Finding Most Popular Indoor Semantic Locations Using Uncertain Mobility Data

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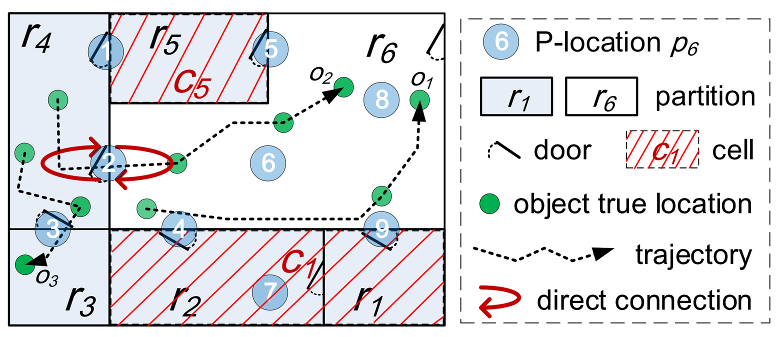
1. Introduction

- Indoor movements are increasingly datafied due to the rapid growth of indoor LBS infrastructures. Proper analysis can reveal insights that are otherwise difficult to obtain.
  - **Indoor flow analysis.** the number of people passing by particular indoor regions during a past time interval. Application include exhibition planning, location-based advertising, etc.
- The problem of finding the top-k popular *indoor semantic locations* with the highest flows during a past time interval.
  - The mobility information of an object at a time t is captured by a set of *probabilistic samples* in the format of $(loc, prob)$.
  - **The first challenge** is the difficulty in obtaining *reliable* flow values due to the inherent uncertainty in multiple samples reported at discrete timestamps. The data uncertainty together with complex indoor topology entails an appropriate formulation of indoor flows.
  - **The second challenge** comes from the heavy computational workloads on the samples for large numbers of indoor objects.
- A complete set of novel techniques for indoor flow analysis.
  - We formulate the definition of *indoor flows* by taking into account both data uncertainty and indoor topology.
  - We devise *data structures* to facilitate accessing the data relevant to flow computing, and a *data reduction method* to significantly reduce the intermediate data to be processed.
  - We design *search algorithms* for finding indoor top-k popular locations.

2. Problem Formulation

- ***Semantic locations*** (S-locations) refer to regions relevant to applications, e.g., a shop.
- ***Positioning locations*** (P-locations) refer to points returned by indoor positioning system.
  - **Partitioning P-locations** partition space into *cells* in that objects cannot move from one to another without passing these P-locations. **Presence P-locations** only imply the presence of a positioned object.
- A record (o, X, t) is reported to an ***Indoor Uncertain Positioning Table*** non-periodically, meaning o's location at t is described by a sample set X. Each sample $e(loc, prob)$ in X means that o is at a P-location loc with probability $prob$.
- ***Uncertainty-aware object presence*** in a S-location q during time interval $[t_s, t_e]$.
  - For each object o's sample sets sequence $(X_1, \dots, X_n)$ ➔ Obtain possible paths in the *Cartesian product* $\phi_i = (loc^i_1, \dots, loc^i_n)$ ➔ Compute path probability as $pr_i = \prod_{1\le j\le n} prob^i_j$ where $prob^i_j$ is the probability associated with P-location loc^i_j in X_j.
  - The *pass probability* that ϕ passes q is 1 minus the probability that none of consecutive P-location pairs in ϕ passes q ➔ o's *presence* in q is $\Phi_{t_s,t_e}(q, o) = \frac{\sum_{\phi_i\in P}(pr_{\phi_i\rightsquigarrow q}\cdot pr_i)}{\sum_{\phi_i\in P} pr_i}$.
- ***Indoor Flow.*** Given an S-location q, a set O of indoor moving objects, and a time interval $[t_s, t_e]$, the indoor flow for q is $\Theta_{t_s,t_e,O}(q) = \sum_{o\in O}\Phi_{t_s,t_e}(q, o)$.
- ***Top-k Popular Location Query, TkPLQ.*** Given a set Q of indoor semantic locations, and a time interval $[t_s, t_e]$, an indoor top-k popular location query returns k S-locations in a k-subset $Q_k \subseteq Q$ such that $\forall q \in Q_k, \forall q' \in Q \setminus Q_k, \Theta_{t_s,t_e,O}(q) \ge \Theta_{t_s,t_e,O}(q')$.

