

Leveraging Mobility Data for Better Transport Simulation Outcomes

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Advancing Infrastructure

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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"*

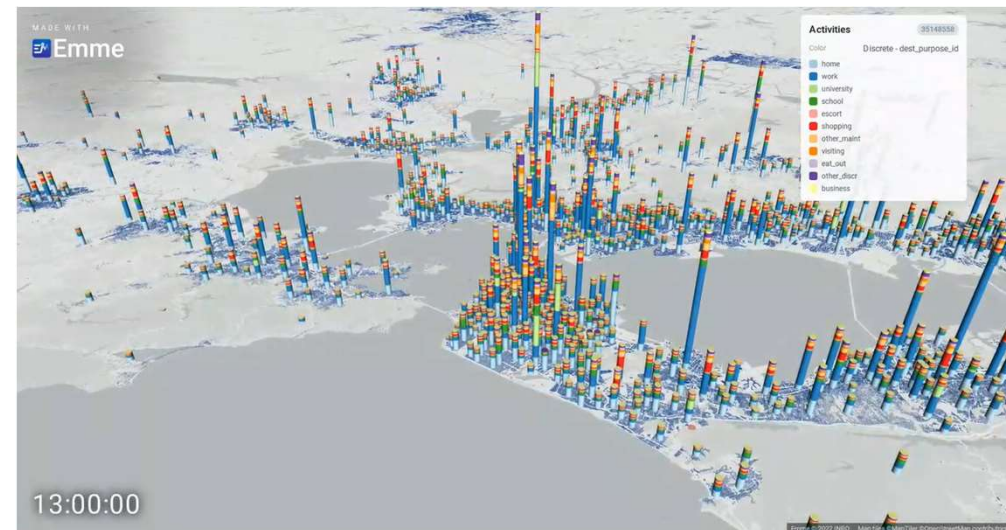
- Survey responses from ~1000 global participants attending Bentley webinar "Advancing travel demand models with AGENT" webinar, February 2022.

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

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

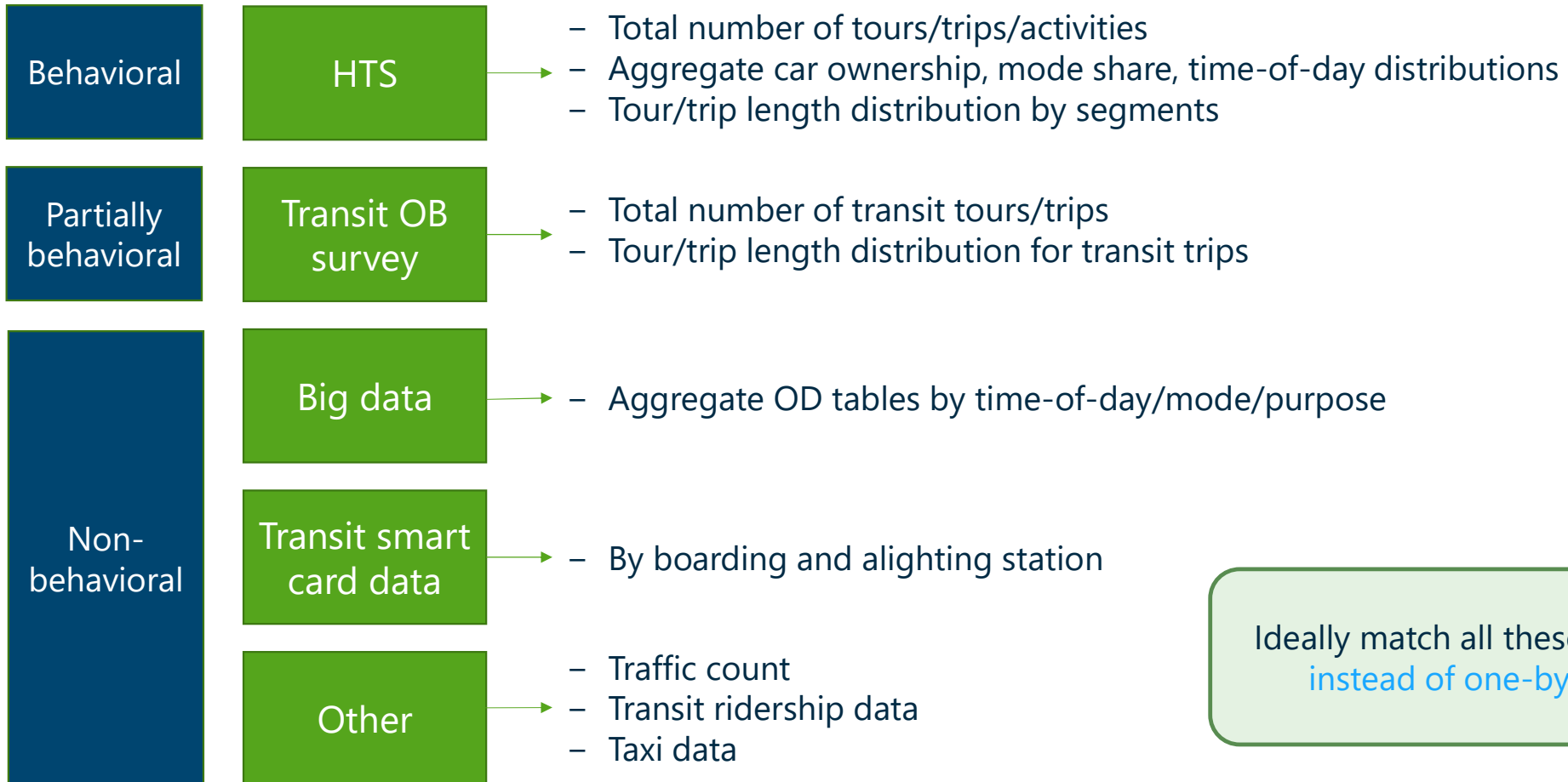
LOS i.e., accessibilities are assumed fixed and external

