# Replica



### **How it Works**

# Raw Data Layer

We leverage a diverse set of third-party source data to create our models.

This composite approach is both a risk-mitigation strategy and aligned with our objective to show a holistic view of the built environment.



Location Data



Consumer & Resident Data



**Built Environment** 



**Economic Activity** 



Ground Truth Data

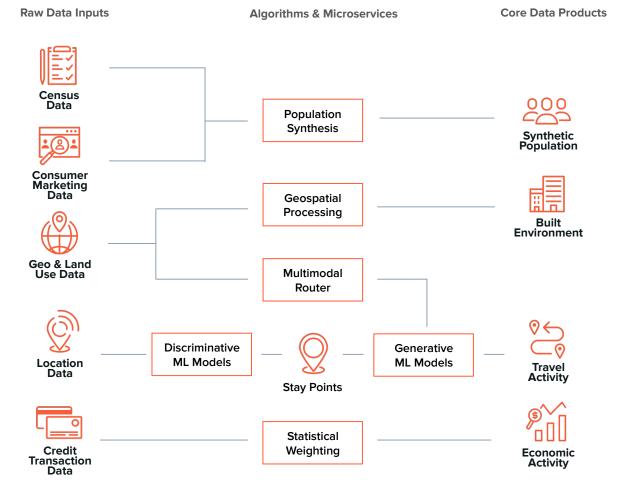


### **How it Works**

# Algorithms Layer

Replica generates its data by running large scale, computationally-intensive simulations — a "replica" of transportation and economic patterns.

As the quantity and variety of available raw data continues to grow, we introduced a privacy-preserving algorithms layer that produces composite synthetic core data sets in a unified schema.





## Core Data Access APIs

The Core Data
Products produced
by the Algorithms
Layer both feed our
platform applications
and can be delivered directly
to customers.

3rd party applications are built via core data access API.

#### **Core Data Products**







travel activity



# Studio UI + Apps

#### **Platform Applications**



#### **Trends**

Weekly updates, less geospatial fidelity, essential feature set



#### **Places**

Seasonal updates, more geospatial fidelity, exhaustive feature set



#### **Direct Access + Apps**

Customer ingestion of CDPs for proprietary or custom use and/or applications targeting high value use cases

# Population

### Census Households Surveys + Consumer Marketing Data

#### Public Use Microdata Files • 1



- Records of individual households and household members, 100s of attributes
- 1% of Public Use Micro Area population, 100K+ people

### American Community Survey



- aggregates at Census Tracts level, censored at low values
- 10 to 50 Tracts per PUMA, 100s of attributes, 25% or 100% sample

#### Consumer Marketing Data

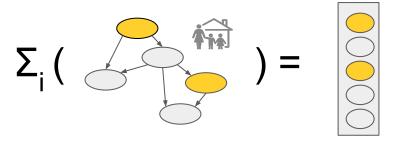
EV ownership



# Synthetic Population - Methods

### Allocation with Convex Optimization

- Allocate N households composed of M people into T tracts so that the attributes match Census totals
- Census expansion weights vs fit to marginals trade-off formulated as a constrained convex optimization problem

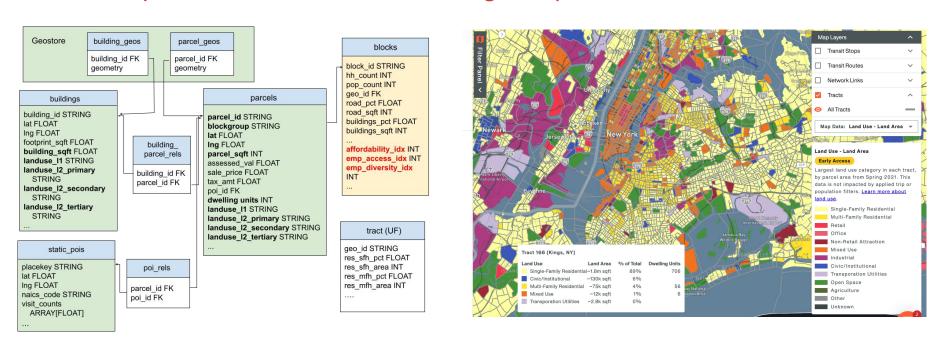


- Within each tract, allocate households to housing units matching block-level household totals
- Assign work and school locations, using iterative proportional fitting from a combination of CTPP, LEHD, and LBS data sources



# Land use

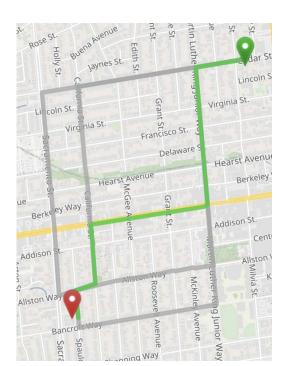
### Nationwide parcel-level land use with buildings footprints and POIs

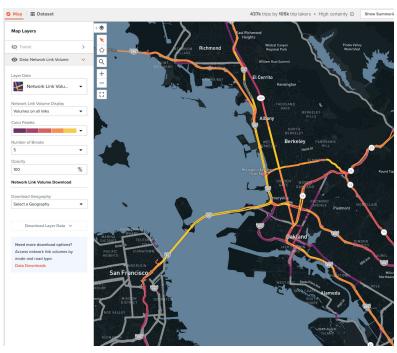


# Transportation networks

### Nationwide, OSM + GTFS

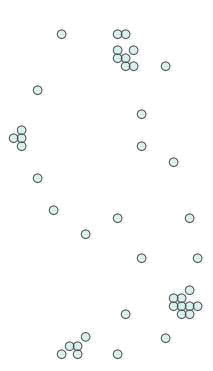
- Multimodal nationwide router (auto, freight, transit, walking, biking)
- Time-dependent routing to account for congestion; multiple profiles for local / long distance trips
- Places build takes (330M ppl) x (4 modes) x (4 trips a day) = 5B requests per release
- Nationwide transit routing, GTFS data repo





