



机器学习时代下的城市 交通行为分析

Tao Feng (冯 涛)

Professor, Advanced Science and Engineering, Hiroshima University, Japan

Department of the Built Environment, TU/e

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Tao Feng

Professor

Urban and Data Science

Graduate School of Advanced Science
and Engineering

Hiroshima University

Japan

taofeng@hiroshima-u.ac.jp

Guest Professor

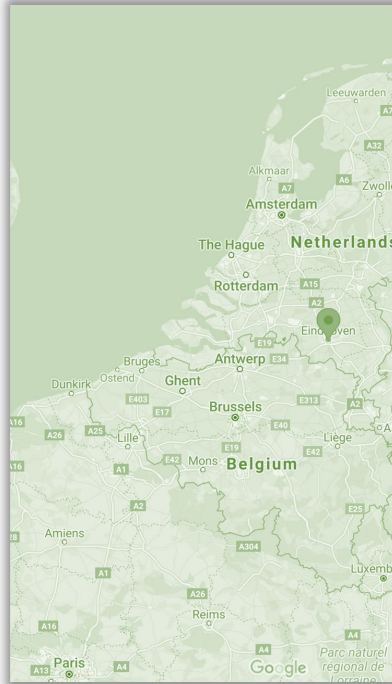
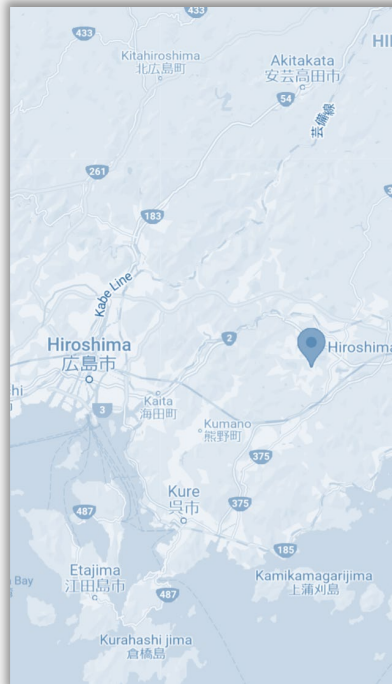
Urban Planning and Transportation

Department of the Built Environment

Eindhoven University of Technology

The Netherlands

t.feng@tue.nl



Research interests

- ✓ Urban planning
- ✓ Smart mobility
- ✓ Travel behaviour
- ✓ Transport network analysis
- ✓ Data driven technology
- ✓ Mobility in built environment
- ✓ Spatial planning
- ✓ Urban environment analysis
- ✓ Decision making in smart energy
- ✓ Big data & machine learning for urban research

<https://research.tue.nl/en/persons/tao-feng>

*Website of Hiroshima University is under construction.

