# Developing Massachusetts-Specific Trip Generation Models for Land Use Projects

Yuanchang Xie, PhD, PE
University of Massachusetts Lowell

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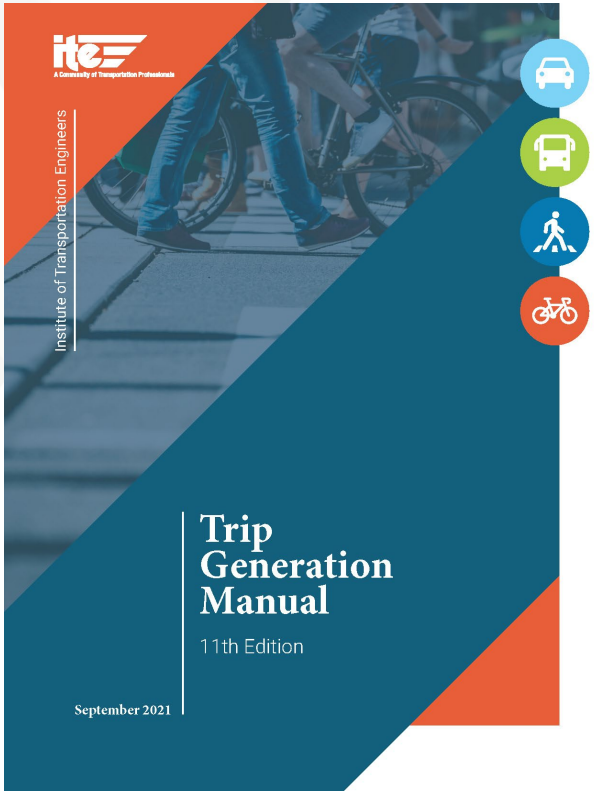
# OUTLINE

- Background
- Emerging Data Sources
- Trip Generation Models based on LBS Data
- Deep Learning Model for Counting Trip Rates
- Conclusions and Future Research

# BACKGROUND




- In the United States, trip rate estimation typically relies on the ITE Trip Generation Manual.
- The ITE manual uses trip generation data derived primarily from suburban project sites that are highly auto-dependent.
- For some land use categories, the ITE data collection sample sizes are relatively small, with data collected many years ago.
- Collecting and updating trip rate data is both time-consuming and expensive.



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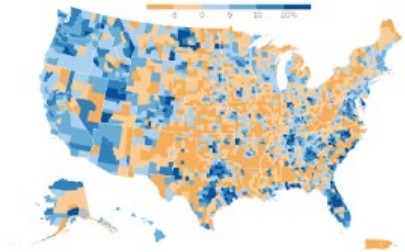
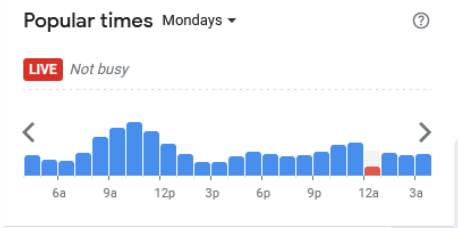
# EMERGING DATA SOURCES

- StreetLight
- Cuebiq
- SafeGraph
- AirSage
- Teralytics
- Gravy Analytics
- Foursquare
- Census
- Employment
- Google
- ……