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



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

2 of 2 required features – Calibration Instrumentation

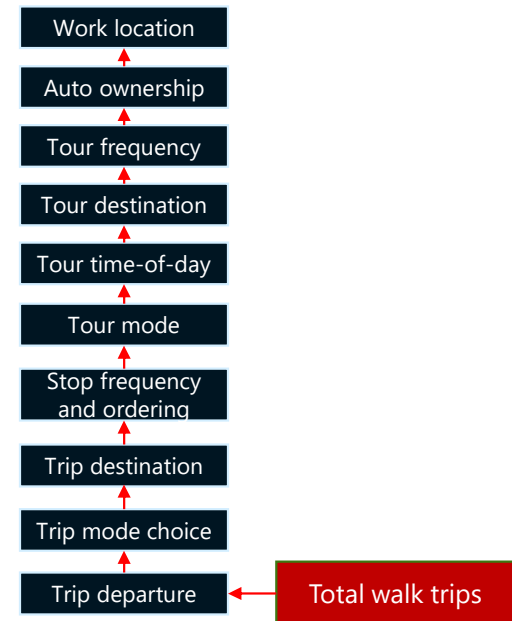
- Calibration expressed as interlinkages between sub-models
 - Resulting in many-to-many relationship between targets and sub-models
- Contrary to conventional calibration schema
 - Sub-models are calibrated sequentially one by one with its own targets

Parameters that can be updated

Q: Which parameters should we change?

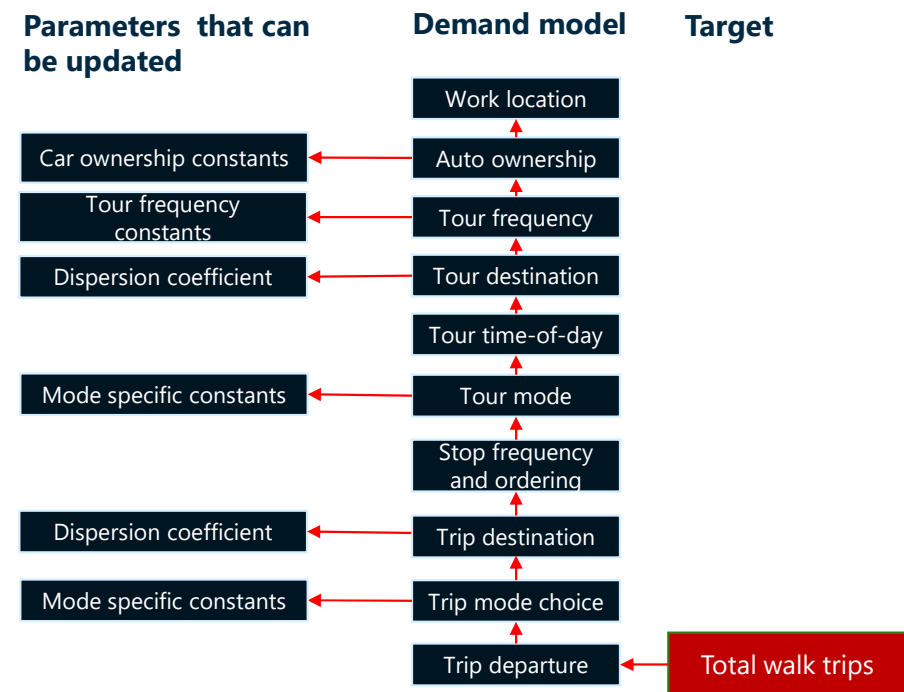
Demand model

Target



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



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

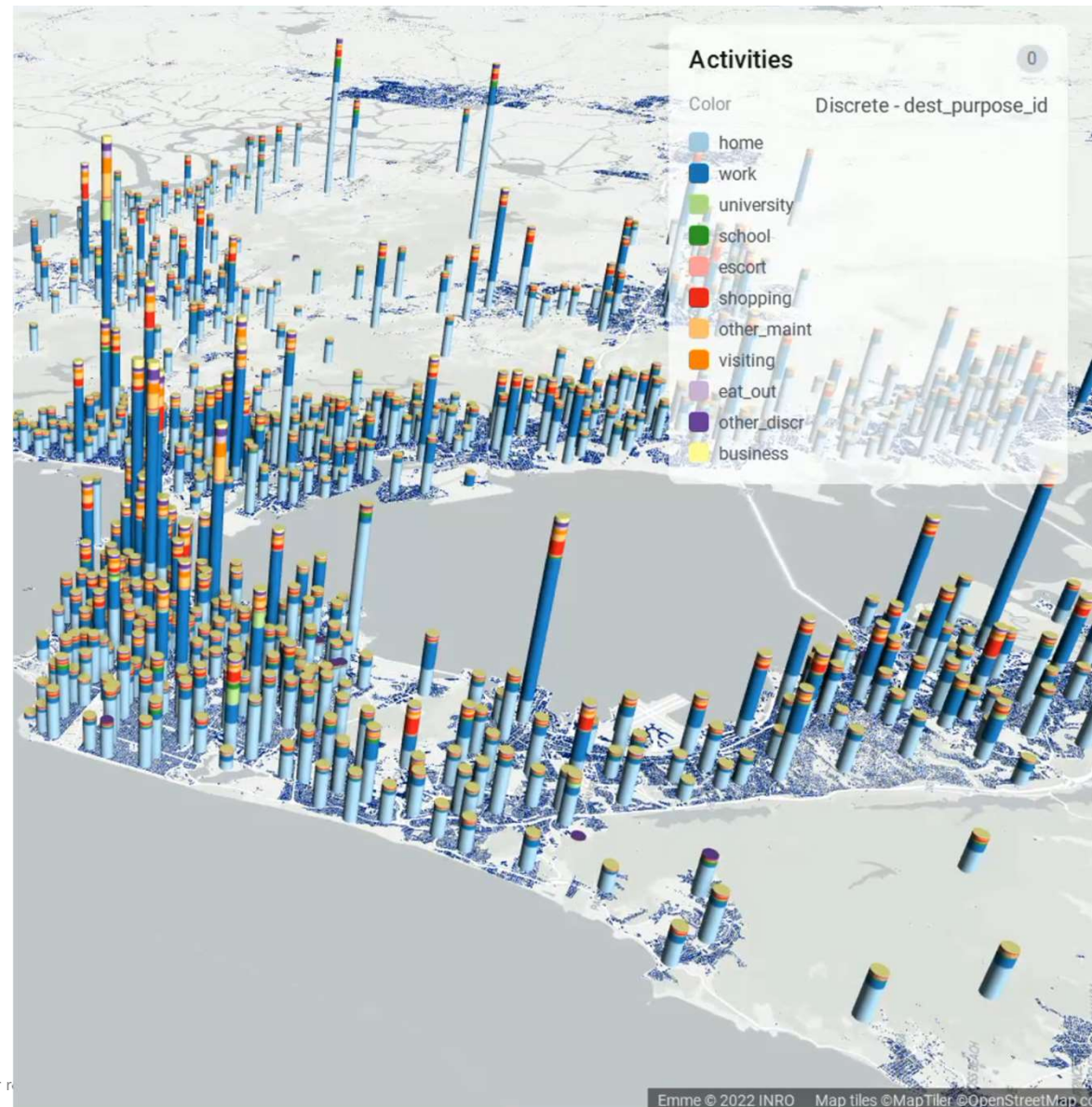
How is Big-data used for manual calibration in practice so far?

