Strategic Decision-Making in Smart Mobility Networks Integrating Supply and Demand

Youngseo Kim
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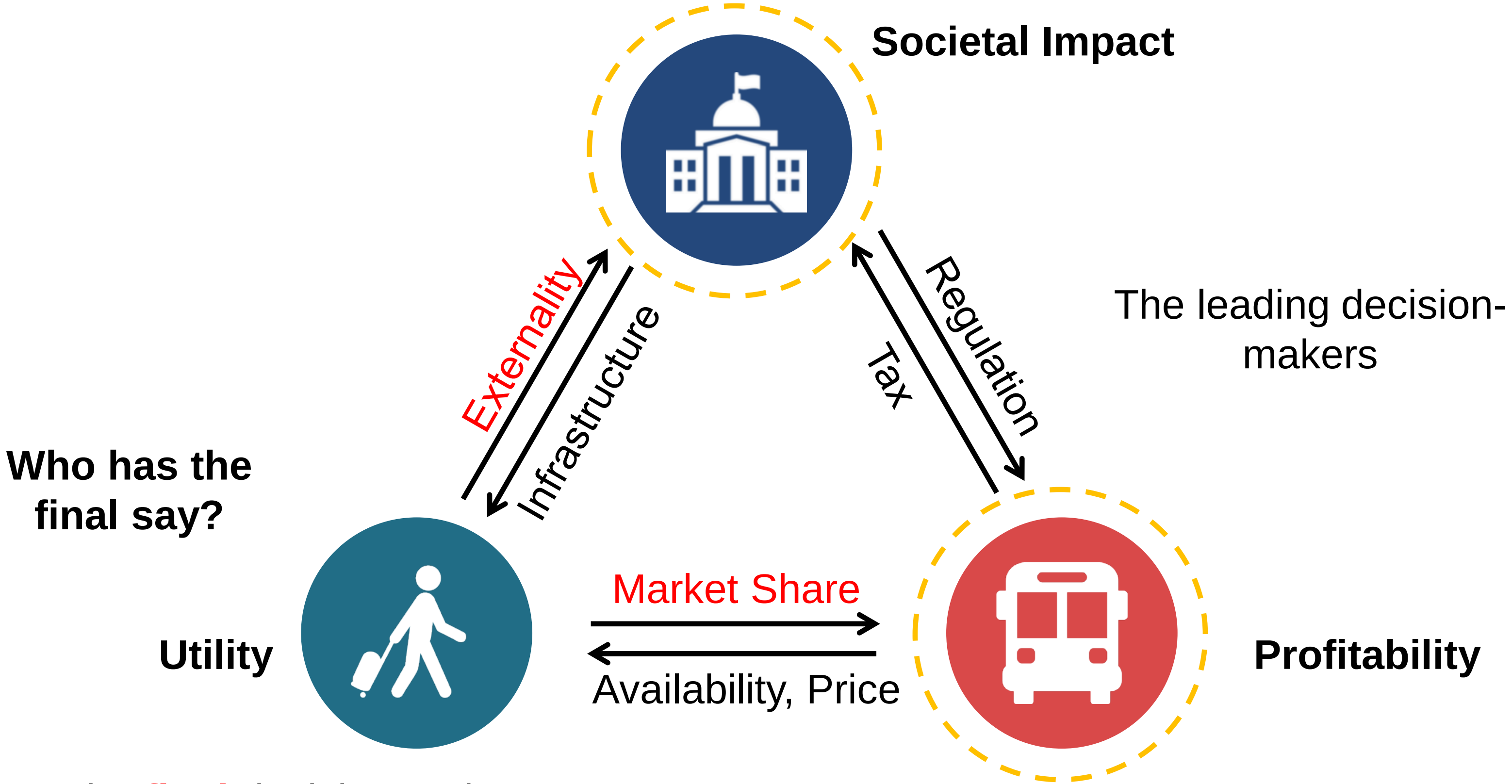
Complexity from Interactions among Multiple Stakeholders



