AALBORG UNIVERSITY

Learning to Route

Bin Yang

In collaboration with Razvan-Gabriel Cirstea, Jian Dai, Chenjuan Guo, Jilin Hu, Christian S. Jensen, Tung Kieu, Simon A. Pedersen and Sean B. Yang

Center for Data-intensive Systems

Background and Motivation

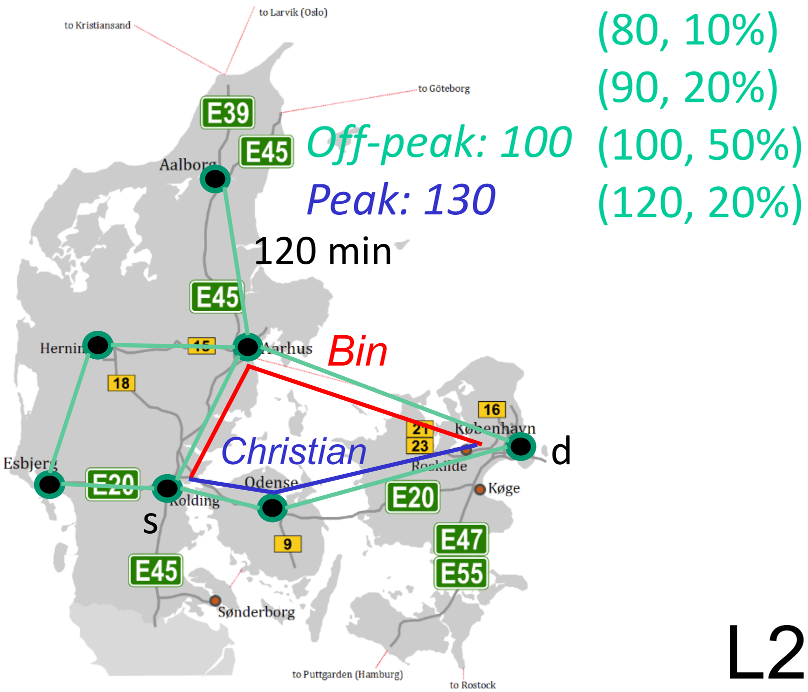
- Vehicular transportation is an important aspect of the daily lives of many people and is also essential to many businesses as well as society as a whole.

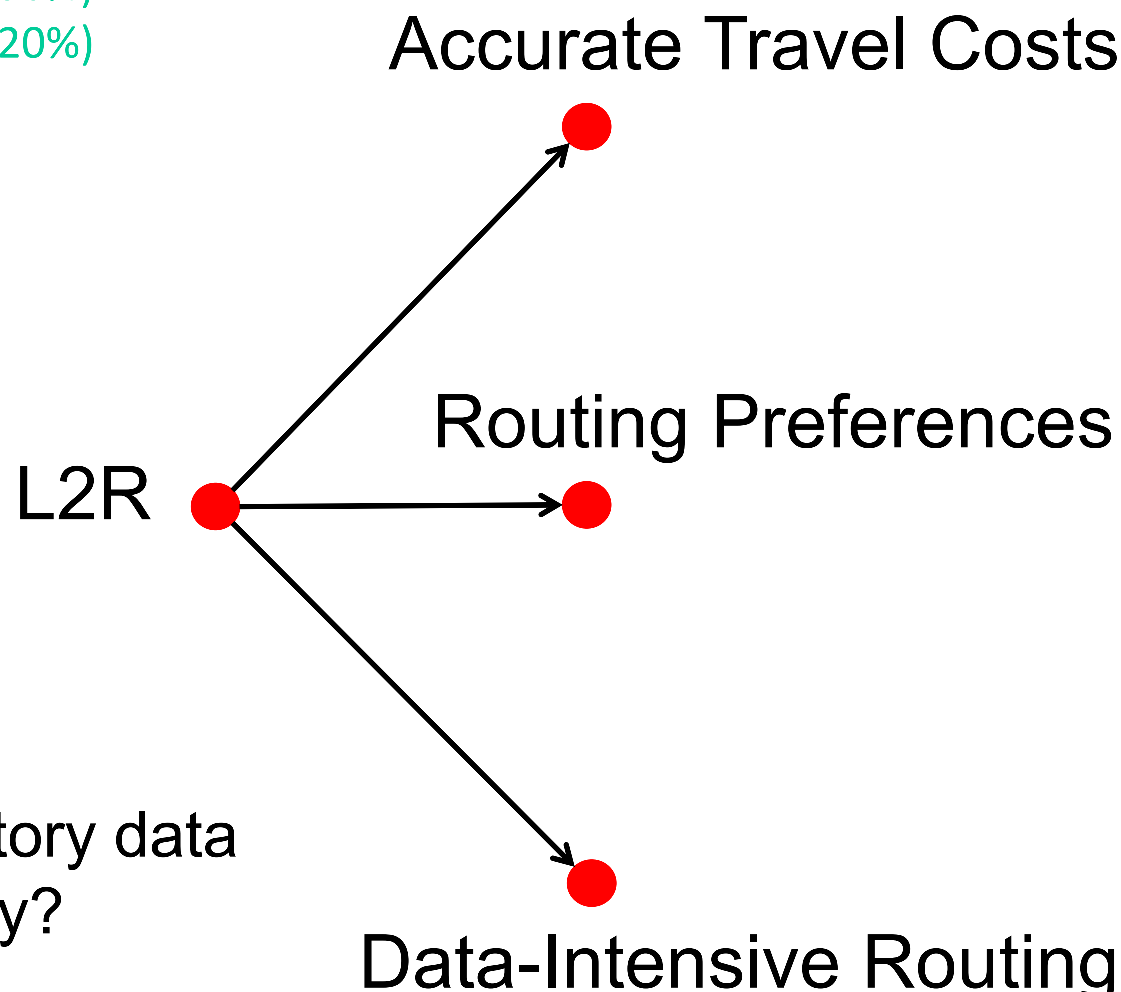
- Routing is a core functionality in vehicular transportation.
  - Given an (*s*, *d*) pair, identify a "best" path from *s* to *d*.

