The 22nd summer course:
Behavior Modeling in Transportation Networks
September 18-20, 2023

Review of Recent Behavior Modeling

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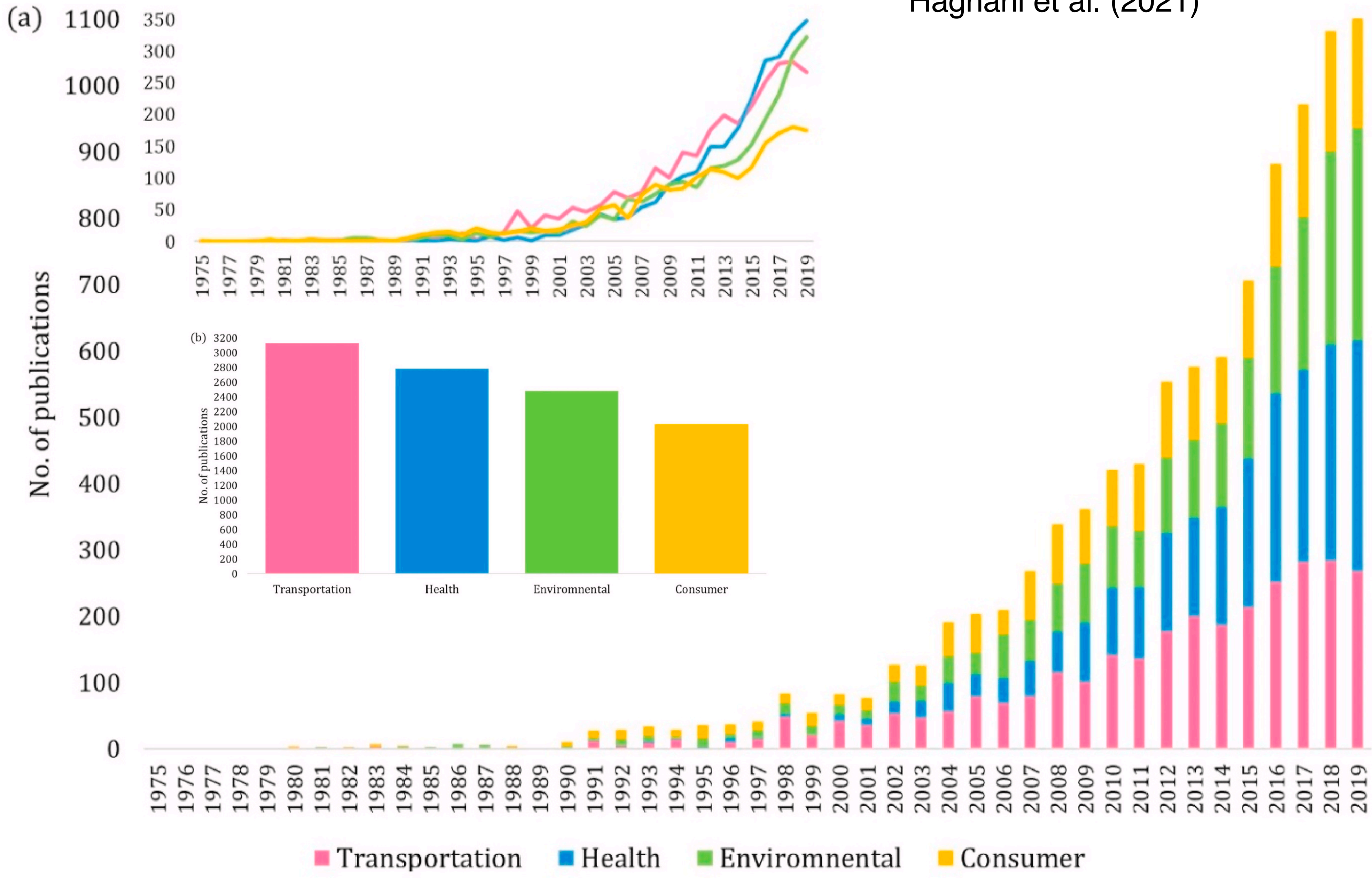
Recent treads in DCM

Haghani, M., Bliemer, M.C.J., Hensher, D.A.: The landscape of econometric discrete choice modelling research. *Journal of Choice Modelling* 40, 100303, 2021.

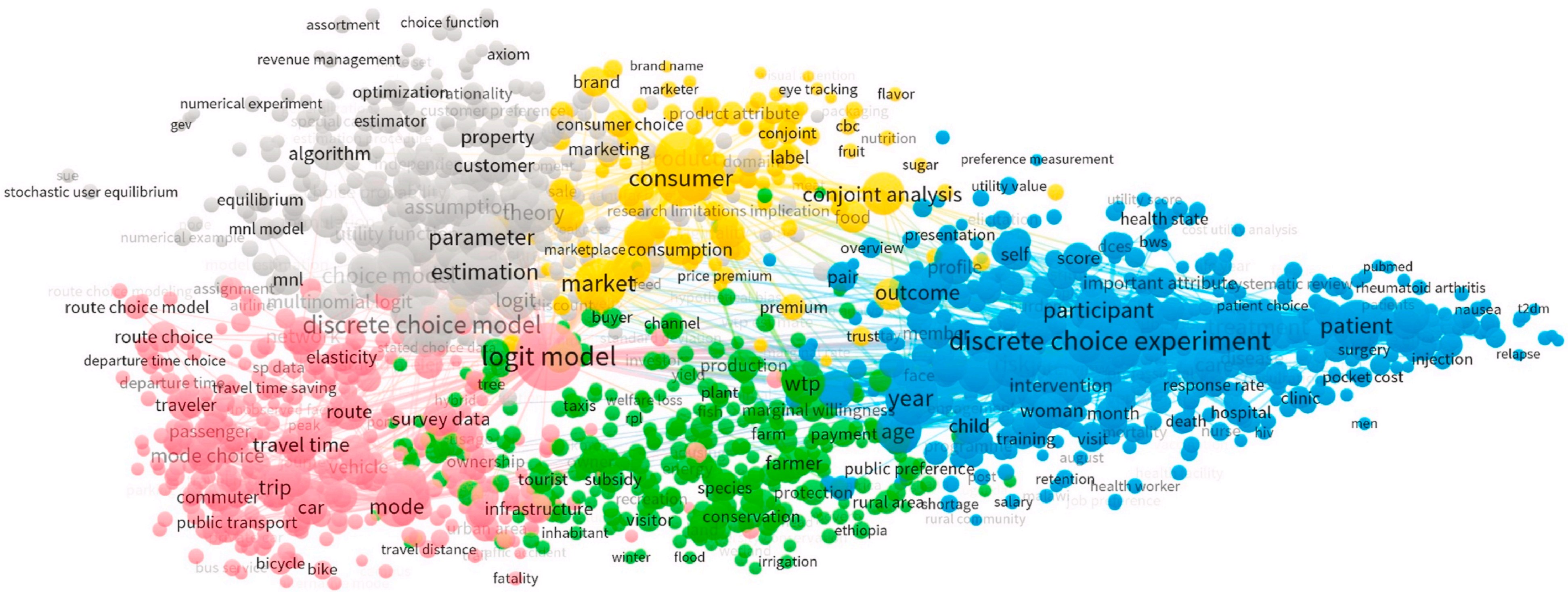
While the largest portion of this literature is concentrated in the transportation sector, the methods are currently most trendy in health economics. This is striking given that health economists come late to adopt econometric choice methods compared to other major disciplines. Since 2014, more applications of discrete choice models have been reported in health-related studies than any other domain. Also, while the number of applications in consumer and transportation studies have been fluctuating over the past few years, applications in environmental studies are steadily on the rise at a rate comparable to that of health. Activities in the methodological cluster of this field have rather notably slowed down during the recent years although not extinct. Also, despite slowing down of choice modelling applications in transportation compared to the previous decades, such applications have not disappeared from the transportation sector. A partic-

Treads in Research Domains

Haghani et al. (2021)



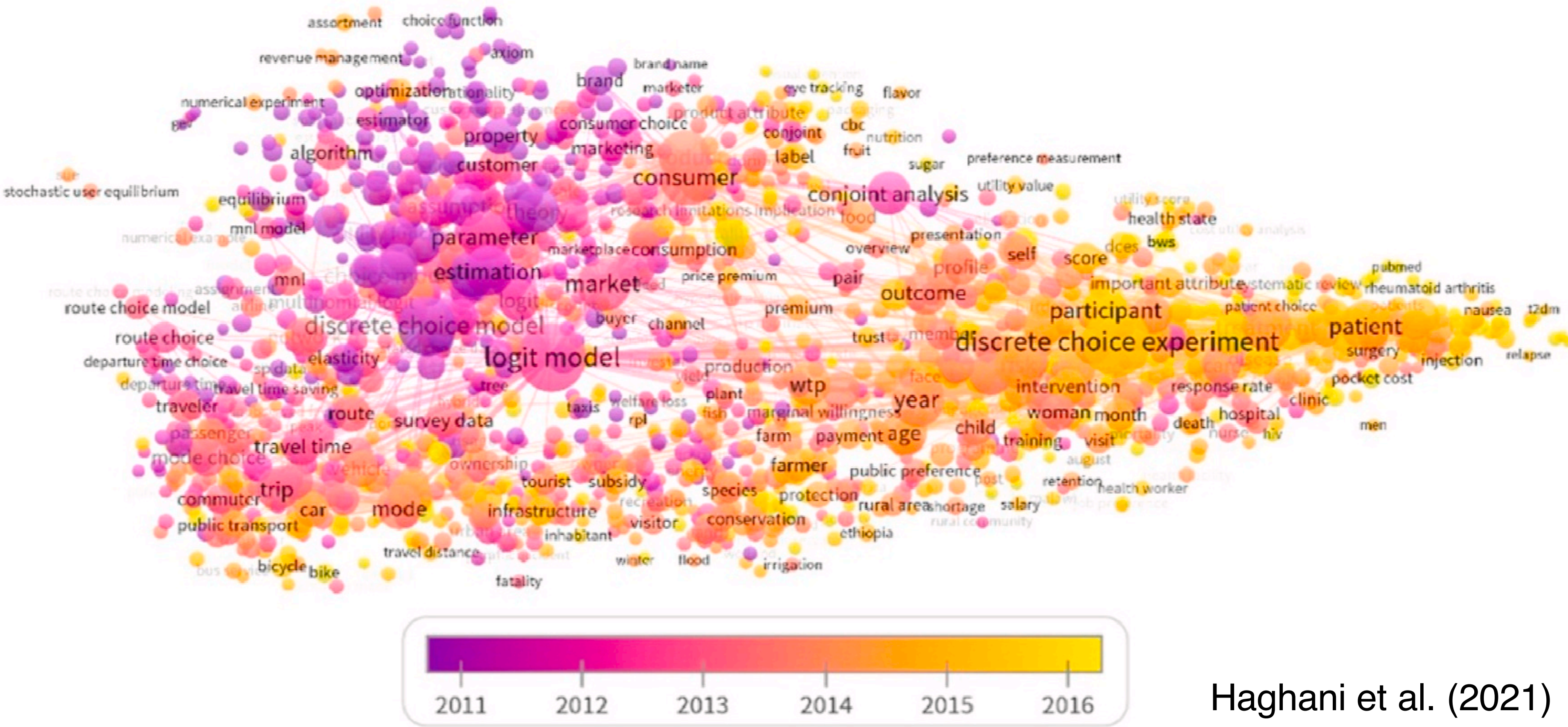
Trends in Keywords



Haghani et al. (2021)

Network map of title and abstract terms by research domain

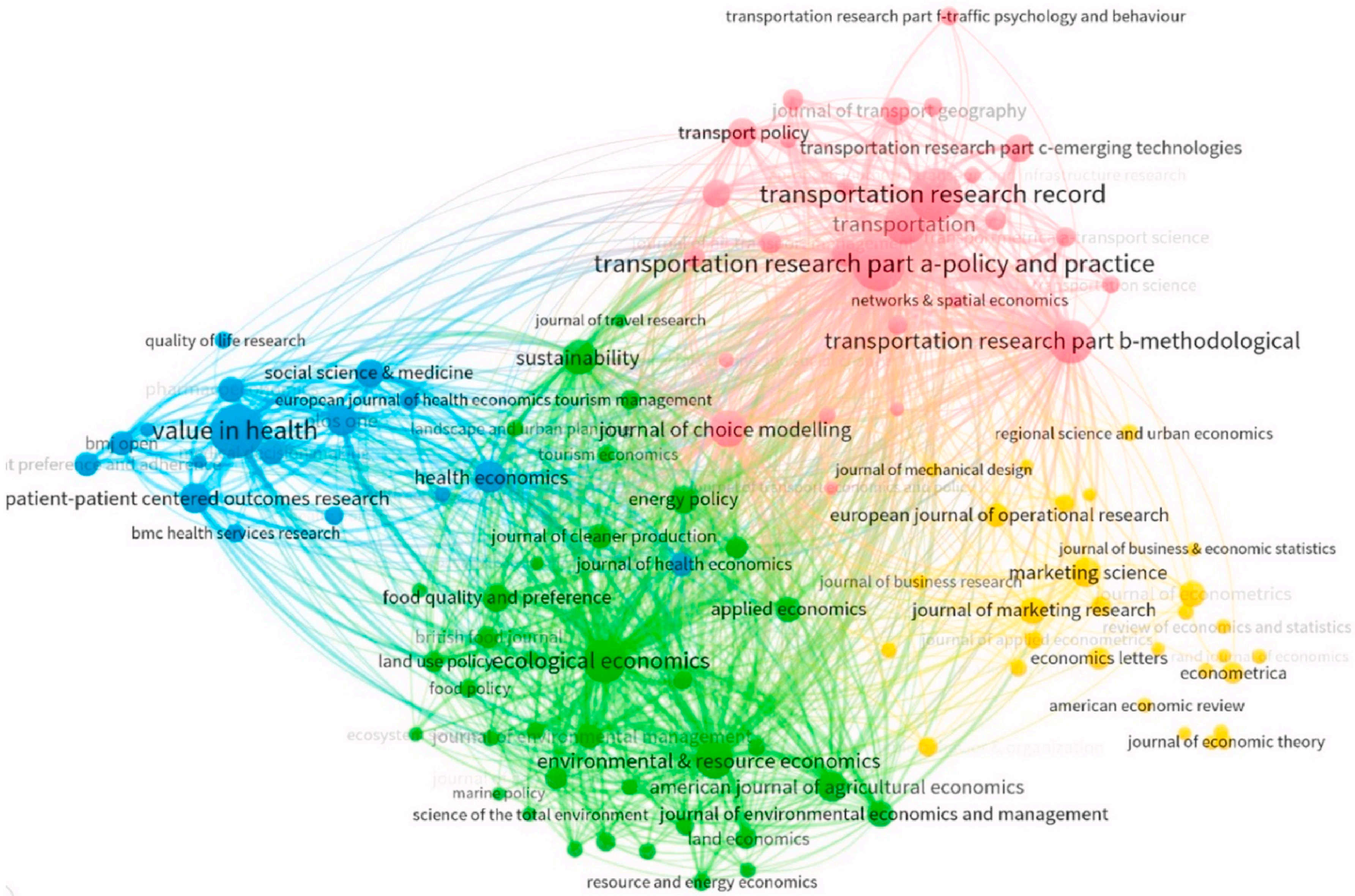
Trends in Keywords



Haghani et al. (2021)