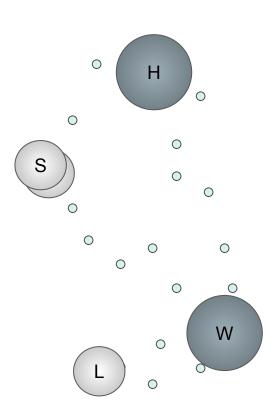
### LBS Data Processing and Modeling

- Locational data analysis
  - Typically, 3 weeks up to 3 month of data per device
  - Mobility traces segmentation into staypoints and trips
  - Attributes of visited places and travel choices context
- Modeling: interpretable and policy responsive models
  - Day structure and activity sequence model (ASM)
  - Location choice model (LCM)
  - Mode choice model (MCM)



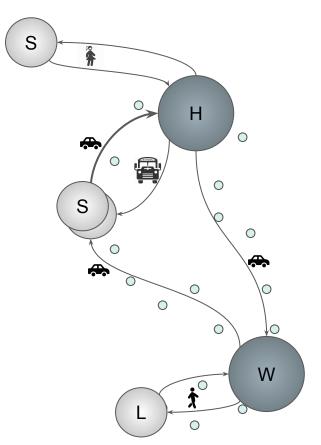
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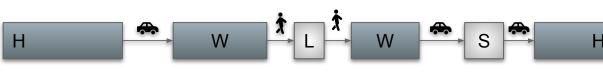
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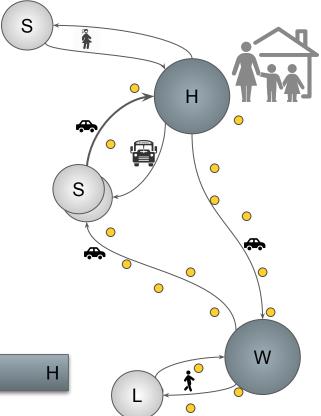
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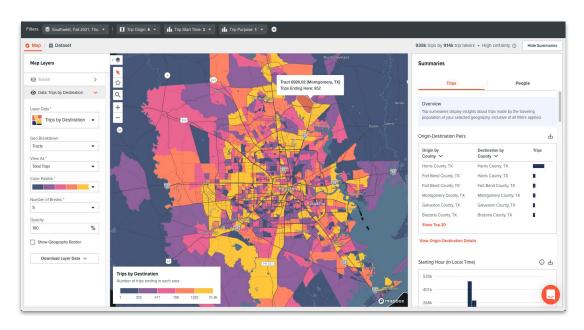






## **Places**

High-fidelity activity-based travel models, representing specific regions during specific seasons, with data outputs down to the network link level.



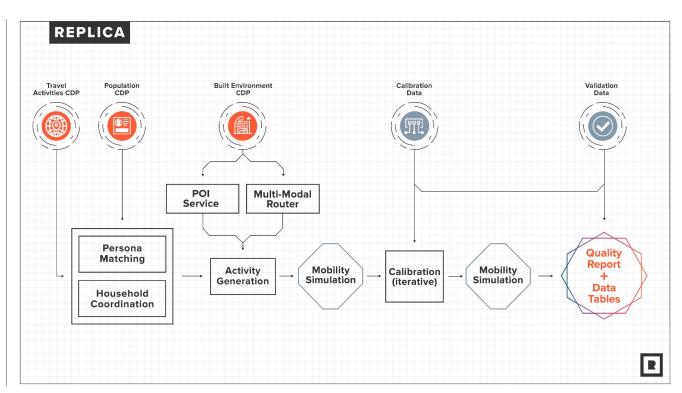
Activity ID	Trip Origin Block Group ▼	Trip Origin Tract ▼	Trip Origin County ▼	Trip Origin State ▼	Trip Destination Block Group ▼	Trip Destination Tract ▼	Trip Destination County	Trip Destination State ▼	Primary Mode ▼	Trip Purpose
8673634482875025000	2 (Tract 3402.01, Harris, TX)	3402.01 (Harris, TX)	Harris County, TX	Texas	2 (Tract 3332.02, Harris, TX)	3332.02 (Harris, TX)	Harris County, TX	Texas	private_auto	work
12320064160658230000	3 (Tract 3422, Harris, TX)	3422 (Harris, TX)	Harris County, TX	Texas	1 (Tract 3506.01, Harris, TX)	3506.01 (Harris, TX)	Harris County, TX	Texas	private_auto	work
14828863641052529000	1 (Tract 3403.02, Harris, TX)	3403.02 (Harris, TX)	Harris County, TX	Texas	1 (Tract 3506.01, Harris, TX)	3506.01 (Harris, TX)	Harris County, TX	Texas	private_auto	work
3990376502905317000	2 (Tract 3421, Harris, TX)	3421 (Harris, TX)	Harris County, TX	Texas	4 (Tract 3502, Harris, TX)	3502 (Harris, TX)	Harris County, TX	Texas	private_auto	work
13724276556411600000	1 (Tract 3430, Harris, TX)	3430 (Harris, TX)	Harris County, TX	Texas	1 (Tract 3340.01, Harris, TX)	3340.01 (Harris, TX)	Harris County, TX	Texas	carpool	work
1032375517898096000	1 (Tract 3402.02, Harris, TX)	3402.02 (Harris, TX)	Harris County, TX	Texas	1 (Tract 3333, Harris, TX)	3333 (Harris, TX)	Harris County, TX	Texas	private_auto	work



### **How it Works**

# Places Typical Day

- Generative models of travel demand
  - Activity-based, individual level
  - Responsive to changes (travel delays, road closures, accessibility)
- Model of network dynamics
  - Traffic flow and congestion
  - o Transit route choice
  - TNC supply
  - Walkability

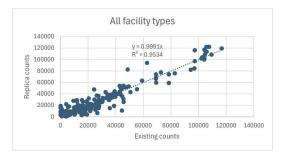


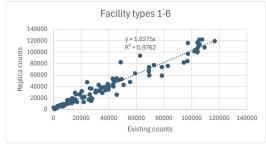


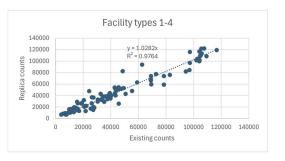
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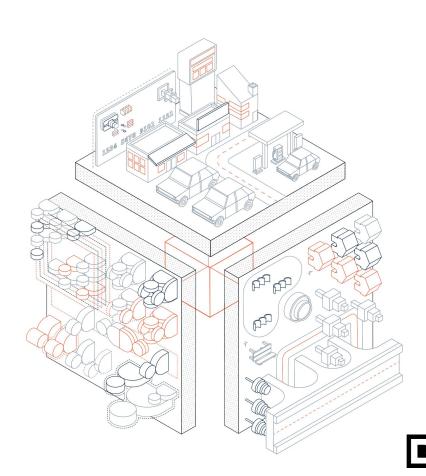




### Scenario

Uses our data and activity-based model to forecast future conditions based on potential changes to the population, land use, and transportation infrastructure.