Contents

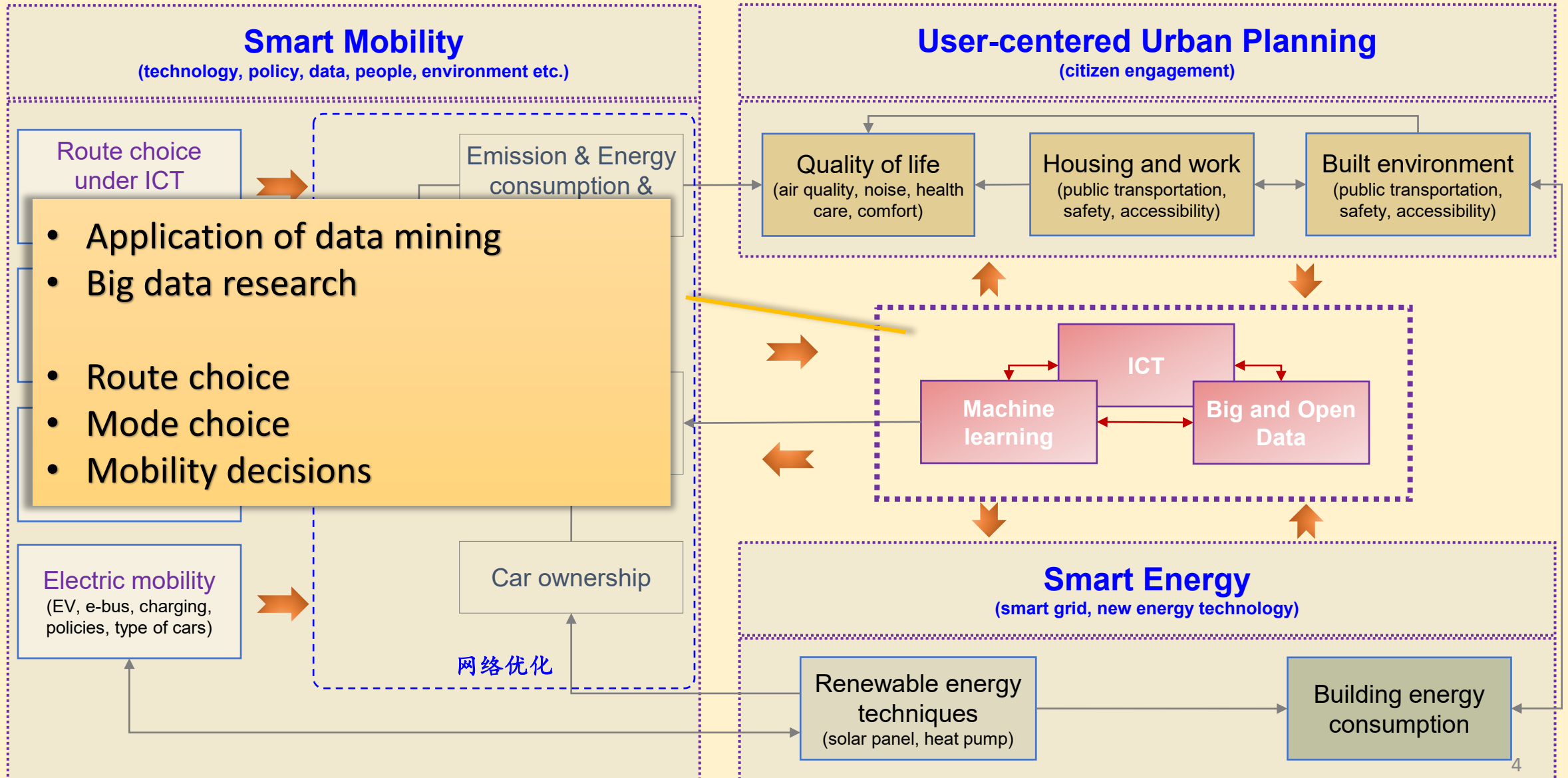


Our research
+
Travel behavior
analysis

The diagram consists of two overlapping circles. The left circle is green and contains the text 'Our research + Travel behavior analysis'. The right circle is blue and contains the text 'Mobility decision + Data mining & AI'. The circles overlap in the center, creating a darker blue area. The background features abstract, flowing lines in shades of green and blue.

