



Interactive Visual Exploration of Most Likely Movements

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Outline

- Introduction
- Problem formulation
- Methodology
- Demonstration
- Conclusions and future work



Introduction

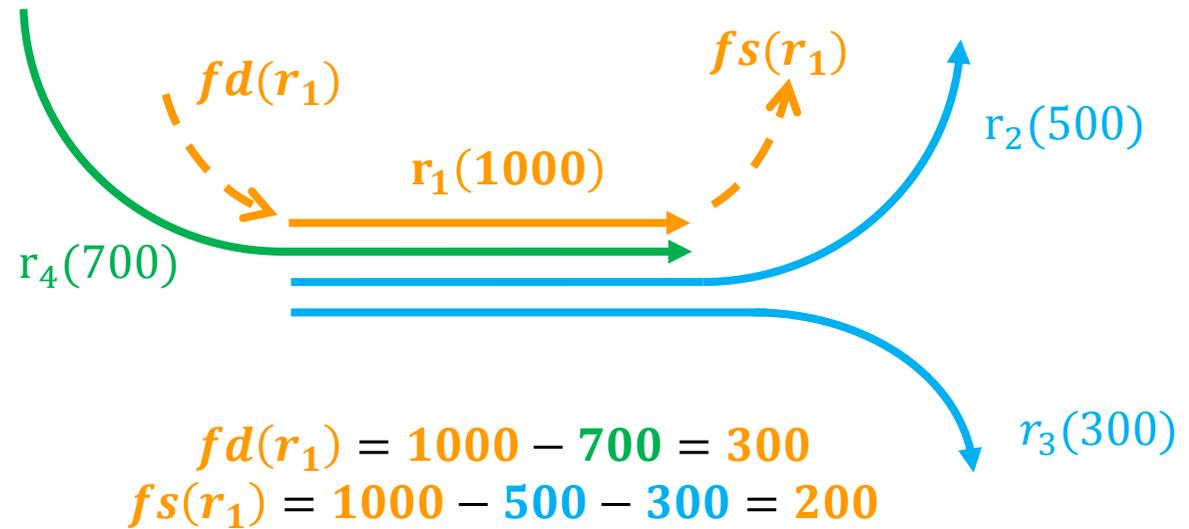
- With location-enabled devices widely adopted, **massive streams of trajectories** have been generated. One way to **compress the data** is to store **frequent patterns**. However, **infrequent movements are lost**.
- In this paper, the proposed method and system
 - aggregates a massive trajectory stream to **limited storage** as time-varying patterns of movements
 - reconstructs from this information the **k most likely movements** for a selected time period and origin-destination region
 - facilitates querying and explorations of these likely movements using a web based user interface

Introduction – Intuition of Pattern Transition

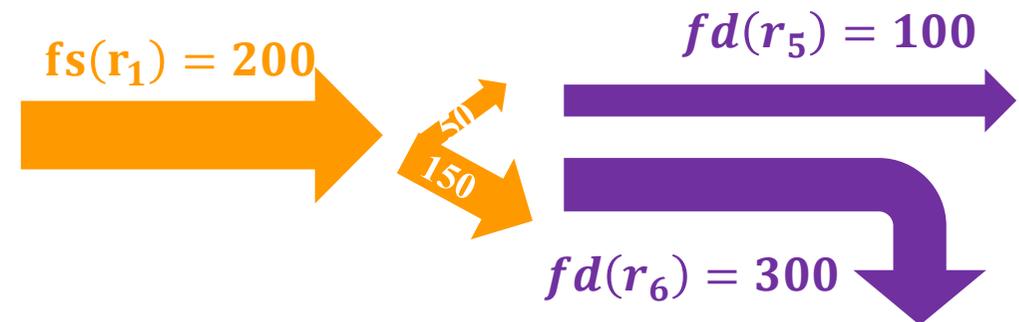
When only frequent pattern r_i is stored, infrequent movements are lost but some information can be inferred from **free demand** and **free supply** of patterns.

- **free demand** $fd(r_i)$: objects that enter a pattern r_i but not from its **preceding patterns**, $[+, r_i]$
- **free supply** $fs(r_i)$: objects that leave a pattern r_i and do not follow its **succeeding patterns** $[r_i, +]$

Objects in the **free supply** of a pattern can transit to its **connected patterns** proportionally to the free demand of these patterns.



