

PHD RESEARCH PLAN INTERVIEW

Sequence-Aware Probabilistic GPS Stay-Cluster Assignment

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human-centric urban planning



Infrastructure



Human Activity

Understand where and how human activity actually occurs, at fine spatial and temporal resolution.

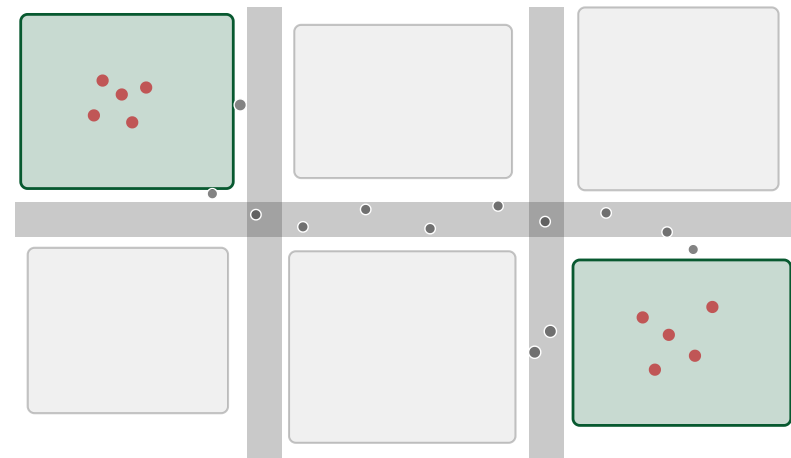
- Surveys and direct observation are costly and limited in coverage.
- GPS trajectories offer a continuous, large-scale alternative.¹
- But raw trajectories capture where people moved, not what activity occurred.
- Spatial enrichment turns raw movement into activity information.²

1. Sila-Nowicka et al., 2016; Wolf et al., 2003 2. Alvares et al., 2007; Parent et al., 2013

the 'only-building' concern

- Existing methods are deterministic and treat buildings as the only legitimate target.¹
- Even recent multi-target work still assigns to the nearest entity, deterministically.²
- Urban theorists show streets and open spaces are sites of everyday activity and unplanned encounters, not just corridors; face-to-face co-presence there remains fundamental to social ties.³
- This study expands assignment targets to include streets and open spaces in their own right.

Streets are spaces where urban configuration indirectly affects the frequency and nature of human interaction.



a stay-move-stay trajectory: only the points inside a building footprint register, the rest fade into unassigned space

1. Alvares et al., 2007; Ashbrook & Starner, 2003; Suzuki et al., 2019 2. Wu et al., 2026 3. Gehl, 2010; Jacobs, 1961; Whyte, 2010; Chikaraishi et al., 2025

master's foundation: a probabilistic assignment framework

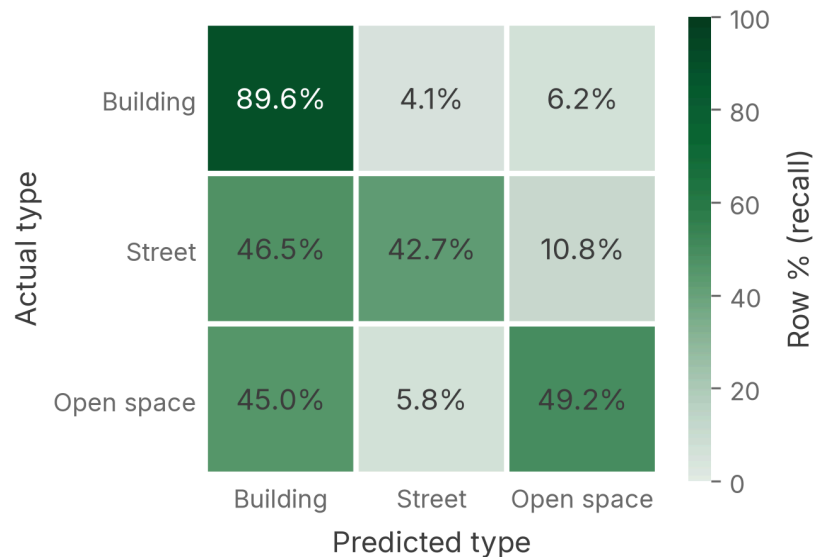
My master's thesis built a **Probability Assignment Framework** that treats streets (and open spaces) as legitimate entities alongside buildings, instead of resolving every GPS stay to the nearest building.



