Choice Behavior

A stochastic time-dependent (STD) network has link travel times that are jointly distributed time-dependent random variables, and is denoted as $G = (N, A, H, p)$, where N is the set of nodes, A the set of links with $|A| = m$, H the set of time intervals $\{0,1, \dots, K-1\}$ with an equal length δ and P the probabilistic representation of link travel times. Beyond the end of time interval $K-1$, travel times are static and deterministic. $F(i,j,k,t)$ is the deterministic turning penalty from link (i,j) to link (j,k) when turning at node j happens at time period t.

A support point is defined as a distinctive value that a discrete random variable can take, or a distinctive vector of values that a discrete random vector can take depending on the context. Thus a probability mass function (PMF) of a random variable (or vector) is a combination of support points and the associated probabilities. A joint PMF of all time-dependent link travel time random variables is used: $P = \{v_1, v_2, \dots, v_R\}$, where v_i is a vector with a dimension Km, $\forall i$ and R is the number of support points. The r^{th} support point has a probability p_r, and $\sum_{r=1} p_r = 1$. When link travel time observations from multiple days are available, a support point can be viewed as a day, R is the number of days, and $p_r = \frac{1}{R}, \forall r$.

Real-time information is assumed to include realized travel times of certain links at certain time periods. For example, perfect online information (POI) includes realized travel times on all links up to the current time, while global pre-trip information includes realized travel times of all links up to the departure time. See Gao and Huang (2012) for discussions on a number of real-time information access. The passive GPS readings of taxi drivers used in this study cannot tell us what real-time information the drivers have. POI is assumed, since taxi drivers are in general highly sensitive to traffic conditions and stay informed at all times. The discussion in the remainder of the research is therefore specific to POI.

With the help of online information, a traveler becomes more certain about the future traffic conditions, that is, the network becomes less stochastic. At a given time period t, the available real-time information is represented by a joint realization of travel times on all links at previous time periods $0, 1, \dots, t$. The joint realization corresponds to a unique subset of compatible support points, defined as an event collection, EV. It represents the conditional distribution of future link travel times given the realization of past link travel times. As more information becomes available, the size of an event collection decreases or remains the same. When an event collection becomes a singleton, the network becomes deterministic.

When a traveler is at the end of link (i, j) at time t with event collection EV, she makes a decision to take the next link (j, k). Upon arrival at the end of link (j, k), she will be in a different time period due to the traversal time on link (j, k) and the turning penalty $F(i, j, k, t)$. She will also have a potentially different event collection $EV^{/}$, which accounts for realized link travel times between t and the arrival time at the end of link (j, k). She continues the routing decision process based on dynamically involved event collections. Define x as a state with three elements: link (i, j), time t and event collection EV. A routing policy μ is therefore defined as a mapping from all possible states to the decision of the link to take next.

A routing policy can capture traveler's looking-ahead capability in that the decision at state x depends on the evaluation of all possible future states throughout the remainder of the trip. Specifically, the fact that more information will be available in the future is represented by the series of $EV^{/}$ that could be encountered. A routing policy is realized as a path for a given support point (day), and the realized path topologies potentially vary from day to day due to the randomness of travel times.

2.2 Model Specification and Estimation

It is hypothesized that there are two classes of travelers, routing policy users who follow routing policies, and path users who follow fixed paths. λ is defined as the probability of a traveler belonging to the policy user class, and thus (1 - λ) is the probability of a traveler belonging to the path user class. The major difference between the two classes is the choice sets, where the routing policy choice set $\tilde{C}_n$ is a superset of the path choice set C_n, as a path is a special routing policy where routing decisions are independent of real-time information. In general its attribute (e.g., travel time, # of intersections) is calculated as the expected value of the attribute for the realized paths. Eqs. (1) and (2) show that the choice of an alternative (path i or policy μ) for individual n from either class is described by a Logit model with systematic utility V, which is a function of explanatory variables and the parameters of the variables (β or β') are to be estimated from data. *PS* (Path Size) is a deterministic correction for overlapping of paths, and *PoS* (Policy Size) is its counterpart for routing policies, calculated as the expected path size. The utility functions and parameter sets could differ by class, and a simplified case is when the difference is only by a scale, i.e. β = Scale * β'. PS_i and PoS_μ can be calculated by Eqs. (3) and (4) respectively.