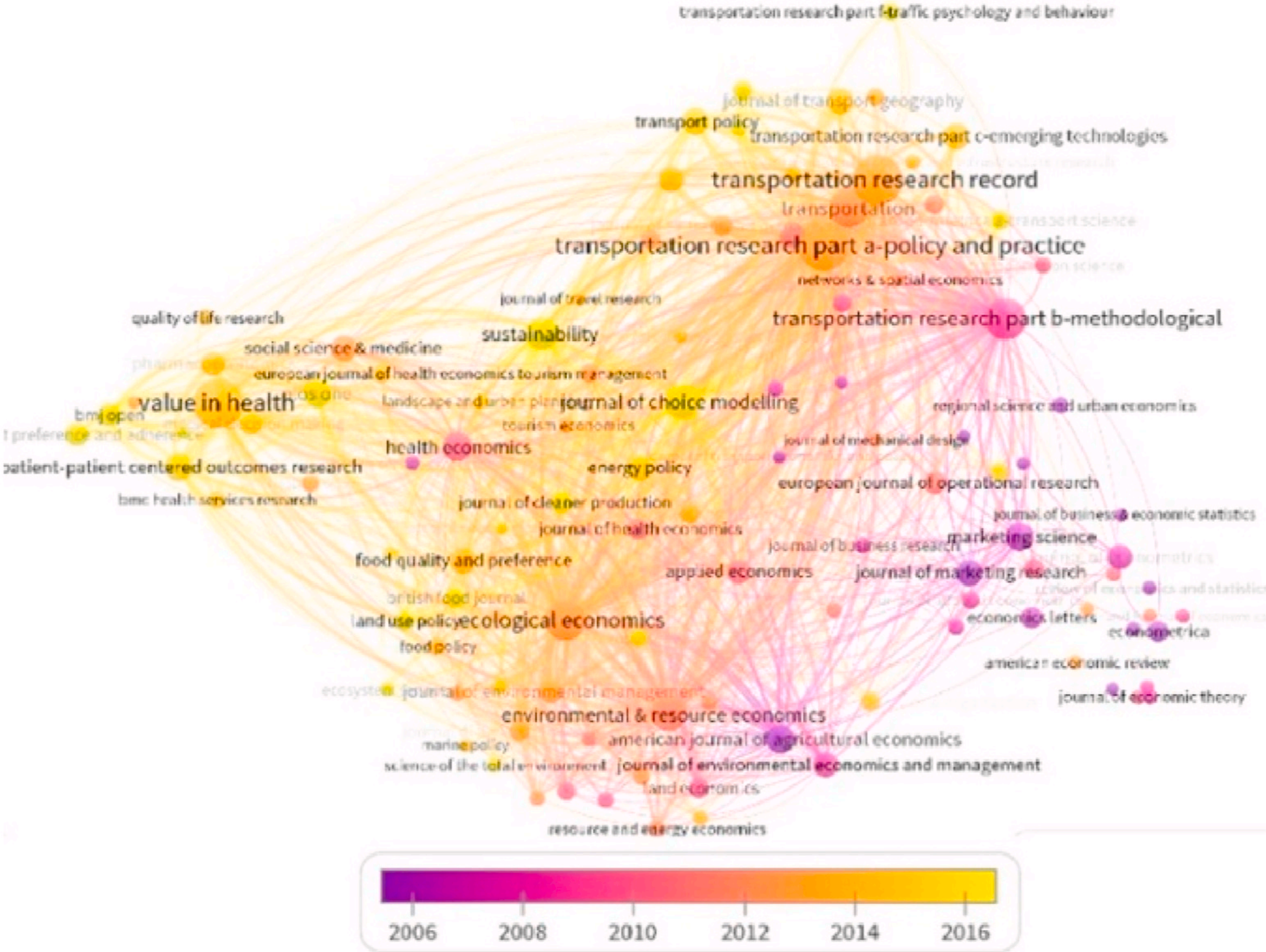
Network map of title and abstract terms overlaid with the average publication year