- 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?

Input Schema

Agent Schema

Constants

Time of Day

THROUGH-SEGMENTS

Purposes

Modes

Person Types

Daily Activity Patterns

CONSTRAINTS



Agent Schema

AGGREGATE

- Zones
- Network zones
- O-D

POPULATION

- Households
- Persons

TRAVEL

- Tours
- Sub-tours
- Trips

JOINT TRAVEL

- Fully joint tours
- Joint tour participants

Joint travel in Agent schema

How is the model configured in Agent?

Sequence of model steps

The screenshot shows a software interface for configuring a model. On the left, a tree view is expanded to 'MTC TM 15 style'. Underneath, there is a 'Properties' section and a 'Model Steps' section. The 'Model Steps' section contains a list of 20 steps, each with an icon and a three-dot menu. The steps are: Prep, Calculate dc size terms, Compute exponentiated utility, Compute accessibility, School location, Work location, Add OD relation for home to work, Calculate person auto savings ratio, Auto ownership, Free parking, CDAP, Mandatory tours models, Add primary location to tours, Mandator tour scheduling, Joint tour frequency, Insert joint tours, and Joint tour composition. A '51' badge is visible next to the 'Model Steps' header.

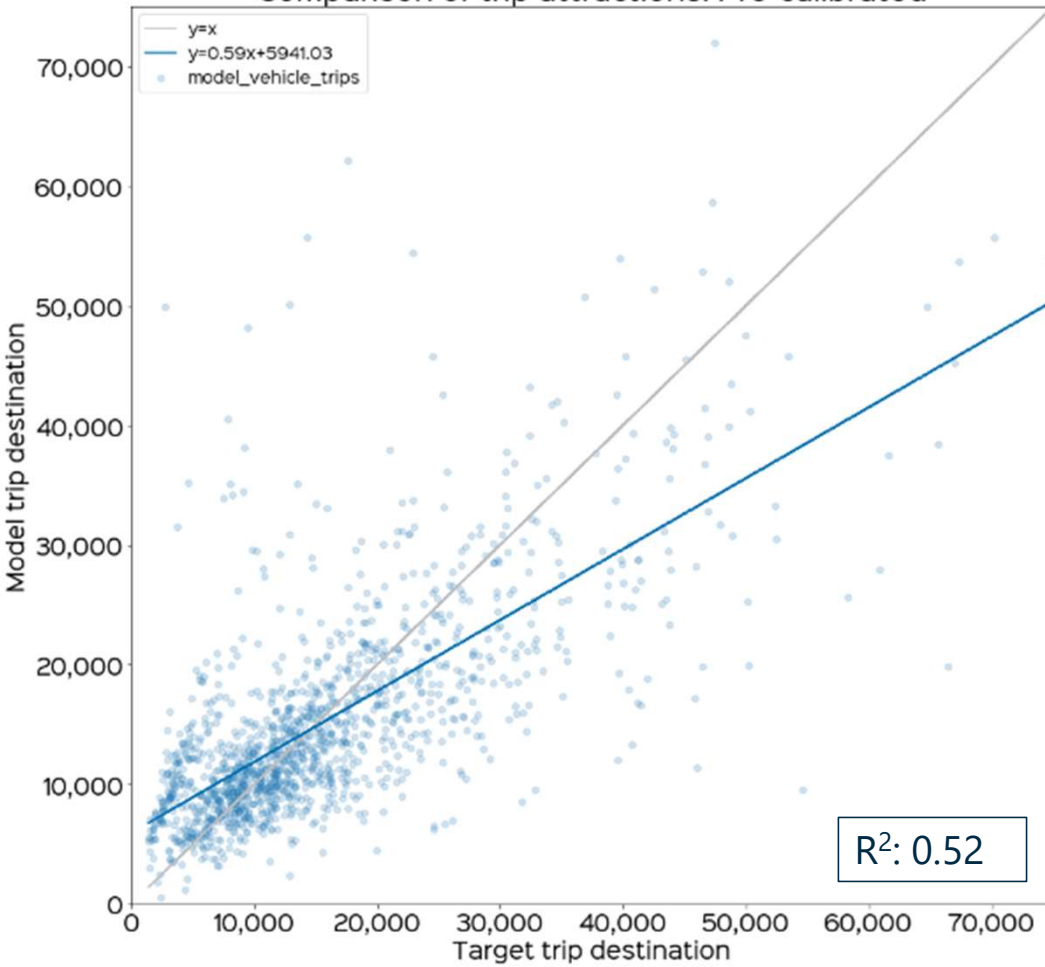
Generalized framework for modelling coordinated choices

The screenshot shows the 'CDAP' configuration interface. At the top, there is a title 'CDAP' and a 'Generic' label. Below this, there are four tabs: 'Decision-maker', 'Choice set' (which is selected), 'Statistical model', and 'Temporary attributes'. Underneath, there are three tabs: 'Agent', 'Sub-agent' (which is selected), and 'Combined'. The main area shows a 'Through-segments' tab selected, with a 'Custom table' option. Below this, there is a dropdown menu labeled 'Daily Activity Patterns' and a checkbox for 'Frequency'. To the right, there is a table with a filter and a data table.

