Performance Evaluation of Choice Set Generation Algorithms for Modeling Truck Route Choice: Insights from Large Streams of Truck-GPS Data

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March 5, 2018
Tampa, Florida

Outline

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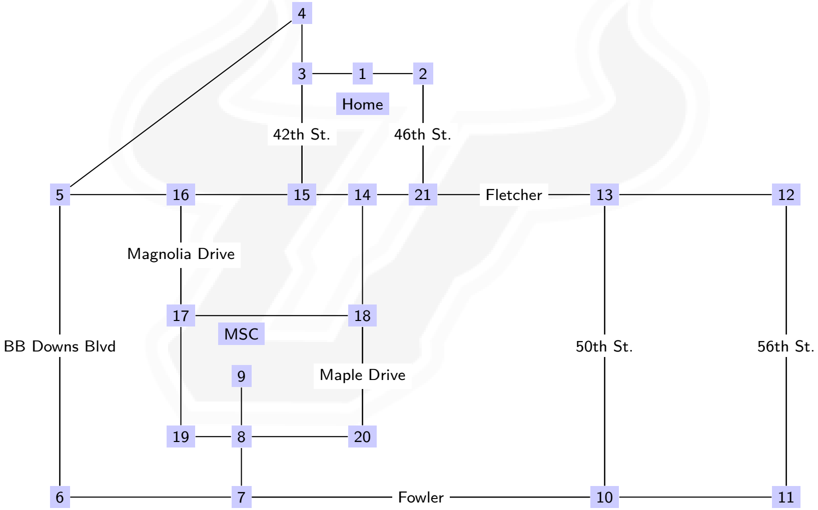
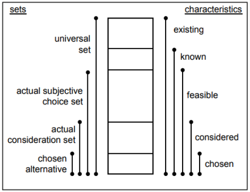
Route Choice Modeling



Route Choice Set Generation

1. **Route Choice Set Generation**: an essential precursor to route choice modeling.
2. It is important as the quality of choice sets can significantly affect model estimation and prediction results.



Hierarchy of route choice sets from traveler's perspective[1]

3. Ideally, it would be best to estimate the model using consideration choice set. However, it is difficult to observe.

[1] Source: Hoogendoorn-Lanser, S., & Van Nes, R. (2004). Multimodal choice set composition: Analysis of reported and generated choice sets. Transportation Research Record: Journal of the Transportation Research Board, (1898), 79-86.

Performance Evaluation of Algorithms

1. Most algorithms focus on generating *feasible routes* or the routes that are behaviorally realistic (*i.e. no loops, no large detours etc.*).
2. Primary goal is to maximize the generation of relevant routes (*or routes that are likely to be chosen by travelers*).
3. Performance of choice set generation algorithms is measured as the extent to which the generated choice sets include the observed routes.

Traditional Evaluation Approach

1. *Coverage:* Calculated as percentage of trips for which the traveled route was generated by the choice set generation algorithm.
2. Coverage can be improved by:
   - generating more route (but this increases computation time);
   - using a better algorithm;
   - combining routes generated from different algorithms.
3. Evaluation approach works at trip level (although route choice modeling is done at OD pair level) and doesn't offer ways to determine generation of irrelevant routes (*i.e. routes which are unlikely to be ever chosen by the travels*).

Our Approach

1. Perform the evaluation at an OD pair level.
2. If the relevant route choice set between an OD pair can be observed, it can be compared with generated route choice set to evaluate the performance of a route choice set generation algorithm.
3. How to observe relevant route choice set?

   "Observe sufficiently large number of trips between an OD pair, such that it is reasonable to assume that the observed routes are same as the relevant route choice set."

4. Proposed evaluation might have been impossible earlier, but now feasible due to increasing availability of large streams of GPS data (*which allows analyst to observed multiple trips between same OD pair*).

Issues with OD Pair Level Approach

1. A sufficiently large number of trips must be observed between an OD pair for unbiased evaluation.
2. How to define OD pairs?
   - If the OD pairs are too small in size, it might not be possible to observe large number of trips between an OD pair.
   - Even if large number of trips are observed, the observed trips might not be diverse enough as these might belong to data from just one or a few travelers (trucking companies in our study).
   - If they are too large, it becomes behaviorally inconsistent.