A running example



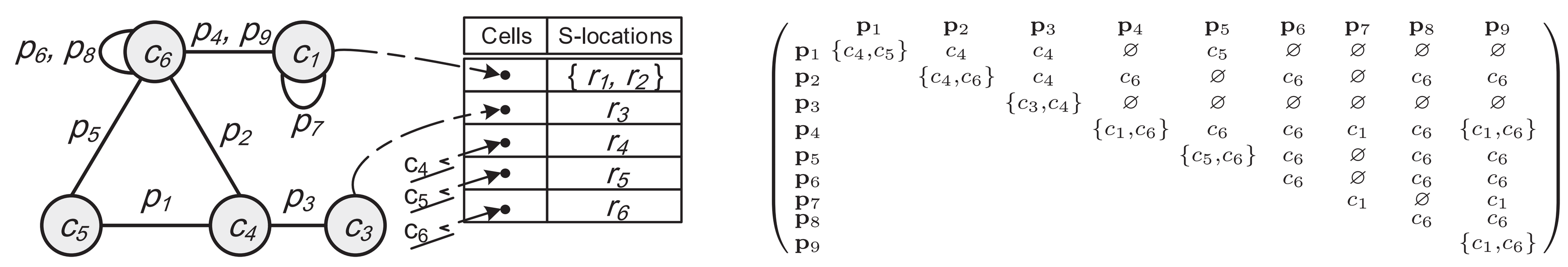
oid , *X* , *t*	*oid* , *X* , *t*
o_1 , $\{(p_4, 1.0)\}$, t_1	o_1 , $\{(p_8, 1.0)\}$, t_4
o_2 , $\{(p_1, 0.5), (p_2, 0.5)\}$, t_1	o_2 , $\{(p_5, 0.3), (p_6, 0.6), (p_8, 0.1)\}$, t_5
o_3 , $\{(p_2, 0.6), (p_3, 0.4)\}$, t_2	o_3 , $\{(p_2, 0.4), (p_3, 0.6)\}$, t_5
o_1 , $\{(p_9, 1.0)\}$, t_3	o_2 , $\{(p_5, 0.2), (p_6, 0.3), (p_8, 0.5)\}$, t_6
o_2 , $\{(p_2, 0.7), (p_4, 0.3)\}$, t_3	o_3 , $\{(p_3, 1.0)\}$, t_8

- An object o_3 has 4 possible paths during $[t_1, t_8]$, i.e., $\phi_1 = (p_2, p_2, p_3)$, $\phi_2 = (p_2, p_3, p_3)$, $\phi_3 = (p_3, p_2, p_3)$ and $\phi_4 = (p_3, p_3, p_3)$. In particular, ϕ_1's probability is $0.6 \times 0.4 \times 1.0 = 0.24$.
- The possible path ϕ_1 contains sequential P-location pairs (p_2, p_2) and (p_2, p_3). For (p_2, p_2), we find two direct connections, and have $pr_{p_2,p_2\rightsquigarrow r_6} = pr_{p_2,p_2\rightsquigarrow r_4} = 1/2$. Likewise, for pair (p_2, p_3), $pr_{p_2,p_3\rightsquigarrow r_4} = 1$ and $pr_{p_2,p_3\rightsquigarrow r_6} = 0$. The pass probability $pr_{\phi_1\rightsquigarrow r_6} = 1 - (1 - 1/2)\cdot(1 - 0) = 0.5$.
- The presence $\Phi_{t_1,t_8}(r_6, o_3) = 0.5 \cdot 0.24 = 0.12$, and $\Phi_{t_1,t_8}(r_1, o_3) = 0$.
- S-location r_6's indoor flow is $\Theta_{t_1,t_8,O}(r_6) = \sum_{1\le i\le 3}\Phi_{t_1,t_8}(r_6, o_i) = 1+0.85+0.12 = 1.97$, r_1's is $\Theta_{t_1,t_8,O}(r_1) = \sum_{1\le i\le 3}\Phi_{t_1,t_8}(r_1, o_i) = 0.5 + 0 + 0 = 0.5$. A T1PLQ during $[t_1, t_8]$ returns room r_6.

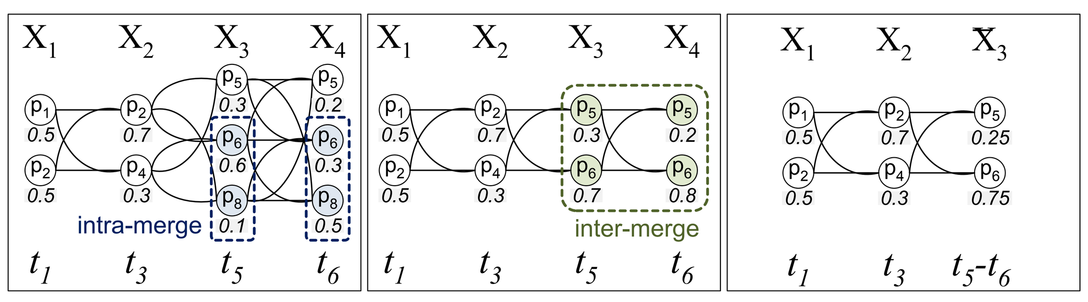
3. Algorithms for TkPLQ

3.1 Data structures and data reduction method.

- To bridge the gap between P-locations and S-locations, we devise an ***indoor space location graph***. A cell c_1 ➔ rooms r_1 and r_2 ➔ partitioning P-locations p_4 and p_9.
- We further build an ***indoor location matrix*** M_{IL} for quickly searching relevant cells (S-locations) of two sequential P-locations in a path. $M_{IL}[p_4, p_9] = \{c_1, c_6\}$ and $M_{IL}[p_8, p_8] = c_6$.

