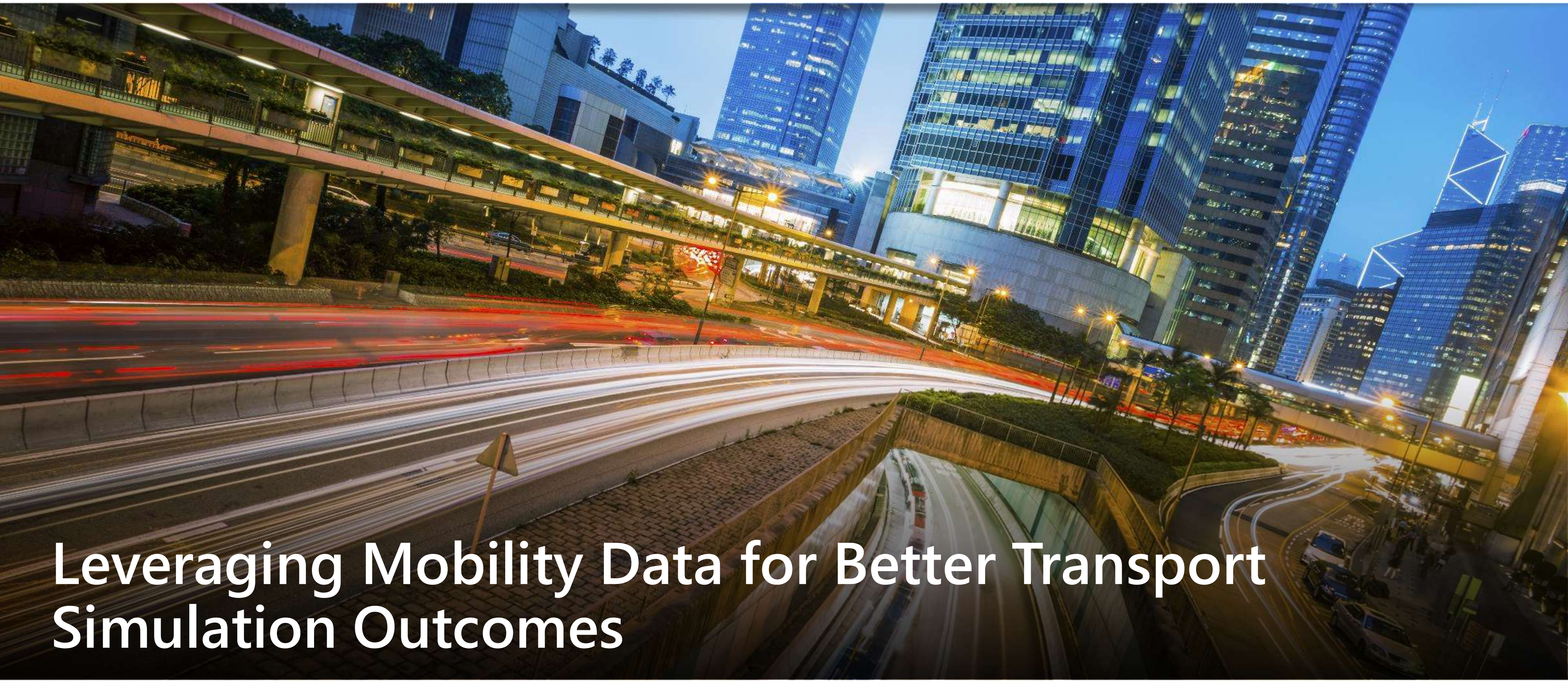


Leveraging Mobility Data for Better Transport Simulation Outcomes

Gaurav Vyas, Product Manager

Bentley
Advancing Infrastructure

Planning decision-support increasingly requires activity-based models

- *55% "use an ABM or have plans to use one"*

What are the barriers to adoption?

- *69% felt "ABMs are difficult to calibrate"*

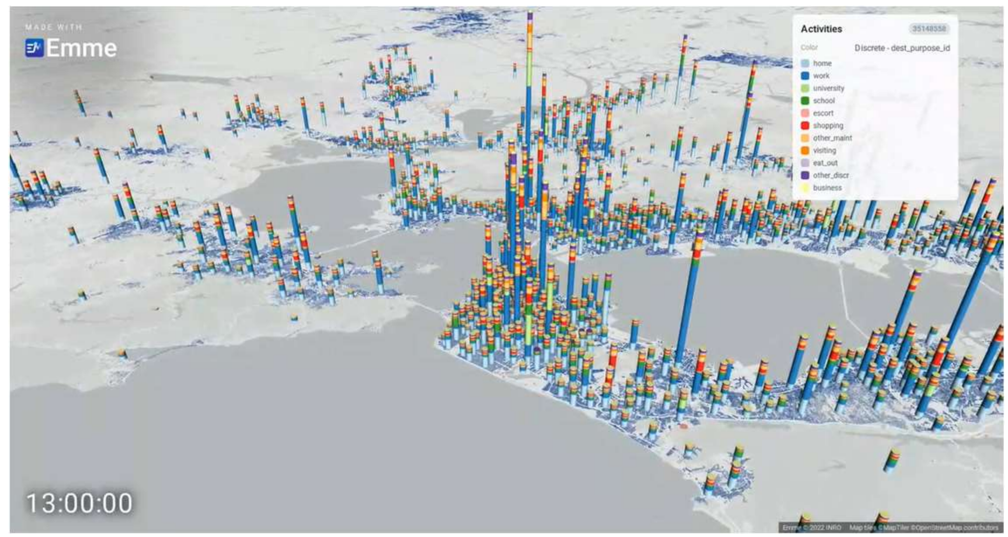
\- Survey responses from ~1000 global participants attending Bentley webinar "Advancing travel demand models with AGENT" webinar, February 2022.

Travel behavior changes

- Pandemic
- Work-from-home / telecommuting
- E-shopping
- Car ownership

Model changes

- 4-step
- Hybrid
- Tour-based
- **Activity-based (ABM)**



Data changes

- HHTS data updates come too late
- Passively collected data available
- Transit ridership/fare card data
- Traffic counts

New technology

- Connected/Autonomous Vehicles
- Electric Vehicles
- MaaS

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Common Data Sources in Model Development

- Household travel survey (HHTS) data
  - Main source of disaggregate estimation
  - But large-scale HHTS is expensive and difficult to recruit
  - Even 3,000 – 5,000 households are becoming increasingly problematic

- Other data sources include
  - Traffic counts
  - Transit ridership (APC, e-ticketing / smartcard, on-board survey)
  - Primarily only used for model validation and manual calibration

“Big data” as a replacement?

Pros

- Becoming increasingly available from vendors
- “Big data” trip tables can be used to support aggregate 4-step models in practice

Cons

- Not behavioral (no details about trip purposes or individual attributes)
- No person ID to identify individual activity patterns
- Gap between aggregate data structure and disaggregate ABM structure

Reality of transportation industry

Minimize the need of large-scale HTS and take advantage of new types of data

Central question
How can big data or traffic counts be effectively used for the simultaneous calibration of travel demand model systems in addition to other data sources?

Known Limitations of conventional estimation

Sub-models are estimated one at a time based on the “perfect” observed prior choices

However, they are applied conditional upon each other

LOS i.e., accessibilities are assumed fixed and external

However, in model application LOS is equilibrated and it deviates from the LOS used in model estimation

Aggregate data such as traffic or transit counts or “big data” cannot be utilized

However, matching these types of data is important in practice

1 of 2 required features - Data Fusion

Behavioral	HTS	– Total number of tours/trips/activities – Aggregate car ownership, mode share, time-of-day distributions – Tour/trip length distribution by segments
Partially behavioral	Transit OB survey	– Total number of transit tours/trips – Tour/trip length distribution for transit trips
Non-behavioral	Big data	– Aggregate OD tables by time-of-day/mode/purpose
	Transit smart card data	– By boarding and alighting station
	Other	– Traffic count – Transit ridership data – Taxi data