The **final** decision-makers

Toward Smart Mobility that is Good for All

Challenges

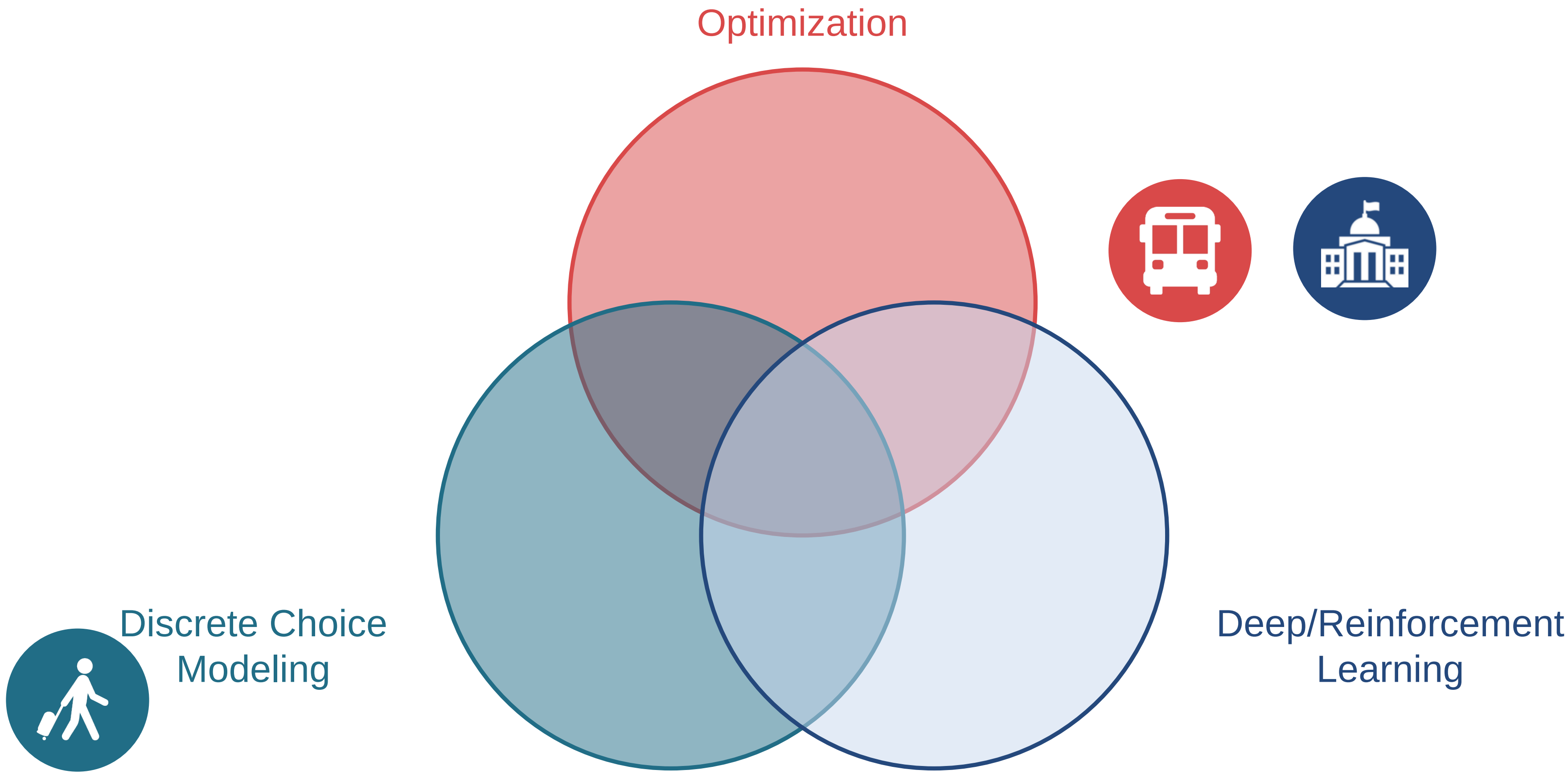
Human Behavior | Multiple Stakeholders | Network Complexity

Challenge 1: Innovative smart mobility involves **transformative changes** in **human behavior**.

Challenge 2: Strategic interactions among **multiple stakeholders**.

Challenge 3: **Network complexity** makes system-level decision-making challenging.

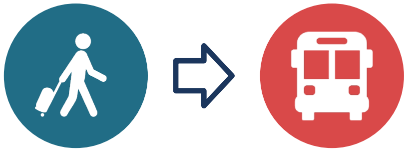
Research Tools



Organization of the Talk

Short term ⟷ Long term

Real-time Operation	Tactical Policy Development	Long-term Planning



[YK et al., TR part C, in revision]

[YK et al., TCNS, 2025]

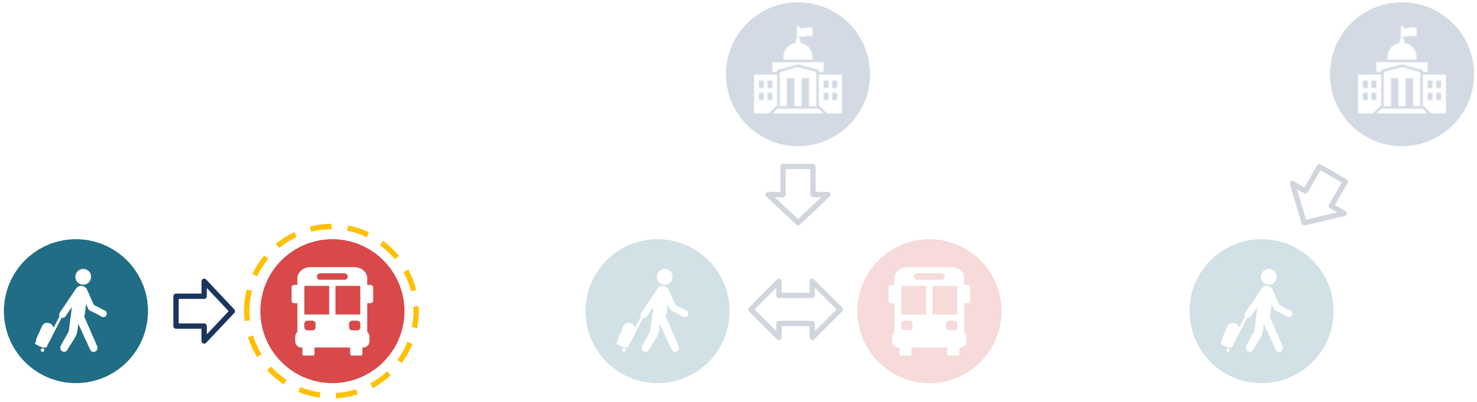
[YK et al., TR part B, in revision]