- As part of the continued society-wide digitization, more and more trajectory data is becoming available.

- ***Learning to Route*** studies how to best utilize trajectory data to enhance routing quality.

Learning to Route





How to best utilize trajectory data to enhance routing quality?

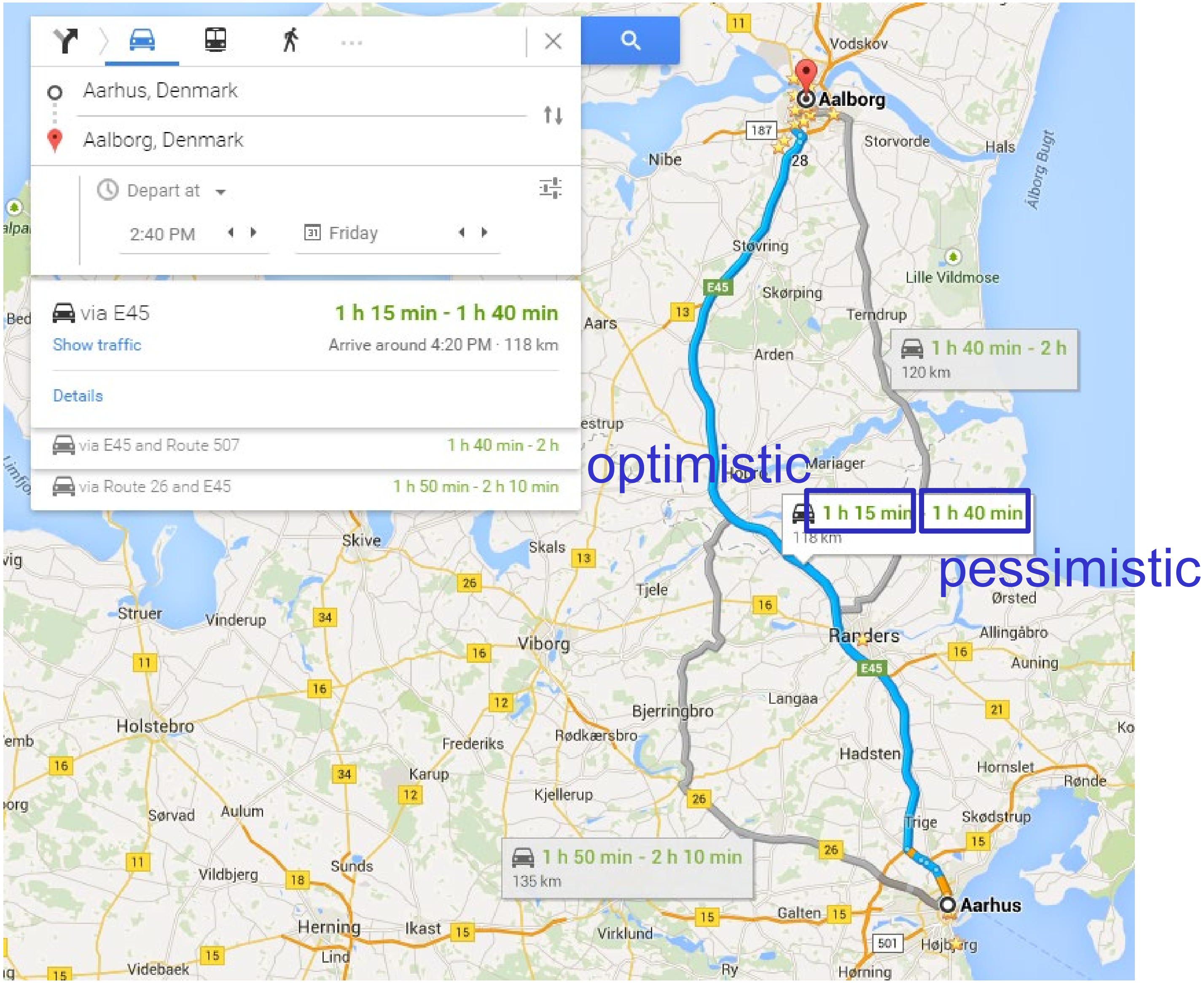
Outline

- Motivation
- Learn accurate travel costs
- Learn routing preferences
- Data-intensive routing

Learn Accurate Travel Costs

- Employ spatio-temporal data to derive accurate travel costs, e.g., travel time and fuel consumption.
- A core challenge is to capture ***travel cost uncertainty***.
  - Google Maps offers three types of travel times: optimistic, pessimistic and best-guess.

Google Maps



Aarhus, Denmark
Aalborg, Denmark
Depart at
2:40 PM
Friday
via E45
1 h 15 min - 1 h 40 min
Show traffic
Arrive around 4:20 PM · 118 km
Details
via E45 and Route 507
1 h 40 min - 2 h
via Route 26 and E45
1 h 50 min - 2 h 10 min
1 h 40 min - 2 h
120 km
1 h 15 min
1 h 40 min
118 km
1 h 50 min - 2 h 10 min
135 km
optimistic
pessimistic
Aalborg
Aarhus
Randers
Viborg
Skive
Holstebro
Herning

Travel Time Distributions

- Our goal is to push the resolution of traffic uncertainty modeling further by providing *travel time distributions*.
  - Considering two paths P_1 and P_2 from home to airport.

Travel Time	[40, 50)	[50, 60)	[60, 70]
P_1	0.3	0.6	0.1
P_2	0.6	0.2	0.2

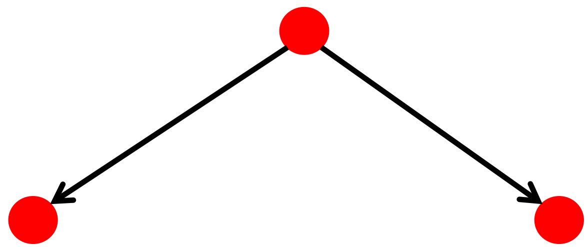
  - Which path should a self-driving taxi take in order to delivery a passenger to airport within 60 mins?
    - Probability($P_1 \leq 60$) = 0.9
    - Probability($P_2 \leq 60$) = 0.8

    $\Rightarrow$ P_1
  - Google's approach:
    - Both paths have the same optimistic (40) and pessimistic (70) travel time.
  - Traditional, deterministic approach: using expected travel time:
    - P_1 has 53 and P_2 has 51, so P_2 is chosen, which is a bad decision.

