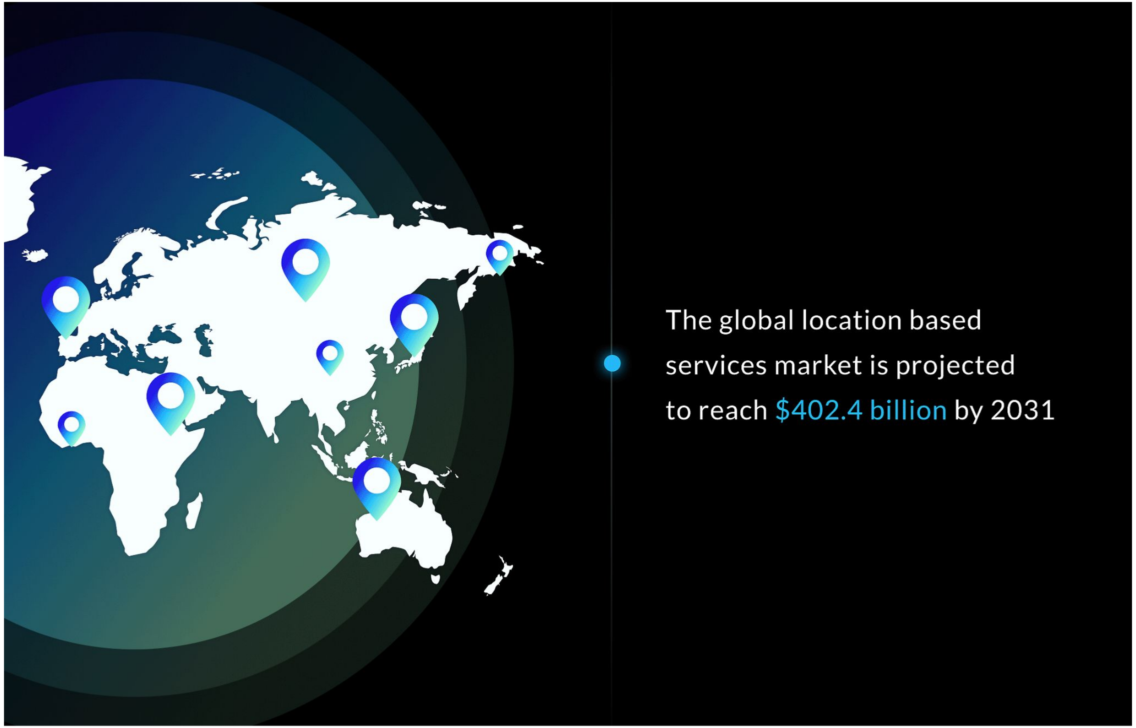
Trajectory based routing / Reachability Analysis

CSCI 587: Lecture 17

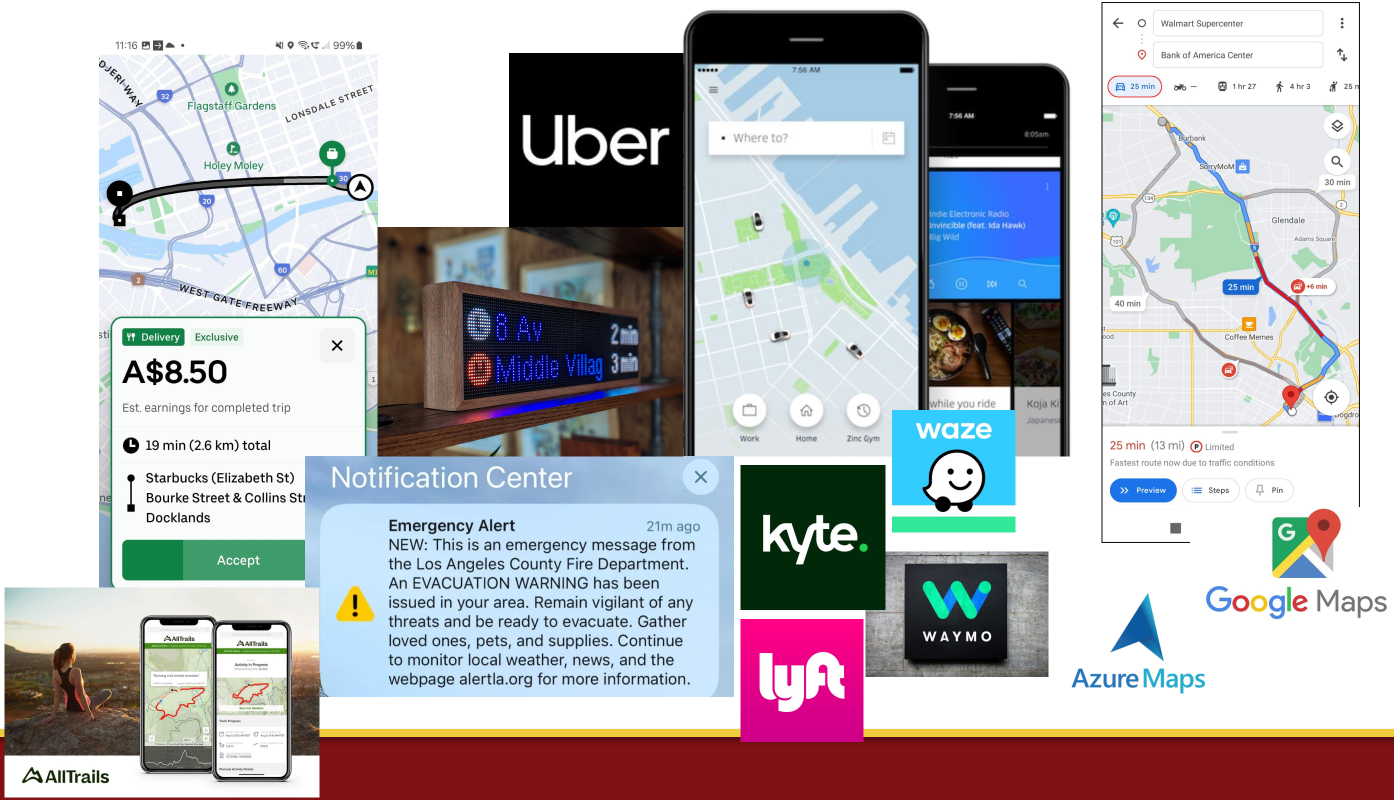
04/26/2025

Location-based services are everywhere



Location-based services are everywhere

- Delivery services
- Navigation
- Ride hailing / sharing
- Emergency response
- Public Transit
- Fleet Management
- Outdoors & Recreation



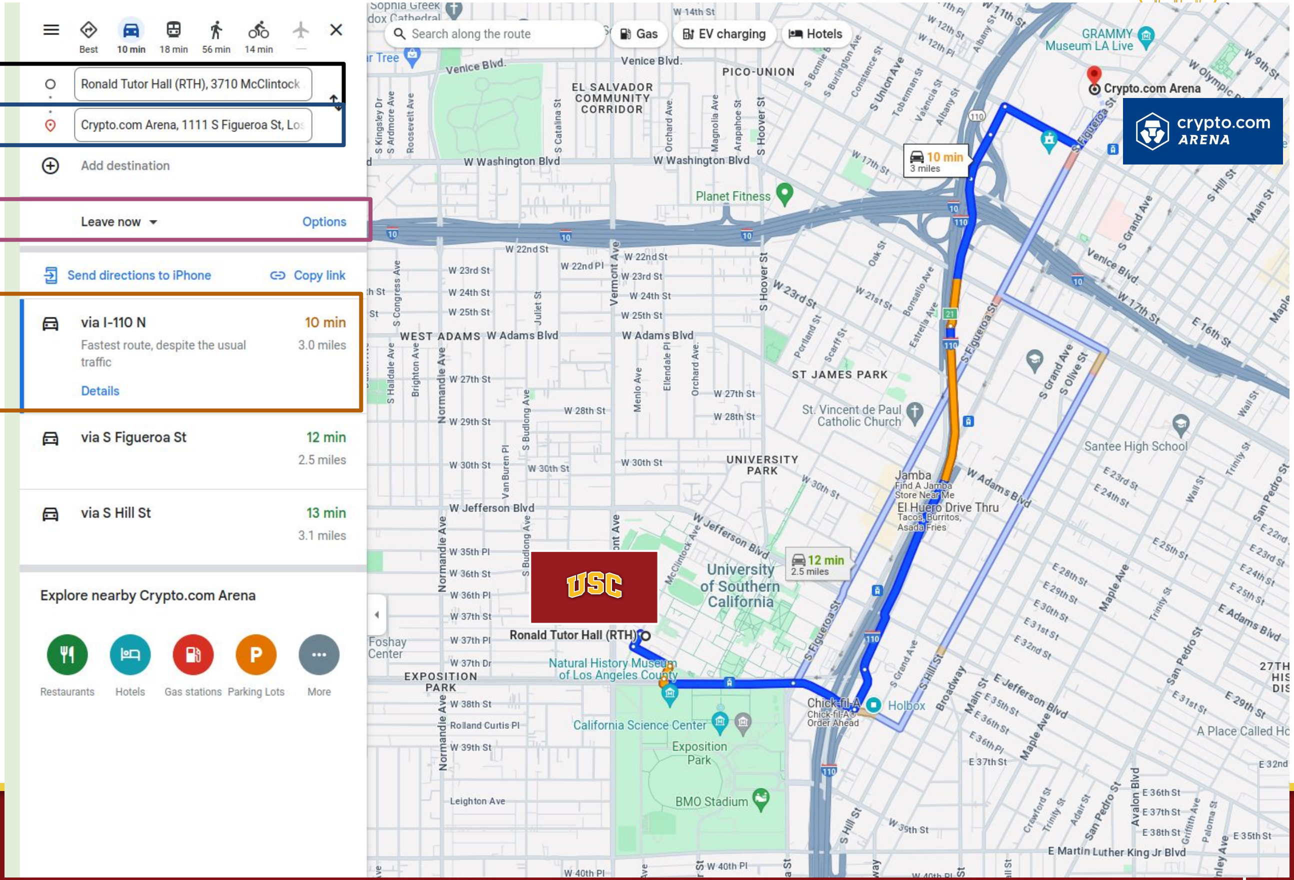
Origin Destination Queries

Origin point

Destination point

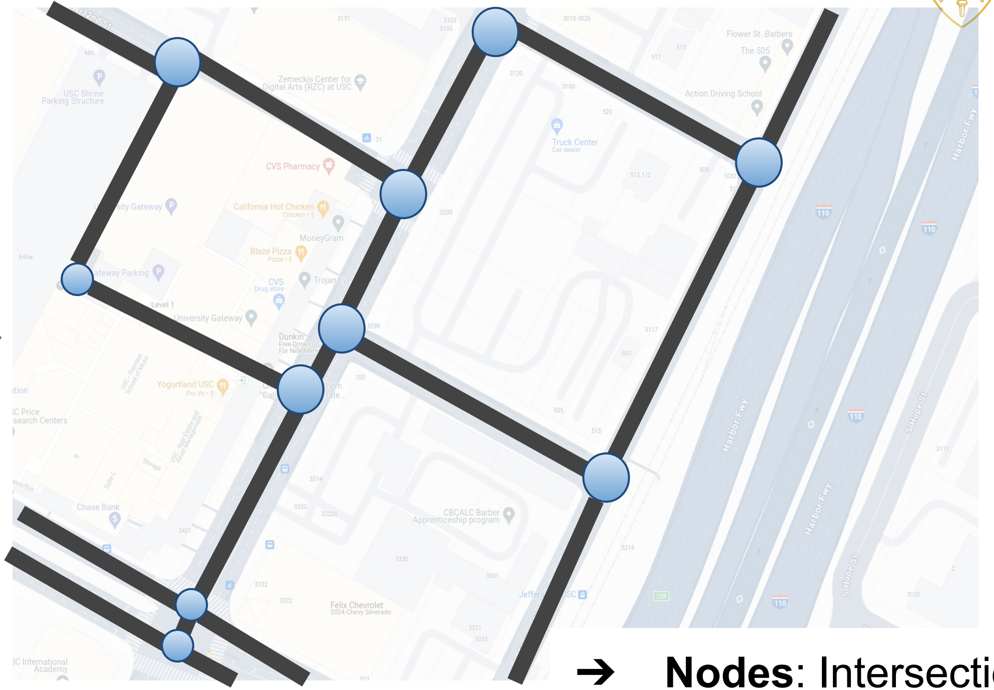
Timestamp

Route & Estimated time of arrival



Road Network as a Graph

city road network extracted from OpenStreetMaps (OSM)

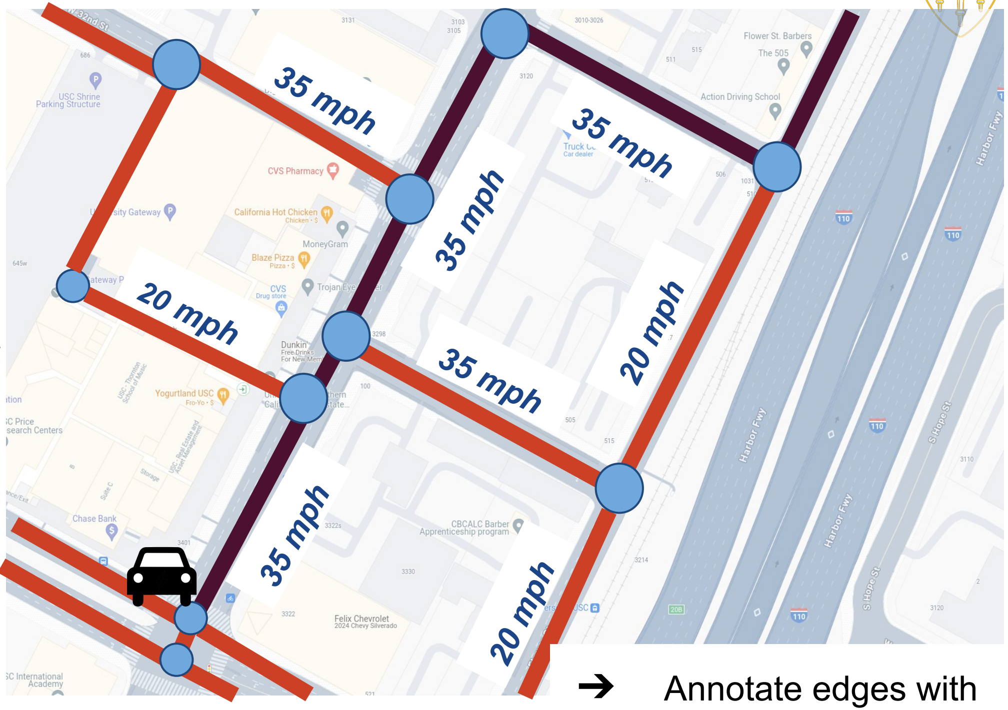


➔ **Nodes**: Intersections

➔ **Edges:** Roads

Road Network as a Graph

city road network extracted from OpenStreetMaps (OSM)



➔ Annotate edges with *weights e.g. road speed limits*

Road Network as a Graph

★ How can we get accurate, time dependent weights?