Free demand and supply of patterns



Pattern transitions



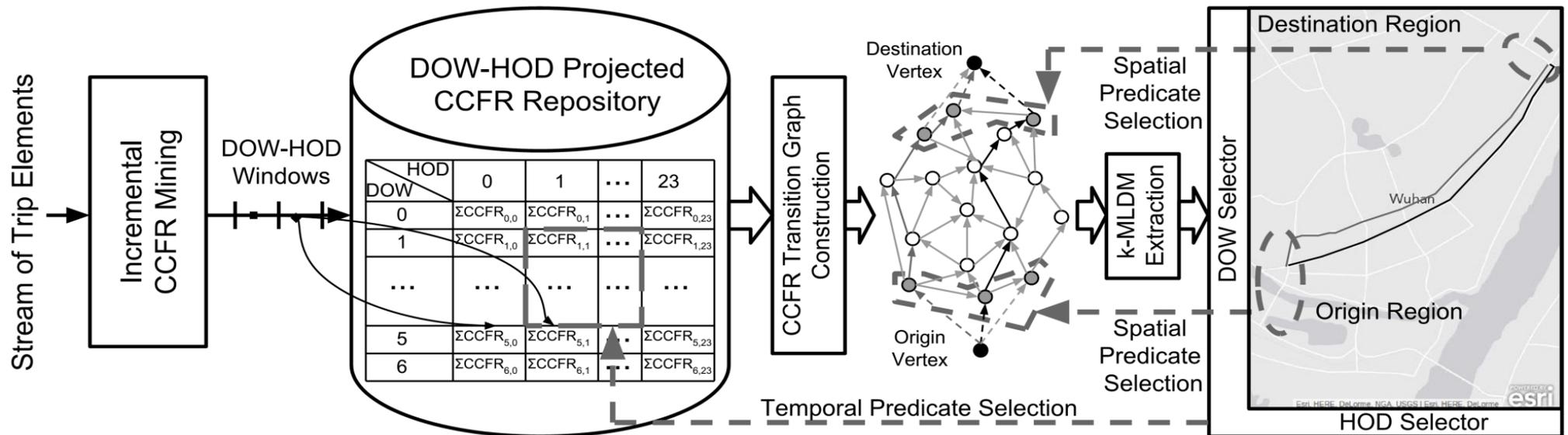
Problem Formulation

The distinct k-Most Likely Movements (MLM) problem is defined as estimating the **distinct k most likely movements** of the population given **temporal** predicates such as time periods and **spatial** predicates such as origin and destination.

For instance, what are the likely movements/route choices from the train station to the airport from 8 am to 10 am on Mondays?

Methodology

1. **Extract** and **Store** closed continuous frequent routes / patterns (CCFR) from GPS data
2. **Build** pattern transition graph
3. **Estimate** distinct k-MLMs



Schematic diagram of methodology

Methodology- CCFR and Pattern Transition Model

- Info in CCFR

- Sequence of spatial units traversed + Count of objects

- CCFR movement model

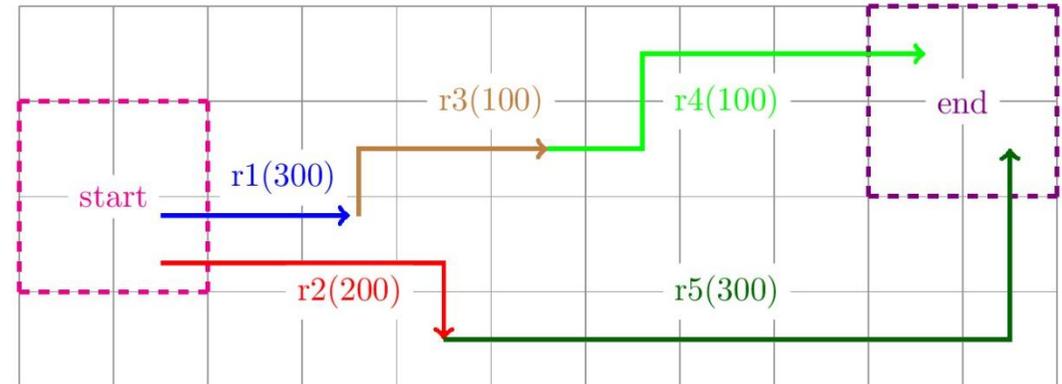
- At the end of a CCFR an object either probabilistically transit to “connected” CCFRs or stops moving.