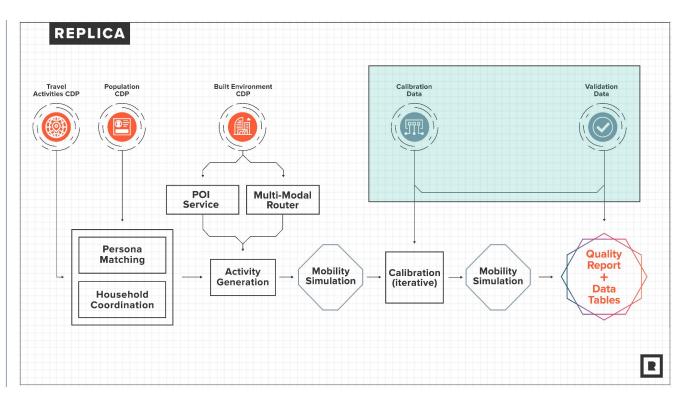
- The first release of Scenario can evaluate
   Growth Scenarios changes to population and employment and the associated impact on travel and infra demand, with no infra changes
- Custom Scenarios (available now)
   A managed service where we re-run our ABM with custom inputs, assumptions, and geographies



### **How it Works**

## **Scenario**

- Generative models of travel demand
  - Activity-based, individual level
  - Responsive to changes (travel delays, road closures, accessibility)
- Model of network dynamics
  - Traffic flow and congestion
  - Transit route choice
  - TNC supply
  - Walkability







### **Trends**

### Nationwide activity-based model,

with near-real time data at the census-tract level covering mobility, consumer spend, and land use.



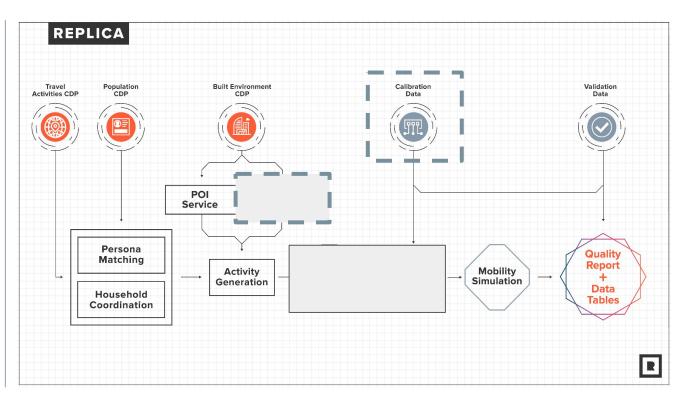




### **How it Works**

## **Trends**

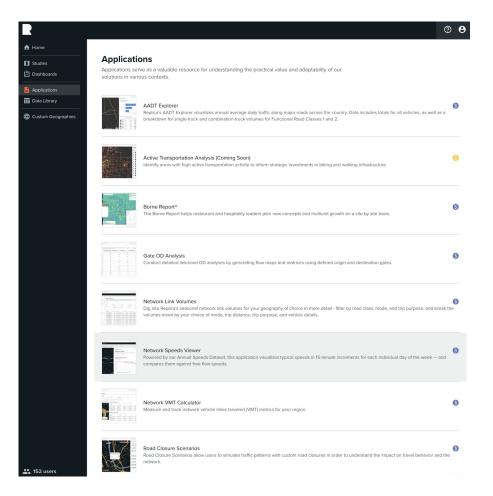
- Generative models of travel demand
  - Activity-based, individual level
  - Responsive to changes (travel delays, road closures, accessibility)
- Travel time / accessibility
  - Proxy traffic flow and congestion
  - Proxy transit accessibility
  - Walkability



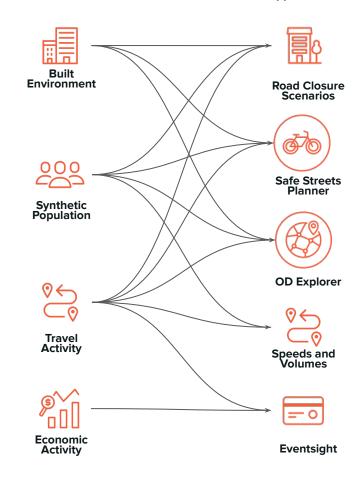


## **Applications**

API access to all Core Data Products and derivative data (Places and Scenario) allows building targeted applications, both by Replica and 3rd parties







# Patterns

Measure the relative uptick (or drop-off) in popularity at specific locations on specific days and times.

Create a custom geography, select the date and time of interest, and choose the comparison window.

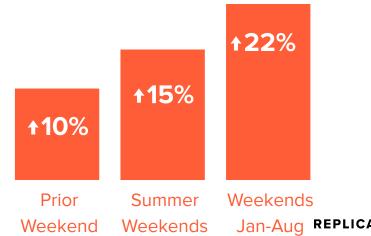
The tool quantifies the relative change in activity in that location between the two periods and unlocks dozens of analysis:

- **ROI** on Major Investments
- Economic Impact + Spillover,
- Impacts of Work from Home
- Weather Impacts on Economic Activity
- YoY and MoM Comparisons
- Traffic, Tourism, Public Safety Management



Highlighted area is the downtown zone for analysis.

### **Uptick in Visits As Compared To:**

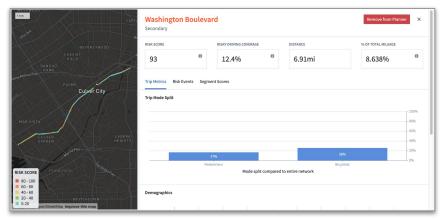


# Culver City

Replica's detailed multimodal data with driving event data, enables agencies to map existing conditions, analyze specific corridors, generate their own High Conflict Corridor and Safety Action Plans and Reports.