Area 1: Operational Efficiency of Mobility-on-Demand

Real-time Operation

Tactical Policy Development

Long-term Planning



[YK et al., TR part C, in revision]

On-demand Pooling Services

Ride-pooling

Uber blog

Microtransit

American Public Transportation Association

Benefits: (1) Reducing vehicle miles traveled and (2) complementing fixed-line transit

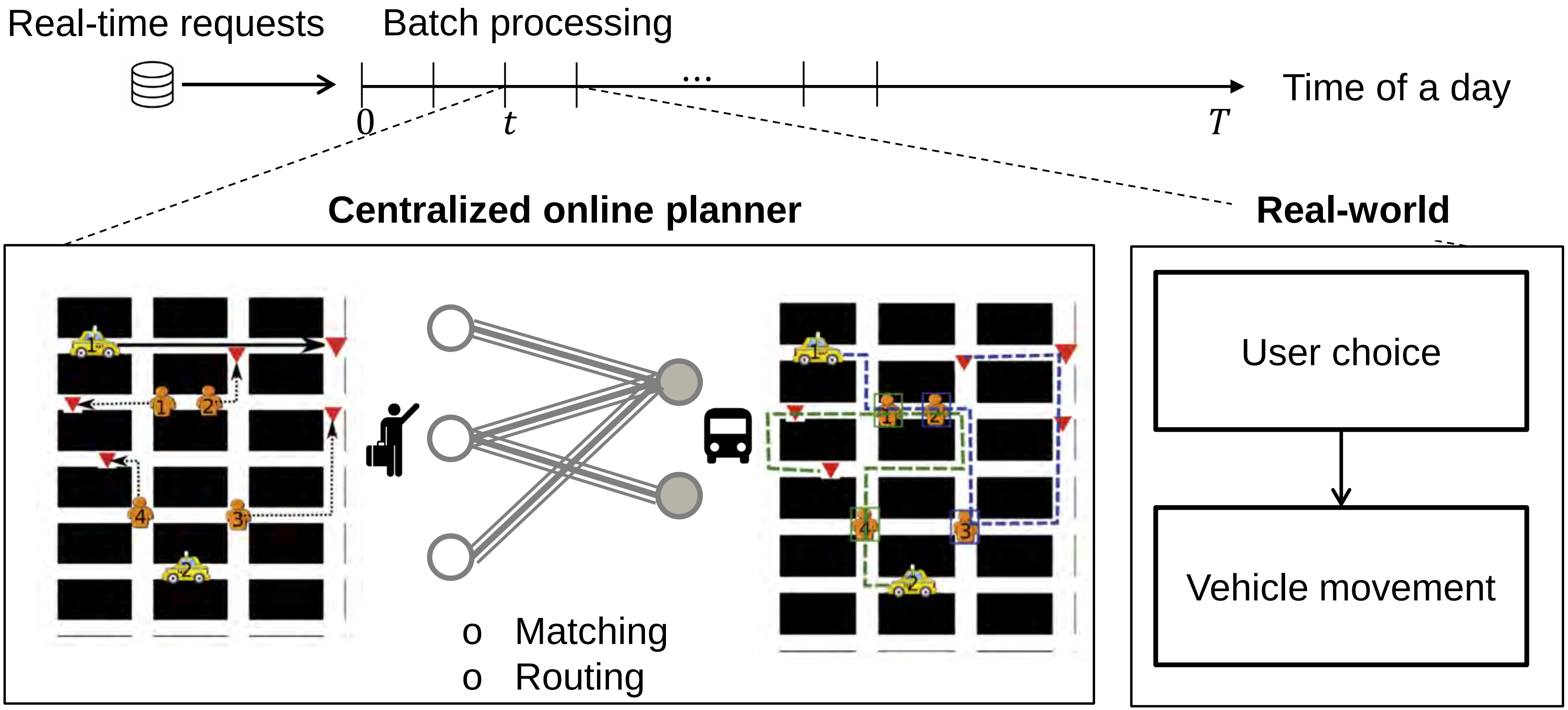
Pilot Operation in Real Cities

Microtransit to transit hubs
City of Kent in King County, WA

Paratransit
Chattanooga area, TN

Efficient operation algorithms for on-demand pooling is key to **successful** adoption.