Mobility decision
+
Data mining & AI

Research topics

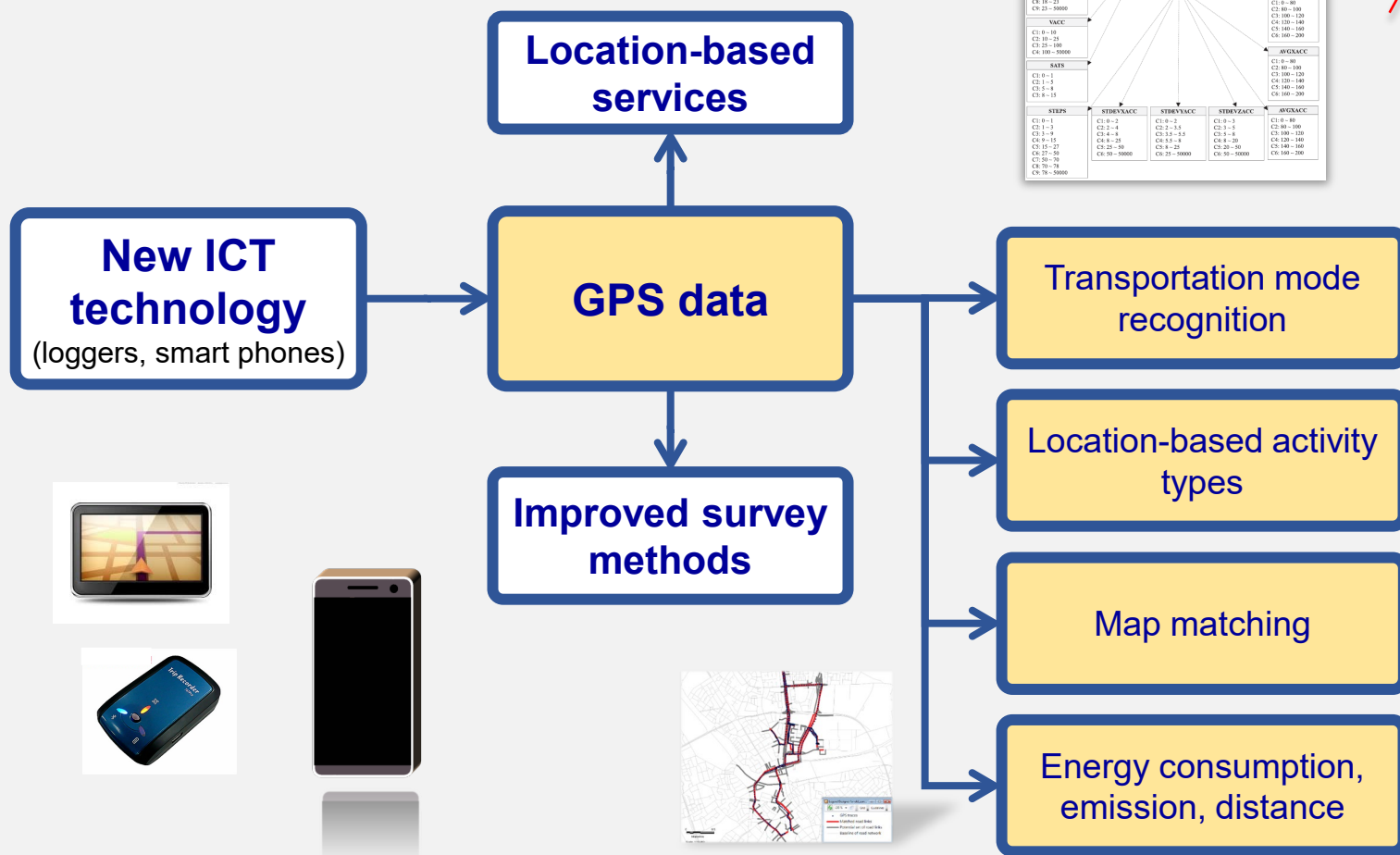


Data imputation & mining

GPS辅助居民出行调查

Trace Annotator

An integrated data imputation tool



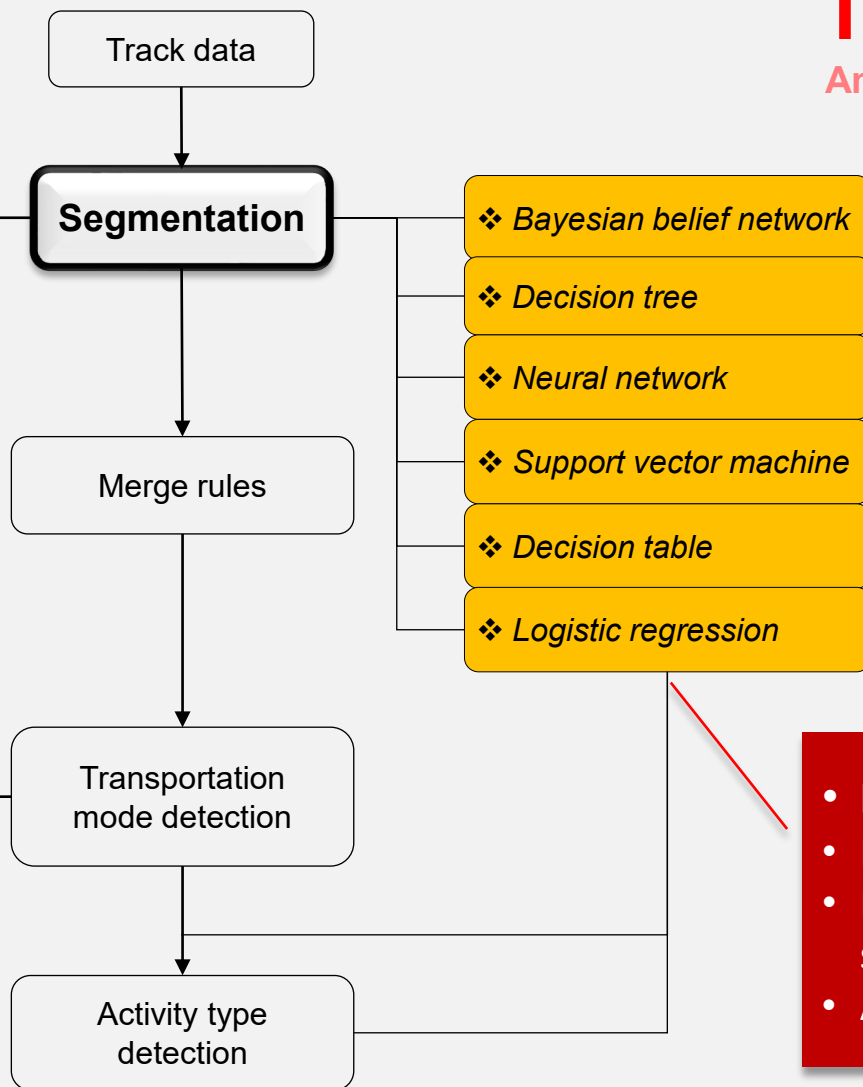
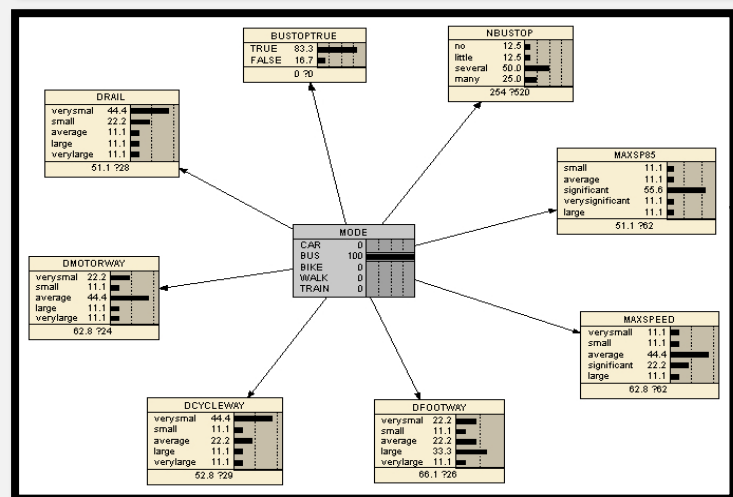
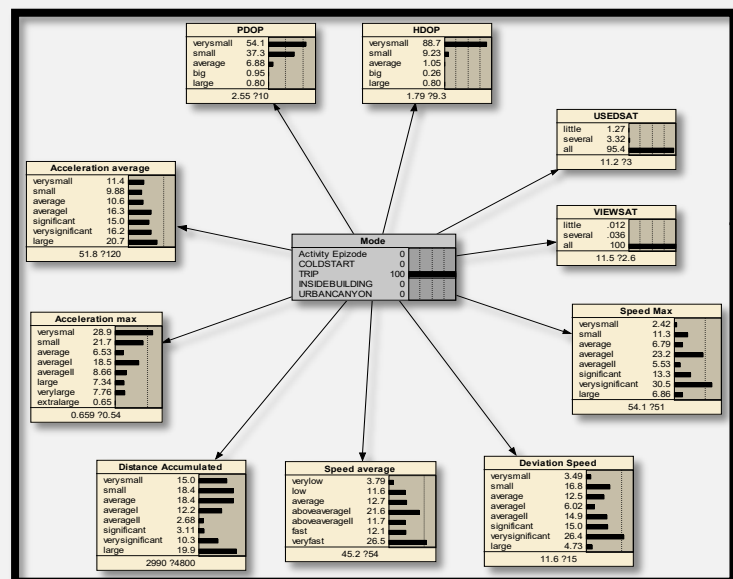
Machine learning algorithms

(Bayesian belief network, support vector machine, decision table, logistic regression, neural networks)

- [Feng, T. & Timmermans, H.J.P. \(2013\)](#) Transportation mode recognition using GPS and accelerometer data. *Transportation Research Part C: Emerging Technologies*, 37, 118-130.
- [Feng, T. & Timmermans, H.J.P. \(2016\)](#) Comparison of advanced imputation algorithms for detection of transportation mode and activity episode using GPS data. *Transportation Planning and Technology*, 39, 2, 180-194.
- [Feng, T. & Timmermans, H.J.P. \(2015\)](#) Detecting activity type from GPS traces using spatial and temporal information. *European Journal of Transport and Infrastructure Research*, 15, 4, 662-674.
- [Feng, T. & Timmermans, H.J.P. \(2015\)](#) Enhanced imputation of GPS traces forcing full or partial consistency in activity-travel sequences: Comparison of algorithms. *Transportation Research Record*, 2430, 20-27.
- [Feng, T. & Timmermans, H.J.P. \(2013\)](#) Map matching of GPS data with Bayesian belief networks. *Journal of the Eastern Asia Society for Transportation Studies*, 10, 100-112.
- [Yao, B. & Feng, T. \(2018\)](#) Machine learning in automotive industry. *Advances in Mechanical Engineering*, 10, 10, 1-2.

