From Space to Flow: Modeling Human Mobility with Satellite Imagery and Deep Learning

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Context and Motivation

The hosting company

Locatium, the hosting company for this thesis, is a retail-optimization company specializing in geospatial analytics.It helps businesses make data-driven decisions on where to open new stores, understand local competition, and optimize their networks through on-demand spatial intelligence.

Locatium.AI

Context and Motivation

The Objective

This thesis uses a U.S. case study focused on the state of Alabama, where Locatium aimed to estimate gas-station sales on behalf of its clients. The goal was to build a framework that first automates the creation of georeferenced polygons for points of interest, an essential prerequisite for working with human mobility data and then develops a predictive model that estimates mobility within those polygons as a proxy for sales.

Context and Motivation

Industry Demands

- Generate accurate georeferenced polygons for all gas station sites to serve as the spatial foundation for analytics.
- Develop a predictive framework for gas station sales, leveraging the polygons and human mobility data as inputs

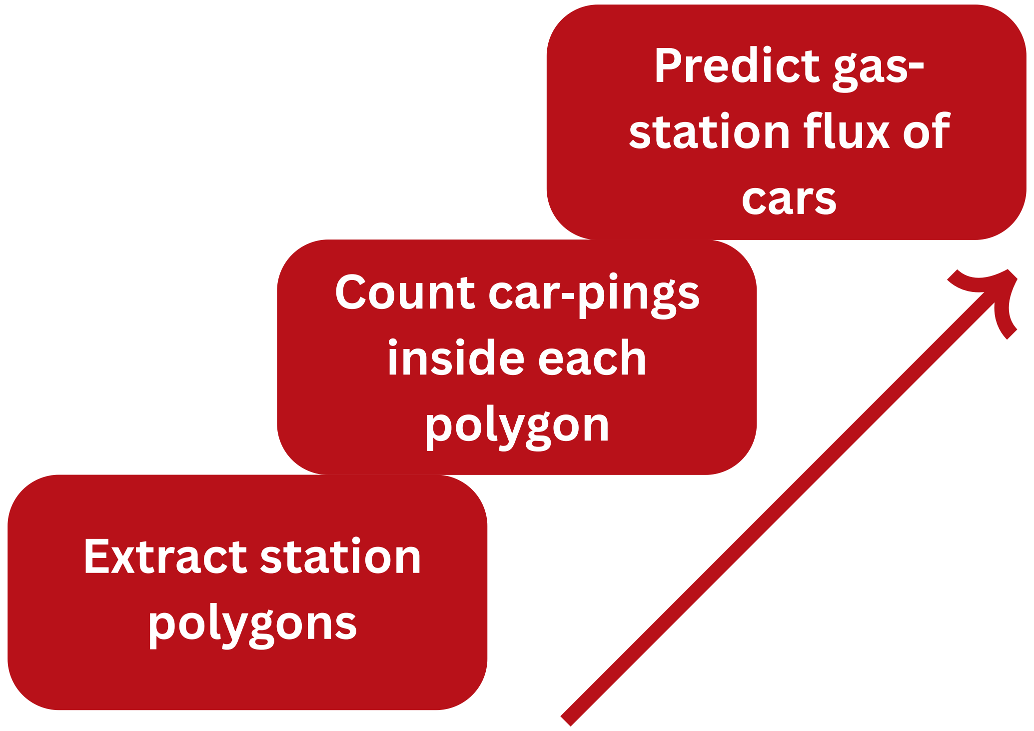
Research Questions

- Extend existing computer-vision methods for extracting site geometry from satellite imagery, contributing to the advancement of automated geospatial feature acquisition.
- Develop a case-specific human-mobility modelling framework that refines and adapts gravity-based approaches, contributing methodological improvements to spatial interaction modelling.