Origin Destination Queries

Origin point
Destination point
Timestamp

→ ? →

Route
Estimated time of arrival

Origin Destination Queries

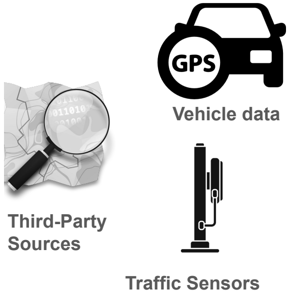
Origin point
Destination point
Timestamp

→ ? →

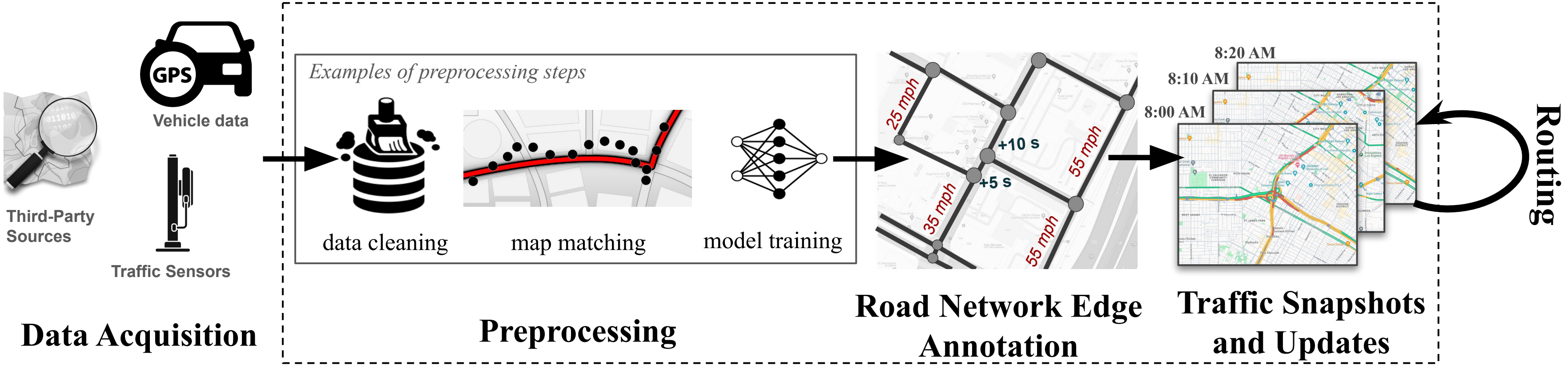
Route
Estimated time of arrival

- Spatial / Temporal Information
  - road conditions
  - stop signs / intersection signals
- Traffic conditions

- Personalized Information
  - preferred routes
  - driving style
- Augmented information
  - weather
  - road closures

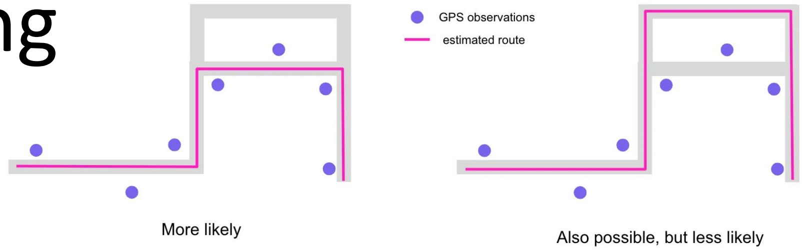


Typical Pipeline of Routing Services



- Large scale, *up-to date GPS data* are continuously collected
- Several cost-intensive preprocessing steps to extract *time dependent "features"*
  - E.g. Map matching: GPS data is aligned with the road network
- Road network edges are dynamically updated (*e.g. every 5 minutes*) and *new traffic snapshots* are created

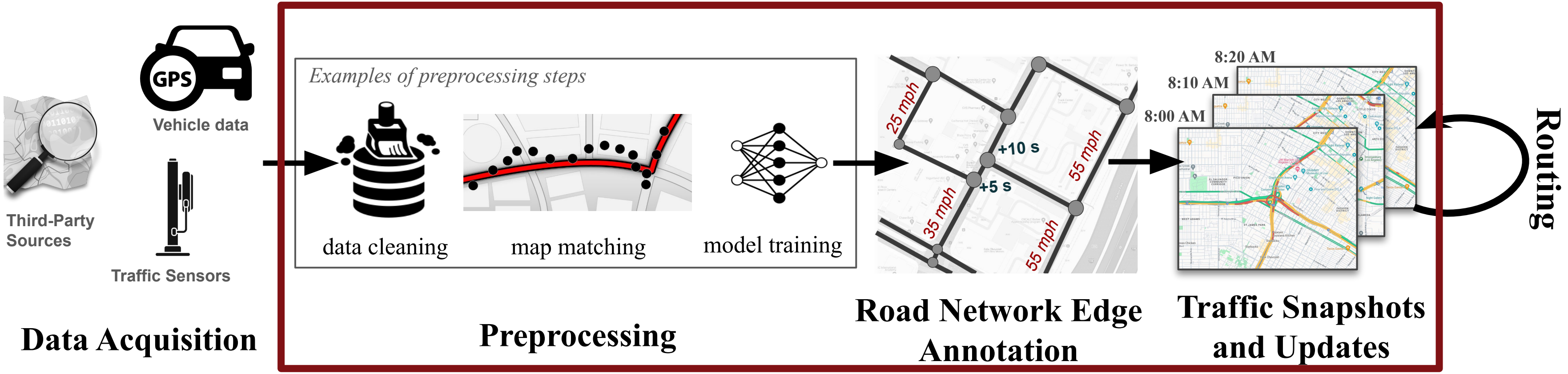
Map Matching



Example of a driver trajectory

- Lyft and Uber use map matching to:
  - To compute the distance travelled by a driver to calculate the fare
  - Dispatch decisions and to display the drivers' cars on the rider app
  - Detect reckless driving
- Why map matching for Origin-Destination Queries?
  - Map past trajectories to road segments
    - Utilize the features of those segments
- Approaches for Map Matching
  - Hidden Markov Model: *Newson & Krumm @ SIGSPATIAL '09* [1]
    - DiDi's IJCAI-19 Tutorial [2]
    - Map Matching @ Uber [3]

Typical Pipeline of Routing Services



Repeats as new data becomes available

- Large scale, *up-to date GPS data* are continuously collected
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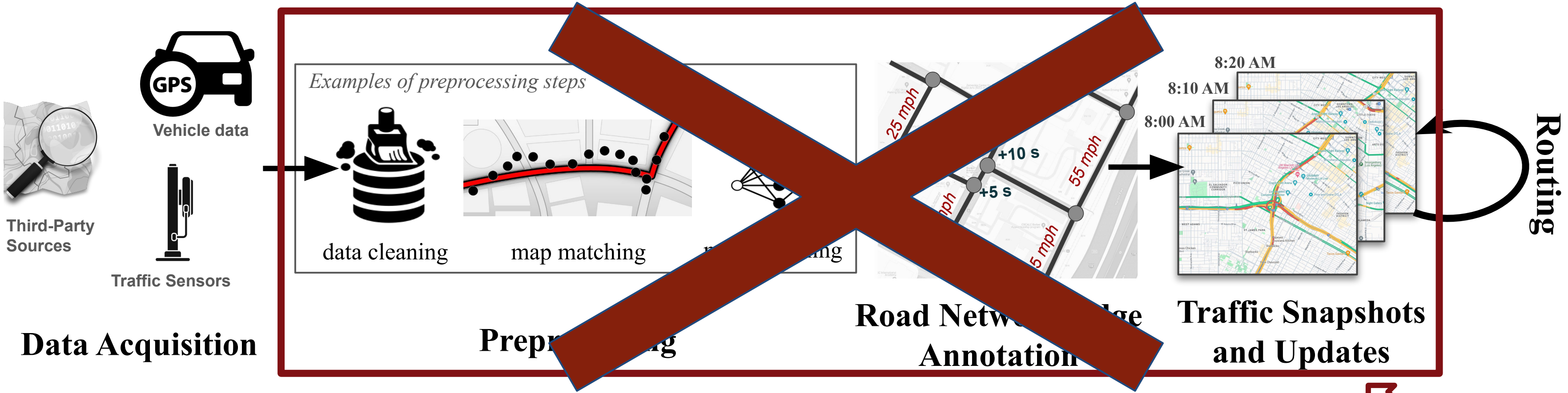
Typical Pipeline of Routing Services



Repeats as new data becomes available

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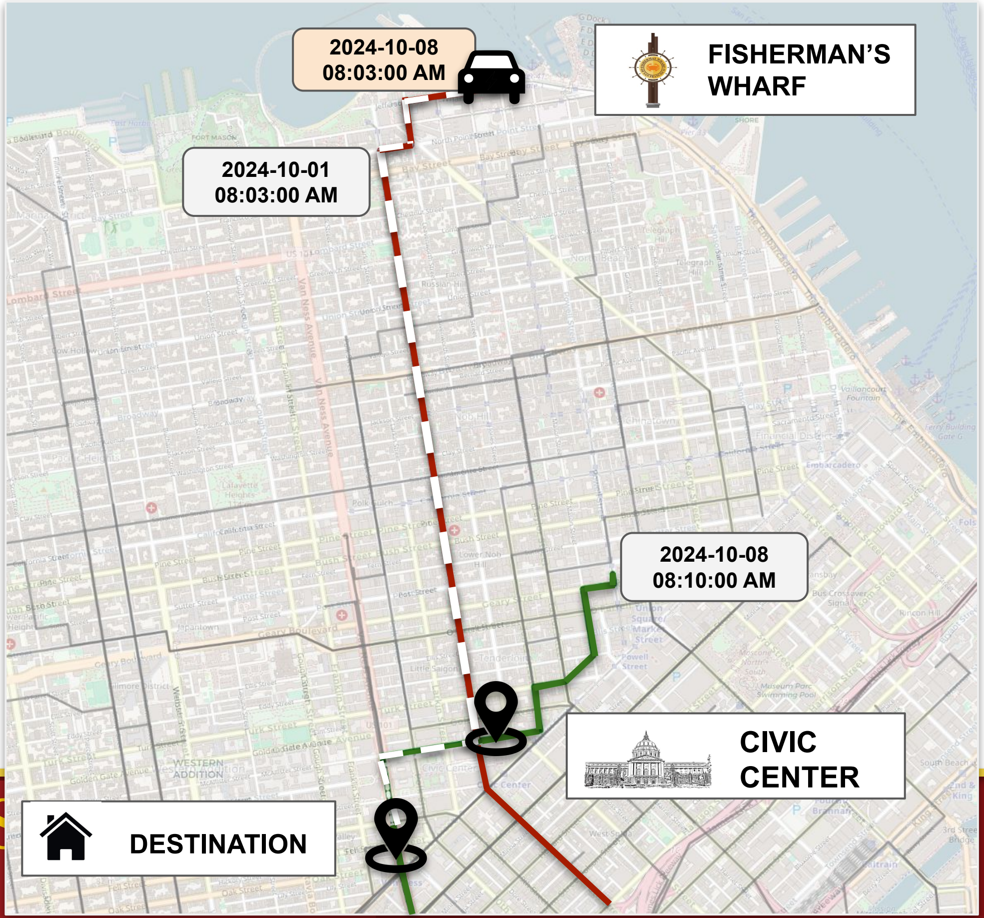
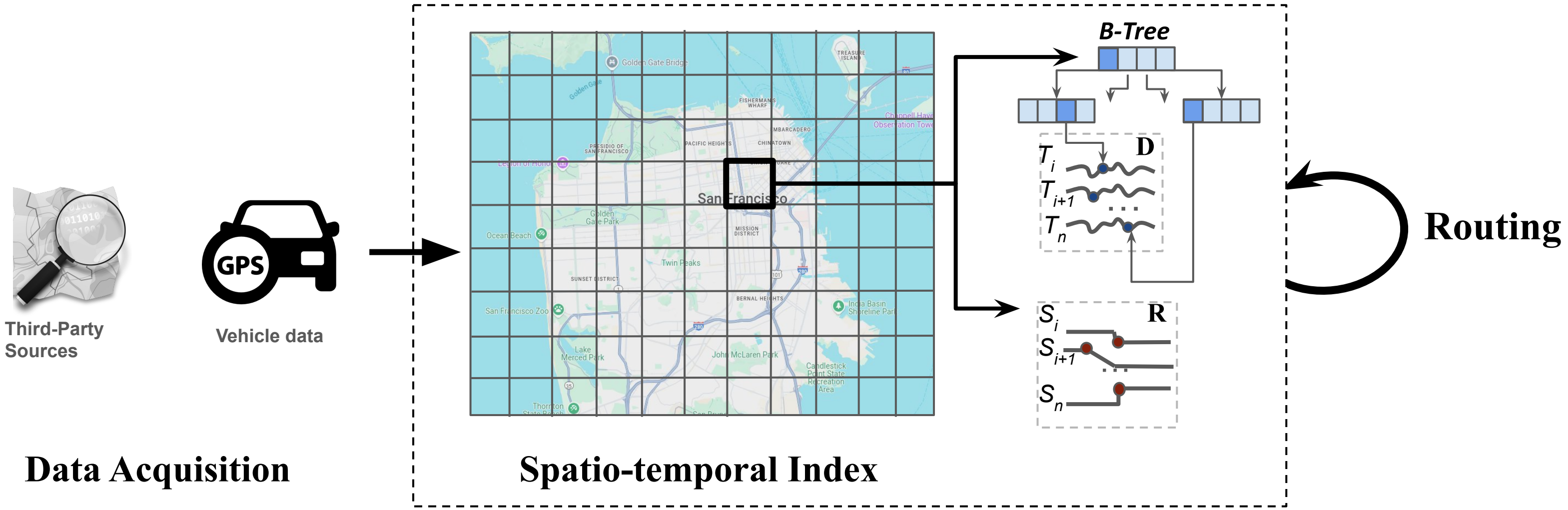
TrajRoute *(Motivation)*



