

From Machine Learning to Large Models for Spatial Human Mobility

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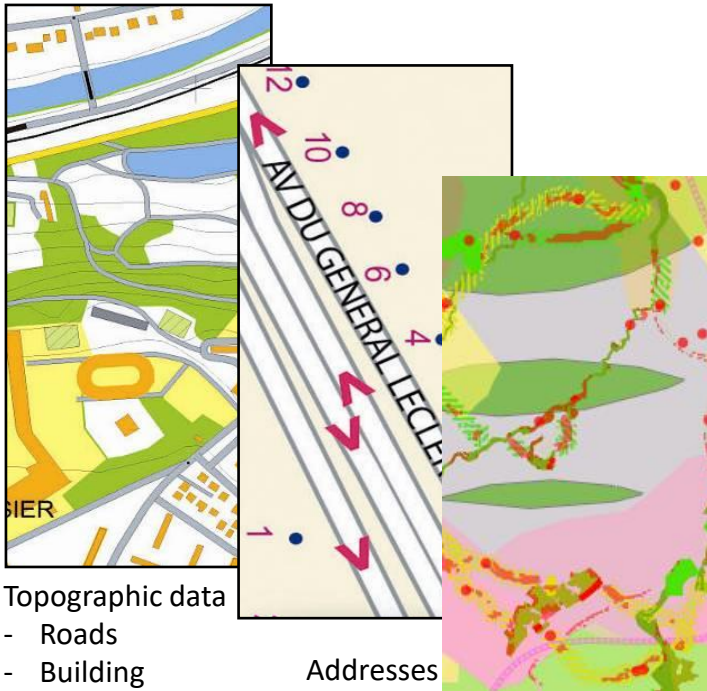
Amir Badawi, Ana-Maria Olteanu-Raimond, Arnaud Le Guilcher, Karine Zeitouni, Harnessing Large Language Models for Predicting Mobility Modes 2025 26th IEEE International Conference on Mobile Data Management (MDM), June 2025, Irvine, France. pp.222-227

**FAAI 2025
October 20 2025**

Context: VGI vs. authoritative data

■ Authoritative geographic data

- Produced by an institution in response to a public mission



Topographic data

- Roads
- Building
- Landmarks
- Etc.