Ideally match all these targets
instead of one-by-one

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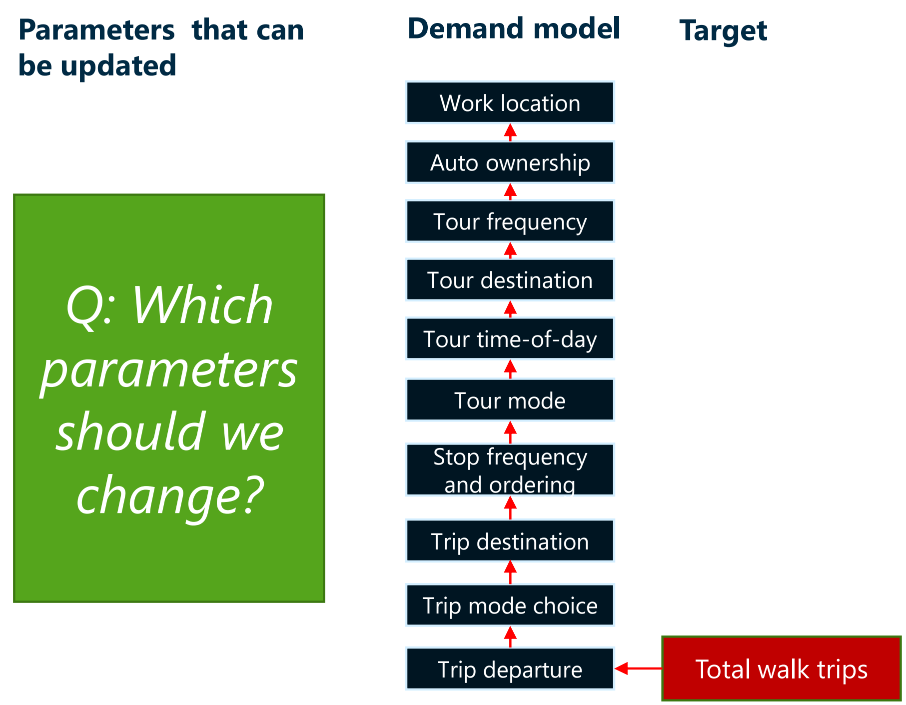
2 of 2 required features – Calibration Instrumentation

- Calibration expressed as interlinkages between sub-models
  - Resulting in many-to-many relationship between targets and sub-models

- Contrary to conventional calibration schema
  - Sub-models are calibrated sequentially one by one with its own targets



2 of 2 required features – Calibration Instrumentation

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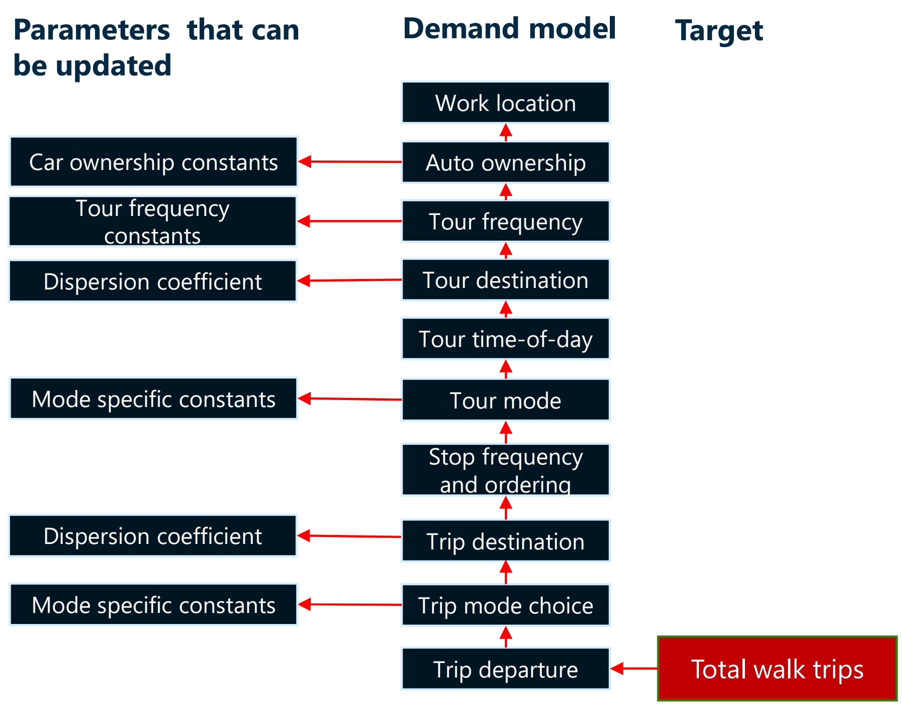


Principally different from conventional methods in practice

Trip adjustment and pivoting

Directly adds or removes trips

Pros:
- Achieves good validation

Cons:
- Only applicable for short term forecast
- Tend to over-specify (K-factors)
- Only applicable to 4-step models

Suggested approach

Adjusts existing model parameters

Pros:
- Can utilize trip adjustment as an intermediate step
- Equally applicable to base and forecast year
- Avoids overspecification
- Fully compatible with both ABM and 4-step models

How is Big-data used for manual calibration in practice so far?

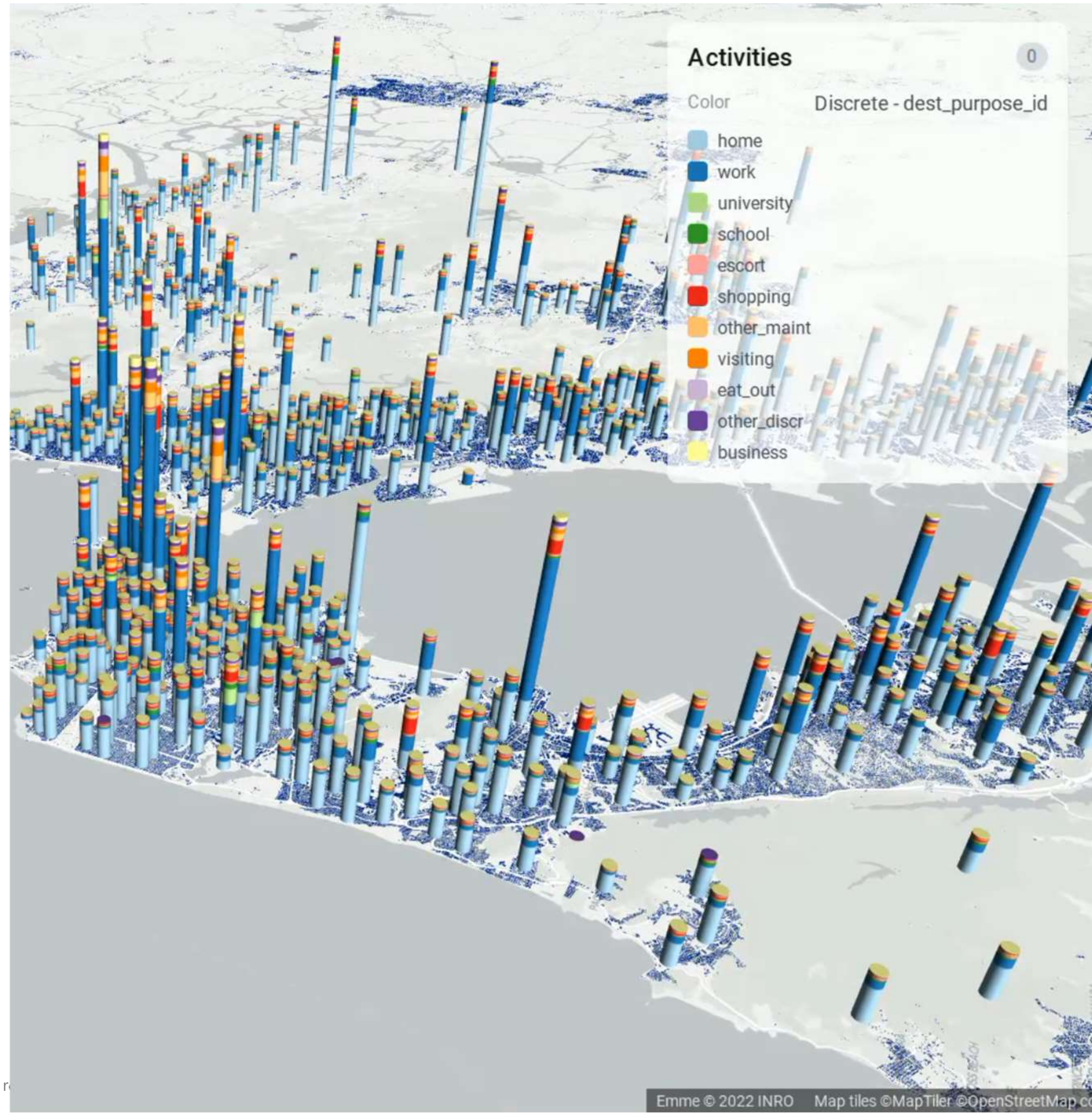
- Pre-processing of O-D level data to create sub-model specific targets:
  - For example: O-D total trips is typically processed to calculate target for tour/trip frequency models
- No systematic approach to identify outliers