OR: Fisherman's Wharf
DEST: Home
Time: 08:03:00 AM

TrajRoute: Approach



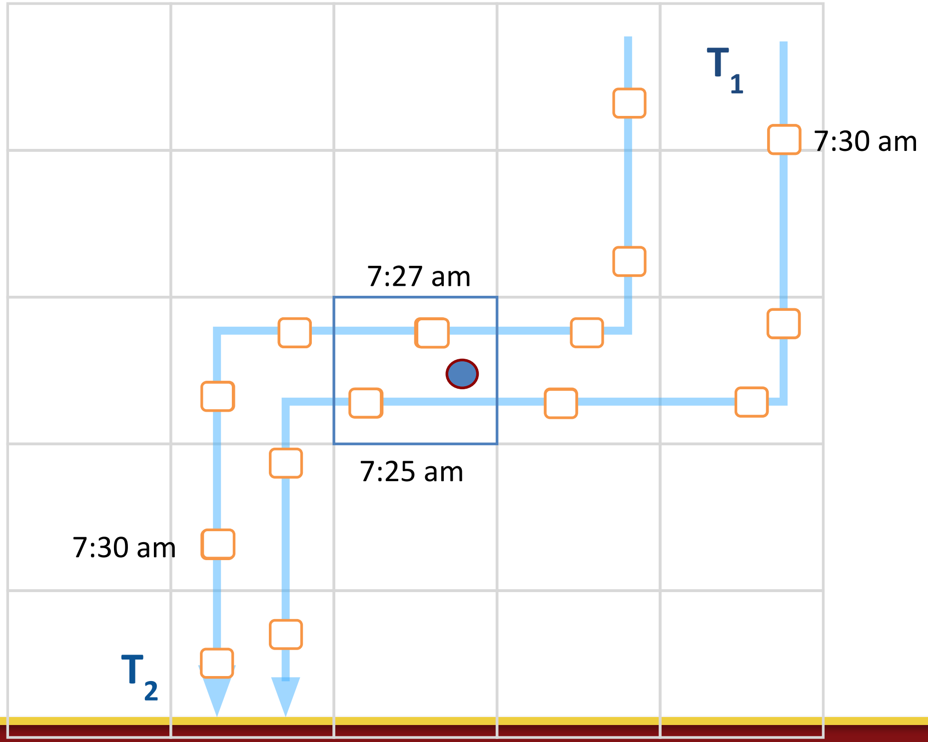
- Routing based on *raw historical trajectories*
  - Ensure that only trajectories that are *spatially* and *temporarily* close to current position are considered
- *Fallback* to the road network when trajectories are not available

TrajRoute: Approach

☐ GPS Point: <p_J = (lat_J, lon_J), ts_J>

Query Point: <p_{OR} , p_{DEST} , dtime>

Current Position(● , 7:30am)



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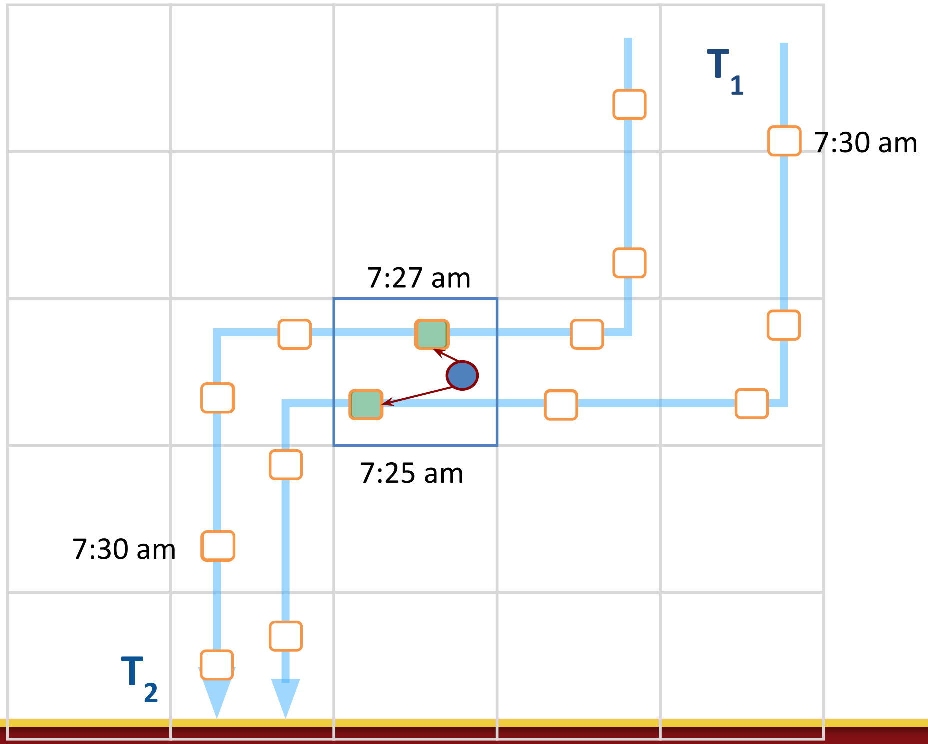
TrajRoute: Approach

GPS Point: <p_J = (lat_J, lon_J), ts_J>

Query Point: <p_{OR} , p_{DEST} , dtime>

Current Position(, 7:30am)



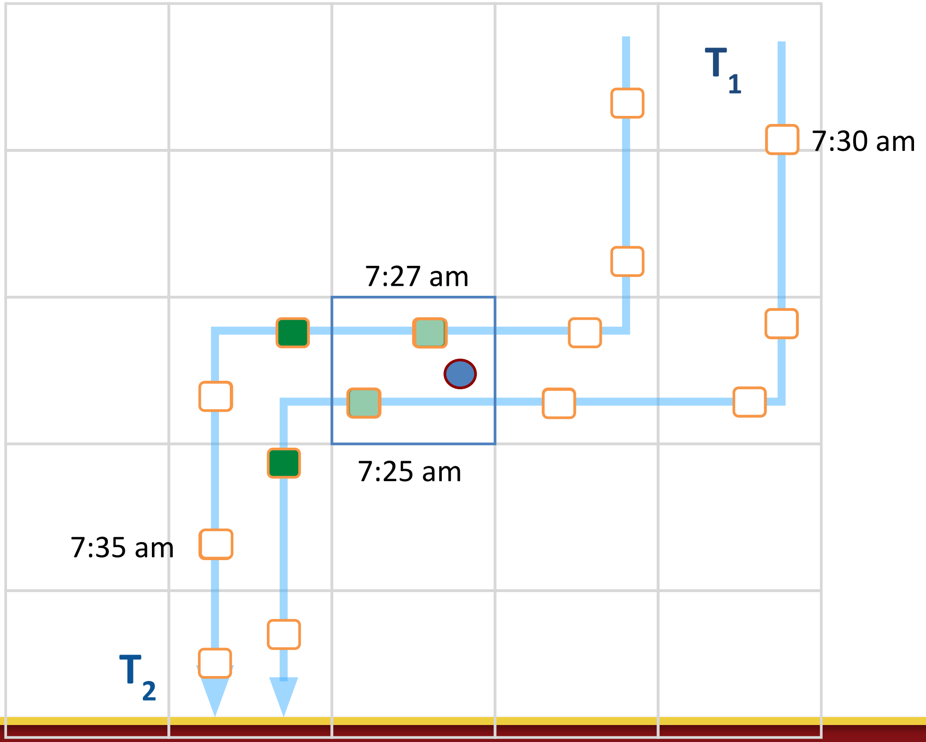
TrajRoute: Approach

GPS Point: <p_J = (lat_J, lon_J), ts_J>

Query Point: <p_{OR} , p_{DEST} , dtime>

Trajectory neighbors to

Current Position(, 7:30am)



TrajRoute: Approach

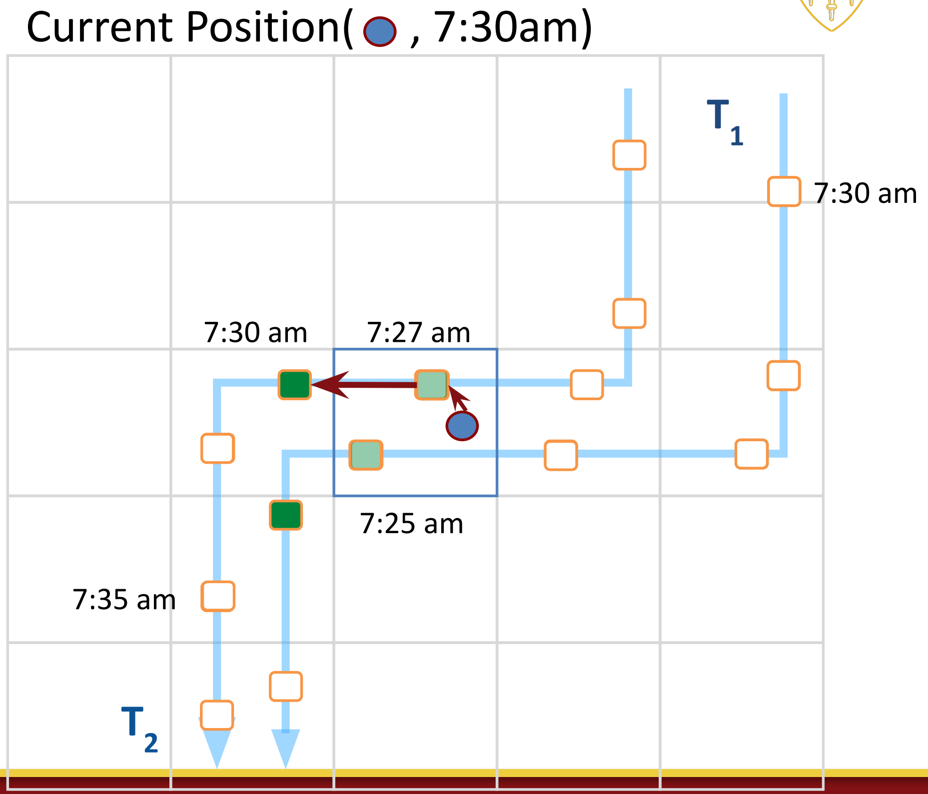
GPS Point: $<p_J = (lat_J, lon_J), ts_J>$

Query Point: $<p_{OR}, p_{DEST}, dtime>$

Trajectory neighbors to ●

$C_{traj}(●, ■) = \tau c + ts(■) - ts(●)$

- **τc:** Cost of transition, constant, depends on the size of the cell

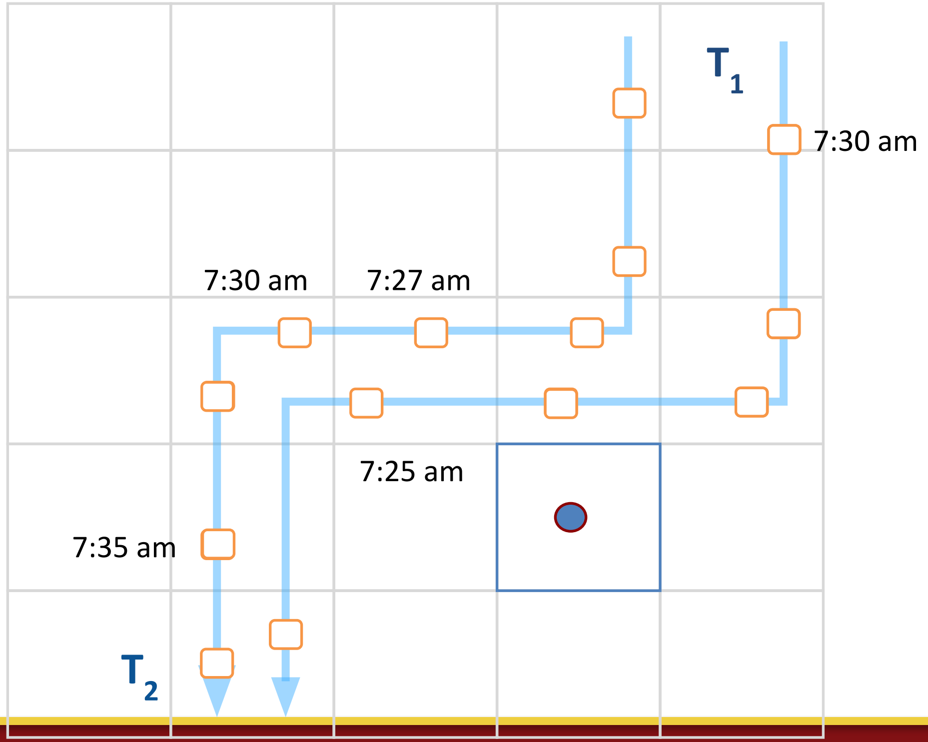


TrajRoute: Approach

GPS Point: $<p_J = (lat_J, lon_J), ts_J>$

Query Point: $<p_{OR}, p_{DEST}, dtime>$

Current Position(● , 7:30am)