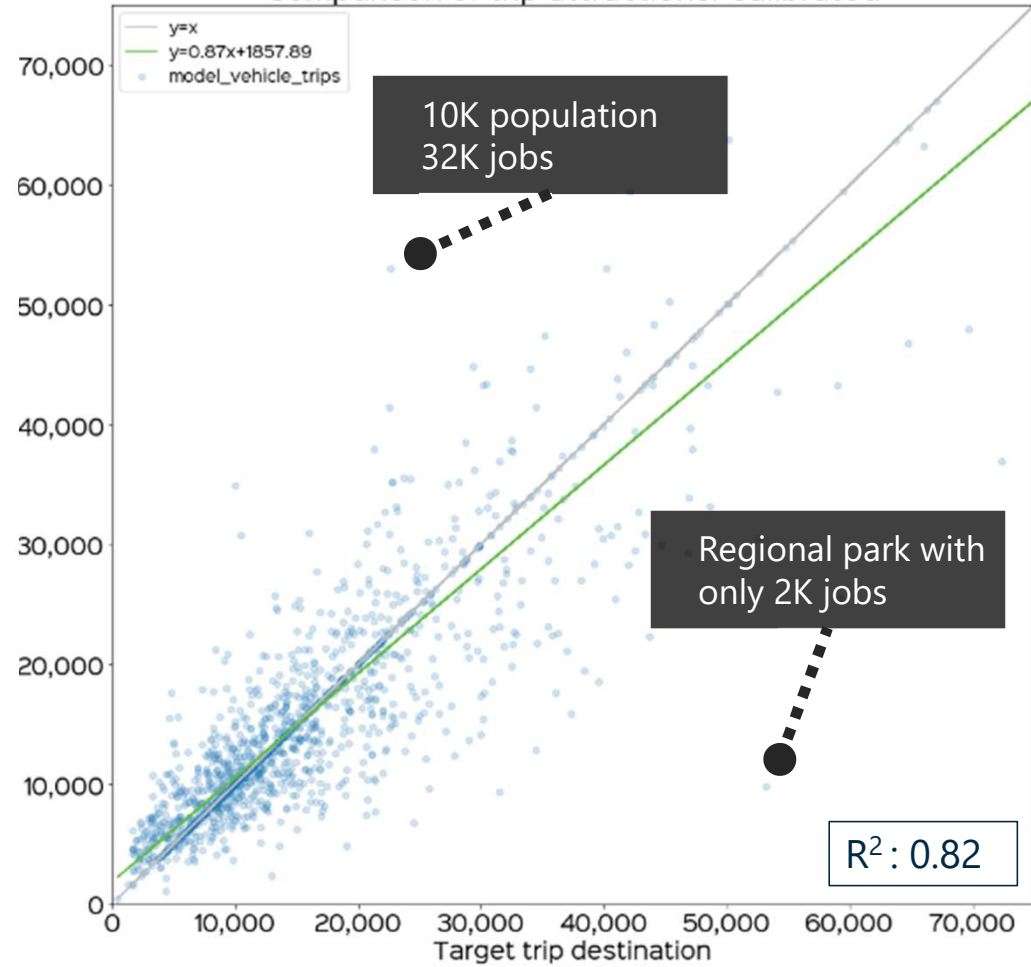
	dap_type_id	label
1	1	mandatory
2	2	non_mandatory
3	3	home

MTC 1.5 calibration: Comparison at zonal level

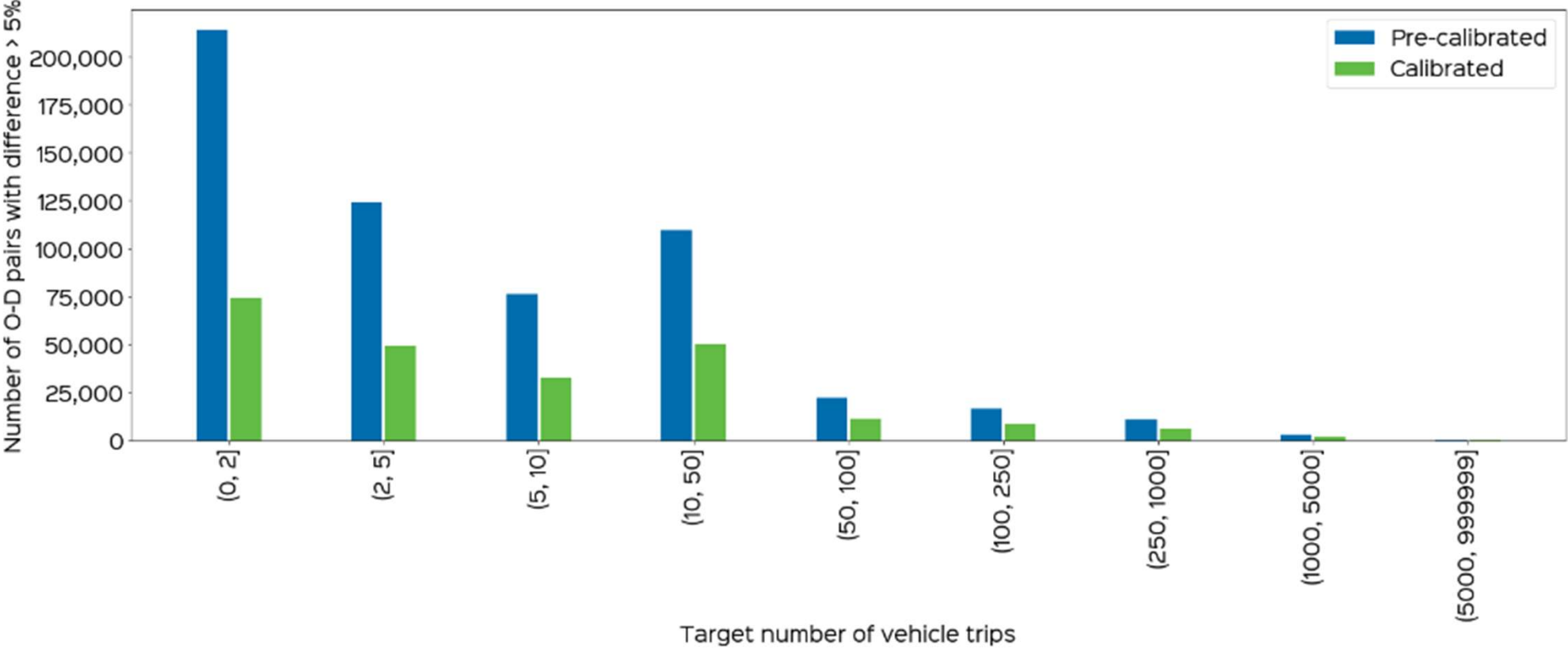
Comparison of trip attractions: Pre-calibrated