## Location-Based Service (LBS) data



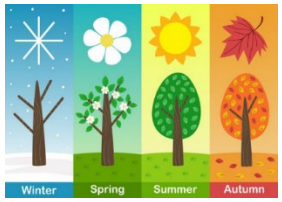




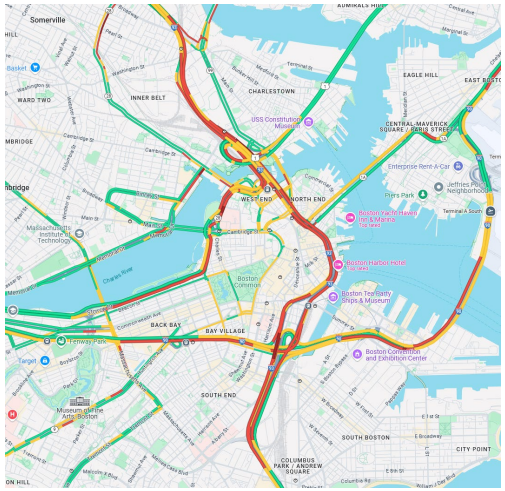
# STREETLIGHT DATA

| | A | B | D | H | I | J | K |
|---|---|---|---|---|---|---|---|
| 1 | Mode of Travel | Zone Type | Zone Name | Day Type | Day Part | Average Daily Zone Traffic (StL Volume) | Avg Travel Time (sec) |
| 2 | All Vehicles - StL All Vehicles Volume | Trip Start | 15 Tobey Road | 0: All Days (M-Su) | 00: All Day (12am-12am) | 3652 | 1891 |
| 3 | All Vehicles - StL All Vehicles Volume | Trip Start | 15 Tobey Road | 0: All Days (M-Su) | 01: 12am (12am-1am) | 1 | 481 |
| 4 | All Vehicles - StL All Vehicles Volume | Trip Start | 15 Tobey Road | 0: All Days (M-Su) | 02: 1am (1am-2am) | 7 | 2459 |
| 5 | All Vehicles - StL All Vehicles Volume | Trip Start | 15 Tobey Road | 0: All Days (M-Su) | 03: 2am (2am-3am) | 6 | 2244 |
| 6 | All Vehicles - StL All Vehicles Volume | Trip Start | 15 Tobey Road | 0: All Days (M-Su) | 05: 4am (4am-5am) | 2 | 1532 |
| 7 | All Vehicles - StL All Vehicles Volume | Trip Start | 15 Tobey Road | 0: All Days (M-Su) | 06: 5am (5am-6am) | 3 | 1933 |
| 8 | All Vehicles - StL All Vehicles Volume | Trip Start | 15 Tobey Road | 0: All Days (M-Su) | 07: 6am (6am-7am) | 16 | 1803 |
| 9 | All Vehicles - StL All Vehicles Volume | Trip Start | 15 Tobey Road | 0: All Days (M-Su) | 08: 7am (7am-8am) | 57 | 1669 |
| 10 | All Vehicles - StL All Vehicles Volume | Trip Start | 15 Tobey Road | 0: All Days (M-Su) | 09: 8am (8am-9am) | 109 | 1972 |
| 11 | All Vehicles - StL All Vehicles Volume | Trip Start | 15 Tobey Road | 0: All Days (M-Su) | 10: 9am (9am-10am) | 165 | 2020 |
| 12 | All Vehicles - StL All Vehicles Volume | Trip Start | 15 Tobey Road | 0: All Days (M-Su) | 11: 10am (10am-11am) | 233 | 1935 |

- Average Daily Zone Traffic (StL Volume)
- Avg Travel Time (sec)
- Avg Trip Length (mi)
- Avg Trip Speed (mph)
- Avg All Trip Circuity
- ……
- Trip Length 0-1 mi (percent)
- ……
- Trip Speed 0-10 mph (percent)
- ……