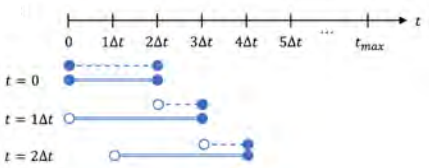
Vehicle Scheduling Engine

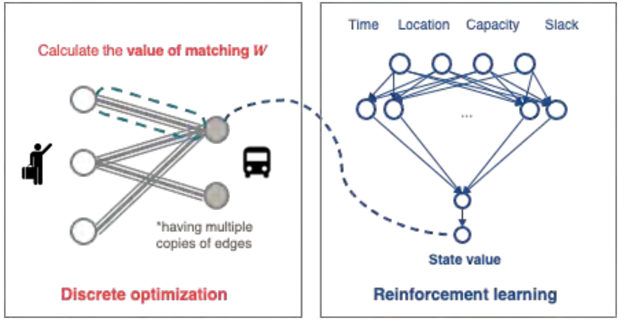


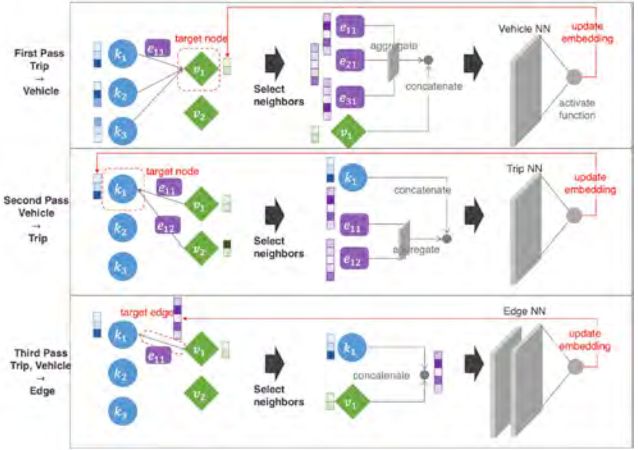
[Alonso-Mora et al., 2017]

Vehicle Scheduling Algorithm for Operational Efficiency

Operations Research + Computer Science







Control Technique

To solve **day-ahead** scheduling problem

VANDERBILT UNIVERSITY PennState

[YK et al., 2023, AAAI]

Reinforcement Learning

To overcome the **myopic** nature of real-time decision-making

Massachusetts Institute of Technology

[YK et al., TR part C, in revision]

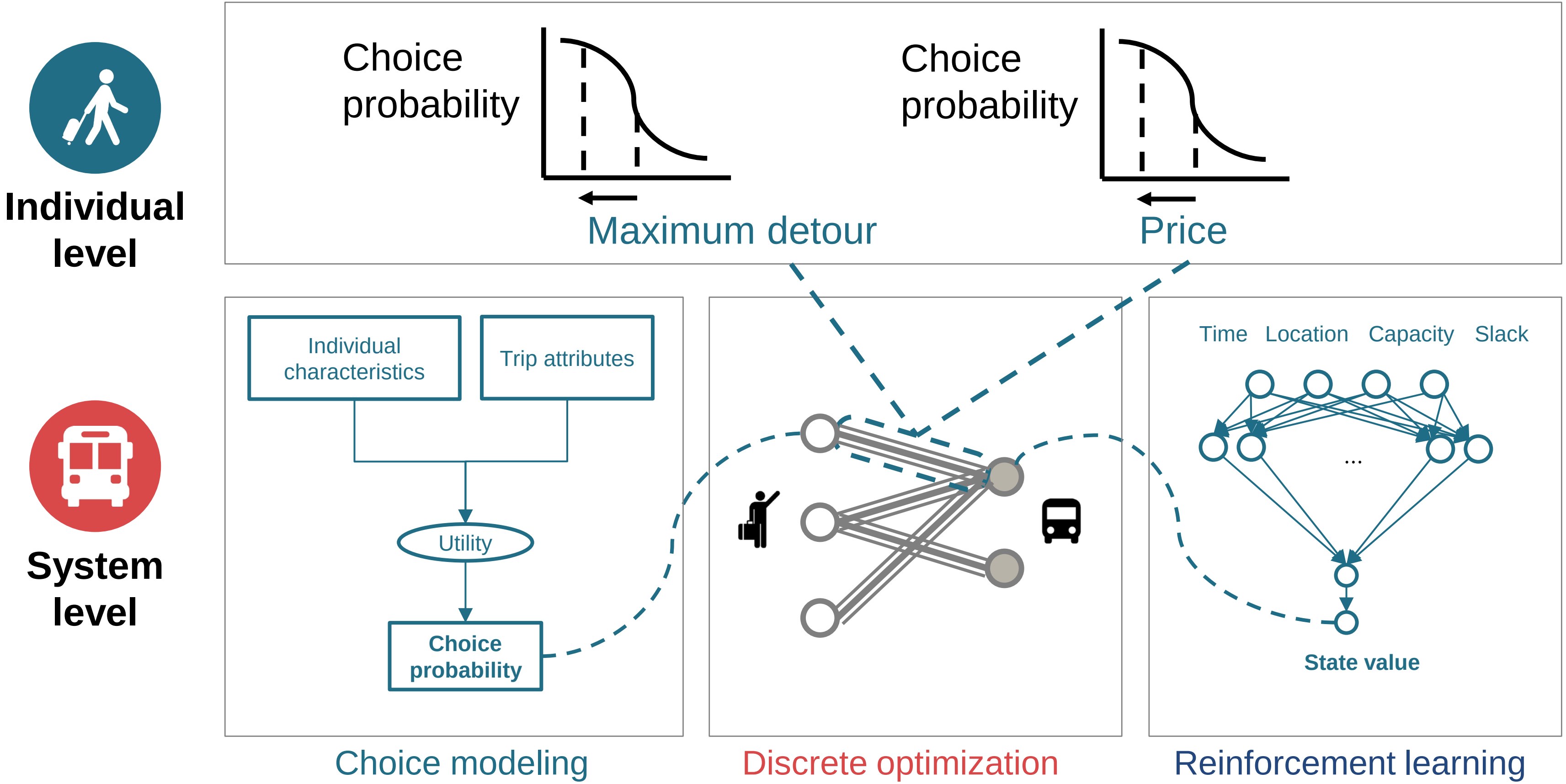
Deep Learning

To solve optimization **faster** by learning from distribution

Massachusetts Institute of Technology

[YK et al., TRISTAN, 2025]

