

The background of the slide is a collage of various transportation planning visualizations. It includes a network map with colored lines (green, purple, orange) representing different transit routes or road types. There are also several pie charts and circular diagrams scattered across the upper half, likely representing data analysis or land use patterns. The lower half of the background shows a detailed map of a highway interchange with multiple lanes and ramps, labeled with 'KY-4'.

EVOLUTION OF MODELING METHODS AND SOFTWARE FROM THE PAST TO THE PRESENT

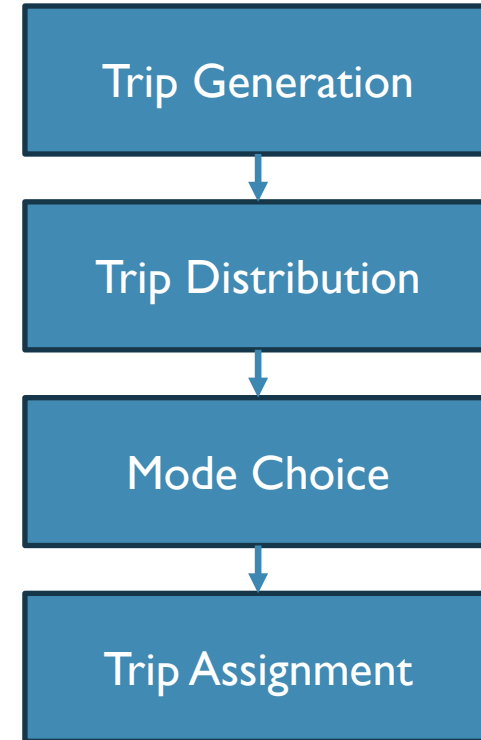


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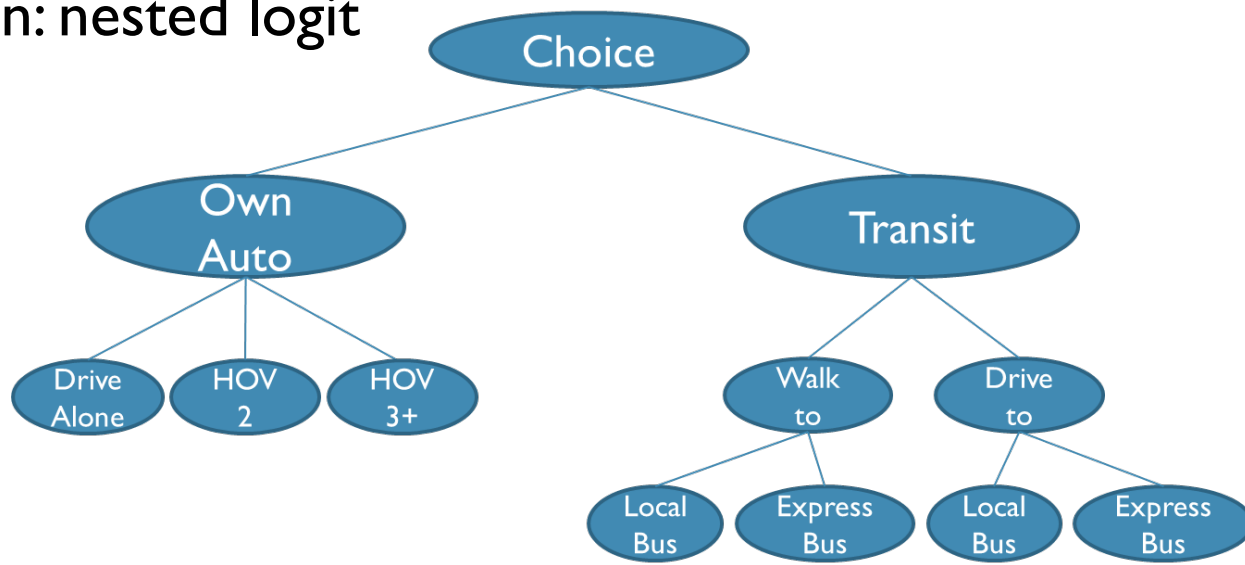
IN THE BEGINNING...

- There was UTPS – FHWA's mainframe software (1970s)
 - Standard “Four-Step” model:
 - Trip Generation
 - Cross-classification
 - Regression
 - Trip Distribution
 - Gravity
 - Mode Choice
 - Multinomial Logit
 - Trip Assignment
 - Frank-Wolfe User Equilibrium



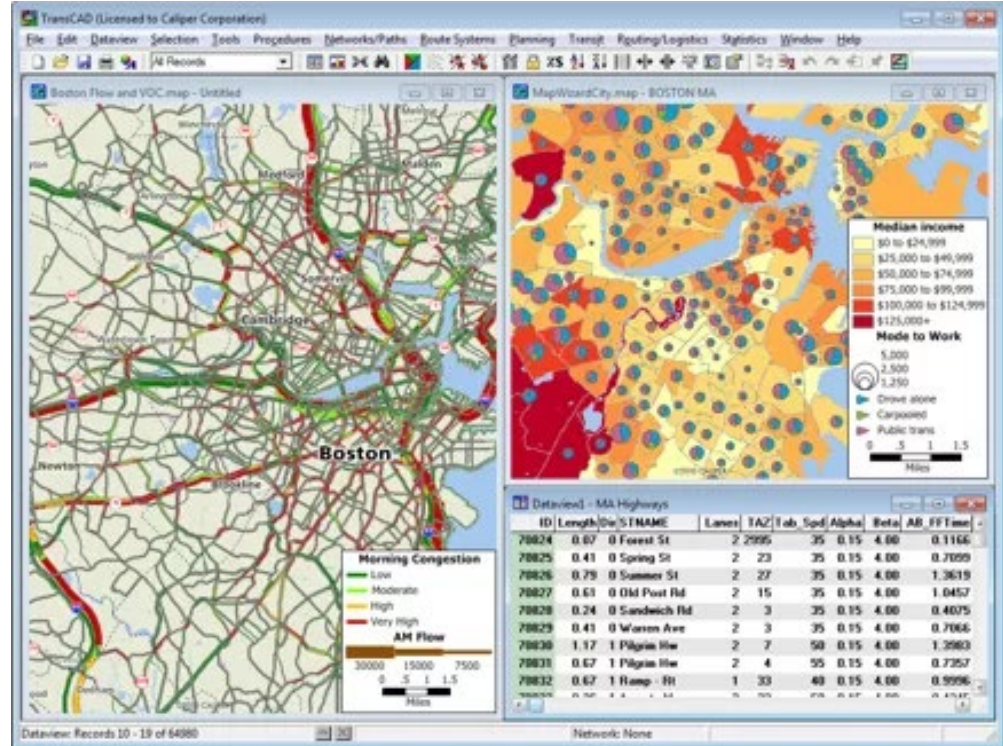
IN THE 1980's

- MINUTP and TRANPLAN for PCs
- Some customization of the four-step model
- Main innovation: nested logit



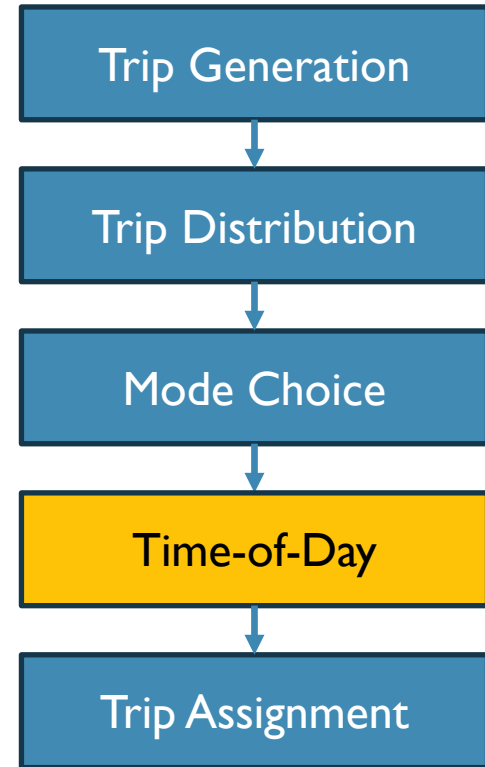
IN THE 1990's

- TransCAD for Windows
- GIS integration
 - “True Shape” road networks replace stick networks