"Question: What is the optimal combination of spatial aggregation and minimum number of trips to observe for each OD pair?"

Current Research

1. To evaluate the performance of truck route choice set generation algorithms using large streams of GPS data.
2. Derive guidance on use of such algorithms for effective generation of choice set generation algorithm.
3. Specifically, performance of breadth-first-search link elimination (BFS-LE)[2] algorithm is evaluated.
4. BFS-LE is chosen as it has gained a lot of traction due to its ability to efficiently generate choice sets in very high generation networks.

[2] Rieser-Schüssler, N., Balmer, M. and Axhausen, K.W., 2013. Route choice sets for very high-resolution data. Transportmetrica A: Transport Science, 9(9), pp.825-845.

Outline

Raw Truck-GPS Data

Raw Truck-GPS Data

- Primary data provided by American Transportation Research Institute (ATRI)
  - 96 million GPS records.
  - Spanned 6 counties of Tampa Bay region.
  - Belonged to 60 days of 2015 and 2016.

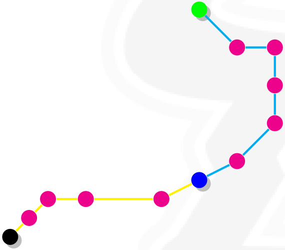
GPS Data to Trip Conversion

Identified Trip Ends

- Raw GPS data converted to a database of trips using a GPS-to-trip conversion algorithm[3].
  - Algorithm identifies trip ends by detecting stops of a certain minimum duration and land-use information.
  - Over 1 million trips generated
  - Validation procedures used to eliminate problematic trips

[3] Thakur, A., Pinjari, A.R., Zanjani, A.B., Short, J., Mysore, V. and Tabatabaee, S.F., 2015. Development of Algorithms to Convert Large Streams of Truck GPS Data into Truck Trips. Transportation Research Record: Journal of the Transportation Research Board, (2529), pp.66-73.

Map-Matching



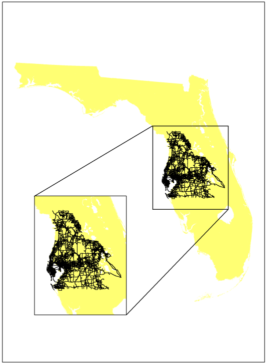
Routes derived after map-matching

- GPS data corresponding to derived trips map-matched to the road network to derive a database of 212,800 traveled routes.
  - High-resolution NAVTEQ roadway network of state of Florida was used.
  - Network was converted to connected, weighted, directed graph with 1.8 million links and 6.9 million nodes.
  - Procedures developed by Kamali et al. (2016)[4] and Tahlyan et al. (2017)[5] used for map-matching.

[4] Kamali, M., Ermagun, A., Viswanathan, K., & Pinjari, A. R. (2016). Deriving Truck Route Choice from Large GPS Data Streams. Transportation Research Record: Journal of the Transportation Research Board, (2563), 62-70.

[5] Tahlyan, D., Luong, T.D., & Pinjari, A.R., Ozkul, S. (2017). Development and Analysis of Truck Route Choice Data for the Tampa Bay Region using GPS Data. Report BDK25-730-3. Florida Department of Transportation.

Route Attributes



- For each derived routes, a number of attributes were extracted:
  - length;
  - free flow travel time;
  - travel time;
  - no. of intersections;
  - no. of left/right turns;
  - proportion of different road types (interstate, major/minor arterial, collector etc.)
  - path size (measure of degree of overlap of a route with other routes)

Outline

BFS-LE

1. Belongs to repeated least cost path search class of algorithms.
2. Algorithm is designed for extraction of routes from large-scale high-resolution networks.
3. Route generation is done by link elimination technique, where links from current shortest path are eliminated (one by one) to generate subsequent paths. The algorithm is aborted when:
   - a certain pre-defined number of routes are found;
   - a pre-defined time threshold is reached;
   - there are no more feasible routes to be found.
4. The choice of cost function (*e.g. travel time*), maximum number of routes to generate, and time threshold are at the discretion of the analyst.
5. Uses topologically equivalent network reduction technique and A-star landmarks routing algorithm (instead of Dijkstra's algorithm) for quicker search of least cost path.