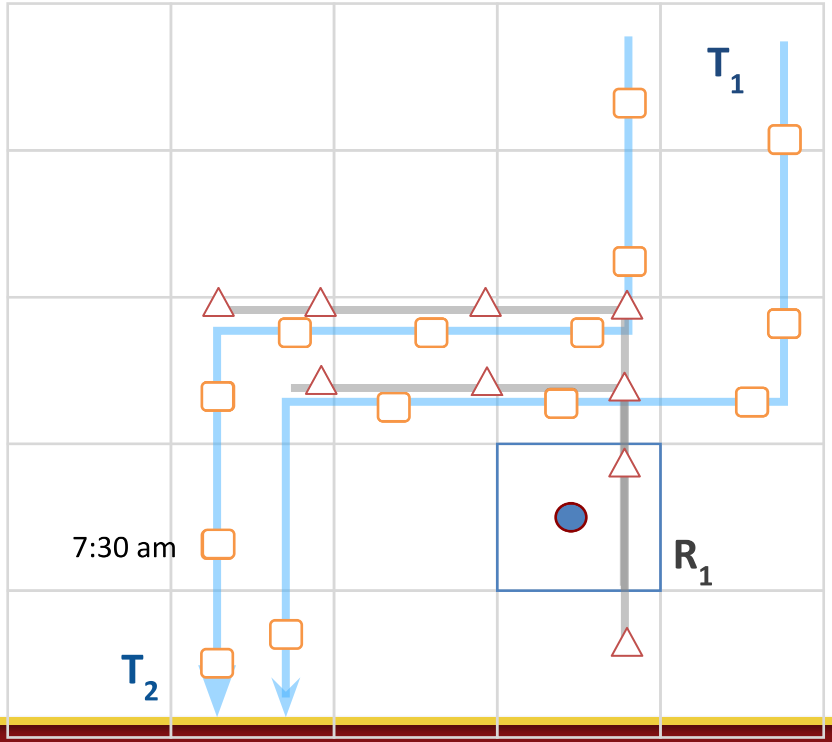
TrajRoute: Approach

GPS Point: <p_J = (lat_J, lon_J), ts_J>

Road Point: <p_I = (lat_I, lon_I)>

Query Point: <p_{OR} , p_{DEST} , dtime>

Current Position(, 7:30am)



TrajRoute: Approach

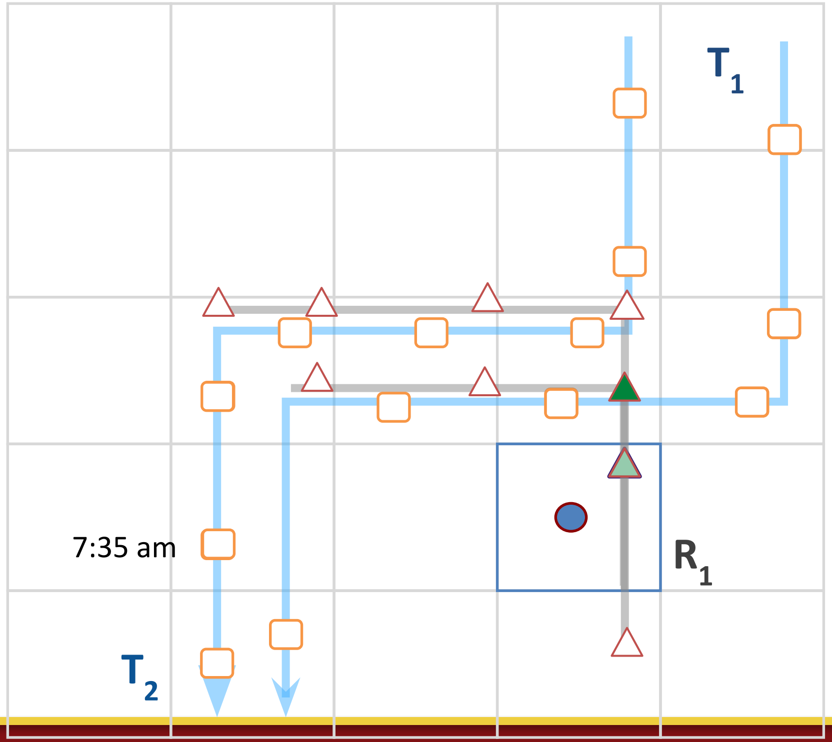
GPS Point: <$p_J = (lat_J, lon_J), ts_J$>

Road Point: <$p_I = (lat_I, lon_I)$>

Query Point: <p_{OR}, p_{DEST}, dtime>

Road neighbors to

Current Position(, 7:30am)



TrajRoute: Approach

□ GPS Point: <p_J = (lat_J, lon_J), ts_J>

△ Road Point: <p_I = (lat_I, lon_I)>

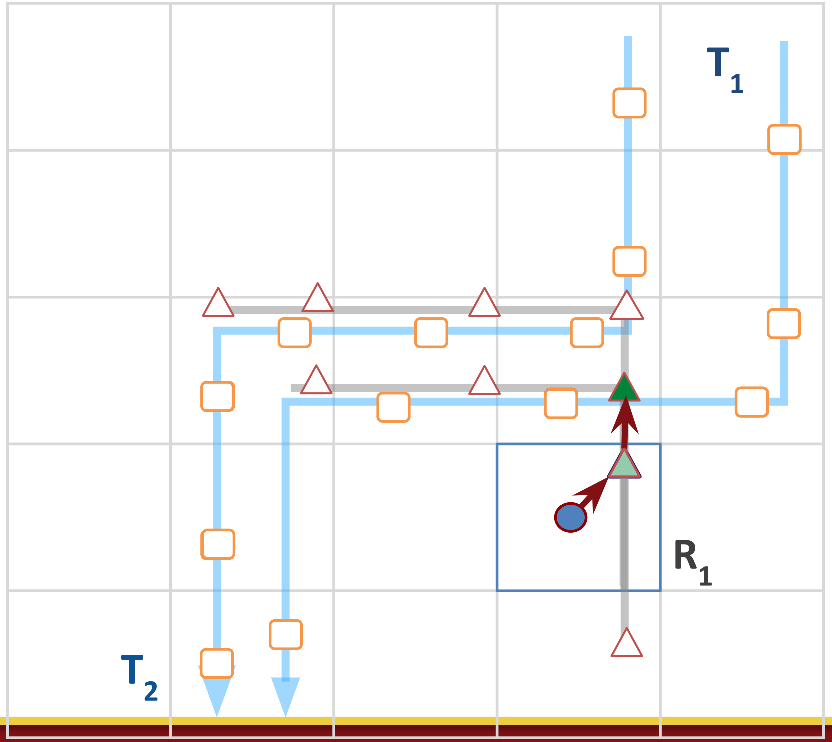
Query Point: <p_{OR} , p_{DEST} , dtime>

▲ Road neighbors to ●

C_{road} (● , ▲) = τc + [dist(△ , ▲) / v (▲)]

- dist: Haversine distance between road points
- v: Speed limit of road segment

Current Position(● , 7:30am)



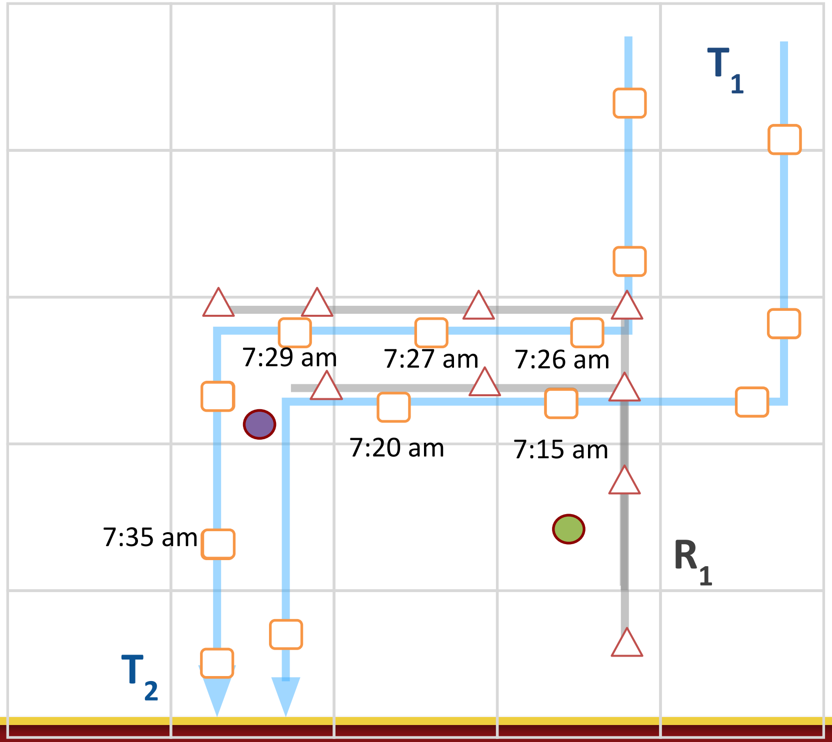
TrajRoute: Approach

GPS Point: $\langle p_J = (lat_J, lon_J), ts_J \rangle$

Road Point: $\langle p_I = (lat_I, lon_I) \rangle$

Query Point: $\langle p_{OR}, p_{DEST}, dtime \rangle$

7:30 am



TrajRoute: Approach

□ GPS Point: <$p_J = (lat_J, lon_J), ts_J$>

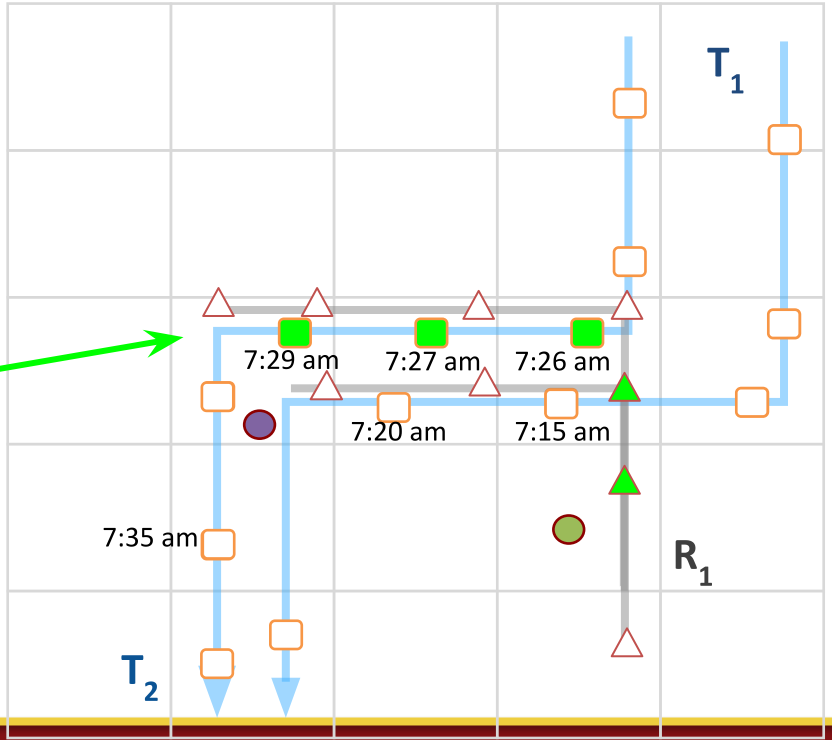
△ Road Point: <$p_I = (lat_I, lon_I)$>

Query Point: <p_{OR} , p_{DEST} , dtime>

↓ ↓ ↓

7:30 am

Ideal Path



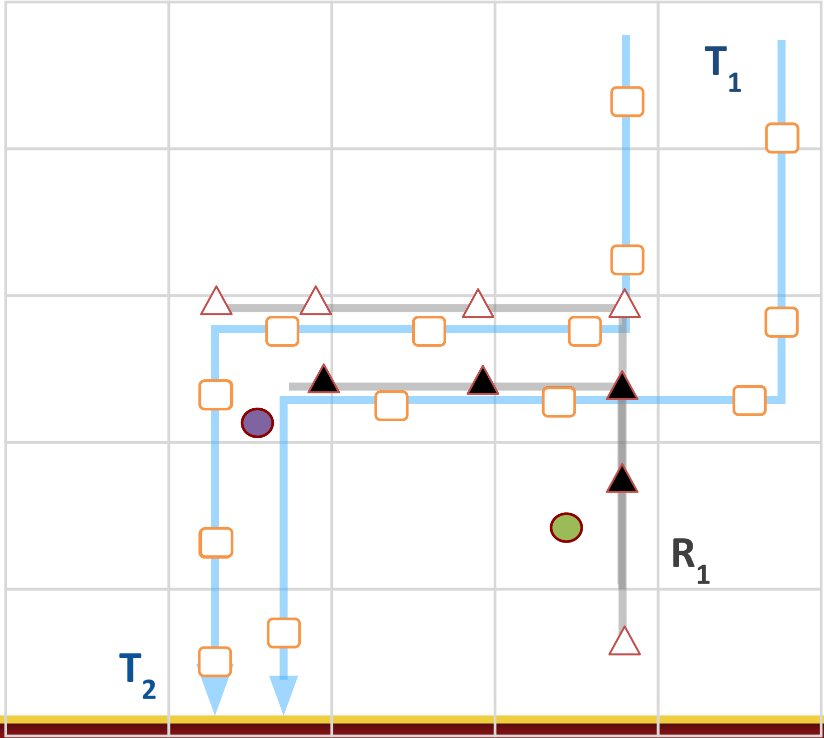
TrajRoute: Approach

- GPS Point: <p_J = (lat_J, lon_J), ts_J>
- Road Point: <p_I = (lat_I, lon_I)>

Query Point: <p_{OR} , p_{DEST} , dtime>

7:30 am

$C_{road} < C_{traj}$. Why?



TrajRoute: Approach

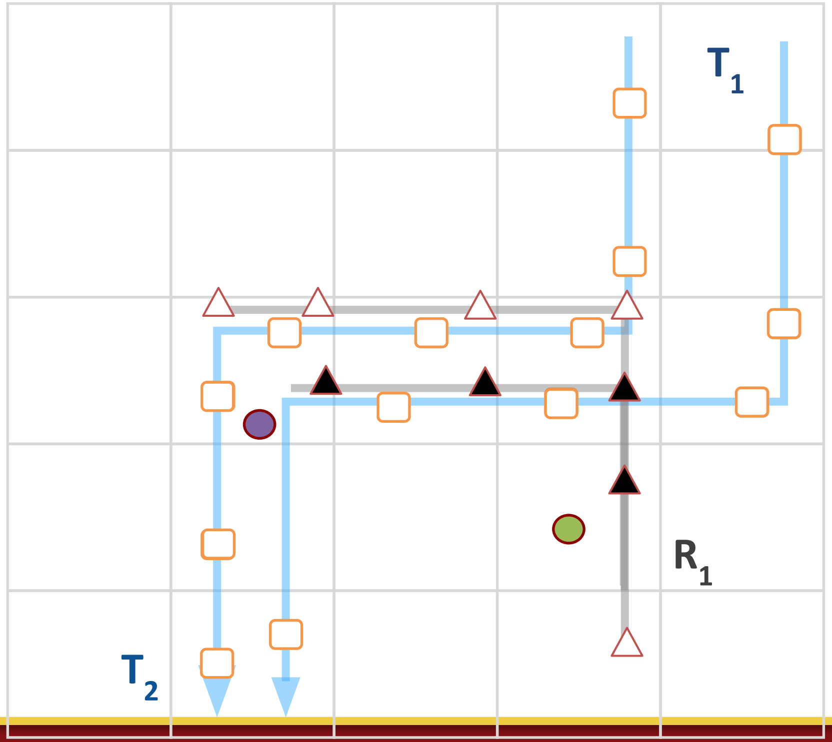
□ GPS Point: $\langle p_J = (lat_J, lon_J), ts_J \rangle$

△ Road Point: $\langle p_I = (lat_I, lon_I) \rangle$

Query Point: $\langle p_{OR}, p_{DEST}, dtime \rangle$

↓ ↓ ↓

● ● 7:30 am



Using speed limit does not account for:

- Intersection costs
- Acceleration/Deceleration
- Traffic Lights
- Traffic Congestion etc.