Addresses

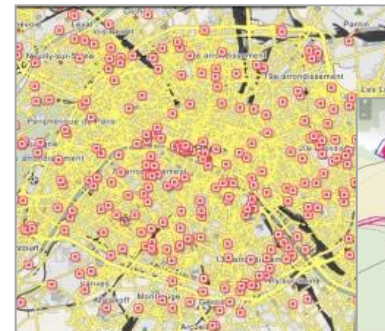
LULC data

■ VGI: Volunteered Geographic Information

- Produced by non-institutional community to build a shareable commons

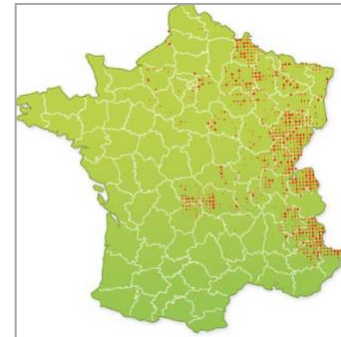


OpenStreetMap



Wikimapia :
public gardens
in Paris

VigiNature :
Birds observations



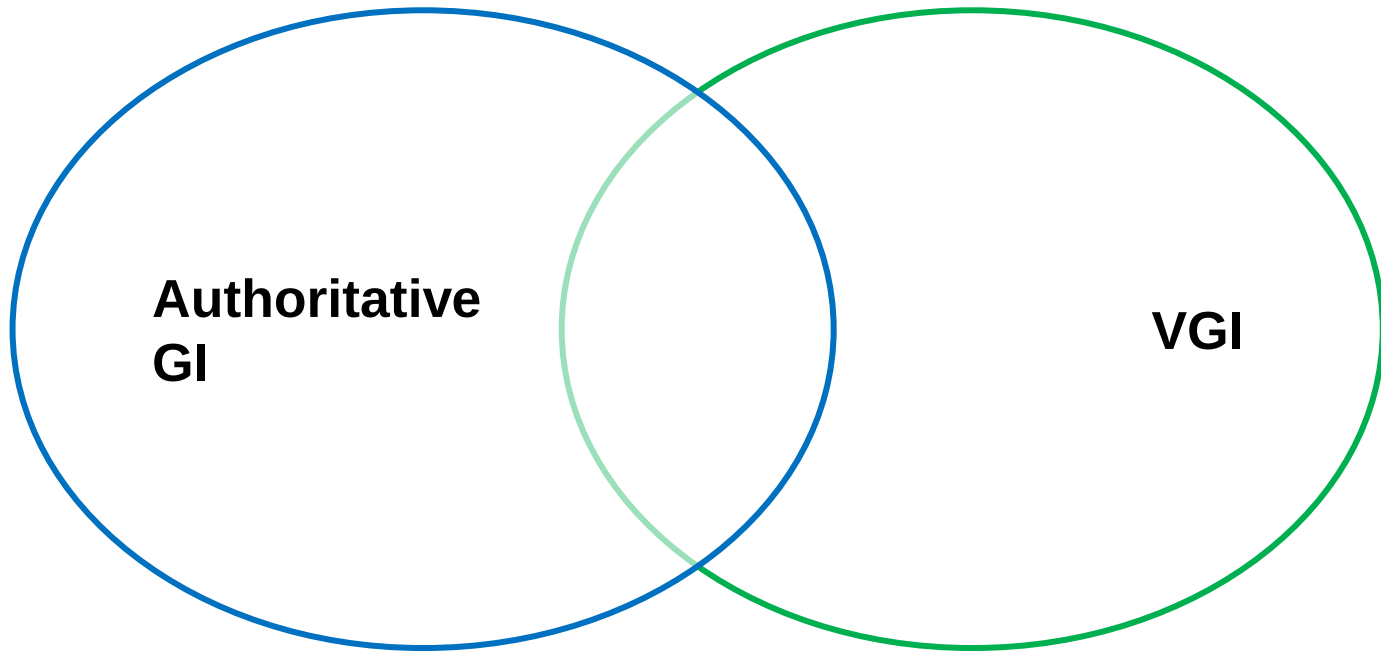
Websites sharing GPS traces



Crisp boundary

Research hypothesis

Two pieces of information that enrich each other...



... and generate new applications

Active human mobility

ACTIVE MOBILITY

- **Active mobility**: any form of travel that involves human physical activity as the main source of movement, rather than relying on motorized vehicles
 - Walking, biking, scooters, running, etc.



Source image: ©IA

ACTIVE MOBILITY

- Why *active mobility* is important ?
 - Sustainable Transport planning
 - is central to urban and non urban transport planning for a more sustainable, livable, and accessible areas.
 - Health
 - improves physical health, supports well-being

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 - Health
 - improves physical health, supports well-being

Increase of outdoor activities

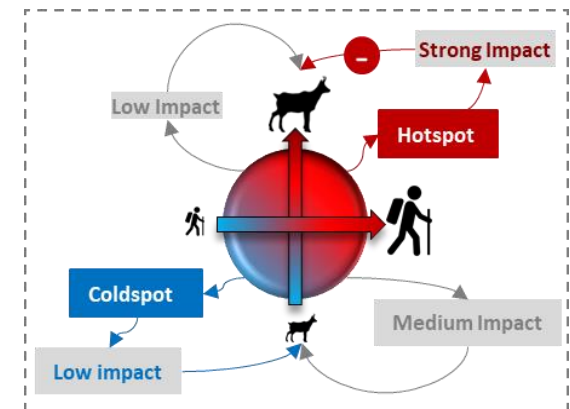


ACTIVE MOBILITY

- Why *active mobility* is important ?
 - Sustainable Transport planning
 - is central to urban and non urban transport planning in the push for more sustainable, livable, and accessible areas.
 - Health
 - improves physical health, supports well-being
 - Sustainable tourism
 - Less congestion and noise for tourist destinations, promotes local and slow tourism, preserves heritage sites
 - Ecosystems protection
 - measures the pression of outdoor activities and bring sustainable solutions



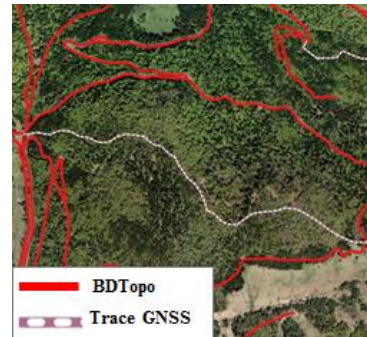
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© ANR IntForOut Project **IGN**