Rather than investing in a one-off analysis or third-party report that will quickly become out of date as conditions on the ground change, Replica's Safe Streets Planner updates each season with the most recent data tied to specific road segments, including:

- Rapid acceleration events
- Hard braking / near miss events
- Speeding events
- Collisions
- Phone handling



#### **Analyze Individual Corridors**



**High Conflict Corridor Map** 

Large-Scale and Small-Scale Event Planning Major Infrastructure Updates Safety and Construction Planning

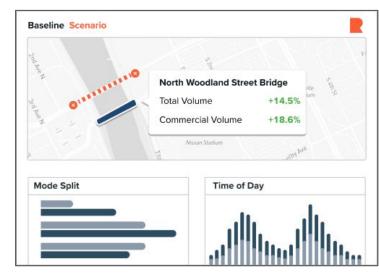
**Emergency Planning** and Preparedness

#### What this Unlocks:

- Identify Traffic Diversion Patterns: Find alternative routes with ease and understand congestion impacts.
- Estimate Impacts on Daily Travel: Quantify changes in travel volumes, trip distances, mode split, and more.
- Understand Socio-Economic Impacts: Identify who is most impacted by these closures and how.
- Assess Environmental Impact: Understand changes in emissions and vehicle miles traveled (VMT).

#### **Key Features:**

- Interactive Map-Based Tooling: Easily designate roads for closure, and visualize traffic diversion patterns and changes in travel time for affected routes.
- Comprehensive Analysis: Dynamic charts and visualizations showing forecasted impacts.
- Collaborate and Share: Share insights with your colleagues for review and collaboration.



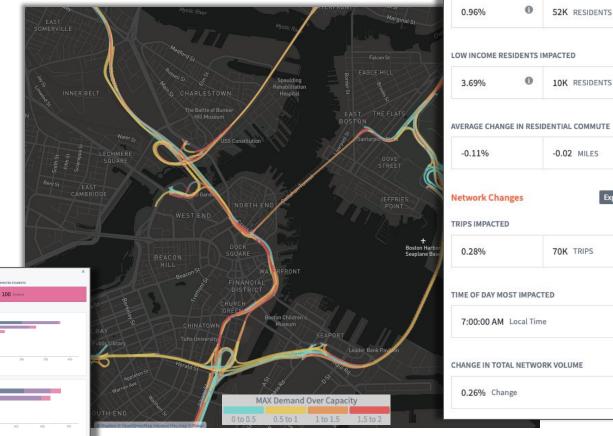
ROAD CLOSURE SCENARIO: MASSACHUSETTS

# Sumner Tunnel Restoration

The Sumner Tunnel is undergoing a restoration that began in the spring of 2022. This work requires the tunnel to be closed to traffic periodically.

MassDOT performed a Road Closure Scenario to quantify traffic diversions and to understand people impacted.

72.64





People Impacted

RESIDENTS IMPACTED

#### ROAD CLOSURE SCENARIO

# San Ramon Bollinger Canyon

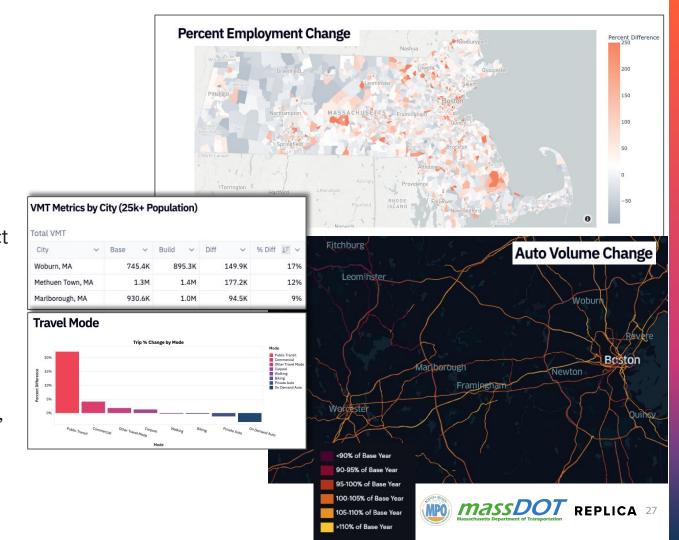
In order to install a bike and pedestrian overcrossing, the City of San Ramon needed to stop traffic on Bollinger Canyon Road for nine days, forcing roughly 40,000 trips to be rerouted each day.

The findings of this Scenario run helped San Ramon create **a** data-driven outreach plan that centered around the most congested pain points and informed a diversion plan that includes consideration of a shortcut through a parking lot that Replica's router identified.



# **MassDOT**

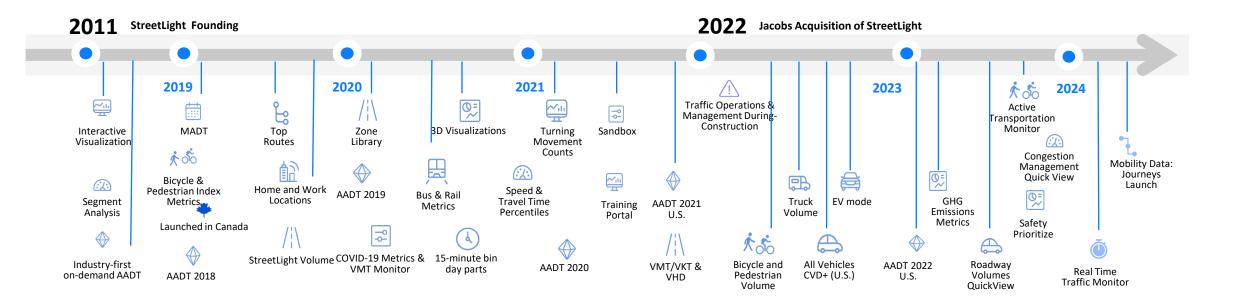
MassDOT and Boston Region MPO (CTPS) used Replica's Scenario product to model mobility and employment changes by their proprietary TAZs, to understand the future demand for transit. stressors to road network. and changes to VMT based on their population growth estimates.