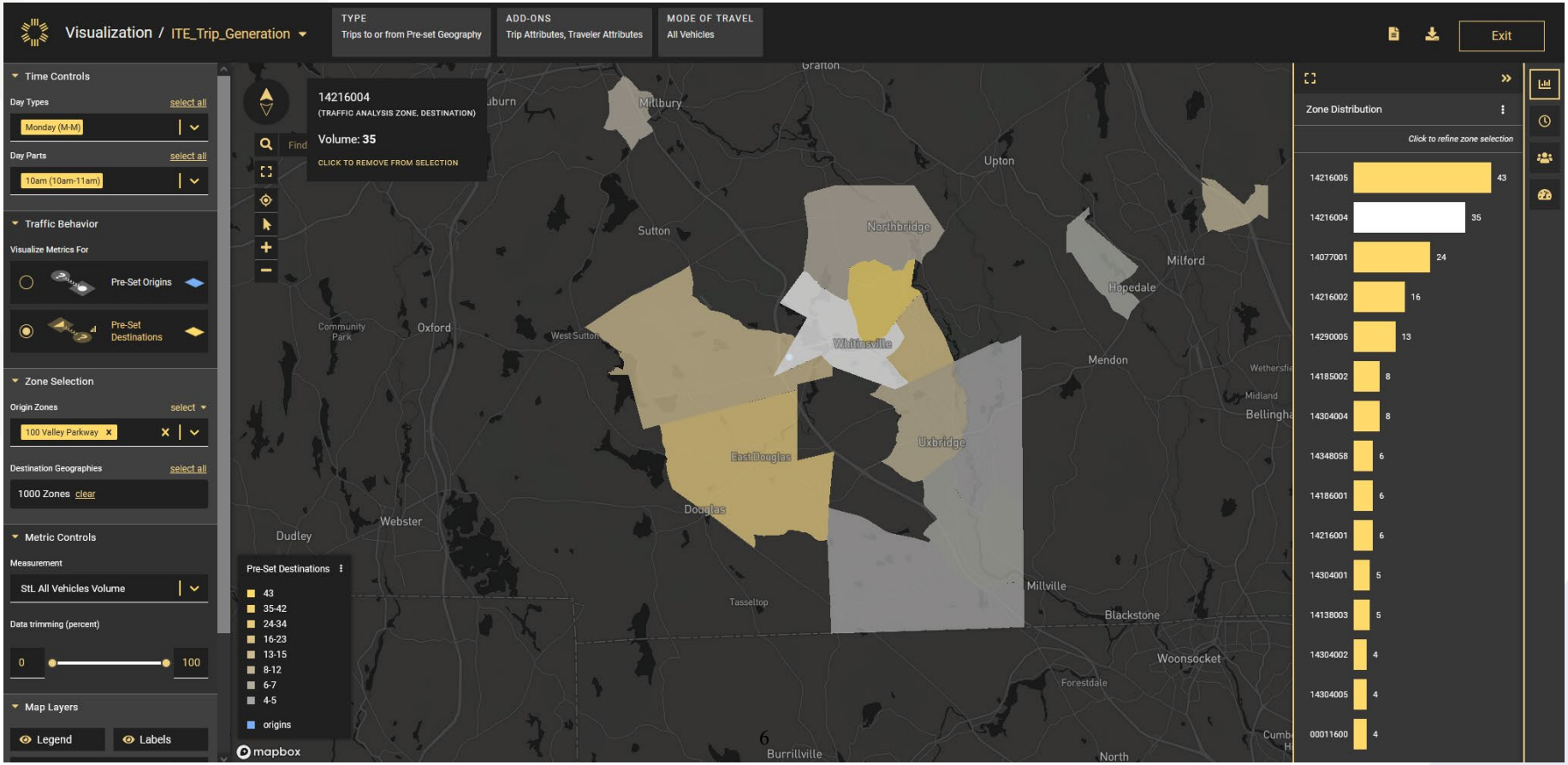






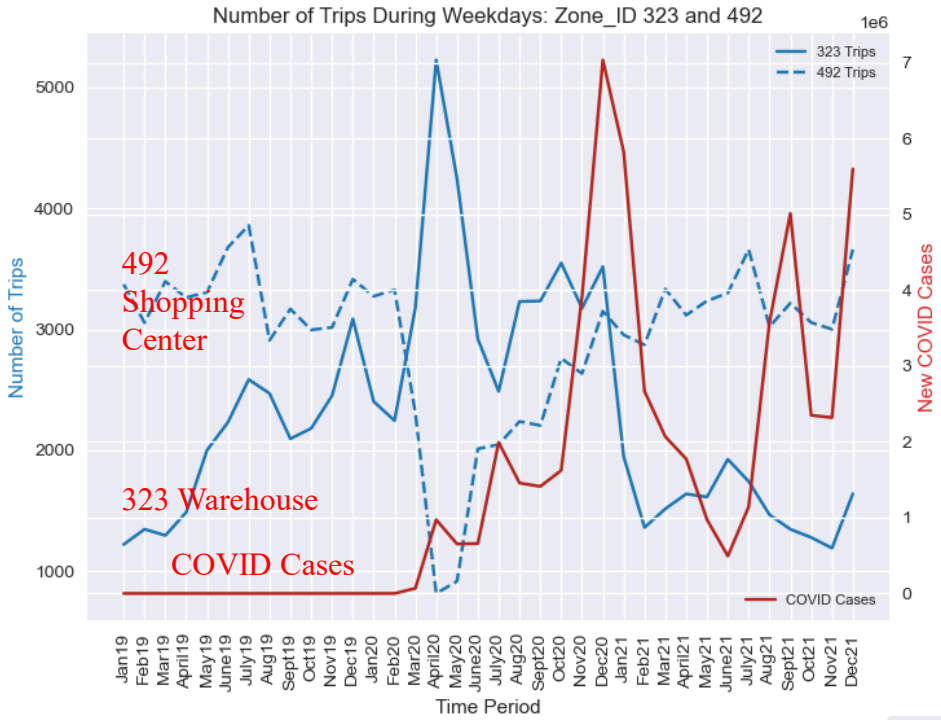
**4pm on Friday** **vs** **4pm on Saturday**

# STREETLIGHT DATA (CONT.)



# STREETLIGHT DATA (CONT.)

- Land use code 150 (high-cube fulfillment center warehouse such as Amazon warehouse), Zone 323.
- Land use code 820 (shopping centers), Zone 492.
- This figure essentially suggests an inverse relationship between trips generated by warehouses and shopping centers.



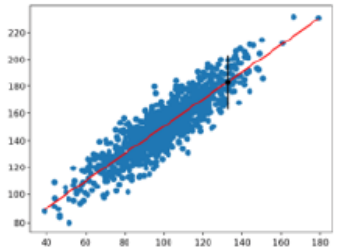

Trip generation results for Zones 323 (high-cube fulfillment center warehouse) and 492 (shopping centers)