Context and Motivation

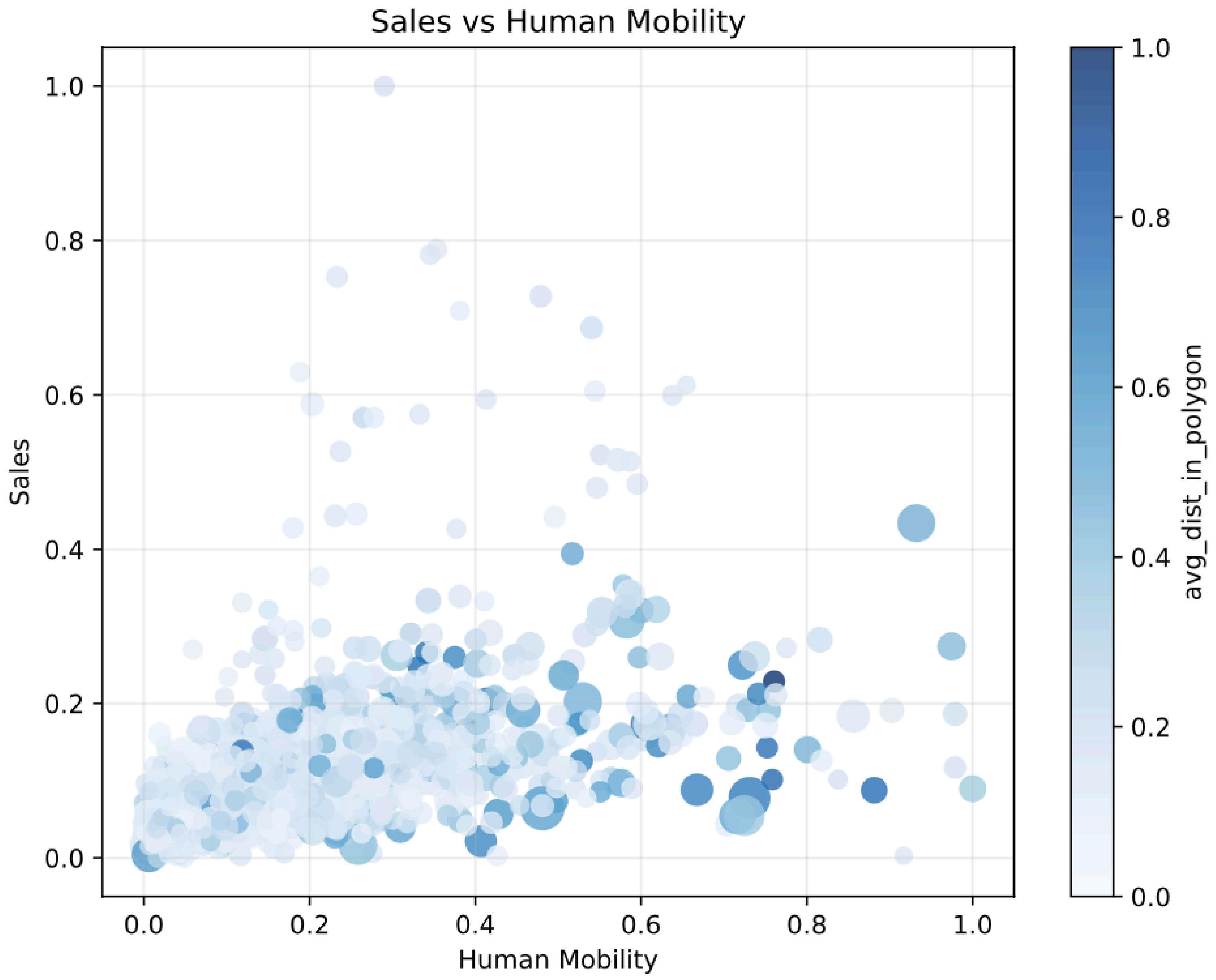
Overview of the workflow

1. **Collect and preprocess data:** human mobility and satellite imagery of gas station sites.
2. **Segment gas station parcels:** train computer vision model and generate polygons.
3. **Aggregate car trajectories:** count pings within each gas station polygon and link site-specific features.
4. **Predict gas station flux:** train the mobility model and obtain predicted flows.