# **StreetLight Data – Big Data to Make Transportation Better**







7+
BILLION MONTHLY
TRIPS PROCESSED

100s
OF DATA SOURCES
INCORPORATED

>5PB
IN OUR HISTORY WE'VE PROCESSED OVER 5PB
POINTS OF DATA

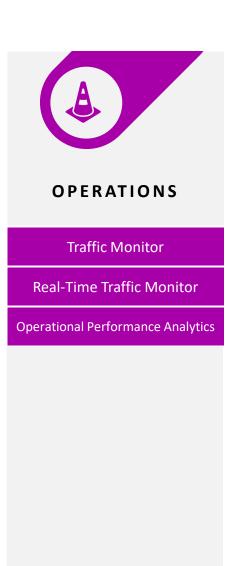
20,000+

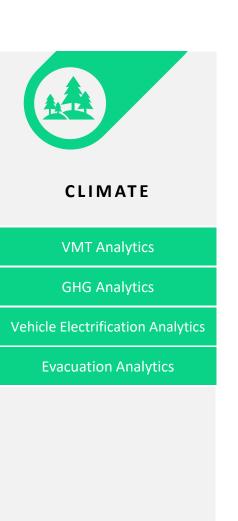
POWERING ANALYSES PER MONTH

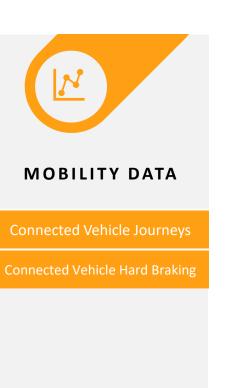
©StreetLight Data, Inc. 2024

# StreetLight's product suite tackles a wide array of transportation challenges with the most complete portfolio in the industry







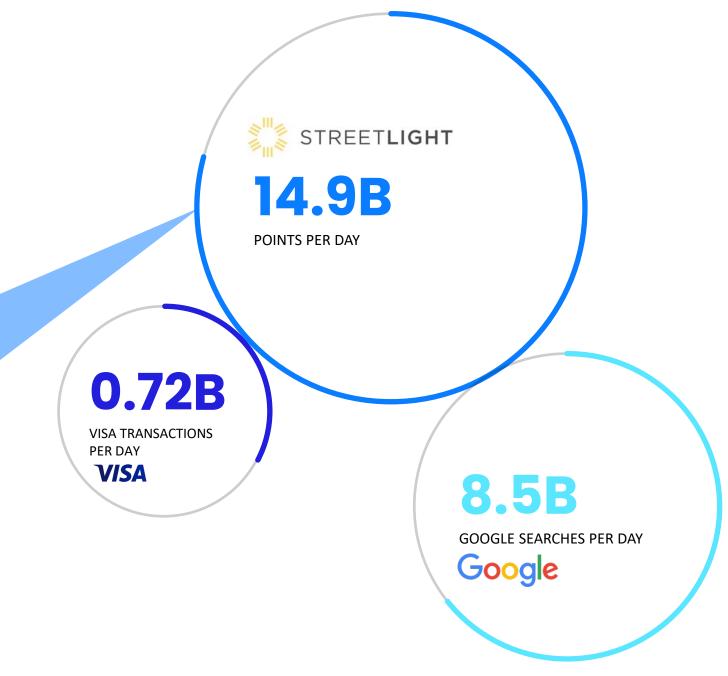




# **Mobility Data IS Big Data!**

# Snapshot of data points averaged over a week

- **14.9 billion** points
- 10.2 million vehicles (expect ~10+ million when we look across the whole month)
- **39 million** journeys
- Ping count every 3 seconds



### **Fleet Statistics**

### Nationwide:

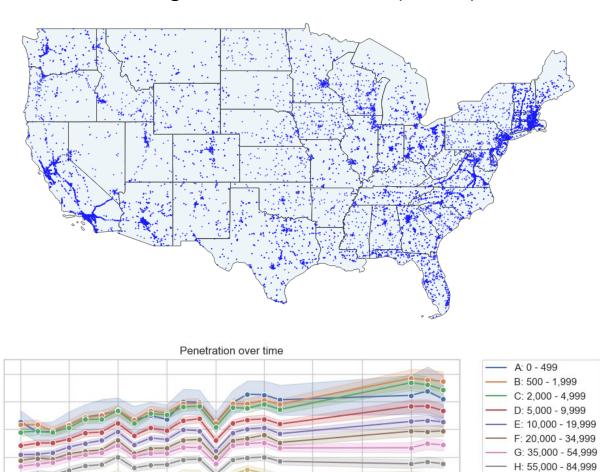
- 10M+ unique vehicles sampled every 3secs
- Model year 2015 and later
- 55% SUV, 30% Pickup Truck, 15% Sedan/Saloon
- Most drive 25+ days/month



4.5

2022-01 2022-04 2022-07 2022-10

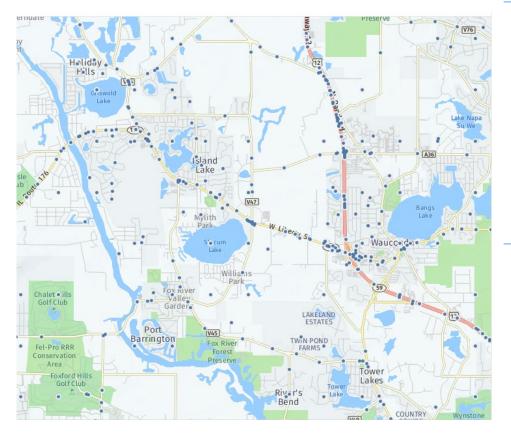
### StreetLight's Counter Network (14,000)



datetime

I: 85,000 - 124,999J: 125,000 +

# Data privacy rules in place to protect StreetLight CVD



### **Location Blurring**

Lat/Long coordinates will be truncated to two decimal points to blur trip points that fall within approximately 0.5 miles of a frequently visited location. Frequently visited locations are defined as the top 5 locations a vehicle visited in the past 30 days. This definition may be changed by a Third-Party Licensor at any time, and we will notify customers with reasonable notice, if possible.

## Low Density Filtering

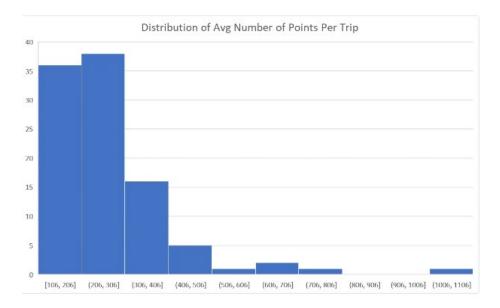
Data points representing locations in any individual square half mile area where the Data contains only one or two vehicles within that area during the most recent 3-month period.