- Pattern transition graph

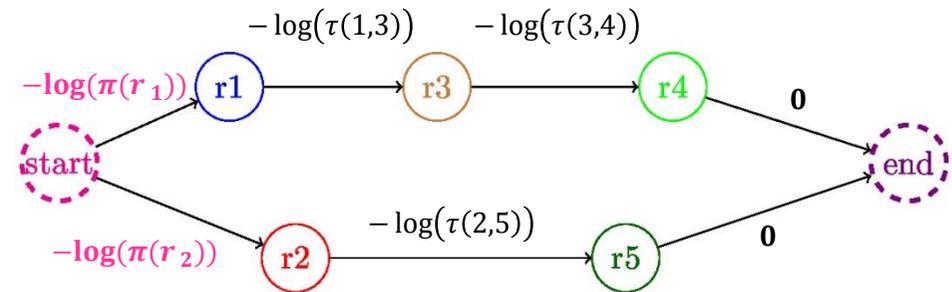
- 1-1 map of CCFRs to nodes and connections of CCFRs to directed edges
- weight of edge from r_i to r_j is $-\log(\tau(i,j))$

where $\tau(i,j)$ is the transition probability from r_i to r_j based on and adhering free supply and free demand of patterns

- weight of edge from **start** to r_i is $-\log(\pi(r_i))$, where $\pi(r_i)$ is the initial probability of a pattern which is the relative free supply of r_i



Pattern topology relationship

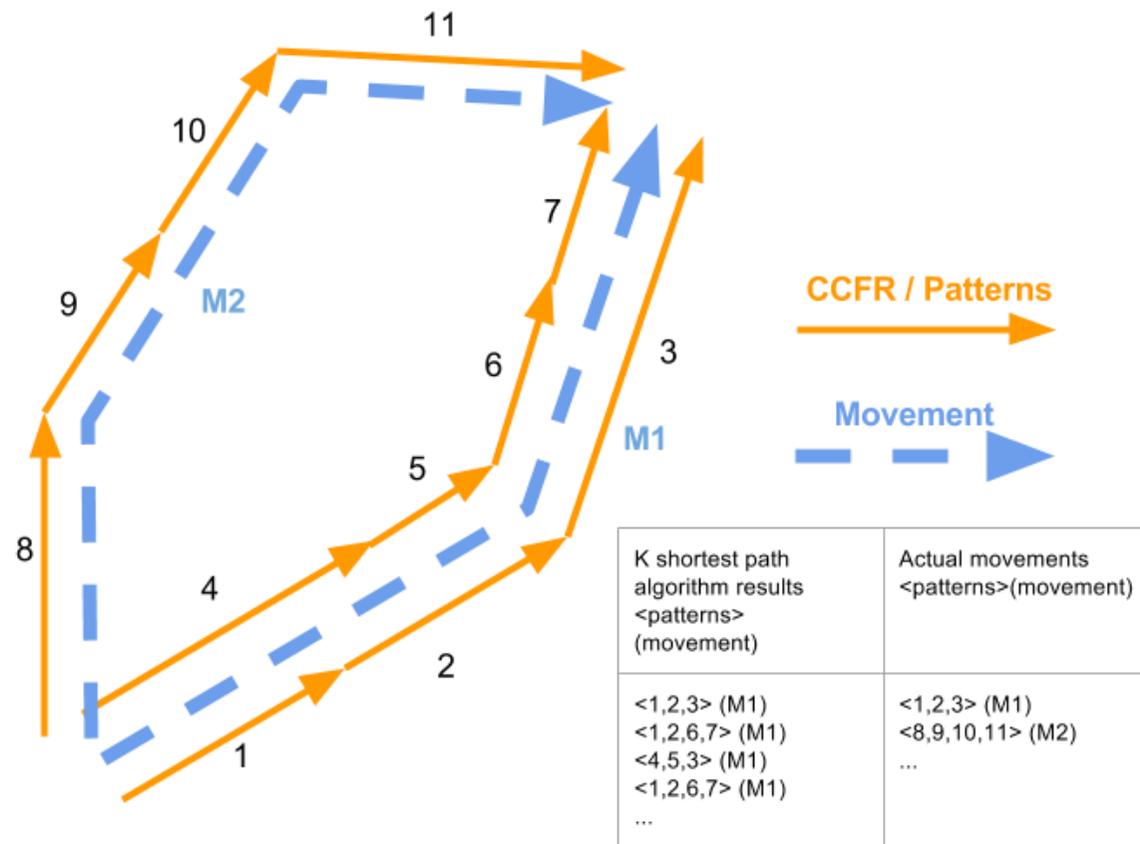


Pattern transition graph

Methodology- Distinct k-MLMs

Problem setting: a **movement** is a sequence of spatial units and can be generated by a large number of sequences of CCFRs.