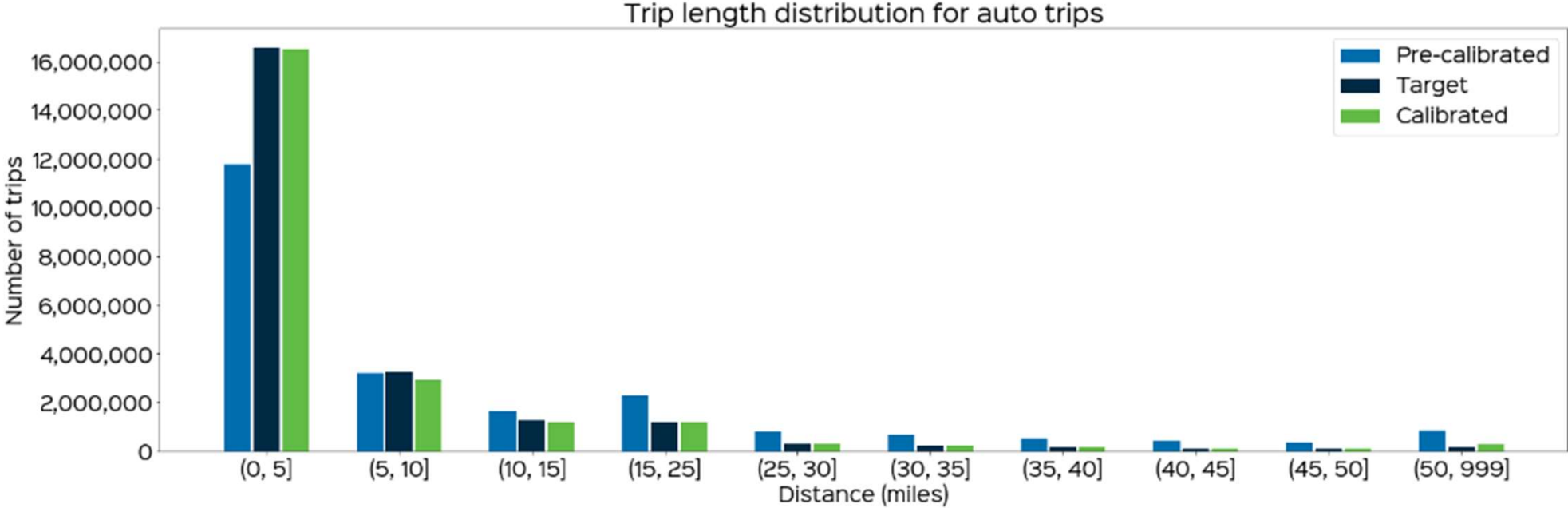
Comparison of trip attractions: Calibrated



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



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

Regional

Zonal

O-D

MTC TM 15 style calibrated



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

Bentley

What model parameters are affected by Teralytics data?

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

Work location

Location

Decision-maker Choice set Statistical model Temporary attributes Time-space constraints Utility expressions Result attributes Calibration instructions

Displaying 2 of 2 rows

Filter

	target_type	calibration_target	decision_maker	alternative_filter	alternative_expression	agent_filter	agent_expression	agent_result_attribute..	agent_result_attribute..	correction_fact
1	O-D	vehicle_trips	Persons				od.DIST * -0.2		hw.DIST	Inversely proportional
2	O-D	vehicle_trips	Persons			alt.zone_id == :		hh.zone_id == w		Logarithmic