Journals publishing DCM papers

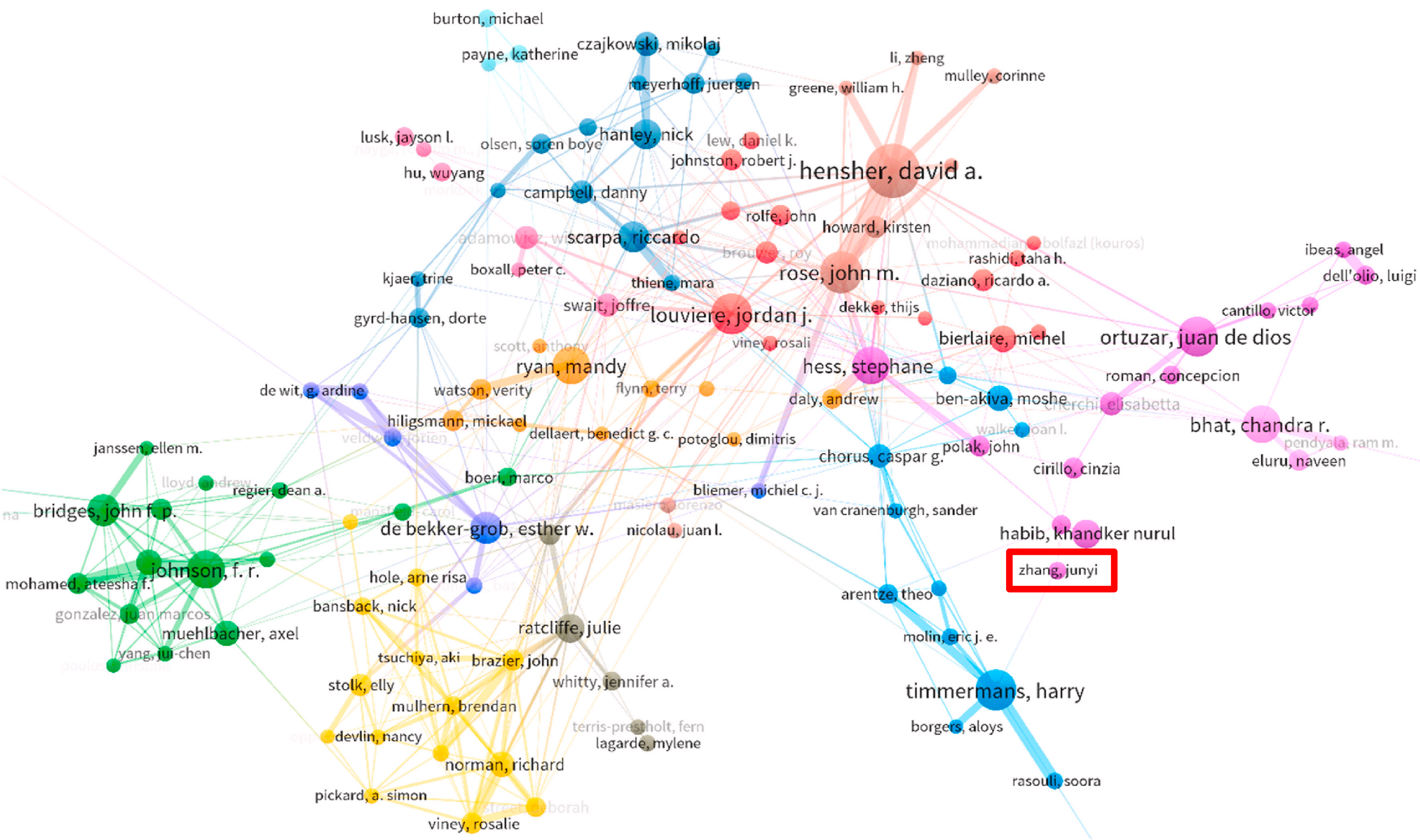


Network map of journals

Journals publishing DCM papers

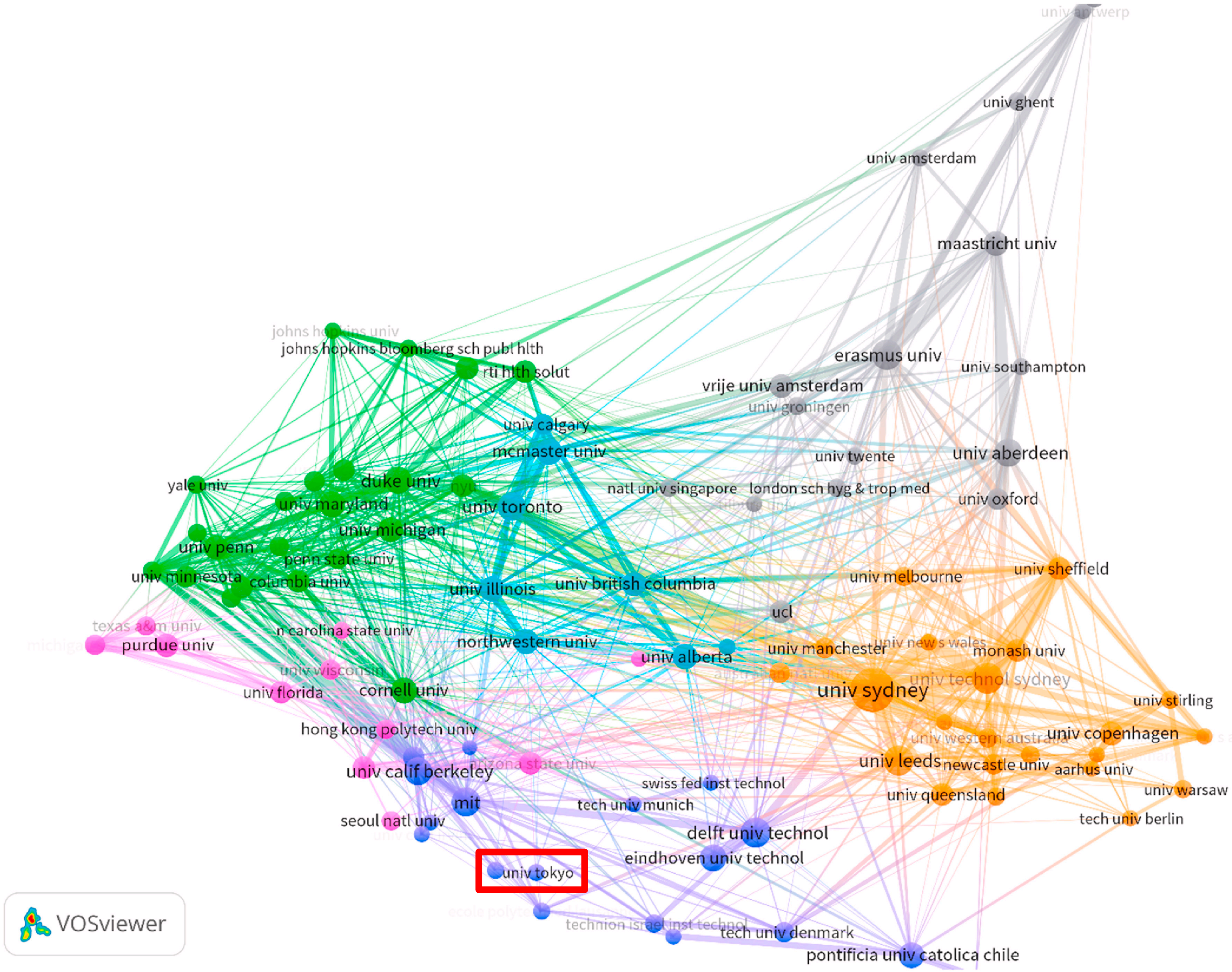


Network of collaborations



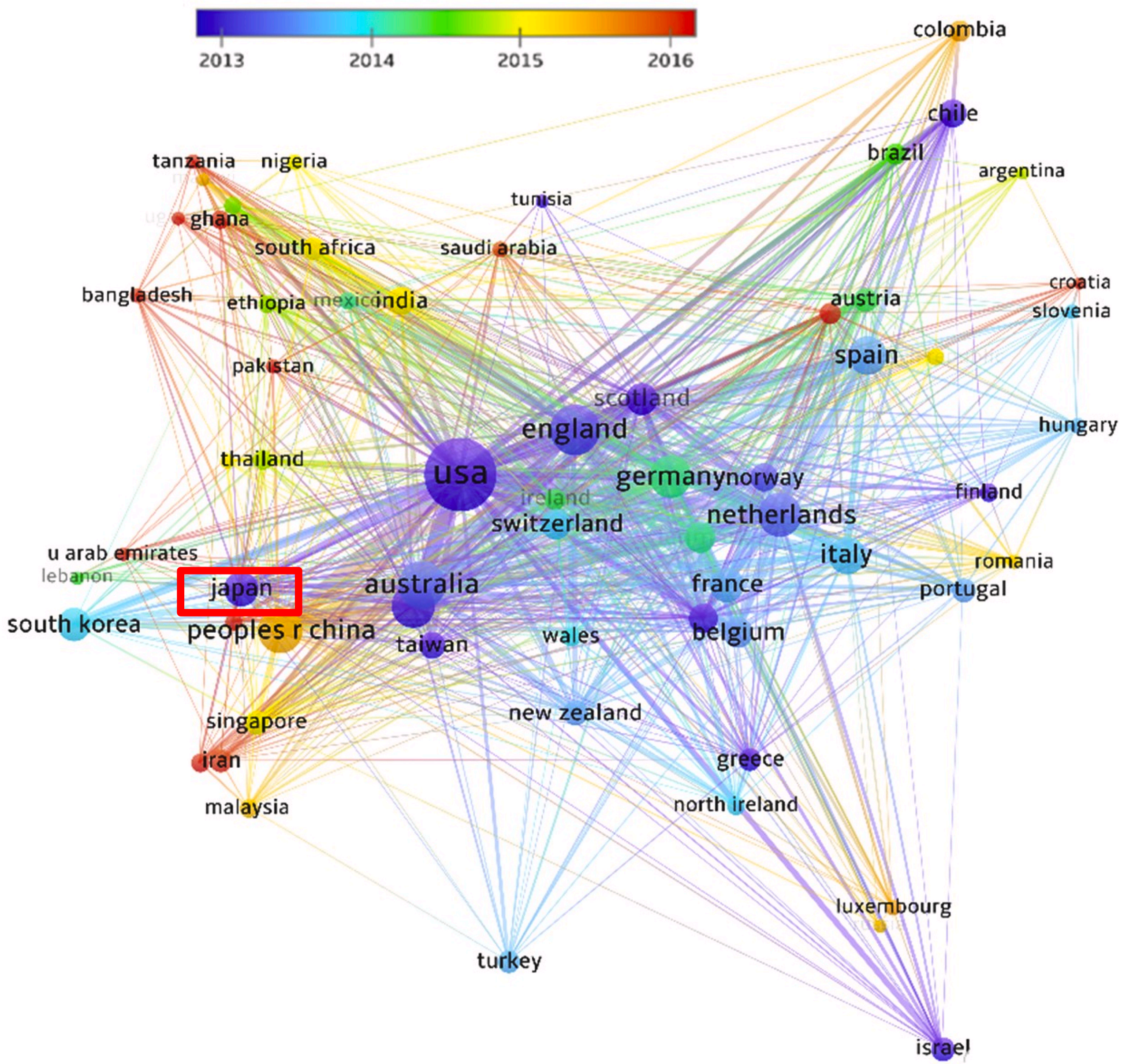
Network of collaborations between authors

Network of collaborations



Network of collaborations between organizations

Network of collaborations



Network of collaborations between countries/regions

Today's Contents

1. Enriching passively collected data

2. Diving into more detailed decision-making process

1. Enriching passively collected data

Inverse Discrete Choice Modeling (IDCM)

- ✓ Zhao, Y., Pawlak, J.and Sivakumar, A.: Theory for socio-demographic enrichment performance using the inverse discrete choice modelling approach. Transportation Research Part B 155, 101-134, 2022.
- ✓ Zhao, Y., Pawlak, J.and Polak, J.W.: Inverse discrete choice modelling: theoretical and practical considerations for imputing respondent attributes from the patterns of observed choices. Transportation Planning and Technology 41, 58-79, 2018.

Enriching data

- "**Data enrichment**" has long been conducted in transportation field.
  - Map matching (source: GPS trajectory data) [e.g., Lou et al., 2009]
  - Travel mode (source: GPS trajectory data) [e.g., Feng & Timmermans, 2013]
  - OD estimation (source: traffic count data) [e.g., Yang et al., 1992]
  - Trip purpose (source: smart card data) [e.g., Kusakabe & Asakura, 2014]
  - Traffic state (source: vehicle trajectory) [e.g., Seo & Kusakabe, 2015]
  - Comprehensive Package (source: GPS trajectory data) [Hara, 2017]
- Further improvements are needed, with gaining the popularity of **digital twin** concept.
  - Digital twin: A digital model of an actual real-world urban and transportation system.
  - Passively collected data (such as GPS data) would be good candidates as inputs for digital twin, but these are **big-but-thin dataset**, e.g., no socio-demographic data included. **→ IDCM**

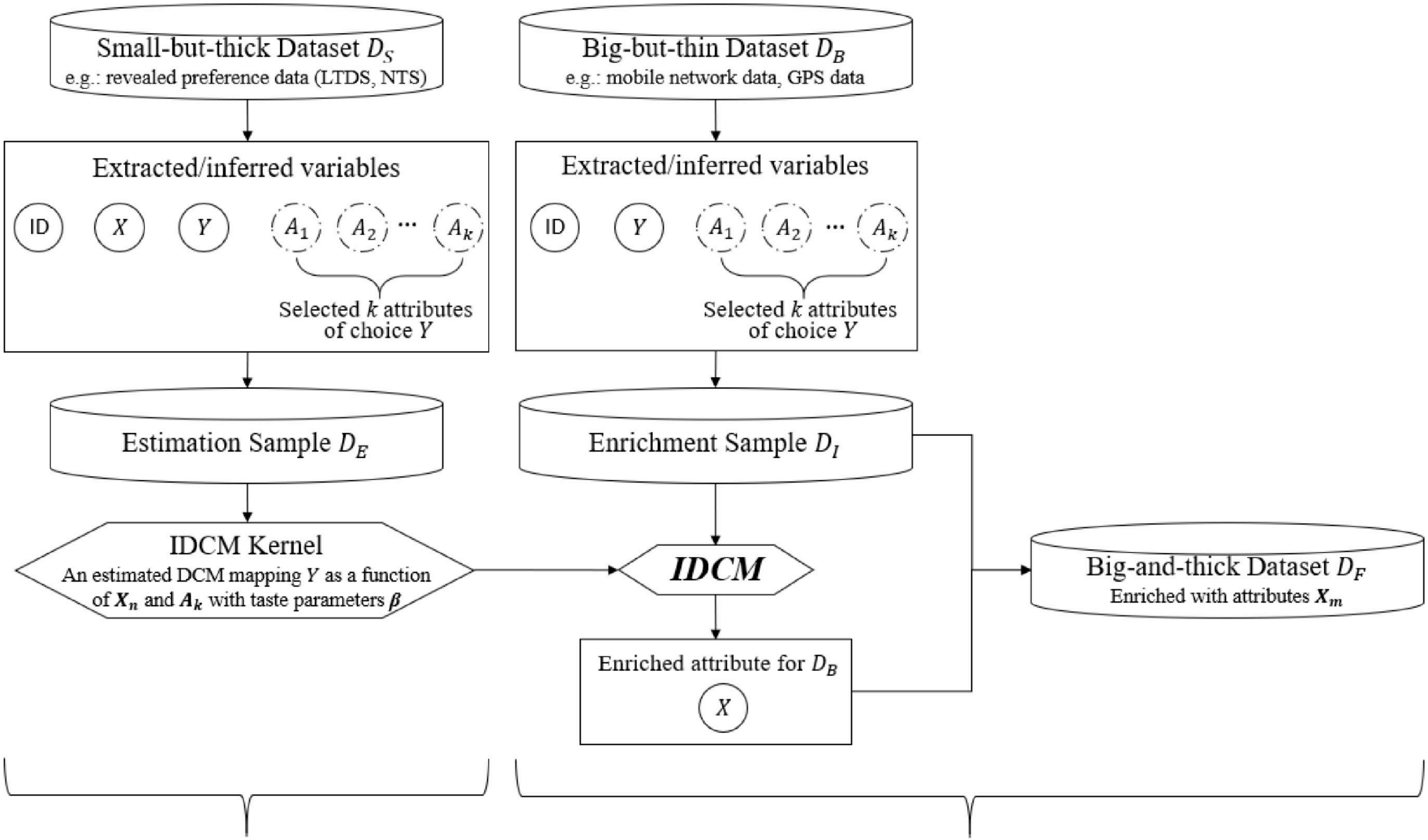
Basic idea of IDCM

	Conventional (e.g., LGR and SVM)	IDCM
Develop a model from small-but-thick dataset (X_{D_S}, Y_{D_S})	$X_{D_s} = f(Y_{D_s})$	$Y_{D_s} = g(X_{D_s})$
	$\downarrow$ $\hat{f}$ $\downarrow$	$\downarrow$ $\hat{g}$ $\downarrow$
Apply the model to big-but-thin dataset (Y_{D_B})	$\tilde{X}_{D_B} = \hat{f}(Y_{D_B})$	$\tilde{X}_{D_B} \cong \hat{g}^{-1}(Y_{D_B})$
	$\hat{f}$ is tuned to maximize the predictability of X_{D_s}	$\hat{g}$ is tuned under DCM assumption

LGR: Logistic regression
SVM: Support Vector Machine

Framework for IDCM enrichment

(Zhao et al., 2022)



An creation of IDCM kernel

The socio-demographic enrichment

Implementing IDCM

A: attributes of alternatives
X: attributes of respondents
Y: choice

An creation of IDCM kernel

$$\beta^*_{\mathrm{MAP}} = \arg\max_{\beta} P(Y|A,X,\beta)\underbrace{P(\beta|A,X)}_{\text{Prior distribution of } \beta}$$

$$\beta^*_{\mathrm{MLE}} = \arg\max_{\beta} P(Y|A,X,\beta)$$

The socio-demographic enrichment

$$X^*_{\mathrm{MAP}} = \arg\max_{X} P(Y|A,X,\beta^*)\underbrace{P(X|A,\beta^*)}_{\text{Prior distribution of } X}$$

$$X^*_{\mathrm{MLE}} = \arg\max_{X} P(Y|A,X,\beta^*)$$

Differently from β, X is often of discrete nature, and thus:
β^* : Newton's method-based gradient-descent algorithms (e.g., BFGS)
X^*: exhaustive search (brute force)

MAP: Maximum a posteriori; MLE: Maximum likelihood

Performance of IDCM

Comparison between PCPs using LGR, SVM and IDCM, and Relevant Statistics in LTDS Application

ExpNo.	LGR-PCP (%)	SVM-PCP (%)	MAP-PCP (%)	MAP vs LGR		MAP vs SVM		MLE-PCP (%)	MLE vs LGR		MLE vs SVM	
				t-value	*p*-value	*t*-value	*p*-value		*t*-value	*p*-value	*t*-value	*p*-value
1	51.85	52.07	51.85	0.000	1.000	-1.831	0.083	50.89	-9.901	0.000	-28.720	0.000
2	73.17	73.17	73.17	0.000	1.000	0.000	1.000	52.91	-613.862	0.000	-613.862	0.000
3	69.93	69.93	69.93	0.000	1.000	0.000	1.000	53.05	-520.433	0.000	-520.433	0.000
4	69.79	69.79	69.79	0.000	1.000	0.000	1.000	55.59	-451.506	0.000	-451.506	0.000
5	67.40	67.40	67.40	0.000	1.000	0.000	1.000	55.91	-298.764	0.000	-298.764	0.000
6	95.79	95.79	95.79	0.000	1.000	0.000	1.000	64.63	-822.136	0.000	-822.136	0.000
7	93.15	93.15	93.15	0.000	1.000	0.000	1.000	63.44	-862.793	0.000	-862.793	0.000
8	90.48	90.48	90.48	0.000	1.000	0.000	1.000	62.92	-836.382	0.000	-836.382	0.000
9	91.88	91.88	91.88	0.000	1.000	0.000	1.000	63.57	-772.176	0.000	-772.176	0.000
10	91.75	91.75	91.75	0.000	1.000	0.000	1.000	63.64	-783.993	0.000	-783.993	0.000
11	87.50	87.50	87.50	0.000	1.000	0.000	1.000	62.33	-722.154	0.000	-722.154	0.000
12	85.16	85.16	85.16	0.000	1.000	0.000	1.000	62.15	-566.345	0.000	-566.345	0.000
13	84.49	84.49	84.49	0.000	1.000	0.000	1.000	61.92	-516.847	0.000	-516.847	0.000
14	92.54	92.54	92.54	0.000	1.000	0.000	1.000	64.59	-718.019	0.000	-718.019	0.000
15	87.19	87.19	87.19	0.000	1.000	0.000	1.000	62.63	-883.026	0.000	-883.026	0.000
16	51.64	51.72	51.64	0.000	1.000	-1.830	0.083	51.34	-9.506	0.000	-20.612	0.000
17	76.57	76.57	76.57	0.000	1.000	0.000	1.000	63.20	-773.912	0.000	-773.912	0.000
18	69.85	69.85	69.85	0.000	1.000	0.000	1.000	62.44	-322.826	0.000	-322.826	0.000
19	65.58	65.98	65.58	0.000	1.000	-14.460	0.000	65.57	-1.000	0.330	-18.854	0.000
20	66.36	66.36	66.36	0.000	1.000	0.000	1.000	62.08	-320.019	0.000	-320.019	0.000

Conventional

IDCM

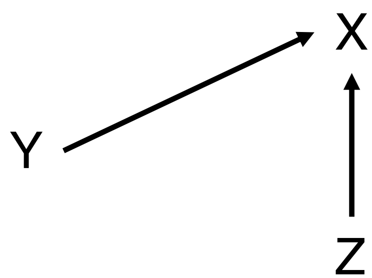
PCP: percentage correctly predicted
LGR: Logistic regression
SVM: Support Vector Machine
LTDS: London Travel Demand Survey

IDCM does not outperform conventional methods.
Then why IDCM was proposed?