Route Choice Set Generation

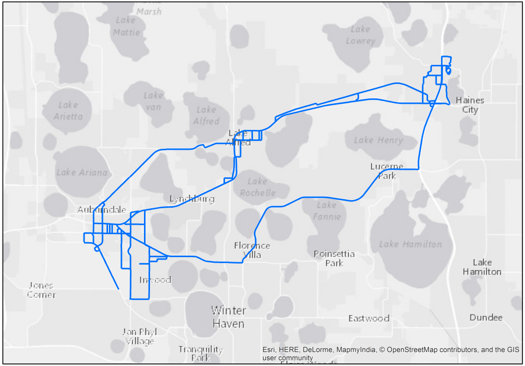
1. NAVTEQ network used for route choice set generation.
2. BFS-LE implemented in the python programming language.
3. Route choice set generation done at *unique route* level instead of route level.
   - Newly generated route considered unique (and hence part of choice set) if and only if it is at least 5% different from all previously generated routes.
   - Commonality factor[6] (C_{ij}) was used to determine uniqueness of generated routes.

$$C_{ij} = l_{ij}/\sqrt{L_i L_j}$$

where, l_{ij} is length of shared portion between routes i and j; L_i is length of route i; L_j is length of route j.

[6] Cascetta, E., Nuzzolo, A., Russo, F. and Vitetta, A., 1996. A modified logit route choice model overcoming path overlapping problems. Specification and some calibration results for interurban networks. In TRANSPORTATION AND TRAFFIC THEORY. PROCEEDINGS OF THE 13TH INTERNATIONAL SYMPOSIUM ON TRANSPORTATION AND TRAFFIC THEORY, LYON, FRANCE, 24-26 JULY 1996.

Example of generated choice set



Time Threshold = 1 hour; Maximum no. of unique routes to be generated = 15

Outline

Spatial Aggregation

1. Spatial aggregation
   - Link-level aggregation: O-D Locations represented as network links at trip ends;
   - XY-level aggregation: Trip ends aggregated by simply rounding off longitude and latitude values from 5 decimal places to 2 decimal places. This leads to spatial aggregation of roughly $1km^2$
   - TAZ-level aggregation: Aggregation done using TAZs defined in the Florida Statewide Travel Demand model. TAZs larger than $10km^2$ were not used to avoid spurious diversity in trip ends. Three levels of aggregation were considered: TAZs with maximum size of $2km^2$,$5km^2$,$10km^2$.
   - Spatial clusters: Trip ends belonging to larger TAZs divided into smaller clusters using leader clustering technique. The cluster radius was set to 2 km while retaining the TAZ boundaries.

Minimum no. of trips

1. As it is necessary to observe sufficiently large number of trips for fair evaluation of generated choice sets, OD pairs with minimum 20, 30, 50, 100 trips were considered.

Observed and Generated Unique Routes

1. Observed Unique Route: Observed route set in each OD pair converted to unique route set using CF threshold of 0.95.
2. Generated Unique Routes: BFS-LE used to generate choice sets at Link-Level and then the derived choice sets aggregated to larger aggregations using CF threshold of 0.95.
3. Sets of observed and generated Unique routes are compared for performance evaluation.

Evaluation Metrics

1. False negative error: Measure of percentage of observed unique routes which are not generated.

$$\varepsilon_n^- = 1 - \frac{\sum_{i=1}^{I_n} \delta_i}{I_n}$$

2. Weighted false negative error: Measure of percentage of observed trips whose unique routes are not generated.

$$\varepsilon_{wn}^- = 1 - \frac{\sum_{i=1}^{I_n} k_i \delta_i}{\sum_{i=1}^{I_n} k_i}$$

3. False positive error: Measure of percentage of generated routes which are not observed.

$$\varepsilon_n^+ = 1 - \frac{\sum_{j=1}^{J_n} \delta_J}{J_n}$$

Outline

"What is the appropriate combination of spatial aggregation and minimum no. of trips to be observed for performance evaluation?"