} Inherently encoded in trajectory timestamps

TrajRoute: Approach

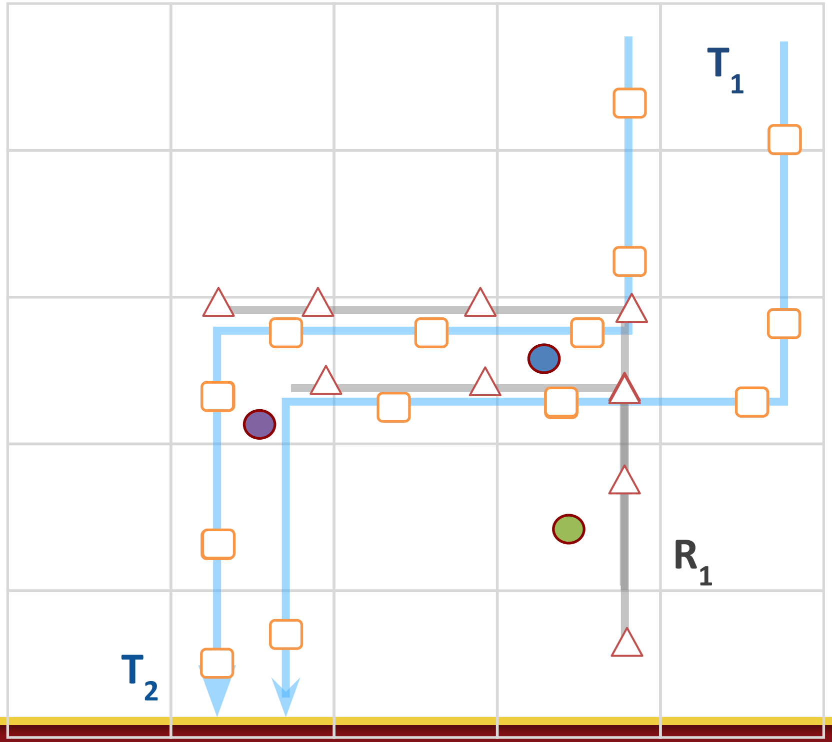
GPS Point: $<p_J = (lat_J, lon_J), ts_J>$

Road Point: $<p_I = (lat_I, lon_I)>$

Query Point: $<p_{OR}, p_{DEST}, dtime>$

7:30 am

Current Position(, 7:30am)



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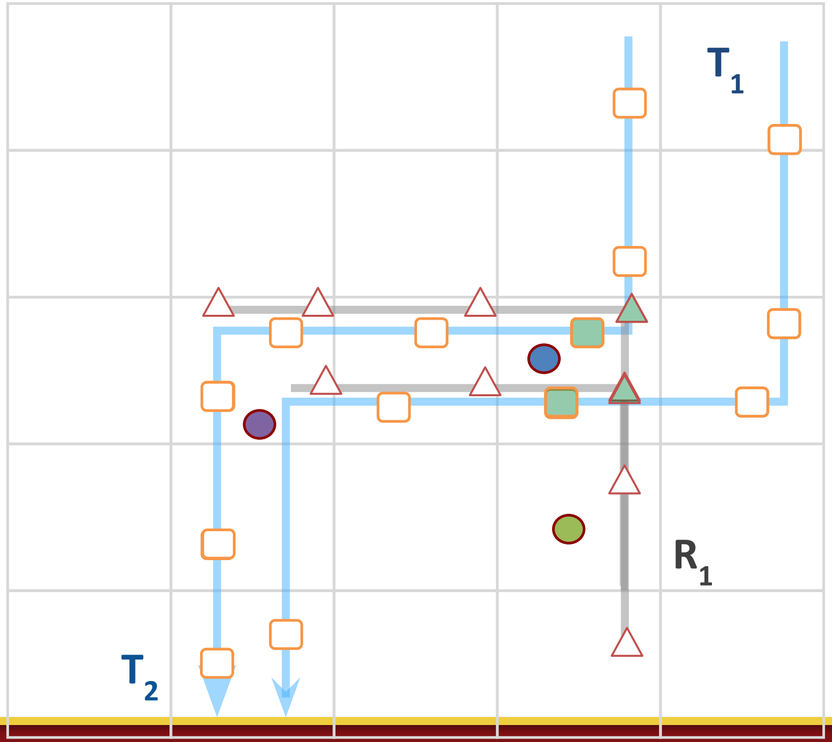
7:30 am

Current Position(, 7:30am)



TrajRoute: Approach

GPS Point: <p_J = (lat_J, lon_J), ts_J>

Road Point: <p_I = (lat_I, lon_I)>

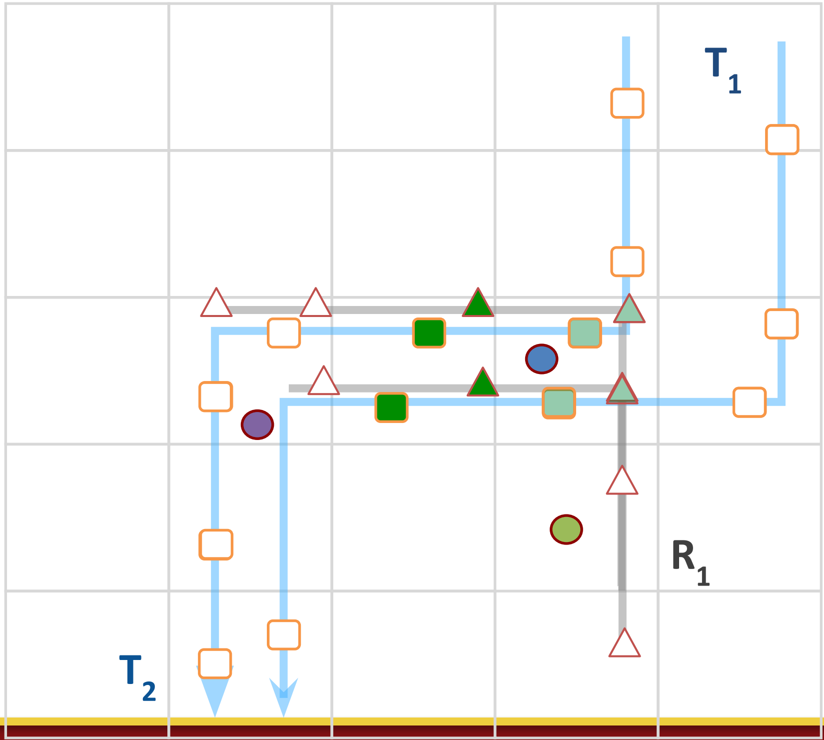
Query Point: <p_{OR} , p_{DEST} , dtime>

7:30 am

C_{base} = C_{road} (,), : Road Neighbor

C_{traj} (,), : Traj. Neighbor

Current Position(, 7:30am)



TrajRoute: Approach

□ GPS Point: <p_J = (lat_J, lon_J), ts_J>

△ Road Point: <p_I = (lat_I, lon_I)>

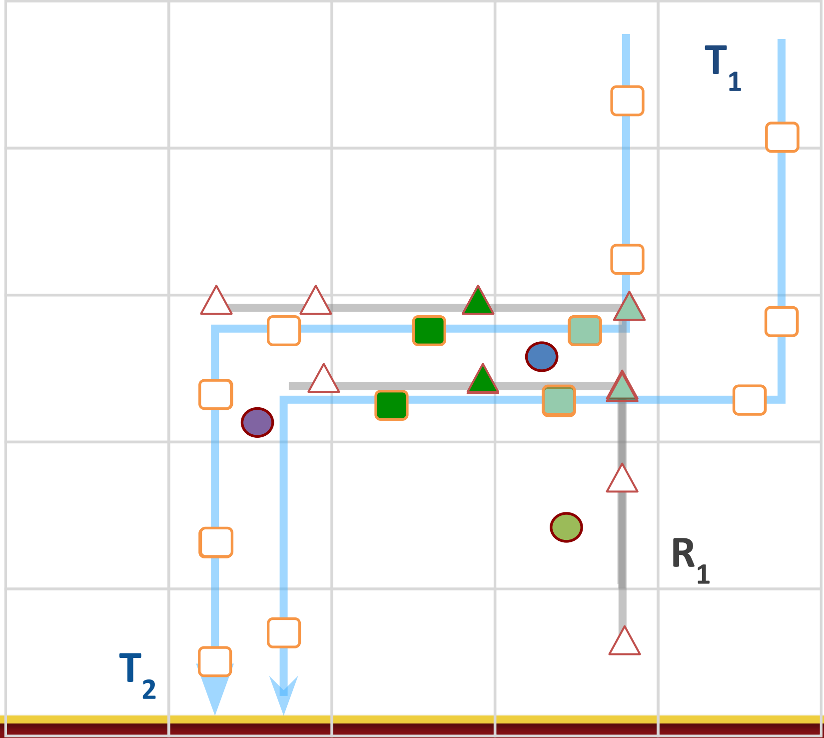
Query Point: <p_{OR}, p_{DEST}, dtime>

7:30 am

C_{pref} =
- **(1+ α)** C_{road} (●, ▲), ▲ : Road Neighbor
- C_{traj} (●, ■), ■ : Traj. Neighbor

- α: road penalty factor (> 0)

Current Position(●, 7:30am)



TrajRoute: Approach

GPS Point: <p_J = (lat_J, lon_J), ts_J>

Road Point: <p_I = (lat_I, lon_I)>

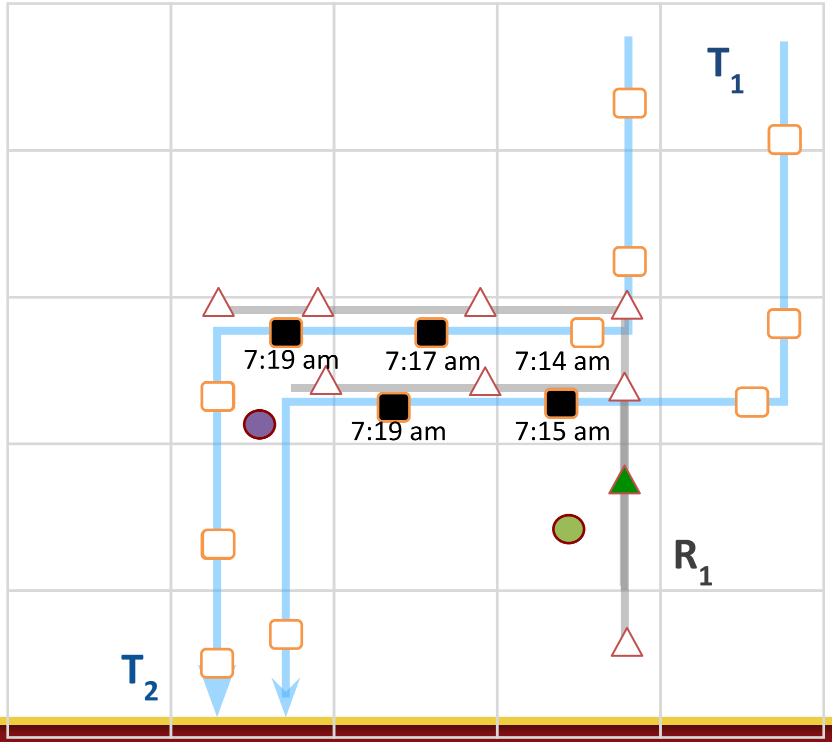
Query Point: <p_{OR} , p_{DEST} , dtime>

7:30 am

$$C_{pref} = \begin{cases} \mathbf{(1+\alpha)}\ C_{road}(\bullet, \blacktriangle), \blacktriangle : \text{Road Neighbor} \\ C_{traj}(\bullet, \blacksquare), \blacksquare : \text{Traj. Neighbor} \end{cases}$$

- α: road penalty factor (> 0)

Current Position(● , 7:30am)



TrajRoute: Approach

GPS Point: $<p_J = (lat_J, lon_J), ts_J>$

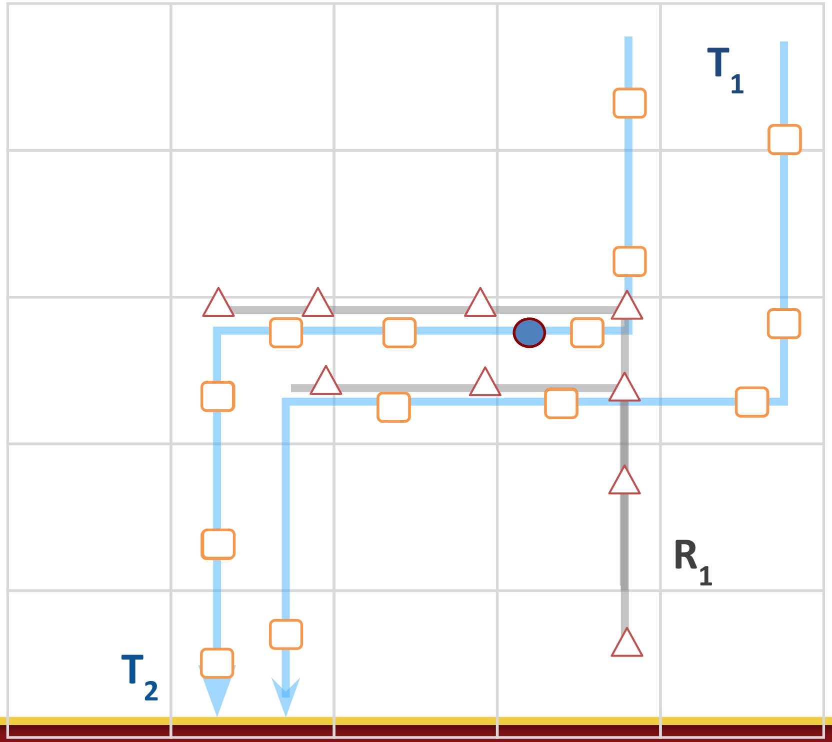
Road Point: $<p_I = (lat_I, lon_I)>$

Query Point: $<p_{OR}, p_{DEST}, dtime>$

↓ ↓ ↓

7:30 am

Current Position(, 7:30am)