ACTIVE MOBILITY: APPLICATIONS

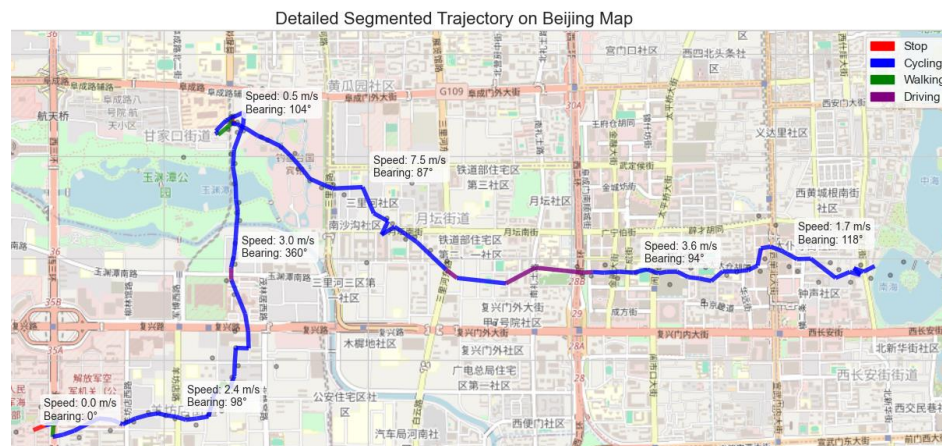
Update active mobility network



Missing paths detected from GPS data

Stefan Ivanovic, Phd 2018

Detect active mobility transportation mode

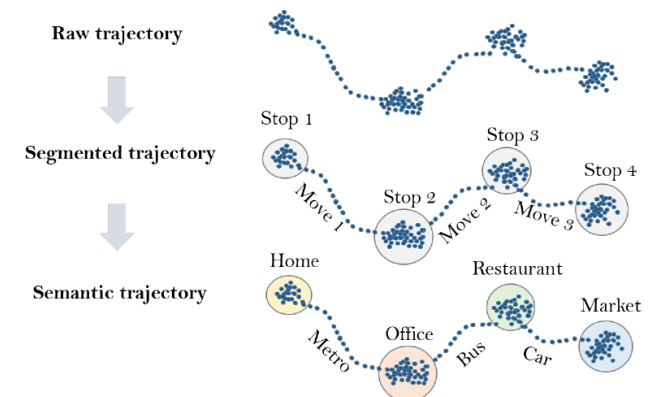


Amir Badawi, Phd; Mob-scit-dat Factory ANR Project

- GNSS trajectories : crowdsourced data or surveys



9/



(El Hafyani, 2023) 

OUTLINE

1. Context
2. Research goals and approach
3. Proposed approach
4. Results
5. Conclusion



Active Mobility **Transportation Mode**: Challenges

■ Lack of Labeled Data

- Labeled datasets specifically focused on walking and cycling behavior are scarce
 - limiting supervised learning approaches

■ Missing Contextual Information

- Trajectories often lack essential contextual information such as land use, road types, sidewalk presence, or elevation profiles
 - making behavioral interpretation difficult

■ Similar characteristics of different transportation mode

- Bike and scooters, walking and running on high slopes
 - confusion between transportation modes

■ Traditional ML Limitations

- Due to the availability of labeled active mobility datasets, traditional machine learning performs well
 - Struggle to generalize across different areas and different datasets

Active Mobility **Transportation Mode**: objectives

■ Research Question:

- **Can Large Language Models reason over structured trajectory descriptors to infer transportation modes without using labeled training data?**

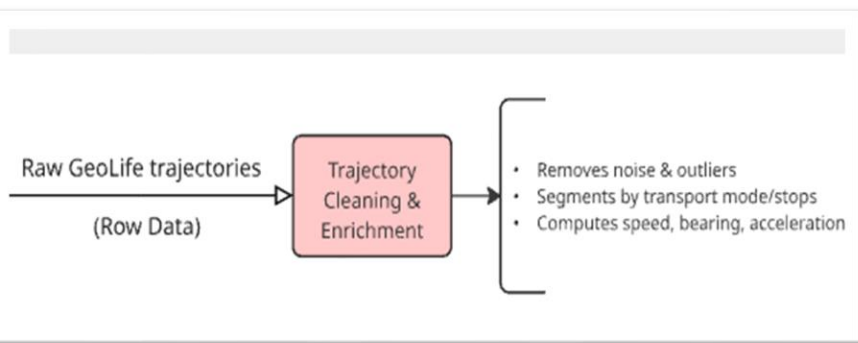
■ Objectives:

- Investigate if LLMs can classify transport modes accurately without task-specific training data.
- Develop structured textual prompts to transform trajectory-derived features into interpretable descriptions.
- Benchmark zero-shot LLM performance against traditional supervised ML methods (Random Forest, XGBoost).