Aggregation Level	Minimum trips	No. of OD pairs	No. of trips	No. of observed unique routes		No. of generated unique routes	
				Mean	S.D.	Mean	S.D.
Link level	20	615	29,003	2.6	2.3	9.2	4.4
	30	335	22,327	2.8	2.4	8.9	4.5
	50	145	15,315	3.0	2.9	8.3	4.4
	100	48	8,995	3.4	2.8	7.2	4.5
XY cluster	20	1071	51,556	4.0	3.3	17.7	10.7
	30	615	40,654	4.6	3.6	18.3	11.2
	50	282	28,266	5.0	4.2	18.9	12.7
	100	80	15,008	6.2	5.4	19.9	14.4
Spatial cluster	20	966	58,774	5.5	4.3	26.0	20.1
	30	574	49,491	6.4	4.9	26.7	20.3
	50	294	39,001	7.4	5.7	28.0	19.8
	100	111	26,417	9.4	7.4	29.6	22.1
TAZ level (max. $2km^2$)	20	373	16,851	6.0	4.1	32.2	22.1
	30	205	12,989	6.8	4.5	32.6	22.6
	50	84	8,211	7.6	5.2	33.0	28.5
	100	28	4,336	8.3	6.2	33.4	28.4
TAZ level (max. $5km^2$)	20	723	40,229	6.8	4.7	36.9	28.4
	30	423	33,181	7.8	5.1	38.8	29.6
	50	196	24,602	8.9	5.8	39.2	27.1
	100	74	16,307	11.0	6.5	43.3	34.0
TAZ level (max. $10km^2$)	20	1152	70,494	7.7	5.8	41.4	33.2
	30	697	59,726	9.0	6.6	44.1	36.5
	50	336	46,047	10.7	7.8	47.6	38.0
	100	132	31,986	13.1	9.6	51.1	42.5

Comparison of no. of observed and generated unique routes

Findings

1. No. of OD pairs with minimum no. of trips decreased as we move from 20 trips to 100 trips.
2. No. of observed unique routes increase with minimum no. of observed trips per OD pair.
3. However, rate of increase in observed unique routes stabilizes with increase in the minimum no. of observed trips.
4. Observing minimum of 50 trips in an OD pair was enough to derive an observed route choice set.

Aggregation level	Minimum no. of trips	False negative error		Weighted false negative error		False positive error	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
Link level	20	0.34	0.34	0.17	0.32	0.81	0.19
	30	0.38	0.35	0.19	0.35	0.81	0.19
	50	0.43	0.35	0.19	0.36	0.81	0.19
	100	0.53	0.33	0.26	0.41	0.79	0.2
XY cluster	20	0.39	0.31	0.19	0.29	0.87	0.10
	30	0.44	0.29	0.18	0.28	0.87	0.10
	50	0.45	0.30	0.17	0.27	0.86	0.10
	100	0.55	0.24	0.19	0.29	0.86	0.09
Spatial cluster	20	0.41	0.29	0.18	0.25	0.87	0.09
	30	0.45	0.29	0.18	0.25	0.86	0.09
	50	0.49	0.27	0.18	0.26	0.86	0.10
	100	0.52	0.24	0.17	0.25	0.84	0.11
TAZ level (max. $2km^2$)	20	0.38	0.27	0.15	0.21	0.89	0.07
	30	0.43	0.26	0.14	0.19	0.88	0.07
	50	0.47	0.23	0.11	0.15	0.88	0.07
	100	0.54	0.21	0.11	0.18	0.88	0.08
TAZ level (max. $5km^2$)	20	0.38	0.26	0.17	0.22	0.88	0.07
	30	0.41	0.26	0.16	0.20	0.88	0.07
	50	0.44	0.23	0.14	0.19	0.87	0.07
	100	0.48	0.21	0.15	0.19	0.86	0.08
TAZ level (max. $10km^2$)	20	0.38	0.25	0.18	0.23	0.88	0.08
	30	0.41	0.25	0.18	0.24	0.87	0.09
	50	0.44	0.24	0.17	0.23	0.87	0.09
	100	0.47	0.22	0.16	0.22	0.85	0.11

Comparison of errors

Findings

1. Weighted false negative errors within 20% for all spatial aggregations suggesting BFS-LE performs well in generating observed routes.
2. Weighted false negative errors least for TAZ level (max. area = $2km^2$) spatial aggregation.
3. Considerable presence of irrelevant routes in choice set, as evident from false positive error.