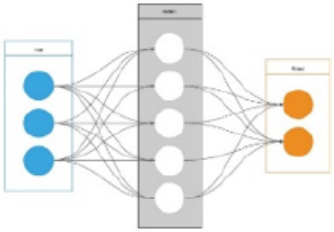
# PROPOSED SOLUTION

**Model Inputs**

- Attributes of the development (e.g., units, sq_ft, # of beds)
- Census
- Employment
- .....

**Statistical/Machine Learning models that connect inputs with outputs**



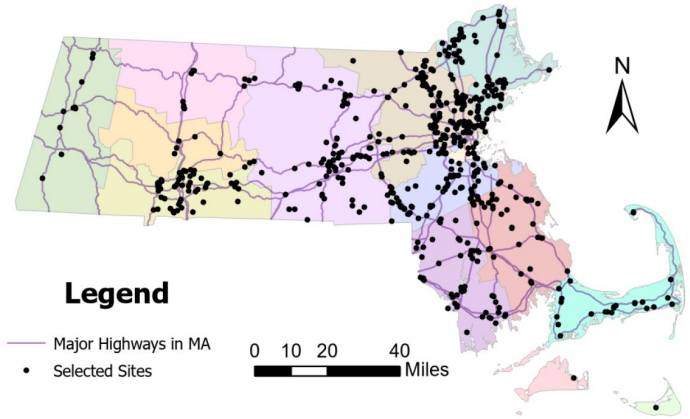



**Model Outputs**

Inbound and outbound trips estimated based on LBS data.

# HIGH-PRIORITY LAND USE CATEGORIES

- Based on the feedback from MassDOT, the following 10 high-priority land use categories were identified.