- Our approach → Use of O-D data directly for model calibration

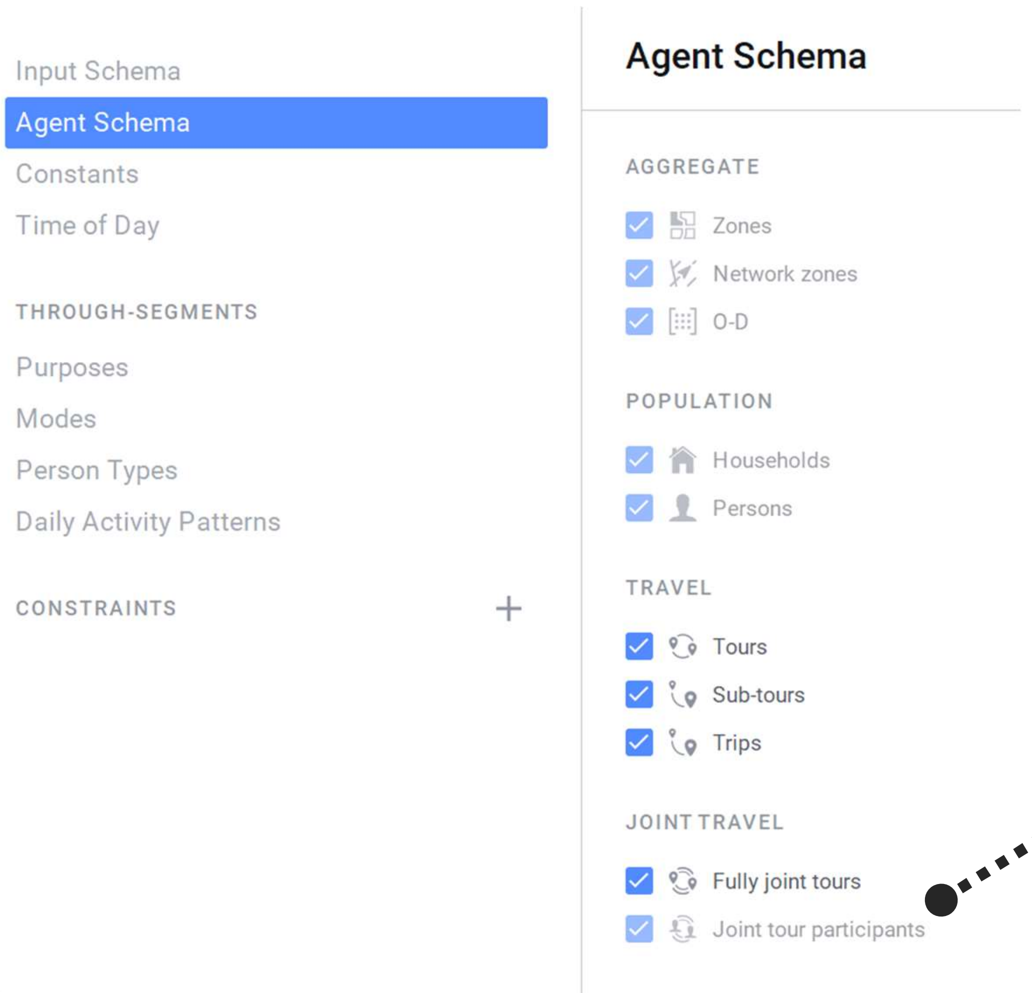
Automated Calibration Example 1

- MTC 1.5-Style ABM PoC
- Calibrated to “big data” O-D Trip Tables
- Project duration - 2 Weeks

- Model data
  – https://github.com/ActivitySim/activitysim_resources/tree/master/mtc_data_full
- O-D Trip Tables data
  – Courtesy TERALYTICS



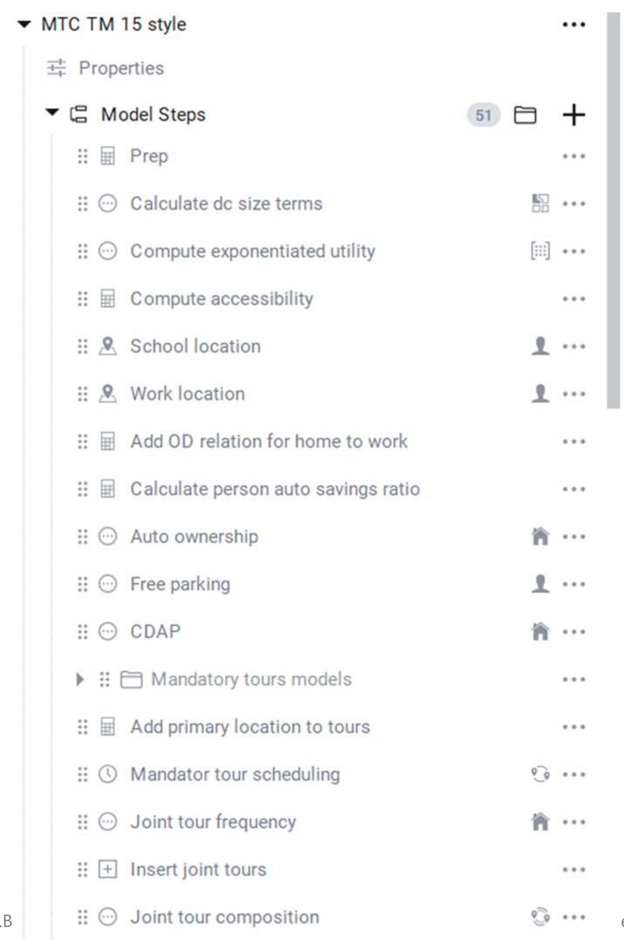
How is the model configured in Agent?



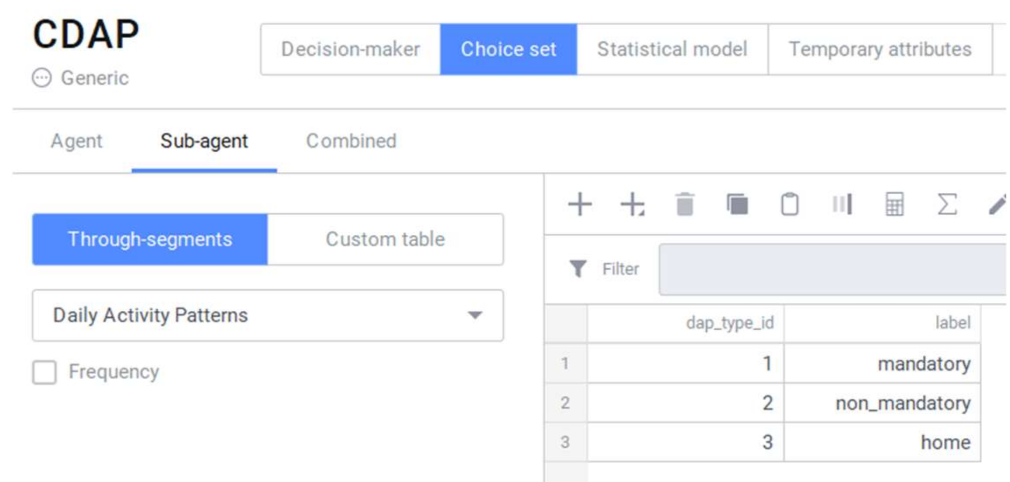
Joint travel in Agent schema

How is the model configured in Agent?