TrajRoute: Approach

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△ Road Point: <$p_I = (lat_I, lon_I)$>

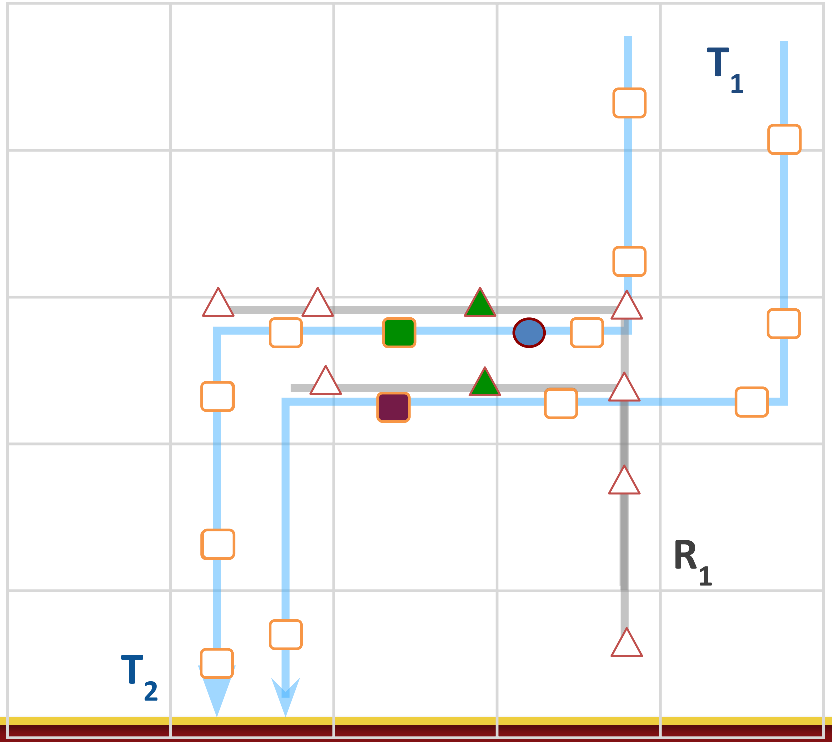
Query Point: <p_{OR} , p_{DEST} , dtime>

● ● 7:30 am

$$C = \begin{cases} (1+\alpha)\ C_{road}(●, ▲), ▲ : \text{Road Neighbor} \\ e^{-rw}\ C_{traj}(●, ■), ■ \in T_1, ● \in T_1 \\ C_{traj}(●, ■), ■ \in T_2, ● \in T_1 \end{cases}$$

- α: road penalty factor (> 0)
- rw: continuity reward ∈ [0, 1]

Current Position(● , 7:30am)



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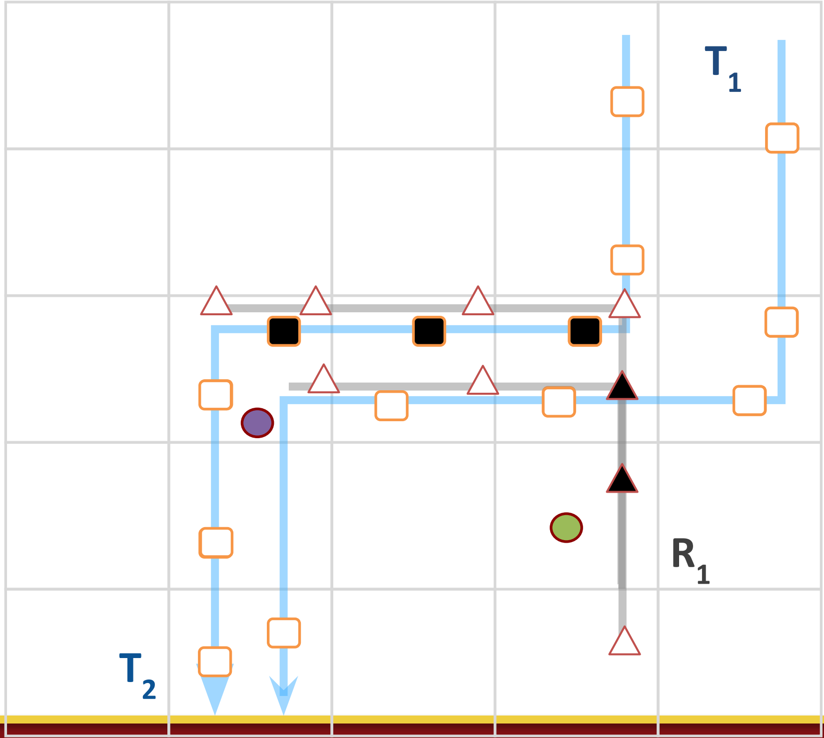
7:30 am

Current Position(, 7:30am)



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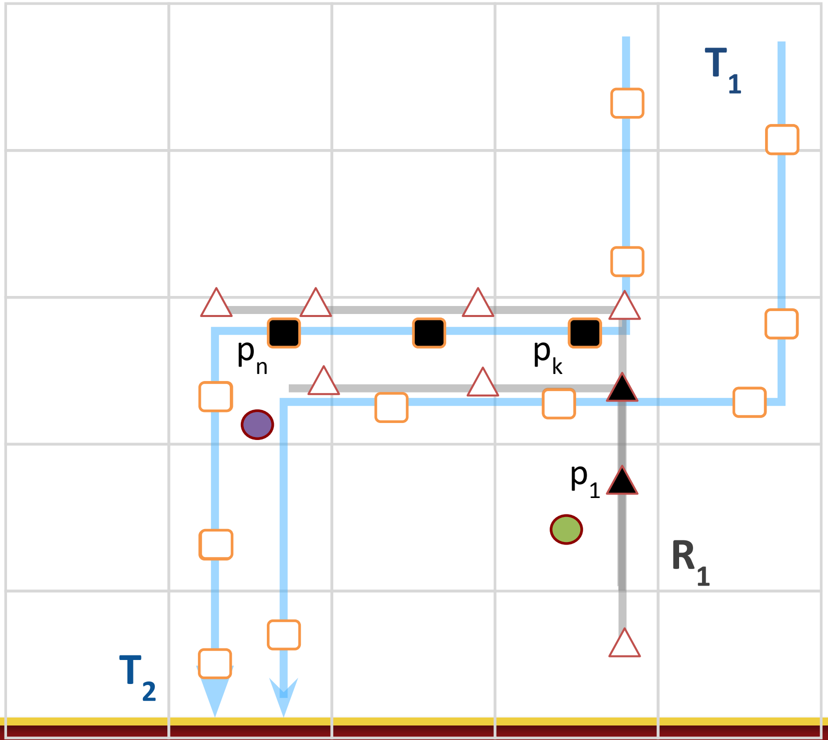
Road Point: <p_I = (lat_I, lon_I)>

Query Point: <p_{OR} , p_{DEST} , dtime>

7:30 am

- Any pathfinding algorithm can be applied.
- For Dijkstra:
  - $$g(p_k) = \sum_{i=1}^{|P|} C(p_{i-1}, p_i), \quad p_i \in P$$
- For A*:
  - $$h(p_k) = \frac{dist(p_k, Q.p_{DEST})}{v_{max}}$$ ➡ always underestimates the cost

Current Position(, 7:30am)



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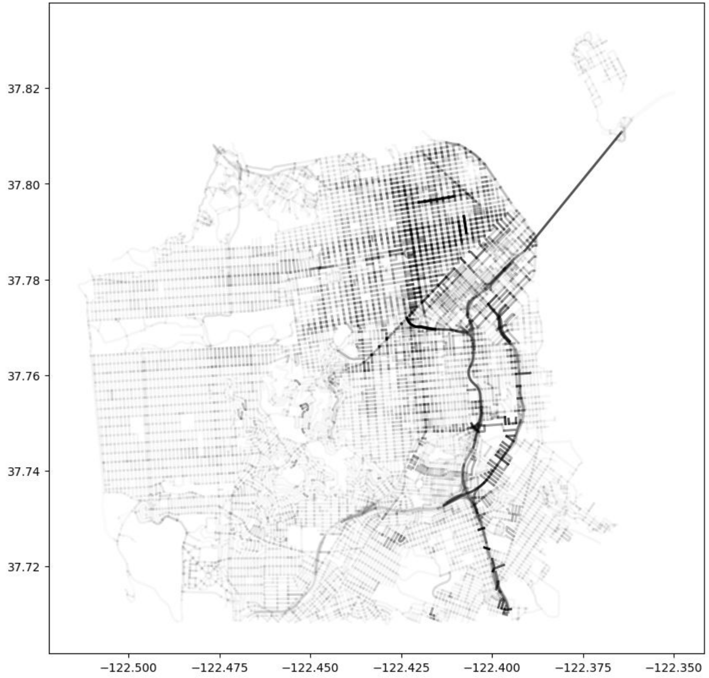
TrajRoute: Experiments

- Data Source
  - San Francisco Taxi Data
  - OSM for road network
- Data Statistics
  - > 1M trajectories, 27.279 roads
  - 99% spatial coverage
  - Peak: ~25%, Off-peak: ~75%
  - Weekend: ~35%, Weekday: ~65%
- Evaluation
  - Random Origin-Destination Queries from trajectories.
  - Comparison of routes with Azure Maps
    - Length of route
    - ETA of route



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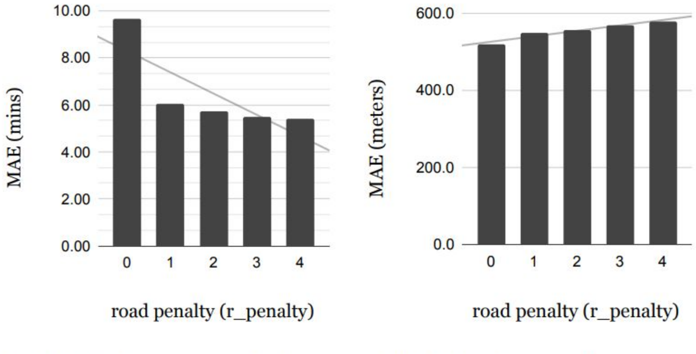
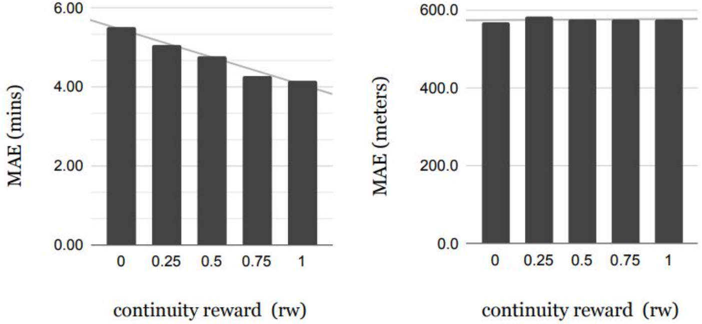


(a) MAE of route travel time (b) MAE of route distance



(a) MAE of route travel time (b) MAE of route distance

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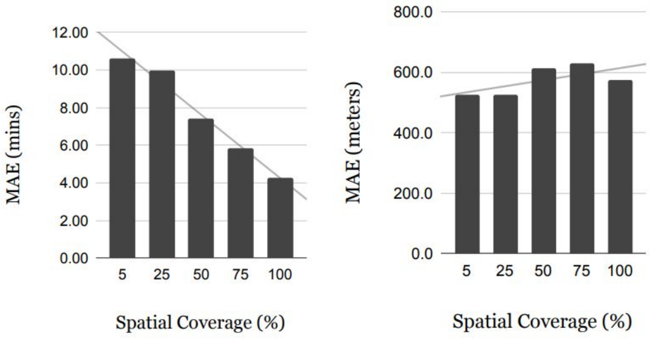
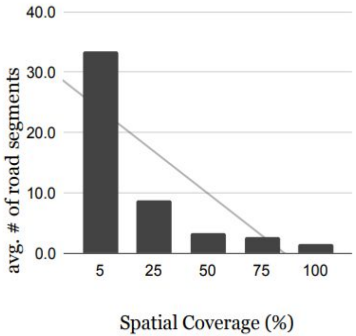
TrajRoute: Experiments

- Evaluation
  - Random Origin-Destination Queries from trajectories.
  - Comparison of routes with Azure Maps
    - Length of route
    - ETA of route
  - Spatial Coverage
    - Keep trajectories that cover x% of the area
    - Keep *α=3.0* and *rw=0.75* constant



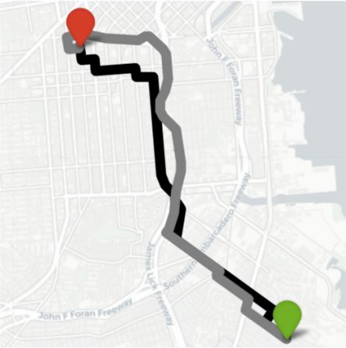
(a) MAE of route travel time (b) MAE of route distance

Figure 7: Results for different levels of spatial coverage.



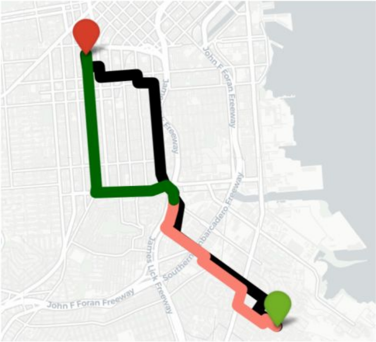
TrajRoute: Experiments

Query Time: *06:01 PM*
Azure Maps ETA: 21 mins



(a) Route for $r_{penalty} = 0$ and $rw = 0$.
TrajRoute ETA: 10 mins.