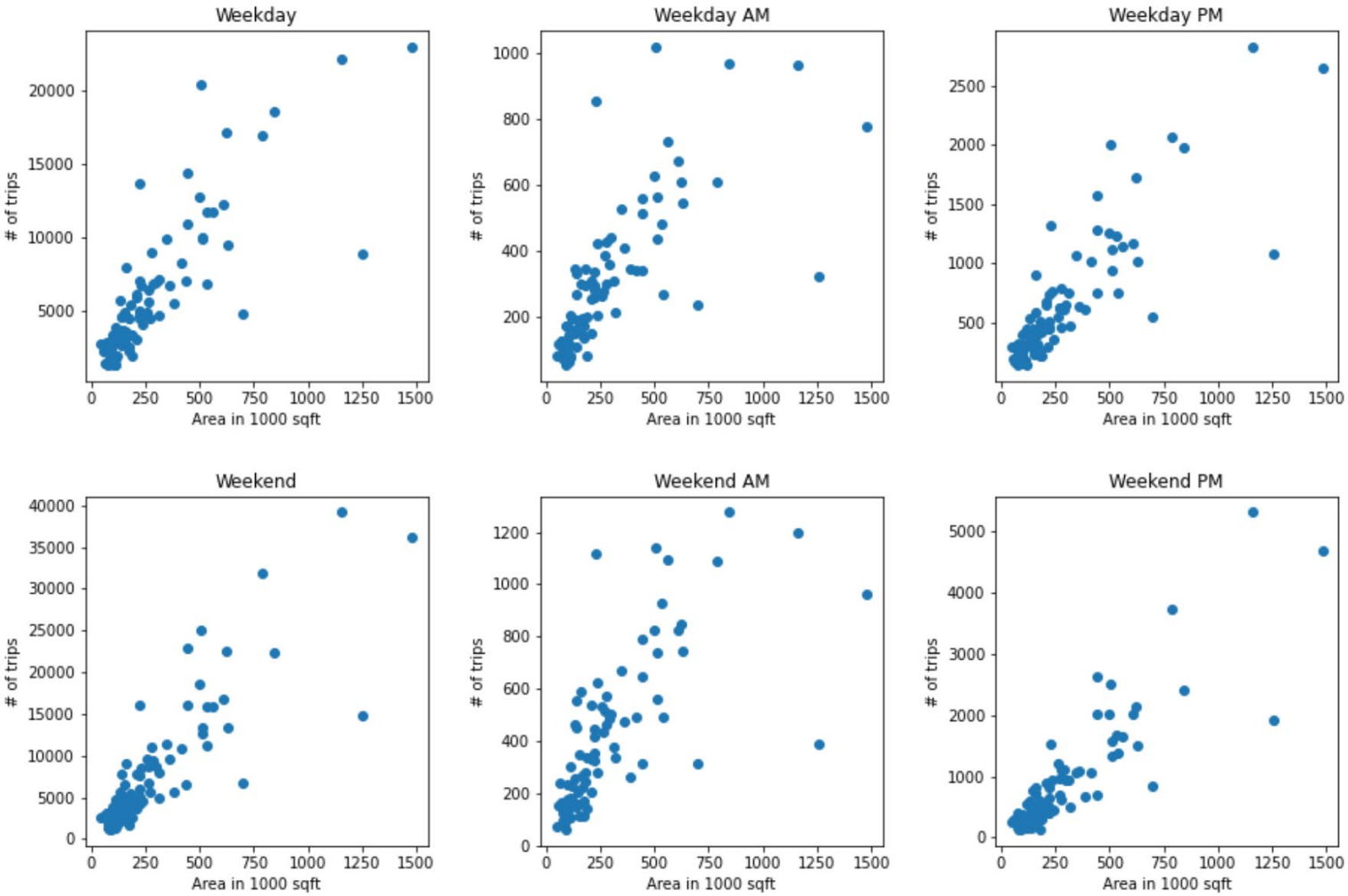

| ID | ITE Code | # of Developments | Land Use Type |
|---|---|---|---|
| 1 | 140 | 75 | Industrial - manufacturing |
| 2 | 150 | 52 | Warehouse |
| 3 | 155 | 19 | High-cube fulfillment center warehouse (e.g., Amazon) |
| 4 | 221 | 49 | Mid-rise multifamily housing |
| 5 | 710 | 72 | General office building |
| 6 | 760 | 41 | Research and development |
| 7 | 813 | 38 | Free standing discount superstore |
| | 815 | 12 | Free standing discount store |
| 8 | 820 | 85 | Shopping centers |
| 9 | 850 | 84 | Supermarket |
| 10 | 960 | 73 | Convenience market /gas station |

- Three datasets were developed:
  - Dataset 1 (before COVID): 11/15/2018-1/15/2019, 2/1/2019-4/1/2019, 6/1/2019-8/1/2019, and 9/1/2019-11/1/2019.
  - Dataset 2 (during COVID): 9/1/2021-11/1/2021.
  - Dataset 3 (toward the end of COVID): 1/1/2022-4/1/2022.

# MODEL DEVELOPMENT

- The following variables have been considered in model fitting:
  - Building square footage (sqft): This was measured based on the tax parcel data and calibrated using Google satellite images.
  - Employment opportunity density (workers/square mile): Based on the center of a site/polygon, the corresponding traffic analysis zone (TAZ) was identified. The TAZ's worker density was used as the employment opportunity density (calculated based on the 2012-2016 CTPP data).