Uncertain Graph Models

- Weights are distributions but not deterministic values anymore.

Uncertain Graph Models

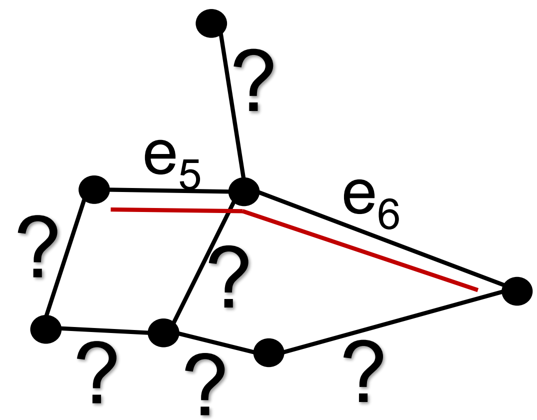


Edge-Centric Model: Weights are assigned to edges.

Path-Centric Model: Weights are assigned to paths.

Edge-Centric Model

- Edge weights, classic way, graph theory.
  - Split trajectories into small pieces that fit edges.
  - Use the small pieces to assign edges with travel time distributions.



- Example: P=<e_5, e_6>
  - Trajectory 1: 10 s, 20 s
  - Trajectory 2: 15 s, 25 s

e_5

Cost	Prob
10	0.5
15	0.5

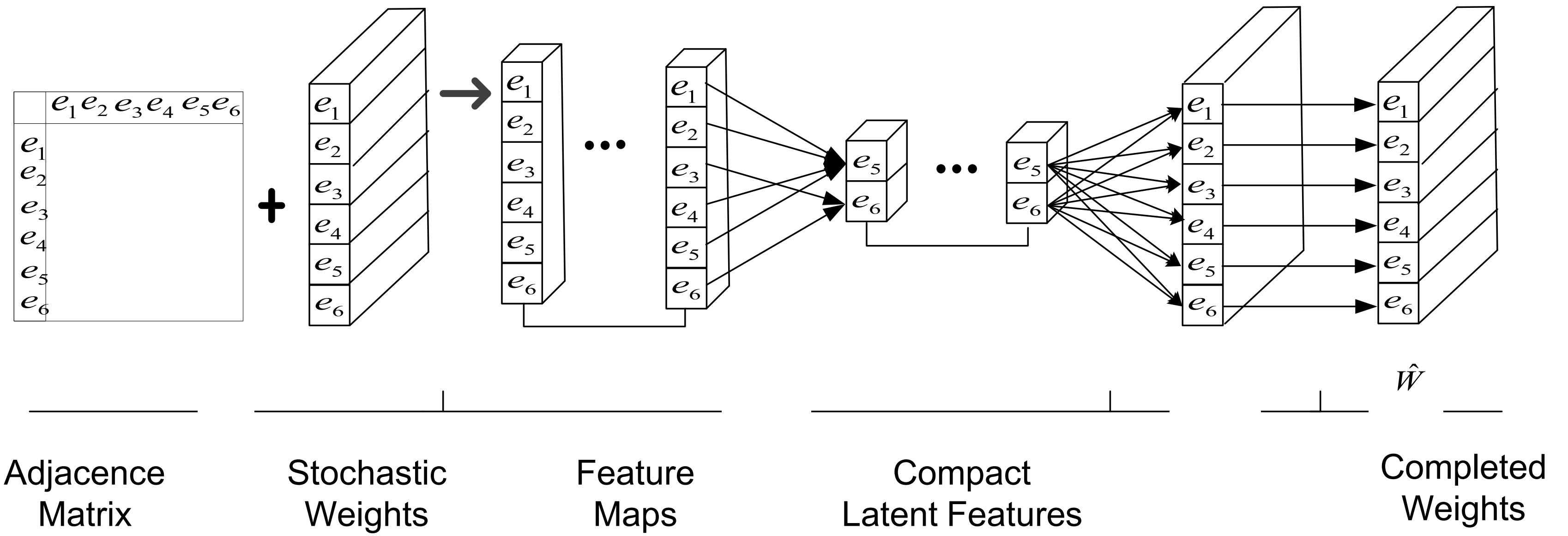
e_6

Cost	Prob
20	0.5
25	0.5

- Challenge: data sparseness.
  - Even big trajectory data is skewed, which cannot cover all edges.
- Solution: stochastic weight completion.
  - Propagate distributions from edges with trajectories to edges without trajectories.

Weight Completion Architecture

- Autoencoder + Graph Convolutional Neural Network.



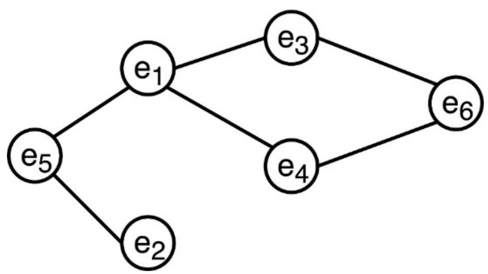
	[5, 10)	[10, 15)	[15, 20)
e_1	?	?	?
e_2	?	?	?
e_3	?	?	?
e_4	?	?	?
e_5	0.3	0.5	0.2
e_6	0.2	0.3	0.5

[5, 10)	[10, 15)	[15, 20)
0.4	0.5	0.1
0.1	0.7	0.2
0.4	0.2	0.2
0.2	0.8	0
0.3	0.5	0.2
0.2	0.3	0.5

J. Hu, C. Guo, B. Yang, and C. S. Jensen. Stochastic Weight Completion for Road Networks using Graph Convolutional Networks. ICDE 2019, 1274-1285.