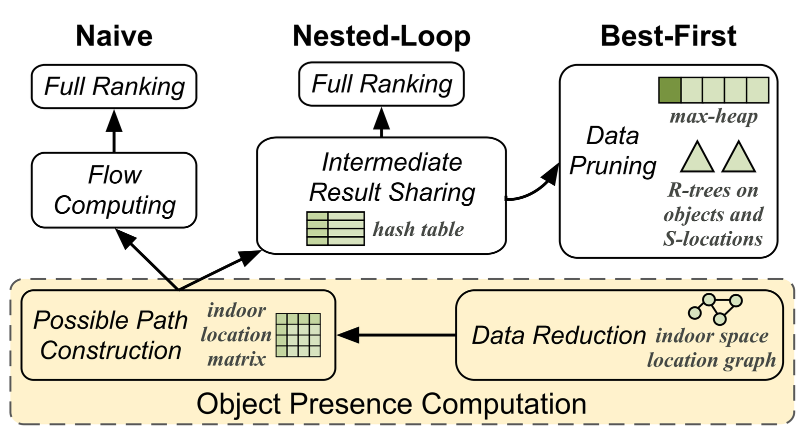


- For sequence $(X_1, \dots, X_n)$, the *maximum* number of possible paths is as large as $\prod_{1\le i\le n}|X_i|$.
  - For each set X_i, we use an ***intra-merge*** operation to combine the samples from the P-locations that are logically equivalent in constructing M_{IL} (e.g., p_6 and p_8).
  - We use an ***inter-merge*** operation to compress the sequence length $|\mathcal{X}|$ by merging the consecutive sets that contain the identical P-locations.



3.2 Flow computing and TkPLQ search.

- Flow computing for individual an S-location ☛ fetch and go through all relevant positioning records within $[t_s, t_e]$ that are indexed by an 1DR-tree.
  - The matrix M_{IL} is checked to determine if the current path to be generated is valid, and only the valid ones will be involved in subsequent path generation.
- **Naive algorithm** sorts top-k results after blindly computing each query location's flow.
- **Nested-Loop** caches each encountered object's presences to avoid re-computation.
- **Best-First** gives priority to those promising query locations with greater flow overestimates. To quickly locate the relevant object samples, we carry out a join of a query location R-tree and an object COUNT-aggregate R-tree.



4. Experimental Results

- We compare Naive, Nested-Loop and Best-First to several alternatives.
  - SC (simple counting) method picks the sample with the highest probability and adds 1 to all its containing S-locations' flow values.
  - SC-ρ differs from SC only in that it picks all the samples whose probability exceeds a threshold ρ.
  - MC (Monte Carlo) method executes a certain number of simulations, in each of which all the positioning records are sampled to be certain. As a result, the top-k locations are ranked based on their average flows in all the simulations.

4.1 Performance comparisons using a real-world dataset.

- **Efficiency metrics** ☛ Average running time and *Pruning ratio*; **Effectiveness metrics** ☛ *Recall* and *Kendall coefficient* τ w.r.t the ground truth.
- SC and SC-ρ incur short time costs but yield very poor effectiveness; MC that uses simulations incurs extremely long running time.
- By applying uncertainty-aware flow computing, BF and NL's effectiveness measures are significantly higher; BF achieves a good balance between efficiency and effectiveness.

Methods	Running time (sec.)	Pruning ratio (%)	Kendall coefficient	Recall (%)
SC	**0.6**	-	0.007	62.2
SC-ρ ($\rho = 0.25$)	1.1	-	0.382	75.6
MC, *900 rounds*	1.7×10^4	-	0.712	86.7
BF	4.4	**59.4**	0.859	93.3
NL	9.5	19.2	same as above.	
Naive	59.1	19.2	same as above.	

4.2 Studies on data uncertainty using a synthetic dataset.

- A larger T (*maximum positioning period*) makes location updates less frequent, which causes data uncertainty to increase and query result quality to degrade. BF still outperforms the best; its τ keeps above 0.77 in all tests.
- When *indoor positioning error* μ increases, SC and SC-ρ's τ decrease clearly as they are sensitive to data errors. Still, BF outperforms MC as BF considers valid possible paths thoroughly on uncertain positioning data.