(b) Route for $r_{penalty} = 3$ and $rw = 0$.
TrajRoute ETA: 16.21 mins.



(c) Route for $r_{penalty} = 3$ and $rw = 0.75$.
TrajRoute ETA: 19.53 mins.

Query Time: *01:25 AM*
Azure Maps ETA: 12 mins

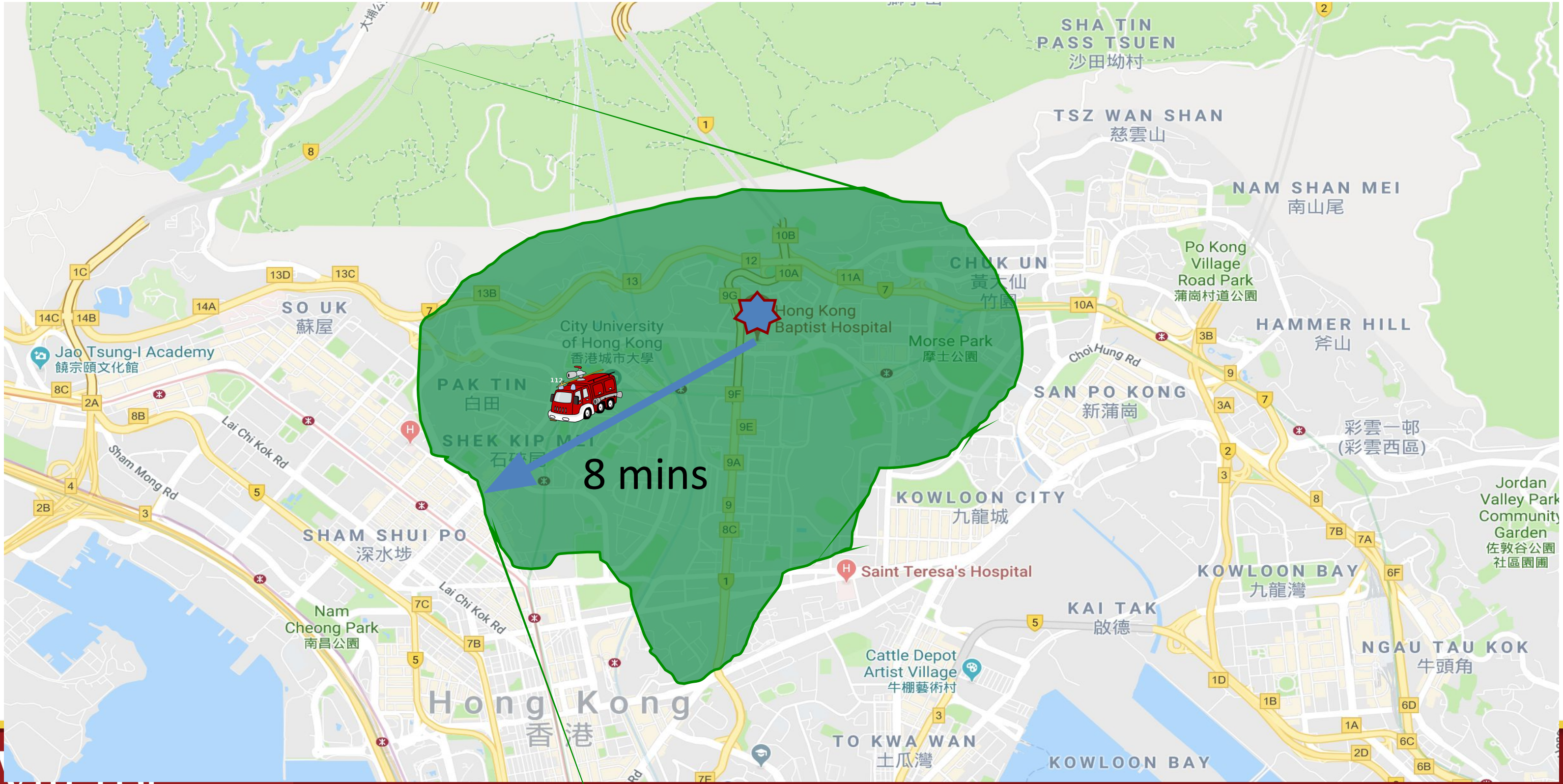
(a) Route for $r_{penalty} = 0$ and $rw = 0$.
TrajRoute ETA: 8.3 mins.

(b) Route for $r_{penalty} = 3$ and $rw = 0$.
TrajRoute ETA: 10.15 mins.

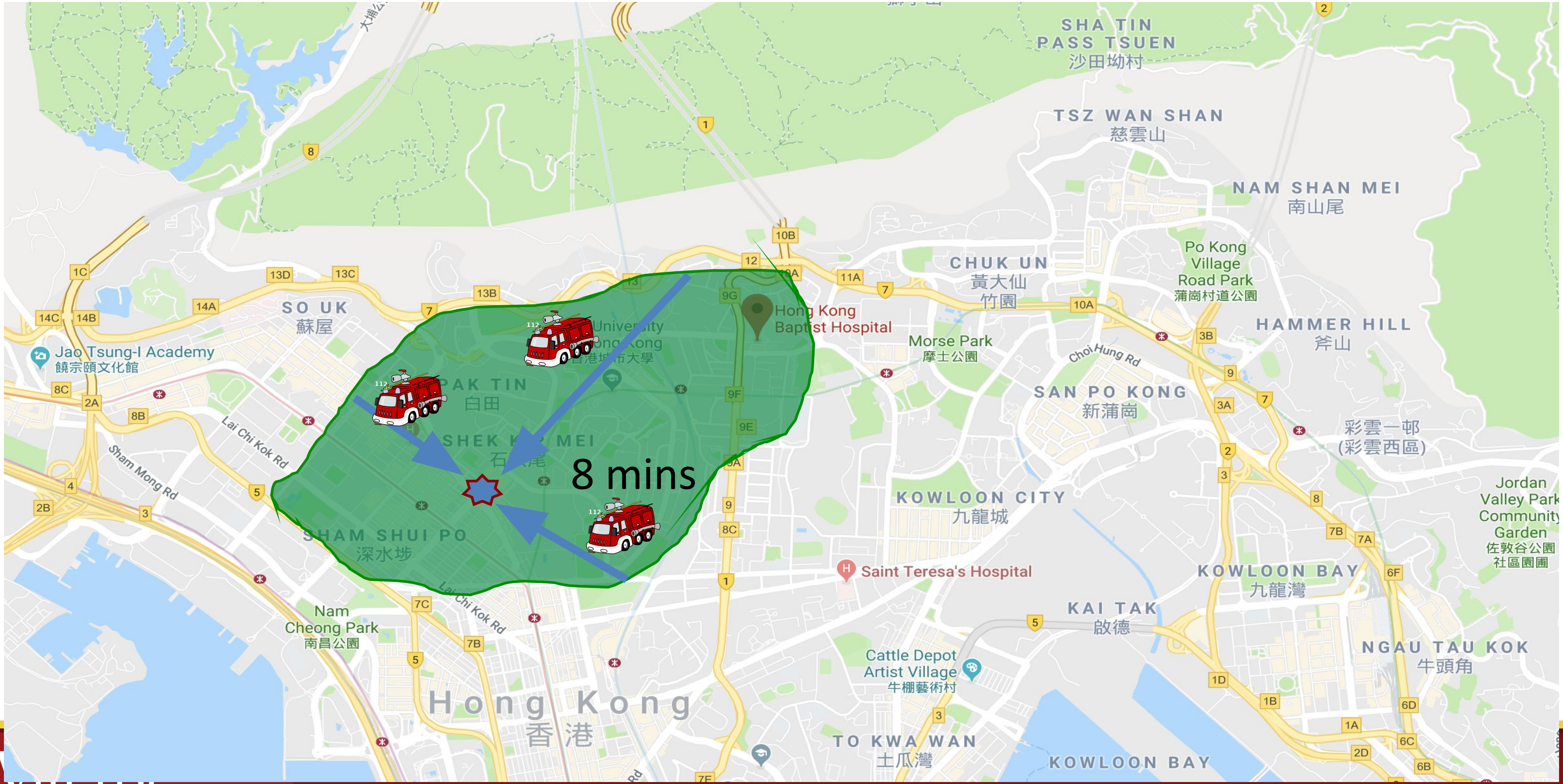
(c) Route for $r_{penalty} = 3$ and $rw = 0.75$.
TrajRoute ETA: 11.58 mins.

Isochrone Maps

**Actual travel times might vary*

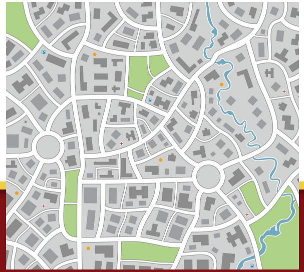


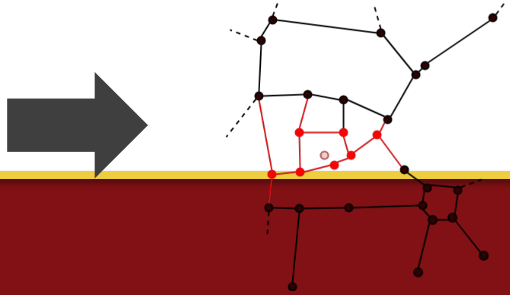
Reverse Reachability Analysis



Graph-based Approaches

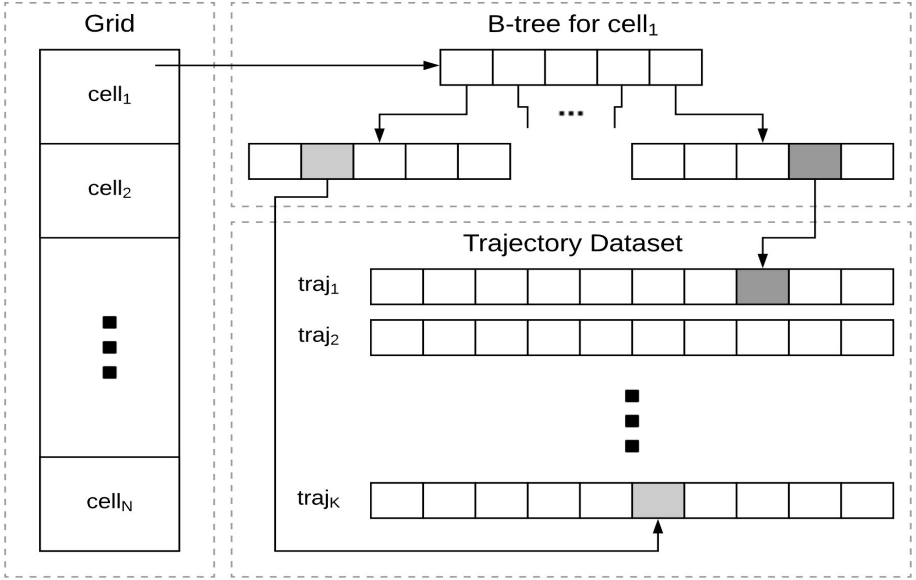
- **Isochrone maps** extensively studied in the databases community
- In **graph theory** defined as the minimal subgraph that can be reached from a query vertex given a limited path cost that is equivalent to travel time.
  - More precisely, it's the set of all reachable vertices, fully traversed edges, and possibly partially traversed edges
- Standard solutions are based on **Dijkstra**'s (or **Dreyfus**) shortest path algorithm
  - **[ICDE'06]** Finding fastest paths on a road network with speed patterns, *Kanoulas et al.*
  - **[GIS'08]** Computing isochrones in multi-modal, schedule-based transport networks, *Bauer et al.*
  - **[EDBT'08]** Finding time-dependent shortest paths over large graphs, *Ding et al.*
  - **[CIKM'11]** Defining isochrones in multi-modal spatial networks, *Gamber et al.*
  - **[SEA'16]** Fast exact computation of isochrones in road networks, *Baum et al.*





Data-Driven Reachability

- Remove the *expensive map-matching* step
  - Can take days to compute time-dependent weights for big data
- Remove the traversal step of *complex* graphs
  - The higher the query time limit the more edges need to be explored
- Compute isochrone maps *directly from data*
  - Only process trajectories that satisfy query criteria
- Support multiple *Reachability Queries*
  - Single-Source & Multi-Source (Normal)
  - Single-Target & Multi-Target (Reverse)

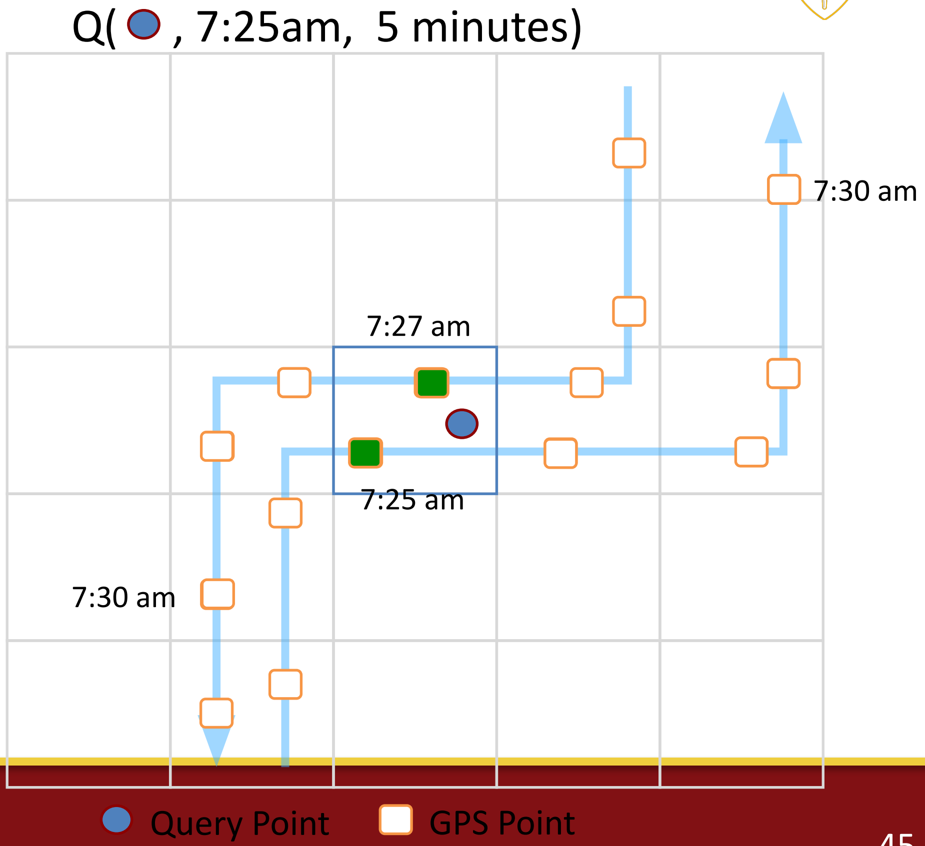


Single-Source & Multi-Source Queries

Reachability Query

- Q(s, t, d)
  - s: source location
  - t: departure time
  - d: time limit in minutes

```
c ← findCell(G, Q.s)
r ← {} // Initialize result to empty set
for (traj, i) ∈ c.gpsInWindow(Q.t, Q.t + Q.d) do
    while i < traj.length and traj[i].ts ≤ Q.t + Q.d do
        r ← r ∪ {traj[i].loc}
        i ← i + 1
    end while
end for
return r // Return the set of all reachable points
```