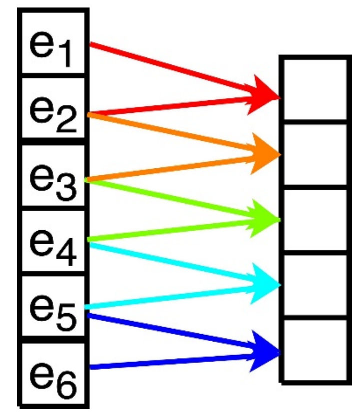
Classic Convolution vs. Graph Convolution

- Classic convolution filter 2×2.



	[5, 10)	[10, 15)	[15, 20)
e_1	?	?	?
e_2	?	?	?
e_3	?	?	?
e_4	?	?	?
e_5	0.3	0.5	0.2
e_6	0.2	0.3	0.5

W



- Classic convolution
  - None of the adjacent rows in W is spatially adjacent.
    - Thus, spatial correlations are not captured.
- Graph convolution
  - Considers its neighbors' features by using adjacency matrix A.
  - $W^{(l)}=\delta\ (A\ W^{(l-1)}\ w)$
  - E.g.: when convoluting the features of e_1, graph convolution considers the features of e_3, e_4, and e_5.

Empirical Studies

- Setup:
  - Highway tollgates network (24 edges) and a road network (172 edges).
  - Equi-width histograms with 8 buckets, 96 intervals per day.
- MKLR: Mean KL-Divergence Ratio
  - KL-divergence measures the distance between two distributions.
  - How much we can reduce the KL-divergence compared to a naïve baseline just using histograms obtained from all historical data.

rm	**GP**	**RF**	**LSM**	**CNN**	**DR**	**GCWC**	**A-GCWC**
0.5	1.00	0.96	1.08	0.55	0.85	0.48	0.48
0.6	1.00	0.97	1.07	0.59	0.68	0.50	0.49
0.7	1.00	0.98	1.26	0.58	0.55	0.50	0.49
0.8	1.00	0.99	1.35	0.66	0.61	0.49	0.49

Path-Centric Model

- Example: P=<e_5, e_6>
  - Trajectory 1: 10 s, 20 s
  - Trajectory 2: 15 s, 25 s

e_5

Cost	Prob
10	0.5
15	0.5

e_6

Cost	Prob
20	0.5
25	0.5

- The distribution of a path is computed by summing the distributions of edges while assuming they are indepdennt.

Independence

<e_5, e_6>

Cost	Prob
10, 20	0.25
15, 20	0.25
10, 25	0.25
15, 25	0.25

Joint distribution

P

Cost	Prob
30	0.25
35	0.50
40	0.25

Dependence

<e_5, e_6>

Cost	Prob
10, 20	0.5
15, 25	0.5

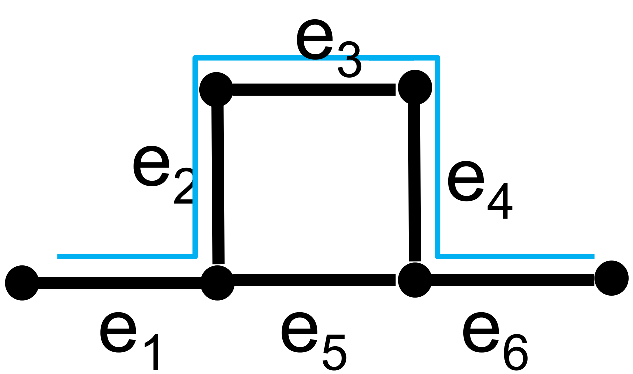
Path weight

P

Cost	Prob
30	0.5
40	0.5

Path-Centric Model

- Better capture cost dependency
  - Path weights: weights are assigned to paths, which maintain the dependency among the edges in the paths.
- Challenge: more than one combination to compute the cost distribution of a path.



Edge weights:

$e_1, e_2, e_3, e_4, e_5, e_6$

Path weights:

$\langle e_1, e_2 \rangle, \langle e_4, e_6 \rangle, \langle e_3, e_4, e_6 \rangle$

More accurate ***More efficient***

The blue path $\langle e_1, e_2, e_3, e_4, e_6 \rangle$:

Edge-centric: $e_1 \odot e_2 \odot e_3 \odot e_4 \odot e_6$

Path-centric: $\boxed{\langle e_1, e_2 \rangle \odot \langle e_3, e_4, e_6 \rangle}$

$\langle e_1, e_2 \rangle \odot e_3 \odot \langle e_4, e_6 \rangle$

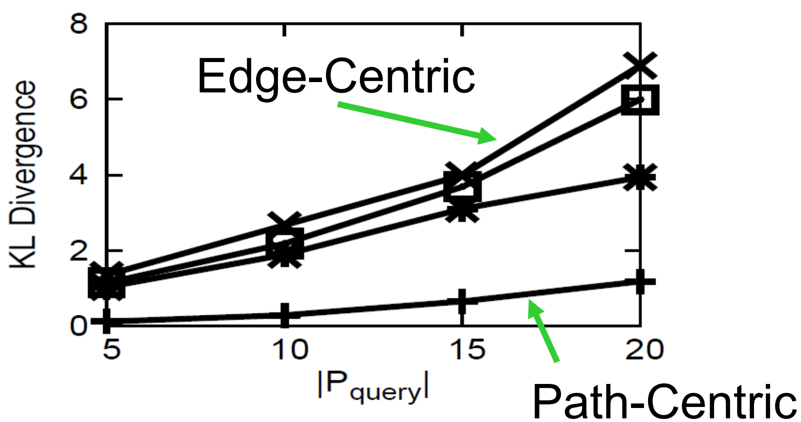
$e_1 \odot e_2 \odot \langle e_3, e_4, e_6 \rangle$

Dai, Yang, Guo, Jensen, Hu. Path Cost Distribution Estimation Using Trajectory Data. PVLDB 10(3): 85-96 (2016).