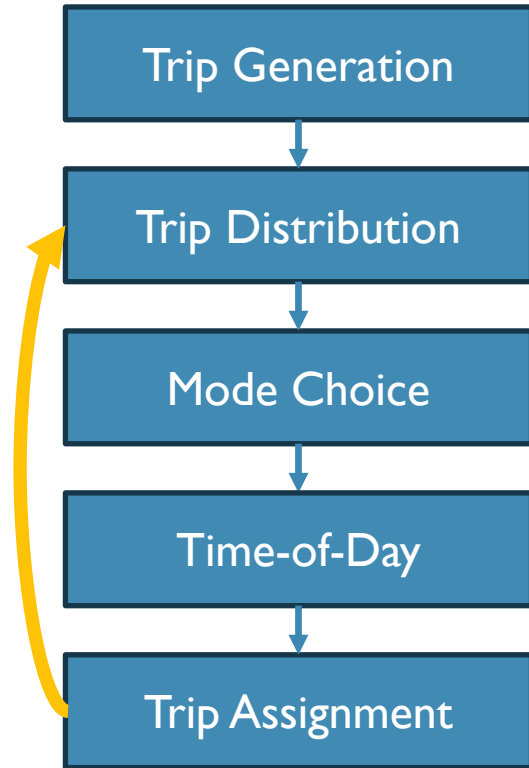
TIME-OF-DAY

- Air quality conformity led to focus on speeds
- Speeds vary by time-of-day
- Models began to represent demand by time-of-day
- Most commonly trips split into time periods just before assignment in PA to OD conversion



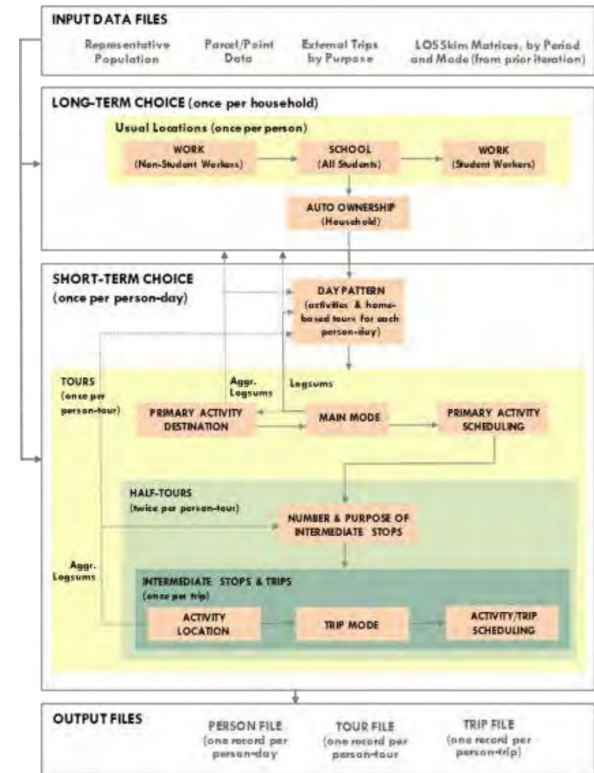
FEEDBACK

- Air quality conformity also led to concerns about the consistency of travel times assumed in trip distribution and resulting from trip assignment
- Travel times were 'fed back' and the model looped until convergence



ACTIVITY-BASED MODELS

- Born out of academic desire to address inconsistencies in traditional models
- Began to be adopted as useful for land use effects, walk/bike planning, time sensitive pricing/policies, equity analyses
- People as basic unit of analysis (synthetic population)
- Discrete choice models with many variables
- Monte Carlo simulation
- Relational database

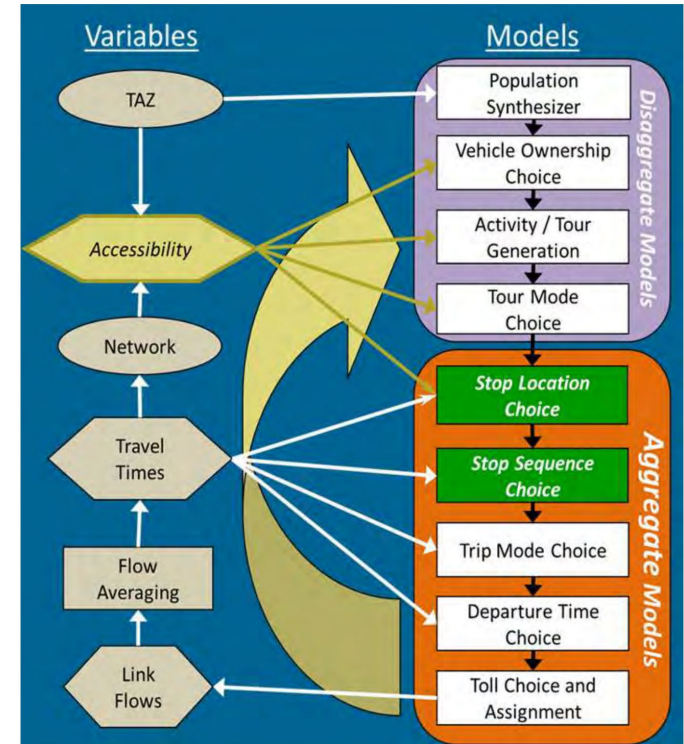


ACTIVITY-BASED MODELS

- Limited adoption, mostly by very large MPOs
 - Many of which also maintain & use trip-based model
- Require large surveys
- Costly development
- Long runtimes

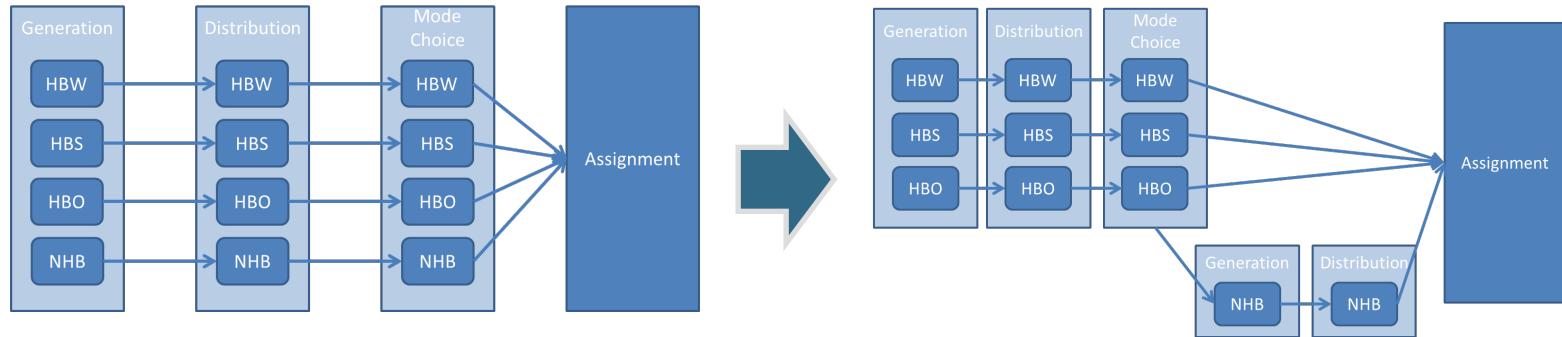
HYBRID MODELS

- Developed after activity-based, as an attempt to compromise between theoretical and practical concerns
- Discrete choice models like activity-based, but no Monte Carlo simulation
 - Mode choice often before destination choice
- Some use of persons; some use of trip matrices