Sequence of model steps



Generalized framework for modelling coordinated choices



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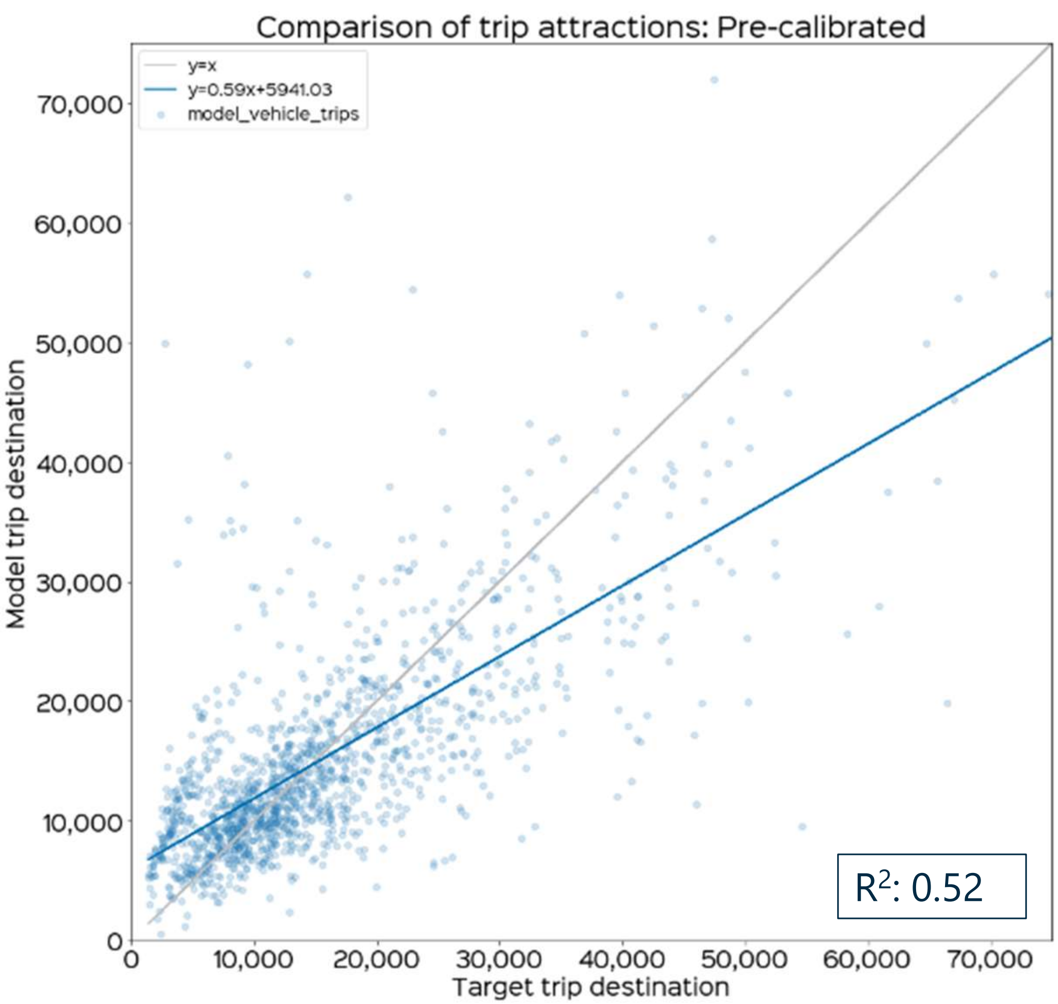
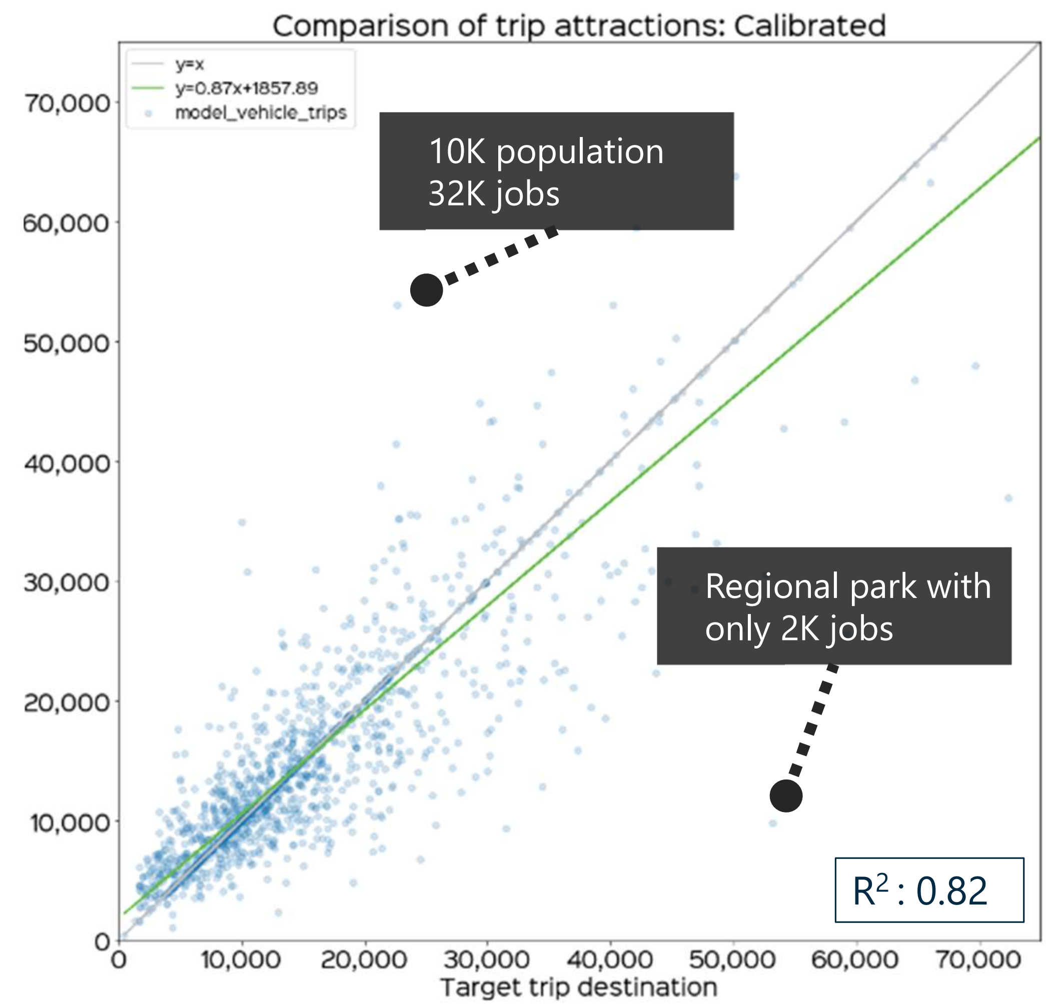
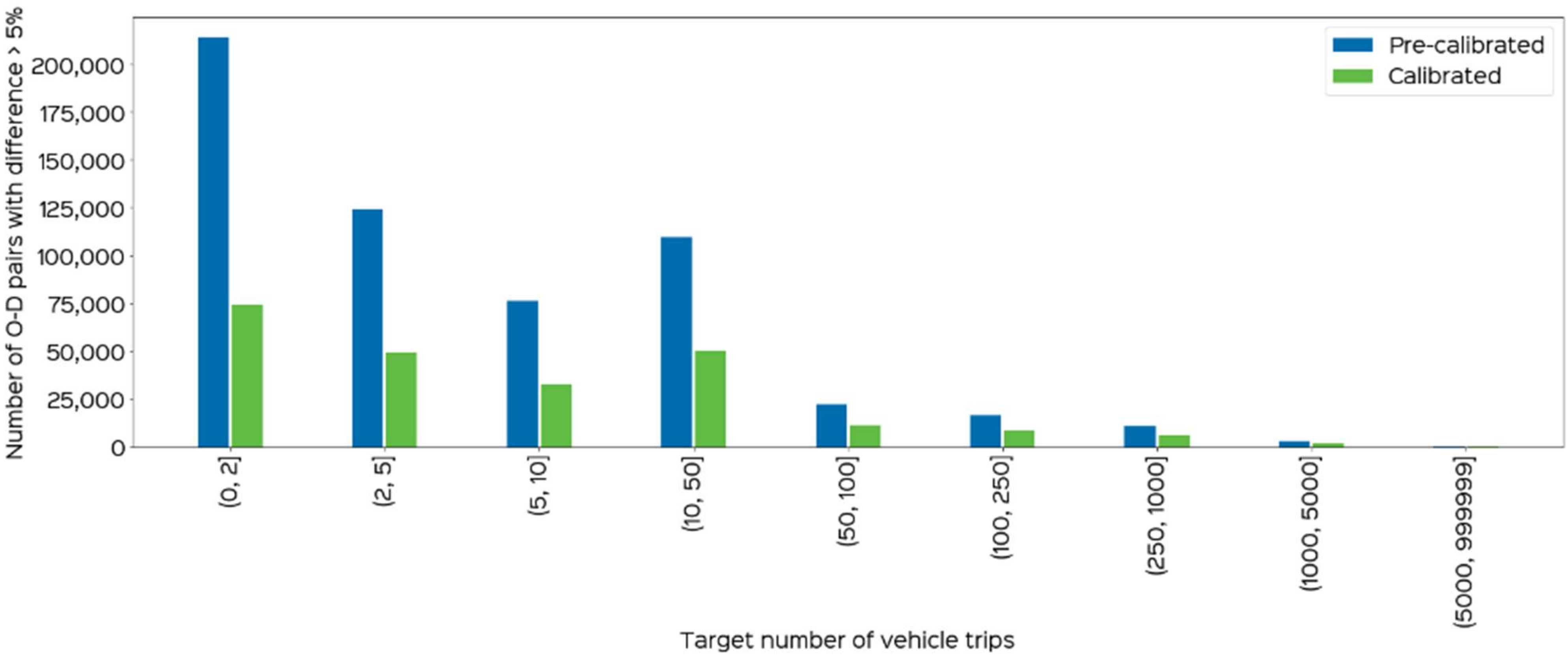
MTC 1.5 calibration: Comparison at zonal level