$$P(i|C_n;\boldsymbol{\beta}) = \frac{\exp(V_i(\boldsymbol{\beta}) + \ln PS_i)}{\sum_{j\in C_n}\exp(V_j(\boldsymbol{\beta}) + \ln PS_j)} \tag{1}$$

$$P(\mu|\tilde{C}_n;\boldsymbol{\beta}') = \frac{\exp(V_\mu(\boldsymbol{\beta}') + \ln PoS_\mu)}{\sum_{\boldsymbol{\theta}\in \tilde{C}_n}\exp(V_\theta(\boldsymbol{\beta}') + \ln PoS_\theta)} \tag{2}$$

$$PS_i = \sum_{l\in I_i}\left(\frac{T_l}{T_i}\right)\frac{1}{M_{l,n}} \tag{3}$$

where

I_i = set of links of path i,

T_l = travel time of link l,

T_i = travel time of path i,

$M_{l,n}$ = number of paths in choice set C_n using link l.

$$PoS_\mu = \sum_{r=1}^{R} \left(\sum_{l \in I_\mu^r} \left(\frac{T_l^r}{T_\mu^r} \right) \frac{1}{M_{l,n}^r} \right) P(r) \quad (4)$$

where

I_μ^r = set of links on the realized path of routing policy μ for support point r,

T_l^r = travel time of link l for support point r,

T_μ^r = realized travel time for routing policy μ for support point r,

$M_{l,n}^r$ = number of routing policies in choice set $\tilde{C}_n$ using link l for support point r, and

$P(r)$ = probability of support point r.

Route choice observations are obtained from individual level passive GPS readings. In some applications these readings are sparse with large gaps (e.g., longer than 1 minute), and thus an individual's chosen route cannot be uniquely identified. The estimation problem is thus based on maximizing the likelihood of observing vehicle traces, where a trace is an ordered set of map-matched links between an OD pair where the links are generally not consecutive.

Eq. (5) describes the likelihood of observing trace g for a path user n on day r. The first equality shows that day r is irrelevant, since the individual does not adapt her choice to realized traffic conditions on any given day. The likelihood of observing trace g is the sum of the likelihood of observing paths from the choice set C_n that contain trace g. $P(g|i)$ is a binary indicator which is equal to 1 if path i contains trace g and 0 otherwise.

$$P_{n,r}^{path}(g|\boldsymbol{\beta}) = P_n^{path}(g|\boldsymbol{\beta}) = \sum_{i \in C_n} P(i|C_n;\boldsymbol{\beta})P(g|i) \quad (5)$$

$$P_{n,r}^{policy}(g|\boldsymbol{\beta}') = \sum_{\mu \in \tilde{C}_n} P(\mu|\tilde{C}_n;\boldsymbol{\beta}')P_r(g|\mu) \quad (6)$$

Eq. (6) describes the likelihood of observing trace g for a policy user n on day r as the sum of the likelihood of choosing policies from the choice set $\tilde{C}_n$ that contain GPS trace g. A routing policy μ is not observable and it is viewed as chosen if the realized path i on day r contains trace g. $P_r(g|\mu)$ is a binary indicator which is equal to 1, if the realized path of routing policy μ on day r contains trace g, and 0 otherwise.

Eq. (7) describes the likelihood of observing a GPS trace g on day r for individual n as the convex combination of the likelihood from the two classes. λ is represented by a logit form membership function in Eq. (8), where W is a linear function of an constant and explanatory variables for being a routing policy user. The explanatory variables could include trip attributes, such as an indicator of a long trip, and, characteristics of the travelers, such as an indicator of an experienced driver. These variables are not alternative-specific.

$$P_{n,r}(g|\boldsymbol{\beta}, \boldsymbol{\beta}') = \lambda P_{n,r}^{Policy}(g|\boldsymbol{\beta}') + (1-\lambda) P_{n,r}^{Path}(g|\boldsymbol{\beta}) \tag{7}$$

$$\lambda = \frac{exp(W)}{exp(W)+1} \tag{8}$$

3 Stockholm Case Study

Figure 1: Road Network in the Stockholm Case Study

As the capital and the largest city of Sweden, Stockholm constitutes the most populated urban area in Scandinavia. As for transportation network, Stockholm is at the junction of the European routes E4, E18 and E20, and a half-completed motorway ring road exists on the south and west sides of the City Center.