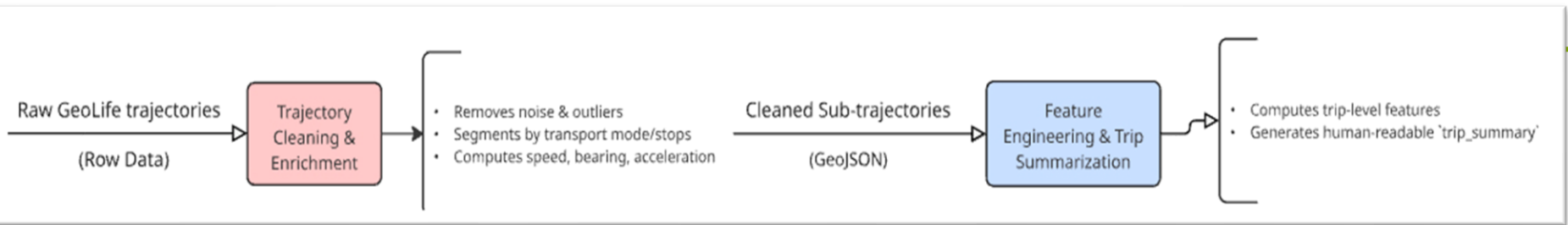
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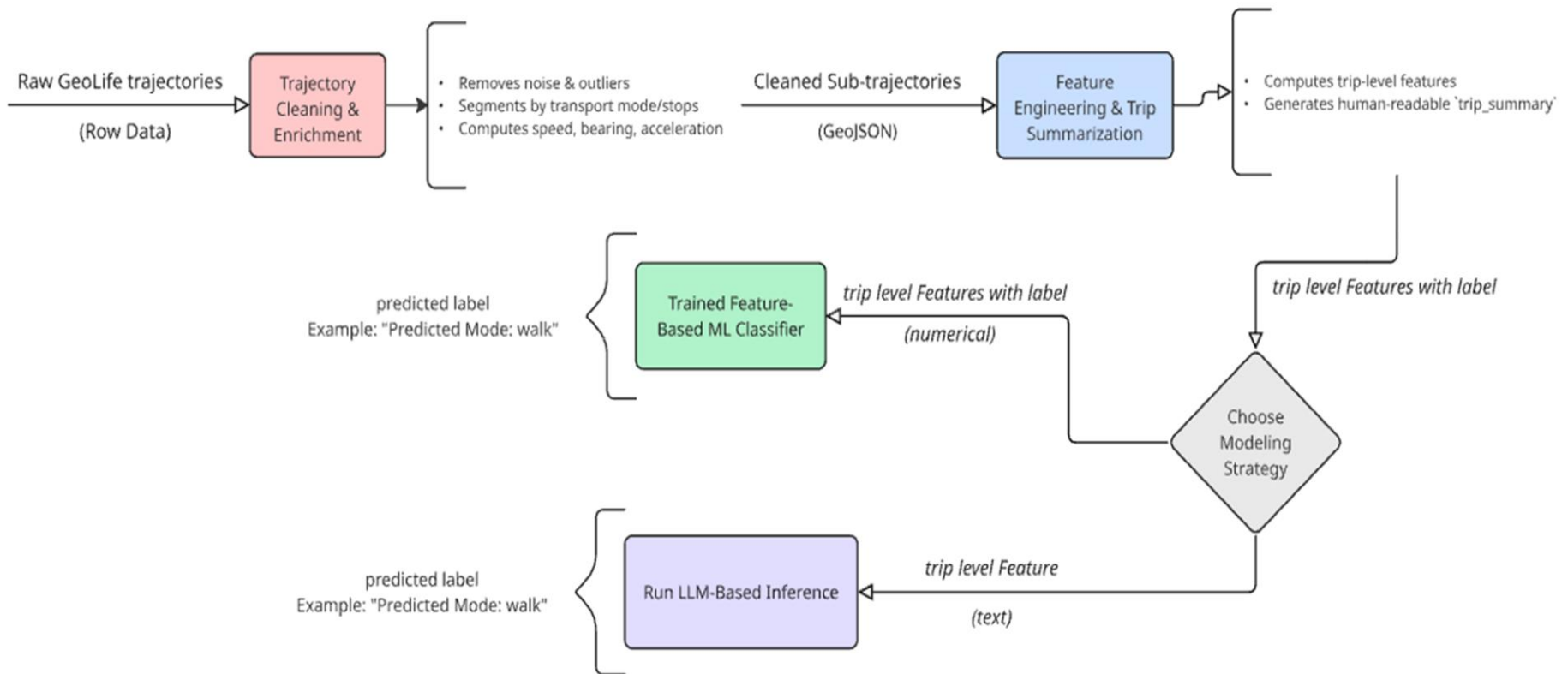




Proposed approach: Pipeline Overview (Badawi et al. 2025)



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Proposed approach : Data-processing

1. DATA PREPROCESSING (SHARED STEP)

▪ Trajectory Cleaning:

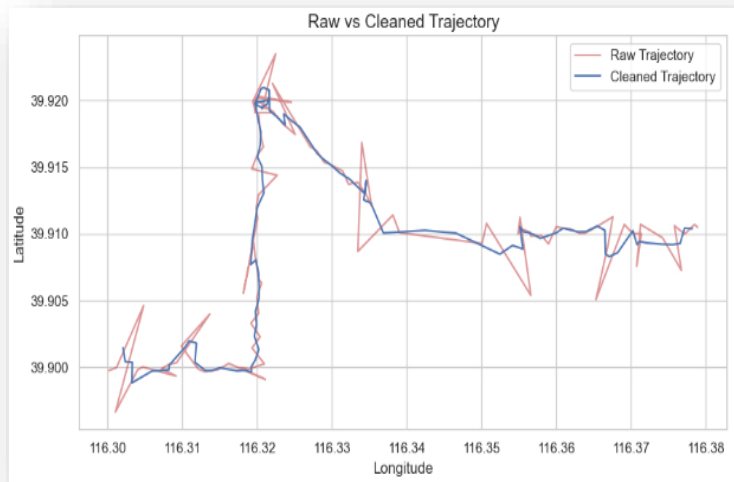
- Noise reduction (median filtering, Kalman smoothing)
- Remove duplicates, invalid coordinates, sparse or irregular samples

