FREQUENT ROUTE BASED CONTINIOUS MOVING OBJECT LOCATION- AND DENSITY PREDICTION ON ROAD NETWORKS

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Problem Statement

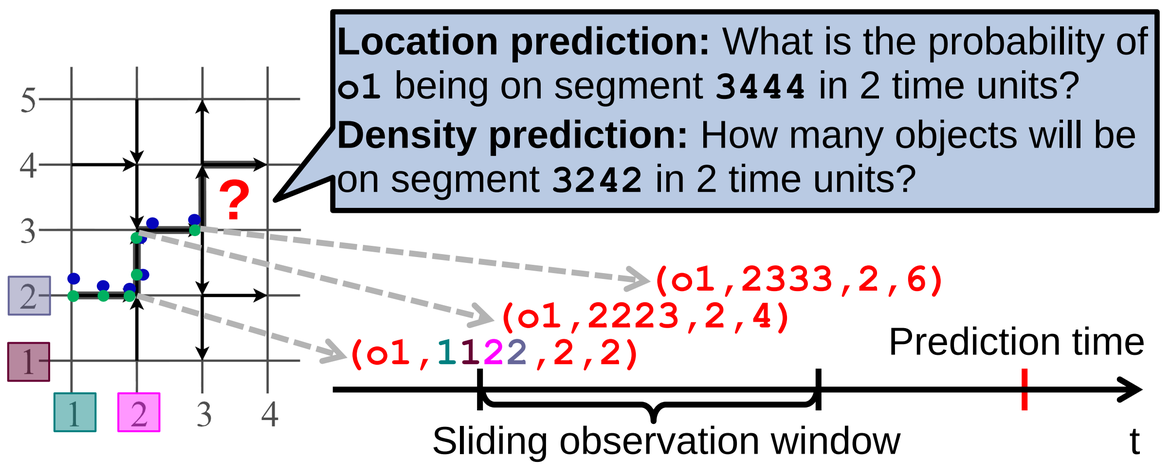
Given the current and historical movements of vehicles, predict their near-future location on the road network to:

1. Estimate near-future traffic conditions: (density/speed/flow)
2. Provide actionable travel information based on future estimates

- Inform the relevant vehicles in case of an (actual/predicted) event
- Suggest how and which vehicles to re-route in case of an event

Preliminaries

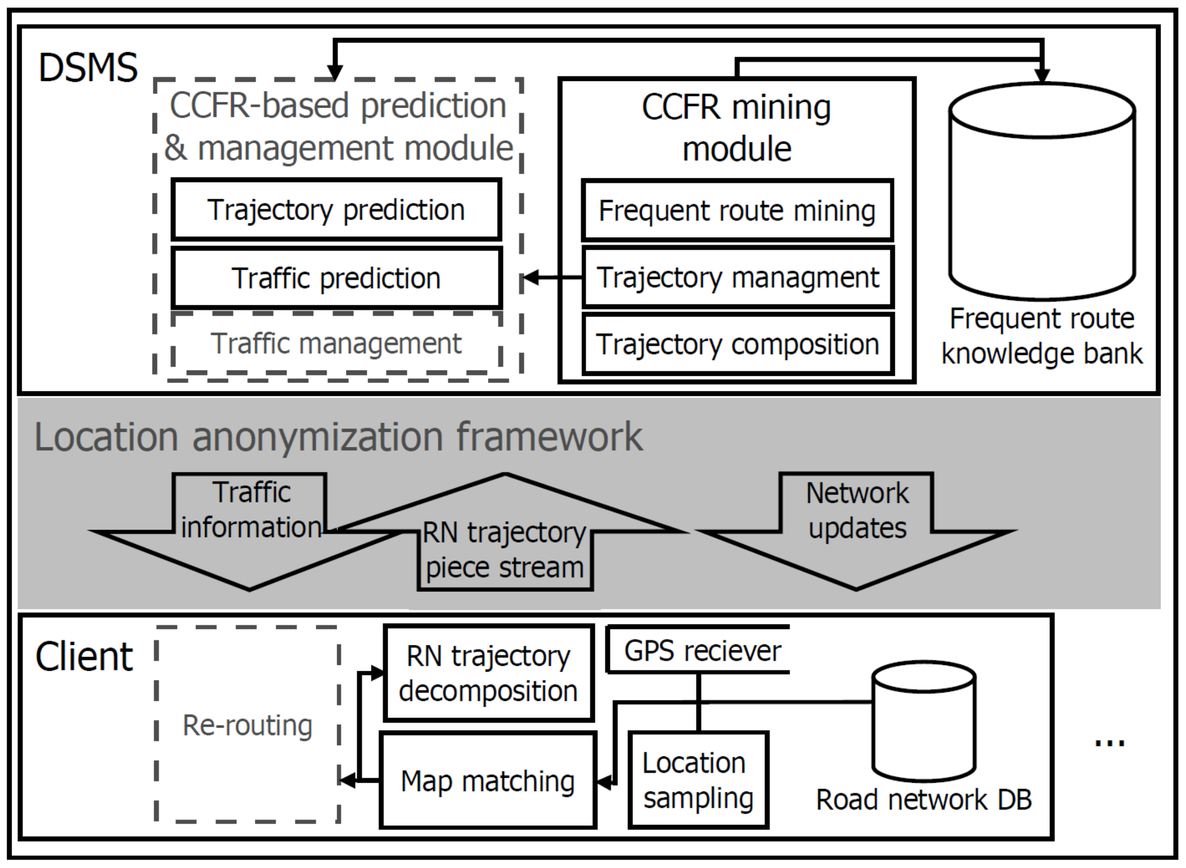
Movement representation: Map matching clients align noisy GPS measurements to precise RN locations. When an RN segment is fully traversed a *trajectory piece* `(oid,segment,traversal time,[arrival_time])` is sent to the sever, i.e., the RN trajectory is a sequence of trajectory pieces. *Stops* subdivide RN trajectories into a discontinuous sequence of *trip trajectories*. Object movement is observed as a *stream of evolving trip trajectories*.