- Regional
- Regional group
- Zonal
- O-D

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

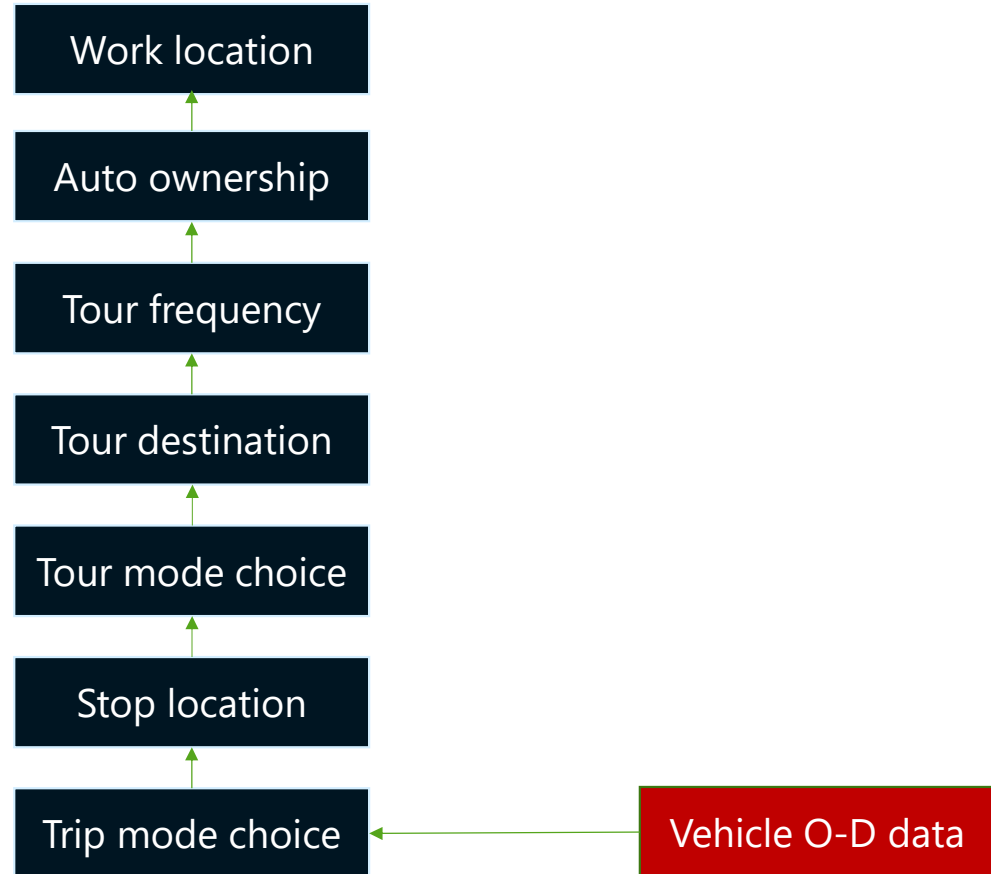
- Tour frequency constants

- Dispersion coefficient
- Intra-zonal preference

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

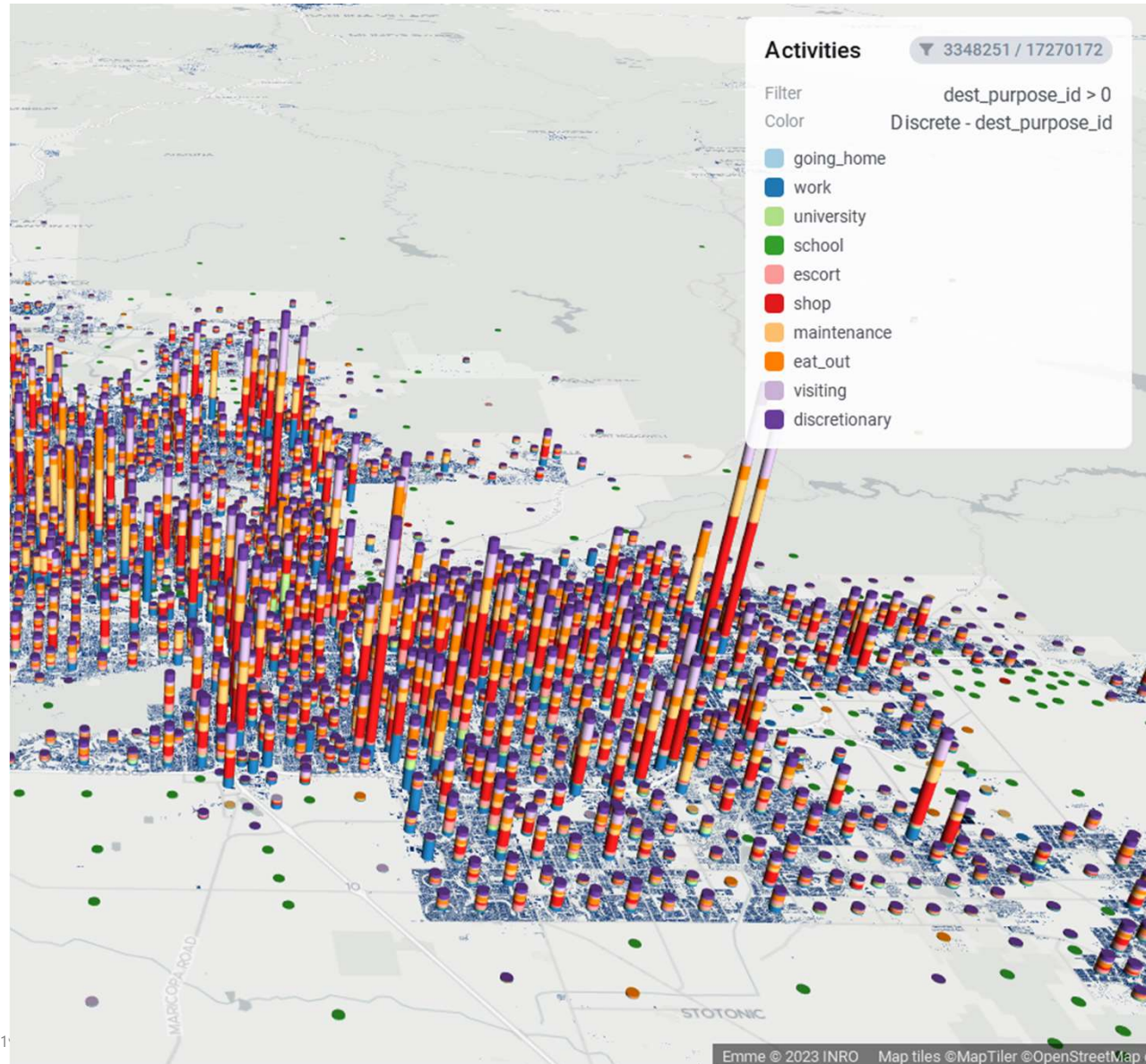
- Dispersion coefficient
- Intra-zonal preference

- 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)



MAG weekend model: Calibration targets

Weekend ABM with calibration targets

Regional

+ + - -

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.	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				0	86171.000000	Logarithmic	▼

Number of activities by purpose for weekend based on iteration review

MAG weekend model: Calibration targets

Weekend ABM with calibration targets

Regional



Filter

Name	Description	Group label (optional)	Table	Filter expression	Value expression	Aggregation function	Target min	Target max	Correction
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

What model parameters are affected by calibration targets?