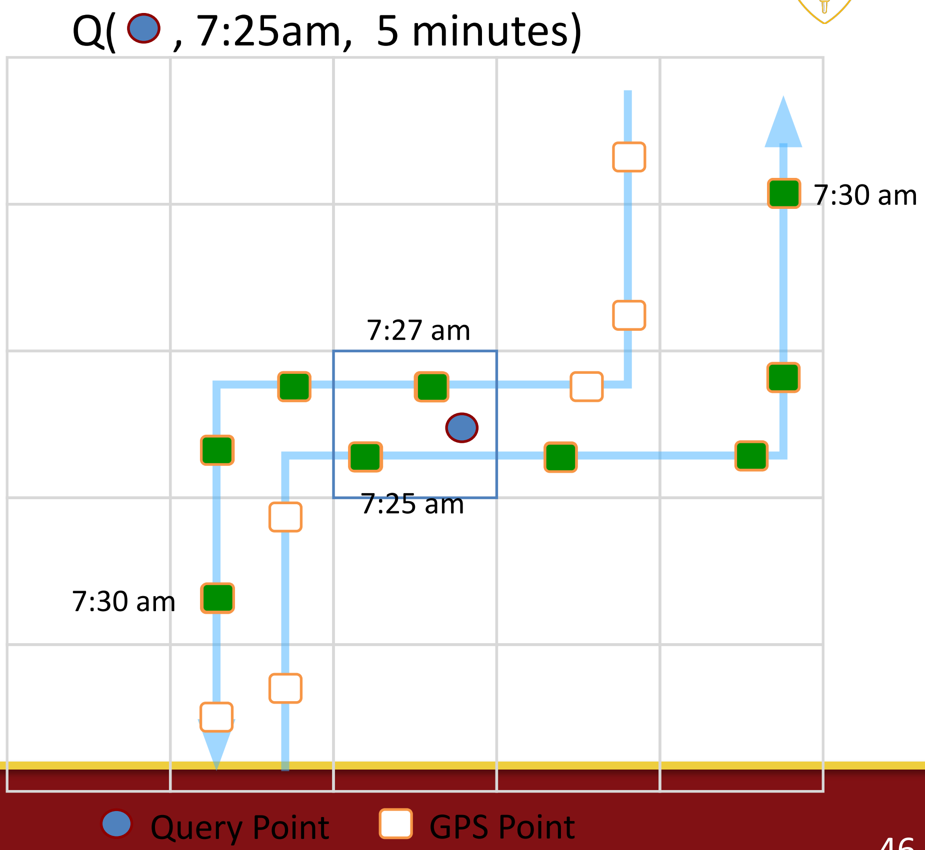


Single-Source & Multi-Source Queries

Reachability Query

- Q(s, t, d)
  - s: source location
  - t: departure time
  - d: time limit in minutes

$c \leftarrow findCell(G, Q.s)$
$r \leftarrow \{\}$ // Initialize result to empty set
for $(traj, i) \in c.gpsInWindow(Q.t, Q.t + Q.d)$ **do**
  while $i < traj.length$ **and** $traj[i].ts \leq Q.t + Q.d$ **do**
    $r \leftarrow r \cup \{traj[i].loc\}$
    $i \leftarrow i + 1$
  end while
end for
return r // Return the set of all reachable points

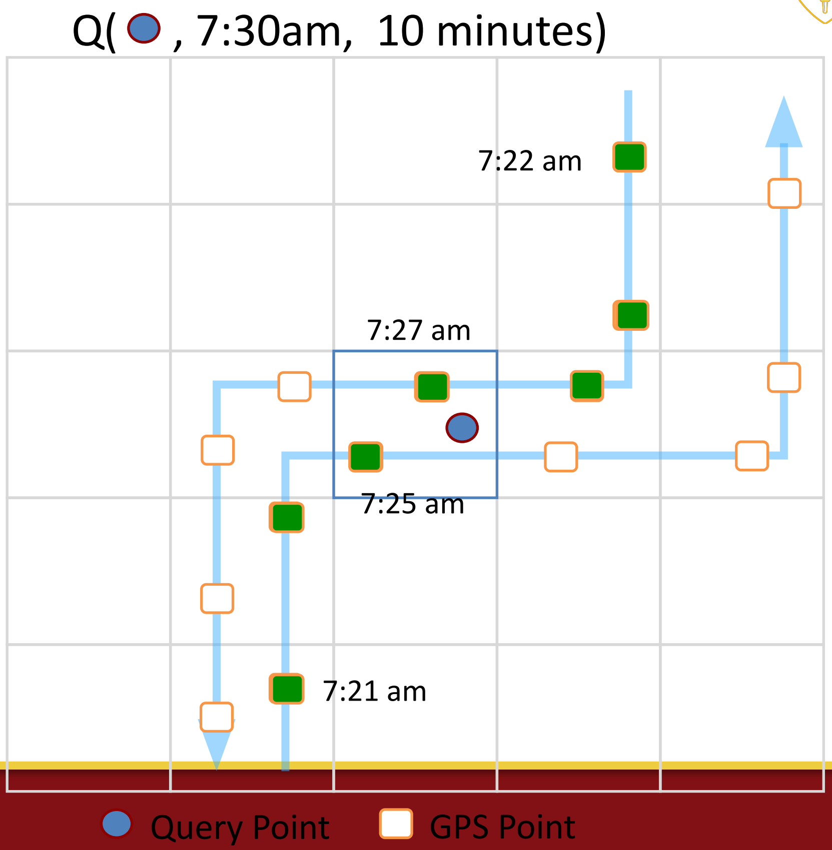


Single-Target & Multi-Target Queries

Reverse Reachability Query

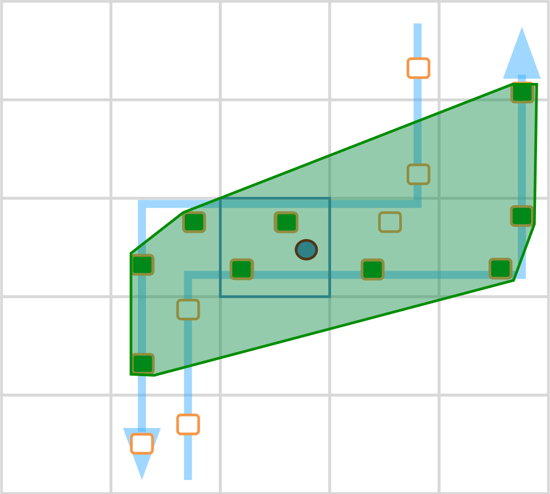
- Q(q, t, d)
  - q: target location
  - t: arrival time
  - d: time limit in minutes

```
c ← findCell(G, Q.q)
r ← {} // Initialize result to empty set
for (traj, i) ∈ c.gpsInWindow(Q.t − Q.d, Q.t) do
    while i ≥ 0 and Q.t − Q.d ≤ traj[i].ts do
        r ← r ∪ {traj[i].loc}
        i ← i − 1
    end while
end for
return r // Return the set of all reachable points
```

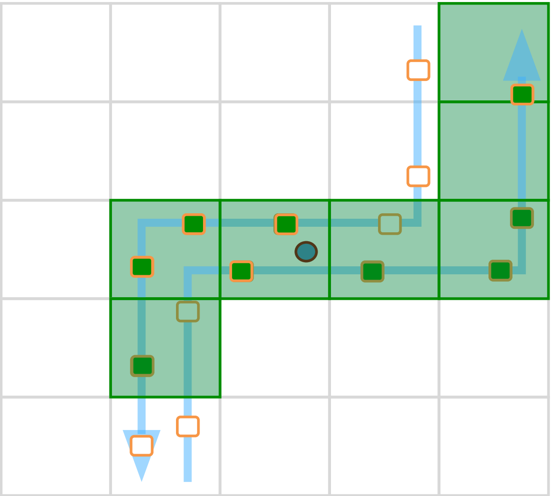


Visualization Methods

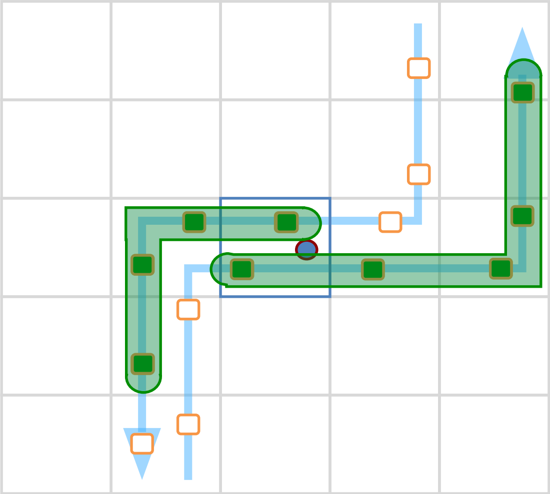
Convex Hull



Cells



Trajectory Buffer



Query Point GPS Point

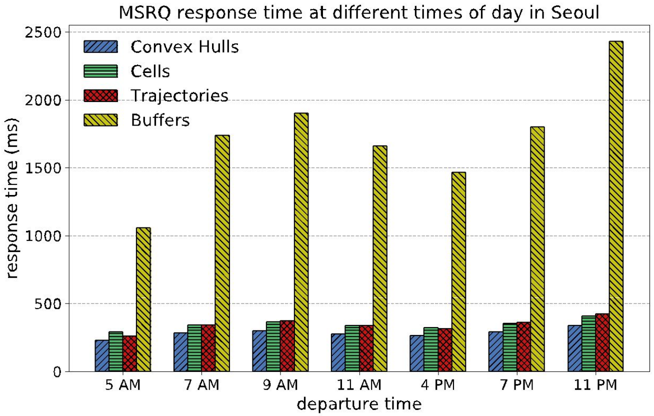
Visualization Methods

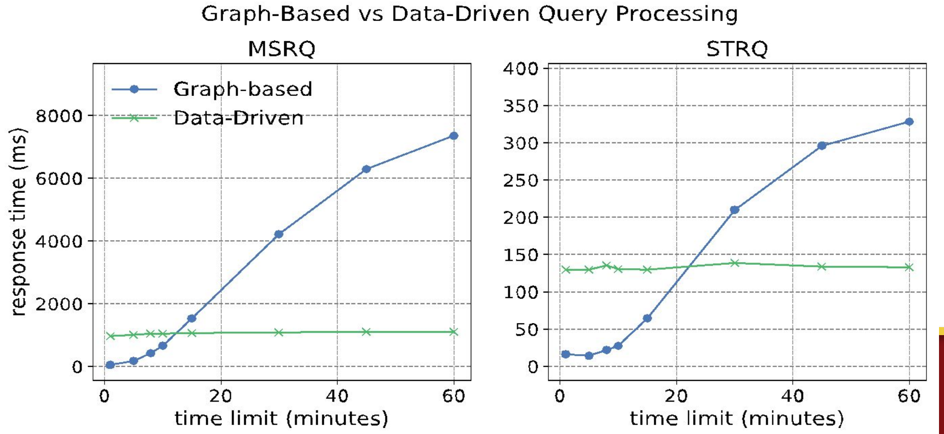
(a) Convex Hull (b) Cells (c) Buffers

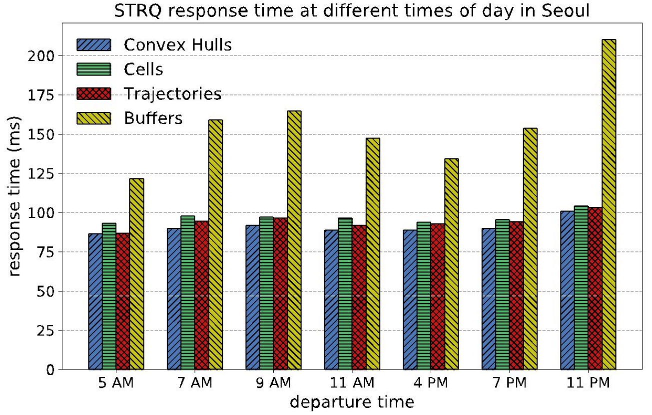
(d) Convex Hull Reverse (e) Cells Reverse (f) Buffers Reverse

Experiments

- Data Source
  - Navicall (Seoul Brand Taxi Call Company)
- Data collection period
  - July 2016 – November 2016
- Data Statistics
  - 5,000 taxies
  - 1 min unit sensing data
  - ~600M readings
  - ~50 GB total







References

[1] Newson P. & Krumm J., "Hidden Markov map matching through noise and sparseness," Proceedings of the 17th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems GIS 09, 336, 2009

[2] DiDi's IJCAI-19 Tutorial: Artificial Intelligence in Transportation (slides 28–40)

[3] Map Matching @ Uber

[4] Anastasiou, C., Huang, C., Kim, S. H., & Shahabi, C. (2019, June). Time-Dependent Reachability Analysis: A Data-Driven Approach. In *2019 20th IEEE International Conference on Mobile Data Management (MDM)* (pp. 138-143). IEEE.

[5] Siampou, MD., Anastasiou, C., Krumm, J., & Shahabi, C. (2024). TrajRoute: Rethinking Routing with a Simple Trajectory-based Approach: Forget the Maps and Traffic!. To *appear @ IEEE International Conference on Mobile Data Management (MDM) .*