Route Choice Modeling
Discrete choices

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Introduction

Four-Step Travel Demand Modelling

- First step – Trip Generation: How many trips are generated?
    - The goal of trip generation step is to estimate the number of trips that are produced or originate in each Traffic Analysis Zone (TAZ)
- Second step – Trip Distribution : Where do the generated trips go?
    - In this step matches between origins and destinations are developed. Trip ends are linked to create complete trips.
- Third step – Mode Choice: What travel mode is used for each trip?
    - Mode choice predicts the choices that individuals or groups make in selecting their transportation modes. For instance, an important objective is to predict the share of trips attracted to public transportation.
- Fourth step – Trip Assignment: What is the route of each trip?
    - The final step is to determine the routes travelers choose to reach their destinations.

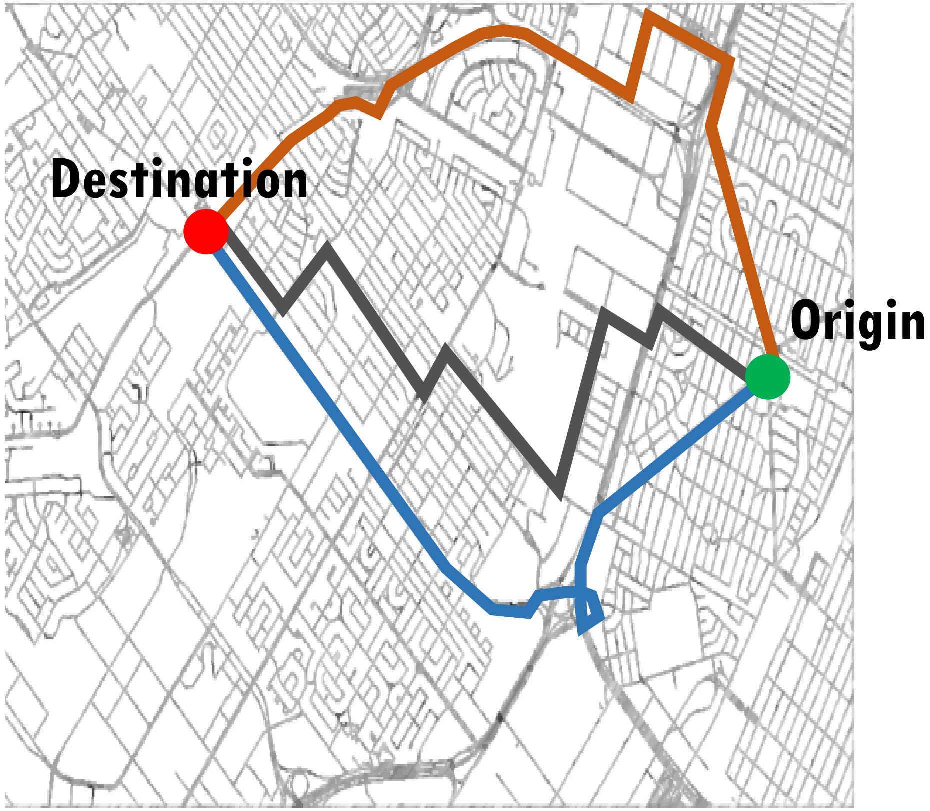
Introduction

Route Choice Modeling

Having:

- A road network
- Origin – Destination pair

A route choice model predicts the <u>selection probability</u> of a given path between an O-D pair, based on both the characteristics of the traveler and the route.



<u>Why is it important?</u>

- ➢ To better understand travelers' behavior.
- ➢ To forecast the impact of different measures and policies on traffic conditions.
- ➢ To forecast future traffic conditions.
- ➢ To evaluate the impact of traffic information.
- ➢ To enrich the route selection procedure of traffic assignment models.

Introduction

Important Factors

Preferences
Prejudices
Abilities
Life-styles
Attitudes
Habits
Cultural Norms

Route Choice?

Driver Attributes

- Age
- Gender
- Occupation
- Household composition
- …

Trip Attributes

- Travel time
- Travel Distance
- Trip purpose
- Reliability of travel time
- …

Route Attributes

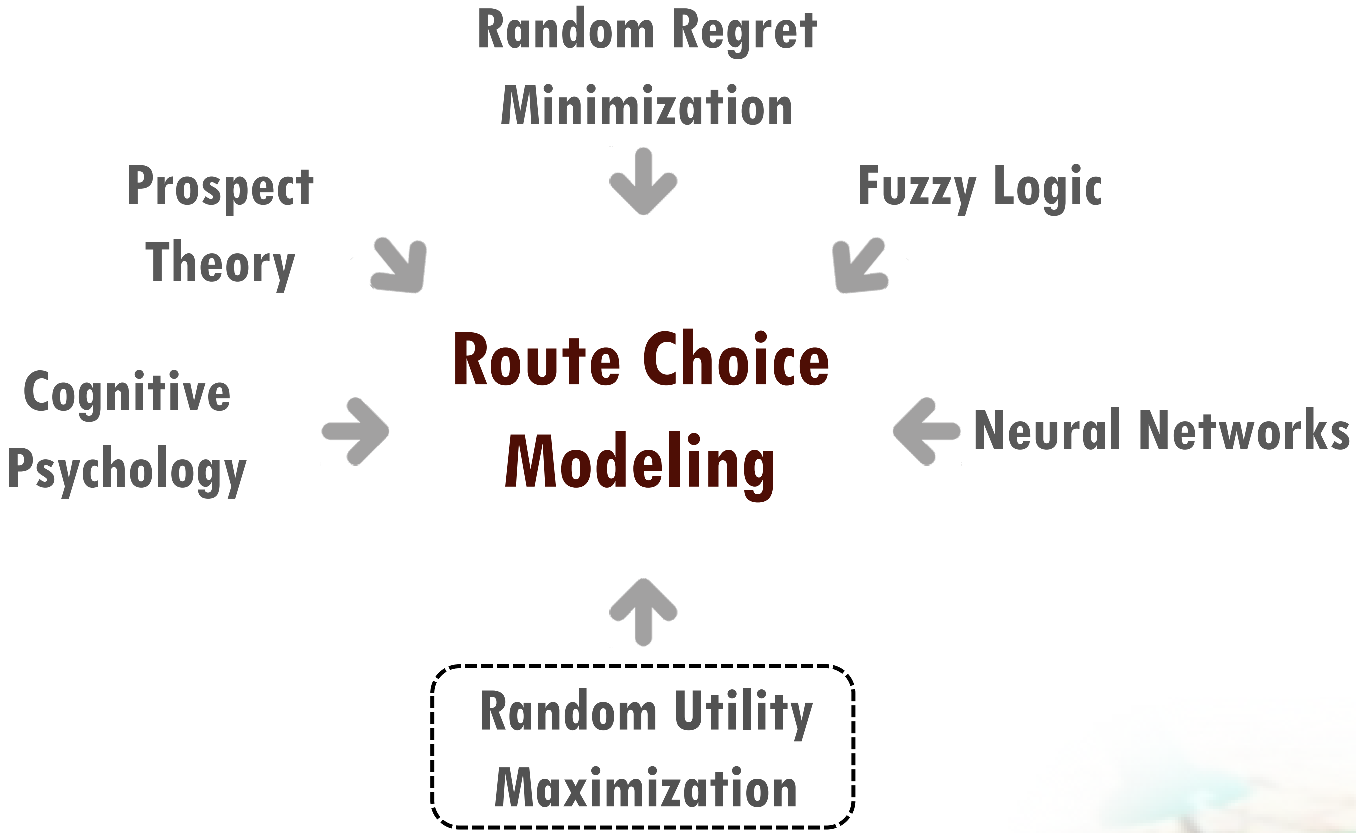
- # of intersections
- # of stop signs
- # of traffic lights
- # of turns
- …