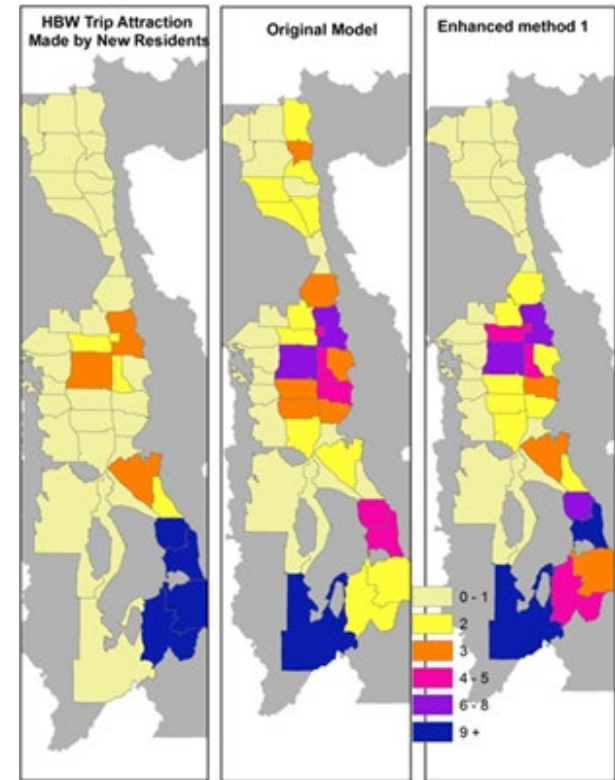
LINKING NON-HOME-BASED TRIPS (TMIP METHOD)

- After and conditional on HB trip models
 - NHB trips generated separately by mode based on HB trip destinations by mode (~Markov transition probabilities)



LINKING NHB TRIPS

- Linking NHB to HB trips provides consistency between modes and destinations chosen
- In the original/traditional Salt Lake City model adding population down in Provo (S) added NHBW trips in Ogden (N) – linking trips fixes this



NHB TRIP GENERATION BY MODE

■ Example: Nonwork Tour Non-home-based SOV

term	estimated_as	estimate	std.error	statistic	p.value
N_HB_OD_Long_hov	N_HB_OD_All_hov	0.0209	0.0037	5.6162	0
N_HB_OD_Short_hov	N_HB_OD_All_hov	0.0209	0.0037	5.6162	0
N_HB_OD_Long_sov	N_HB_OD_All_sov	0.1034	0.0041	25.021	0
N_HB_OD_Short_sov	N_HB_OD_All_sov	0.1034	0.0041	25.021	0
N_HB_OME_All_hov	N_HB_OME_All_hov	0.0026	0.0034	0.7798	0.4355
N_HB_OMED_All_hov	N_HB_OME_All_hov	0.0026	0.0034	0.7798	0.4355
N_HB_OME_All_sov	N_HB_OME_All_sov	0.0292	0.0044	6.6661	0
N_HB_OMED_All_sov	N_HB_OME_All_sov	0.0292	0.0044	6.6661	0

- All HB trip types (on Nonwork tours) by auto modes generate NHB SOV trips
- No HB trips by non-auto modes generate NHB SOV trips
 - You have to have taken a car with you make a NHB trip by SOV.

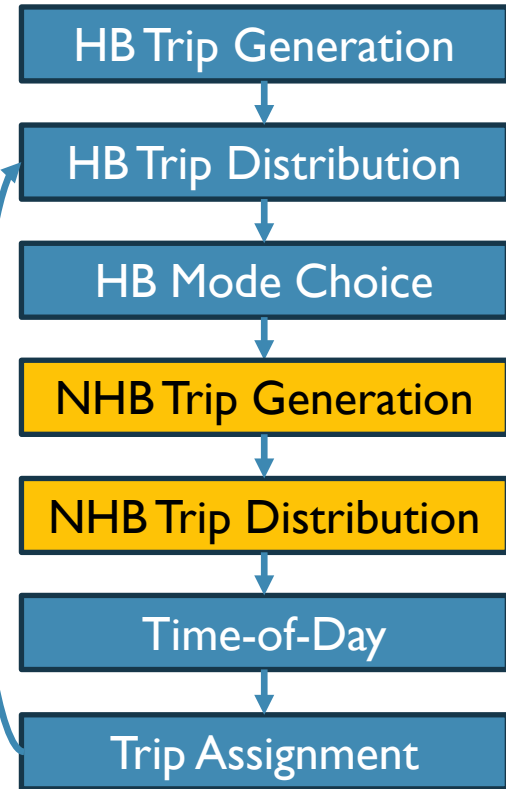
NHB TRIP GENERATION BY MODE

- **Example:**
Nonwork Tour
Non-home-based
Maintenance / Eat
WALK
- NHB walk trips can be made by many more modes – because they don't require having a vehicle with you
- Note how likely auto-pay HB trips are to generate NHB walk trips

term	estimated_as	estimate	std.error	statistic	p.value
N_HB_K12_All_t	N_HB_K12_All_t	0.0813	0.0472	1.7235	0.0848
N_HB_OD_Long_auto_pay	N_HB_O_All_auto_pay	0.5896	0.0225	26.237	0
N_HB_OD_Short_auto_pay	N_HB_O_All_auto_pay	0.5896	0.0225	26.237	0
N_HB_OME_All_auto_pay	N_HB_O_All_auto_pay	0.5896	0.0225	26.237	0
N_HB_OMED_All_auto_pay	N_HB_O_All_auto_pay	0.5896	0.0225	26.237	0
N_HB_OD_Long_hov	N_HB_OD_All_hov	0.0062	0.0028	2.238	0.0252
N_HB_OD_Short_hov	N_HB_OD_All_hov	0.0062	0.0028	2.238	0.0252
N_HB_OD_Long_t	N_HB_OD_All_t	0.0681	0.0218	3.1296	0.0018
N_HB_OD_Short_t	N_HB_OD_All_t	0.0681	0.0218	3.1296	0.0018
N_HB_OD_Long_walk	N_HB_OD_Long_walk	0.0398	0.0082	4.831	0
N_HB_OD_Short_sov	N_HB_OD_Short_sov	0.0129	0.0055	2.3628	0.0181
N_HB_OD_Short_walk	N_HB_OD_Short_walk	0.0131	0.004	3.261	0.0011
N_HB_OME_All_bike	N_HB_OME_All_bike	0.1197	0.0477	2.5095	0.0121
N_HB_OME_All_hov	N_HB_OME_All_hov	0.0075	0.0026	2.8264	0.0047
N_HB_OME_All_sov	N_HB_OME_All_sov	0.0251	0.0034	7.3015	0
N_HB_OME_All_t	N_HB_OME_All_t	0.0695	0.0276	2.5216	0.0117
N_HB_OME_All_walk	N_HB_OME_All_walk	0.1767	0.0089	19.884	0
N_HB_OMED_All_walk	N_HB_OME_All_walk	0.1767	0.0089	19.884	0
N_HB_OMED_All_hov	N_HB_OMED_All_hov	0.0168	0.0091	1.8509	0.0642

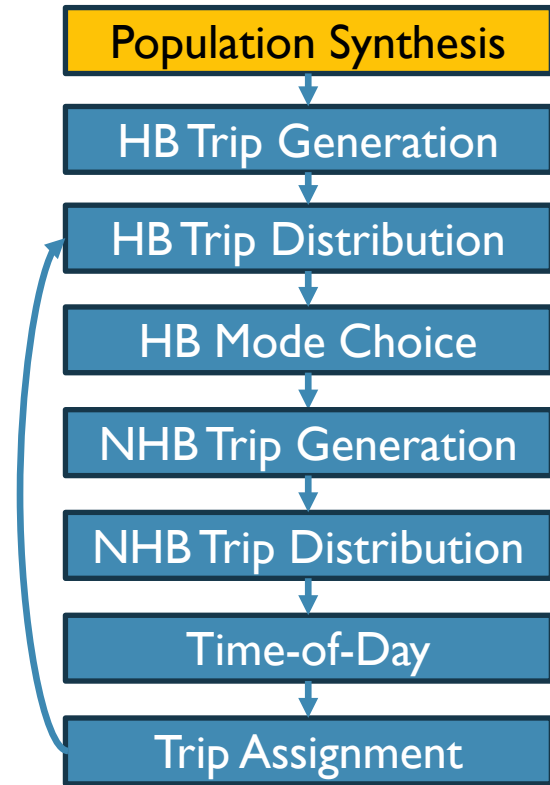
LINKING NHB TRIPS TO HB TRIPS

- This relatively simple shift makes the model's trip tables consistent with tours
- The rest of what makes a model a hybrid is generally improvements to the individual modeling steps