Knowledge representation: **Closed Contiguous Frequent Routes (CCFR)**:

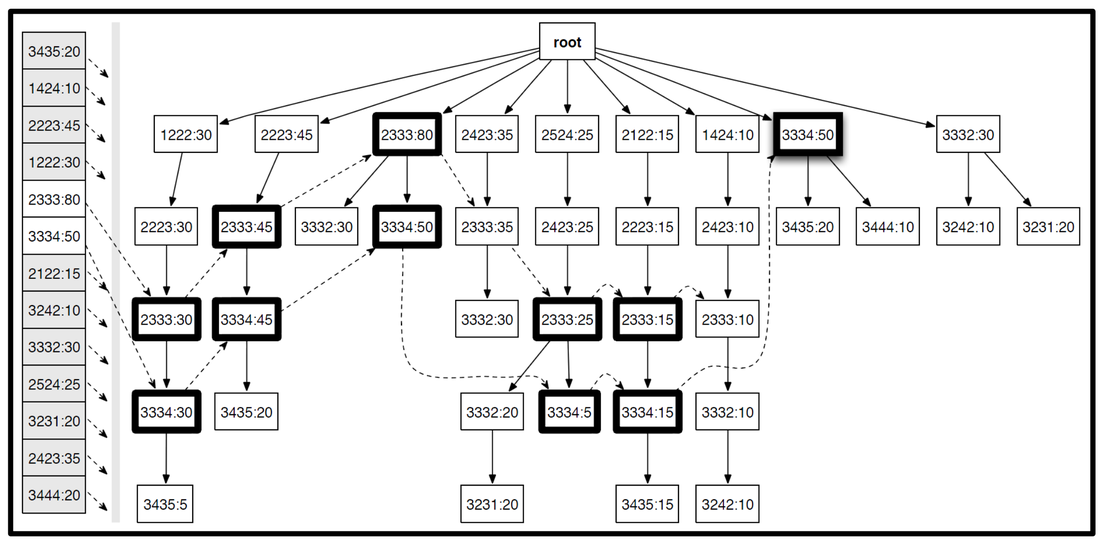
- **Closed** → lossless compression of knowledge
- **Contiguous** = ”no gaps” → effective prediction

Architecture



CCFR-Based Prediction

1. **Mine and store CCFRs continuously.**
   Depth-first search
   Closedness: direct check of pattern extension
   Also calculate *turn statistics*
2. **Retrieve and insert previously mined, relevant CCFRs in an FP-tree *τ*.**



3. **Given an object’s current trajectory *qv*:**
   I. Find the branches that ”best” match *qv* in *τ*.
   (NOTE: Turn statistics guarantee a match)
   II. Calculate the probability of each possible next segment from the *closed* pattern supports.
   III. Distribute the probability mass of the object proportional to the segment probabilities, extend *qv*, and recurs until the time horizon is reached.
   IV. Aggregate the predicted object locations at the time horizon → predicted network density.

Empirical Evaluation

Hardware: Macbook Pro, Intel Core 2 Duo 2.4 GHz CPU, 4MB L2 Cache, 800 MHz Bus speed, and 4GB memory

Data set:

- Real-world trajectories of 1500 taxis and 400 trucks in Stockholm
- Road network: 6000 directed, 55 meter long segments with a connectivity of degree of 2.3
- 17000 trip trajectories during the course of a day

Results

Throughput and scalability: Even for large mining windows (24 hours ≈ 17K trajectories) and very low support values (0.1%) the execution time is within real-time processing limits (<1 minute). Scales nearly linearly with the number of trajectories.

Prediction accuracy: Outperforms the “turn statistics only" approach by 10-30%. The additional prediction utility of the proposed approach becomes increasingly pronounced as the time horizon is increased.

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