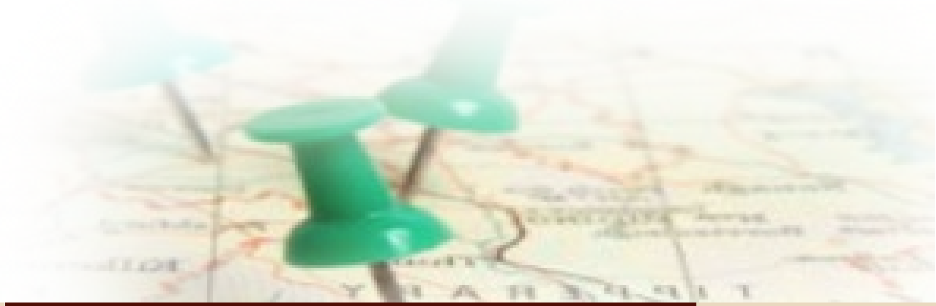
Temporal & Environmental

- Day of the week
- Time of the day
- Scenery
- …

Modeling Framework

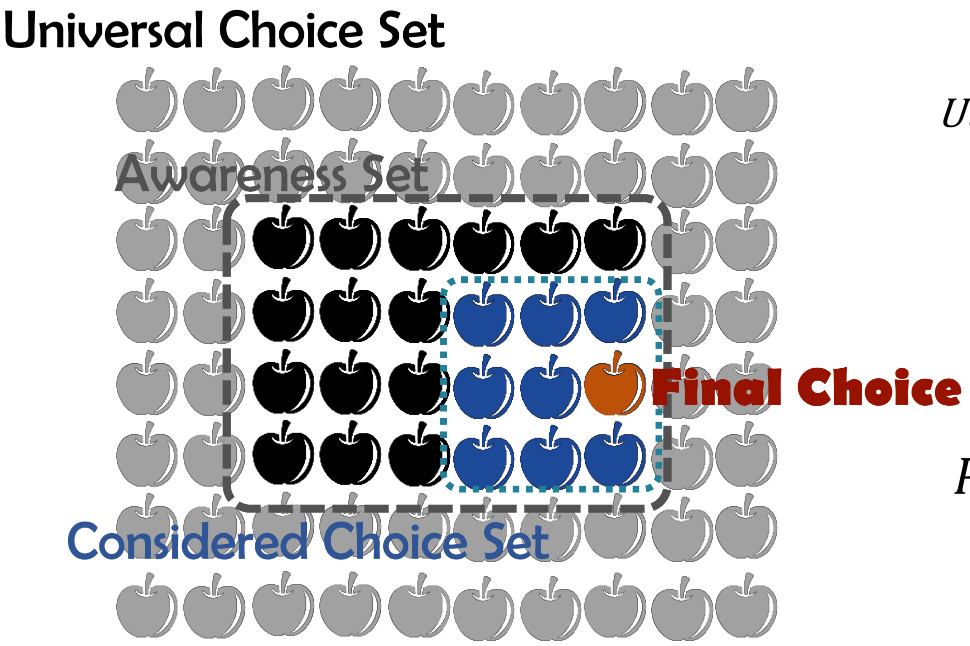
Modeling Frameworks





Utility Maximization Framework

Context



Captures uncertainty, taste variation, measurement errors and unobservable factors…

Utility

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

$$\beta_1 X_{1n} + \beta_2 X_{2n} + \ldots$$

ε is the maximum of many independent and identically distributed (i.i.d) random variables

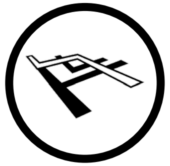
Follows extreme value distribution

$$P(i|C_n) = P(U_{in} = max_{j \in C_n} U_{jn})$$

$$P(i|C_n) = \frac{e^{\mu V_{in}}}{\sum_{j \in C_n} e^{\mu V_{jn}}}$$

Challenges in Route Choice Modeling

➢ Defining a proper consideration set of route alternatives.



➢ Capturing the correlation structure (e.g. overlaps) among various route alternatives.

➢ Representing the underlying behavioral process of drivers' route perception.

➢ Collecting data using customized surveys for route choice purposes.

➢ The stochasticity of individuals' preferences, the ambiguity of the decision-making process, and the sophisticated nature of human behaviour.

Challenges in Route Choice Modeling

- Defining a proper consideration set of route alternatives.
- Capturing the correlation structure (e.g. overlaps) among various route alternatives.
- Representing the underlying behavioral process of drivers’ route perception.
- Collecting data using customized surveys for route choice purposes.
- The stochasticity of individuals’ preferences, the ambiguity of the decision-making process, and the sophisticated nature of human behaviour.

Definition of a Proper Choice Set

Particularity of Route Choice Modeling

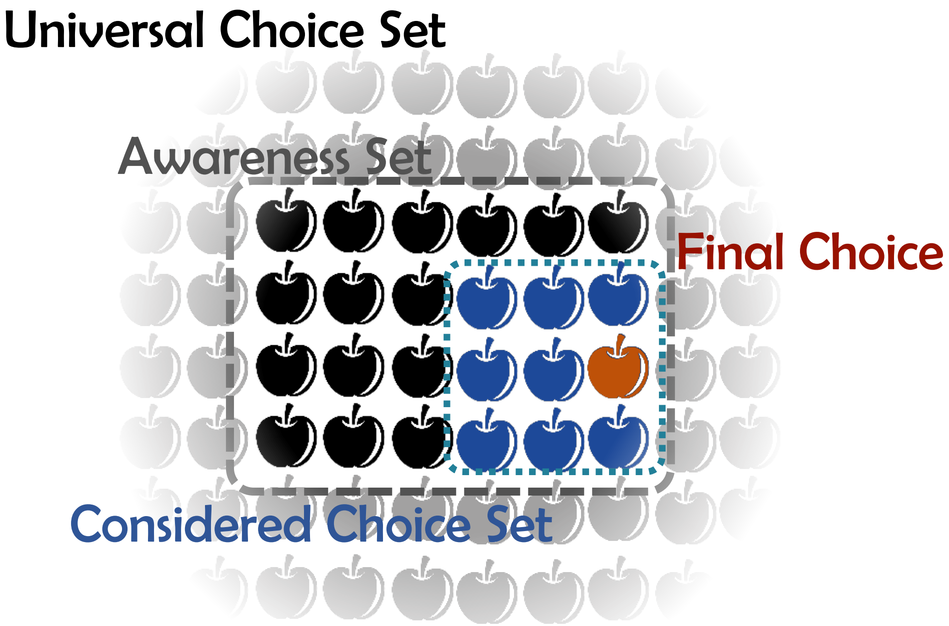
- There are substantial differences between route choice and other travel choices such as mode choice.
- There are usually small number of alternatives that are easy to define and to visualize:
  - ✓ Mode choice: car, bus, train, bicycle, walking, etc.
- When there are larger number of alternatives involved, they are relatively more complicated to identify and to envision:
  - ✓ Destination choice: regions, cities, traffic analysis zones, etc.
- In dense urban networks, a vast number of alternative routes are difficult to enumerate and even to visualize!
- Routes are mostly unknown and “hidden” in the network from which they need to be explicitly extracted.
- The explicit extraction of the routes from the network requires an explicit path generation process.