A subset of the Stockholm network is studied, which includes the Arlanda airport area, E4 motorway between the airport and the city, and northeast part of the inner city. In this sub-network, according to the observations of local residents, taxi drivers adapt to traffic conditions when making route choices going into and out of the city center. In particular, between point A and point B shown in Figure 3, there is a choice among two common routes, either the western route along E4 or the eastern route along E18 and LV276.

3.1 Data Processing

Network and Map-Matching The network is represented as a directed graph with links for streets, nodes for intersections, and locations where link attributes change. Each link has a number of attributes including speed limit, functional class and presence of traffic signal. The network is simplified so that links in series with identical speed limit and functional class attributes are merged, reducing time and memory requirements of subsequent processing.

Time-stamped GPS coordinates of taxis from a fleet management system in Stockholm were obtained from November 1, 2012 through January 18, 2013, covering the time periods of Mondays through Fridays, resulting in 56 days (sup- port points). They are matched to the road network using a 4-step map-matching method designed for sparse Floating Car Data (FCD), which is data collected from traced vehicles that "float" with the traffic. The method first finds candidate links in the vicinity of each GPS coordinate, then connects the candidate links of each pair of coordinates. The method then creates a candidate graph between a sequence of coordinates and, finally, finds the most likely path (inferred path) from the candidate graph.

Vehicle Traces Vehicle traces are the route choice observations against which the proposed model is estimated as shown in Eq. (7). Only hired taxi traces are used, since when there are passengers on board, taxi drivers have clearly specified origins and destinations, and their objectives and behaviors are conceivably similar to those of regular commuters, whereas for-hire taxis roam the network in order to pick up passengers. It is likely that taxi drivers are more experienced, aggressive, and knowledgeable about the area than regular commuters Therefore, the developed model represents behaviors of a subset of the general drivers who are knowledgeable about the network and sensitive to real-time traffic information. The methodology, however, is general and can be applied to model regular commuters' behaviors if data is available.

Empirical, Joint Link Travel Time Distribution The distribution is represented as a collection of support points, where a support point is comprised of travel times on all links over all times for a given day. A non-parametric method is used to compute the link travel times per time interval using the map-matched GPS data. For each road segment between a pair of GPS coordinates, the observed travel time (i.e., the difference between the time stamps) is decomposed to the traversed links proportionally to their free-flow speeds and overlapping lengths. The weighted average, where the weight reflects the overlap with both the considered link and other links, over observations from different vehicles within the same time interval is the estimated link travel time. The travel time estimation is per formed for each time interval separately for each day in the data set, producing an empirical, joint travel time distribution.

With the available data, there are link-day-interval combinations for which the travel time cannot be estimated due to lack of observations. These missing values are filled in through a sequence of inter/extrapolation steps. Furthermore, unreasonably high or low link travel times are removed to produce reliable estimates.

A link is treated as deterministic when there is not enough variation of travel time over time and day, or not enough observations to derive reliable travel time estimates. In this case, a single mean travel time is estimated across all days and time intervals.

Vehicle Trace Sampling 500 out of 4,520 hired taxi traces are sampled for model estimation. To ensure geographic spread, the airport area is divided into three zones and the downtown area is divided into nine zones. A total of 500 trips are then sampled with trip ends (Os and Ds) evenly distributed across the airport and downtown zones.

Table 1: Statistics for the Stockholm network

# of Nodes	2,872
# of Links	5,447
# of Stochastic Links	619
# of Taxis	1,500
#of Support Points	56
GPS Reading Time Gap	1-2 min
#of Hired Taxi Traces	4,520
# of Traces for Model Estimation	500
Time Interval Length	5 min
Study Period Duration	7:30 AM - 11:30 AM
Departure Time Duration	7:30 AM - 9:00 AM

3.2 Systematic Utility Specification and Model Estimation

3.2.1 Systematic Utility Functions

Long Trip Dummy and Alternative Specific Constant (ASC) are in the membership function for routing policy user probability. Long Trip Dummy is a dummy variable that equals 1 if the shortest path travel time between the OD is at least 15 minutes, and 0 otherwise.