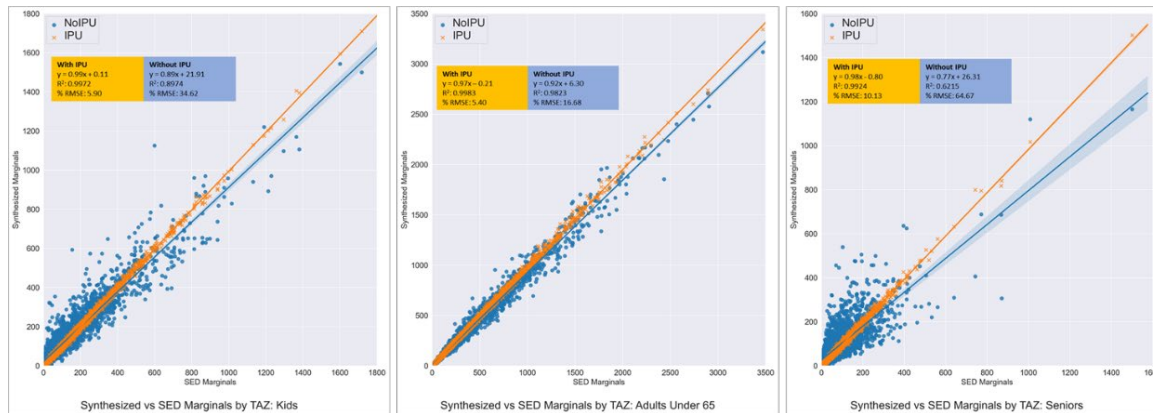
POPULATION SYNTHESIS

- Creates linked lists of individual persons and households with the same aggregate characteristics as the real population as described by the Census

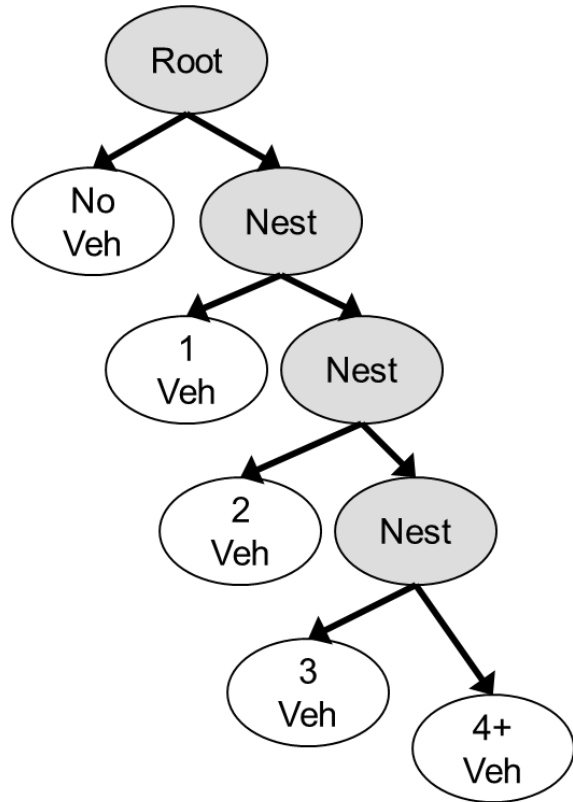


POPULATION SYNTHESIS

- TransCAD's Iterative Proportional Updating (IPU)
 - Household and Person level controls
 - Support for controls at multiple levels of geography
 - Extremely fast, ~ 2 minutes – run during model run
- Person level attributes show benefit of IPU over IPF



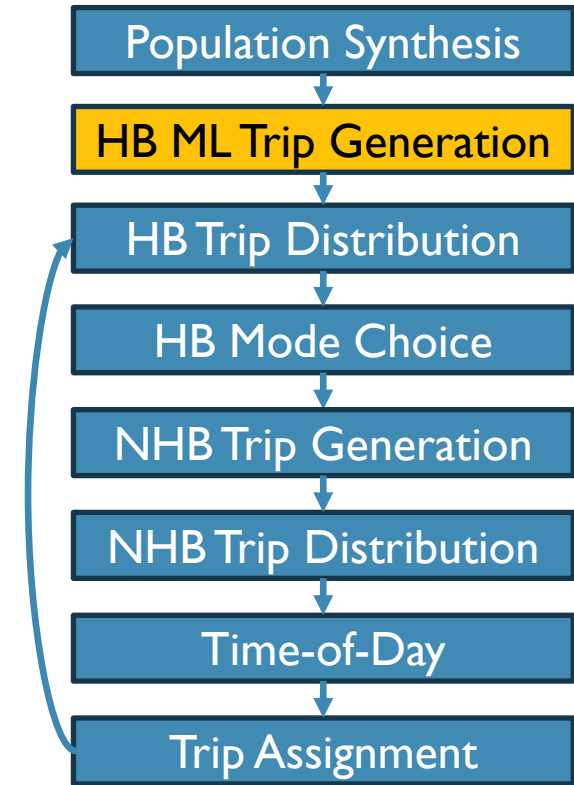
AUTOMOBILE AVAILABILITY



- Each household chooses how many vehicles to own / lease
- No aggregation bias
- Vehicle ownership levels respond to
 - Demographics (household size, income, number of workers, seniors, etc.)
 - Transit Availability
 - Urban Design Factors (network density and intersection approach density ~ pedestrian environment / grid vs. cul-de-sac design)

DISAGGREGATE ML TRIP GENERATION

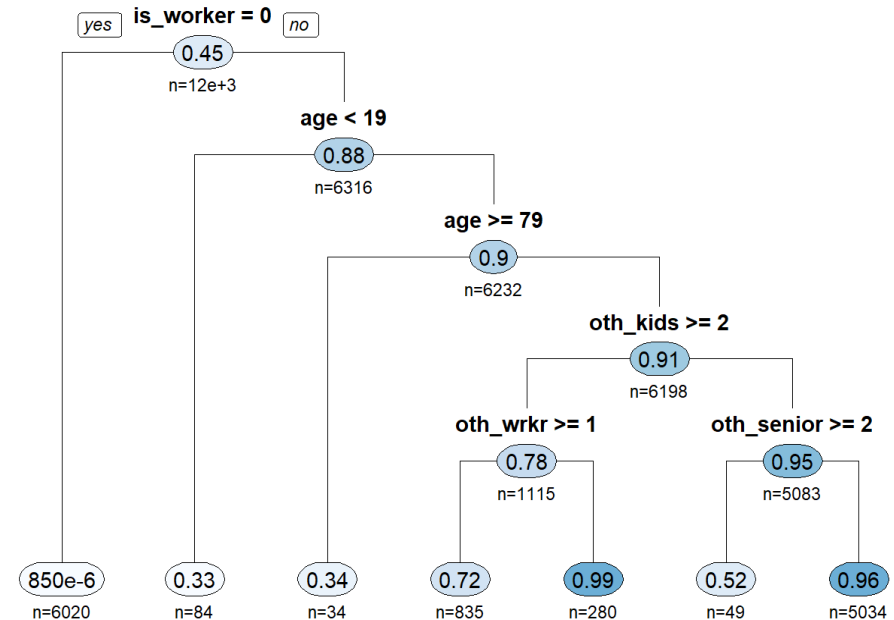
- Individual people decide how many HB trips / tours to make
- Many different model forms
 - Cross-classification
 - GLM (up to and including zero-inflated negative binomial)
 - Logit (ordered logit)
 - Decision Trees (machine learning)
- Machine learning outperforms traditional statistical models