"How different are the observed routes from shortest time and short length routes?"

Findings

1. More than 80% routes had commonality factor above 0.90 with respect to shortest time route in corresponding OD pair.
2. About 70 % routes had commonality factor above 0.90 with respect to shortest length route in corresponding OD pair.

Findings

"How the errors vary if the commonality factor threshold value (0.95) is reduced to 0.90, 0.85 or 0.80?"

Findings

Overlapping Threshold	Measure	False Negative	Weighted False Negative	False Positive
0.95	Mean S.D.	0.47 0.23	0.11 0.15	0.88 0.07
0.90	Mean S.D.	0.16 0.19	0.04 0.08	0.79 0.14
0.85	Mean S.D.	0.09 0.16	0.02 0.07	0.76 0.17
0.80	Mean S.D.	0.06 0.12	0.01 0.03	0.74 0.20

Comparison of errors at various overlapping thresholds

1. Weighted false negative errors decreased substantially as overlapping threshold values are decreased.
2. Results suggest that most un-captured observed routes are not substantially different from generated routes and points toward good performance of BFS-LE algorithm.

"Which is Better: Spatial Aggregation of a Limited Number of Generated Routes or Increasing the Number of Routes Generated from BFS-LE?"

Findings

Limit on No. of Unique Routes	Measure	TAZ Level (max. area = 2 sq. km)				Link Level			
		No. of Generated Unique Routes	False Negative	Weighted False Negative	False Positive	No. of Generated Unique Routes	False Negative	Weighted False Negative	False Positive
5	Mean	21.10	0.49	0.11	0.83	4.50	0.45	0.20	0.75
	S.D.	10.23	0.23	0.16	0.09	0.97	0.35	0.37	0.20
10	Mean	27.90	0.47	0.11	0.86	7.04	0.43	0.19	0.80
	S.D.	16.75	0.23	0.15	0.07	2.91	0.35	0.36	0.19
15	Mean	32.16	0.47	0.11	0.88	8.28	0.43	0.19	0.81
	S.D.	22.11	0.23	0.15	0.07	4.44	0.35	0.36	0.19
20	Mean	36.19	0.46	0.11	0.88	8.59	0.42	0.19	0.81
	S.D.	25.19	0.23	0.15	0.07	4.98	0.35	0.36	0.19
No limit	Mean	37.56	0.46	0.11	0.89	8.68	0.42	0.19	0.81
	S.D.	26.69	0.23	0.15	0.07	5.24	0.35	0.36	0.19

Comparison of errors at various limits on max. no. of unique routes for link level and TAZ (max. area = 2 sq. km) level

Findings

1. TAZ-5 choice sets provide better capture of observed routes than any link level choice set.
2. An effective approach to maximize generation of observed routes could be to aggregate limited no. of alternatives at dis- aggregate level from nearby OD pairs.
3. However, it must be noted than spatial aggregation comes with increase in false positive error.

Route Choice Models

1. Route choice models estimated and applied (to validation dataset) to confirm the hypothesis that spatially aggregated choice sets perform better.
2. Three different empirical specifications: path size logit (PSL), error components logit (ECL), and error components logit with random parameters (ECL-RP)
3. Models estimated using 6,453 observed trips and and applied on validation dataset of 1,758 trips.

Path Size Logit

1. Proposed by Ben-Akiva and Bierlaire (1999)[7], captures correlation between overlapping routes. Uses a path size (PS_i) variable in the utility of a route alternative

$$PS_i = \sum_{a \epsilon \Gamma_i} \left(\frac{l_a}{L_i}\right) \frac{1}{\sum_{j \epsilon C_n} \delta_{aj}} \tag{1}$$

2. Simple closed form expression

$$P_{in} = \frac{exp(\beta' X_{in} + \beta_{PS} lnPS_{in})}{\sum_{j \epsilon C_n} exp(\beta' X_{in} + \beta_{PS} lnPS_{in})} \tag{2}$$

[7] Ben-Akiva, M., & Bierlaire, M. (1999). Discrete choice methods and their applications to short term travel decisions. In Handbook of transportation science (pp. 5-33). Springer, Boston, MA.