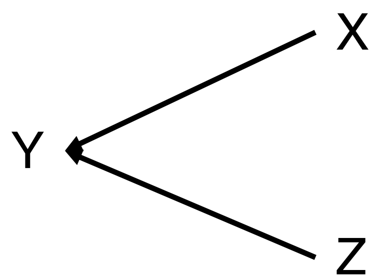
Transferability of the methods

- The trained LGR and SVM using the estimation sample inevitably learn information about the attribute distribution of the enrichment sample, limiting the transferability of LGR and SVM in the socio-demographic enrichment under different data conditions.

Conventional
(e.g., LGR and SVM)



IDCM



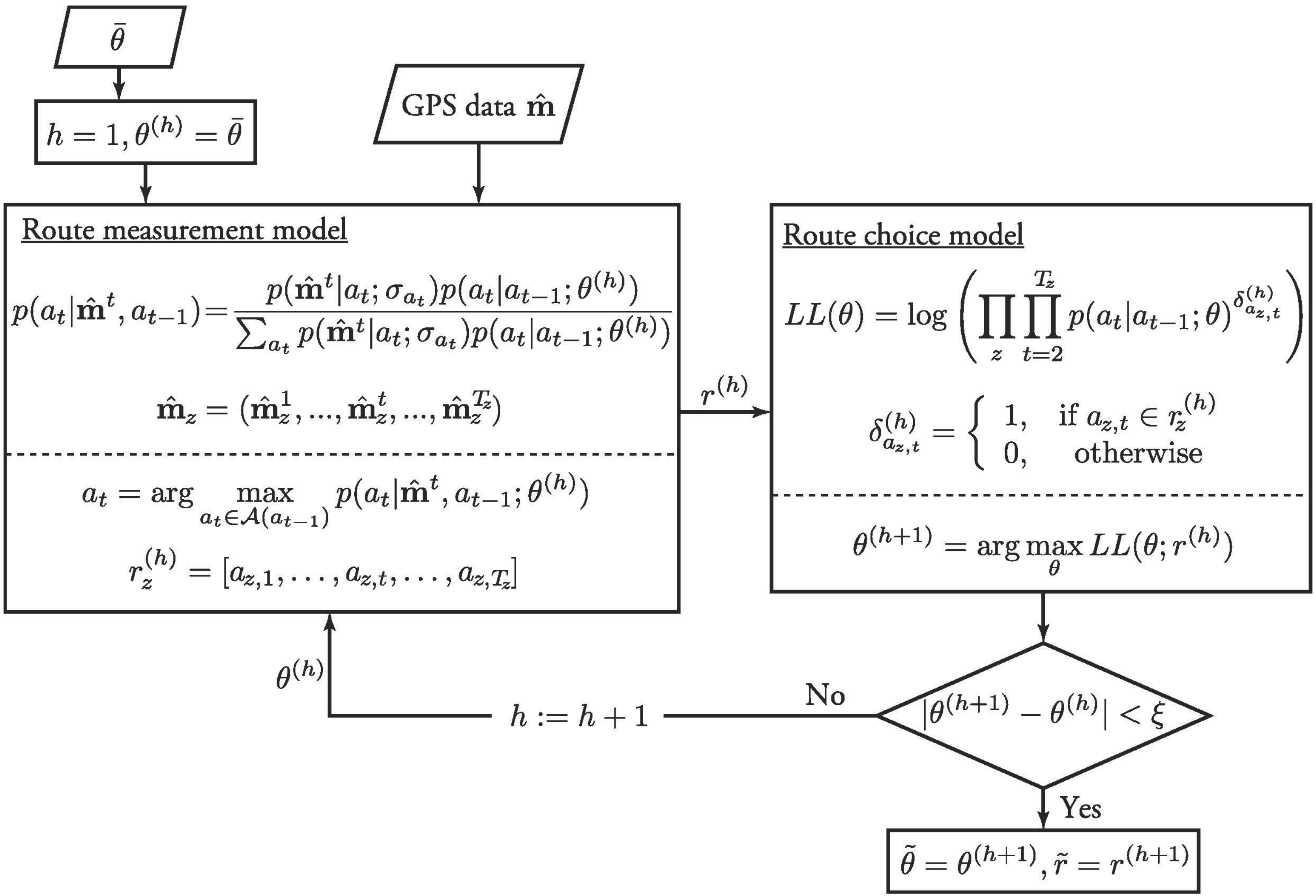
Condition to use conventional methods:
the distribution of the enriched attribute in the estimation sample is similar to the true attribute distribution in the enrichment sample.

And, given the theoretical consideration of the mechanism, IDCM would be more preferable than conventional methods.

Future directions

- An initial empirical trial of IDCM approach was made in Zhao et al. (2018), followed by further theoretical investigation by Zhao et al. (2022) restricted to the context of enrichment of a binary attribute from a single, binary choice behavior.
- Future directions
  – IDCM framework for multiple choices and multi-class/multiple attributes (empirical investigations would relatively be easy)
  – Adding a feedback loop using structural estimation.
  – Linking with small-but-thick data collection strategy

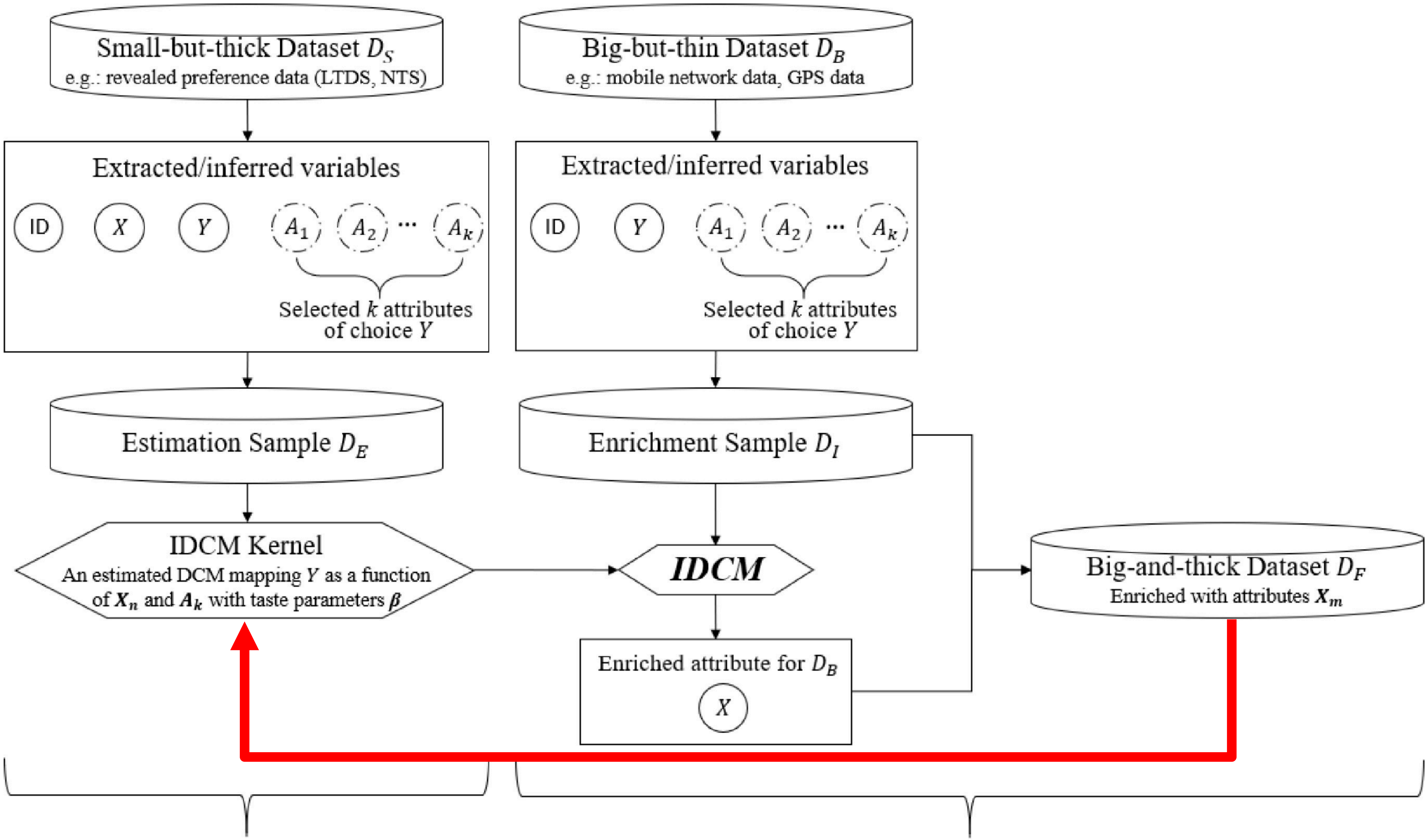
Structural estimation (Oyama & Hato, 2018)



Oyama, Y.and Hato, E.: Link-based measurement model to estimate route choice parameters in urban pedestrian networks. Transportation Research Part C: Emerging Technologies 93, 62-78, 2018.

Structural estimation for IDCM

(Zhao et al., 2022)