DECISION TREES FOR TRIP GENERATION

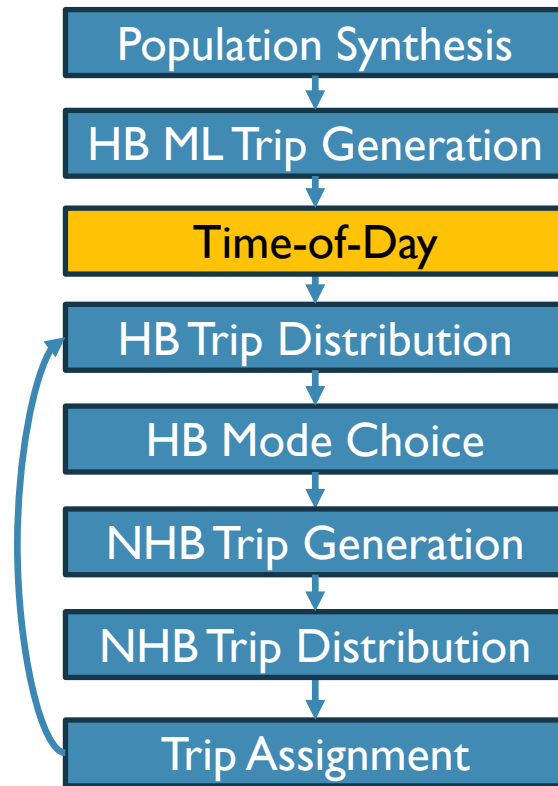
■ Advantages of ANOVA-based decision trees

- Sensitivity
 - **Age**
 - **Neighborhood / Accessibility**
 - Income
 - Vehicle ownership
 - Household composition
- Nonlinear effects
- Full survey support
 - No empty cells like with cross-class



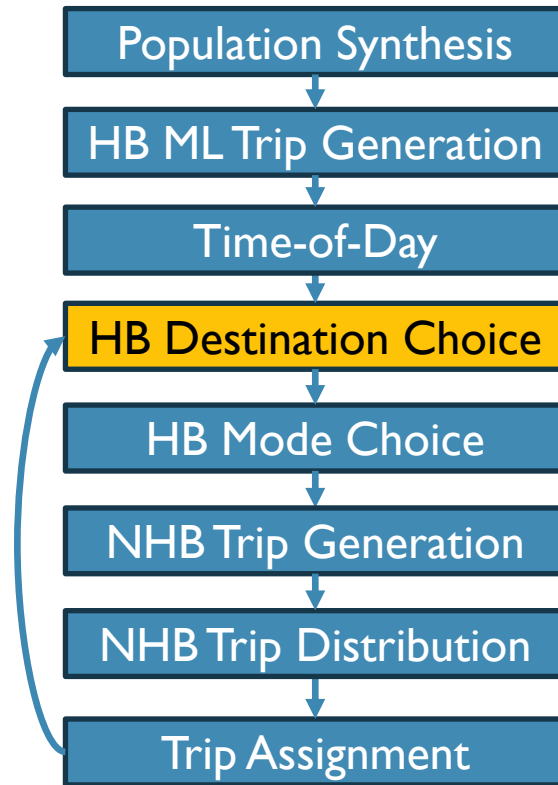
DISTRIBUTION BY TIME-OF-DAY

- Moving Time-of-Day up means trip distribution for each time of day is based on travel times at that time of day



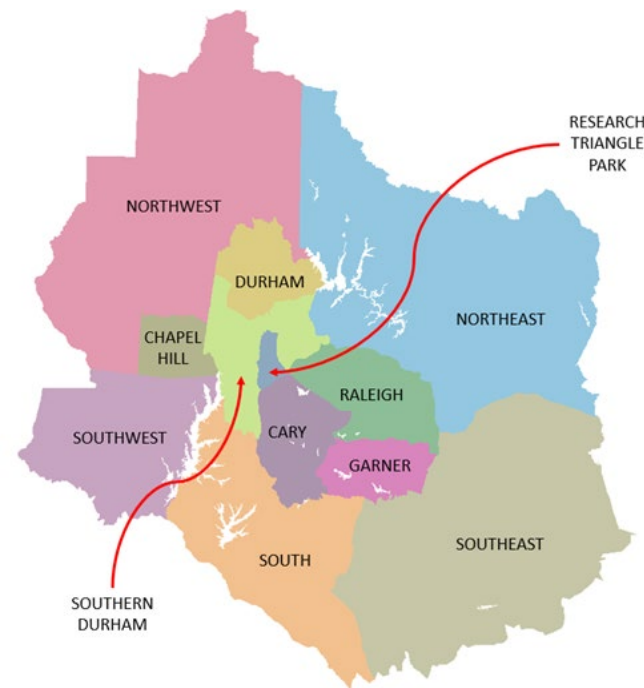
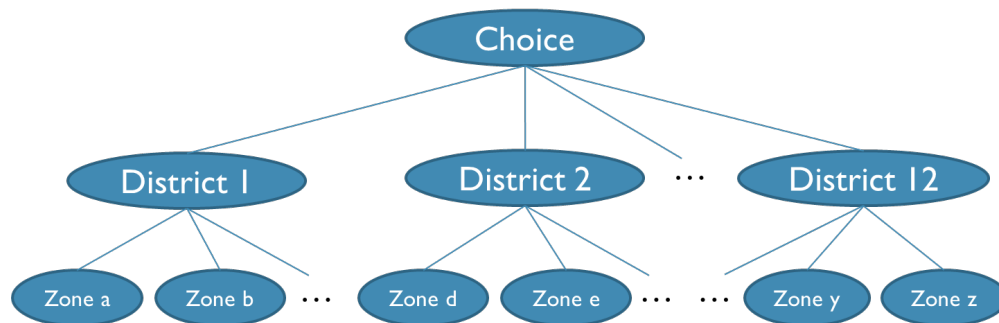
DESTINATION CHOICE

- Trip distribution is the largest source of error in travel models
- Destination choice models improve over gravity by taking more factors into account in determining where people go
 - Accessibilities
 - Bias constants
 - Psychological barriers



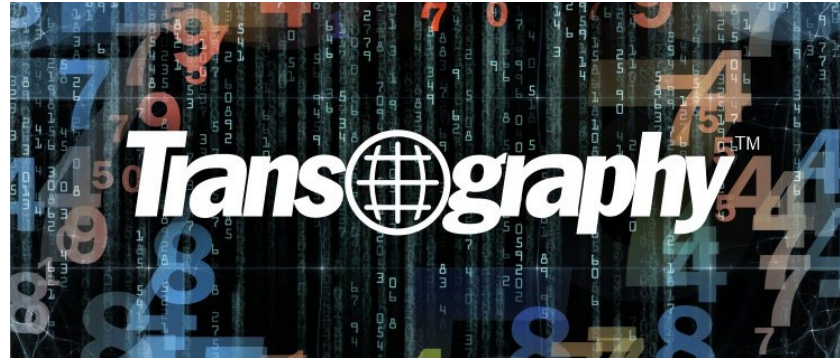
NESTED DESTINATION CHOICE

- **First**, travelers choose a destination district
- **Second**, travelers choose the exact zone
- Allows much better representation of travel in multinucleated regions

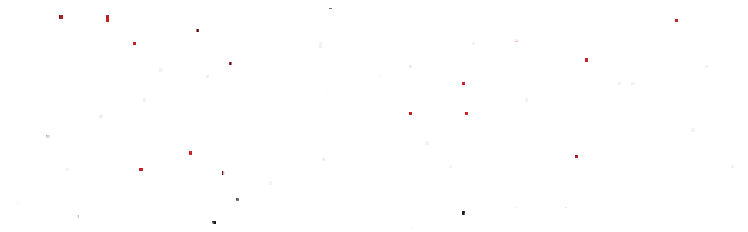


BIG DATA

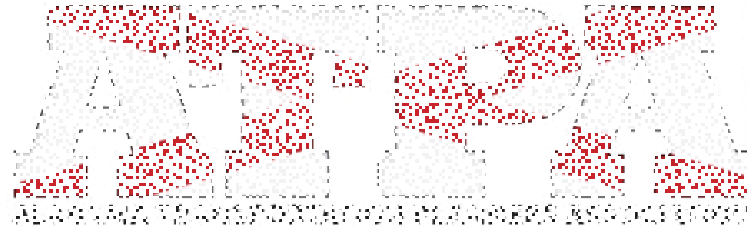
- Destination choice models can now be calibrated with big data
- Traditional household surveys typically have observations in less than 1% of the cells in an origin-destination (OD) matrix
- Big data often has observations of 20% of the cells in an OD matrix



CAN YOU RECOGNIZE THE PATTERN FROM ~1%?