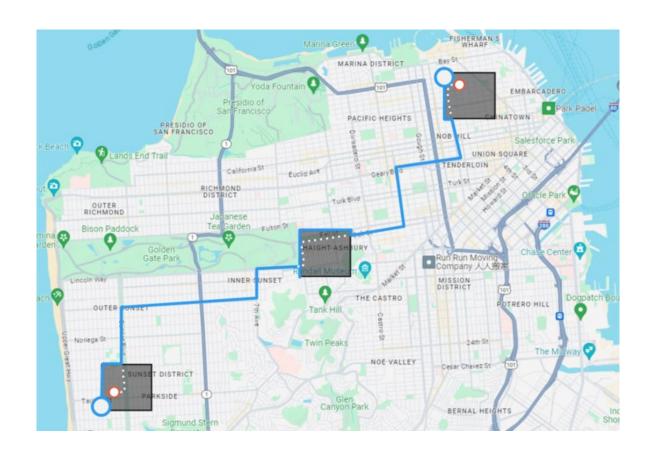
©StreetLight Data, Inc. 2024

# **Privacy Blurring - Statistics**

Nationwide: ~15B points,~40M Journeys daily

- ~20% of all points are blurred
- ~23% of KeyON points blurred
- ~23% of KeyOFF points blurred
- ~14% of Journeys have both KeyON and KeyOFF blurred
- ~9% of journeys are completely blurred



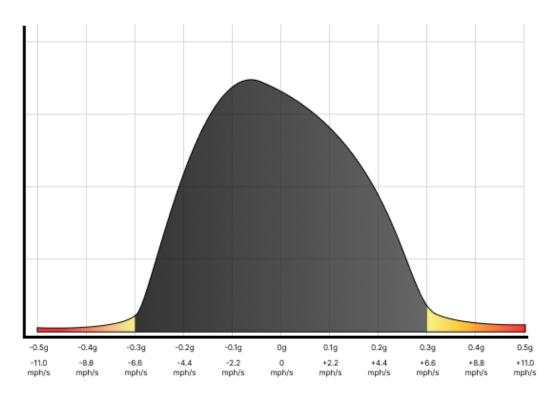


Most trips 100-300 points, assuming 3s interval, 5-15 mins

©StreetLight Data, Inc. 2024

# **Hard Braking/Acceleration Data**

- 10M+ unique vehicles, telemetry data every 3s
- Acceleration derived using vehicle-reported speeds
- 99.95% of pings are removed, leaving only hard braking + acceleration events
- gForce is kept as an attribute, allowing for exploration of different severity of acceleration behaviors





#### **Established Thresholds:**

Purdue (2024): -0.27g Purdue (2023): -0.4g to -0.5g

Jun et al. (2007): -0.4g

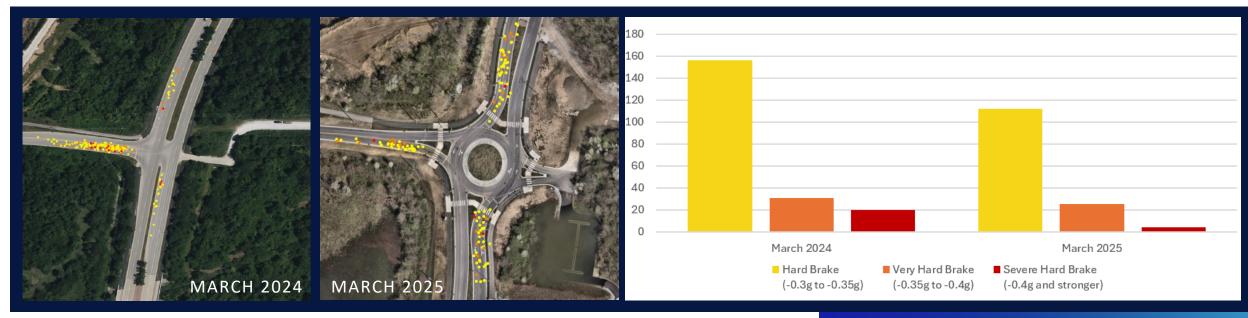
Geotab (<u>2023</u>): -0.27g Wejo (2022): -0.32g

(<u>Mousavi, 2015</u>): -.37g

(Kamla et al., 2019): -0.2g to -0.8g



# Safer Turns in the Roundabout Capital of America: Measuring Impact with Hard Braking Data



#### **CHALLENGE**

Carmel, Indiana aimed to improve safety at the busy three-way intersection of 106th Street and Hazel Dell Parkway.

With high traffic volumes on both roads, the city needed a way to reduce risky driving behavior.

#### **DATA-BASED SOLUTION**

StreetLight analyzed hard braking events before and after the intersection's conversion to a multi-lane roundabout.

Using a high magnitude of precise locations for hard braking & acceleration events data, the study compared March 2024 to March 2025 to evaluate changes in driver behavior and quantify the safety impact of the new design.



#### **AGENCY & PUBLIC BENEFIT**

The analysis revealed a 32% drop in total hard braking events, with the sharpest decline in severe incidents at 80%.

This immediate, measurable insight can help validate the roundabout's effectiveness, support future design decisions, and demonstrate the power of using braking data as a rapid safety indicator.