Validated against a 907-stay, manually verified ground truth: out-of-sample accuracy **0.716**.

Birant & Kut, 2007 (ST-DBSCAN)

validated, but built on an independence assumption



- Every stay cluster is scored and assigned **on its own**, with no reference to the stays before or after it.
- A stay ambiguous between a cafe and the street outside cannot be resolved by geometry alone, it needs the sequence around it.
- The model cannot yet tell a *transit stop* (waiting) apart from an *interactional stay* (socializing).

Human activity-travel behavior is not a set of independent events, it has sequential dependencies the current framework doesn't use.¹

1. Zheng et al., 2010

why sequence matters



Strong sequential structure

Mobility exhibits strong sequential dependencies and temporal rhythms, not random ordering.¹



The unit of analysis should change

Disambiguating a single ambiguous stay requires analyzing the whole activity sequence around it, not that one isolated event.

1. Watanabe et al., 2021

objective & research goals

Extend the Probability Assignment Framework with sequential modeling grounded in activity-travel behavior theory, to resolve street-side ambiguity that geometry alone cannot.

①

Develop a Sequential Probabilistic Framework that computes assignment probabilities from optimal activity sequences, not isolated stays.

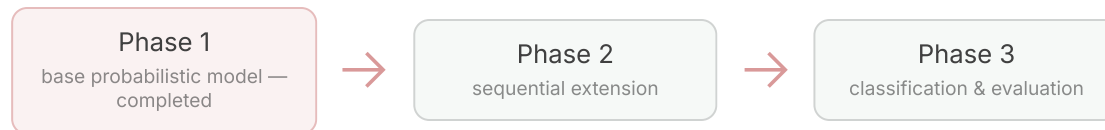
②

Differentiate transit stays from interaction stays through semantic enrichment of temporal trip-chain composition.

③

Benchmark sequential against independent models to quantify the accuracy gain on ambiguous street-side cases.

three phases, one extension



Phase 1 is the master's thesis framework, already built, calibrated, and validated. The PhD extends it in Phases 2 and 3.

phase 1 — base probabilistic model

COMPLETED

$$P(E_k | C_i)$$

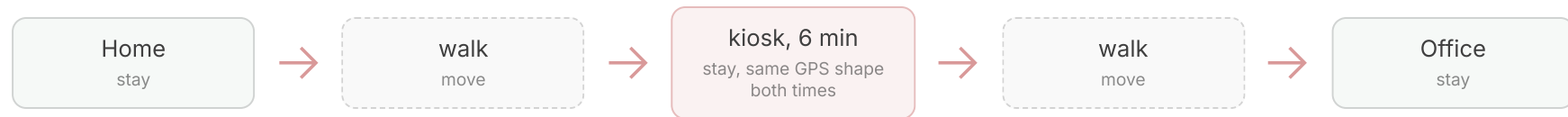
E_k spatial entity (building / street / open space) $k \cdot C_i$ GPS stay-cluster i

- Candidates: any entity within a fixed buffer of the cluster (inclusive enough to avoid missing the true entity, tight enough to stay robust to outliers).
- Four score components: spatial distribution, distance decay (scaled by cluster dispersion), temporal concentration, directional alignment.
- Components combine into a per-candidate utility, calibrated via conditional logit (12 parameters, $\alpha = 2.430$).
- Out-of-sample accuracy 0.716, validated against a 907-stay ground truth spanning all three types.

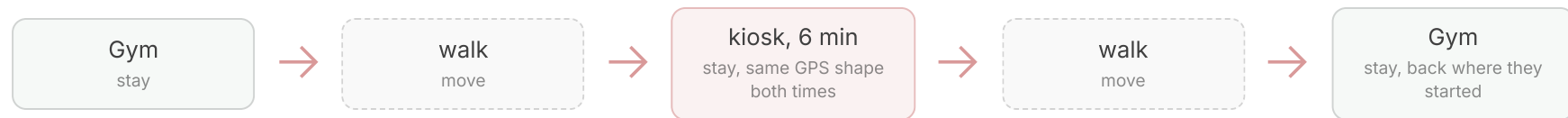
phase 2 — same stay, different meaning

The same six-minute pause, at the same kiosk, can mean two different things, depending on what happens around it. Phase 1 alone can't tell them apart.

CHAIN A, A MORNING COMMUTE



CHAIN B, A MIDDAY ERRAND



What Phase 1 sees

identical, both times

Same location, same six minutes, same shape. Phase 1 scores both stays exactly the same way, it has no way to tell them apart.