▪ Trajectory Segmentation:

- Split trajectories into trips based on temporal gaps (>300 seconds) or abrupt changes in dynamics
- Ensures each segment represents a consistent mobility mode

▪ Feature Enrichment (metrics computed per trip):

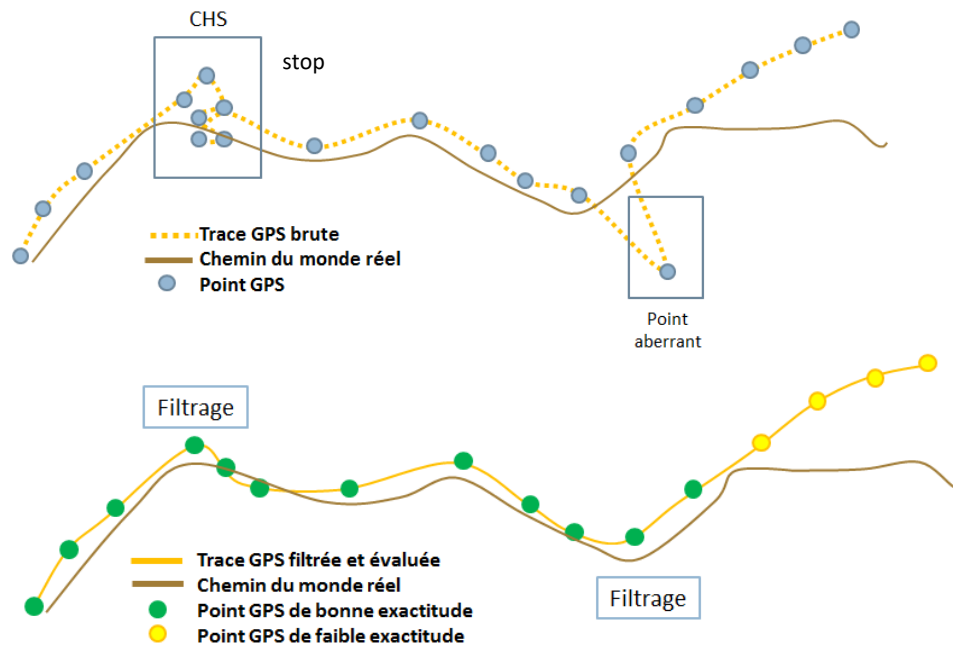
- **Temporal & Sampling Details:** Duration, sampling interval statistics
- **Spatial Metrics:** Start/end coordinates, total distance, average speed
- **Kinematic Metrics:** Speed range, acceleration stats (mean, min/max), Turn angles and course variation
- **Contextual Features:** Number of stops, stop rates, stop duration
- **Altitude & Vertical Metrics:** Total ascent/descent, vertical acceleration



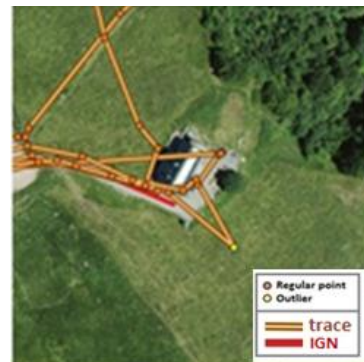
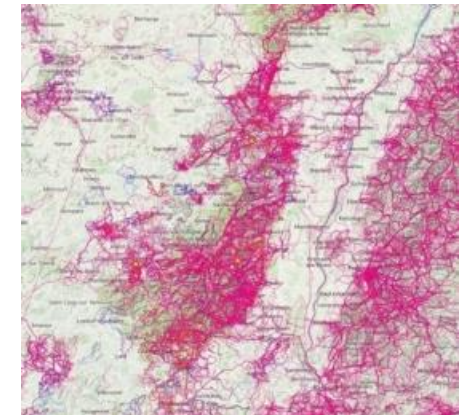
A **trip** is defined as a continuous movement using one transport mode, segmented from raw GPS data based on time gaps and dynamics.

Proposed approach : Data-processing

Quality assessment : **spatial analysis** and **supervised machine learning techniques** (RIPART algorithm) to improve track geometry and assess the GPS points accuracy