Data imputation & mining

GPS辅助居民出行调查



Trace Annotator

An integrated data imputation tool

- Programmed by Java
- Incorporated AI algorithms
- Fast processing and flexible structure
- Applied for many applications

Big data research

Ridership and the built environment
(smart card data and land use data)

Metro-bike sharing for
the last mile travel

- Metro smart card
- Shared bike
- Mobike

Open Data
(OSM, GTFS, POI,
land use, buildings,
public transport,
road network, etc.)

ICT
+
Analytical models

Big Data

(Smart card, shared bike,
call record data, social
media data (Twitter,
Flickr), transaction data,
taxi, smartphone GPS
data)

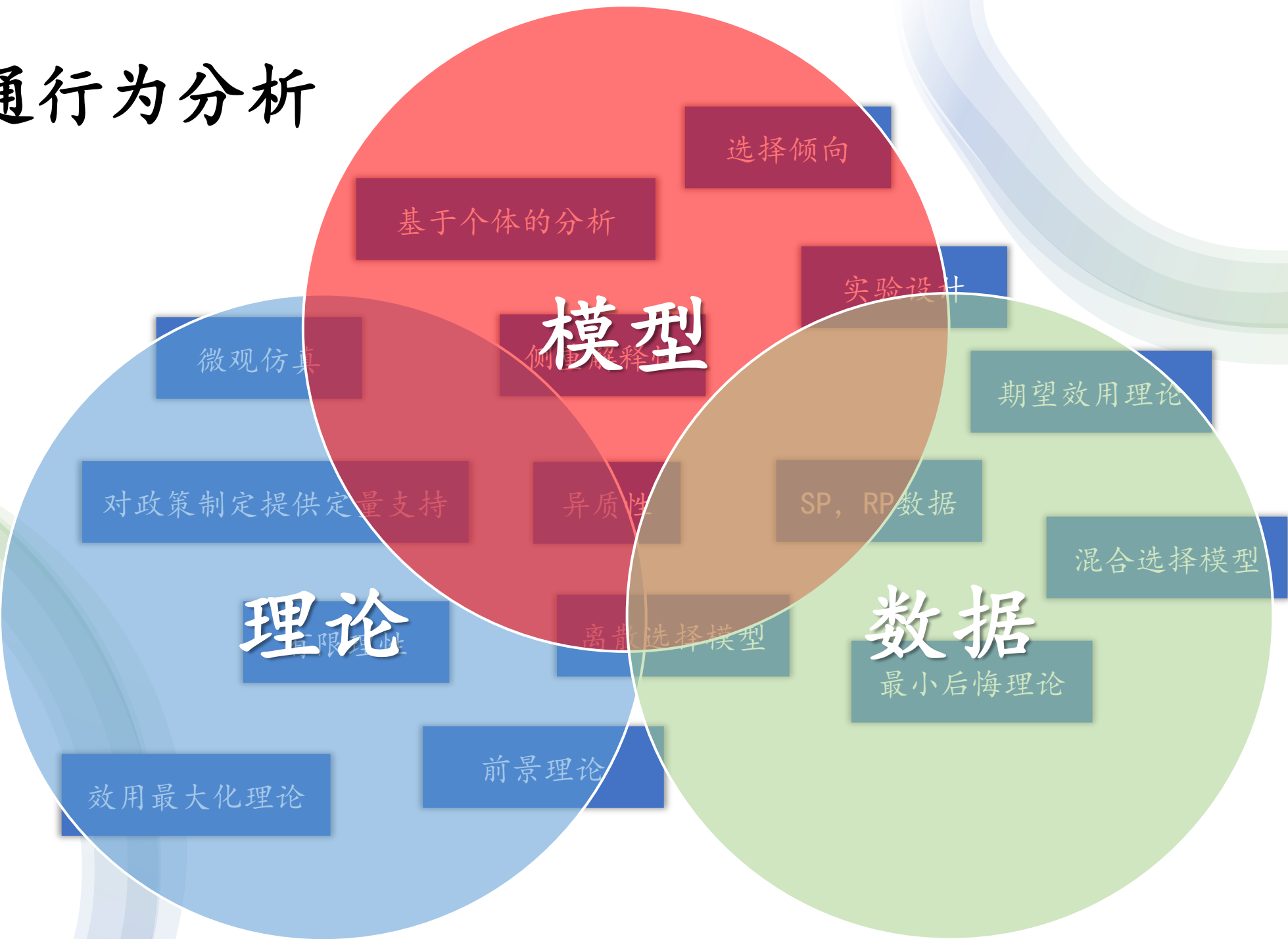
GPS Taxi data

Flickr, Twitter data

**Sensor
Data**
(weather)

- Cycling data
- GPS data from smart phones
- Weather data