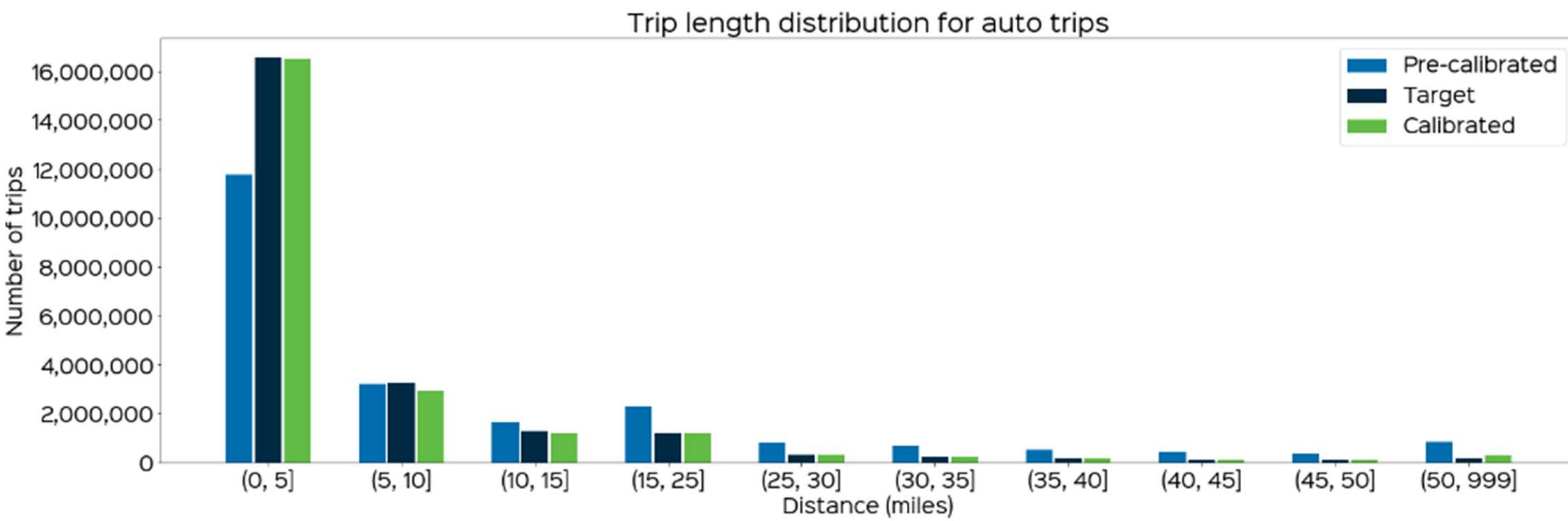




MTC 1.5 calibration: Comparison at O-D level



MTC 1.5 calibration: Impact on trip length distribution



How are the calibration targets configured in Agent?

MTC 15 style calibrated

Regional targets from HTS

Regional | Zo

Display

Filter

	Name	Description	Group label (optional)	Table	Filter expression	Value expression	Aggregation function	Target min	Target max
1	ft_eat_out	Number of eating out tours f...		Persons	ptype == 1	num_eat_out_tours	Mean	0.047884	0.047884
2	pt_eat_out	Number of eating out tours f...		Persons	ptype == 2	num_eat_out_tours	Mean	0.081915	0.081915
3	us_eat_out	Number of eating out tours f...		Persons	ptype == 3	num_eat_out_tours	Mean	0.081663	0.081663
4	nw_eat_out	Number of eating out tours f...		Persons	ptype == 4	num_eat_out_tours	Mean	0.077062	0.077062
5	rt_eat_out	Number of eating out tours f...		Persons	ptype == 5	num_eat_out_tours	Mean	0.081213	0.081213

Teralytics data added as O-D target

MTC TM 15 style calibrated

Regional | Zonal | O-D

Displaying 1 of 1 row

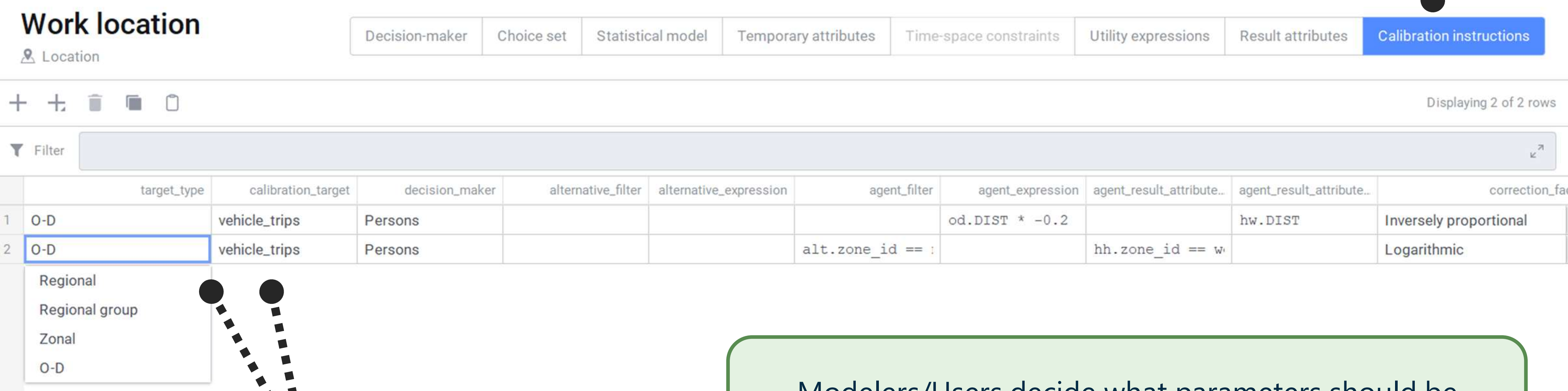
Filter

	Name	Description	Table	Filter expression	Value expression	Origin ID expression	Destination ID expression	Target expression	Importance
1	vehicle_trips	Daily vehicle trips from Teralytics	Trips	mode.is_drive_m	tour.person.hh.	orig_zone_id	dest_zone_id	TL_daily_trips	1.000000

Importance of the target

What model parameters are affected by Teralytics data?

Targets can be connected to choice model in *Calibration instructions*



Select target type and calibration target

Modelers/Users decide what parameters should be affected by a calibration target

What model parameters are affected by the Teralytics data?