- 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

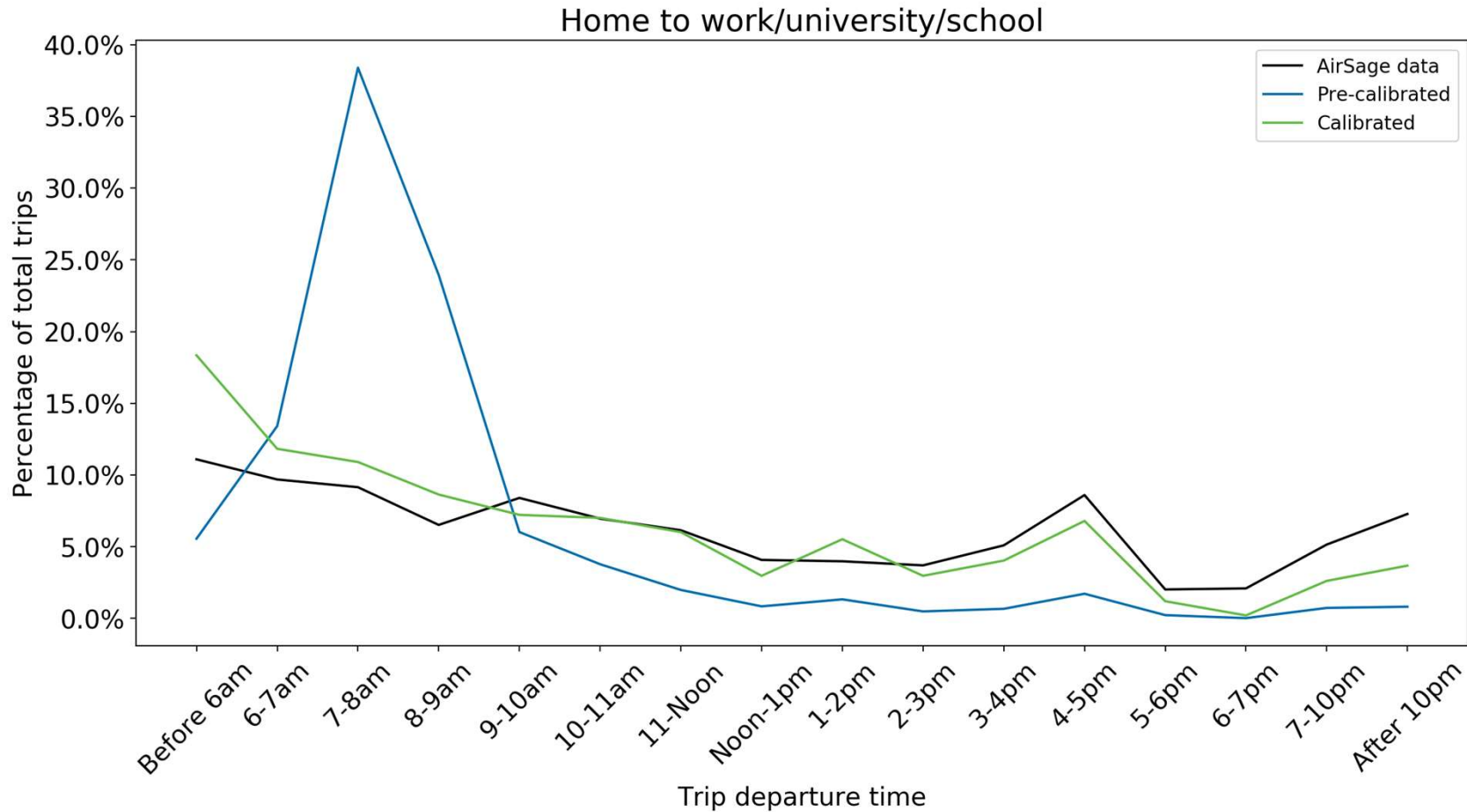
- Time-of-day constants

Trip departure

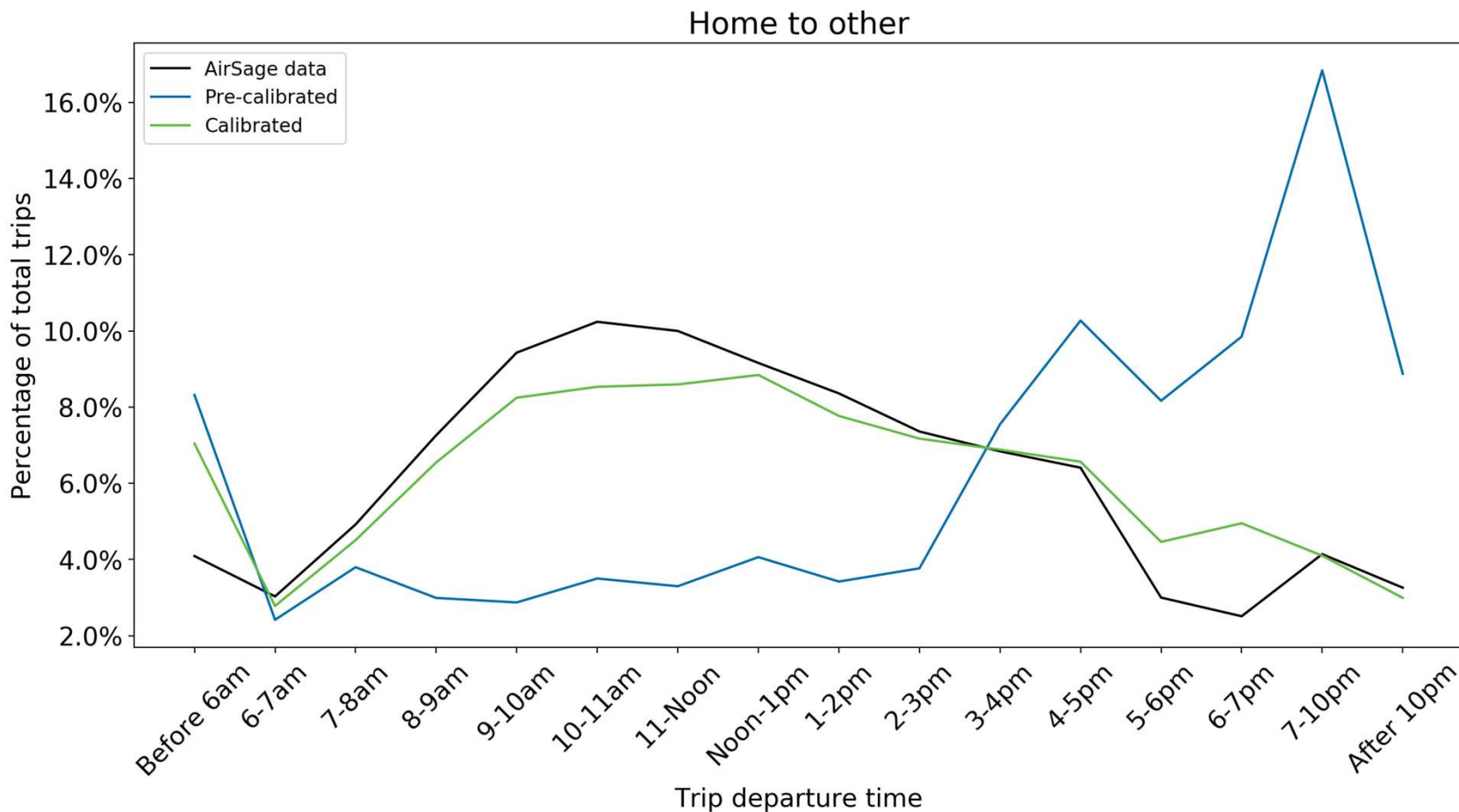
Trip departure profile

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

MAG Weekend model: Comparison of trip departure distribution



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)