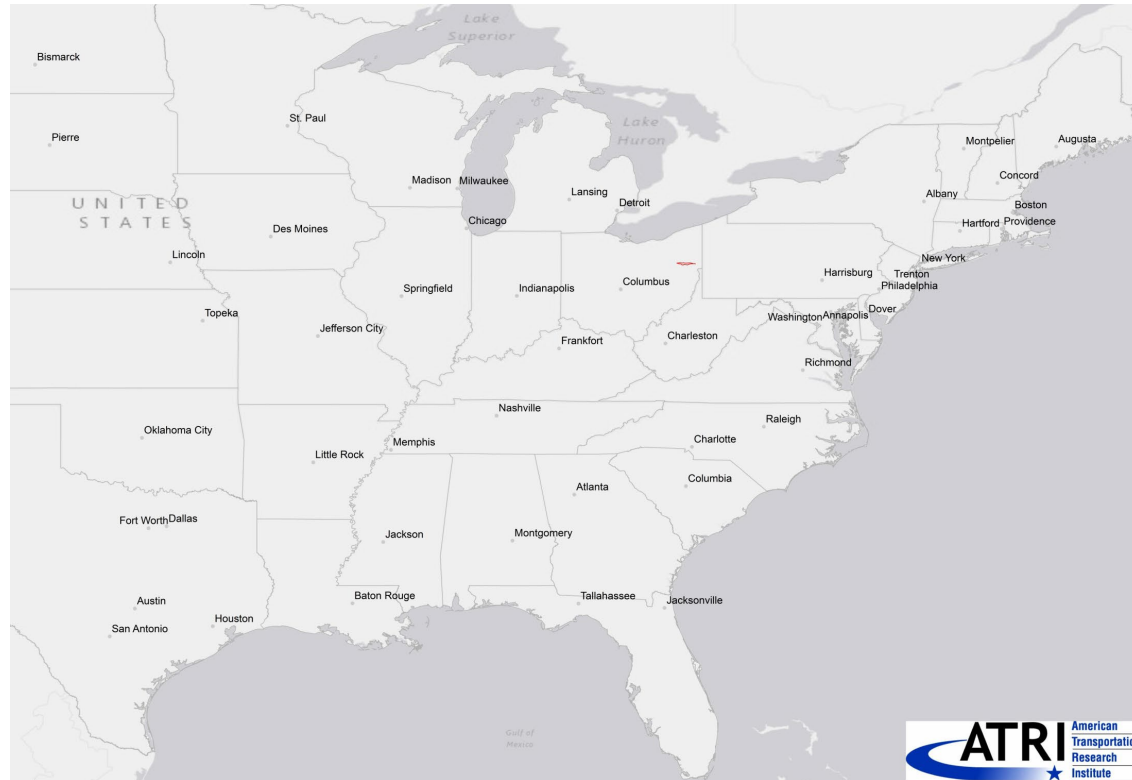
HOW ABOUT BASED ON ~20%?