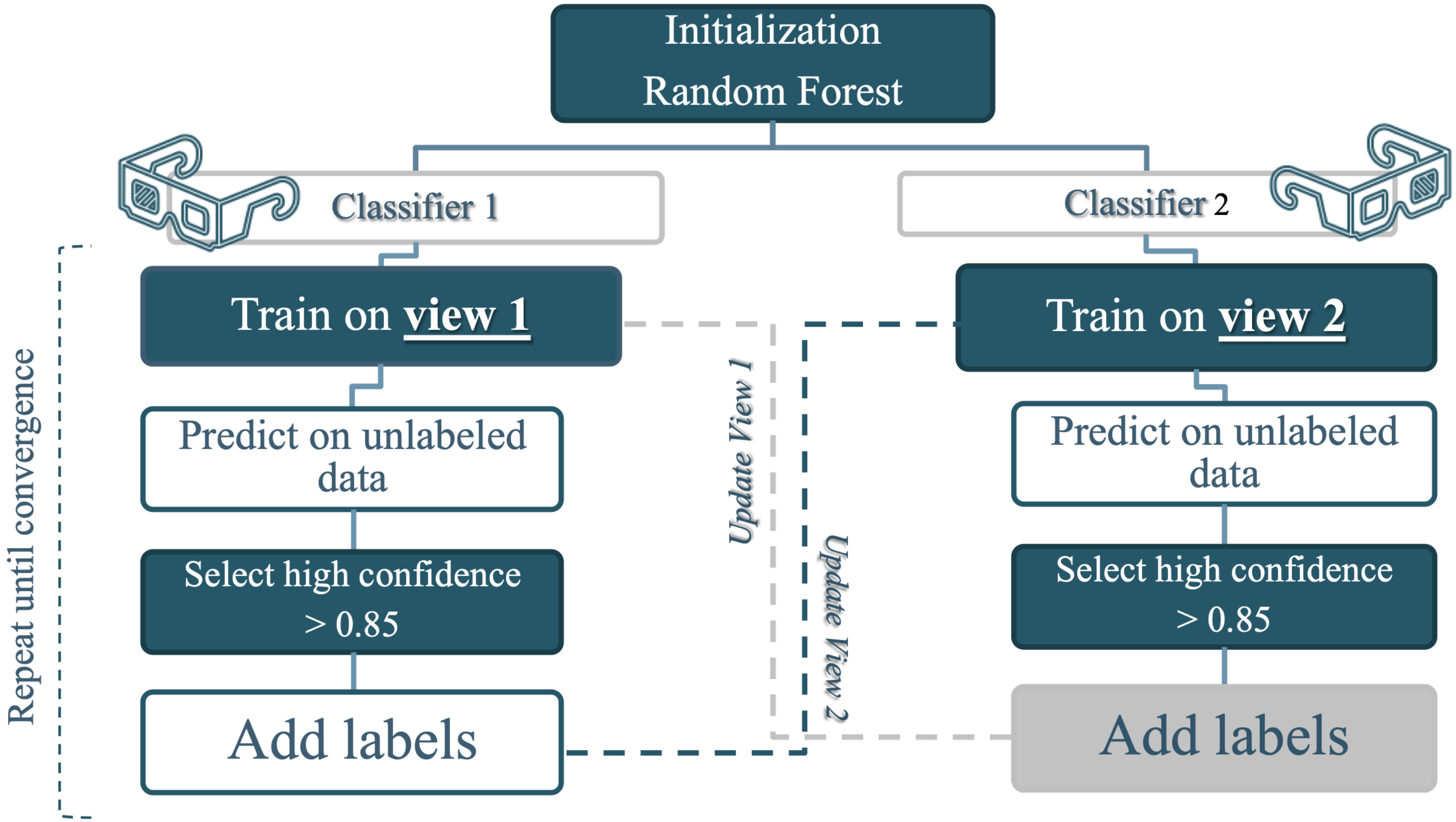


An creation of IDCM kernel

The socio-demographic enrichment

Utilizing semi-supervised learning

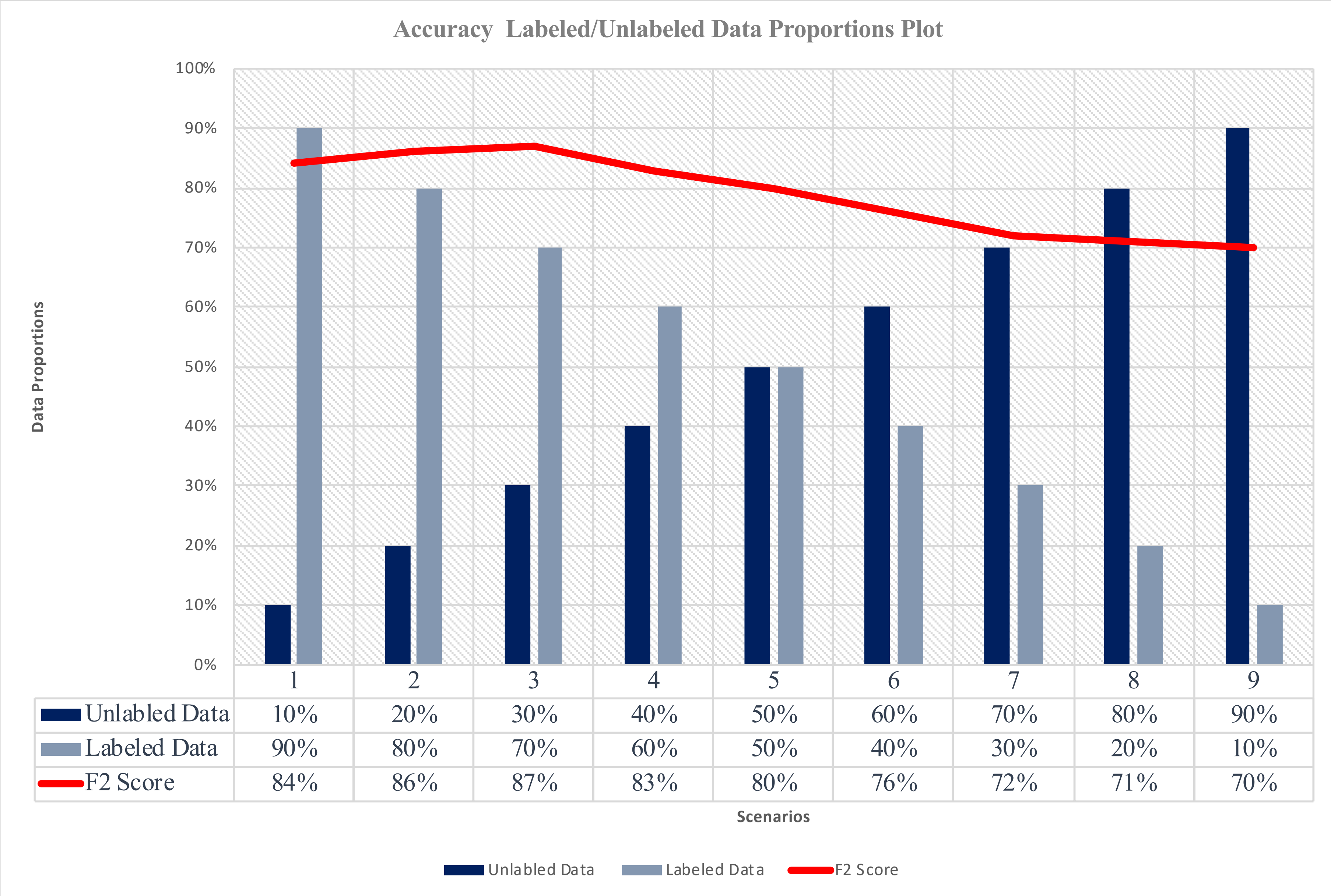
Reem & Chikaraishi (2024), submitted to TRB



Co-learning algorithm

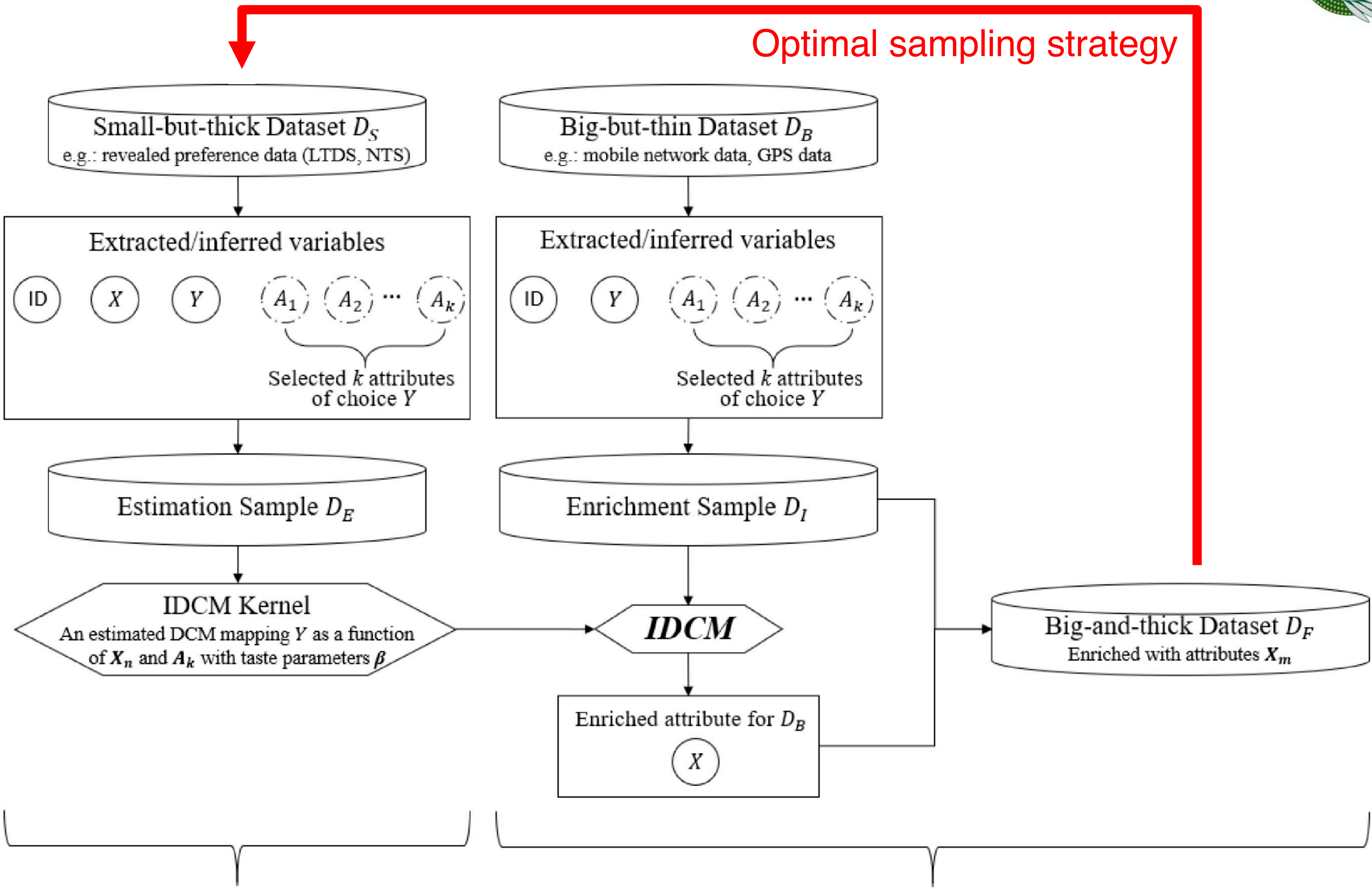
Utilizing semi-supervised learning

Reem & Chikaraishi (2024), submitted to TRB



	1	2	3	4	5	6	7	8	9
Unlabled Data	10%	20%	30%	40%	50%	60%	70%	80%	90%
Labeled Data	90%	80%	70%	60%	50%	40%	30%	20%	10%
F2 Score	84%	86%	87%	83%	80%	76%	72%	71%	70%

Feedback to survey design



An creation of IDCM kernel

The socio-demographic enrichment

2. Diving into more detailed decision-making process

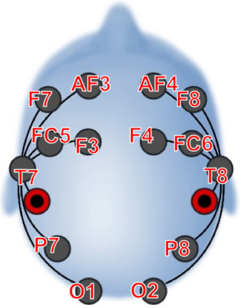
Decision Field Theory (DFT)

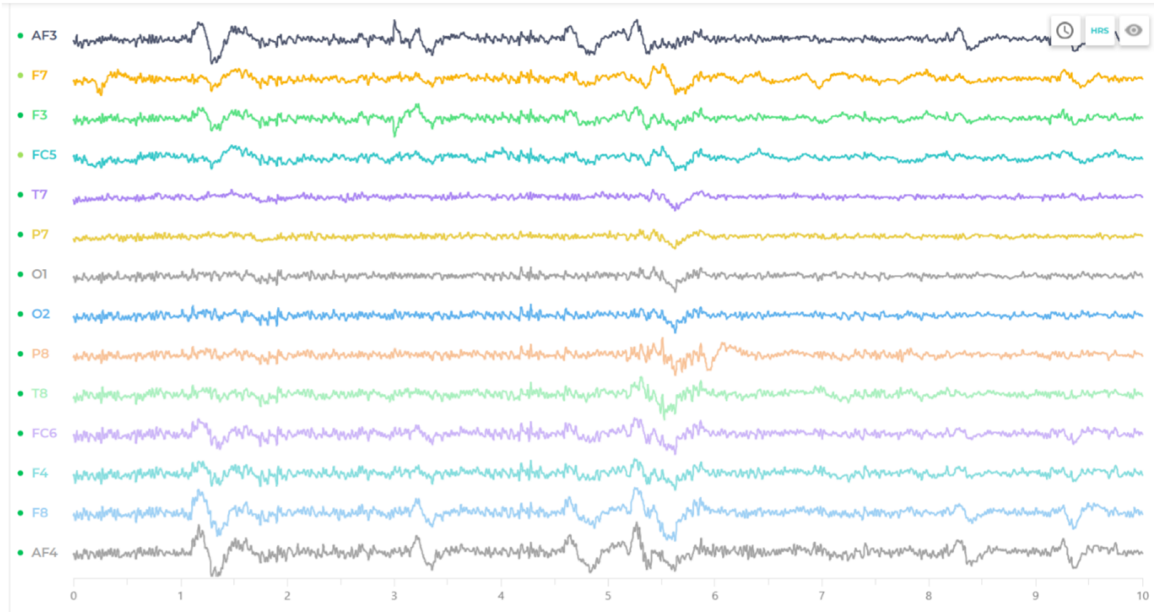
- ✓ Roe, R.M., Busemeyer, J.R.and Townsend, J.T.: Multialternative decision field theory: A dynamic connectionst model of decision making. Psychological Review 108, 370, 2001.
- ✓ Hancock, T.O., Hess, S.and Choudhury, C.F.: Decision field theory: Improvements to current methodology and comparisons with standard choice modelling techniques. Transportation Research Part B 107, 18-40, 2018.
- ✓ Hancock, T.O., Hess, S., Marley, A.A.J.and Choudhury, C.F.: An accumulation of preference: Two alternative dynamic models for understanding transport choices. Transportation Research Part B 149, 250-282, 2021.

Background

- Revisiting choice decision-making process
  - Searching better options
  - Evaluating trade-offs across different attributes
  - Discriminating one option from the others
- These indicate that a choice task inevitably involve a cognitive process to understand options and to differentiate one from the others, where a decision maker spends a certain time in the process.
- Decision field theory (DFT) is a theory modeling such a dynamic nature of decision-making process in a straightforward manner.
  - Information is sequentially sampled and accumulated over time to make a decision.
- Increased availability of biosensor data, such as EEG (Electroencephalogram) and eye-trucking data, needs a model that can incorporate the dynamic nature of decision-making process.
  - Incorporating a bunch of observations (with timesteps) to model one single decision-making.

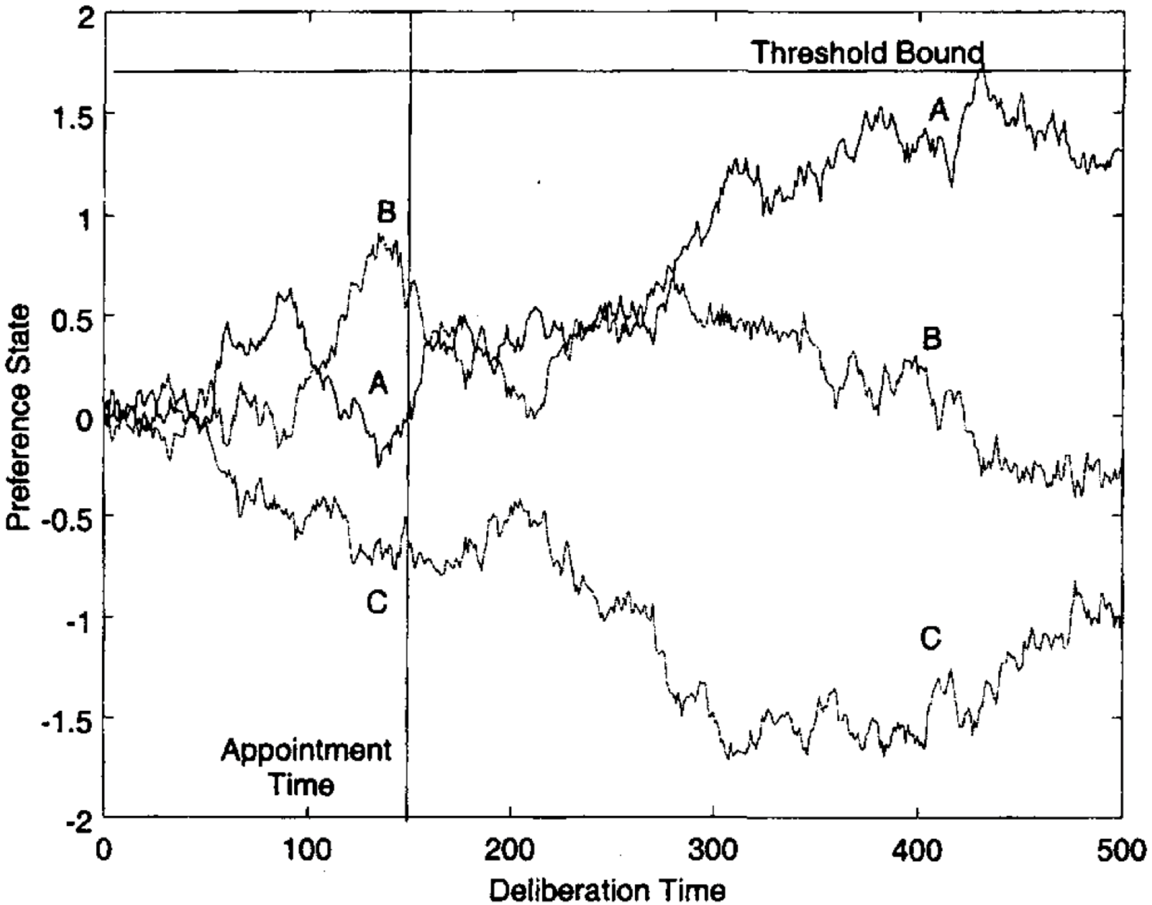
Example of EEG





Decision Field Theory (DFT)