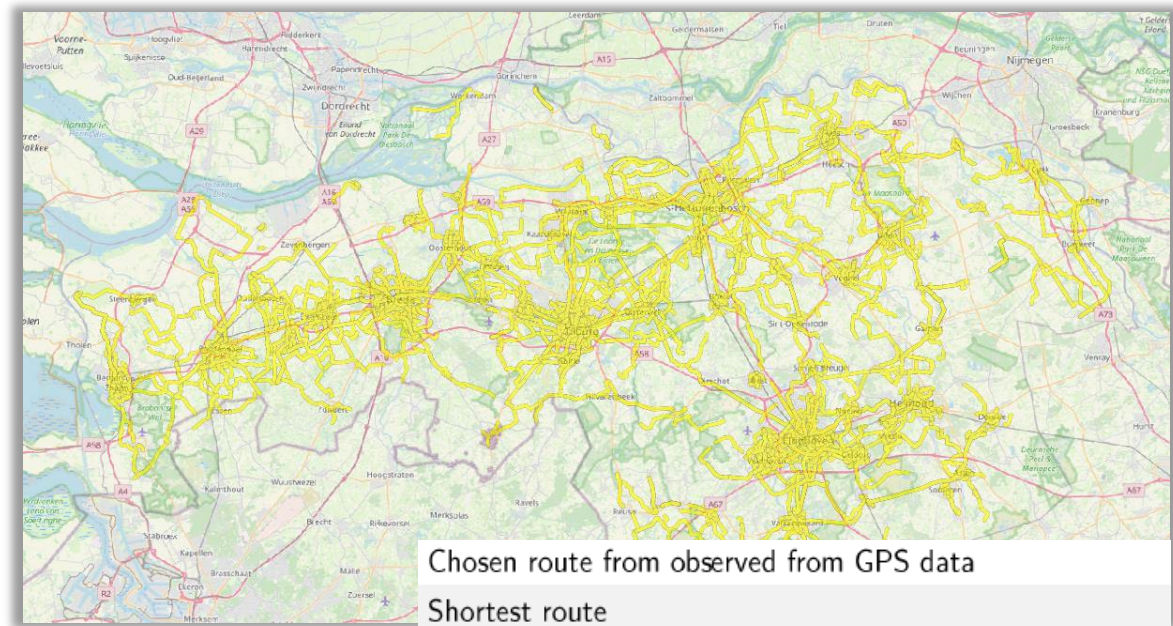
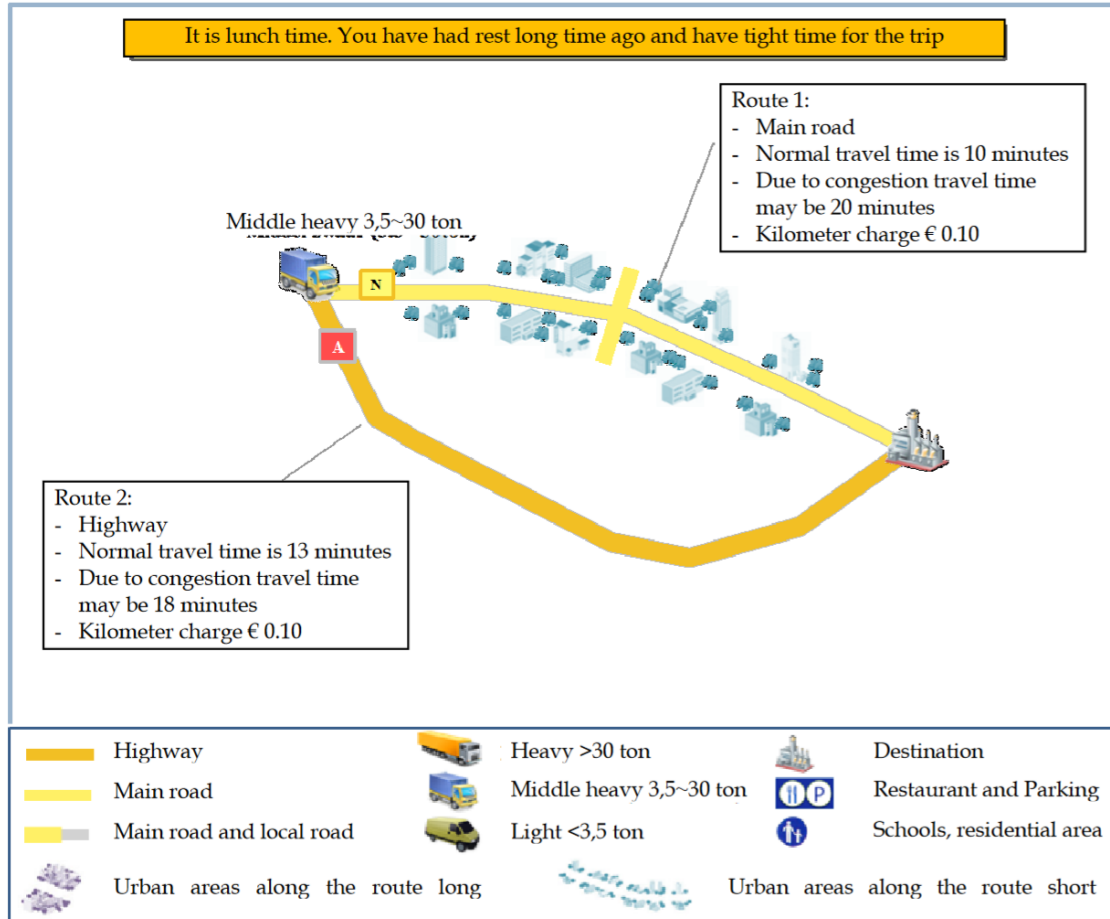
交通行为分析



Mobility decision

Route choice as an example

- Route choice using SP data



Shortest route

Fastest route

Least links route

Most attractive environment route

Environment attractiveness as distance weight

Most attractive cycle path route

“Primary cycle route” (PSR) categorization as distance weight

Shortest path when link lengths are randomly varied +/- 50%

Shortest path when link lengths are randomly varied +/- 50%, with opposite effect of A9

- Route choice using RP data

Dane, G., Feng, T., Luub, F. & Arentze, T. (2019) Route Choice Decisions of E-bike Users: Analysis of GPS Tracking Data in the Netherlands, *Geospatial Technologies for Local and Regional Development*, 109-124, DOI:10.1007/978-3-030-14745-7_7