Future: System-level Decision with Individual-level Analysis

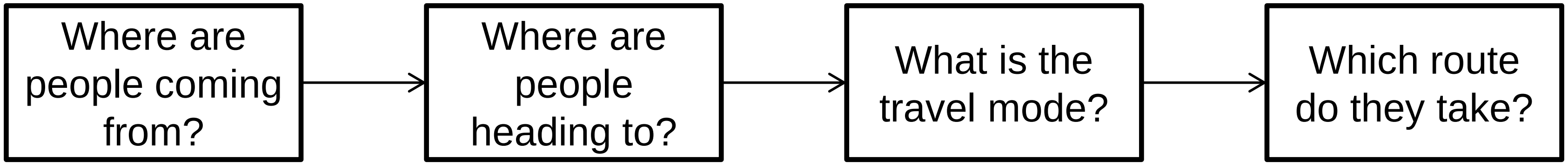


Area 3: Travel Demand Modeling for Infrastructure Planning

[YK et al., TR part B, in revision]

What is Travel Demand Modeling?

To fully understand **travel demand patterns** in the city network



What is Travel Demand Modeling?

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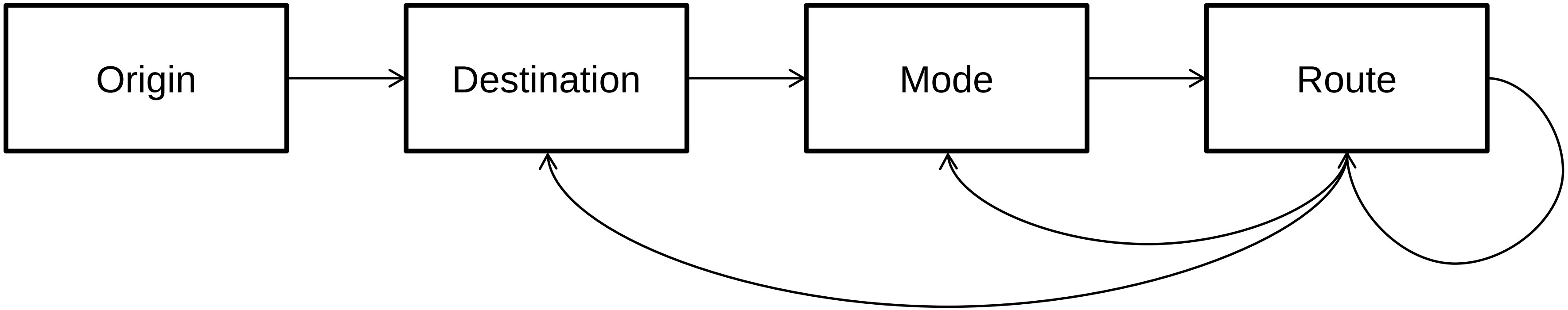
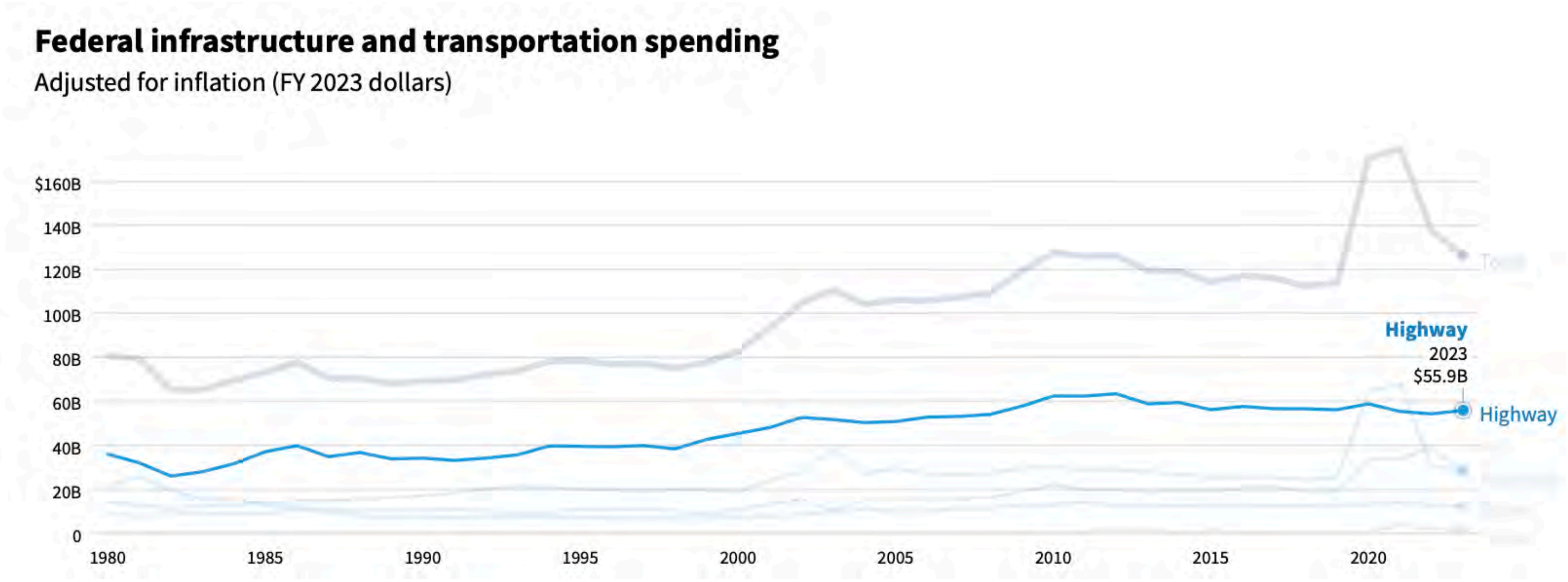