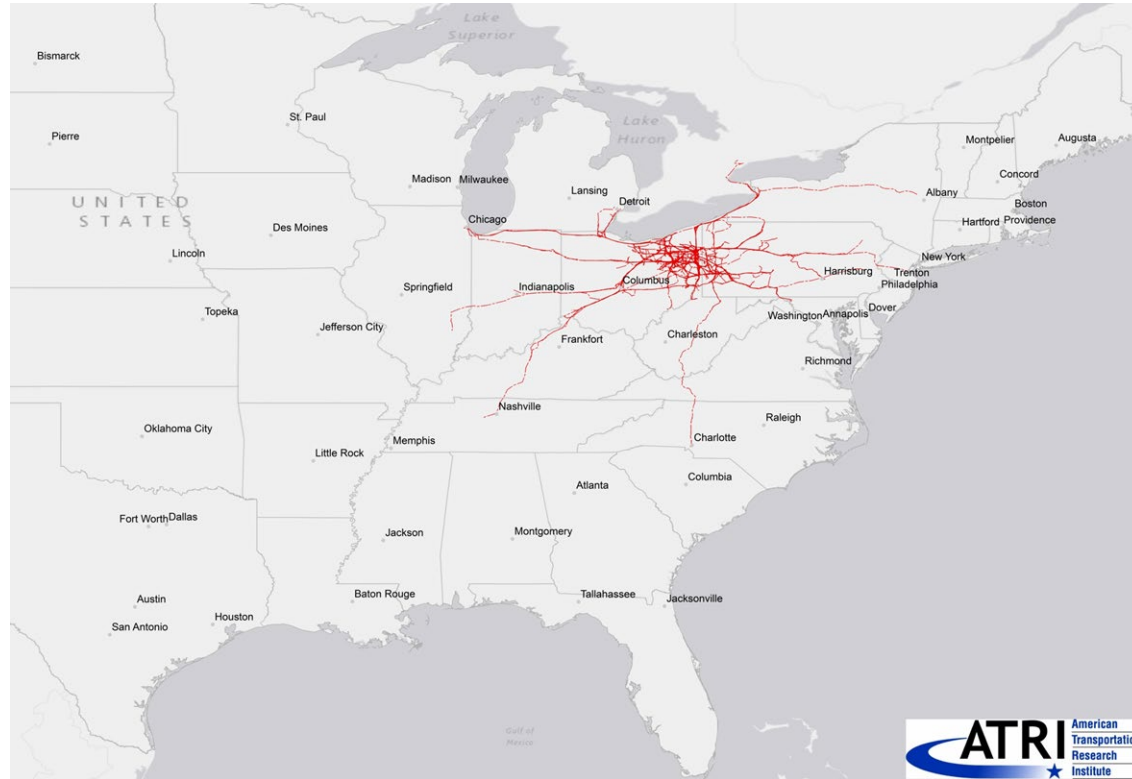
BIG DATA ALLOWS US TO SEE THE BIG PICTURE



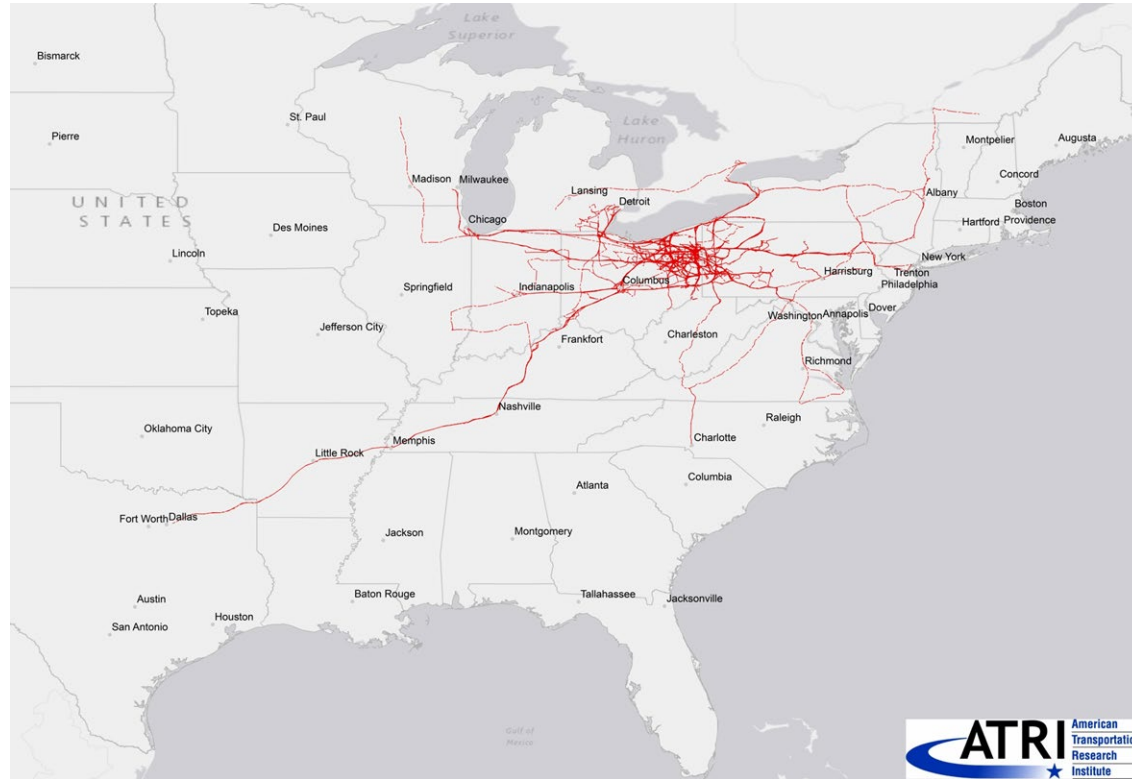
REAL EXAMPLE: US 30 STUDY IN OHIO



TRUCKS USING US 30 – 1 DAY



TRUCKS USING US 30 – AFTER 2 DAYS

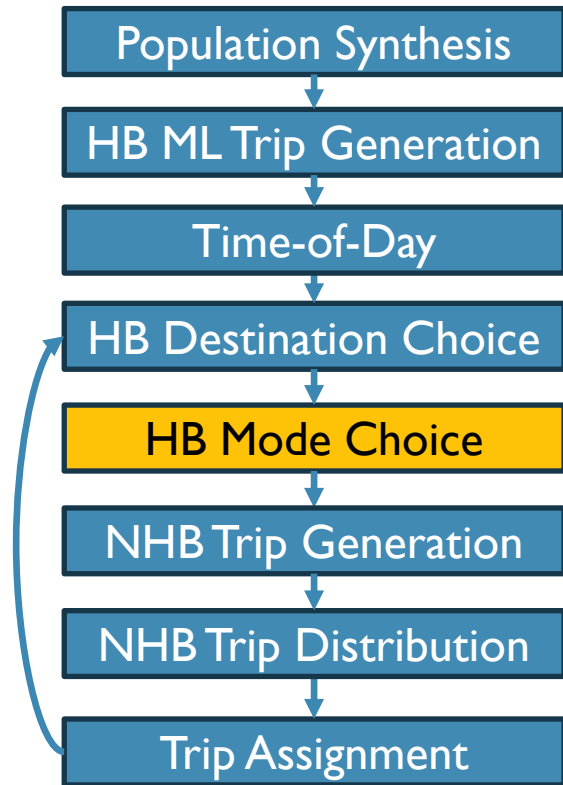
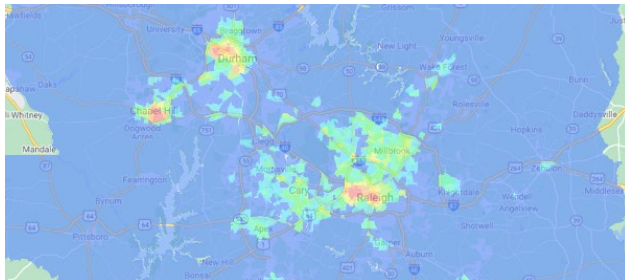


TRUCKS USING US 30 – AFTER 5 DAYS



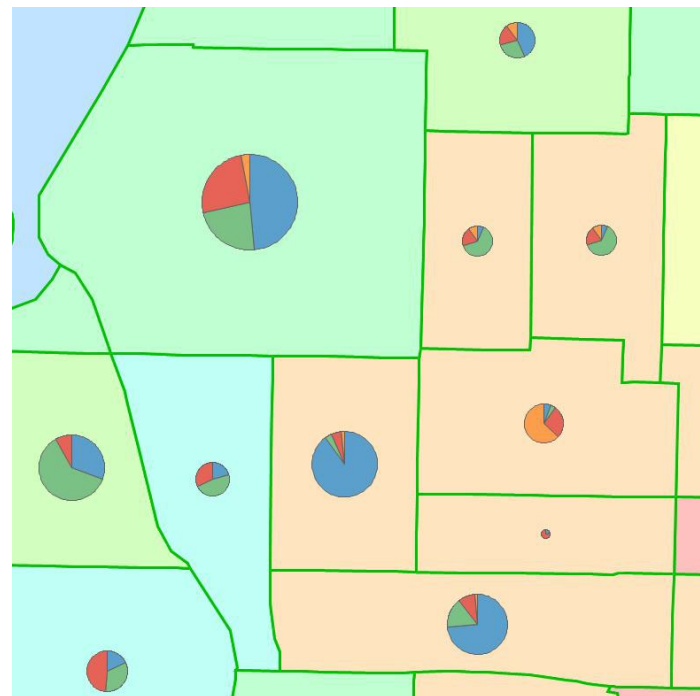
MODE CHOICE IMPROVEMENTS

- Model form still nested logit
- Addition of modes for walk/bike and Uber/Lyft
- Model sensitivity to neighborhood walkability
- Use of all-streets networks, more TAZs



SIMPLE MODE CHOICE

- Simplified, pre-distribution mode choice, especially for smaller MPOs where there is no need for route level transit forecasts
- Produces
 - Transit system ridership
 - Walk/bike trips by residence TAZ