Two-stage choice modeling

Probabilistic Choice Set

Two-stage choice modeling process
(Manski, 1977)

- Decision makers reduce the total number of possible alternatives to a smaller set called the considered choice set, C_n.
- They make their final choice from the considered set of route alternatives.



$$P(i) = \sum_{C_n \subset H_n} P(i|C_n) P(C_n)$$

Probability of route i being chosen

Probability of route i given C_n

Probability of choosing the considered set C_n among all the possible non-empty subsets of route alternatives H_n

Two-stage choice modeling

Correction Term

- Defining a probabilistic choice set of route alternatives, $P(C_n)$, is a very complex and mathematically intractable problem due to the size of H_n, and has never been used in real-world route choice applications.

Correction for sampling bias

(McFadden, 1978)

Alternative specific correction term

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

- The correction term, which is based on the probability of sampling C_n given that route i has been chosen is added to correct for sampling bias.

Choice Set Generation

Choice Set Size and Composition

- Studies have shown that choice set size and composition affect model estimates and choice probabilities
- The misspecification of the “size” and “composition” of the considered choice set greatly affect model’s estimates and may lead to fallacious predicted demand levels.
- For prediction purposes, all “relevant routes” have to be included within the generated choice set.
- The addition of irrelevant routes to the choice set biases route choice probabilities and causes attractive routes to become less attractive.
- However, an objective definition of “relevant route” in real networks is currently missing.
- Drivers’ choice sets of route alternatives are rarely observed and usually latent to the analyst.

Choice Set Generation

Deterministic Algorithms

- We only discuss deterministic methods.
- Simulation techniques, stochastic approaches, constrained enumeration methods, and probabilistic approaches are among other methods.

K-Shortest Paths

- ✓ The most straightforward approach
- ✓ The best K paths according to some link additive generalized cost function
- ✓ The behavioral assumption behind the search for *K* shortest paths is that travelers limit their choices among a certain number of minimum cost paths and avoid extremely costly alternatives
- ✓ It may result over circuitous and extremely similar routes that are highly unattractive to travelers

Labeling Approach

- ✓ Shortest paths are generated based on cost functions including labels, such as scenery, travel time, travel distance, number of lights, etc.
- ✓ The behavioral assumption underneath the labeling approach is that travelers have different objectives, e.g. comfort, travel time minimization, familiar landmarks, scenery, etc.

Choice Set Generation

Deterministic Algorithms

Link Elimination

- ✓ Repetitive search for the shortest path after removal of part or all the shortest path links from previous searches
- ✓ Behaviorally, it guarantees dissimilarity among alternative paths
- ✓ Heuristic methods can be used to select the links to be eliminated
- ✓ Its shortcoming is the network disconnection resulting from the removal of centroid connectors and major crossings ➔ does not allow generating all attractive routes using alternative access to major crossings.

Link Penalty

- ✓ This method is also based on the repetitive search for the shortest path
- ✓ A penalty on the impedance of all links in the resulting shortest path is imposed instead of the link removal.
- ✓ The advantage is that network connectivity remains intact and similarity among alternative paths is discouraged.
- ✓ Definition of an adequate penalty factor to prevent the generation of high impedance paths remains a serious challenge.

Choice Set Generation

Sampling Correction Factor

- The major downside of using these methods is that they do not provide researchers with sampling probabilities of the generated alternatives.

- Model estimates based on these path generation methods are biased, unless the sampling probability of every alternative in the universal set is equal, which is not the case in route choice modeling.

Alternative specific correction term

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

Flötteröd and Bierlaire (2013)

- ✓ Metropolis-Hastings algorithm
- ✓ requires a road network and a definition of path weight as an input
- ✓ An underlying Markov Chain process samples alternatives and calculates their sampling probability without the need to normalize over the full choice set

Challenges in Route Choice Modeling

- Defining a proper consideration set of route alternatives.
- Capturing the correlation structure (e.g. overlaps) among various route alternatives.
- Representing the underlying behavioral process of drivers’ route perception.
- Collecting data using customized surveys for route choice purposes.
- The stochasticity of individuals’ preferences, the ambiguity of the decision-making process, and the sophisticated nature of human behaviour.

Correlation between Alternatives

Route Choice Context

- Route choice models should exhibit robustness in utility parameter estimates with respect to the choice set size.

- This requires the definition of choice sets with a reasonable number of attractive alternatives in order to obtain reliable model estimates.

- Route alternatives in dense urban networks show a high degree of similarity and have overlapping segments.

- Most of the literature focuses on the correlation between alternatives, which alters choice probabilities of overlapping routes.

Correlation between Alternatives

Red Bus / Blue Bus Paradox

- Mode Choice Model I:
  - ✓ Two alternative:
  - ✓ Car, Bus
  - ✓ Utility function only considers travel time, T
  - ✓ Car and Bus have same travel times

- Utility functions:
  - ✓ $U_{auto} = \beta . T_{auto} + \varepsilon_{auto}$
  - ✓ $U_{bus} = \beta . T_{bus} + \varepsilon_{bus}$

- Choice probability:

$$P(auto|\{auto, bus\}) = P(bus|\{auto, bus\})$$

$$= \frac{e^{\beta T_{auto}}}{e^{\beta T_{bus}} + e^{\beta T_{auto}}} = \frac{e^{\beta T_{bus}}}{e^{\beta T_{bus}} + e^{\beta T_{auto}}} = {}^{1}/_{2}$$

Correlation between Alternatives

Red Bus / Blue Bus Paradox

- Mode Choice Model II:
  - ✓ Paint half the buses red and half blue
  - ✓ Car, Blue bus, Red bus
  - ✓ Utility function only considers travel time, T
  - ✓ Car, Blue bus and Red bus have same travel times

- Utility functions:
  - ✓ $U_{auto} = \beta.T_{auto} + \varepsilon_{auto}$
  - ✓ $U_{red\_bus} = \beta.T_{U_{red\_bus}} + \varepsilon_{U_{red\_bus}}$
  - ✓ $U_{blue\_bus} = \beta.T_{blue\_bus} + \varepsilon_{blue\_bus}$

- Choice probability:

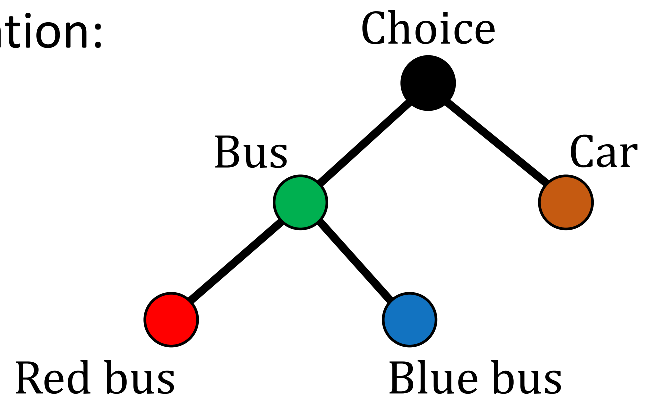
$P(auto|\{auto, blue\_bus, red\_bus\})$ =
$P(red\_bus|\{auto, blue\_bus, red\_bus\}) =$
$P(blue\_bus|\{auto, blue\_bus, red\_bus\})$

$$= \frac{e^{\beta T_{auto}}}{e^{\beta T_{red\_bus}} + e^{\beta T_{blue\_bus}} + e^{\beta T_{auto}}} = {}^{1}\!/_{3}$$

Correlation between Alternatives

Red Bus / Blue Bus Paradox

- The utility function only considers travel time.
- The effect of other attributes and unobserved variables are captured by the error term.
- Many of these effects are shared between ε_{red_bus} and ε_{blue_bus}, such as comfort, convenience, fare, headways etc.
- The logit model assumes that ε_{red_bus} and ε_{blue_bus} are independent, leading to the IIA property (Independence from Irrelevant Alternatives).
- The market share of any alternative should be independent of all other alternatives.
- Solution? Capturing the correlation:



Correlation between Alternatives

Logit Structure - Correction Factors

- A correction factor is added to the utility function.
- Maintains the simple structure of logit.

