

# Destination Prediction by Sub-Trajectory Synthesis and Privacy Protection Against Such Prediction

Andy Yuan Xue <sup>#1</sup>, Rui Zhang <sup>#2</sup>, Yu Zheng <sup>‡3</sup>, Xing Xie <sup>‡4</sup>,  
Jin Huang <sup>#5</sup>, Zhenghua Xu <sup>#6</sup>

*# University of Melbourne, Victoria, Australia*

<sup>1</sup>andy.xue@unimelb.edu.au   <sup>2</sup>rui@csse.unimelb.edu.au  
<sup>5</sup>jin.h@iojin.com   <sup>6</sup>zhxu@student.unimelb.edu.au

*‡ Microsoft Research Asia, Beijing, P.R.China*

<sup>3,4</sup>{yuzheng, xingx}@microsoft.com

- 1 Introduction
- 2 Destination Prediction
  - Overview
  - Algorithms
- 3 Privacy Protection
- 4 Experimental Study
- 5 Conclusion

# Introduction

**Purpose:** To **predict destinations** of travel based on **public data**.

**A demo:** Visitor drives from **the Forbidden Palace** in Beijing to **the International Airport**.

**Destination Prediction Demo**

Grid Granularity: 30

Number of Predictions: 3

Moving Speed: Moderate

Heatmap

Add Move Reset

Guide Predictions Credits

**What is this?**

When a user sets up a driving route by putting a list of check-in locations, this demo will simulate the driving process and make predictions along the route for potential destinations that the user is heading to. This demo also offers a function to suggest a list of check-ins to be deleted in order to prevent a private destination from being exposed.

# Introduction

## **Applications:**

- Recommend sightseeing places
- Send targeted advertisements
- Automatically set destinations and route in navigation systems

# Introduction

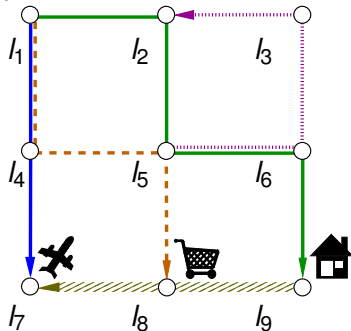
An example of a baseline solution adapted from existing work:

- Grid representation
- Trajectory matching
- A user travels from  $l_1$  to  $l_4$ : Predicted destinations  $l_7$  and  $l_8$
- Query trajectory  $\{l_1, l_2, l_3\}$ : no predicted destination due to lack of training data.

- **Baye's rule**

$$P(d \in l_j | TP) = \frac{P(TP | d \in l_j) \cdot P(d \in l_j)}{\sum_{k=1}^{g^2} P(TP | d \in l_k) \cdot P(d \in l_k)}$$

- **Data Sparsity Problem**



# Destination Prediction

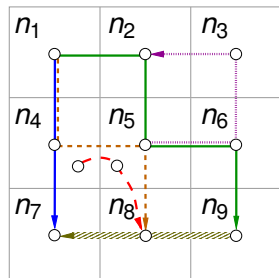
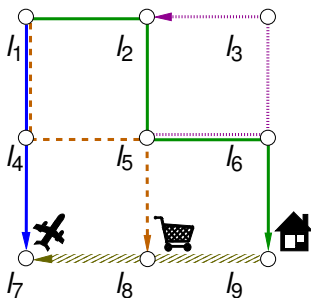
## *Sub-Trajectory Synthesis (SubSyn):*

- Solves the **data sparsity problem** by expanding the historical dataset.
- Two phases: **Decomposition** and **Synthesis**

# Destination Prediction

## *Sub-Trajectory Synthesis (SubSyn): Decomposition*

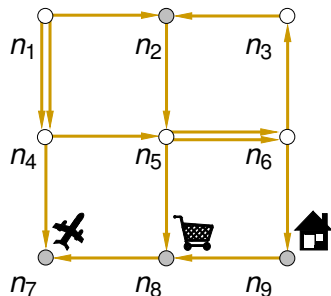
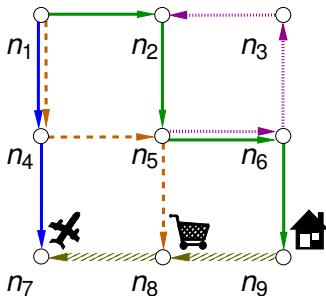
- Partition and group POIs into grid cells.



# Destination Prediction

## *Sub-Trajectory Synthesis (SubSyn): Decomposition*

- Partition and group POIs into grid cells.
- Decompose historical trajectories into *sub-trajectories*.





# Destination Prediction

## Sub-Trajectory Synthesis (SubSyn): Decomposition

- Use Markov model
- Transition matrix  $M$ :  $p_{12}$ ,  $p_{14}$ ,  $p_{78}$ , etc.