Importance of Travel Demand Modeling

Evaluating the **benefit-to-cost ratio** for large-scale infrastructure projects

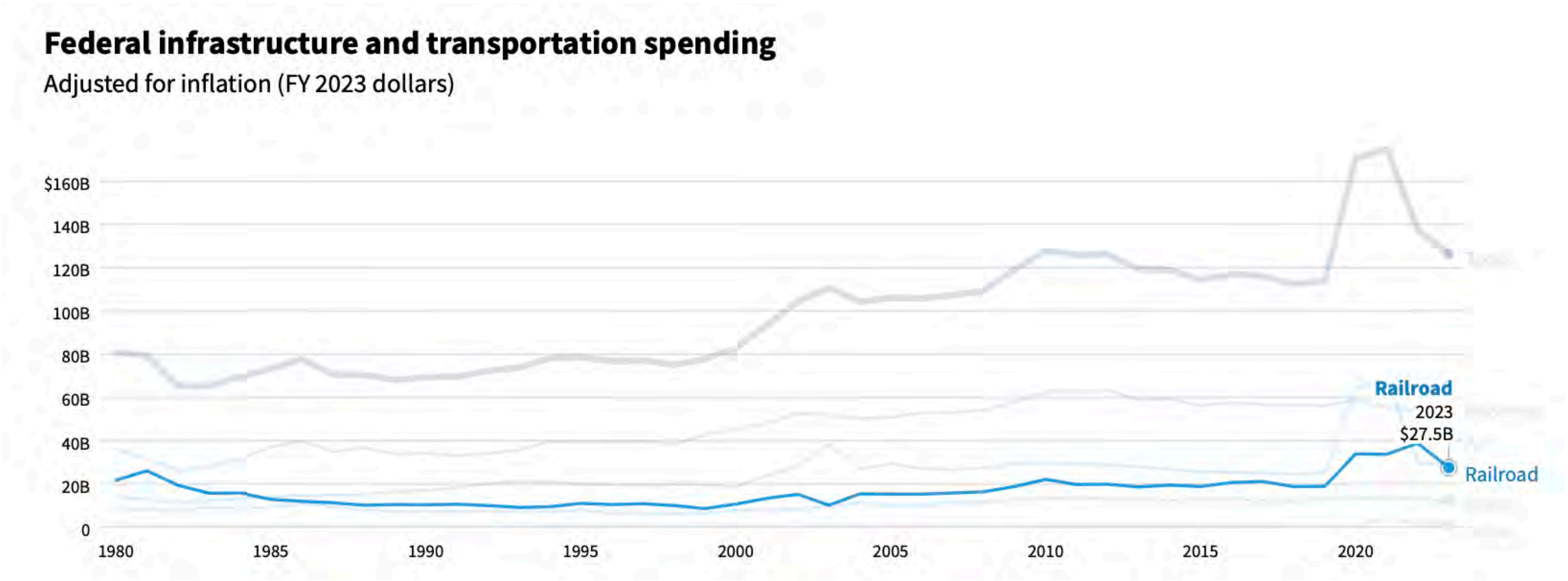
Importance of Travel Demand Modeling



The US federal government spend **$55.9B** on **highway** construction in 2023.

source

Importance of Travel Demand Modeling



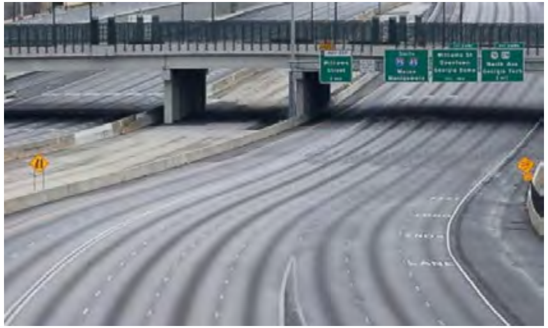
The US federal government spend **$27.5B** on rail and mass **transit** construction in 2023.