- Intuitive explanation of DFT:
  - A decision maker's preference for each option evolves during deliberation by integrating a stream of comparisons of evaluations among options on attributes over time

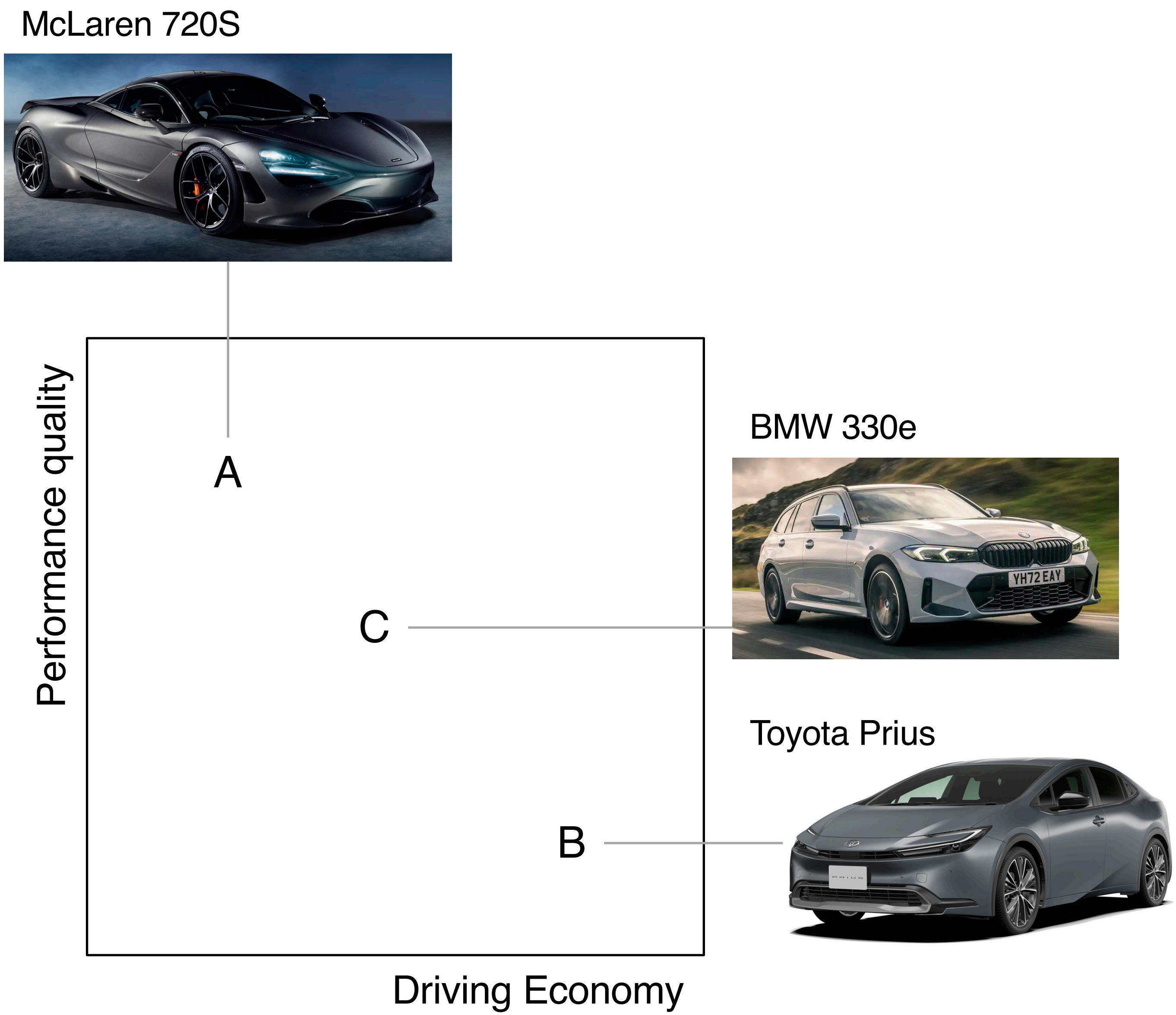


Timing of decision making:

1. An externally imposed time constraint
2. A self-imposed criterion (threshold)

Example (Roe et al., 2001)

Car purchasing behavior



Decision Field Theory (DFT)

- Sequential sampling decision process

Valence $\mathbf{V}(t) = \mathbf{CMW}(t)$

Preferences $\mathbf{P}(t+1) = \mathbf{SP}(t) + \mathbf{V}(t+1)$

$\mathbf{V}(t) = [v_A(t), v_B(t), v_C(t)]'$: valence vector

$v_i(t)$: valence (momentary advantage/disadvantage) for option i at time t

Decision Field Theory (DFT)

- Sequential sampling decision process

Valence $\mathbf{V}(t) = \mathbf{CMW}(t)$

Preferences $\mathbf{P}(t+1) = \mathbf{SP}(t) + \mathbf{V}(t+1)$

$\mathbf{M}$: personal evaluation of each option on each attribute

m_{ij}: the subjective value of option i on attribute j

Ex: $\mathbf{M} = [\mathbf{M_E} | \mathbf{M_Q}]$, where economy: $\mathbf{M_E} = [m_{AE}, m_{BE}, m_{CE}]'$

quality: $\mathbf{M_Q} = [m_{AQ}, m_{BQ}, m_{CQ}]'$

$\mathbf{W}(t)$: attention weight allocated to each attribute at time t

Ex: $\mathbf{W}(t) = [W_E(t), W_Q(t)]'$

$\mathbf{MW}(t)$ looks like the additive utility function in the classical RUM model:

$$\mathbf{MW}(t) = \begin{bmatrix} W_E(t)m_{AE} + W_Q(t)m_{AQ} \\ W_E(t)m_{BE} + W_Q(t)m_{BQ} \\ W_E(t)m_{CE} + W_Q(t)m_{CQ} \end{bmatrix}$$

Decision Field Theory (DFT)

- Sequential sampling decision process

Valence	$\mathbf{V}(t) = \mathbf{CMW}(t) + \boldsymbol{\varepsilon}(t)$
Preferences	$\mathbf{P}(t+1) = \mathbf{SP}(t) + \mathbf{V}(t+1)$

$\mathbf{C}$: Comparison process to determine the relative advantage/disadvantage of each option

$$\mathbf{C} = \begin{bmatrix} 1 & \cdots & -\frac{1}{n-1} \\ \vdots & \ddots & \vdots \\ -\frac{1}{n-1} & \cdots & 1 \end{bmatrix}$$

Ex: $\mathbf{C} = \begin{bmatrix} 1 & -1/2 & -1/2 \\ -1/2 & 1 & -1/2 \\ -1/2 & -1/2 & 1 \end{bmatrix}$

Then we obtain

$$v_A(t) = \underbrace{W_E(t)m_{AE} + W_Q(t)m_{AQ}}_{\text{value for the target alternative}} - \underbrace{\begin{bmatrix} \left(W_E(t)m_{BE} + W_Q(t)m_{BQ}\right) + \\ \left(W_E(t)m_{CE} + W_Q(t)m_{CQ}\right) \end{bmatrix} /2}_{\text{Average value of other alternatives}}$$

* This model specification is similar with relative utility theory (Zhang, 2015)

Decision Field Theory (DFT)

- Sequential sampling decision process

Valence	$\mathbf{V}(t) = \mathbf{CMW}(t) + \boldsymbol{\varepsilon}(t)$
Preferences	$\mathbf{P}(t+1) = \mathbf{SP}(t) + \mathbf{V}(t+1)$

$\mathbf{P}(t) = [P_A(t), P_B(t), P_C(t)]'$

$\mathbf{S} = F[\mathbf{D}]$. EX: $\mathbf{S} = \mathbf{I} - \phi_2 \times \exp(-\phi_1 \times \mathbf{D}^2)$

where: ϕ_2: sensitivity parameter
ϕ_1: memory parameter (capturing similarity effect)
$\mathbf{D}$: distance between the attributes across alternatives

Diagonal: self-feedback loop, i.e., the memory of the previous preference state
Off-diagonal: influence of one alternative on another (e.g., if the inter connections are negative, then strong alternatives suppress weak alternatives)

Decision Field Theory (DFT)

- Sequential sampling decision process

Valence $\mathbf{V}(t) = \mathbf{CMW}(t) + \boldsymbol{\varepsilon}(t)$

Preferences $\mathbf{P}(t+1) = \mathbf{SP}(t) + \mathbf{V}(t+1)$

Transforming from preference to probability

$$\begin{aligned}
&\Pr[A|\{A,B,C\} \text{ at time } t] \\
&\quad = \Pr[P_A(t) - P_B(t) > 0 \text{ and } P_A(t) - P_C(t) > 0] \\
&\quad = \int_{\mathbf{X}>0} \exp\left[-\frac{(\mathbf{X}-\boldsymbol{\Gamma})'\boldsymbol{\Lambda}^{-1}(\mathbf{X}-\boldsymbol{\Gamma})}{2}\right] / (2\pi|\boldsymbol{\Lambda}|^{0.5})\, d\boldsymbol{X}
\end{aligned}$$

Probit model with structured covariance

where $\mathbf{X} = [P_A(t) - P_B(t), P_A(t) - P_C(t)]'$

$\boldsymbol{\Gamma} = \mathbf{L}\boldsymbol{\xi}(t)$, where $\boldsymbol{\xi}(t) = E[\mathbf{P}(t)]$

$\boldsymbol{\Lambda} = \boldsymbol{L}\boldsymbol{\Omega}(t)\boldsymbol{L}'$, where $\boldsymbol{\Omega}(t) = Cov[\mathbf{P}(t)]$

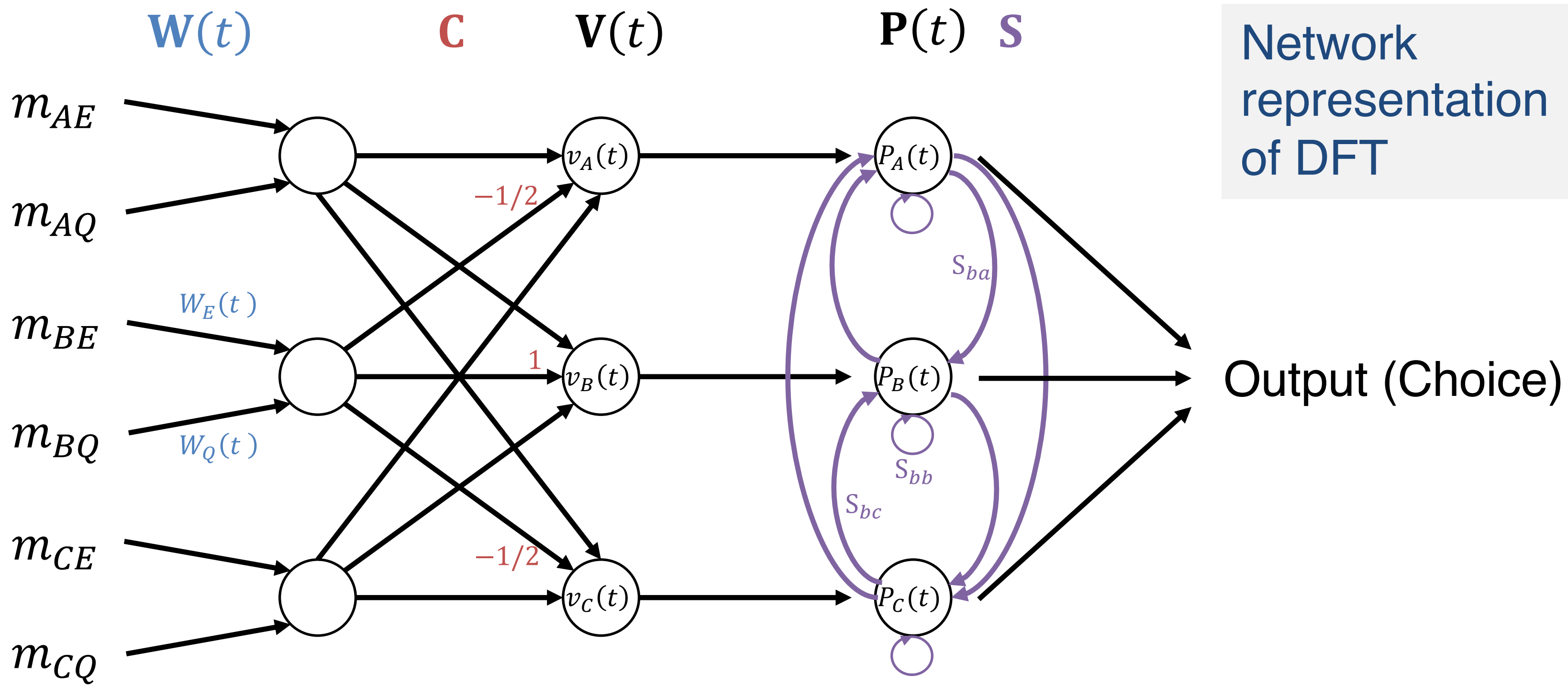
$$\boldsymbol{L} = \begin{bmatrix} 1 & -1 & 0 \\ 1 & 0 & -1 \end{bmatrix}$$