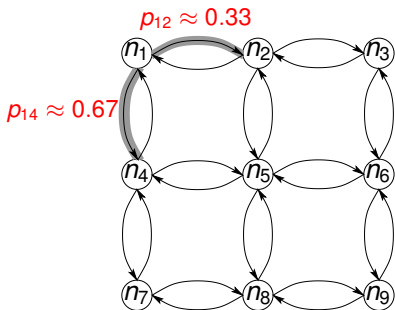
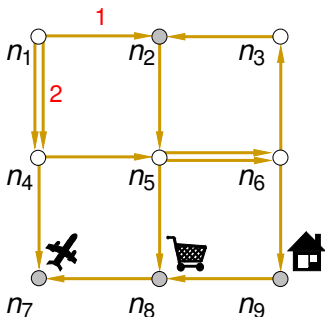
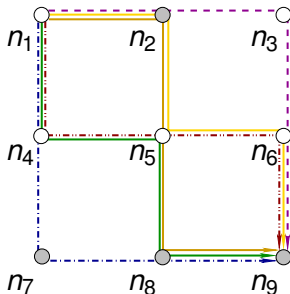


Figure:  $3 \times 3$  Markov model

# Destination Prediction

## Sub-Trajectory Synthesis (SubSyn): Synthesis

- Starting from  $n_1$ , what is the probability of travelling to  $n_9$ ?
- Shortest Path is 4:  $p_{1 \rightarrow 9} = M_{1,9}^4$
- $M^4$ : transition between cells with distance 4.



- Consider detour (within 1.2 times shortest path.  $\alpha = 0.2$ )
- Users may travel either distance 4 or 5 ( $\lceil 4 \times 1.2 \rceil$ ) to reach  $n_9$ :  $p_{1 \rightarrow 9} = M_{1,9}^4 + M_{1,9}^5$

# Destination Prediction

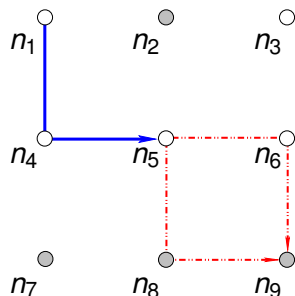
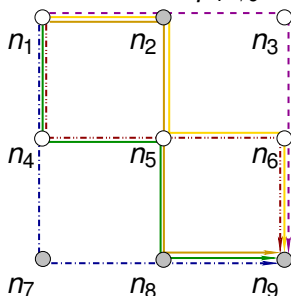
## Sub-Trajectory Synthesis (SubSyn): Synthesis

- Given a user's route:  $T^p = \{n_1, n_4, n_5\}$ ,
- The probability of  $n_9$ :

$$P(n_9|T^p) = P(n_9|n_1, n_4, n_5)$$

$$\propto \frac{p_{5 \rightarrow 9}}{p_{1 \rightarrow 9}} \cdot P(n_9|n_1)$$

(derivation in paper using Bayes' rule)



# Algorithms

$$P(n_k|T^p) \propto \frac{p_{c \rightarrow k}}{p_{s \rightarrow k}} \cdot P(n_k|n_s)$$

- Two stages: **Training** and **Prediction**
- **SubSyn-Training** constructs Markov model and computes various probabilities needed for prediction. (RHS of the equation)
- Efficiently perform **huge matrix multiplications**. E.g., compute  $M^{100}$  where  $M$  is a  $2500 \times 2500$  matrix.
- **SubSyn-Prediction** retrieves these probabilities to compute the destination probabilities  $P(n_k|T^p)$

# Privacy Protection

## Demo

A demo: [check-ins](#) on your way home.

# Privacy Protection

## Methods

### Exhaustive Generation Method

- Iteratively delete each node in query trajectory
- **Inefficient**

### End-Points Generation Method

- **Theorem:** Only the starting and current nodes affect the probabilities of predicted destinations
- Is a property of first-order Markov model
- **Dramatically reduced search space, efficient for online queries**

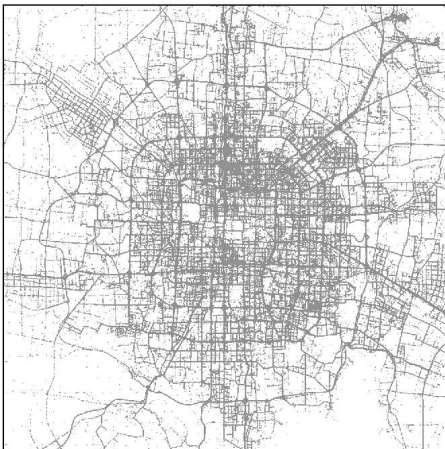
# Experimental Study

## Dataset

Real-world taxi trajectory dataset in the city of Beijing.