Importance of Travel Demand Modeling

Under-estimation

Travelers' dissatisfaction

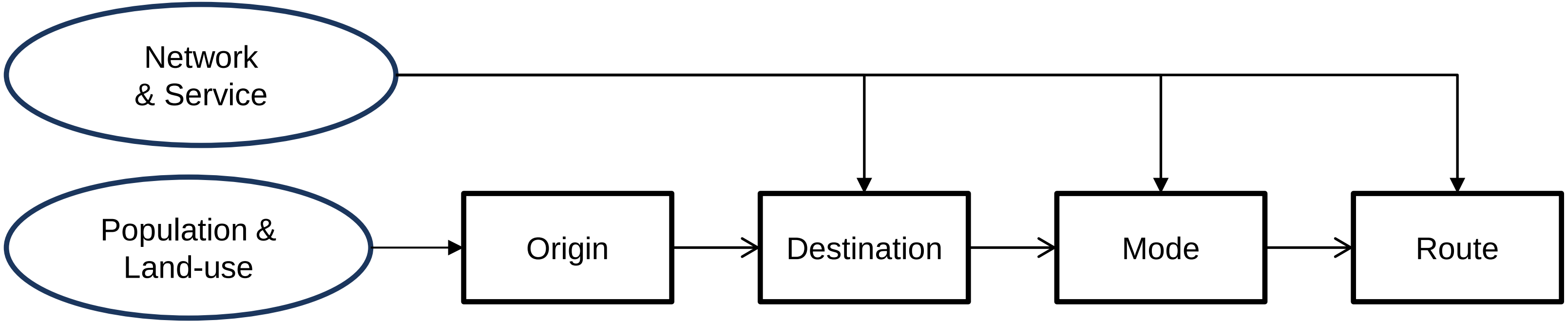
Over-estimation



Wasted government spending

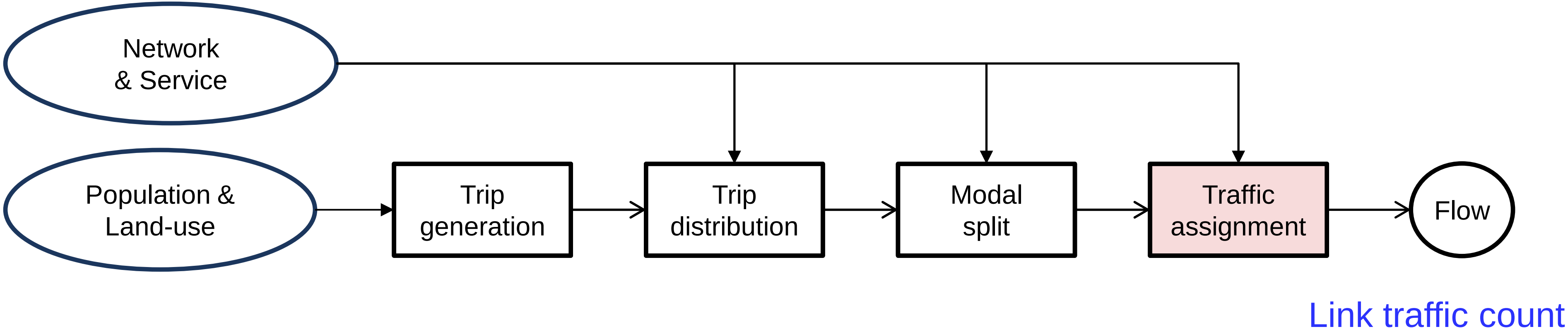
Limitation of the Previous Approach

Traditional four step sequential modeling



Limitation of the Previous Approach

Traditional four step sequential modeling



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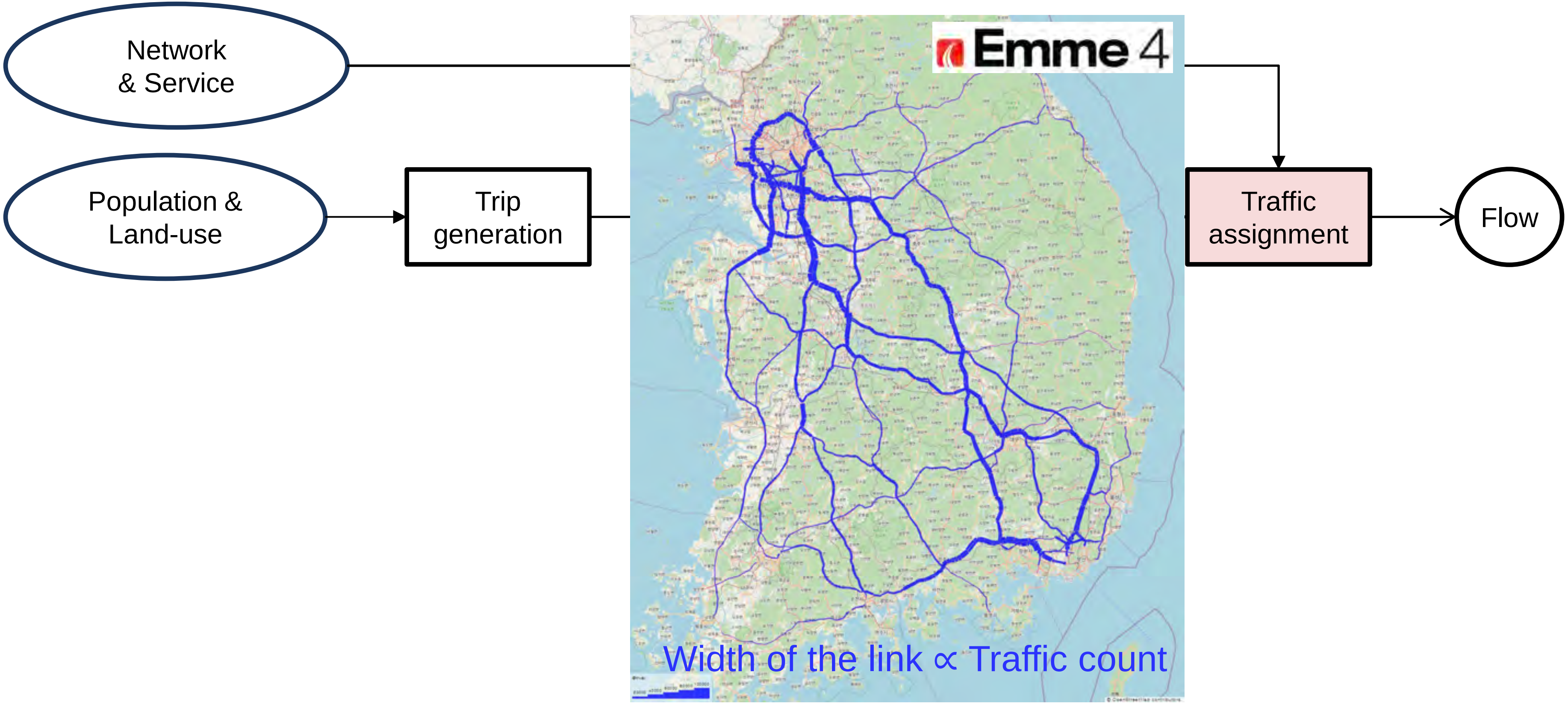