- Dispersion coefficient
- Intra-zonal preference

- Auto ownership constants

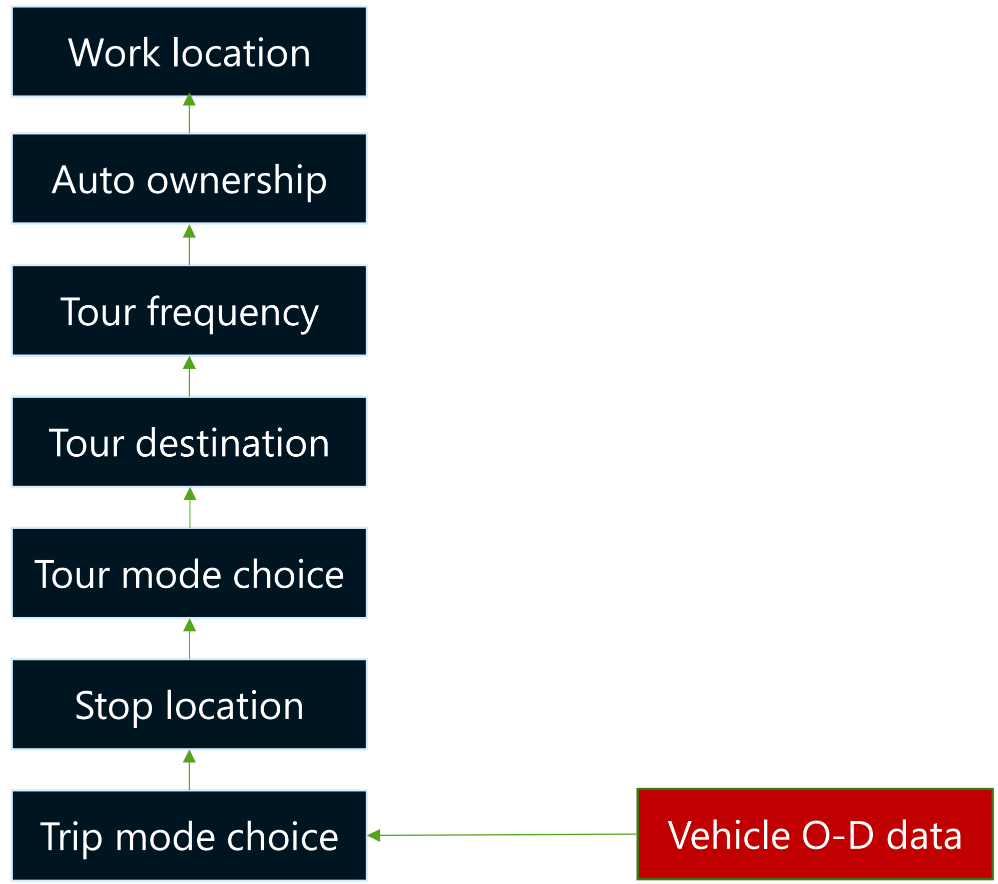
- Tour frequency constants

- Dispersion coefficient
- Intra-zonal preference

- Mode choice constants
- Mode choice constants by area-type

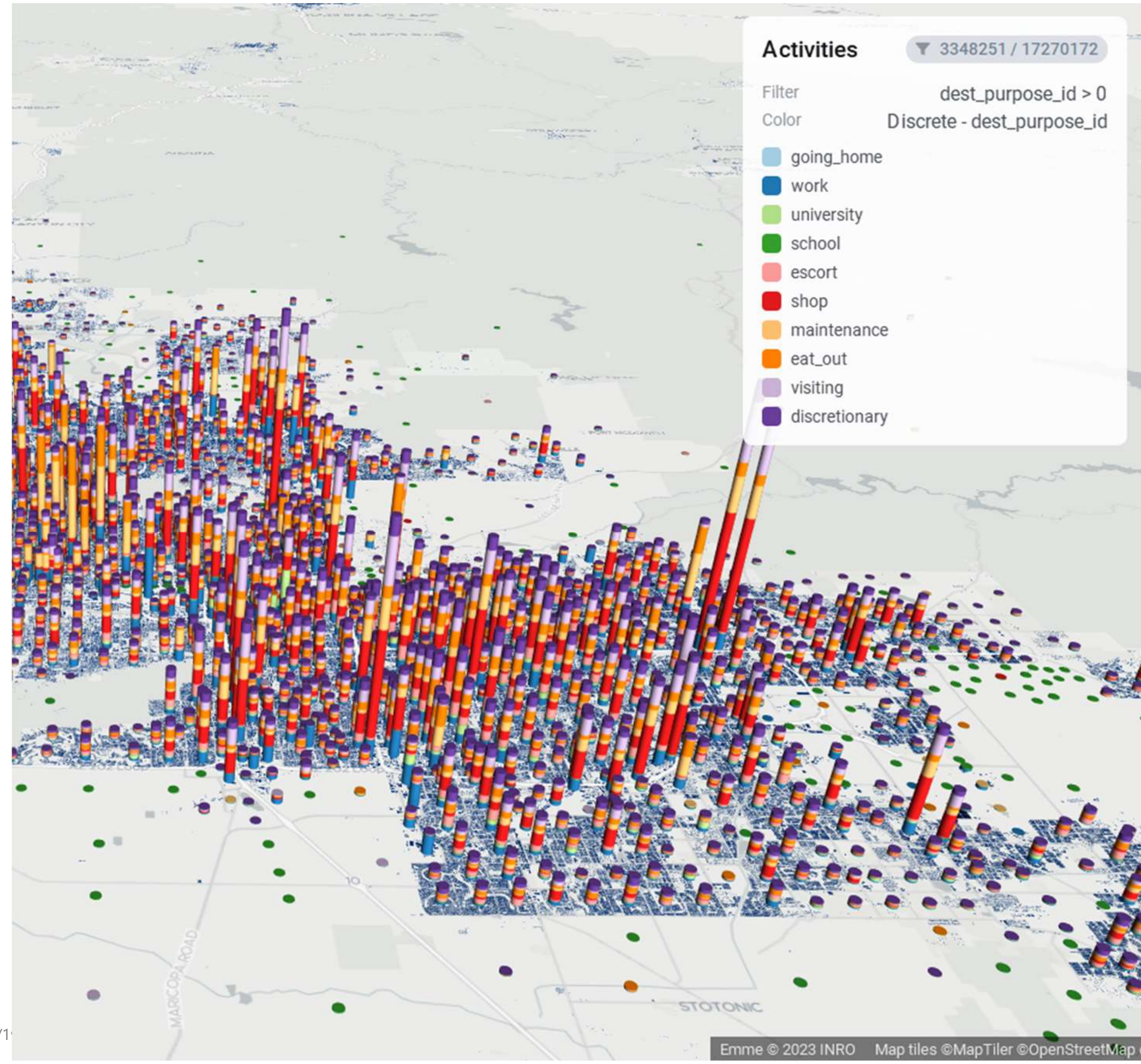
- Dispersion coefficient
- Intra-zonal preference

- Mode choice constants
- Mode choice constants by area-type



Automated Calibration Example 2

- MAG Weekend / Special Event Model
  - Adjustment of weekday model to calibrate to weekend travel behavior
  - No HHTS available for weekend
- "Big data" source
  - AirSage data (OD tables)



MARICOPA ASSOCIATION of GOVERNMENTS

MAG weekend model: Calibration targets

Weekend ABM with calibration targets

Regional

Dis

Filter

	Name	Description	Group label (optional)	Table	Filter expression	Value expression	Aggregation function	Target min	Target max	Correction factor
1	act_work	Number activities for Work		Persons		num_work_activities * hh.	Sum	367228.000000	367228.000000	Logarithmic
2	act_univ	Number activities for University		Persons		num_university_activities	Sum	3699.000000	3699.000000	Logarithmic
3	act_sch	Number activities for School		Persons		num_school_activities * h	Sum	18171.000000	18171.000000	Logarithmic
4	act_esc	Number activities for Total es...		Persons		num_esc_activities * hh.w	Sum	289676.000000	289676.000000	Logarithmic
5	act_ind_shop	Number activities for Shoppin...		Persons		num_ind_shop_activities *	Sum	1244604.000000	1244604.000000	Logarithmic
6	act_ind_maint	Number activities for Mainten...		Persons		num_ind_maint_activities	Sum	410356.000000	410356.000000	Logarithmic
7	act_ind_eat_out	Number activities for Eating o...		Persons		num_ind_eat_out_activitie	Sum	1058921.000000	1058921.000000	Logarithmic
8	act_ind_visit	Number activities for Visiting ...		Persons		num_ind_visit_activities	Sum	450709.000000	450709.000000	Logarithmic
9	act_ind_disc	Number activities for Discreti...		Persons		num_ind_disc_activities *	Sum	1968152.000000	1968152.000000	Logarithmic
10	act_joint_shop	Number activities for Shoppin...		Persons		num_joint_shop_activities	Sum	1755184.000000	1755184.000000	Logarithmic
11	act_joint_maint	Number activities for Mainten...		Persons		num_joint_maint_activitie	Sum	288989.000000	288989.000000	Logarithmic
12	act_joint_eat_out	Number activities for Eating o...		Persons		num_joint_eat_out_activit	Sum	1225708.000000	1225708.000000	Logarithmic
13	act_joint_visit	Number activities for Visiting ...		Persons		num_joint_visit_activitie	Sum	280820.000000	280820.000000	Logarithmic
14	act_joint_disc	Number activities for Discreti...		Persons		num_joint_disc_activities	Sum	838661.000000	838661.000000	Logarithmic
15	act_at_work	Number of at work trips		Persons		[illegible]	[illegible]	[illegible]	86171.000000	Logarithmic

Number of activities by purpose for weekend based on literation review

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MAG weekend model: Calibration targets

Weekend ABM with calibration targets

Regional

Di

Filter

Name	Description	Group label (optional)	Table	Filter expression	Value expression	Aggregation function	Target min	Target max	Correctio
hw_am	trip departure for HW trips in AM ...	trip_tod	Trips	`is_hw`	`departure_time in [1,2,3,`	Mean	0.110935	0.110935	Logarithmic
hw_6_7	trip departure for HW trips in 6-7 p...	trip_tod	Trips	`is_hw`	`departure_time in [7,8]`	Mean	0.096893	0.096893	Logarithmic
hw_7_8	trip departure for HW trips in 7-8 p...	trip_tod	Trips	`is_hw`	`departure_time in [9,10]`	Mean	0.091502	0.091502	Logarithmic

Trip departure profile by purpose from AirSage data

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What model parameters are affected by calibration targets?