VGI: GPS tracks

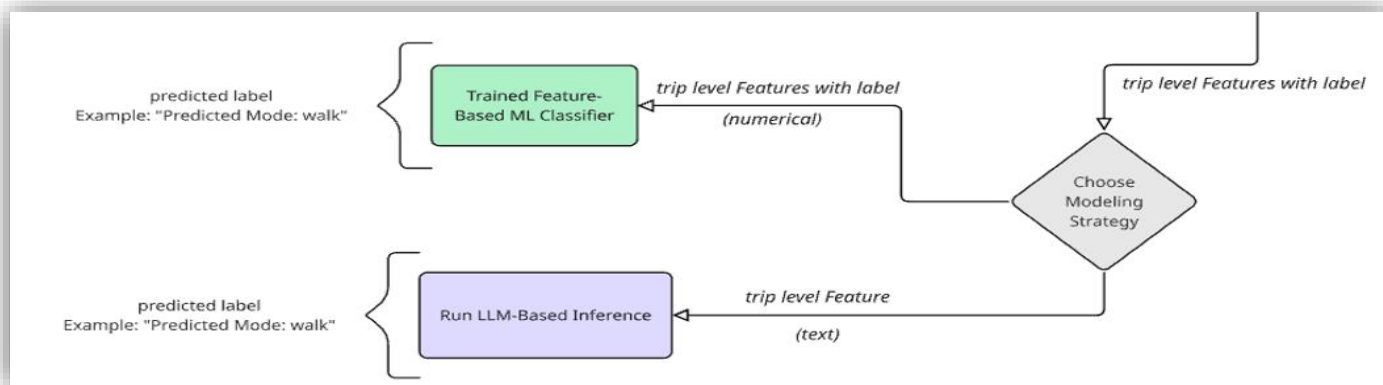


Outliers detection

Stefan Ivanovic, Ana-Maria Olteanu-Raimond, Sébastien Mustière, Thomas Devogele, A Filtering-Based Approach for Improving Crowdsourced GNSS Traces in a Data Update Context, *ISPRS International Journal of Geo-Information*, 2019, 8 (9), pp.380

Proposed approach : Inference path

Step	Zero-Shot LLM Path	Supervised ML Path
Input Data	Structured textual summary of trip metrics	Numeric vector of computed trip metrics
Data Preparation	No additional preparation	Feature normalization (Min-Max scaling)
Training Required?	✗ No (Zero-shot inference, no labeled data)	✓ Yes (Requires labeled training examples)
Model Used	DeepSeek Gwen-32B Large Language Model	Random Forest, XGBoost (traditional ML models)
Inference Process	Model reasons through textual prompt to predict mode	Model learns patterns during training to predict mode
Evaluation Approach	Direct inference on full balanced dataset	Final performance evaluated on a 30% hold-out test set from the balanced dataset.
Interpretability	High (Explicit reasoning in textual prompts)	Moderate to low (Black-box interpretation)



Proposed approach : Prompt generation for LLM inference

You are a transportation-mode analysis expert. Given the trip summary below, choose exactly one: `walk`, `bike`, `bus`, or `car`.

Trip Summary:

###

{summary}

###

INSTRUCTION

No single metric is infallible—our bus vs. car accuracy is still low—so follow **this structured, multi-check decision flow**, then a targeted bus-vs-car tie-break:

1. **Speed envelope**

- Walk: avg ≤ 8 km/h, max ≤ 11
- Bike: avg 10–16, max ≤ 25
- Bus: avg 18–35, max ≤ 40
- Car: avg 20–35, max ≤ 50

Eliminate modes whose speeds fall outside these ranges.

2. **Acceleration profile**

- Count spikes $> 2 \text{ m/s}^2$ and $> 1 \text{ m/s}^2$.
- Cars: many spikes of both accel & decel (> 40 each).
- Buses: decel spikes dominate (≥ 30 decels, < 20 accels).
- Bikes: moderate spikes (10–30, $\pm 1\text{--}2 \text{ m/s}^2$).
- Walks: very few (< 10 spikes).

If magnitude or counts contradict motorized motion, rule out vehicles.

3. **Stop pattern & dwell**

- Verify stops: ≥ 2 consecutive low-speed (< 0.5 km/h) fixes spanning ≥ 5 s.
- Bus: regular, evenly-spaced stops (0.3–1.0 stops/min, $\sim 300\text{--}500$ m apart).
- Car: irregular stops (0.2–0.8 stops/min), varied spacing.
- Bike/Walk: lower rate (0.1–0.5 stops/min), random spacing.

■ Purpose:

- Convert structured trajectory features into a natural-language prompt to guide zero-shot classification using an LLM.

■ Prompt Template (Reasoning-Oriented)

- LLM is instructed to act as a transportation-mode expert:

1. Follows a structured 6-step diagnostic reasoning flow:

- **Speed Envelope**
- **Acceleration Profile**
- **Stop Pattern & Dwell Time**

Proposed approach : Prompt generation for LLM inference

4. **Decel/Accel ratio**

- ratio = (# decel spikes >2) ÷ (# accel spikes >2).
- ratio ≥ 1.5 ⇒ strong brake-dominant → lean **bus**.
- ratio ≤ 0.8 ⇒ lean **car**.

5. **Route geometry**

- Bus: smooth, predictable turns along fixed routes.
- Car: sharper or irregular turns.
- Bike/Walk: highest variation, tight angles.

6. **Elevation & vertical accel**

- Bike/Walk: large total ascent/descent per km, vertical accel ≥ 0.2 m/s².
- Car/Bus: minimal vertical accel; climbs at cruising speed.