Mobility decision

Route choice as an example

- Route choice using neural network

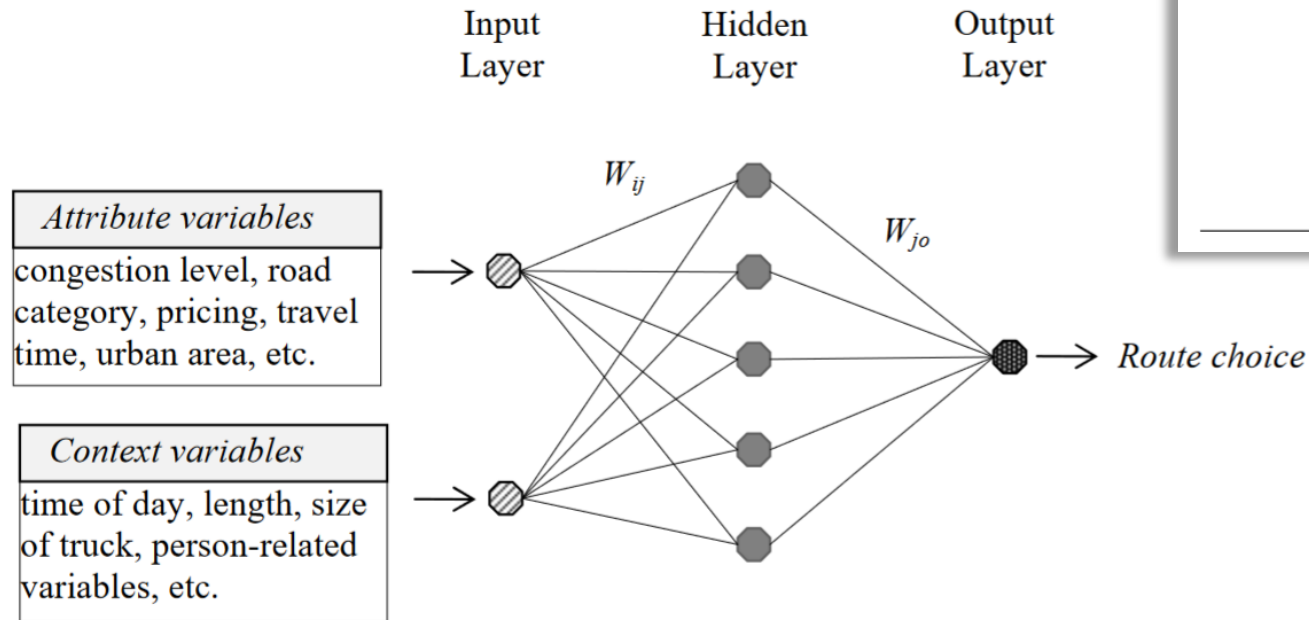


Table 4 Result of relative importance of variables

Groups	Variables	Importance
Attribute variables	Congestion	4.49
	Road category	12.43
	Pricing	11.07
	Bonus	16.71
	Passing through urban area	13.78
	Having restaurant facility	6.12
Context variables	Normal travel time difference	6.67
	Time of day	3.74
	Size of truck	8.43
	Distance to destination	6.44
	Time since rest	4.96
	Time window	5.16

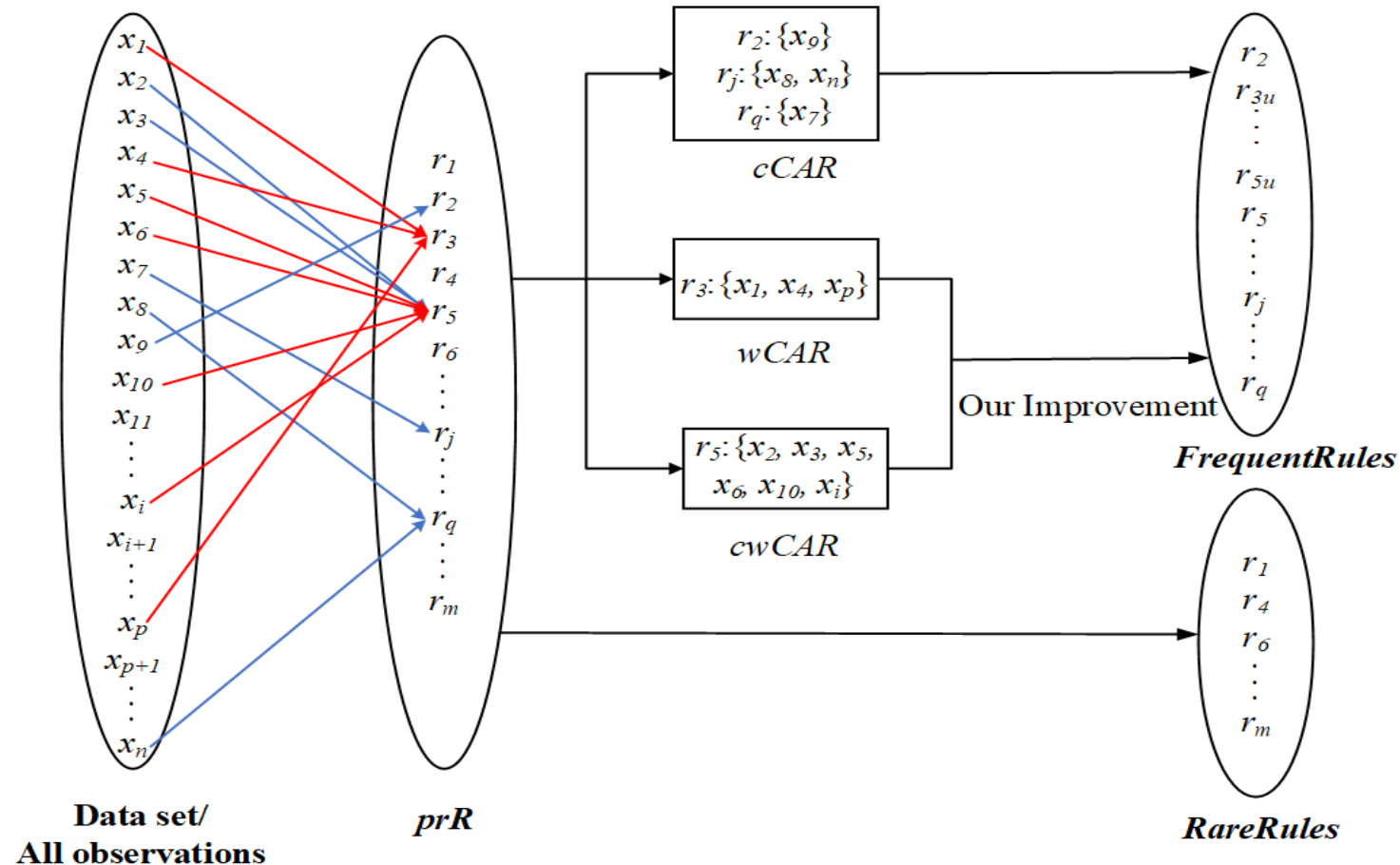
$$RI_i = \frac{C_i}{\sum_{i=1}^M C_i}$$

?