Correction Factor

$$P(i|C_n) = \frac{e^{V_i + \beta_{CF} * CF_i}}{\sum_{j \in C_n} e^{V_j + \beta_{CF} * CF_j}}$$

- Different types of correction factors have been proposed in the literature, such as the Commonality factor, Path-Size factor, Path-Size Correction factor, and the Extended Path-Size factor.
- These factors are usually a function of common lengths between paths and the total length of paths.
- The correction factor is usually designed to increase the probability of choosing an independent route over choosing an alternative with overlap.
- Hence, β_{CF} is usually a negative value and is expected to reduce the utility of paths with common links.

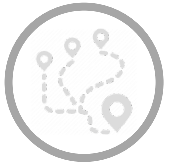
Correlation between Alternatives

Logit Structure - Correction Factors

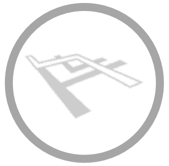
- Other model structures can also account for the correlation between route alternatives by modifying the stochastic component of the utility function.
- For instance:
  - ✓ Nested Logit, captures some of the unobserved similarities among alternatives by dividing the choice set into several nests.
  - ✓ The Cross Nested Logit (CNL) model, in which alternatives can belong to several nests. The upper level nests are formed by common links and routes form the lower level nests.

Underlying Behavioral Process

Challenges in Route Choice Modeling



- Defining a proper consideration set of route alternatives.



- Capturing the correlation structure (e.g. overlaps) among various route alternatives.

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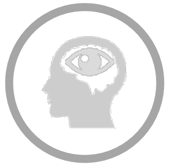


- The stochasticity of individuals’ preferences, the ambiguity of the decision-making process, and the sophisticated nature of human behaviour.

Underlying Behavioral Process

Space Hierarchy

Main question:

What is the underlying behavioral process of drivers' route perception? Are all elements of the route equally important? How do we plan the route we take?

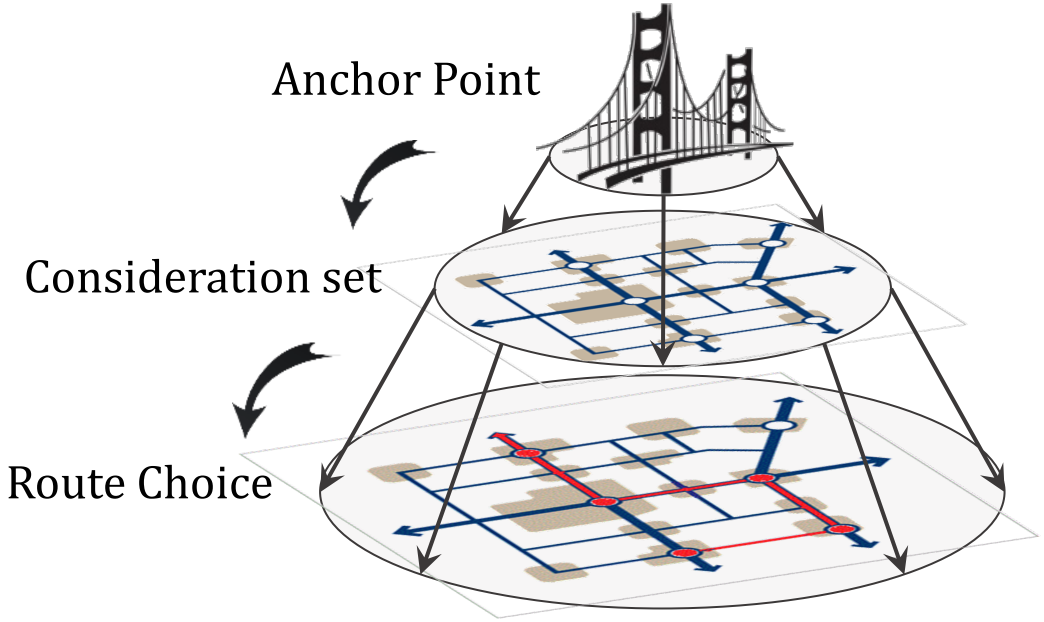
Trigger:

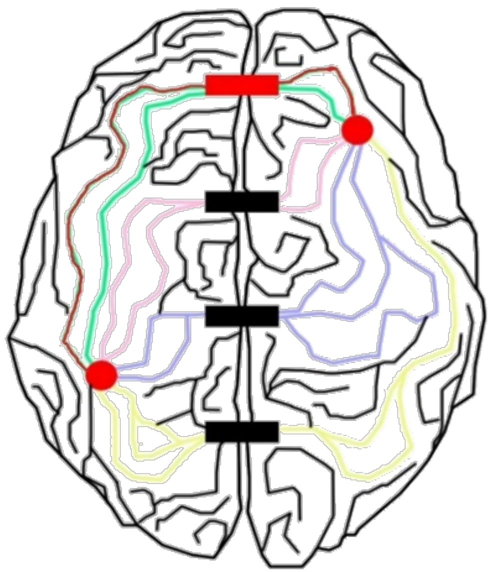
- Drivers follow the hierarchical representation of space.
- Prominent features of the route called anchor points, might affect drivers' decisions.
- Anchor points have applications in cognitive tasks, such as way-finding, distance assessment, and direction estimation.
- Routes crossing same anchor points share unobserved similarities such as safety, scenery, and driving comfort.

Anchor-based navigation process in which individuals orient themselves based on distinguished features of the route.

Underlying Behavioral Process

Schema





The principal objective is to provide a behavioural modeling framework, which explicitly takes into account the effect of anchor points as well as route-level attributes in the route selection process.

Underlying Behavioral Process

Case Study

- The importance of anchor points is emphasized in riverside cities.
- Drivers need to cross one of the several bridges.
- Bridges act as bottlenecks, face recurrent congestion, and have a significant importance on travel time.
- Taxi GPS data – October 2014.
- Taxi trips between the islands of Montreal and Laval.
- 543 trips.
- Bridges are considered as anchor points.

Underlying Behavioral Process

Modeling

Nested Logit (NL)

The effect of anchor points is addressed in upper nests while routes crossing these anchor points are represented in lower nests.

$$P(i|D,D',w) = \frac{e^{V_i + lnEPS_i + \ln\hat{G}_i(D',w) + \ln\pi(D|i)}}{\sum_{j=1}^{J} e^{V_j + lnEPS_j + \ln\hat{G}_j(D',w) + \ln\pi(D|j)}}$$

$$G_i(D',w) = \mu e^{V_i(\mu_m - 1)} \left(\sum_{i=1}^{J_m} e^{\mu_m V_i} \right)^{\frac{\mu}{\mu_m} - 1} \left(\frac{k_j}{E[k_j]} \right)$$

Logit Kernel (LK)

Accounts for the interdependencies of route alternatives crossing the same anchor point through the specification of its error structure.

$$P(i) = \int_{\zeta} \Lambda(i|\zeta_n) \prod_{m=1}^{M} \phi(\zeta_m) d\zeta$$

$$\Lambda(i|\zeta_n) = \frac{e^{\mu(X_{in}\beta + lnEPS_{in} + F_{in}T\zeta_n)}}{\sum_{j=1}^{J_n} e^{\mu(X_{jn}\beta + lnEPS_{jn} + F_{jn}T\zeta_n)}}$$

In behavioural terms, these nested structures suggest that individuals, travelling between Montreal and Laval, consider bridges as important elements, along with other route level attributes that might affect their route choices.