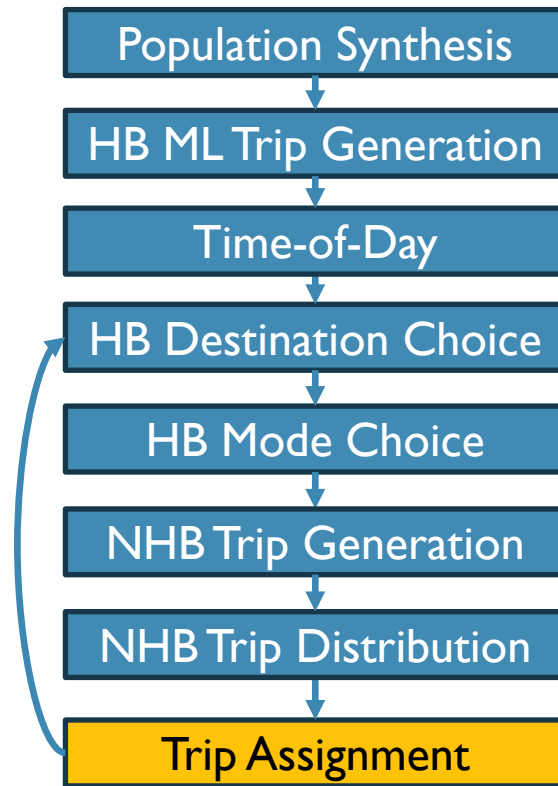


ASSIGNMENT IMPROVEMENTS

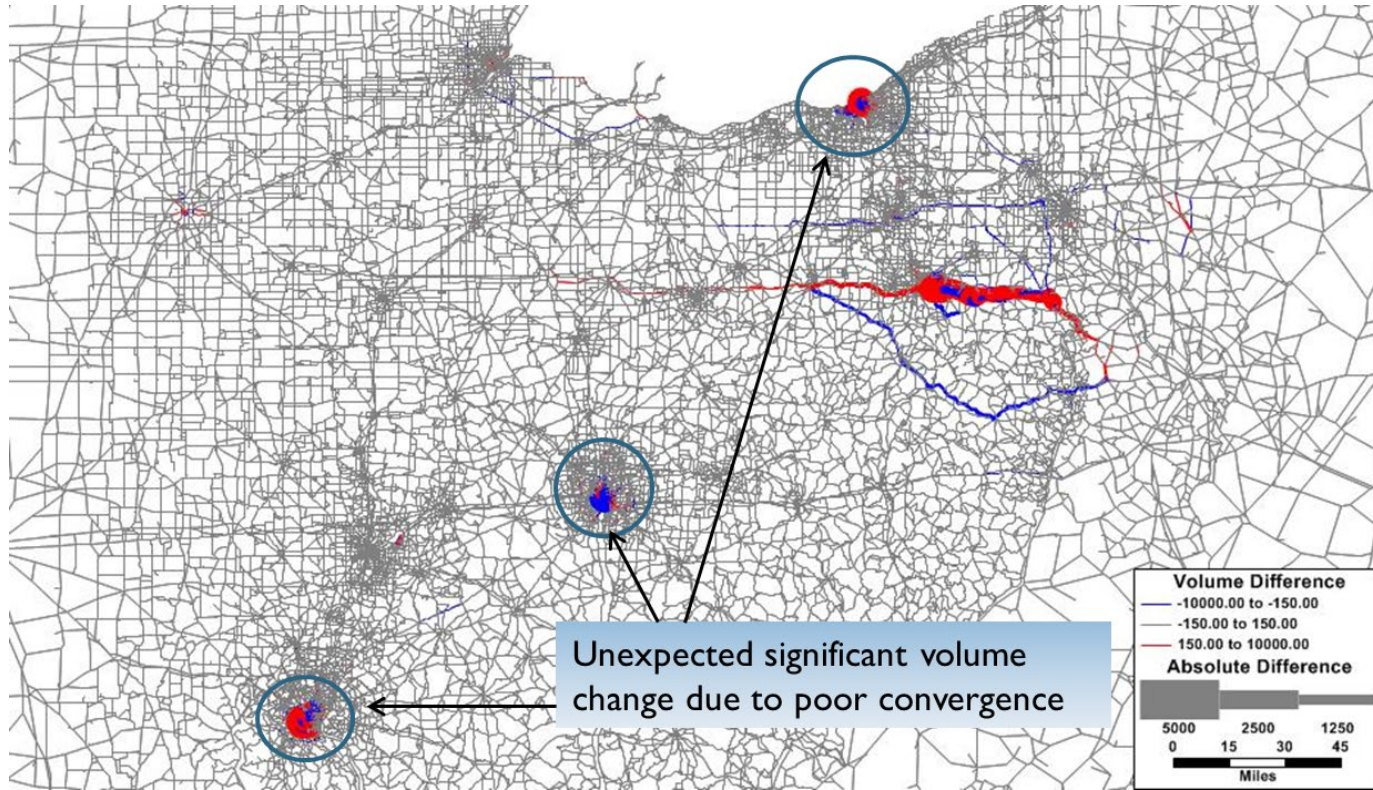
- Greater awareness of the need for assignment convergence



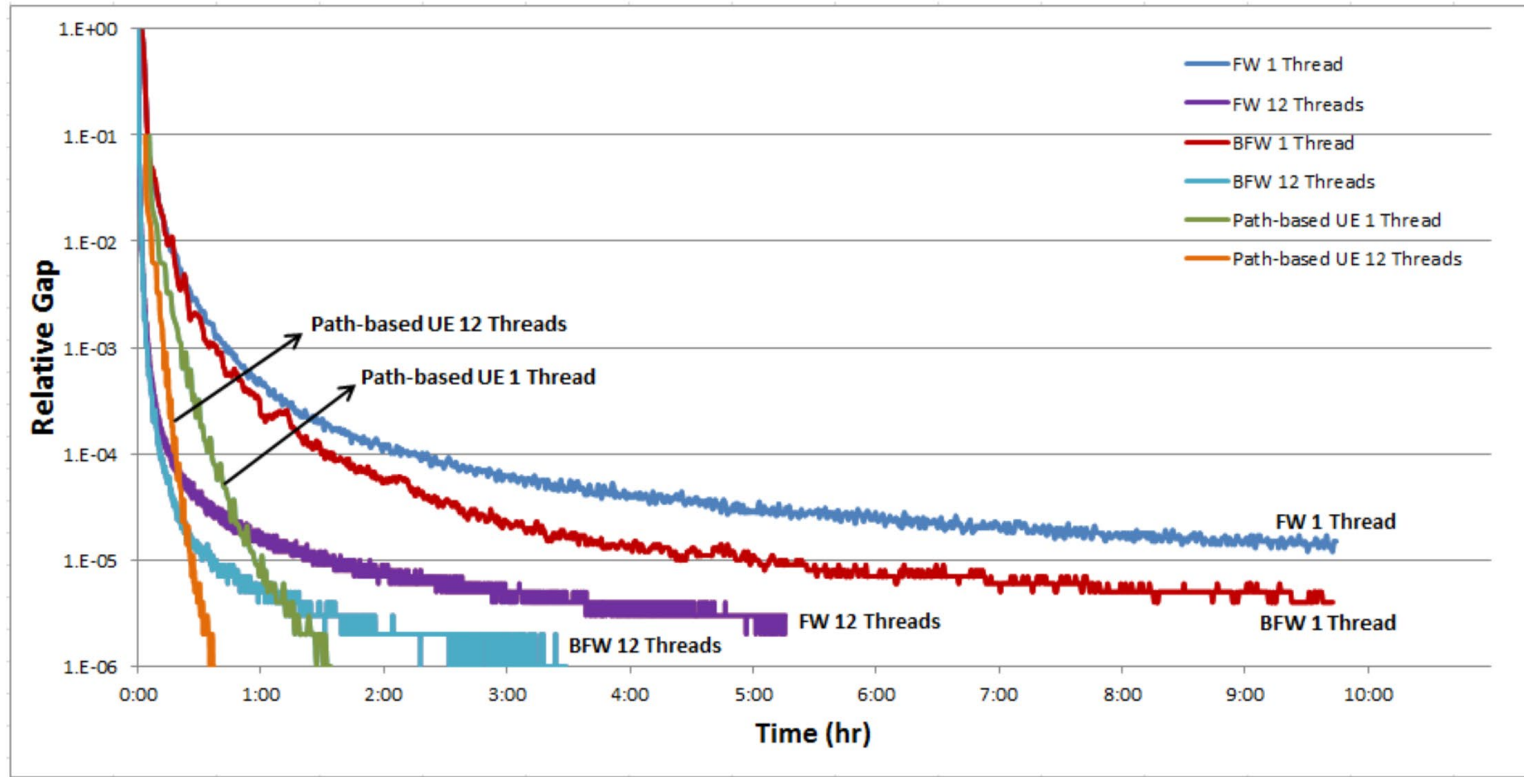
- Faster converging assignment algorithms
 - Bi-/Tri-Conjugate Frank-Wolfe
 - Path-based Assignment



POOR CONVERGENCE PROBLEMS



FAST CONVERGING UE ALGORITHMS



DYNAMIC TRAFFIC ASSIGNMENT (DTA)

- As a post-process not a replacement for static UE
- Evaluate operational improvements



SUMMARY

- Some MPOs are moving to ABMs but most are not
- Some are continuing to use tradition 3 or 4-step models
- Many are migrating towards “hybrid” models
 - Linking NHB and HB trips
 - Improvements to all the modeling steps
- Many are using big data to improve their models
- Some are adding DTA models

CONTACTS

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