Mobility decision

Transportation mode choice with improved rule sets

- Discrete choice models vs. data mining approach



	CARM	CARIG	CBA	DT	MNL
C ₁	92.4	82.8	77.3	76.0	73.3
C ₂	93.4	99.4	90.2	92.8	79.9
C ₃	92.5	96.1	85.3	86.2	75.3
C ₄	88.5	72.6	67.9	61.2	63.2
C ₅	87.8	90.1	77.1	78.4	77.6
Avg.	91.1	88.7	80.6	77.6	74.3

Mobility decision

Housing, job and transportation

Data mining

$$U_{nit} = V_{nit} + \epsilon_{nit} \quad \text{Choice modeling}$$

Status quo:

$$U_{n1t} = \beta_{1o} + \sum_{k=1}^K \left(\bar{\beta}_k + \sigma_k + \sum_{m=1}^M \theta_{km} z_{nm} \right) x_{n1kt} + \lambda_1 Q_{n1} + \epsilon_{n1t}$$

Move house :

$$U_{n2t} = \beta_{2o} + \sum_{k=1}^K \left(\bar{\beta}_k + \sigma_k + \sum_{m=1}^M \theta_{km} z_{nm} \right) x_{n2kt} + \lambda_2 Q_{n2} + \epsilon_{n2t}$$

...

$$U_{n6t} = \beta_{6o} + \sum_{k=1}^K \left(\bar{\beta}_k + \sigma_k + \sum_{m=1}^M \theta_{km} z_{nm} \right) x_{n6kt} + \lambda_2 Q_{n2} + \epsilon_{n6t}$$

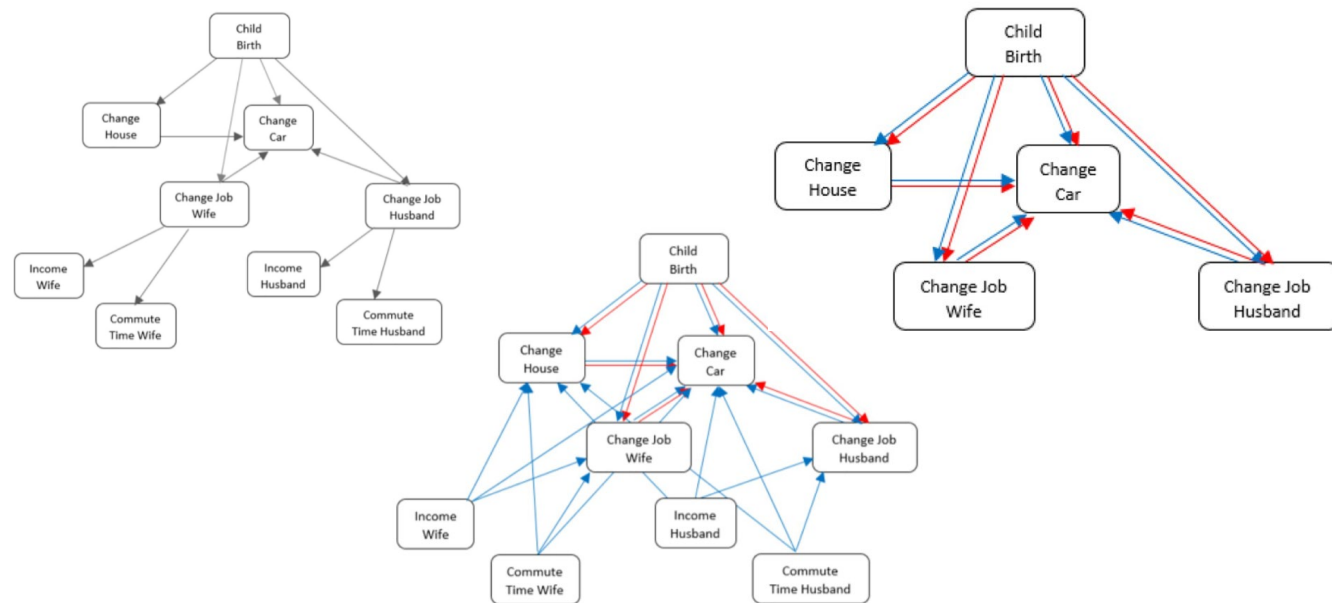
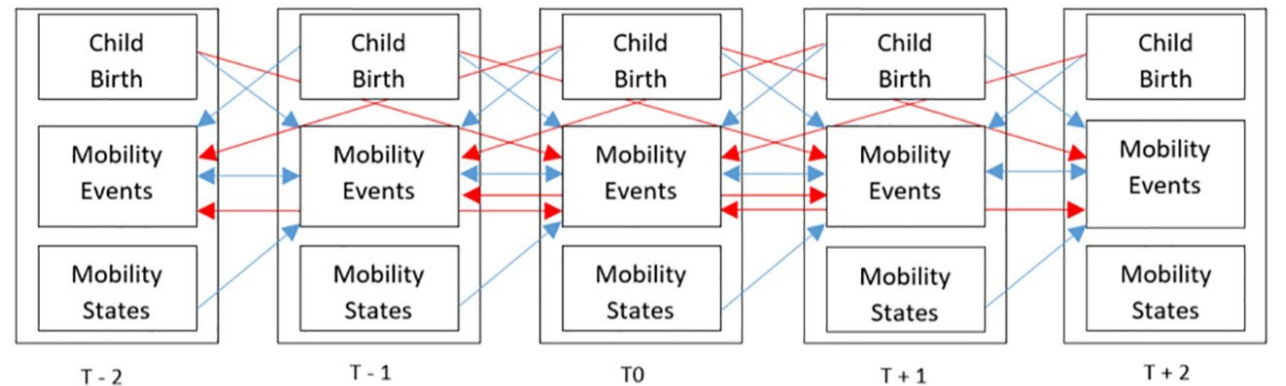
...