Decision Field Theory (DFT)

- Sequential sampling decision process

Valence $\mathbf{V}(t) = \mathbf{CMW}(t) + \boldsymbol{\varepsilon}(t)$

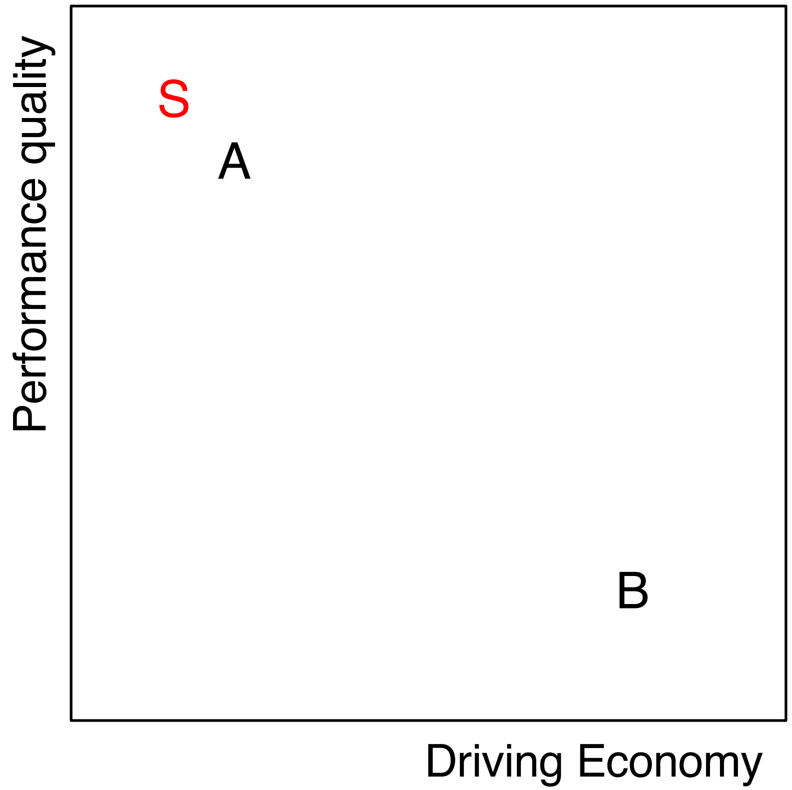
Preferences $\mathbf{P}(t+1) = \mathbf{SP}(t) + \mathbf{V}(t+1)$



Network representation of DFT

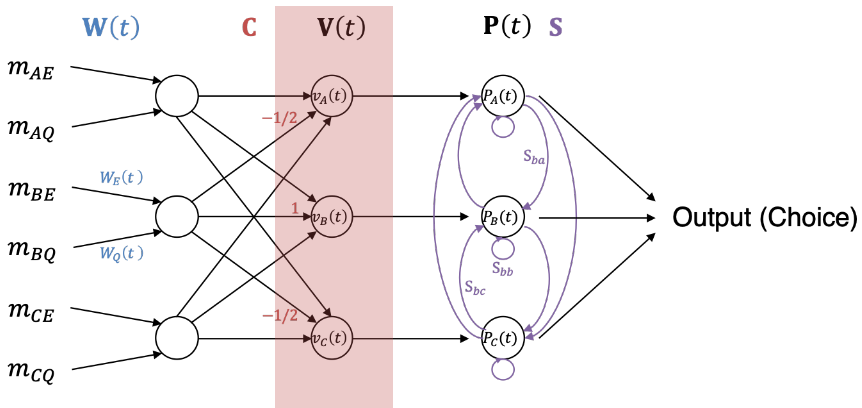
Similarity effect

$\Pr[A|\{A,B\}] > \Pr[B|\{A,B\}]$ but, $\Pr[A|\{A,B,S\}] < \Pr[B|\{A,B,S\}]$



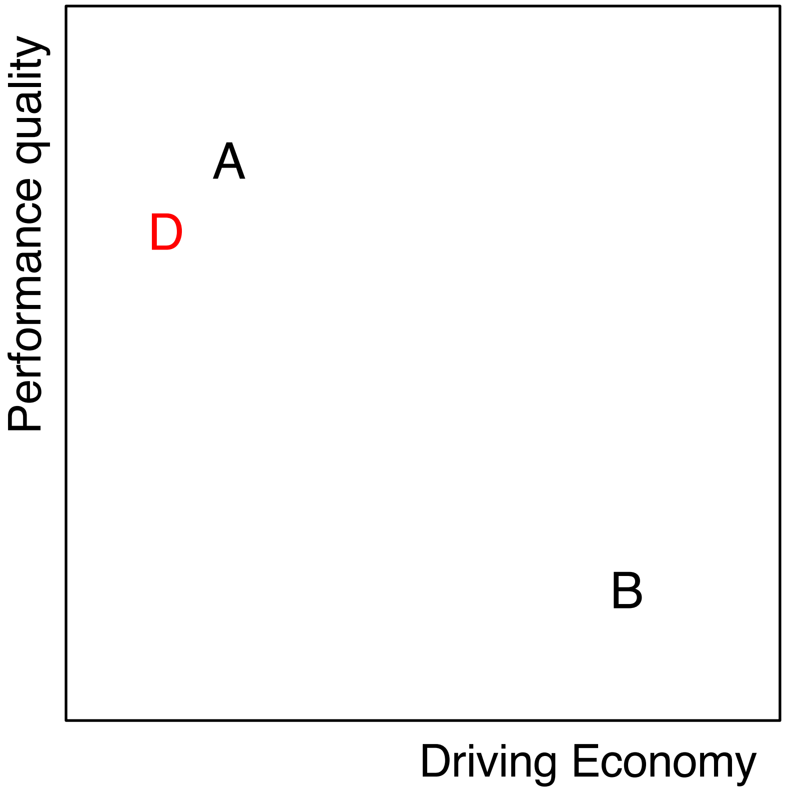
Similarity effects are caused by corrections across valences $v_i(t)$.

The differences between B and A to be positively correlated with the differences between B and S.

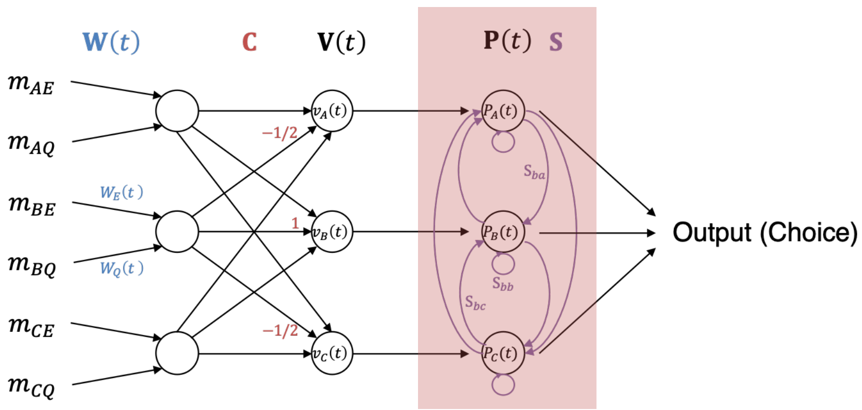


Attraction effect

$$\Pr[A|\{A,B\}] > \Pr[B|\{A,B,D\}]$$



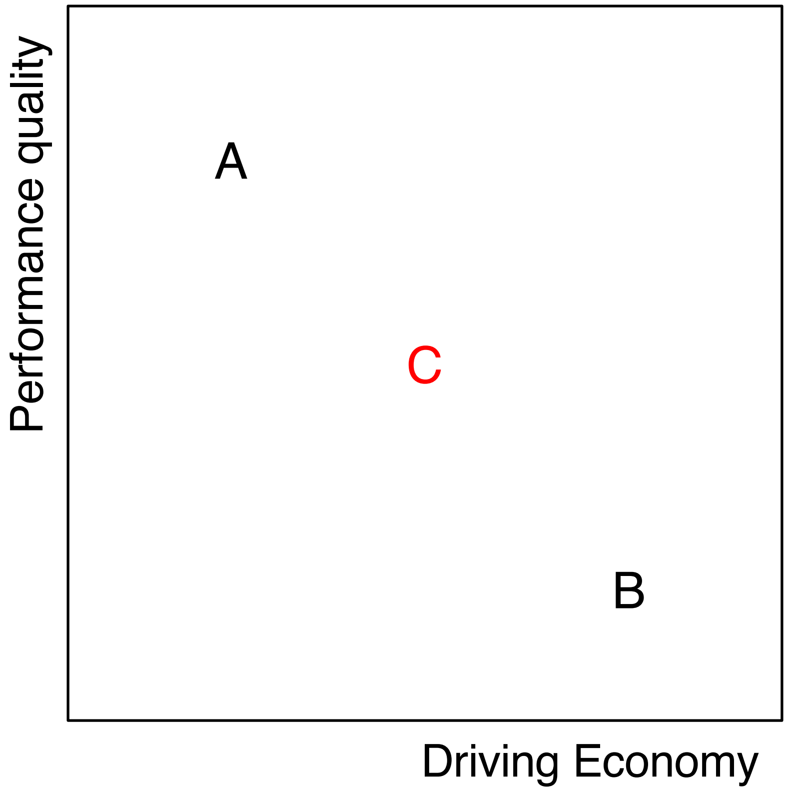
Comparisons of D with the average of the other two options produces a negative preference state for D. This negative preference will feed into closely positioned option (A) with a negative link, increasing the attraction of A.



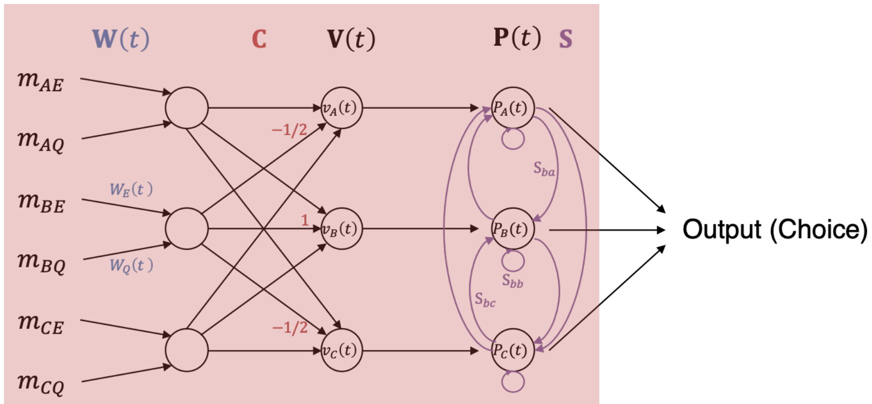
Compromise effect

$\Pr[A|\{A,B\}] = \Pr[A|\{A,C\}] = \Pr[B|\{B,C\}]$ but,

$\Pr[C|\{A,B,C\}] > \Pr[A|\{A,B,C\}]$ and $\Pr[C|\{A,B,C\}] > \Pr[B|\{A,B,C\}]$



The difference in valences between C and A tend to be positively correlated with the difference between C and B, due to the momentary fluctuations in valence. This provides a probabilistic advantage to C over A and B.



Operationalization of DFT

Efforts to operationalize DFT for choice modelers

Hancock et al. (2018 & 2021), Szép et al. (2022)

- Adding heterogeneities across decision makers
  - Observed heterogeneities
  - Unobserved heterogeneities (mixed DFT)
- Equivalence to the probit with structured covariance
- Discussions on identifiability problem
- A way to solve issue of scale-variant
- A way of reflecting finite timesteps, etc., etc.