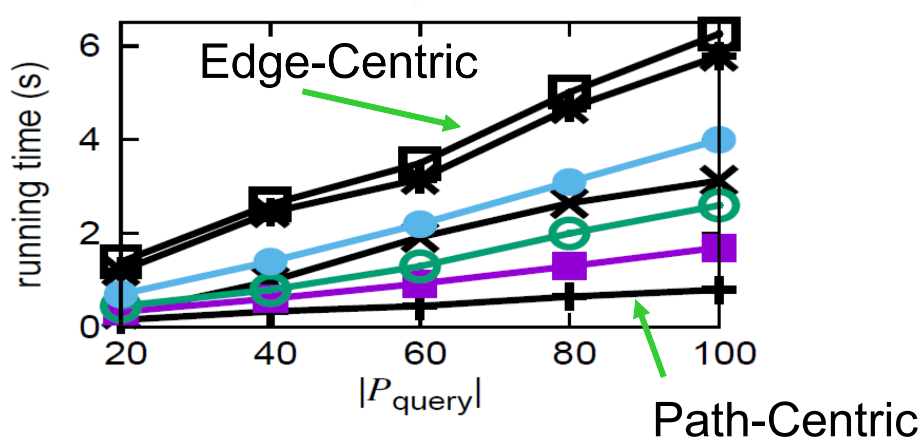
Yang, Dai, Guo, Jensen, Hu. PACE: A PAth-CEntric Paradigm For Stochastic Path Finding. The VLDB Journal 27(2): 153-178 (2018).

Empirical Studies

- Setup
  - 180 Million GPS records from Denmark.



Accuracy



Efficiency

A forward-looking paradigm that promises higher efficiency and accuracy.

Outline

- Motivation
- Learn accurate travel costs
- Learn routing preferences
- Data-intensive routing

Routing Preferences

- Professional and local drivers often follow paths that are neither fastest nor shortest.

- It is of interest to know why drivers chose such paths.
  - Educate new drivers;
  - Provide personalized navigation;
  - Teach self-driving cars to make good routing decisions.

Green: fastest path.
Red: shortest path.
Blue: a driver's actual path.

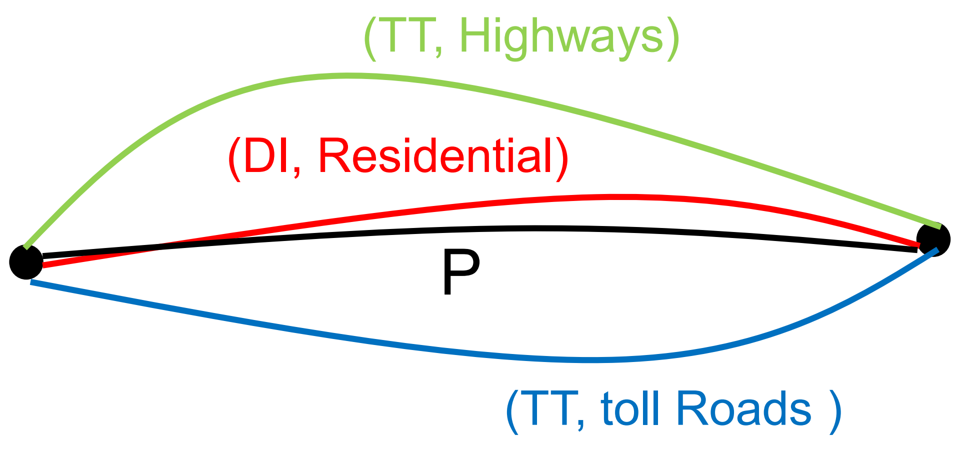
Modeling Routing Preferences

- Consider two categories of features that may affect a driver's routing decisions.
- Travel costs
  - Travel time (TT), distance (DI), fuel consumption (FC).
- Road conditions
  - Highways, residential roads, toll roads;
- Routing preference
  - 2D vector, e.g., V=(TT, Highways)

Learning Preferences

- Given a routing preference V, we are able to identify a corresponding path P_V.
  - V=(TT, Highways): a fastest path that uses highways if possible.

- If V reflects accurately a driver's actual routing preference, P_V should be the same, or very similar, to the path P used by the driver.



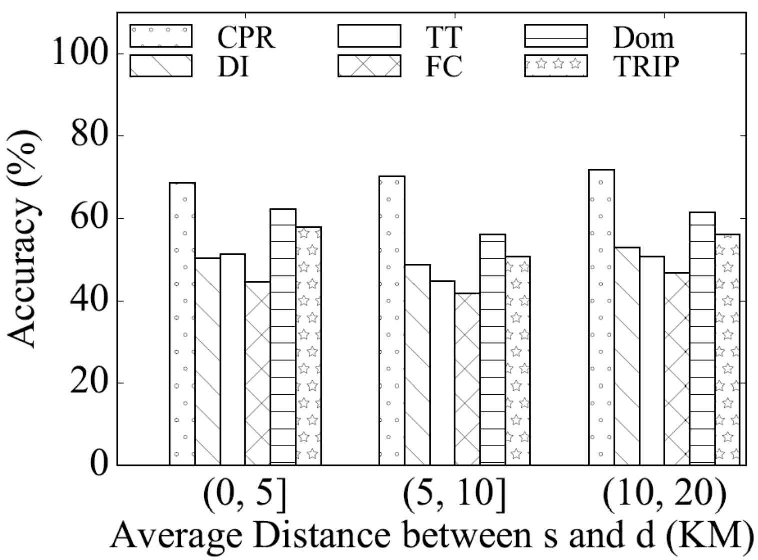
Speed up the learning

- When having *n* travel costs and *m* road conditions.
  - Naïve method: check all *n***m* possible preference vectors.
- Coordinate descent: check only *n*+*m* possible preference vectors.
  - On the first dimension, identify the best travel cost.
    - Is the fastest path, the shortest path, or the most fuel efficient path is the most similar to P?
    - For example, if the shortest path is the most similar to P, DI is chosen.
  - On the second dimension, identify the best road condition.
    - To see whether the shortest path can be further improved when considering different road conditions.
- Checking each preference vector calls for a shortest path finding.
  - Dijkstra’s algorithm is slow.
  - Label-constrained contraction hierarchies.
    - Road conditions are treated as labels.