Underlying Behavioral Process

Model Specification

- Eighty percent of the observations, that is 434 trips, were randomly selected for estimation purposes.
- The remaining twenty percent have been used for validation purposes.
- Results are compared to three other models
  - Path-Size Logit (PSL)
  - Extended Path-Size Logit (EPSL)
  - Independent Availability Logit (IAL)
- Utility function
  - Portion of trip length made on the island of Montreal
  - Portion of trip length made on the island of Laval
  - Portion of trip length made on highways
  - Average length of road segments
- Choice set generation
  - PSL, EPSL, LK: 19 alternatives using the MH algorithm
  - IAL : 8 shortest path alternatives crossing the alternative bridges
  - NL: 9 alternative per nest using the MH algorithm

Underlying Behavioral Process

Model Estimation Results

- 80% Estimation / 20% Validation
- All the estimated models showed that, intuitively, taxi drivers are willing to minimize their travel distance and their travel time.
- The effect of the average length of the segment is expectedly positive, implying that taxi drivers tend to avoid intersections.

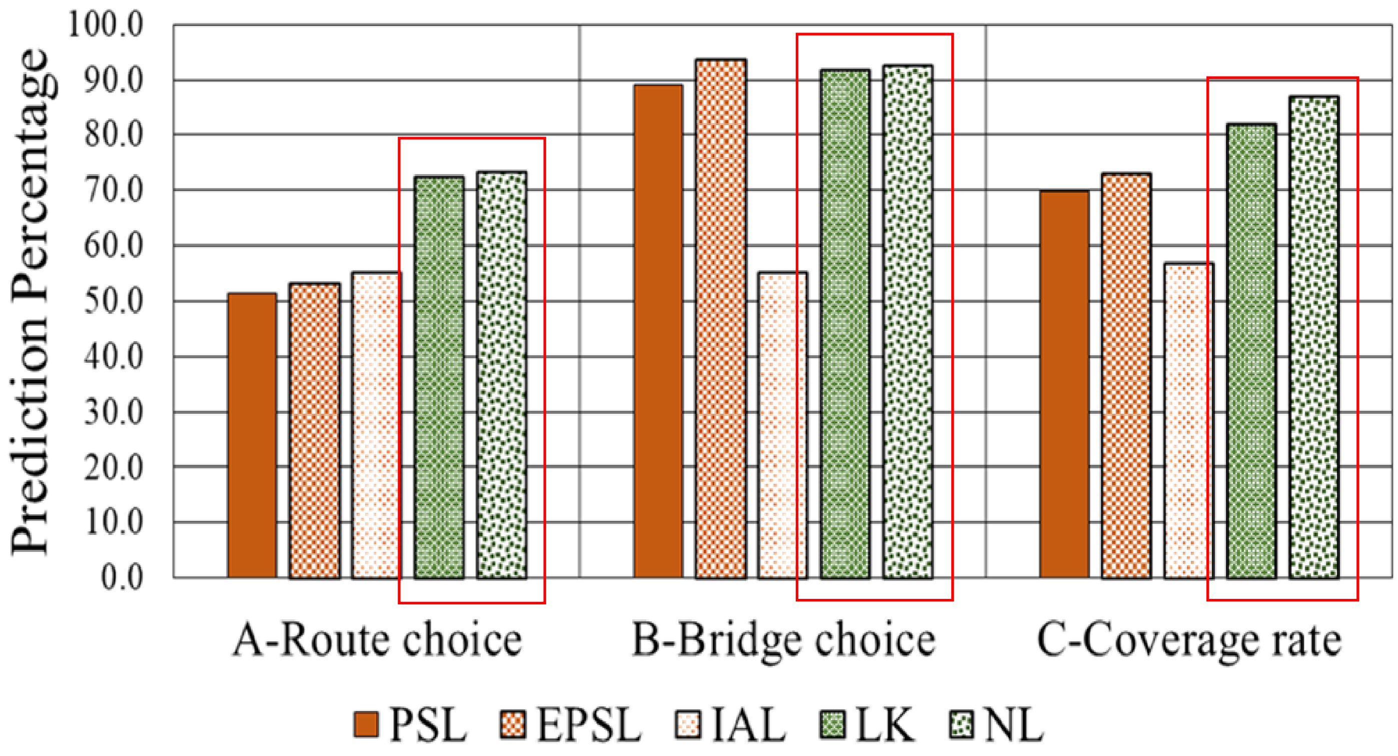
	PSL		EPSL		IAL		LK		NL	
Parameters	*Est.*[a]	*tt.*[b]	*Est.*	*tt.*	*Est.*	*tt.*	*Est.*	*tt.*	*Est.*	*tt.*
Initial LL	-2079.8		-2180.6		-1151.2		-5201.0		-2404.7	
Final LL	-623.9		-606.7		-341.4		-747.7		-336.8	
Rho-square	0.697		0.719		0.697		0.854		0.855	
Est. Time (s)	< 1		< 1		514		2417		123	

Underlying Behavioral Process

Model Prediction Results

The validation has been performed based on the models' abilities to correctly predict:

I. The chosen bridge.
II. The chosen route.
III. The total overlapping percentage (coverage rate).



Specialized Data Collection

étudemobilité

ENQUÊTE ORIGINE-DESTINATION

Itinéraires 2017

Challenges in Route Choice Modeling

- Defining a proper consideration set of route alternatives.
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- The stochasticity of individuals' preferences, the ambiguity of the decision-making process, and the sophisticated nature of human behaviour.

Specialized Data Collection

Context

Main question:

How can we collect behavioral data on drivers' route choices, observe their considered set of route alternatives, and evaluate factors affecting their decisions?

Trigger:

Factors

Observable factors: Tangible and can be directly observed.

Such as route features (i.e. travel distance, number of turns, etc.)

Latent factors: Cannot be directly observed.

Such as attitudinal traits, perceptions and lifestyle preferences.