1. To estimate the likelihood of a movement a dynamic programming approach is used.
2. To extract distinct k -MLMs, extract the **current** MLM and **block** the CCFRs that build it and iteratively extract the remaining $k-1$ MLMs.

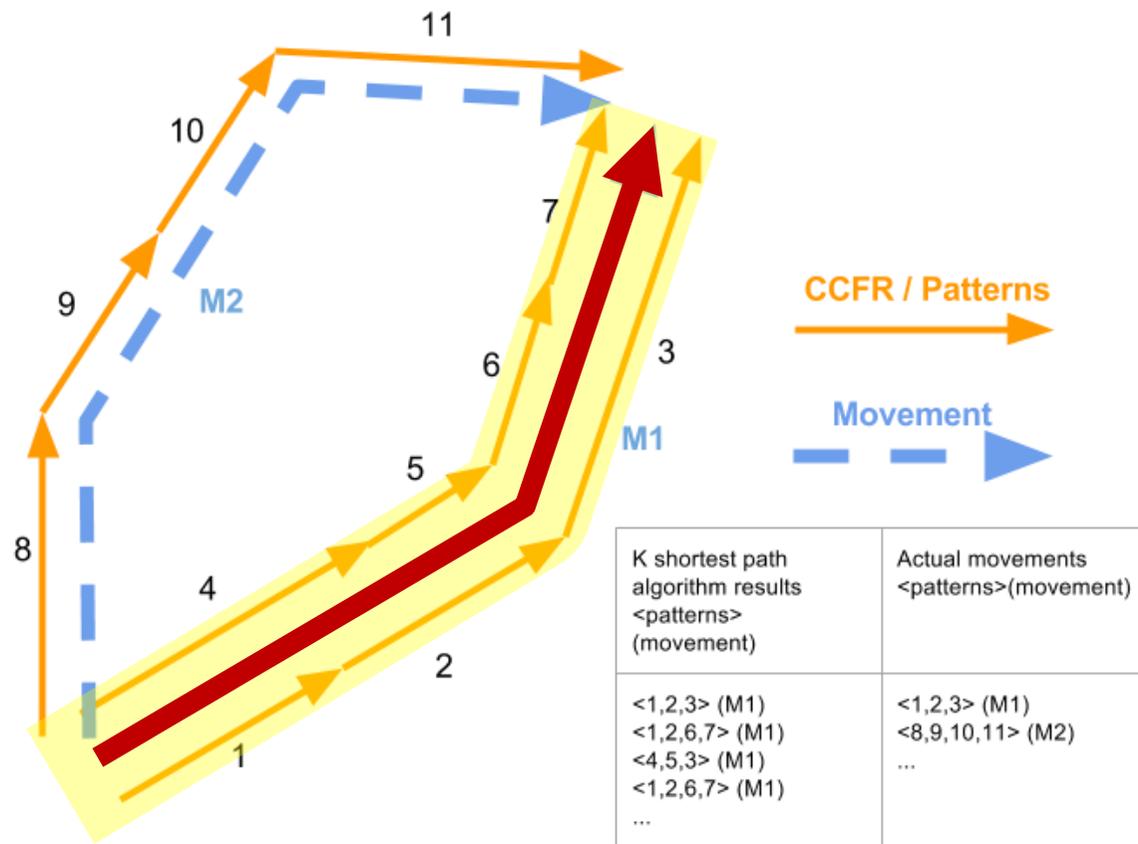


Example of Distinct k-MLMs

Methodology- Distinct k-MLMs

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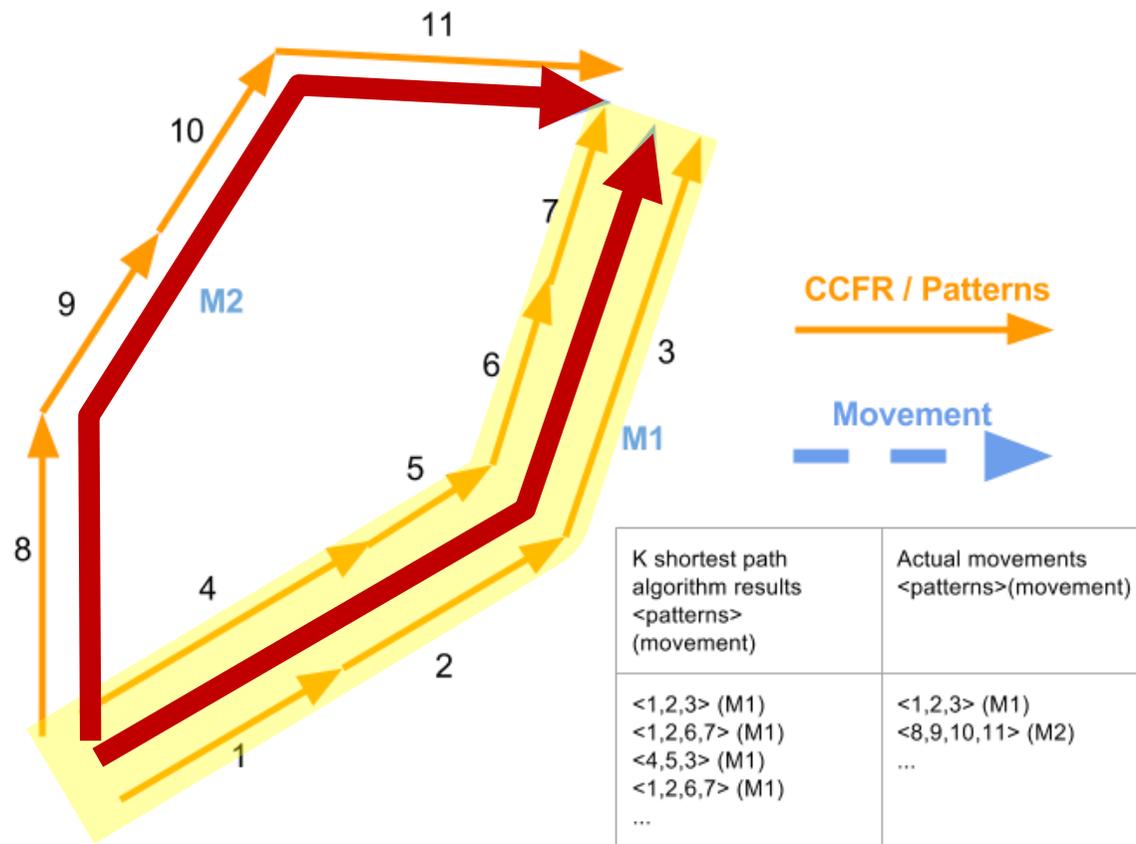