What Phase 2 sees

different, both times

Chain A fits a coffee stop on the way to work. Chain B doesn't, doubling back to the gym looks more like an incidental pause than a real stop.

a hypothetical example to illustrate the idea, Phase 2 and 3 have not been tested yet

phase 2 — sequential extension: transition probabilities

The full sequence always alternates between stays and moves: stay, move, stay, move, and so on. A stay can only lead into a move, and a move can only lead into a stay, never two stays back to back, never two moves back to back.

A stay at a street can never transition straight into a stay at an open space. There is always a move in between: street (stay) → walking (move) → open space (stay).

So a transition is really two linked steps: leaving the stay behind, then arriving at the next one.

$$P(E_{k,t} \mid E_{k,t-1}, M_t) = P(M_t \mid E_{k,t-1}) \cdot P(E_{k,t} \mid M_t)$$

$E_{k,t-1}$ the entity just left · M_t the move connecting them (path, duration, bearing) · $E_{k,t}$ the entity just arrived at

phase 2 — where the sequential dependency comes from



Activity chaining

Consecutive activities are linked by the individual's own constraints and preferences, not independent draws.



Temporal patterns

Regular rhythms, like a morning commute, recur predictably across days.



Spatial constraints

Face-to-face interaction imposes physical co-location requirements on where a sequence can go next.¹

Social network structure shapes which activities people participate in, and participation reshapes the network in turn, through the face-to-face encounters this framework is trying to detect.²

1. Urry, 2002 2. Chikaraishi et al., 2025

phase 2 — scoring the whole trip, not stop by stop

Instead of judging each stay on its own and hoping it's right, the sequential model looks at the **whole trip together**, and picks whichever version of the story fits best overall.

Intuitively. less like guessing one photo out of an album on its own, more like reading the whole album at once, some guesses only make sense once you see what comes right before and after them.

written out, for reference, each piece labeled:

$$\hat{E}_{1:T} = \arg \max_{E_{1:T}} \prod_{t=1}^T \underbrace{P(E_{k,t} \mid C_{i,t})}_{\text{Phase 1: fits its own spot}} \cdot \underbrace{P(M_t \mid E_{k,t-1})}_{\text{Phase 2: leaving the last stay}} \cdot \underbrace{P(E_{k,t} \mid M_t)}_{\text{Phase 2: arriving at this one}}$$

$\hat{E}_{1:T}$ the best-fitting version of the whole trip's stays · $E_{k,t}$ a stay's entity · M_t the move connecting two stays · $C_{i,t}$ that stay's own GPS cluster

phase 3 — classifying street stays by sequential role

Transitional

low interaction

Under 5 minutes, high-velocity approach and departure, consistent with waiting or loading, not socializing.

Stationary

high interaction

Over 15 minutes, lower spatial dispersion, multiple co-located activities, consistent with genuine social interaction.

phase 3 — evaluation design

Benchmarked directly against the Phase 1 independent baseline, same ground truth, same held-out folds.

Metric	Independent (Phase 1)	Sequential (Phase 2 + 3)
Overall accuracy	0.716 · measured	to be measured
Street recall	42.7% · measured	to be measured
Open space recall	49.2% · measured	to be measured
Transit vs. interaction accuracy	not modeled	to be measured

Three things get quantified against this baseline: **(a)** overall accuracy gain, **(b)** false-positive reduction on street-side stays specifically, **(c)** transit vs. interaction accuracy, a distinction Phase 1 cannot make at all.

anticipated challenges



Not enough examples

Some type-to-type transitions, like street to open space, just don't show up very often in the data.



Computational cost

Checking every possible version of a trip, across every candidate at every step, could get expensive as sequences get longer.



Guessed cutoffs

The 5- and 15-minute transit vs. interaction split is just a starting guess, not based on data yet.

expected contributions

Methodological

A sequential probabilistic technique for spatial assignment under uncertainty, grounded in discrete choice theory.¹

Empirical

A direct, quantified comparison of independent vs. sequential assignment on the same ground truth, isolating the accuracy gain sequence provides.

Theoretical

Operationalizes street-level social interaction computationally, bridging classical urban theory with mobility analytics and co-evolutionary network frameworks.²

1. Bierlaire, 2006 2. Chikaraishi et al., 2025

thank you for the attention

your questions and comments are welcome!

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