Bus-vs-Car tie-break

If both bus and car remain after steps 1–6, require **two of three**:

- decel/accel ratio ≥ 1.5
- stops uniform in time or distance
- max speed < 40 km/h

If met ⇒ **bus**, else **car**.

After working **through each step**, answer with exactly one word: ``walk`, `bike`, `bus`, or `car`.`

■ Purpose:

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- LLM is instructed to act as a transportation-mode expert:

1. Follows a structured 6-step diagnostic reasoning flow:

- **Speed Envelope**
- **Acceleration Profile**
- **Stop Pattern & Dwell Time**
- **Deceleration/Acceleration Ratio**
- **Route Geometry**
- **Elevation & Vertical Acceleration**

2. Includes Bus-vs-Car tie-breaking logic for ambiguous cases.

3. Final instruction: predict only one of {walk, bike, bus, car}.

Proposed approach : Prompt generation for LLM inference

- Trip Summary (Input to the Template Prompt)
- Dynamically populated from enriched GPS trip features that we prepared.
- Highly interpretable and readable format.
- Mimics how a human expert might summarize mobility behavior.

The LLM reasons over semantically-rich, structured text instead of raw numbers, allowing it to generalize without training data.

Template trip summary

- Time Window and Sampling
- Start: {start_date} at {start_time}
- End: {end_date} at {end_time}
- Duration: {duration}
- Samples: {num_samples} fix points, recorded at roughly {interval_min}-{interval_max} second intervals
- Endpoints
- Origin: {start_lat} N, {start_lon} E @ {start_elev} m elevation
- Destination: {end_lat} N, {end_lon} E @ {end_elev} m elevation
- Distance and Speed
- Total distance: {total_distance} km
- Average speed: {avg_speed} km/h
- Speed range: {min_speed} km/h → {max_speed} km/h
- Acceleration
- Mean acceleration: {mean_accel} m/s²
- Peaks: +{max_accel} m/s² and -{min_accel} m/s²
- Heading and Course Changes
- Initial bearing: {initial_bearing}°
- Final bearing: {final_bearing}°
- Course variation: {course_variation}°
- Max turn angle: {max_turn_angle}°
- Stops
- Number of stops: {num_stops}
- Stops per minute: {stops_per_min} stops/min
- Stops per kilometer: {stops_per_km} stops/km
- Acceleration/Deceleration Profile
- 90th percentile acceleration: {accel_90} m/s²
- 10th percentile deceleration: {decel_10} m/s²
- Acceleration spikes (>2 m/s²): {accel_spikes}
- Deceleration spikes (<-2 m/s²): {decel_spikes}
- Vertical Movement
- Vertical acceleration: {vertical_accel} m/s²

Proposed approach : supervised ML pipeline path

■ Input Format:

- The *same enriched trip descriptors* as for the LLM pipeline → But **fed as raw numeric feature vectors** (no text generation or prompt engineering)

■ Features Used:

- 33 descriptors for each trip
- Kinematic, spatial, temporal, altitude, and contextual properties

• Preprocessing:

- Min–max normalization applied to all features

• Models Applied:

- Random Forest
- XGBoost

• Training & Validation:

- 70/30
- Ground-truth mode labels are used for supervision

• Evaluation Metrics:

- Accuracy, precision, recall, and class-level confusion matrices

• Implementation:

- Computation done on a MacBook Pro (M1 Pro chip)

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Dataset: **GeoLife GPS Trajectories**

■ Dataset Summary

- Collected by Microsoft Research Asia (2007–2012)
- 182 users, 17,621 GPS trajectories
- Captures daily mobility across urban Beijing
- High-resolution data: 1–5 second intervals or 5–10 meters spacing