Example of Distinct k-MLMs

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Example of Distinct k-MLMs

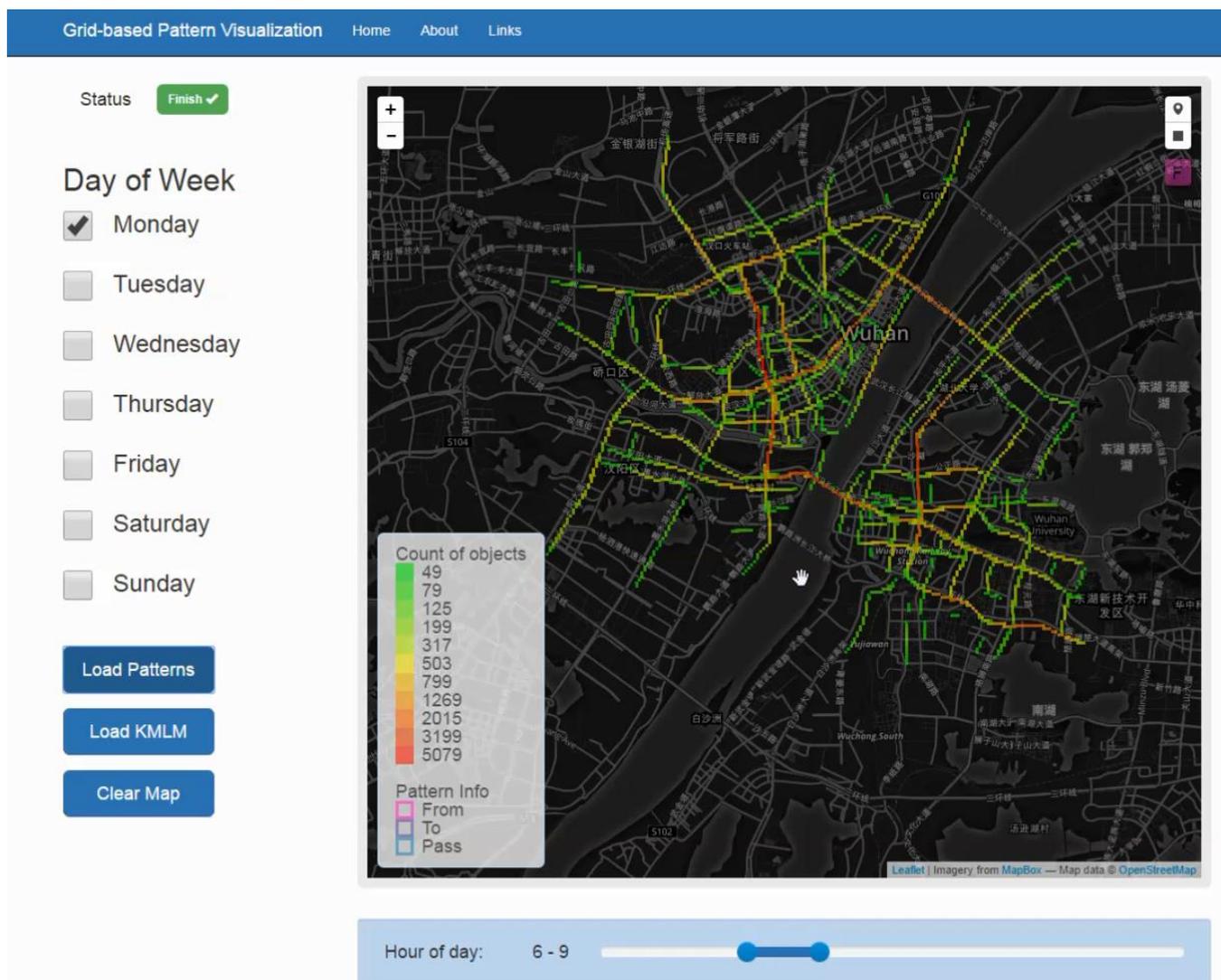
Demonstration

- Implementation

- Server
NodeJS
- Client
Leaflet

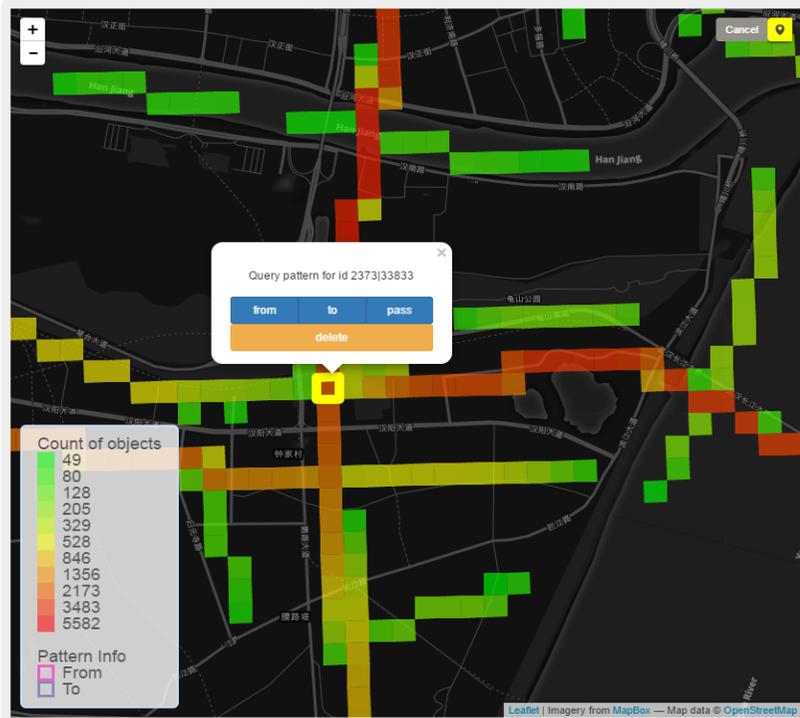
- Data

- Totally **2.26 million** trajectories collected from **11000** taxis over a **6** day period in Wuhan, China.