The systematic utility function for a path or routing policy alternative is linear in parameter with attributes of Expected Travel Time (min), Travel Time Range (min), interaction term between Travel Time Range and Airport Bound (dummy), # of Signals, # of Left Turns, #of Functional Class Changes, Average Speed (m/s), as well as dummy variables for Min Expected Travel Time, Max Expected % of Highway Distance, and Min # of Functional Class Changes. For routing policies, the attributes are averaged over all support points. The parameters of Policy Size and Path Size are fixed at 1 following the original definition of Path Size. The attribute of Travel Time Range (the difference of the maximum and minimum travel time) is a measure of travel time reliability. Other measures of reliability have also been tested, including travel time standard deviation, variance, travel time reserve (difference between 95 per- centile and median travel time), and coefficient of variation (the ratio of the travel time standard deviation and the mean travel time). Average Speed is calculated as the distance divided by Expected Travel Time. The parameters for the two classes of travelers differ by a scale (Path Parameters = Scale Policy Parameters).

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3.2.2 Latent-Class Routing Policy Model Estimation Results

All model estimation was performed using BIOGEME Python 2.0. Table 2 presents the estimation results of the latent-class routing policy choice model as well as two restricted models, based on the 475 covered trips with 100% overlap threshold. Long Trip Dummy coefficient in the routing policy user membership function is positive and significant at the 0.1 level, indicating that travelers are more likely to look ahead for longer trips, which is intuitive since longer trips allow for more division possibilities and travelers plan more carefully for longer trips.

One of the most important factors affecting travelers choices is travel time. Travelers do not like long travel time, and the negative signs of coefficients for Expected Travel Time and Min Expected Travel Time Dummy agree with the intuition. Travelers also in general do not like variations in travel time (repressed by Travel Time Range), and it is shown that the attitude towards travel time variation varies by travel direction. Travelers are risk neutral, that is, the variation in travel time has no impact, when not traveling towards the airport, indicated by the statistically and numerically insignificant parameter estimate. They are risk averse when traveling airport bound, indicted by the statistically significant negative coefficient of the interaction between Travel Time Range and Airport Bound Dummy. This is intuitive since variation in travel time when going to the airport can cause serious consequence of missing your flight. The ratio of the coefficient estimates for travel time range and travel time mean for airport-bound trips is around 0.78, indicating that for travelers are willing to accept 0.78 minutes of average travel time increase to obtain a 1 minute reduction in travel time range.

# of Signals and # of Left Turns estimate show that alternatives with fewer signals and left turns are preferred. # of Functional Class Changes and Min # of Functional Class Changes Dummy estimates suggest that travelers also prefer not to switch on/off highways frequently. Speed is also an important factor that affects travelers' route choice. For instance, given two alternatives of same travel times, many travelers choose the one with faster speed even if it has longer distance. This phenomenon is related to travelers' preference to highways, which is further substantiated by the positive estimate for Max Expected % of Highway Distance Dummy. While Policy Size and Path Size coefficients are fixed at 1, the parameters for path users are 0.491 times of those for routing policy users (statistically different from 0 or 1 at the 0.01 level). This suggests higher random errors in path user utility functions. The reasons for this difference are not immediately clear, and one hypothesis is that path users who are fixated on a particular path might be less knowledgeable about the network, and thus a higher perception errors of the route attributes.

Overall the model achieves a final log likelihood of -265.2, and an adjusted rho squared of 0.620 when compared with a null model. The null model is a path choice model where all parameters are zero except that for Path Size to discount paths that are overlapping. This is a more reasonable benchmark than the equal-probability model, which can be manipulated to have a very low log likelihood (and thus an inflated model fit for the final model) by adding a large number of alternatives to the choice set.