Error Components Logit

1. Proposed by Frejinger and Bierlaire (2007)[8], captures perceptual correlations among routes that might not overlap physically but still share unobserved effects.

$$U_{in} = \beta^{'} X_{in} + \beta_{PS} lnPS_{in} + \sigma_a \sqrt{L_{in,a}} \zeta_{n_a} + \sigma_b \sqrt{L_{in,b}} \zeta_{n_b} + \epsilon_{in} \quad (3)$$

$$U_{jn} = \beta^{'} X_{jn} + \beta_{PS} lnPS_{jn} + \sigma_a \sqrt{L_{jn,a}} \zeta_{n_a} + \epsilon_{jn} \quad (4)$$

$$U_{kn} = \beta^{'} X_{kn} + \beta_{PS} lnPS_{kn} + \sigma_a \sqrt{L_{kn,a}} \zeta_{n_a} + \sigma_b \sqrt{L_{kn,b}} \zeta_{n_b} + \epsilon_{kn} \quad (5)$$

[8] Frejinger, E., & Bierlaire, M. (2007). Capturing correlation with subnetworks in route choice models. Transportation Research Part B: Methodological, 41(3), 363-378.

Estimation Results

Variable Description	Error Components Logit with Random Parameter on Travel Time Variable	
	Parameter Estimate	t-stat
Travel cost($)	-0.1261	-6.513
Travel time (min)	-0.0970(0.6034)	-3.003(30.635)
Proportion of tolled portion of a route	-17.4014	-25.905
No. of turns per minute	-0.3996	-4.989
No. of ramps per minute	-0.2453	-2.489
Proportion of interstate portion of a route*	36.3844	36.552
Proportion of major arterial portion of a route	22.3101	22.372
Proportion of minor arterial portion of a route	12.5747	15.432
Proportion of collector portion of a route	6.2076	8.089
Natural log of path size	-2.8777	-40.71
σ_{I-4}	2.3289	17.512
σ_{I-75}	2.2604	13.956
σ_{Polk}	1.3970	9.986
σ_{US-19}	2.9823	2.72
No. of cases	6,453	
Log-likelihood at convergence	-9,681.31	
Log-likelihood for equal shares model	-19.327.52	
Rho-square	0.4991	
Adjusted rho-square	0.4983	

*Each link in the network was classified into one of five categories: interstate, major arterial, minor arterial, collector, and local road

Route choice model estimated with TAZ level (max. area 2 sq. km) choice sets aggregated from up to 5 BFS-LE alternatives at link level

Model Fit Measures

Model Specification	Model Fit Measures	Link-5	Link-15	TAZ-5	TAZ-15
PSL	LL_C	-5,332.06	-6,915.12	-10,775.18	-11,970.52
	LL_{ES}	-10,590.42	-15,951.96	-19,327.52	-21,674.72
	$\rho^2_{adjusted}$	0.496	0.566	0.442	0.447
	AIC	10,682.12	13,848.24	21,566.36	23,961.04
	BIC	10,672.89	13,839.01	21,559.13	23,949.81
ECL	LL_C	-4,789.81	-6,303.43	-10,067.51	-11,331.78
	LL_{ES}	-10,590.42	-15,951.96	-19,327.52	-21,674.72
	$\rho^2_{adjusted}$	0.546	0.604	0.478	0.477
	AIC	9,607.62	12,634.86	20,163.02	22,691.56
	BIC	9,588.39	12,615.60	20,143.79	22,672.33
ECL-RP$_{cost}$	LL_C	-4,727.12	-6,129.55	-9,994.44	-11,229.98
	LL_{ES}	-10,590.42	-15,951.96	-19,327.52	-21,674.72
	$\rho^2_{adjusted}$	0.552	0.615	0.482	0.481
	AIC	9,482.24	12,287.10	20,018.88	22,487.96
	BIC	9,463.01	12,267.87	19,997.65	22,468.73
ECL-RP$_{TT}$	LL_C	-4,609.86	–	-9,681.31	-10,810.01
	LL_{ES}	-10,590.42	–	-19,327.52	-21,674.72
	$\rho^2_{adjusted}$	0.564	–	0.498	0.501
	AIC	9,245.72	–	19,392.62	21,648.02
	BIC	9,228.49	–	19,371.39	21,628.79

Model fit measures for various models estimated using different choice sets

Validation

1. Validation sample of 1,758 trips used to evaluate the impact of choice set composition on models' predication ability.
2. Expected overlap of route choice predictions with the chosen routes used as measure of models' prediction ability.

$$E(O)_n = \sum_{i=1}^{I} p_i C_{ir} \tag{6}$$

where p_i is probability of choosing route i from the choice set and C_{ir} is proportion of route i common with chosen route r.