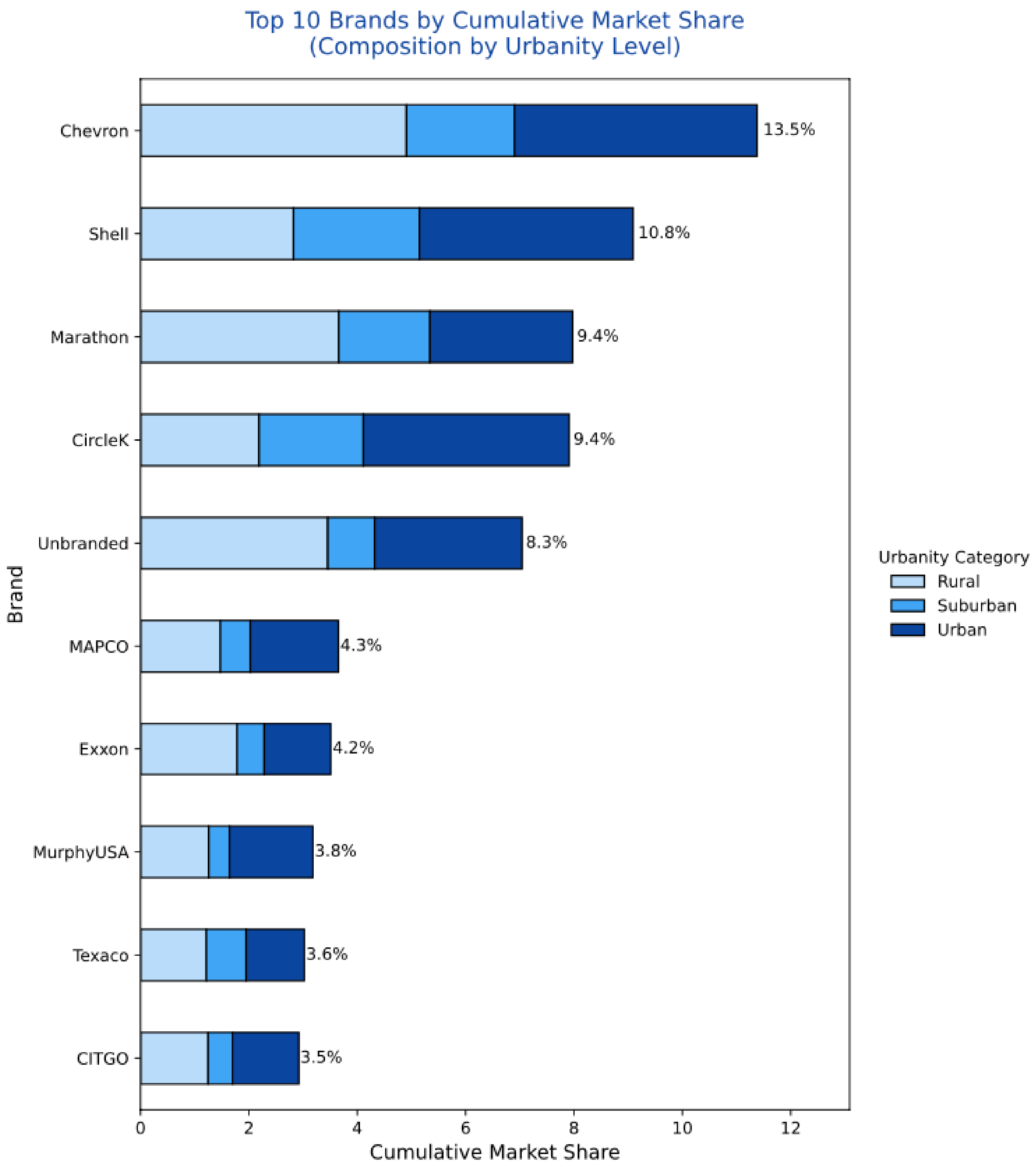
Mobility as a proxy for sales

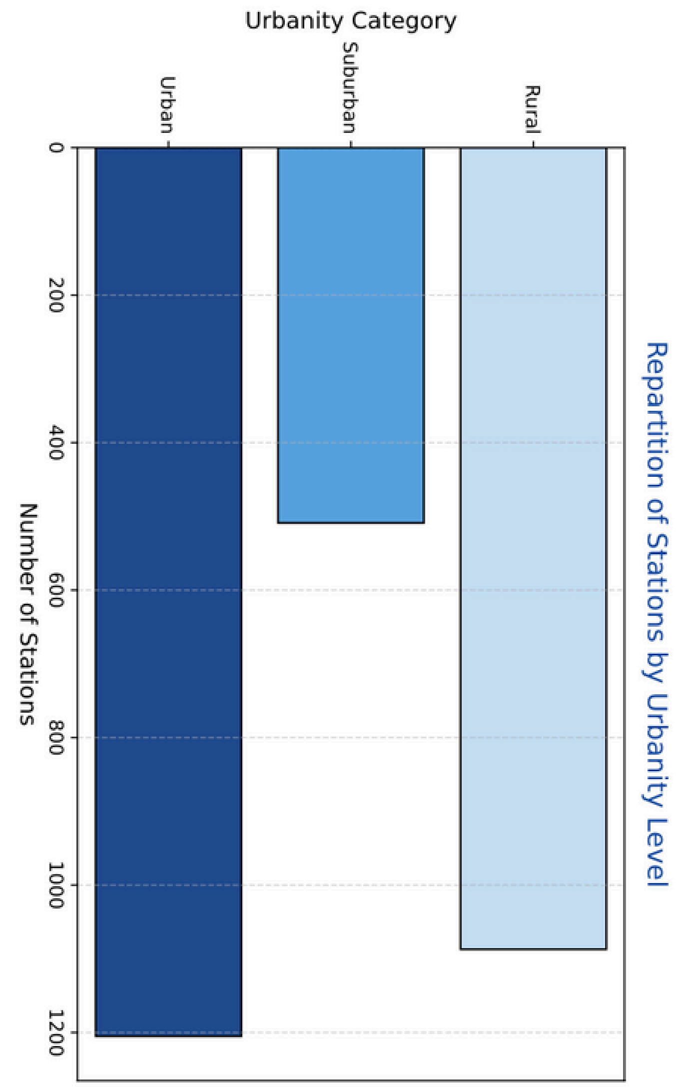
The relationship is noisy, as expected from behavioural data, but there is a clear positive association: the Pearson correlation between mobility and sales is approximately 0.7, indicating a strong linear relationship and supporting the use of mobility as a predictive feature.

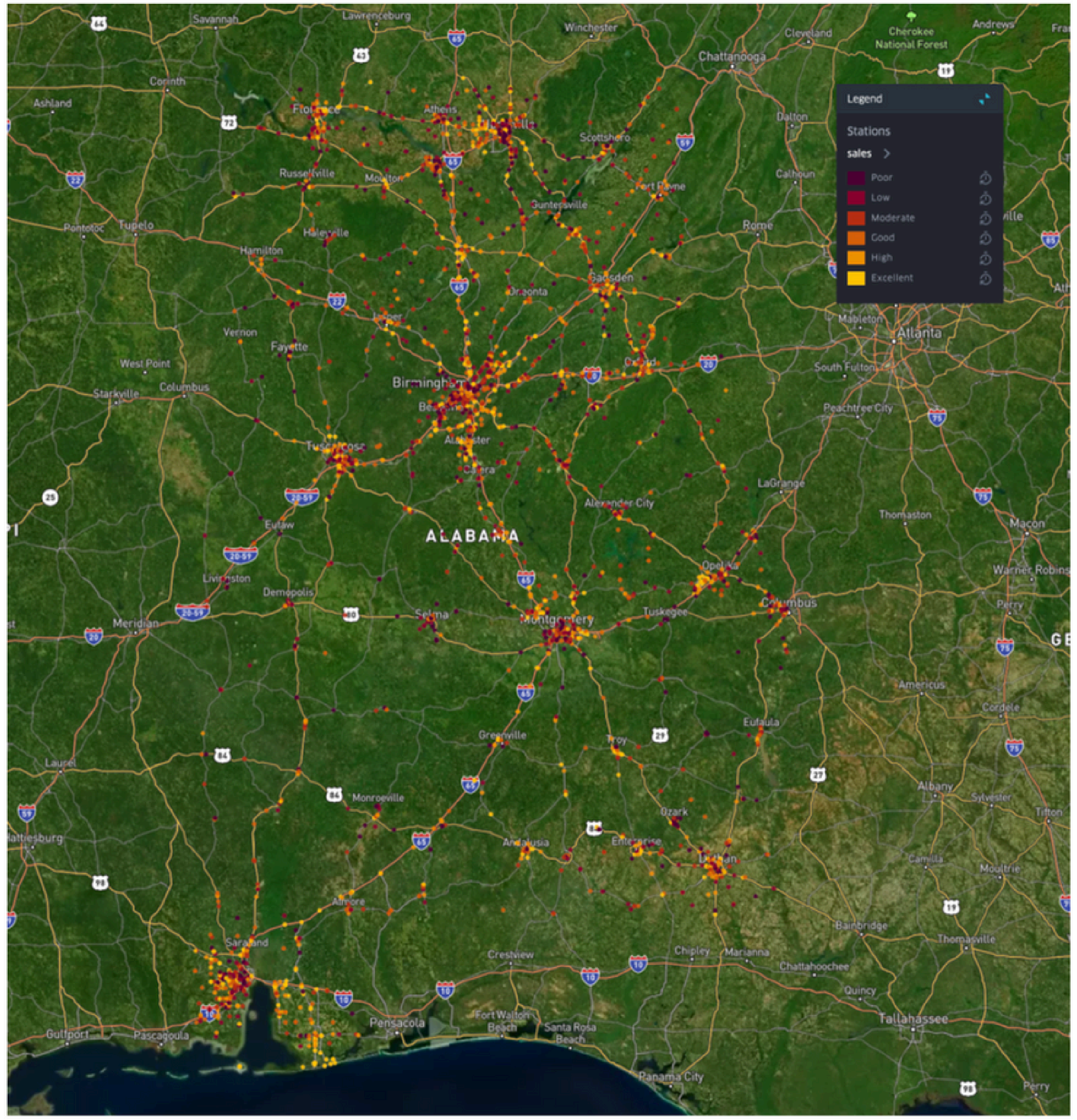


Gas Stations in Alabama

The dataset contains 2,801 fuel stations across Alabama.