Change job :

$$U_{n7t} = \beta_{7o} + \sum_{k=1}^K \left(\bar{\beta}_k + \sigma_k + \sum_{m=1}^M \theta_{km} z_{nm} \right) x_{n7kt} + \lambda_3 Q_{n3} + \epsilon_{n7t}$$

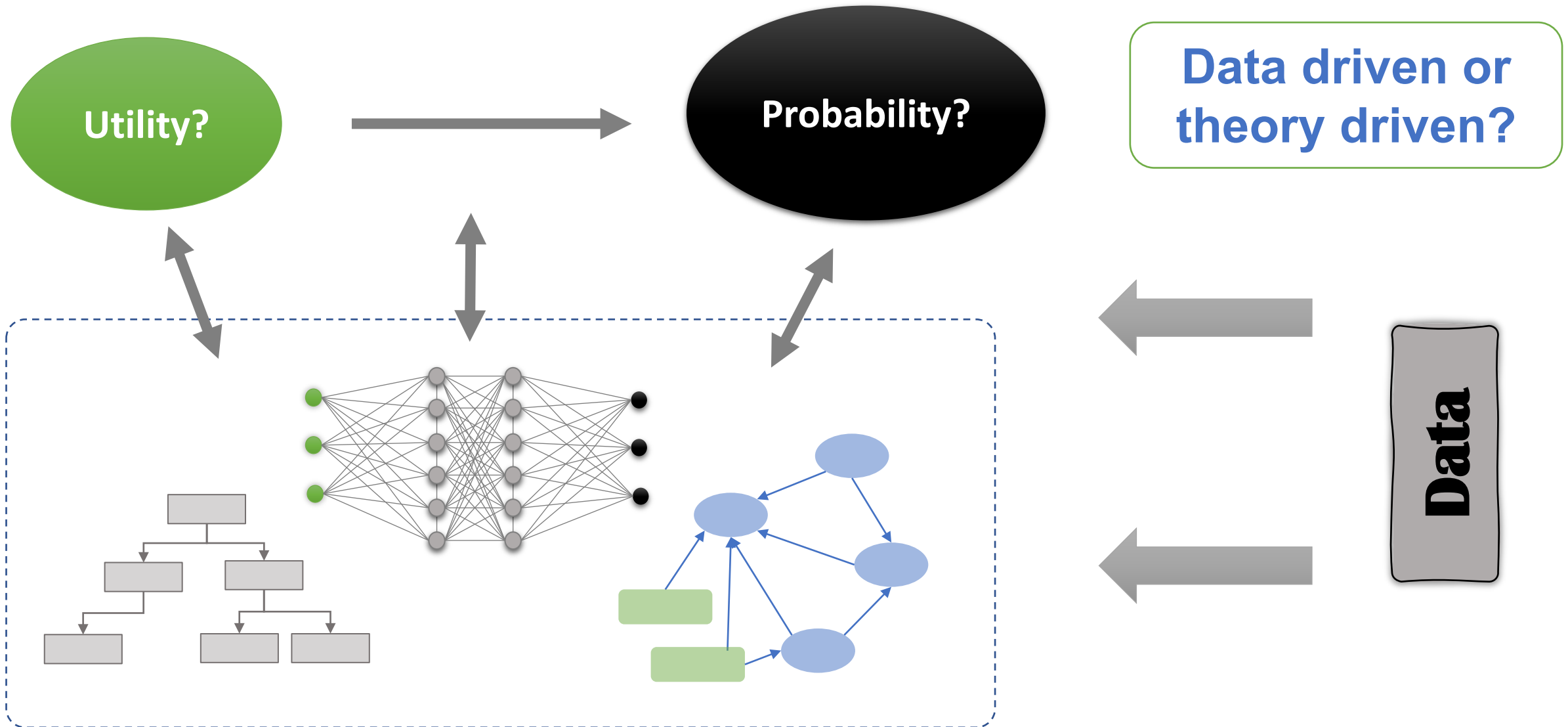
...

$$U_{n11t} = \beta_{11o} + \sum_{k=1}^K \left(\bar{\beta}_k + \sigma_k + \sum_{m=1}^M \theta_{km} z_{nm} \right) x_{n11kt} + \lambda_3 Q_{n3} + \epsilon_{n11t}$$



Synergy between choice modeling & AI

Choice theory + machine learning



感谢大家的倾听！

欢迎有意攻读博士或交流交换的同学来广岛大学！也欢迎到TU Eindhoven！

Contact: taofeng@hiroshima-u.ac.jp, t.feng@tue.nl

欢迎大家来广岛大学深入交流、访问与合作！

冯 涛 (Tao Feng)

Professor, Urban and Data Science

Graduate School of Advanced Science and Engineering, Hiroshima University, Japan

広島大学先進理工系科学研究科 理工学融合プログラム 開発科学分野

<https://www.tue.nl/en/research/researchers/tao-feng> <http://idecdt.hiroshima-u.ac.jp/research-fields/>

张 峻屹

Professor, Mobilities and Urban Policy Lab

モビリティ・都市政策研究室

藤原章正

Professor, Transportation Engineering Lab

交通工学研究室

冯 涛

Professor, Urban and Data Science Lab

城市与数据科学研究室