  - Population density (people/square mile): This was done using the same approach and data source as for calculating the employment opportunity density (2012-2016 CTPP database).

# VISUALIZATION OF BUILDING SQUARE FOOTAGE AND TRIPS




Trip and area data for ITE LU Code=820 (Free standing discount superstore)

# MODEL DEVELOPMENT (CONT.)

Model fitting $R^2$ results based on 2018 data (**Before COVID**).

| Land Use Code | Land Use Type | Sample Size | Weekday | Weekday AM | Weekday PM | Weekend | Weekend AM | Weekend PM |
|---|---|---|---|---|---|---|---|---|
| 140 | Industrial—manufacturing | 75 | 0.5 | 0.4 | 0.4 | 0.32 | 0.33 | 0.23 |
| 150 | Warehouse | 51 | 0.43 | 0.29 | 0.38 | 0.28 | 0.34 | 0.33 |
| 155 | High-cube fulfillment center warehouse | 19 | 0.06 | 0.1 | 0.2 | 0.09 | 0.18 | 0.23 |
| 221 | Mid-rise multifamily housing | 49 | 0.9 | 0.92 | 0.87 | 0.89 | 0.87 | 0.87 |
| 710 | General office building | 72 | 0.68 | 0.58 | 0.56 | 0.16 | 0.07 | 0.07 |
| 760 | Research and development | 41 | 0.47 | 0.45 | 0.55 | 0.04 | 0.14 | 0.02 |
| 820 | Shopping centers | 85 | 0.71 | 0.66 | 0.71 | 0.74 | 0.58 | 0.81 |
| 850 | Supermarket | 84 | 0.5 | 0.43 | 0.48 | 0.52 | 0.47 | 0.49 |
| 960 | Convenience market/gas station | 73 | 0.31 | 0.3 | 0.29 | 0.28 | 0.25 | 0.23 |
| 813 Or 815 | Free standing discount store and superstore | 50 | 0.64 | 0.63 | 0.65 | 0.66 | 0.68 | 0.68 |

# MODEL DEVELOPMENT (CONT.)

Model fitting $R^2$ results based on 2021 data (**During COVID**).