Empirical Studies

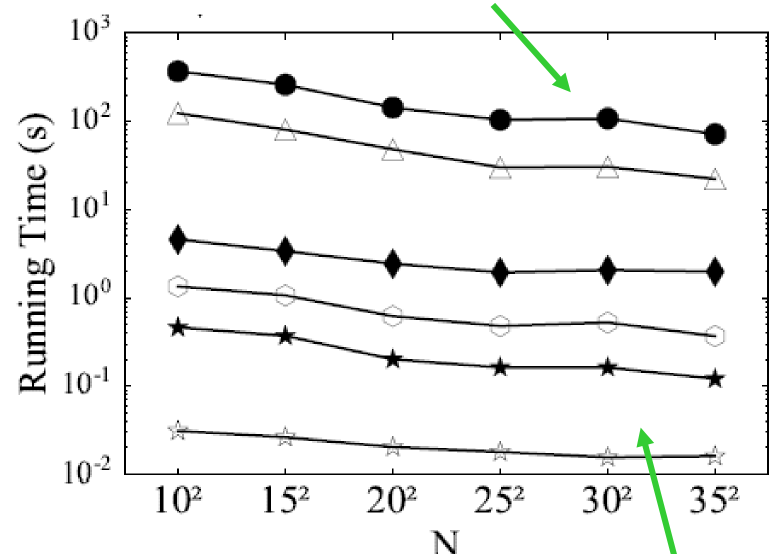
- Setup:
  - 180 Million GPS records from Denmark.
  - 75% data for learning routing preferences. 25% data for testing the accuracy of the learned routing preferences.

Accuracy



Efficiency

Naïve + Dijkstra's alg



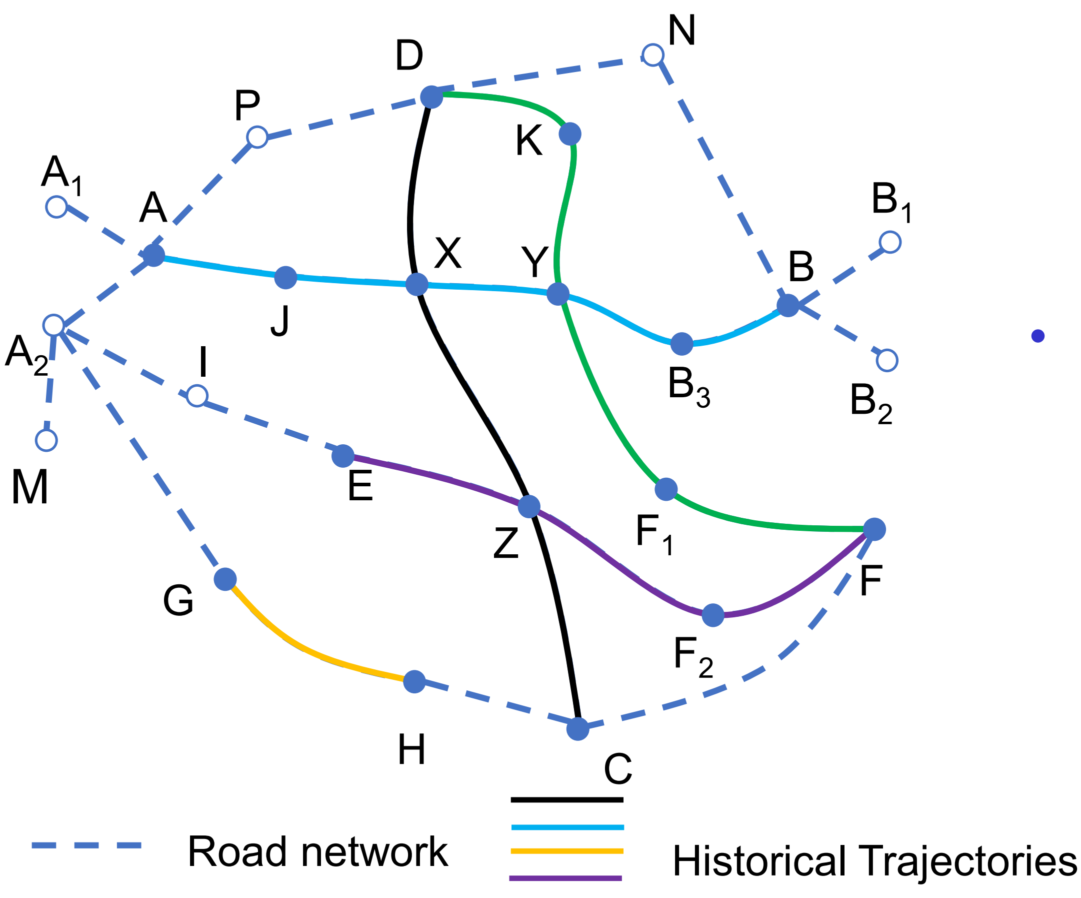
Coordinate descent + Contraction Hierarchies

Outline

- Motivation
- Learn accurate travel costs
- Learn routing preferences
- Data-intensive routing