Contains:

- 580,000 taxi trajectories
- 5 million kilometres of distance travelled



# Experimental Study

## Grid Granularity

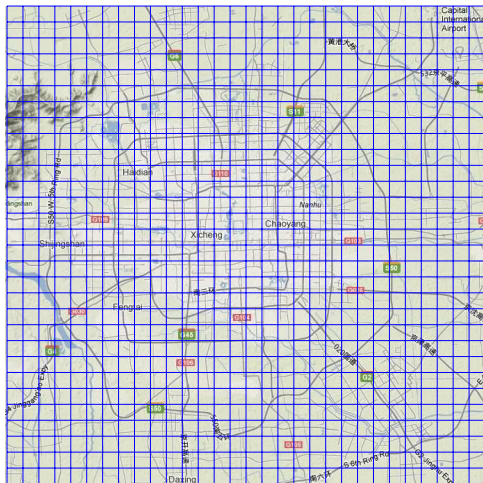


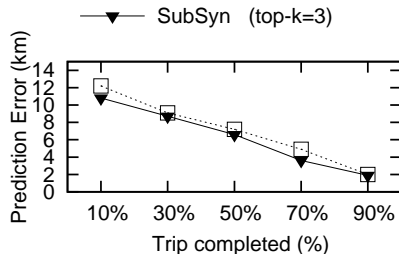
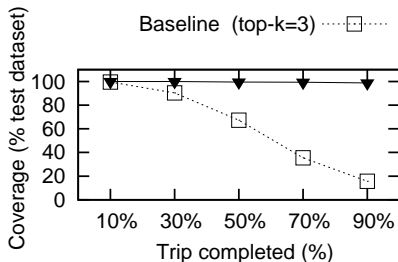
Figure: Map of Beijing with  $30 \times 30$  grid overlay: Each cell  $\approx 1.78\text{km}^2$



# Experimental Study

## Effectiveness

- Randomly pick 1000 test/query trajectories
- Algorithms: **Existing** vs **SubSyn**
- Measurements: **Coverage** and **Prediction Error**



More experiments in the paper

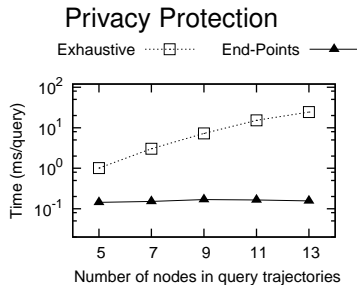
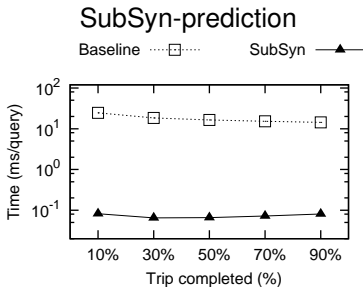
# Experimental Study

## Runtime Efficiency

### SubSyn-Training

Grid Granularity	20	30	40	50
Running Time (hours)	0.03	0.5	3	17

- Commodity computer: Intel i7-860 CPU 4GB RAM



# Conclusion

- Identified **Data Sparsity Problem**, and proposed a **Sub-Trajectory Synthesis (SubSyn)** algorithm which successfully addressed the problem.
- SubSyn decomposes historical trajectories into sub-trajectories to exponentially increase practicality.
- SubSyn can predict destinations for **up to ten times** more query trajectories than the existing algorithm.
- Runs **over two orders of magnitude faster** constantly.
- Also proposed an efficient method (**two orders of magnitude faster**) to avoid privacy leak.

# Questions

## Questions?

### Demo:

<http://spatialanalytics.cis.unimelb.edu.au/subsyndemo/>

### Contacts:

Andy Yuan Xue    [andy.xue@unimelb.edu.au](mailto:andy.xue@unimelb.edu.au)

<http://people.eng.unimelb.edu.au/yuanx/>

Rui Zhang        [rui.zhang@unimelb.edu.au](mailto:rui.zhang@unimelb.edu.au)

<http://people.eng.unimelb.edu.au/zr/>

### References:

- Andy Yuan Xue, Rui Zhang, Yu Zheng, Xing Xie, Jin Huang, Zhenghua Xu. **Destination Prediction by Sub-Trajectory Synthesis and Privacy Protection Against Such Prediction**. IEEE International Conference on Data Engineering (ICDE) 2013.
- Andy Yuan Xue, Rui Zhang, Yu Zheng, Xing Xie, Jianhui Yu, Yong Tang. **DesTeller: A System for Destination Prediction Based on Trajectories with Privacy Protection**. International Conference on Very Large Data Bases (VLDB) 2013 (Demo)