Parameters	Model component	Calibration target
– Work from home constant	Work from home	
– DAP type preference	CDAP	
– Tour frequency constants	Tour frequency	
– Stop frequency constants	Stop frequency	Activity rates
– Time-of-day constants	Tour time-of-day	
– Time-of-day constants	Trip departure	Trip departure profile

Trip and activity level targets connected to tour and person level choices via *Calibration instructions*

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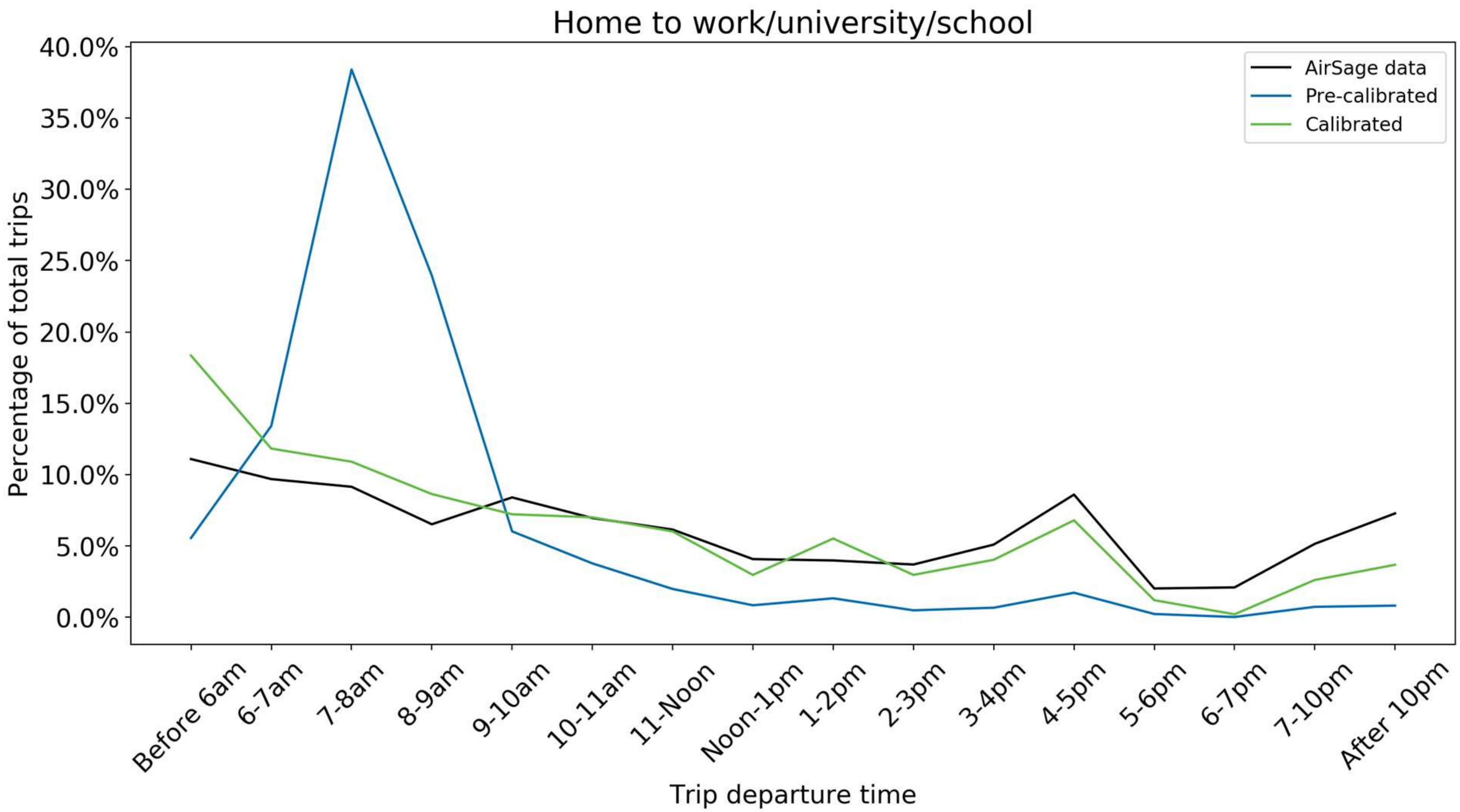
MAG Weekend model: Comparison of trip departure distribution



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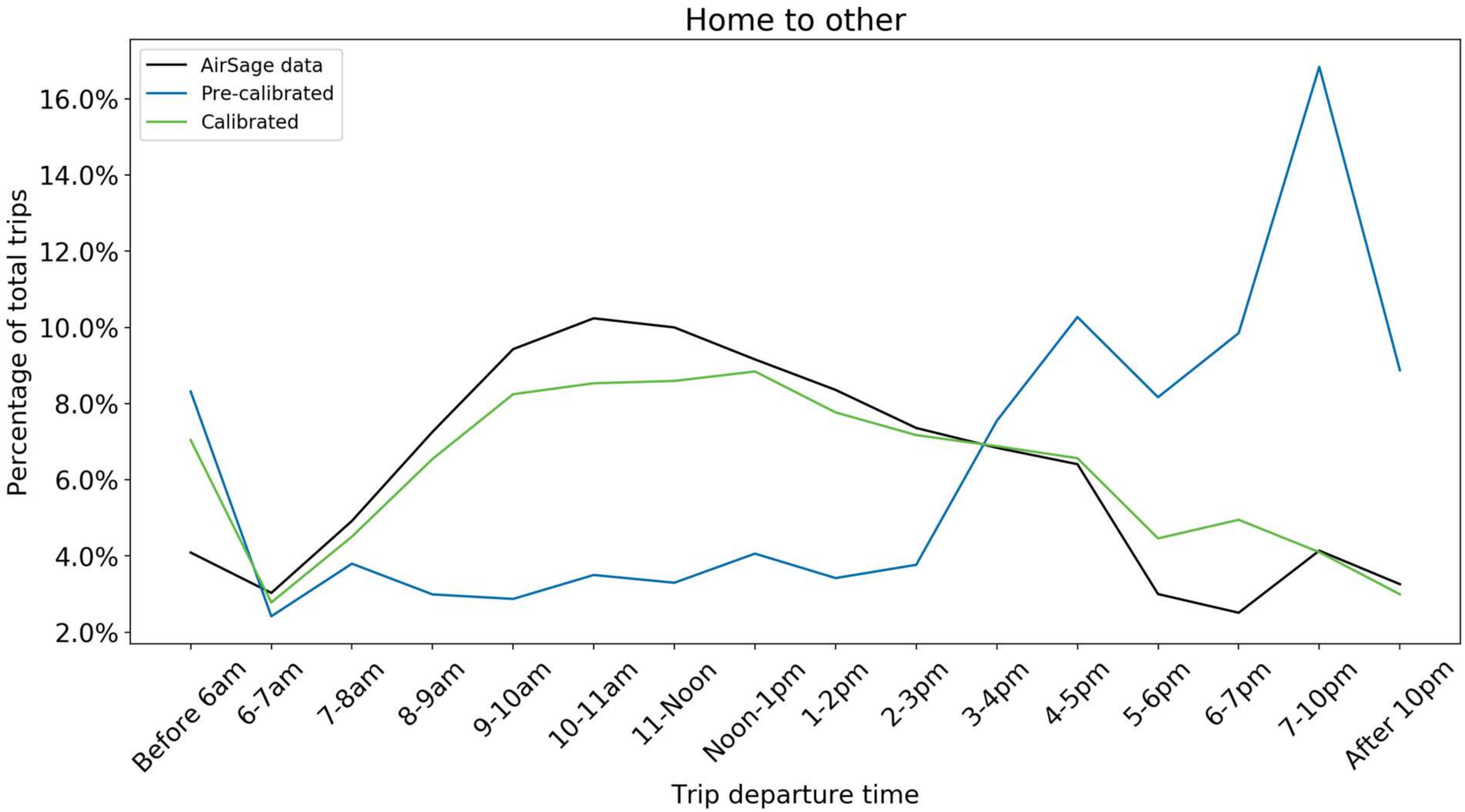
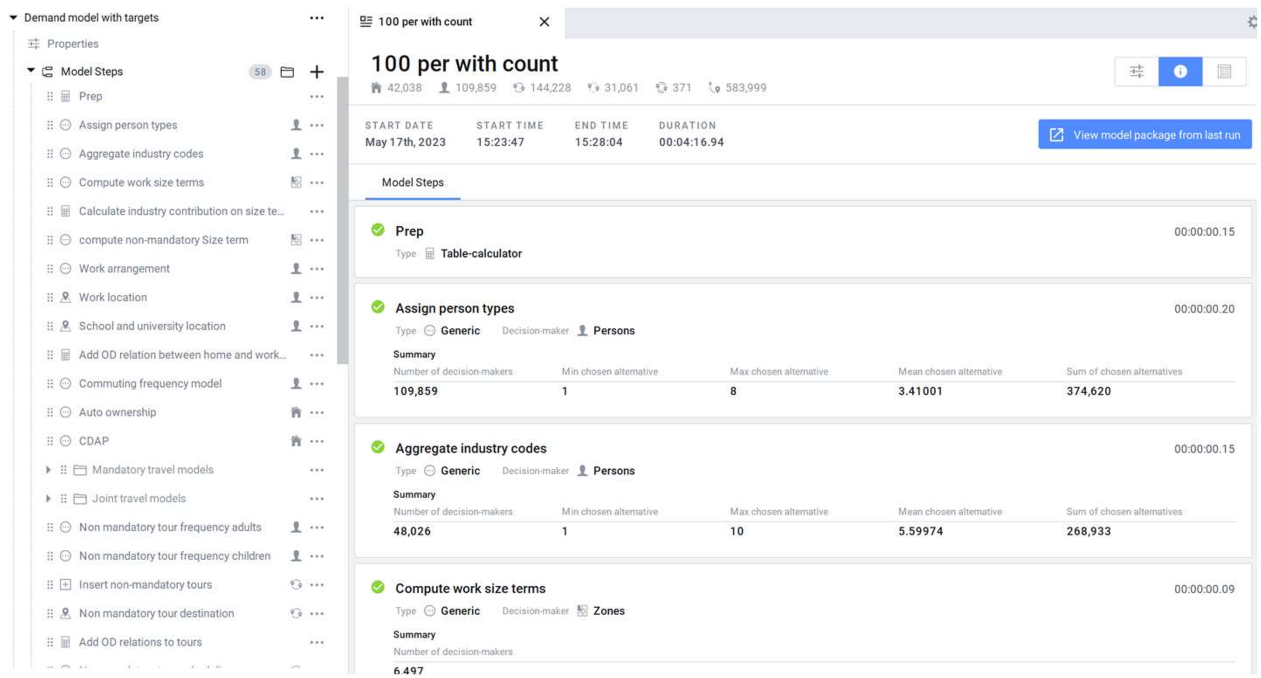
MAG Weekend model: Comparison of trip departure distribution