Trajectory-base Routing

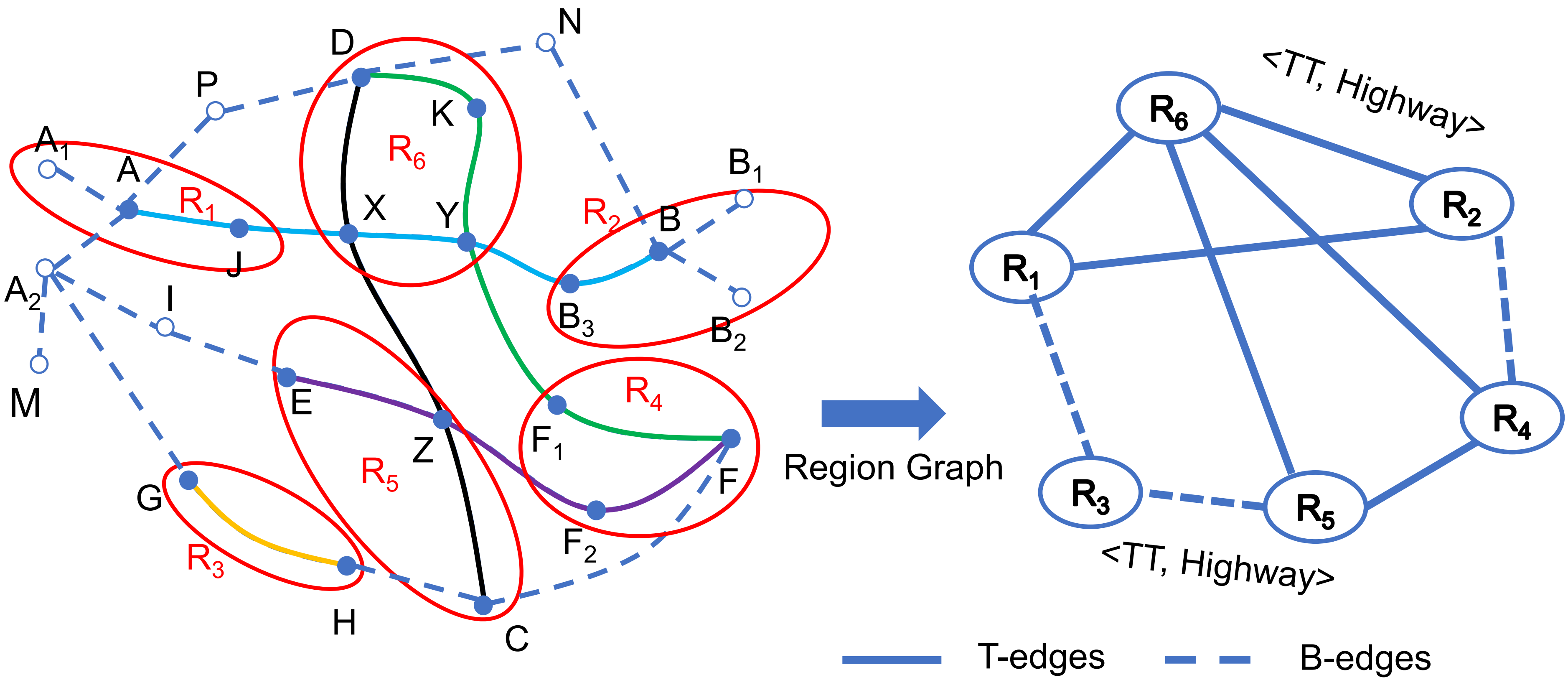
- How to best utilize trajectories from experienced, professional drivers, to recommend routes to new drivers, or self-driving cars?



- Reuse professional drivers' paths
  - Trivial case: D to C
    - Reuse the path <D, X, Z, C> in the black trajectory.
  - Data sparseness challenge!
    - G to B?
- Solution
  - Graph clustering.
  - Semi-supervised preference learning.

Overview

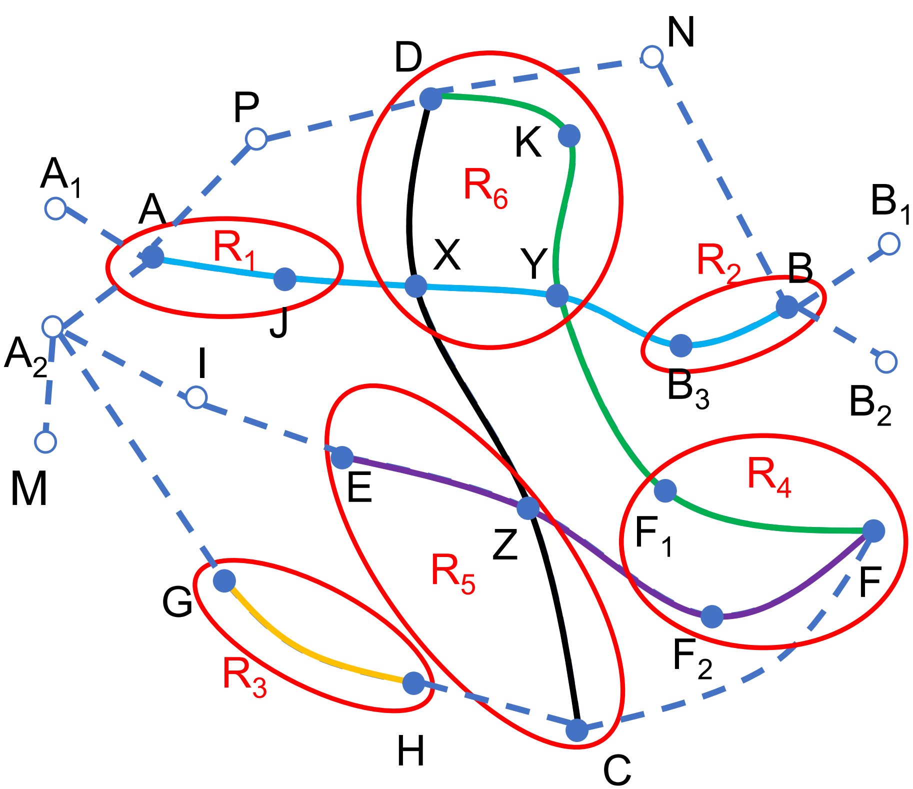
- Cluster vertices into regions and transfer a road network to a region graph.
- Learn a routing preference from T-edges.
- Transfer the preferences from T-edges to similar B-edges.
- Use the transferred preferences to infer paths for B-edges.