Congestion and traffic demand Analysis using Floating-car Data

Ralf-Peter Schaefer / VP Product Management



# **City and DOT Challenges**















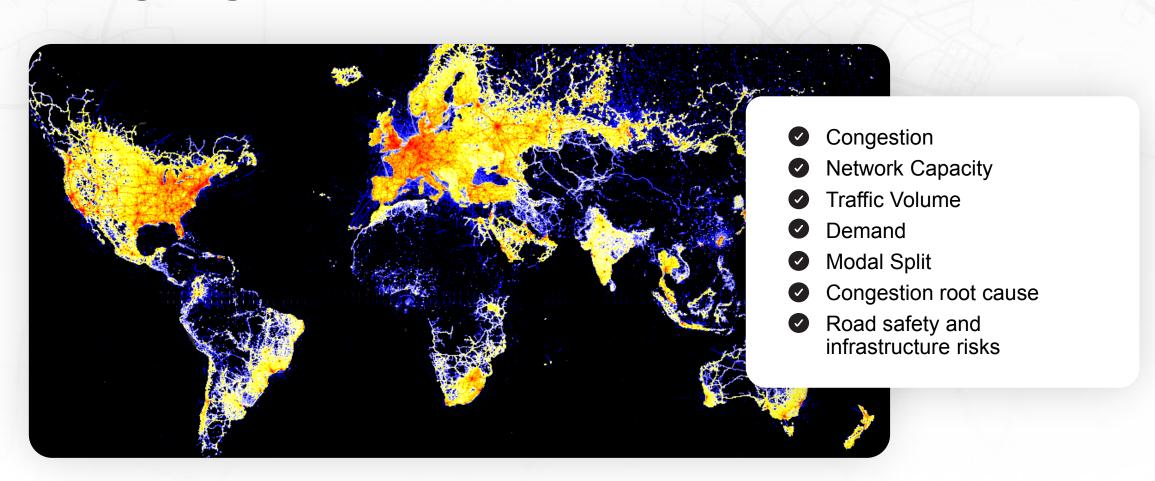




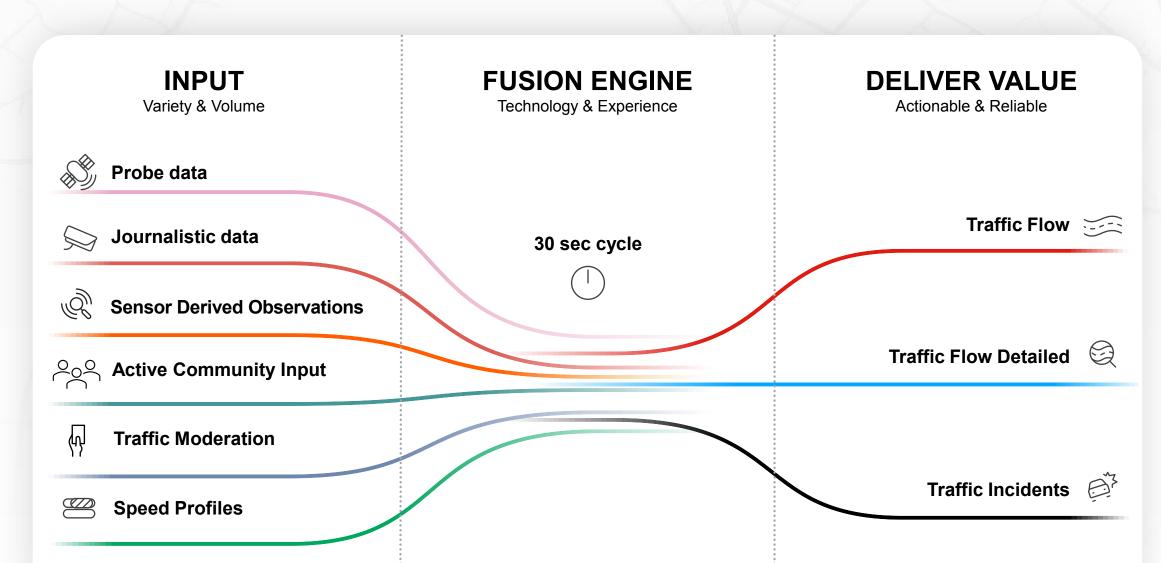




# **Understanding the Challenge** using Big Data

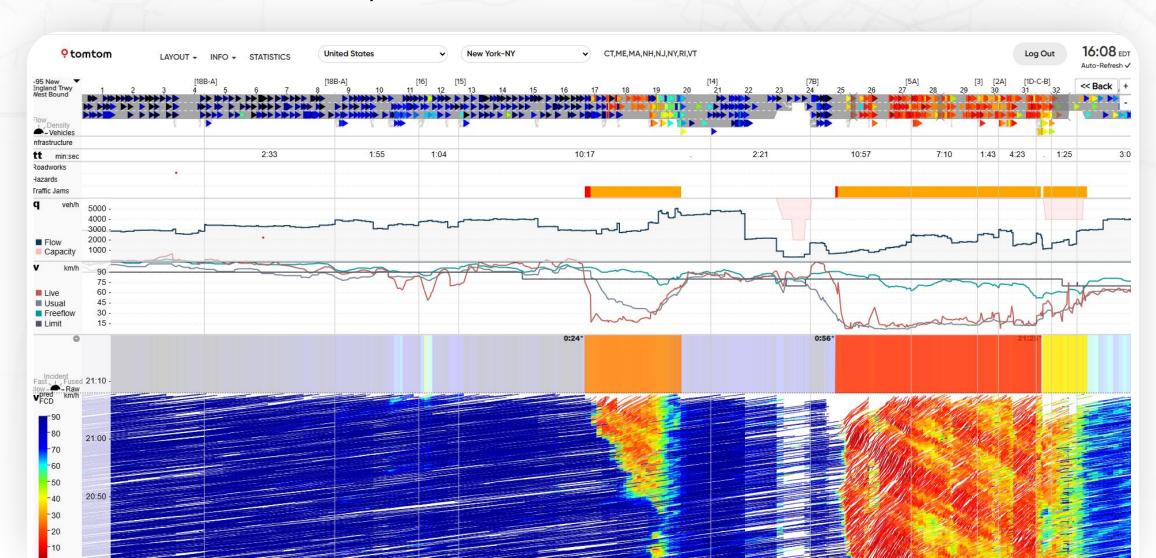


# How we build live traffic



# **Live Traffic Manhattan**

I-95 WB 19 March 2025 4:08pm



# **TomTom MOVE Data Products**

A product suite to build global mobility metrics

# **Traffic Stats**Historical Traffic

- Speeds per segment
- Average speeds
- Average travel-time
- GPS probe counts
- Per segment

### O/D Analysis

Historical Traffic

- Trip based analysis
- Origins, destinations, via-points
- Measure movement between areas, or through selected road connections

### **Route Monitoring**

Real-Time Traffic

- 24/7 measurements of pre-defined routes
- ✓ Real-time speeds and travel-time
- Per route
- Per segment

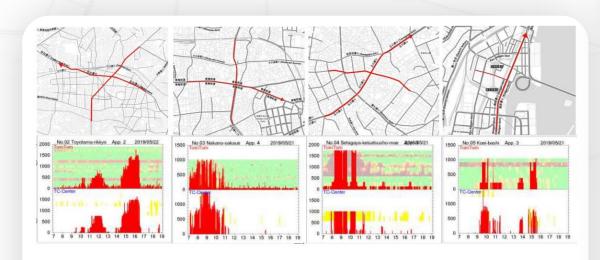
## Junction Analytics

Real-Time Traffic

- Analyze queue length, delay, travel time
- Optimize traffic lights
- Optimize intersections in real-time