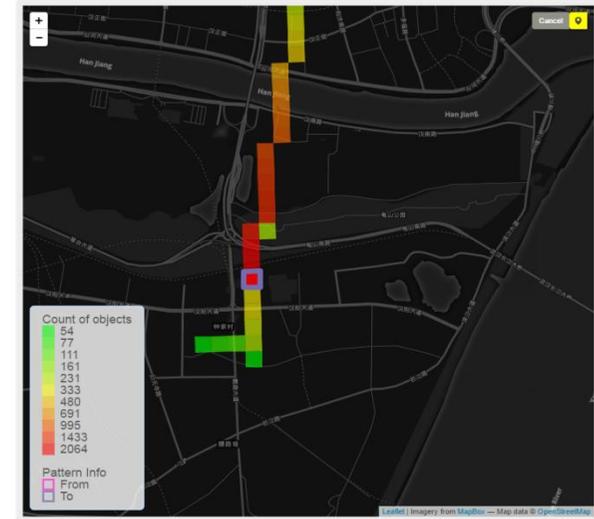


Screenshot of User Interface

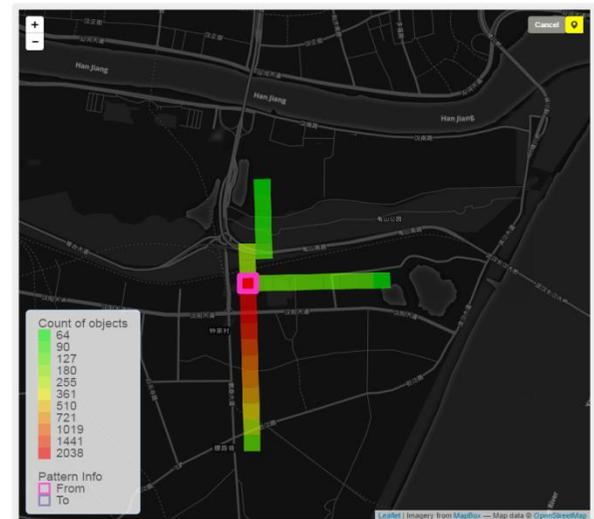
Demonstration- Pattern Exploration



Interactive query of patterns from/to/pass a grid

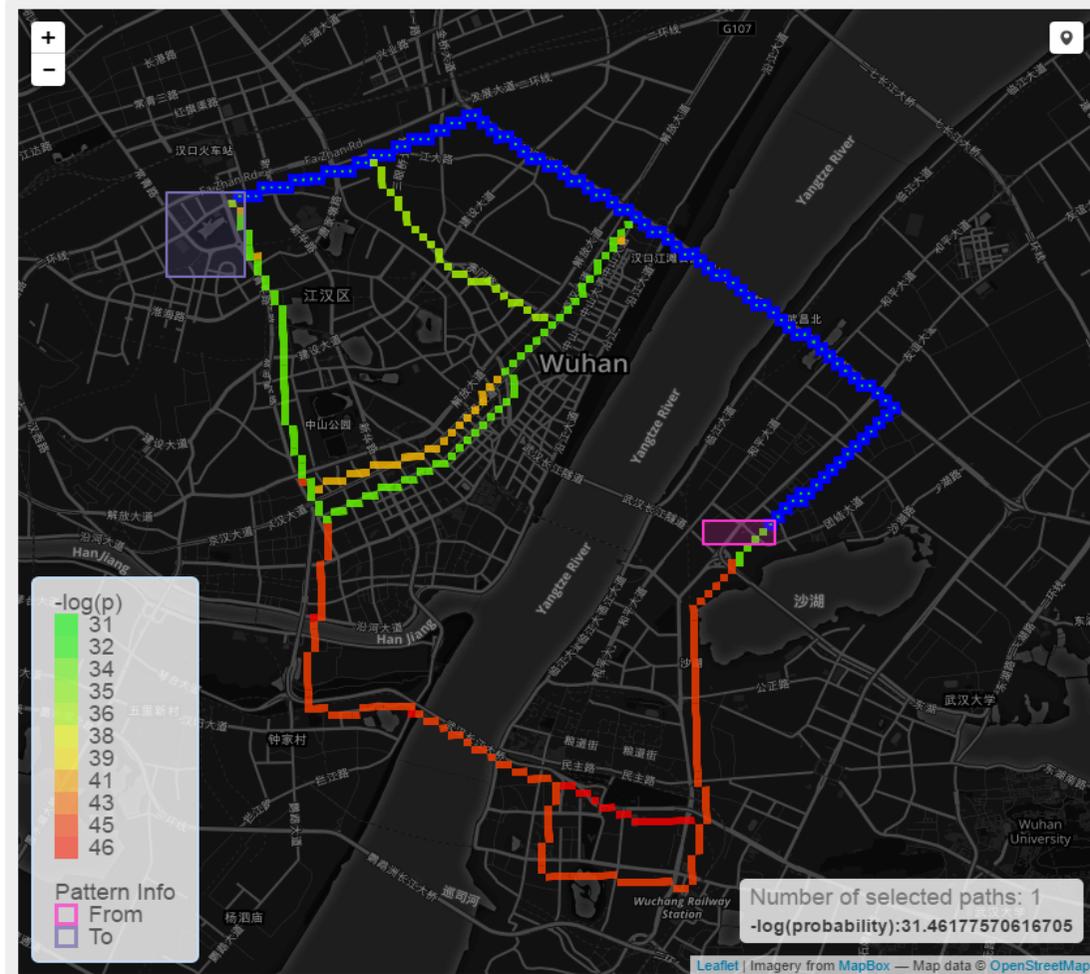
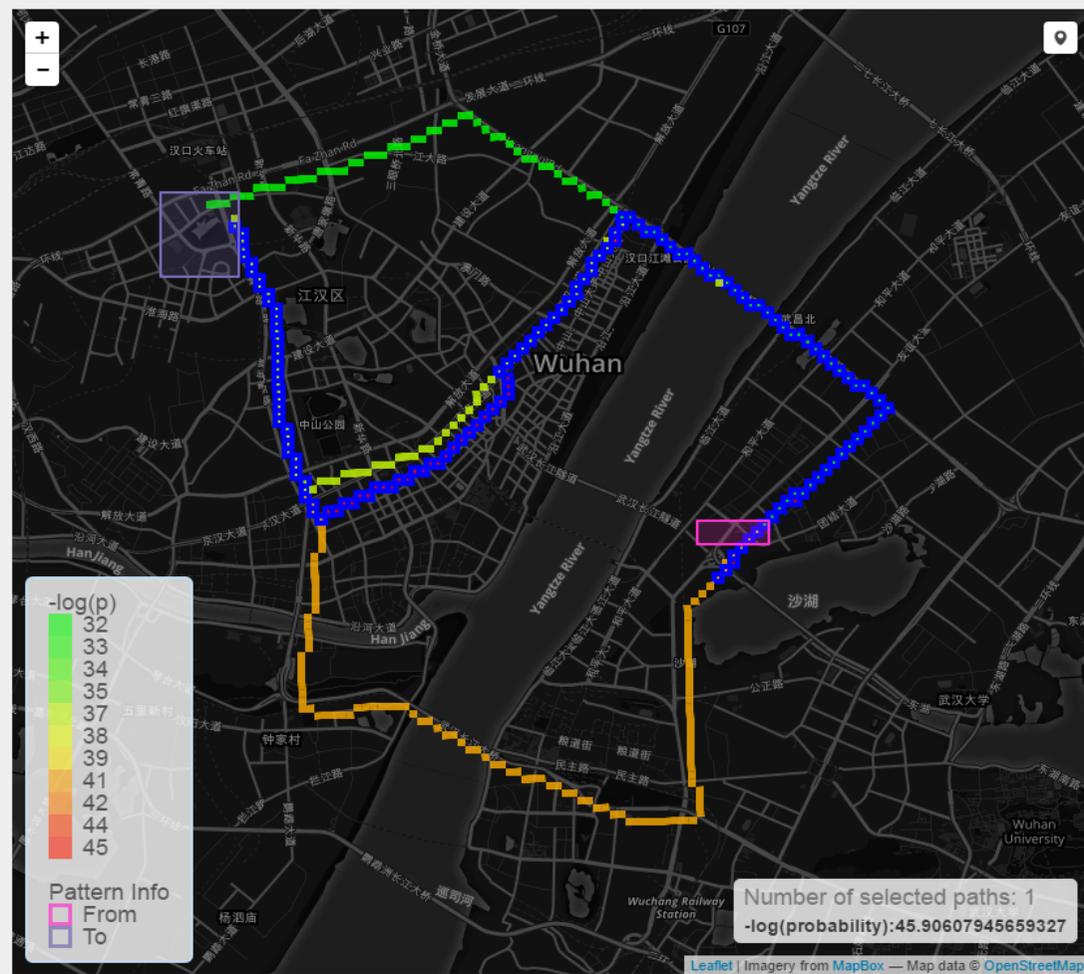


Patterns starting from specific grid



Patterns ending at specific grid

Demonstration – Distinct KMLM



(a) 4 distinct movements between 2 regions in the morning 06:00 – 09:00

(b) 6 distinct movements between 2 regions in the afternoon 16:00 – 19:00

Time-varying Distinct K-MLM generated from the model (the blue path is the movement highlighted by user)



Conclusions and Future Work

- Conclusions
 - The paper proposed a method that in an effective manner extracts complex, time varying movement patterns from a stream of moving object trajectories, regenerates likely movements based on these patterns, and facilitates the visual querying and explorations of these likely movements using a simple map interface.
- Future work:
 - **Alternative models** considering topological relationship between CCFRs
 - **Empirical validation** of the model
 - Extend the model to **other types of spatial units**



Thank you for your attention!
Q/A?