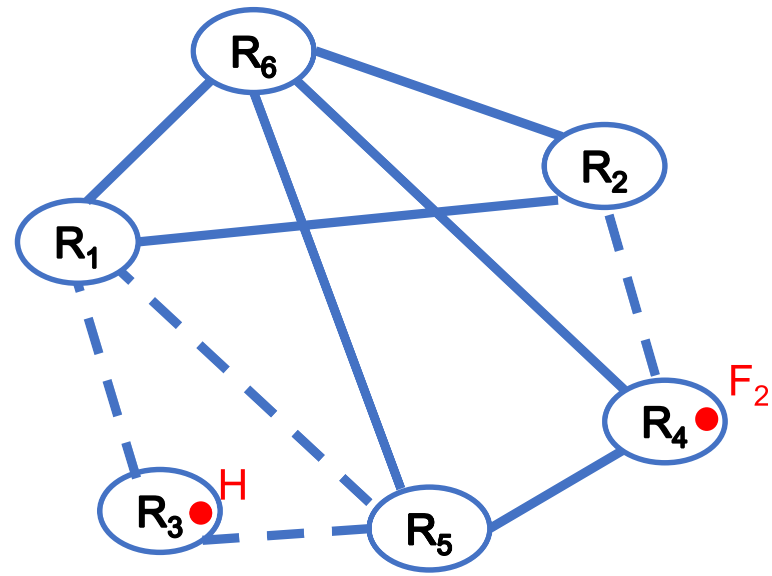


Guo, Yang, Hu, and Jensen. Learning to Route with Sparse Trajectory Sets. ICDE 2018, 1073-1084.

Routing on the Region Graph

- Given arbitrary (s, d) in the original road network,
  - Identify nearest source and destination region.
  - Route in the region graph.
  - Reconstruct paths using the original road network.



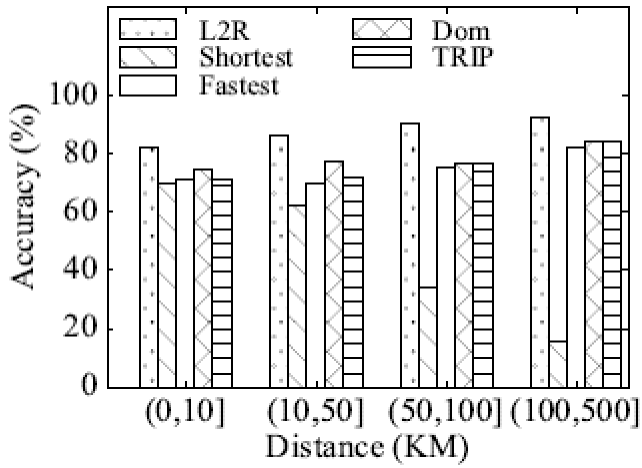


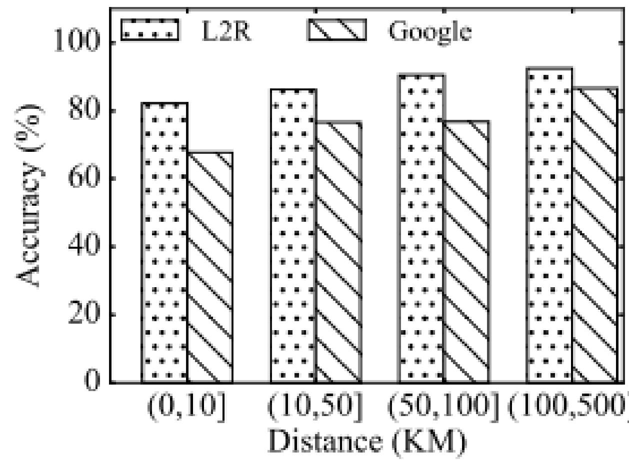
Routing H – F_2:

1. H is in R_3
2. F is in R_4
3. Region graph routing: R_3 – R_5 – R_4
4. R_3 – R_5 is recovered as H – C
5. R_5 – R_4 is recovered as Z – F_2
6. Return H – C – Z – F_2

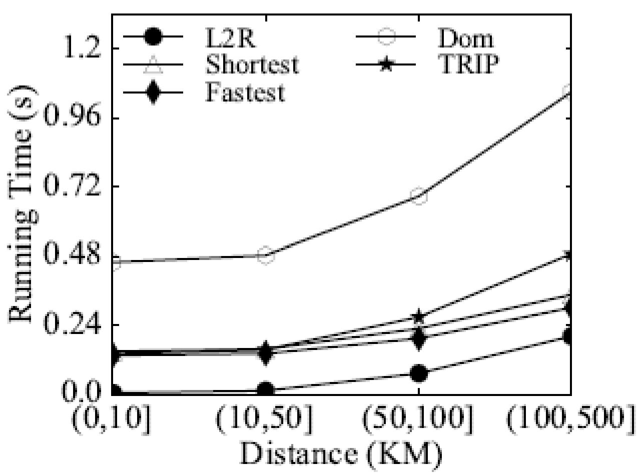
Empirical studies

- Accuracy





- Efficiency



Data Driven Decision Making

- From 4V big data to 3T big knowledge that helps decision making.
- 3T big knowledge
  - Thorough (volume and variety).
    - Conquer the data sparseness challenges.
    - Cover all edges/paths, all time periods, all (s, d) pairs.
  - Timely (velocity).
    - Handle high-speed streaming data, e.g., 100 Hz accelerometer data.
    - Different applications have different requirements.
  - Trustworthy (veracity)
    - Capture traffic uncertainty at high resolution.
    - Make reliable decisions under uncertainty.

Acknowledgment

- Independent research fund Denmark.
- The Danish agency for science and higher education.
- Innovation fund Denmark.
- The Obel family foundation.

INDEPENDENT RESEARCH FUND DENMARK

Ministry of Higher Education and Science

/nnovationsfonden

DET OBELSKE FAMILIEFOND

Thank you!