■ Transport Modes

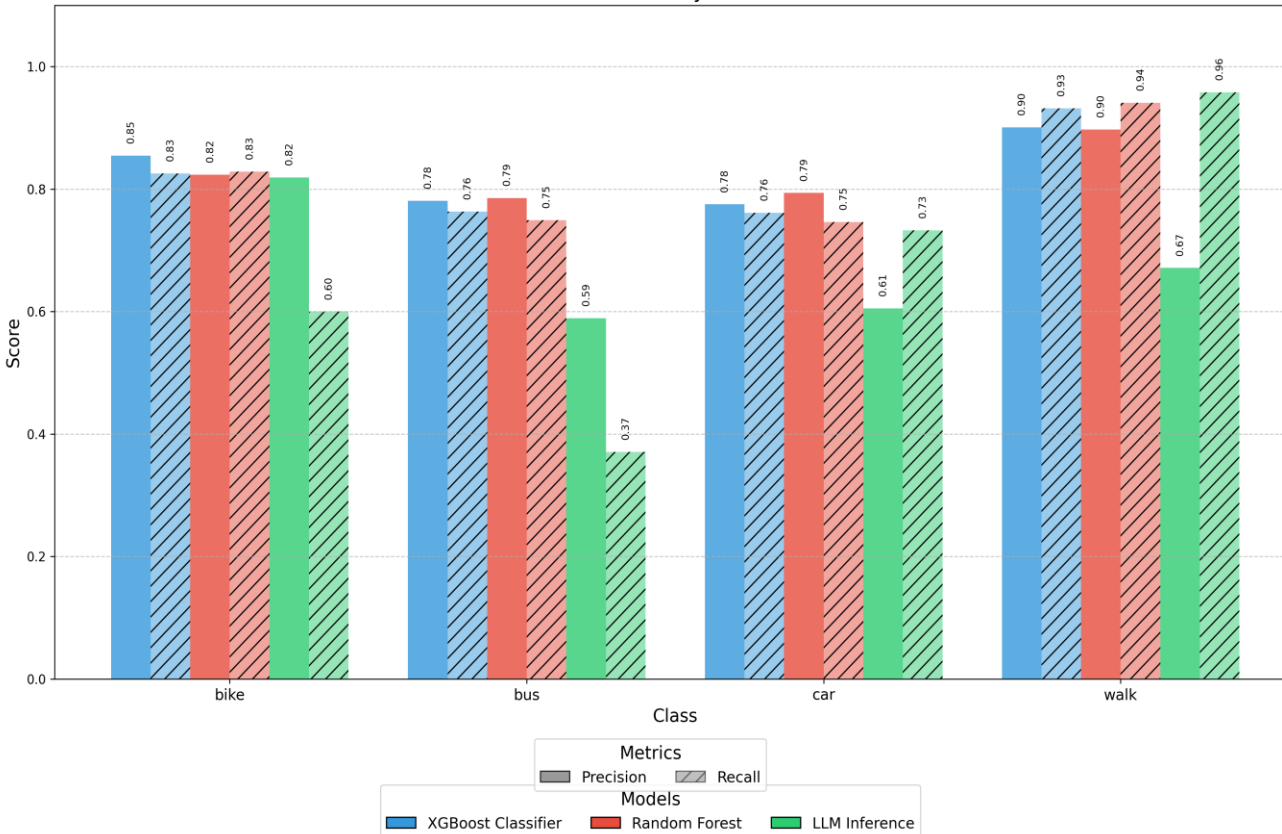
- Original dataset includes 11 labeled modes
- Four transportation modes: [Walk](#), [Bike](#), [Bus](#), [Car](#)
- And only used trajectories that had annotated transport mode labels

■ Study Subset

- Balanced sample: 4,280 trips (1,070 per class)
- Includes ground-truth labels
- Used consistently for both LLM and ML evaluation

Experimental results: Zero-shot LLM

Precision and Recall by Class and Model



Zero-shot LLM shows performance for some classes without any training, but struggles with modes that have similar dynamics, such as bus vs. car.

Model Used:

- **DeepSeek Gwen-32B**
(locally hosted, no task-specific fine-tuning)
- Random Forest, and XGBoost

Inference Setup:

- Inference ran on server with dual NVIDIA H100 GPUs (96 GB VRAM each)

Results:

- **LLM (DeepSeek Gwen-32B, zero-shot): 66.5%**
- **Random Forest: 84.6%**
- **XGBoost: 84.8%**

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CONCLUSION AND FUTURE WORK

- Feasibility of using Large Language Models (LLMs) for zero-shot transportation mode classification by converting trajectory features into structured prompts.
- LLMs achieved 66.5% accuracy without any supervised training, showing promise as interpretable, training-free alternatives, especially for rapid prototyping and data-scarce contexts.
- Results are not yet satisfactory, the experiments provided insights into how such models reason and raised new questions about handling active mobility modes without ground-truth data.
- Future Work:
 - **Integrate additional contextual data:**
 - *Road type (highway, residential, bike path), public transit schedules, land use information*
 - **Use Agentic IA for multi-tasking reasoning**
 - **Test on another GNSS dataset**

Dataset: NetMob2025 GNSS Trajectories

■ Dataset Summary

- 3,300 residents of Paris Region tracked for 1 week
- GNSS at 2-3s interval; validated by diaries and phones survey
- User Data: trips, purposes, socio-demographic, subscriptions.

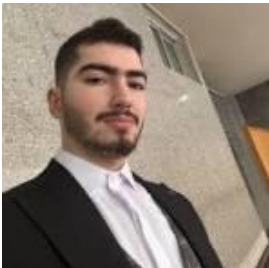
■ Transport Modes

- Transportation modes:
 - Four modes : walk, bike, bus, car
 - Ten modes : car, walk, train, subway, tram, bus, bike, ebike, scooter, moto
- And only used trajectories that had annotated transport mode labels

Thank you for your attention !

Amir Badawi, Ana-Maria Olteanu-Raimond, Arnaud Le Guilcher, Karine Zeitouni, Harnessing Large Language Models for Predicting Mobility Modes 2025 26th IEEE International Conference on Mobile Data Management (MDM), June 2025, Irvine, France. pp.222-227

Thank you for my co-authors!



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