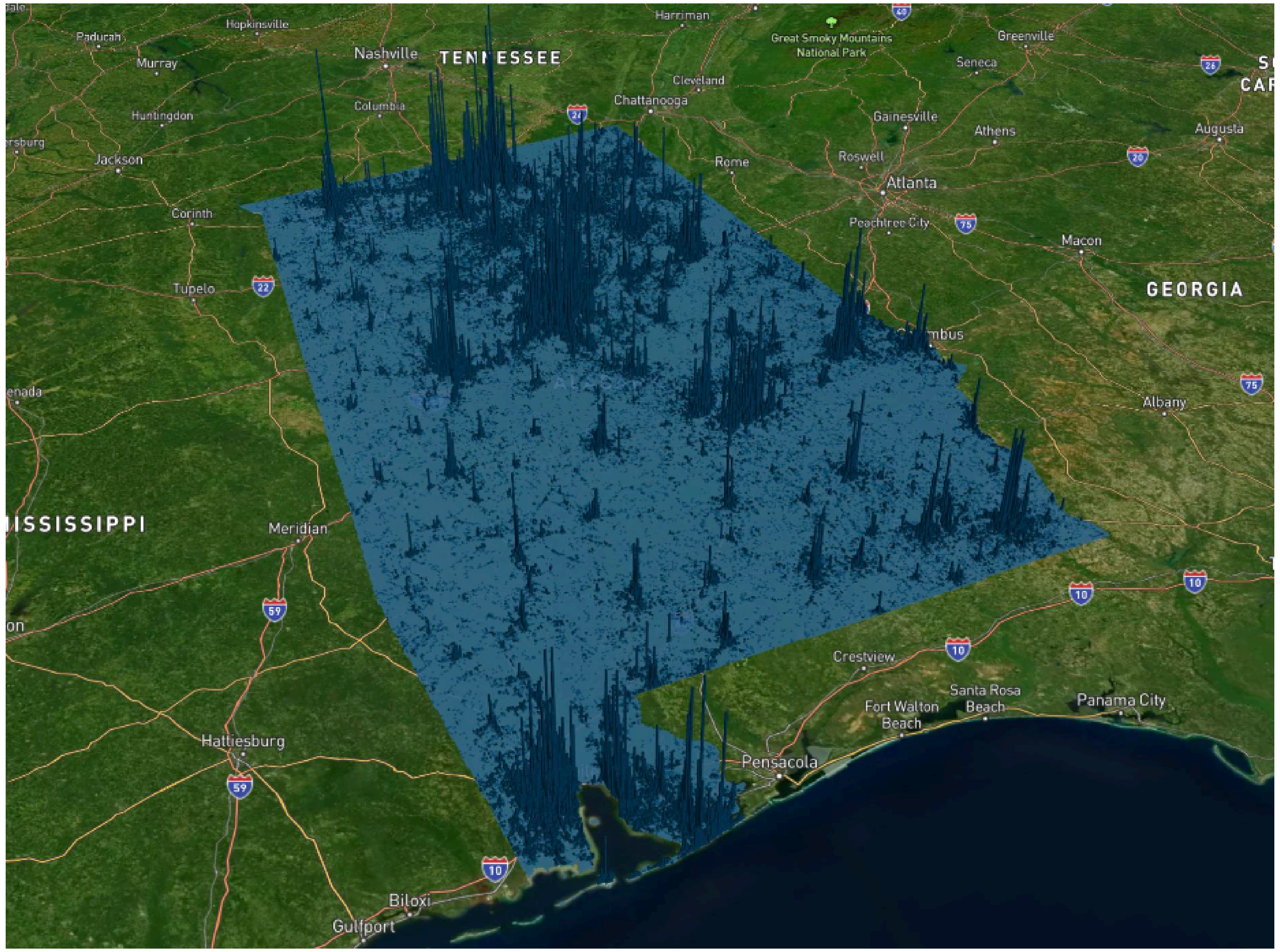






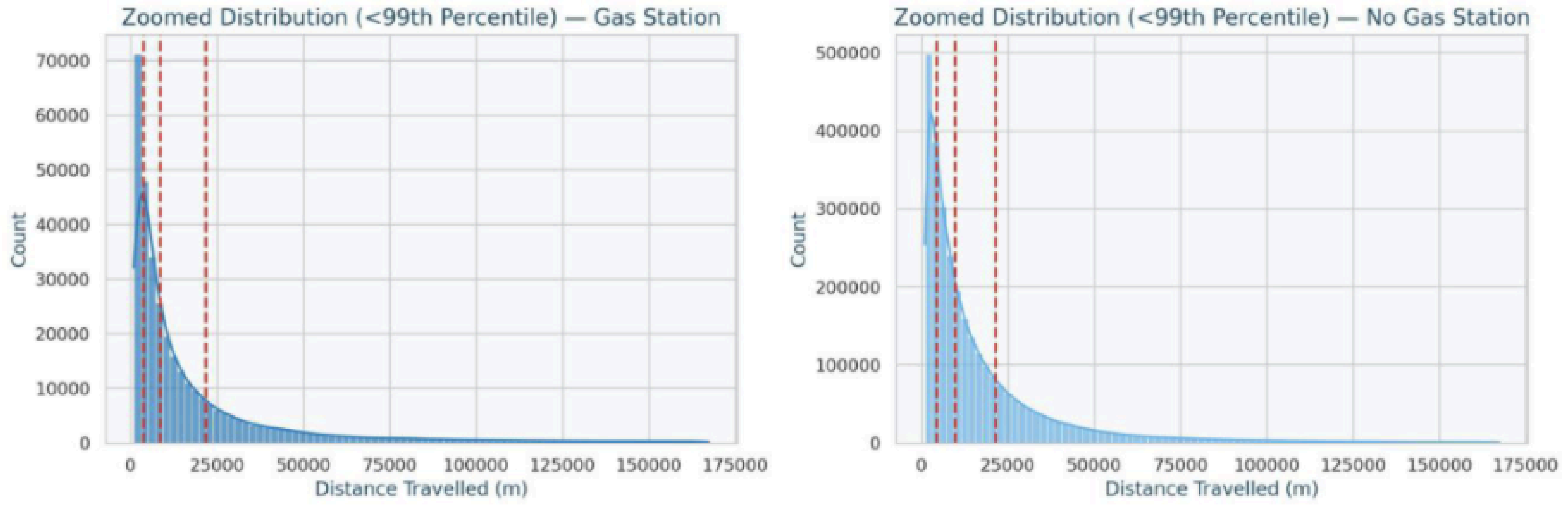
Mobility Data

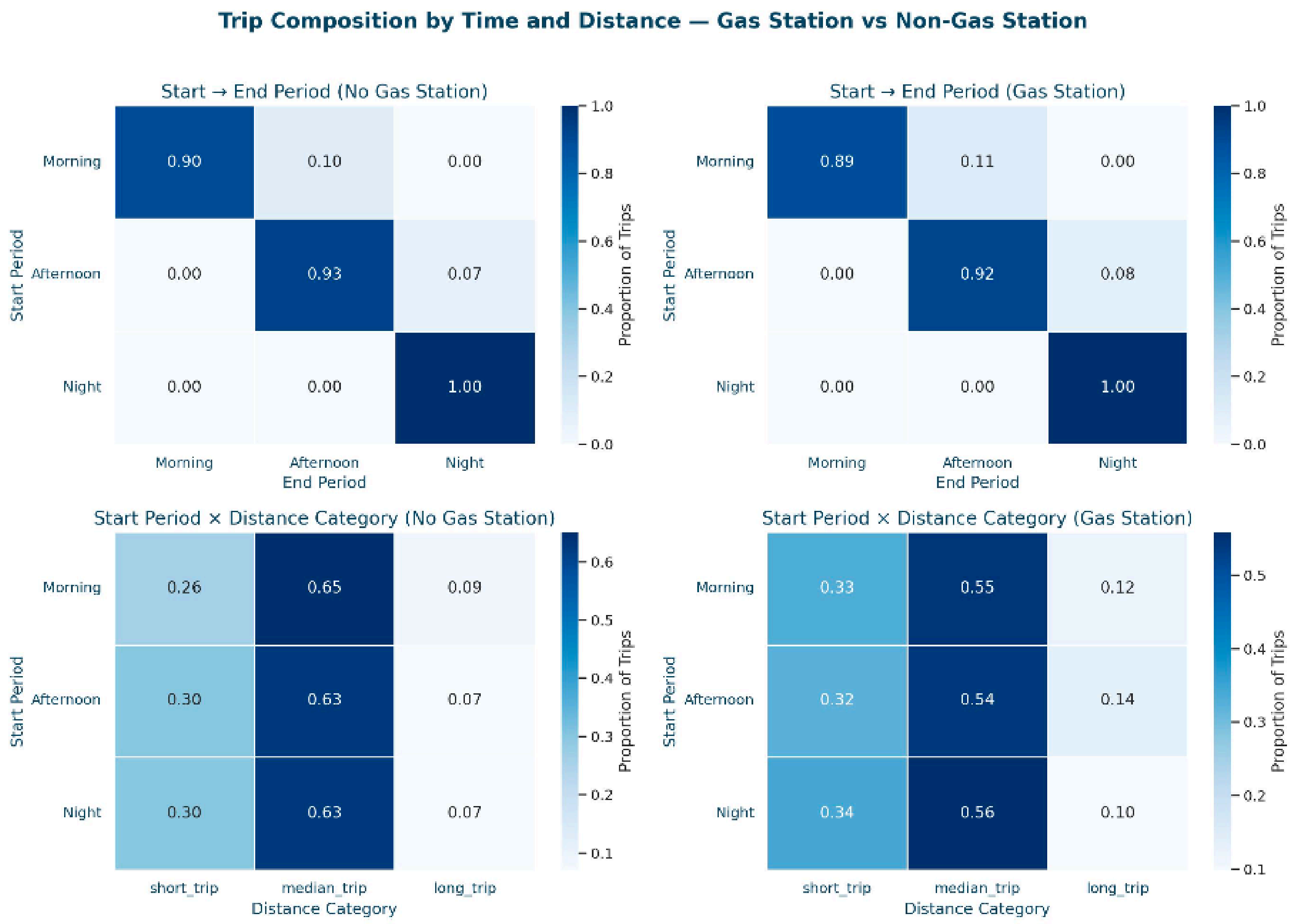
The human mobility dataset consists of car-location pings collected throughout May 2024. The data is trajectory-based, but trajectories do not represent full continuous trips: a new trajectory begins every time a vehicle's engine is turned off, which fragments movement patterns. For internal confidentiality reasons, the identity of the mobility data provider cannot be disclosed.



Mobility Data

The distribution of distances traveled by trajectories that end in a gas station is similar to that of trajectories that do not.





There is also no evident difference in the timing of the trips.

Obtain Site Parcels

Foundational Literature and Methodological Starting Point

While numerous papers apply deep learning to satellite imagery, *Gao et al. (2021)* [1] is particularly relevant for its YOLOv3-based detection of gas-station footprints.

The authors developed an improved YOLO architecture capable of reliably identifying gas-station buildings in remote-sensing images.

Extending this line of work, YOLOv11 is used here to perform precise segmentation of gas-station parcels.

Satellite Imagery

The YOLOv11 model was fine-tuned on a diverse dataset of over 12,000 gas-station images, primarily from California and supplemented with stations from southern and midwestern states.

Images were obtained from the company’s internal provider, whose identity cannot be disclosed, and pre-centered on the station parcels to facilitate segmentation while retaining contextual features.

Obtain Site Parcels

Training Set Up

The dataset was partitioned into training (70%), validation (15%), and test (15%) sets to ensure robust model development and reliable performance evaluation.

Training ran for just over 70 epochs with batch size 16 and a learning rate scheduler that ramped up in the first 5 epochs then decayed linearly. Metrics improved rapidly during the first 15 epochs before plateauing. Data augmentation, including rotations and geometric transformations, was applied to enhance robustness.