3.2.3 The Latent-Class Model vs. Restricted Models

Two restricted models are estimated where all users are path users or routing policy users respectively. The latent-class model reduces to either of the restricted model when the class probability approaches 0 or 1, achieved by setting the ASC in the membership function to either positive or negative infinity. The attributes in the restricted models are similar to those in the unrestricted, latent-class model, except that there are no path user class scale or membership function related parameters. The restricted path choice model uses the path choice sets only, and the restricted routing policy model uses the routing policy choice sets only.

A likelihood ratio test performed on the unrestricted latent-class routing policy model over the two restricted models shows that either of the restricted models is rejected at the 0.05 level. This suggests that travelers are heterogeneous in terms of their ability and willingness to plan ahead and utilize real-time information. Therefore, there could be potential biases when simplified assumptions are applied that travelers follow fixed path choice under real-time information. An appropriate route choice model for uncertain networks should take into account the underlying stochastic travel times and structured traveler heterogeneity in terms of real-time information utilization.

4 Conclusions

A latent-class routing policy choice model in an STD network based on sparse GPS readings is developed and estimated using hired taxi GPS data from Stockholm, Sweden. Two classes of travelers, routing policy users and path users, differ by their choice sets and utility function parameters. A routing policy represents travelers' looking ahead ability to account for traffic information not yet available, and the choice set generation for routing policies is a general- ization of path choice set generation. A path is a special case of a routing policy, and thus the routing policy choice set for any given OD always contains the path choice set.

The ensemble of choice set generation methods (link elimination, simulation, generalized cost) can achieve a 95% coverage with 100% overlap and further achieves a 100% coverage with 90% overlap. Estimation results show that the routing policy user class probability increases with trip length, and the latent-class routing policy choice model fits the data better than a single-class path choice or routing policy choice model. This suggests that travelers are heterogeneous in terms of their ability and/or willingness to plan ahead and utilize real-time information, and an appropriate route choice model for uncertain networks should take into account the underlying stochastic travel times and structured traveler heterogeneity in terms of real-time information utilization. Travelers are risk averse when traveling to the airport and risk neutral otherwise. Path user class parameters have a smaller scale than those of routing policy class, indicating that the two classes differ not only by choice set, but also perception of attributes. Further studies to understand the underlying behavioral processes of travelers' decision making under uncertainty with real-time information could shed light on the sources of the difference.

Table 2: Estimation results for latent-class routing policy model and restricted models

	Latent-class Policy Model		**Policy User Probability = 1**		**Path User Probability = 1**	
Parameters	**Estimate**	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**
ASC	-2.23	-1.60	NA		NA	
Long Trip Dummy (SPT ≥ 15 min)	3.60	1.75*	NA		NA	
Expected Travel Time (min)	-1.15	-2.91***	-0.669	-5.34***	-0.626	-5.19***
Travel Time Range (min)	0.162	0.94	0.153	1.40	0.0558	0.610
Travel Time Range * Air-port Bound	-0.894	-1.96**	-0.591	-2.55**	-0.485	-2.17**
# of Signals	-0.266	-1.86*	-0.149	-1.83*	-0.165	-2.38**
# of Left Turns	-0.992	-2.83***	-0.494	-2.40**	-0.604	-2.99***
# of Functional Class Changes	-2.30	-3.49***	-1.32	-6.21***	-1.15	-6.84***
Average Speed (m/s)	1.82	2.63***	0.877	4.91***	1.04	4.98***
Min Expected Travel Time	2.78	5.07***	1.38	2.71***	1.24	3.91***
Max Expected % of High-way Distance	1.78	2.23**	1.34	2.67***	0.941	2.91***
Min # of Functional Class Changes	2.19	2.40**	2.58	8.01***	1.03	2.39**
Path Class Scale	0.491	3.86***	NA		NA	
Sample Size	475		475		475	
# of Parameters	13		10		10	
Adjusted Rho Squared	0.620		0.602		0.616	
Null Loglikelihood	-731.4		-731.4		-731.4	
Final Loglikelihood	-265.2		-281.4		-271.1	

NA indicates that the parameter is not included in a model

*: significant at the 0.10 level; **: significant at the 0.05 level; ***: significant at the 0.01 level