| Land Use Code | Land Use Type | Sample Size | Weekday | Weekday AM | Weekday PM | Weekend | Weekend AM | Weekend PM |
|---|---|---|---|---|---|---|---|---|
| 140 | Industrial—manufacturing | 75 | 0.5 | 0.24 | 0.25 | 0.18 | 0.02 | 0.06 |
| 150 | Warehouse | 51 | 0.65 | 0.52 | 0.6 | 0.48 | 0.56 | 0.42 |
| 155 | High-cube fulfillment center warehouse | 19 | 0.14 | 0.05 | 0.22 | 0.33 | 0.08 | 0.27 |
| 221 | Mid-rise multifamily housing | 49 | 0.74 | 0.87 | 0.71 | 0.71 | 0.62 | 0.74 |
| 710 | General office building | 72 | 0.34 | 0.32 | 0.3 | 0.15 | 0.22 | 0.13 |
| 760 | Research and development | 41 | 0.25 | 0.24 | 0.15 | 0.11 | 0.17 | 0.11 |
| 820 | Shopping centers | 85 | 0.7 | 0.57 | 0.77 | 0.73 | 0.52 | 0.8 |
| 850 | Supermarket | 84 | 0.49 | 0.45 | 0.42 | 0.48 | 0.43 | 0.44 |
| 960 | Convenience market/gas station | 73 | 0.48 | 0.33 | 0.51 | 0.4 | 0.24 | 0.48 |
| 813 Or 815 | Free standing discount store and superstore | 50 | 0.7 | 0.64 | 0.72 | 0.72 | 0.67 | 0.76 |

# MODEL DEVELOPMENT (CONT.)

Model fitting $R^2$ results based on 2022 data (**End of COVID**).

| Land Use Code | Land Use Type | Sample Size | Weekday | Weekday AM | Weekday PM | Weekend | Weekend AM | Weekend PM |
|---|---|---|---|---|---|---|---|---|
| 140 | Industrial—manufacturing | 75 | 0.42 | 0.19 | 0.12 | 0.24 | 0.1 | 0.14 |
| 150 | Warehouse | 51 | 0.69 | 0.55 | 0.5 | 0.41 | 0.56 | 0.32 |
| 155 | High-cube fulfillment center warehouse | 19 | 0.12 | 0.02 | 0.17 | 0.14 | 0.01 | 0.13 |
| 221 | Mid-rise multifamily housing | 49 | 0.86 | 0.86 | 0.84 | 0.86 | 0.83 | 0.84 |
| 710 | General office building | 72 | 0.35 | 0.29 | 0.21 | 0.16 | 0.13 | 0.1 |
| 760 | Research and development | 41 | 0.29 | 0.28 | 0.23 | 0.16 | 0.09 | 0.11 |
| 820 | Shopping centers | 85 | 0.68 | 0.53 | 0.72 | 0.74 | 0.5 | 0.77 |
| 850 | Supermarket | 84 | 0.44 | 0.37 | 0.4 | 0.46 | 0.36 | 0.44 |
| 960 | Convenience market/gas station | 73 | 0.45 | 0.35 | 0.44 | 0.35 | 0.21 | 0.34 |
| 813 Or 815 | Free standing discount store and superstore | 50 | 0.68 | 0.61 | 0.72 | 0.71 | 0.69 | 0.71 |

# AI-BASED VEHICLE DETECTION & TRACKING

- Deriving trip generation data from the recorded traffic videos is essentially an *object detection and tracking problem*.
- We use YOLOv8 as our object detector.
  - Anchor-free object detection: center-based mechanism to detect objects, making it more efficient and accurate.
  - Comes in various sizes: Nano to Extra-Large.
- We used the YOLOv8-Medium model.
  - Larger models did not perform clearly better than the YOLOv8-Medium model.
- Tracking: Deep-SORT is a reliable and effective tracking algorithm.
  - Associate the detected bounding boxes with unique vehicle identities and track them over multiple frames of the input video.

# AI ANALYSIS RESULTS

YOLOv8 can accurately localize and identify partially visible objects across a variety of contexts and scenarios.