Results

The YOLOv11 model achieved high precision, recall, and mAP in detecting and segmenting gas station parcels. This strong performance is partly due to images being pre-centered on each station, which simplified the task for the model.

Any missed or poorly segmented stations were manually corrected using QGIS, ensuring complete and accurate polygon coverage.

Metric	Precision	Recall	mAP@50	mAP@50:95
Bounding Boxes	0.973	0.964	0.983	0.609
Segmentation Masks	0.960	0.951	0.965	0.574

Human Mobility Modelling

Review of Existing Models for Mobility Prediction

- **Zigh (Intercity Movement of Persons):** Models mobility as a function of attractors and deterrents. [2]
  - takeaway: mobility can be captured through attraction vs. resistance.

- **Gravity Model:** Predicts flows between locations proportional to their “mass” and inversely to distance [3].
  - takeaway: distance decay and mass effects are key.

$$T_{ij} = a_i \, O_i \, b_j \, D_j \, g(c_{ij}), \qquad a_i^{-1} = \sum_k b_k D_k g(c_{ik}), \quad b_j^{-1} = \sum_k a_k O_k g(c_{kj}).$$

- **Radiation Model:** Considers flows based on intervening opportunities between origin and destination [4].
  - takeaway: intermediate locations influence mobility.

$$T_{ij} = \frac{O_i}{1 - m_i/M} \, \frac{m_i \, m_j}{(m_i + s_{ij})\,(m_i + m_j + s_{ij})}.$$

- **Deep Gravity Model:** Uses a neural network to learn spatial interactions from data [5].
  - takeaway: contextual training improves predictive accuracy.

$$s_{ij} = \mathrm{MLP}_\theta\big(\mathbf{z}_i \,\|\, \mathbf{z}_j \,\|\, \phi(d_{ij})\big) \qquad \hat{y}_{ij} = \frac{\exp(s_{ij})}{\sum_{k=1}^{n} \exp(s_{ik})}, \quad \sum_{j=1}^{n} \hat{y}_{ij} = 1 \qquad \widehat{\mathrm{Flow}}_{ij} = O_i \, \hat{y}_{ij}$$

Human Mobility Modelling

Motivation for a Graph-Based Approach

Building on insights from the most relevant literature, an effective model for predicting mobility at a station should combine attraction-like features, contextual information from neighboring stations, and strong predictive power.