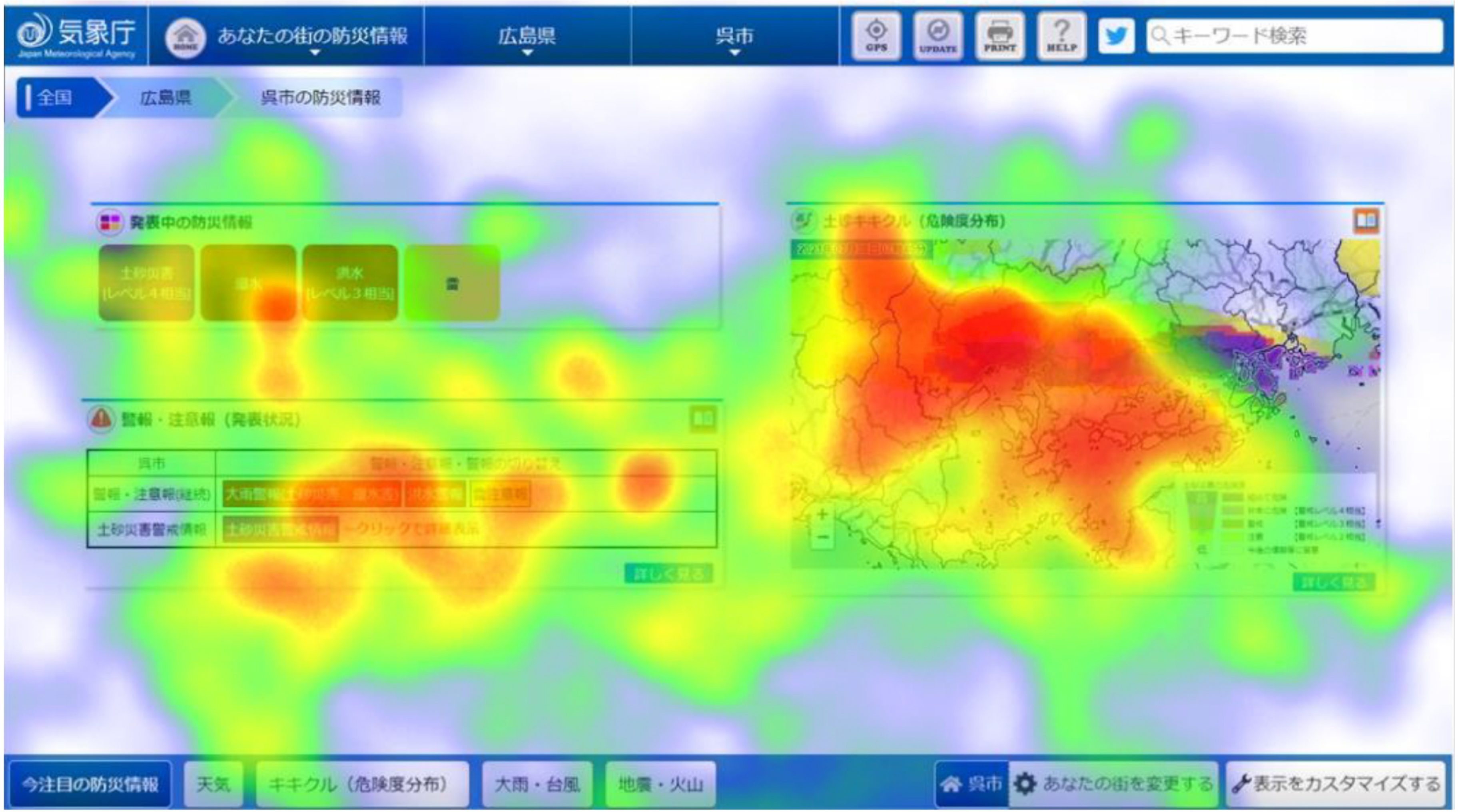
Possible Application 1

Sato (2023) Bachelor thesis (Hiroshima University)

Driving task under semi-automated condition

Possible Application 2

Shimooka (2021) Master thesis (Hiroshima University)



Information acquisition process and evacuation decision

Possible application 3: x-GDP data

(Parady, Oyama & Chikaraishi, 2023)

- Propose Text-aided Group Decision-making Process Observation Method (x-GDP)
  - A novel survey methodology to collect data on joint leisure activities, from all members of a given clique (not egocentric network data collection).
  - Observe not only the outcome (i.e., the joint activity location chosen), but also the decision-making process itself, including:
    - the alternatives that compose the choice set
    - individual and clique characteristics that might affect the choice process
    - the discussion behind the choice via texts
- The first attempt to observe group joint travel decisions in real time through a zoom-moderated experiment.

DFT could be utilized to explore group decision making with x-GDP data

Degree of matching between individually top-ranked locations and clique choice

		Number of individuals whose top-ranked locations are chosen by the clique					
		0	1	2	3	4	5
Clique size	3	18.6%	37.1%	33.0%	11.3%		
	4	14.7%	29.3%	28.0%	18.7%	9.3%	
	5	20.0%	37.8%	24.4%	11.1%	6.7%	0%

- ✓ In less than 12% of cases, all members' individually top-ranked locations were actually chosen
- ✓ Irrespective of clique size in around 17% to 20% of cases, no one's top-ranked location was chosen by the clique

Profiling group decision making process

Case 1

Case study 1
- Clique consisting of five members with no hierarchy (all same-year students)
- Some students under 20 years old who cannot drink alcohol

1a. LINE chat history (major comments extracted)

Mr. A: *"I __really__ want to eat French food at Ginza"*

…discussion continues (oyster bars, ramen, Kalhua milk bar are raised as options)

Mr. A: *"I __really__ want to eat French food at Ginza"*

Pushing his preference

Mr. B : *"Pizza is also good"*

Mr. C : *"My preference is for meat, but if everyone is in for French at Ginza, I don't mind"*

High Agreeableness

Mr. D: *"I want to go to an oyster bar in Shibuya"*

Mr. E : *"I want to go to Japanese BBQ restaurant in Shibuya."*

Mr. A posts a menu of a French restaurant

Mr. A: *"Let me give you an idea of what French at Ginza will be like."*

Pushing his preference

Limitations of other choices

Mr. A: *"Also, I can't drink alcohol."*

Mr. C : *"right! Me neither, so I though that places that sell alcohol are out of the question"*

Mr. D : *"An oyster bar without wine is just sad…"*

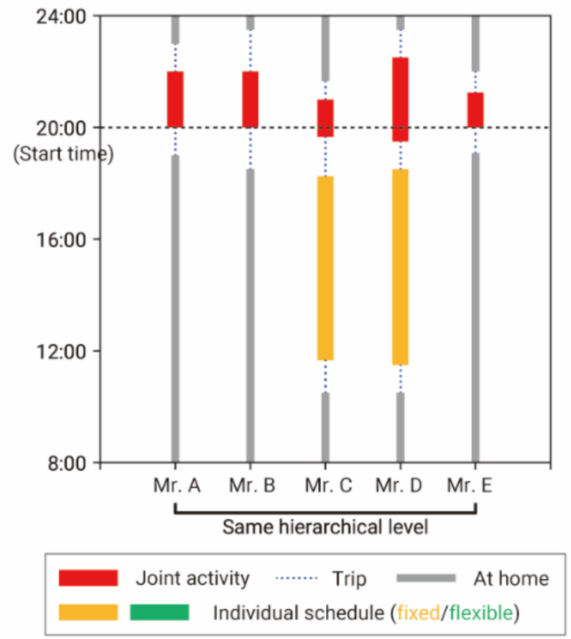
Mr. D : *"So French is the strongest option?"*

Mr. E : *"I guess I'm OK with French too"*

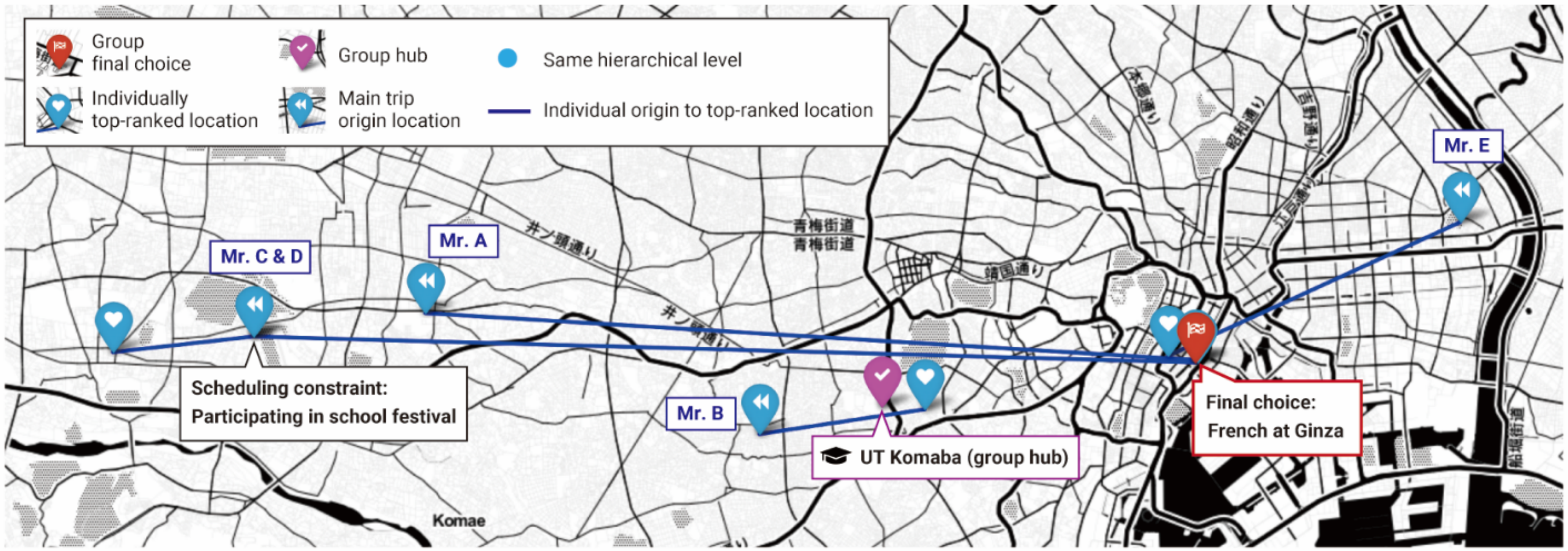
Mr. C : *"I think that everyone's first choice is different, and their second choice is like French at Ginza."*

French at Ginza is decided.

1b. Schedules of the members



1c. Activity places



Profiling group decision making process

Case 2

Case study 2

- Clique consisting of three members (futsal club friends)
- Two-level hierarchy (one year-grade difference)

2a. LINE chat history (major comments extracted)

Mr. C: *"I guess 19:00 would be nice for dinner."*

Mr. A: *"I have a part-time job until 19:00 at Shinjuku, but I can go as soon as it's finished."*

Time-space constraint of a senior member

Mr. B: *"Shall we meet at 19:30? I think starting from 20:00 is too late."*

Mr. C : *"Then let's have dinner from 19:30 to around 21:00, and then watch the game from 22:00."*

They want to watch World-Cup game after dinner

Mr. A & B : *"Perfect."*

… each member presenting candidate restaurants for dinner (without explicit consensus, everyone presents shops at Shinjuku)

Mr. A: *"I want to try this hotpot restaurant although it is expensive."*

Economic constraint

Mr. C: *"Too expensive…"*

Mr. B : *"Brazilian barbecue is a realistic option for us."*

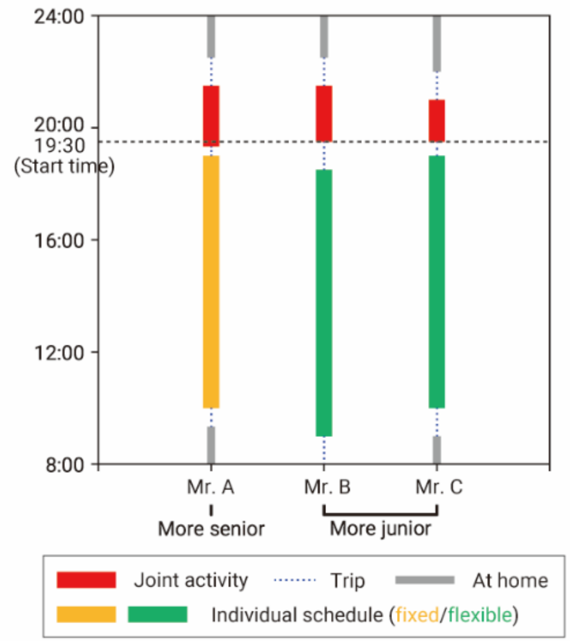
Mr. A : *"Agree. Then let's go for it or to another gibier meat restaurant."*

Mr. B : *"The gibier one often appears in SNS."*

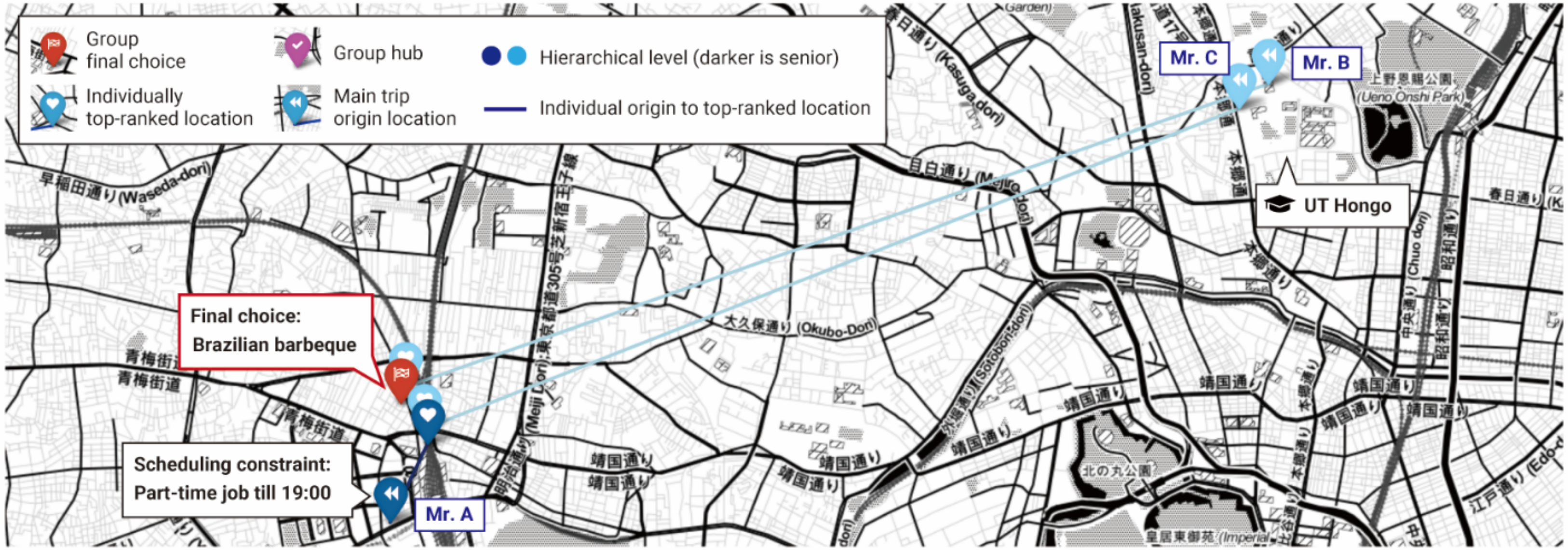
Mr. C : *"Brazilian barbecue is better for us."*

Brazilian barbecue is decided.

2b. Schedules of the members



2c. Activity places



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