# CAMERA PLACEMENT ISSUES

1. Bright headlights blinding the camera at night.

2. Vehicles on the main road obstructing the view of development entry/exit points.




# COMPARISON RESULTS

The absolute percentage errors of the 2022 StreetLight data and ITE estimates compared to the ground truth (2023) data.

| Site | Streetlight Data 7-8 AM | Streetlight Data 8-9 AM | Streetlight Data 4-5 PM | Streetlight Data 5-6 PM | ITE AM | ITE PM |
|---|---|---|---|---|---|---|
| 373 | 42% | 38% | 52% | 25% | 64% | 79% |
| 374 | 85% | 71% | 34% | 30% | 207% | 25% |
| 376 | 267% | 37% | 118% | 145% | 98% | 15% |
| 379 | 201% | 115% | 5% | 42% | 117% | 14% |
| 408 | 24% | 56% | 47% | 45% | 219% | 5% |
| 409 | 56% | 91% | 100% | 100% | 281% | 150% |
| 410 | 18% | 77% | 143% | 111% | 1% | 67% |
| 434 | 63% | 0% | 8% | 0% | 166% | 49% |
| 437 | 71% | 83% | 73% | 57% | 115% | 30% |
| 443 | 69% | 66% | 72% | 88% | 23% | 18% |
| 682 | 67% | 79% | 48% | 9% | 45% | 9% |
| 690 | 100% | 0% | 28% | 35% | 424% | 131% |
| 774 | 222% | 9% | 34% | 34% | 60% | 14% |
| Average Across Sites | 99% | 56% | 59% | 55% | 140% | 47% |

Average for each method: StreetLight data, 67%; ITE, 94%

# ADDITIONAL COMPARISON

| Site Name | Town | Address | ITE Land Use Code | Observed AM/Midday Peak | | StreetLight AM/Midday Peak | | Observed PM Peak | | StreetLight PM Peak | | Date Data Was Observed |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Exit | Enter | Exit | Enter | Exit | Enter | Exit | Enter | |
| **Southfield** | Weymouth | 200 Trotter Road | 220 | 158 | 96 | 117 | 63 | 150 | 155 | 139 | 146 | May 2016 |
| **Stoneham Crossing** | Stoneham | 225 Fallon Road | 221 | 93 | 15 | 73 | 15 | 37 | 81 | 17 | 77 | Nov/Dec 2018 |
| **Upland** | Norwood | 1 Upland Woods Circle | 220 | 81 | 23 | 118 | 21 | 35 | 69 | 36 | 66 | 10/18/2018 |
| **Walmart** | Wareham | 15 Tobey Road | 813 | 490 | 482 | 469 | 404 | 338 | 314 | 323 | 294 | May and July 2018 |
| **Walmart** | North Adams | 1415 Curran Memorial Highway | 813 | 412 | 398 | 467 | 447 | 322 | 325 | 383 | 407 | Sept and Oct 2016 |
| **Walmart** | Northbridge | 100 Valley Parkway | 813 | 431 | 461 | 529 | 514 | 325 | 335 | 453 | 419 | March in 2012 |
| **Wegmans** | Burlington | 53 Third Avenue | 850 | 310 | 311 | 334 | 366 | 274 | 267 | 280 | 299 | June in 2015 |

# CONCLUSIONS

- The proposed method using LBS data to develop trip generation models is both feasible and promising.
  - Square footage, employment density, and population density were considered as explanatory variables; however, only building square footage was found to be statistically significant.
  - Overall, weekday models demonstrated better goodness-of-fit than those developed for weekends.
- Our AI tool performed well, accurately extracting vehicle counts from videos.
- The AI algorithm can enable large-scale collection of ground truth data.

# FUTURE RESEARCH

- Explore alternative data sources
- Incorporate additional variables
- Collect long-term data to establish seasonal adjustment factors
- Investigate edge computing and the use of more advanced sensors

# ONGOING RESEARCH

# ONGOING RESEARCH (CONT.)

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# ONGOING RESEARCH (CONT.)

# Thank you!

For further information, please contact Yuanchang_Xie@uml.edu

**Main contributors:**

Brandon Loesch
Benyuan (Ben) Liu
Danjue Chen
Francesco Logozzo
Zubin Bhuyan

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