This motivates a neural network that leverages spatial context, naturally leading to a graph-based approach where station relationships are encoded and a readout layer generates the final predictions.

Challenges of Fine-Scale Mobility Prediction

Predicting flux at the store level cannot rely on traditional origin-destination approaches due to the fine granularity. Classical models work at larger scales between administrative units, whereas we target mobility to individual gas station polygons.

At this scale, trajectories ending at a station are hard to distinguish by length, speed, or timing, and aggregating fluxes in 1 km^2 grids shows little correlation with distance, exposing the limits of conventional OD methods.

Human Mobility Modelling

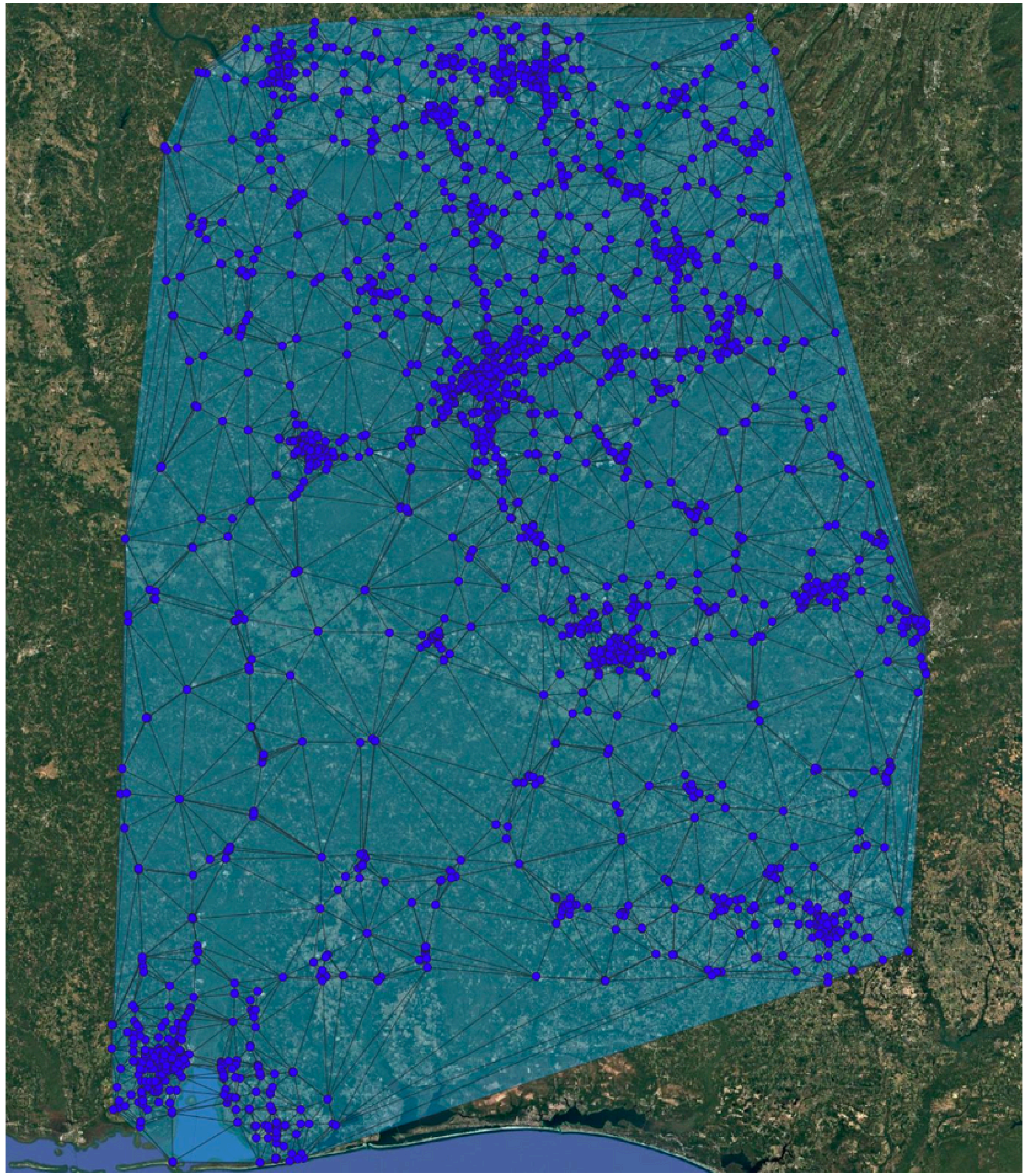
Gas station features

- **Parcel geometry:** area, orientation, rectangularity, elongation
- **Street-network context:** number of neighboring streets, network density, average road level, degree of urbanity
- **Spatial context:** gravity pull of neighboring cities (neighbor_city_gravity_d25000_e15), mean distance to k-nearest neighbors (mean_knn_dist)

Graph Construction

We construct the spatial graph using Delaunay triangulation, chosen for its geometric fidelity and practical interpretability.

- **Competition:** Delaunay triangulation produces a planar, sparse graph that naturally connects stations likely to compete locally while keeping computational complexity low.
- **Edge Weight:** Weighted edges encode interaction strength via distance-decay, ensuring closer stations exert stronger influence than distant ones.
- **Well known:** The method is widely used in geospatial and urban analytics, making the resulting graph intuitive and easy for practitioners to interpret.