Findings

Model Specification	Measure of EO	Link-5	Link-15	TAZ-5	TAZ-15
PSL	Mean	0.9290	0.9340	0.9191	0.9190
	S.D.	0.0741	0.0737	0.0722	0.0743
ECL	Mean	0.9130	0.8203	0.8018	0.7913
	S.D.	0.0734	0.1878	0.2752	0.3530
ECL-RP$_{cost}$	Mean	0.9135	0.8204	0.8017	0.7914
	S.D.	0.0735	0.1880	0.2751	0.3487
ECL-RP$_{TT}$	Mean	0.9136	–	0.8016	0.7914
	S.D.	0.0746	–	0.2752	0.3527

Comparison of expected overlap values across various choice sets and model specifications

1. Models estimated using choice sets at link level aggregations perform better than the models estimated using choice sets at TAZ level aggregations.
2. Possible explanation is greater presence of irrelevant routes in aggregated choice sets.
3. Benefits of spatial aggregation can potentially be harnessed if irrelevant routes are eliminated.

"Are there any systematic differences between route attributes of relevant and irrelevant routes?"

Comparison

Route Characteristics	Relevant Routes		Irrelevant Routes	
	Mean	S.D.	Mean	S.D.
Length (mi)	43.350	22.360	45.050	22.640
Proportion of ramps	0.037	0.039	0.049	0.034
Proportion of tolled roads	0.000	0.062	0.028	0.063
Proportion of interstate highways and major arterials	0.784	0.284	0.667	0.255
Proportion of minor arterials	0.137	0.222	0.173	0.190
Proportion of collectors	0.061	0.105	0.131	0.101
Proportion of local roads	0.018	0.040	0.0290	0.047
No. of links	214.90	123.920	253.200	119.100
No. of links per mile	5.750	3.070	6.460	2.820
No. of intersections	89.770	77.010	119.300	72.510
No. of intersections per mile	2.580	2.070	3.220	1.960
No. of right turns	1.950	1.520	4.750	2.260
No. of left turns	1.920	1.290	4.850	2.480
Average path size	$0.29^{\beta}(0.09)^{\alpha}$	0.19(0.06)	0.140	0.060
$^{\beta}$Pathsize of observed relevant routes with respect to observed routes				
$^{\alpha}$Pathsize of generated relevant routes with respect to generated routes				

Comparison of route attributes of relevant and irrelevant routes

Findings

1. Irrelevant routes are:
   - generally longer
   - have greater proportion of tolled roads
   - involve greater proportion of length through smaller roads
   - have more network links per mile
   - have more intersections per mile

Outline

Conclusions

1. OD pair level evaluation helps in evaluating a choice set generation algorithm's ability to generate relevant routes and generation of irrelevant routes.
2. Effect approach to use of BFS-LE is to generate small number of routes at dis-aggregate level and then aggregate routes from near by OD pairs.
3. Even though spatial aggregation helps capture relevant routes, it also increases irrelevant routes.

Future Research

1. Development of heuristics to identify deterministic thresholds on select route attributes to help identify irrelevant routes.
2. Route choice models with implicit choice set generation.

Acknowledgments

My advisers and thesis committee members
Dr. Abdul R. Pinjari, Dr. Fred L. Mannering, Dr. Robert Bertini

Funding Agencies and UTCs
FDOT, US-DOT, CAIT, TOMNET,ATRI

Dr. Michael Maness

USF CEE
Shivali Vyas, Barbara Johnson, Camille Mourant, Stephanie Lovelace

CUTR

USF ITE

My Family (Happy Birthday Mom!!)

All my friends

Question???

Thank You!!