# **Closing the Loop**

Signal Time Optimization and Time2Green Service



- Comparison of count measurements vs. TomTom Junction Analytics probe measurements
- Ground truth from 4 Junctions in Tokyo, Japan

### **Speed Advice Service using Time2Green Data**





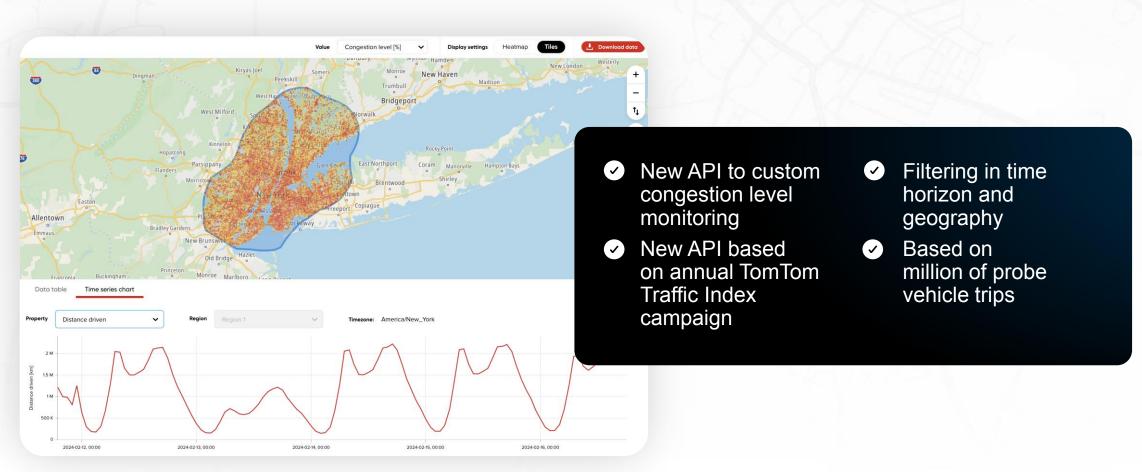
# **TomTom Traffic Index Results 2024**

Annual congestion level comparison of 500 global cities

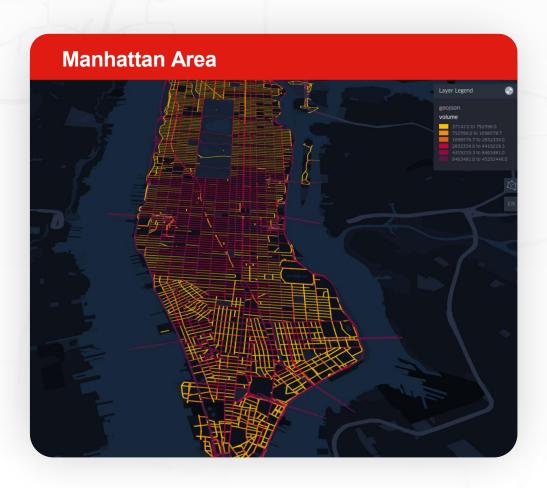
North America Ranking								
Rank by filter	World rank ▼	City	Average travel time per 10 km ▼	Change from 2023 ▼	Congestion level % ▼	Time lost per year at rush hours ▼	Congestion wor	
1	17	Mexico City	31 min 53 s	+ 1 min	52%	152 hours	0	
2	25	New York, NY ■ United States of America	31 min 6 s	+ 40 s	30%	98 hours	222	
3	36	Puebla     Mexico	29 min 57 s	+ 1 min	30%	73 hours	218	
4	65	Guadalajara	27 min 8 s	+ 40 s	42%	103 hours	28	
5	69	Vancouver	27 min 3 s	+ 50 s	35%	86 hours	96	
6	75	San Francisco, CA  ■ United States of America	26 min 32 s	+ 30 s	32%	84 hours	160	
7	79	Leon	26 min 27 s	no change	28%	71 hours	260	
8	95	Toronto	25 min 13 s	+1 min 20 s	31%	77 hours	180	
9	117	Halifax	23 min 31 s	+ 50 s	30%	83 hours	217	
10	129	Winnipeg   -  Canada	23 min 1 s	+ 20 s	26%	74 hours	308	

G	lobal	Ranking					
Rank by filter	World rank ▼	City	Average travel time per 10 km ▼	Change from 2023 ▼	Congestion level % ▼	Time lost per year at rush hours ♥	Congestion world rank ▼
1	0	Barranquilla  Colombia	36 min 6 s	- 20 s	45%	130 hours	16
2	2	Kolkata <b>ヹ</b> India	34 min 33 s	+ 10 s	32%	110 hours	169
3	3	Bengaluru India	34 min 10 s	+ 50 s	38%	117 hours	64
4	4	Pune □ India	33 min 22 s	-1 min	34%	108 hours	128
5	5	London ⊞ United Kingdom	33 min 17 s	+ 40 s	32%	113 hours	150
6	•	• Japan	33 min 16 s	+ 20 s	39%	95 hours	60
7	7	Lima    Peru	33 min 12 s	+1 min 30 s	47%	155 hours	•
8	8	Davao City  Philippines	32 min 59 s	- 30 s	49%	136 hours	3
9	•	Trujillo	32 min 56 s	+ 30 s	34%	102 hours	119
10	10	Dublin I Ireland	32 min 45 s	+ 40 s	47%	155 hours	10

# Measuring Congestion Impact Congestion Index API



# **Analyze Emission Impact** with Traffic Volumes and Traffic flow data



- ✓ In 2023, vehicles in Manhattan drove ~ 4.09 billion miles.
- ✓ Each mile driven emits about 400 grams of CO2. (\*)
- This results in a total of approximately 1.8 million tons of CO2 emissions from vehicle traffic in Manhattan for the year.

(\*) <a href="https://www.epa.gov/greenvehicles/greenhouse-gas-emissions-typical-passenger-vehicle">https://www.epa.gov/greenvehicles/greenhouse-gas-emissions-typical-passenger-vehicle</a>, Neglecting city traffic/congestion/vehicle fleet composition