Human Mobility Modelling

Graph-Convolutional Architectures for Gas Station Mobility Modeling

We implement two complementary graph-based models to predict station-level mobility:

Graph Convolutional Network (GCN)[6]:

- Every neighbor contributes with fixed importance determined purely by graph structure.
- If edge weights exist (e.g., your distance kernel), they modulate the aggregation but they do not allow the model to learn how important each neighbor is.

$$\mathbf{X}' = \hat{\mathbf{D}}^{-1/2}\hat{\mathbf{A}}\hat{\mathbf{D}}^{-1/2}\mathbf{X}\Theta, \quad \alpha_{j,i} = \frac{1}{\sqrt{\hat{d}_j \hat{d}_i}}, \qquad \hat{d}_i = 1 + \sum_{j \in \mathcal{N}(i)} e_{j,i}$$

$$\mathbf{x}'_i = \Theta^\top \sum_{j \in \mathcal{N}(i) \cup \{i\}} \alpha_{j,i}\, e_{j,i}\, \mathbf{x}_j.$$

Graph Attention Network (GAT)[7][8]:

- Each neighbor gets a learned importance weight.
- Weights depend on its features, the target node's features, AND the edge features.
- Neighbors can be emphasized or ignored dynamically.

$$\mathbf{x}'_i = \sum_{j \in \mathcal{N}(i) \cup \{i\}} \alpha_{i,j}\, \Theta \mathbf{x}_j,$$

$$\alpha_{i,j} = \frac{\exp\left(\mathbf{a}^\top \mathrm{LeakyReLU}\left(\Theta_s \mathbf{x}_i + \Theta_t \mathbf{x}_j + \Theta_e \mathbf{e}_{i,j}\right)\right)}{\sum_{k \in \mathcal{N}(i) \cup \{i\}} \exp\left(\mathbf{a}^\top \mathrm{LeakyReLU}\left(\Theta_s \mathbf{x}_i + \Theta_t \mathbf{x}_k + \Theta_e \mathbf{e}_{i,k}\right)\right)}.$$

A final linear readout layer maps the last hidden representation to per-node predictions:

$$\hat{\mathbf{y}} = \mathbf{X}^{(L)} \mathbf{w}_{\text{out}} + b_{\text{out}}$$

Human Mobility Modelling

GCN vs. GAT: Training and Test Performance

Graph Convolutional Network (GCN):

Model	Train R^2	Val R^2	Test R^2
Shallow 64, ReLU	0.150	0.015	0.014
Shallow 128, ELU	0.121	0.031	0.018
Medium 128–64, ReLU + Res	0.412	0.334	0.240
Medium 128–64, GELU	0.185	0.074	0.064
Deep 128–128–64, ReLU + Res	0.435	0.350	0.242
Deep 128–128–64, ELU	0.149	0.050	0.030
Wide 256–128, SELU	0.109	0.062	0.016
Compact 64–32, ReLU	0.152	0.072	0.058

Metric	**Value**
R^2_{overall}	≈ 0.35
RMSE	≈ 32
MAE	≈ 21

Graph Attention Network (GAT):

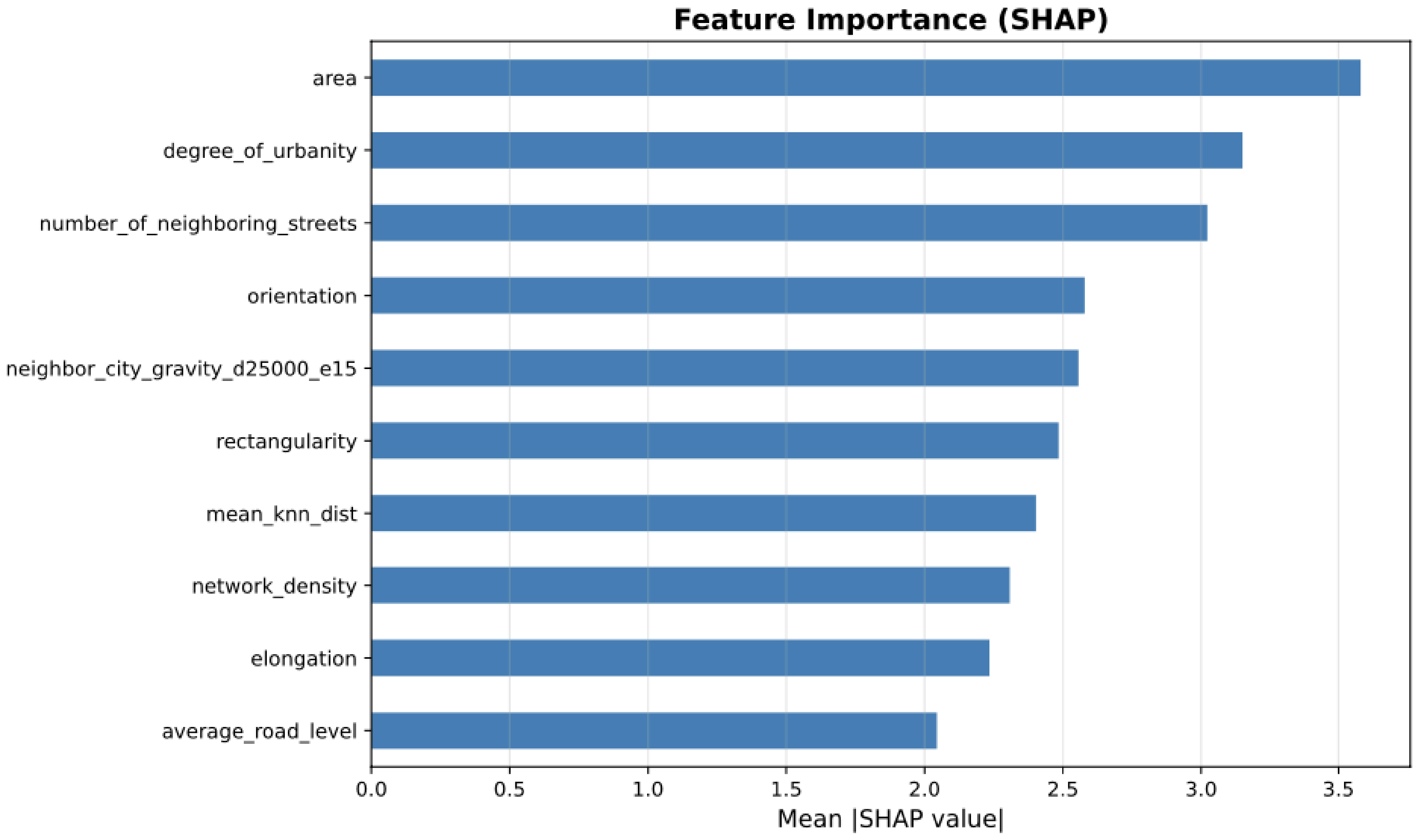
Model	Train R^2	Val R^2	Test R^2
Shallow 64, ReLU	0.382	0.339	0.244
Shallow 128, ELU	0.551	0.378	0.263
Medium 128–64, ReLU	0.493	0.368	0.262
Medium 128–64, GELU	0.448	0.374	0.260
Deep 128–128–64, ReLU	0.428	0.389	0.267
Deep 128–128–64, ELU	0.512	0.371	0.235
Wide 256–128, SELU	0.342	0.345	0.241
Compact 64–32, ReLU	0.508	0.348	0.236
Compact 64–32, GELU	0.443	0.338	0.243
Super-wide 512–256–128	0.616	0.380	0.236