Automated Calibration
Lima ABM 3

- Lima ABM
  - Calibration to big data and traffic counts
- "Big data" source
  - StreetLight (OD tables)



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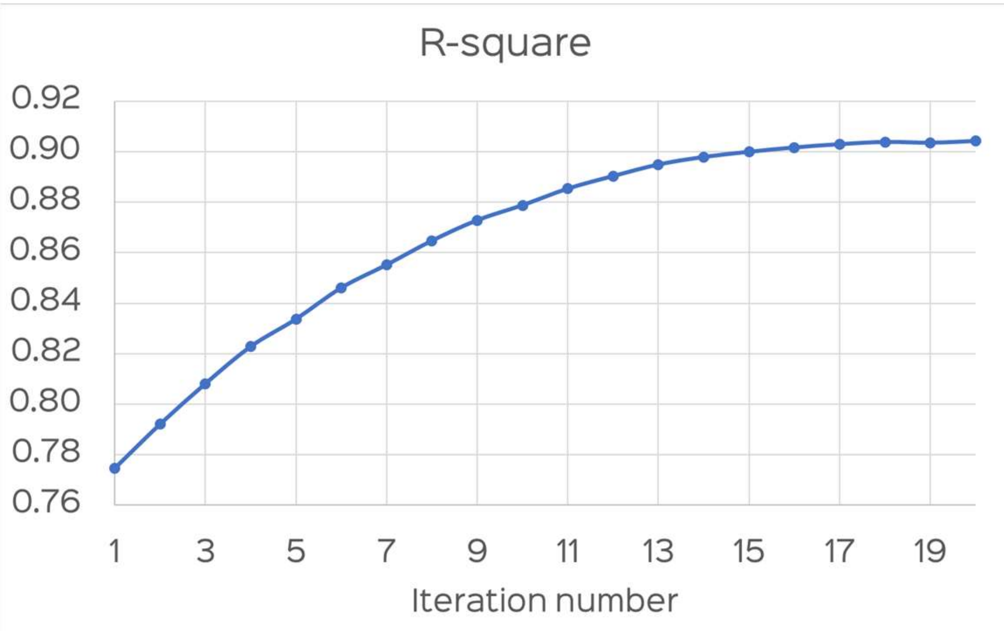
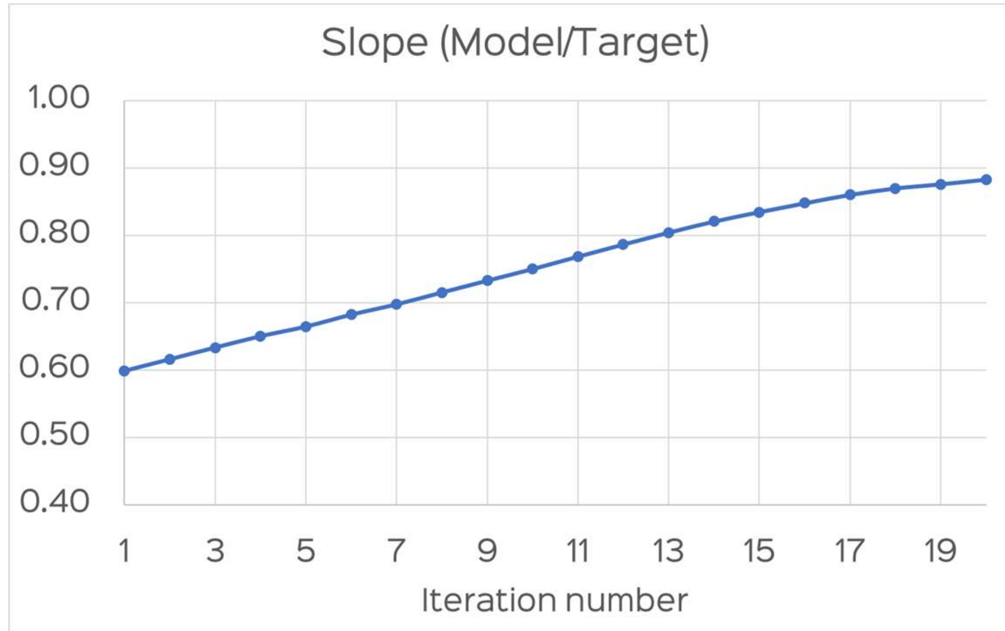
Lima ABM calibration: Validation to big data





Conclusions

- New automated calibration features can help agencies to achieve more meaningful transport simulation outcomes by
  - Achieving better model calibrations than previously possible
  - Automating the work required in model calibration to save time and money
  - Integrating rich mobility data sources for more timely updates
  - Opening the door to continuous delivery (CD) for travel modeling programs
  - Makes it easier to transfer demand models from another region (donor models)
  - Calibration tools can also help in identifying outliers/data inconsistencies

Takeaway

- If you are interested in trying this procedure for your own model, 4-step or ABM, and data sources, please get in touch!

- AGENT is available now as an Add-on for EMME and CUBE

CUBE
Predictive modeling and simulation of transportation

EMME
Multimodal transport planning

LEGION
Improving infrastructure for people

DYNAMEQ
Traffic simulation and dynamic traffic assignment

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