Considered set of alternatives

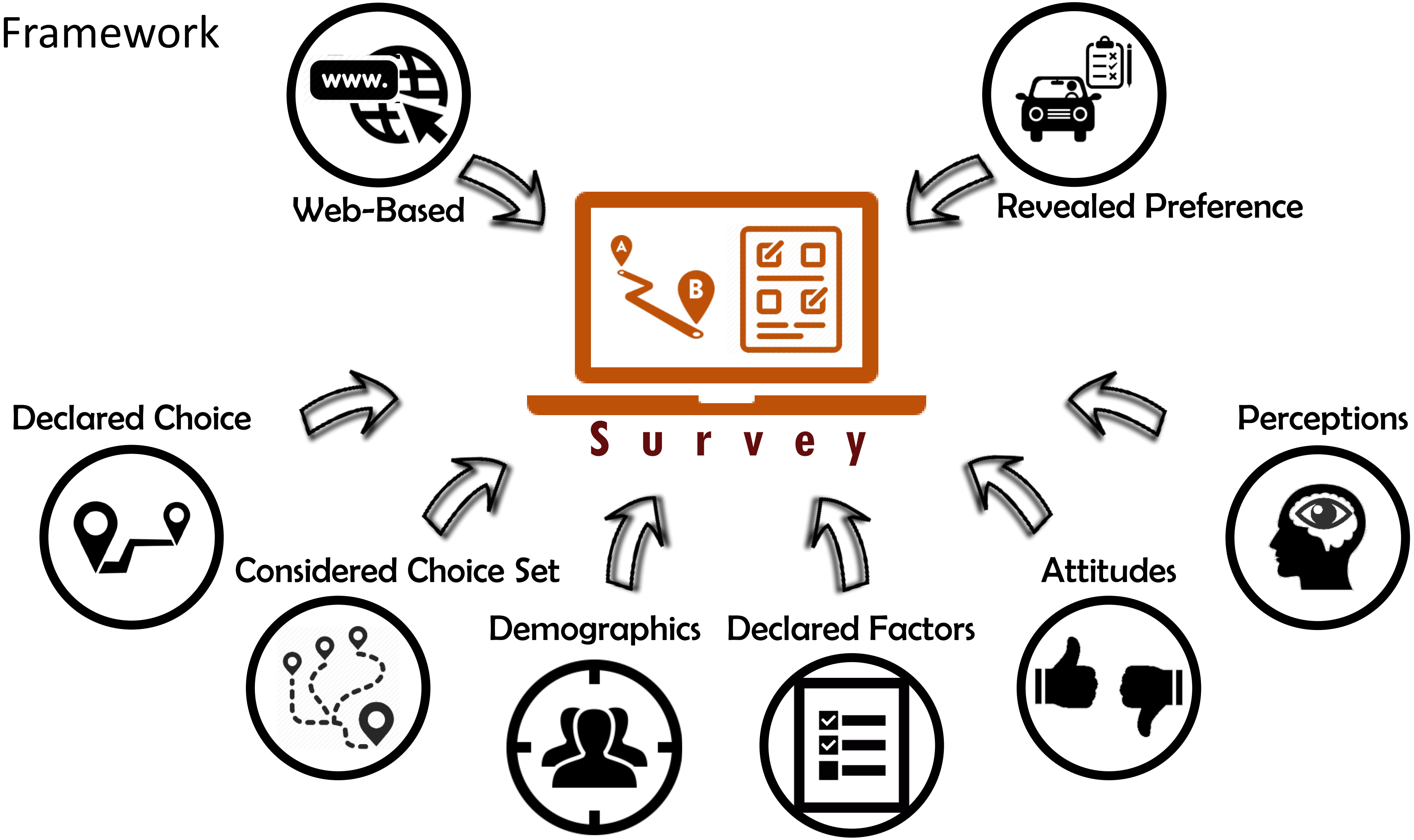
The consideration set of route alternatives is usually latent to the analyst.

Advanced Behavioral Choice Models

The increasing application of advanced behavioral choice models, reflecting the stochasticity of individuals' preferences and the complex nature of human decision-making behavior, requires enhanced data collection methods.

Specialized Data Collection

Survey Framework



Specialized Data Collection

Survey Design

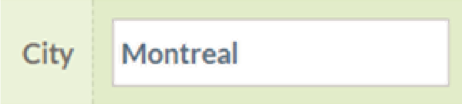
Sections

Profile → Home → Trips → Routes → Preferences → End

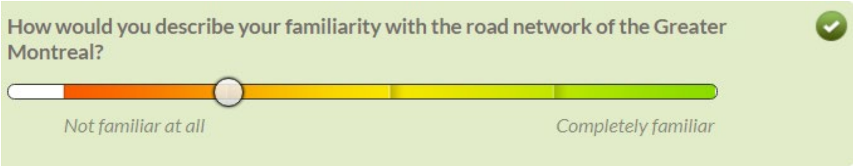
Question types

I. **Dichotomous (Boolean)**

II. **Text box (String)**

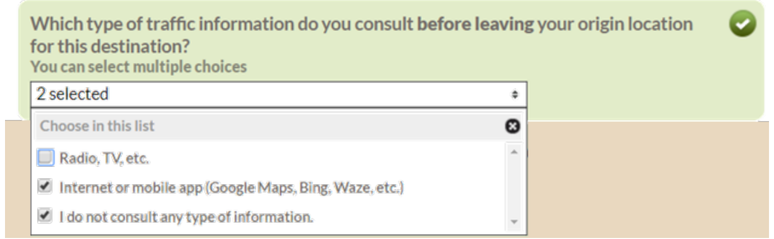


III. **Slider (Integer)**

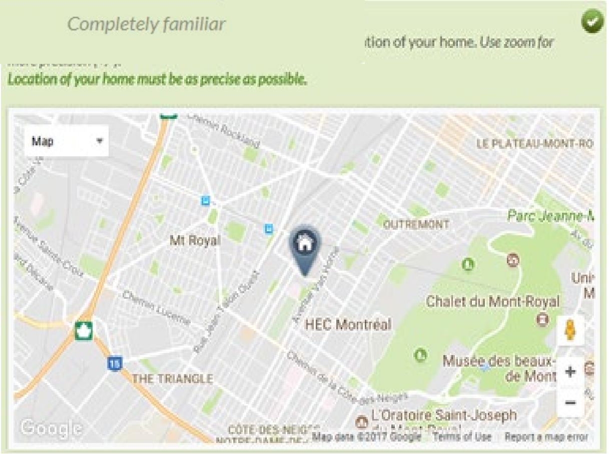


IV. **Select (String)**

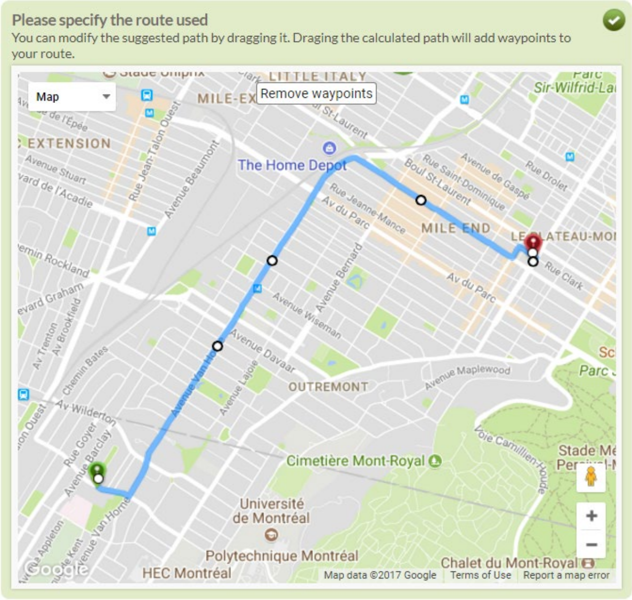
V. **Multi-select (String)**



VI. **Map-point (Point geometry)**



VII. **Map-route (Route + Point geometry)**



Specialized Data Collection

Recruitment and participants

➢ **Target groups:**

Drivers residing and driving in the Greater Montreal Area

1. **Polytechnique Montreal:** Graduate students, postdocs, faculty members, and staff
2. **Social Media:** Facebook, LinkedIn.
3. **Volunteers:** List of E-mails.

➢ **Survey Completion Rate:**

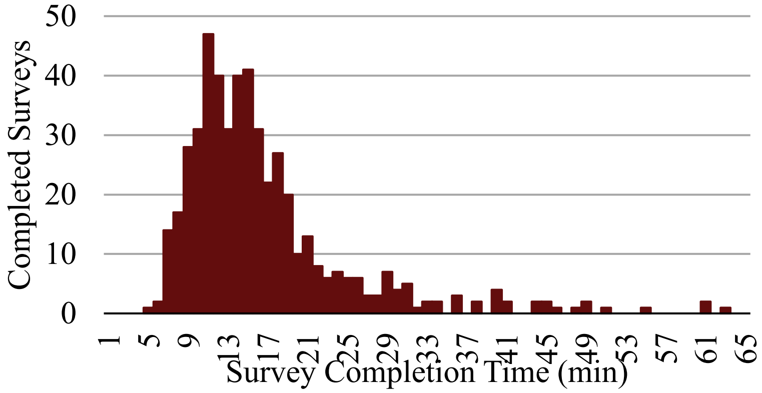
Started: 843

Completed: 539 (64%)

Abandoned: 304 (36 %)

➢ **Survey Response Time:**

Average: 16.1 min.