Metric	**Value**
R^2_{overall}	≈ 0.39
RMSE	≈ 28
MAE	≈ 19

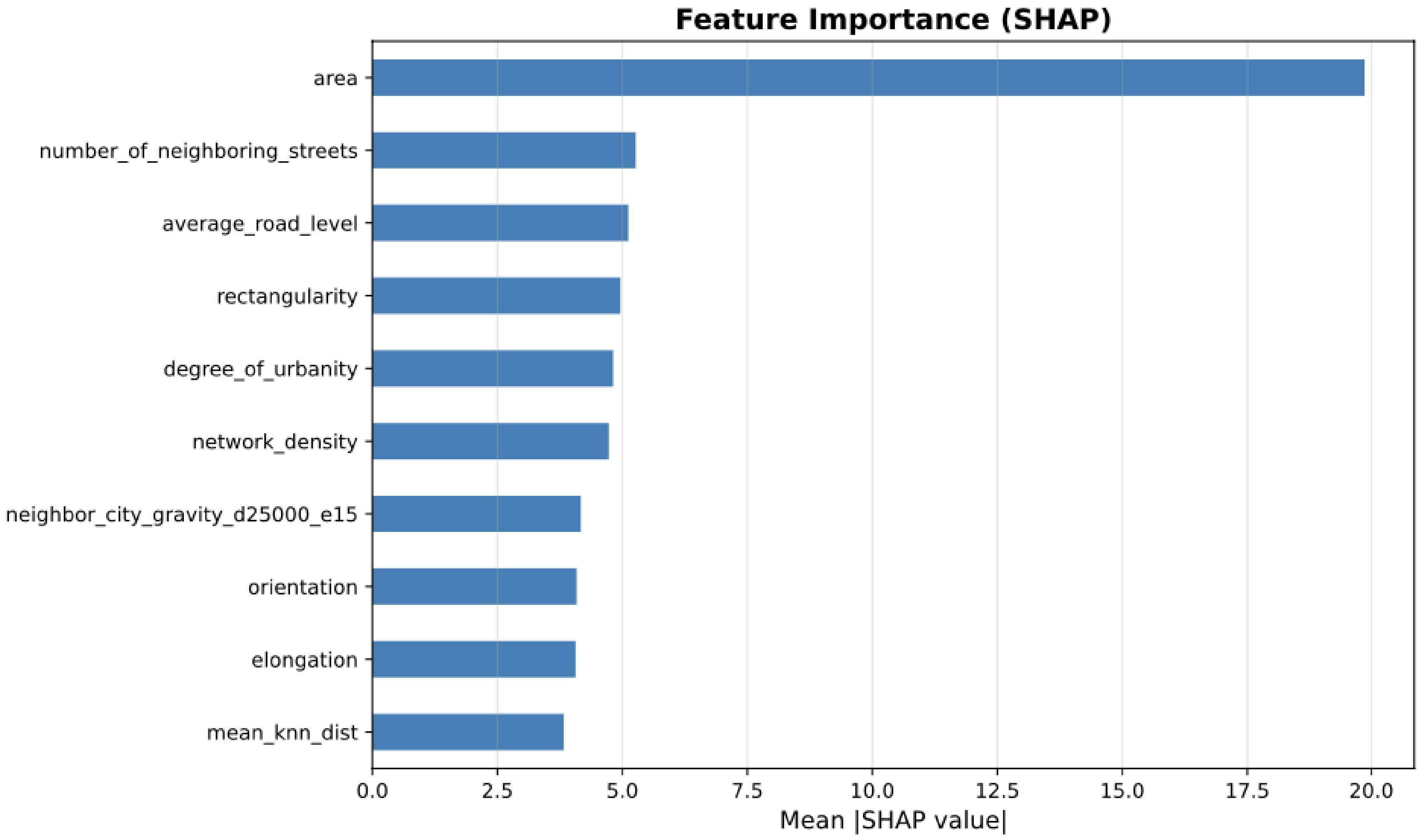
Human Mobility Modelling

GCN vs. GAT: Training and Test Performance

Graph Convolutional Network (GCN):



Graph Attention Network (GAT):



Limitations

- **<u>Month</u>:** Human mobility data is available only for May 2024, preventing the analysis of seasonal or month-to-month patterns that could meaningfully influence fuel demand.

- **<u>Location</u>:** The study is geographically and temporally limited to a single U.S. state and one month of data, which may restrict generalizability.

- **<u>IDs</u>:** Access to individual vehicle IDs would enable socio-economic inference, finer temporal segmentation of flows, and better characterization of different driver classes.

- **<u>Static</u>:** The models are static, without incorporating spatio-temporal dynamics or exploring alternative model families.

Future Work

- **Graph type:** Explore alternative graph constructions, including road-network-based, distance-weighted, or traffic-aware connectivity schemes.
- **More features:** Enrich the set of fuel-station features with additional spatial, demographic, economic, and mobility-derived descriptors.
- **More mobility:** Incorporate mobility data from multiple months or years to capture seasonal variation and long-term behavioral patterns.
- **Driver profiling:** Characterize different classes of users based on home location, trip distribution, and other socio-economic attributes to better understand demand heterogeneity.

Conclusions

We developed a framework to predict U.S. gas station sales using fine-grained human mobility trajectories within YOLO-segmented station parcels. Graph neural networks were employed to explicitly capture local competition and spatial context, integrating multi-scale spatial features with competitive interactions to improve prediction accuracy over traditional gravity-based and shallow models.

This approach highlights the advantage of leveraging **parcel-level mobility data** over coarse county-level aggregates, enabling more actionable insights for location planning, network optimization, and data-driven retail strategy. By incorporating **local competitive dynamics through graph-based hidden states,** it provides a more precise, and robust framework for analyzing and forecasting station performance.

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Thank you for the attention!