The screenshot displays the Bentley software interface for a model named "100 per with count". The left sidebar shows a tree view of "Model Steps" under "Demand model with targets". The main window shows the results of the model steps.

100 per with count
 42,038 109,859 144,228 31,061 371 583,999

START DATE: May 17th, 2023
 START TIME: 15:23:47
 END TIME: 15:28:04
 DURATION: 00:04:16.94

Model Steps

Step Name	Type	Decision-maker	Duration
Prep	Table-calculator		00:00:00.15
Assign person types	Generic	Persons	00:00:00.20
Aggregate industry codes	Generic	Persons	00:00:00.15
Compute work size terms	Generic	Zones	00:00:00.09

Summary for Assign person types:

Number of decision-makers	Min chosen alternative	Max chosen alternative	Mean chosen alternative	Sum of chosen alternatives
109,859	1	8	3.41001	374,620

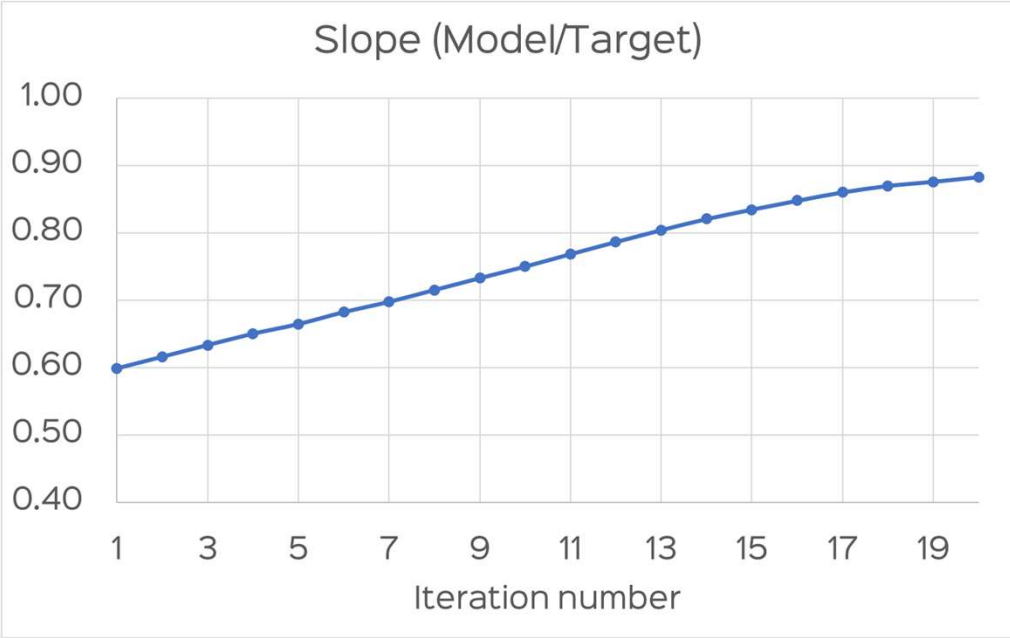
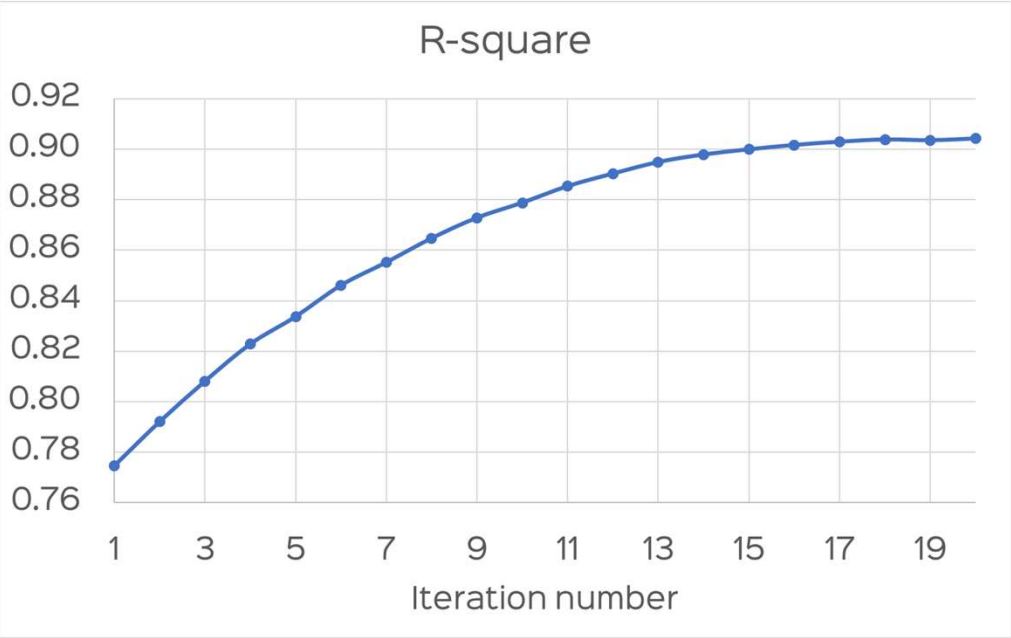
Summary for Aggregate industry codes:

Number of decision-makers	Min chosen alternative	Max chosen alternative	Mean chosen alternative	Sum of chosen alternatives
48,026	1	10	5.59974	268,933

Summary for Compute work size terms:

Number of decision-makers
6.497

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



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Advanced travel demand modeling