Latent Traits

Challenges in Route Choice Modeling

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Latent Traits

Context

Main question:

How can we capture the effects of latent behavioral constructs and segment heterogeneity in drivers’ route choice decisions?

Trigger:

Latent Variables

Route choice decisions are affected by latent variables, which cannot be directly observed, and measured, such as attitudes, perceptions, and lifestyle preferences.

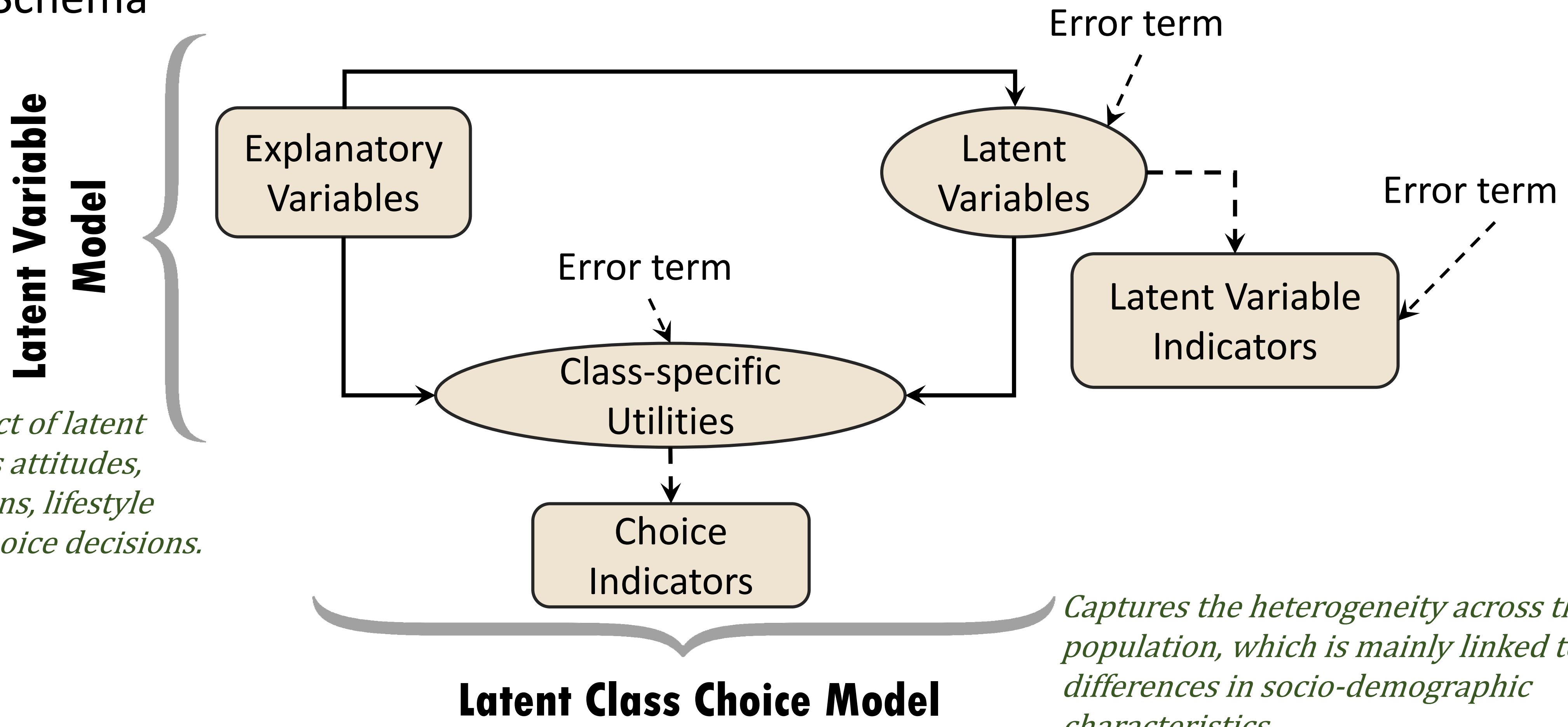
Segment Heterogeneity

Different segments of the population, might also have different choice behaviours

The explicit incorporation of these latent constructs in the choice process improves the explanatory power of choice models.

Latent Traits

Modeling Schema



Captures the effect of latent variables, such as attitudes, norms, perceptions, lifestyle and beliefs, on choice decisions.

Captures the heterogeneity across the population, which is mainly linked to differences in socio-demographic characteristics

Latent Traits

Latent Class Formulation

$$P_n(i) = \sum_{s \epsilon S} P_n(i|s) P_n(s)$$

Probability of an individual n choosing alternative i conditional on class s

$$P_n(i|s) = \frac{e^{V^s(X_{in}, Z_n, \beta^s)}}{\sum_{j \epsilon C_s} e^{V^s(X_{jn}, Z_n, \beta^s)}}$$

Class-specific utility function

$$U_{in}^s = V^s(X_{in}, Z_n, \beta^s) + \varepsilon_{in}^s$$

Attributes of the alternatives

Individuals' characteristics

i.i.d Extreme Value distributed random component

Probability of individual n belonging to class s

$$P_n(s) = \frac{e^{f(Z_n, \gamma^s)}}{\sum_{r \epsilon S} e^{f(Z_n, \gamma^s)}}$$

Class-membership function

$$F_{ns} = f(Z_n, \gamma^s) + \xi_{in}$$

i.i.d Extreme Value distributed random component

Latent Traits

Latent Variable Formulation

Latent variables

$$X_n^* = h(X_n;\lambda) + \omega_n \text{ and } \omega_n \backsim D(0,\Sigma_\omega)$$

Observed variables

$$U_n = V(X_n, X_n^*;\beta) + \varepsilon_n \text{ and } \varepsilon_n \backsim D(0,\Sigma_\varepsilon)$$

Vector of indicators

$$I_n = m(X_n, X_n^*;\alpha) + \upsilon_n \text{ and } \upsilon_n \backsim D(0,\Sigma_\upsilon)$$

$$y_{in} = \begin{cases} 1, & if\ U_{in} \geq U_{jn}\ \forall\, j \neq i \\ 0, & otherwise \end{cases}$$

The distribution of the latent variables given the observed variables

$$P(y_n, I_n | X_n; \alpha, \beta, \lambda, \Sigma_\varepsilon, \Sigma_\upsilon, \Sigma_\omega)$$
$$= \int_{X^*} P(y_n | X_n, X^*; \beta, \Sigma_\varepsilon)\, f_3(I_n | X_n, X^*; \alpha, \Sigma_\upsilon) f_1(X^* | X_n; \lambda, \Sigma_\omega) dX^*$$

The distribution of the indicators conditional on the value of latent variables

Latent Traits

Case Study

Frequent Drivers vs. Regular Drivers

- 5 trips or more per week to the same destination
- 88 observations

- 1 trip per week to the same destination
- 137 observations

Observable Factors

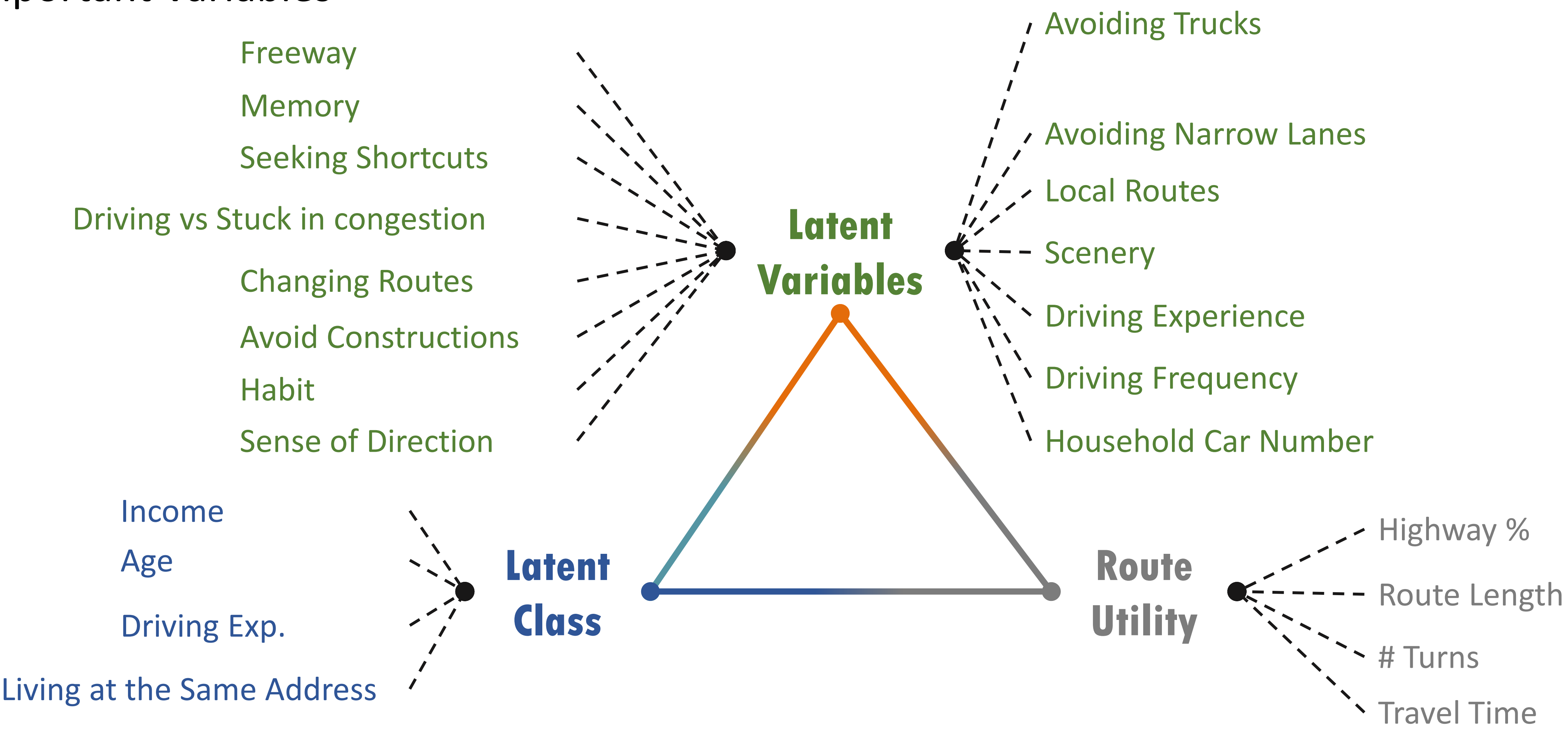
Segment Heterogeneity

Route Choice

Latent Variables

Latent Traits

Important Variables



Latent Traits

Latent Variables

Measurement equation:

Links an unobserved variable to its observable indicators.

$$I_k = \gamma_k + \alpha_k X^* + \upsilon_k$$

Links observable and latent variables to a perceived utility.

Structural equation

$$X^*_{mn} = \lambda_{m1} FREQ_n + \lambda_{m2} CAR_n + \omega_{mn}$$

Attribute	Parameter	Estimate	t-Stat	Attribute	Parameter	Estimate	t-Stat
Consciousness				*Cautiousness*			
CHANGE_RT	α_{CHANGE_RT}	1.00	-	LOCAL	α_{LOCAL}	1.00	-
	σ_{CHANGE_RT}	1.00	-		σ_{LOCAL}	1.00	-
AV_CONST	α_{AV_CONST}	0.20	2.15	AV_TRK	α_{AV_TRK}	0.63	1.76*
	σ_{AV_CONST}	1.09	15.14		σ_{AV_TRK}	1.23	14.10
DRV_STK	α_{DRV_STK}	0.93	9.77	NRW_LN	α_{NRW_LN}	1.71	2.96
	σ_{DRV_STK}	1.10	13.88		σ_{NRW_LN}	1.11	13.16
HGW	α_{HGW}	0.84	7.64	SCEN	α_{SCEN}	0.86	3.04
	σ_{HGW}	1.24	15.59		σ_{SCEN}	1.08	14.71
HABIT	α_{HABIT}	-0.65	-6.87				
	σ_{HABIT}	1.05	14.63				
TRF_LGH	α_{TRF_LGH}	0.10	1.39*				
	σ_{TRF_LGH}	0.91	13.98				
MEM	α_{MEM}	1.07	10.23				
	σ_{MEM}	1.12	12.67				
SOD	α_{SOD}	1.02	7.53				
	σ_{SOD}	1.17	13.19				
SHTC	α_{SHTC}	0.58	6.65				
	σ_{SHTC}	1.02	13.86				
TT_REL	α_{TT_REL}	0.42	5.56				
	σ_{TT_REL}	0.90	16.40				
TT_MIN	α_{TT_MIN}	1.28	9.47				
	σ_{TT_MIN}	1.31	13.18				

*Not statistically significant with $p < 0.05$

Factors	Latent variables			
	Consciousness		Cautiousness	
	Estimate	t-Stat.	Estimate	t-Stat.
FREQ	0.487	2.99	-0.605	-2.06
CAR	1.940	10.35	-0.185	-5.58

Latent Traits

Latent Variables

The probability of belonging to *"Class 1"* increases with:

- Middle-age
- High income
- Duration of living in the same home
- More experienced in driving and more familiar with Montreal's road network

Mostly associated with *"Consciousness"*

Different sensitivities are noticed due to the latent segmentation:
Frequent drivers are more sensitive to travel distance, number of turns, and travel time and prefer to use highways

The inclusion of behavioural traits in the LC model significantly improves its fit over the data.

Variables	LC-ICLV Estimate	LC-ICLV t-Stat.	LC Estimate	LC t-Stat.
Choice Model				
$\beta^{C1}_{ROUTE\_LEN\_CON}$	-0.003	-6.57	-0.004	-2.13
$\beta^{C2}_{ROUTE\_LEN\_CAU}$	-0.001	-2.09	-0.001	-2.44
$\beta^{C1}_{HGW\_PERC}$	0.207	5.81	0.338	2.44
$\beta^{C2}_{HGW\_PERC}$	-0.222	-2.83	-0.044	-2.14
$\beta^{C1}_{TURN\_LEN}$	-0.577	-3.5	-3.530	-5.02
$\beta^{C2}_{TURN\_LEN}$	-1.13	-6.33	-0.290	-1.71*
$\beta^{C1}_{REAL\_TT}$	-0.168	-1.91*	-0.256	-1.09*
$\beta^{C2}_{REAL\_TT}$	0.089	1.47*	0.984	0.88*
β^{C1}_{EPS}	1.50	8.32	0.953	2.94
β^{C2}_{EPS}	1.10	18.95	0.793	12.34
Latent Class				
$\gamma^{1}_{INC\_H}$	1.24	2.05	1.44	2.29
$\gamma^{1}_{FAM\_EXP}$	0.0148	3.82	0.0371	2.46
$\gamma^{1}_{AGE\_MIDDLE}$	0.698	1.59	0.879	2.15
$\gamma^{1}_{LIVE\_HOME}$	0.012	3.34	0.0638	2.14
Number of parameters	44		14	
Initial log-likelihood	-9512.9		-2716.7	
Final log-likelihood	-4139.73		-1409.9	
Rho-square	0.564		0.481	

* Not statistically significant with $p < 0.05$

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Thank You for Your Attention