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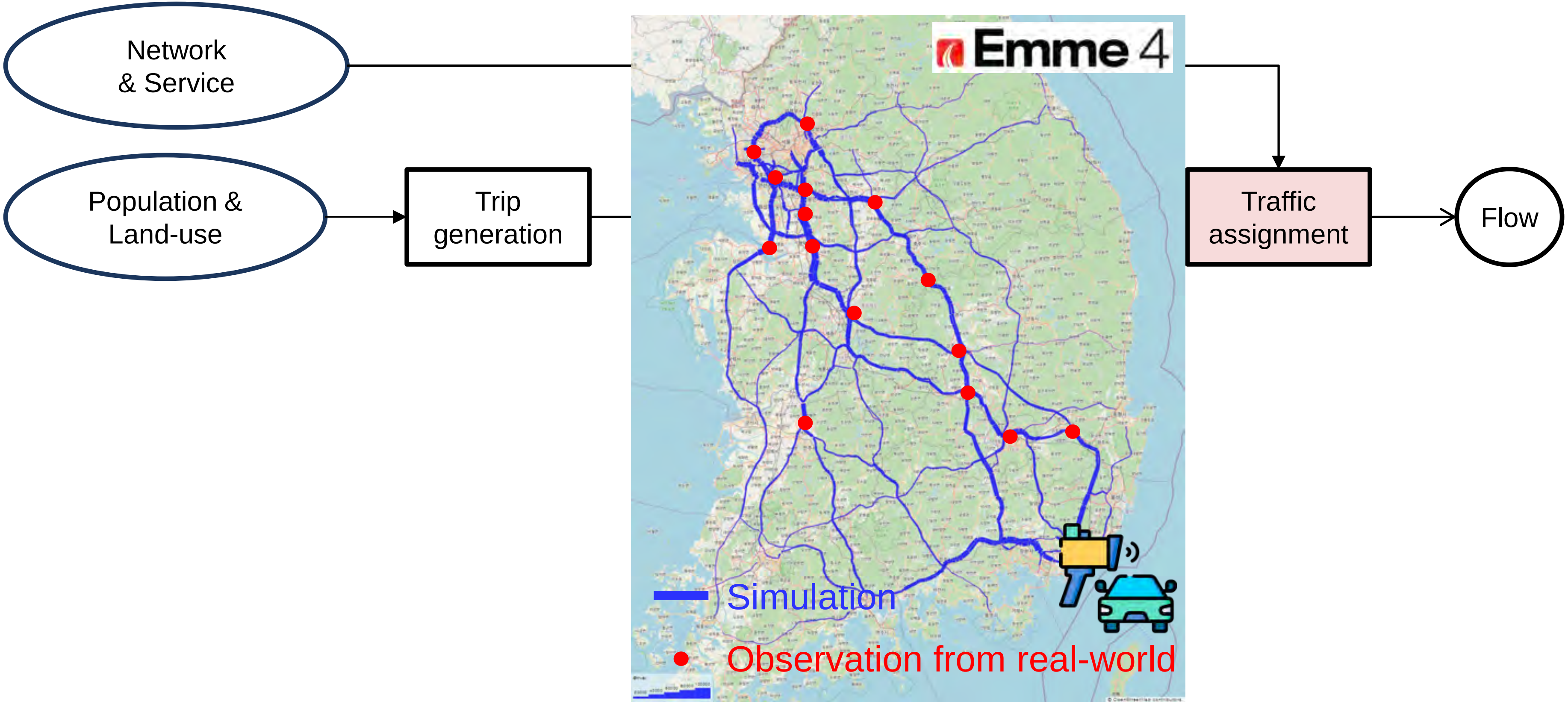

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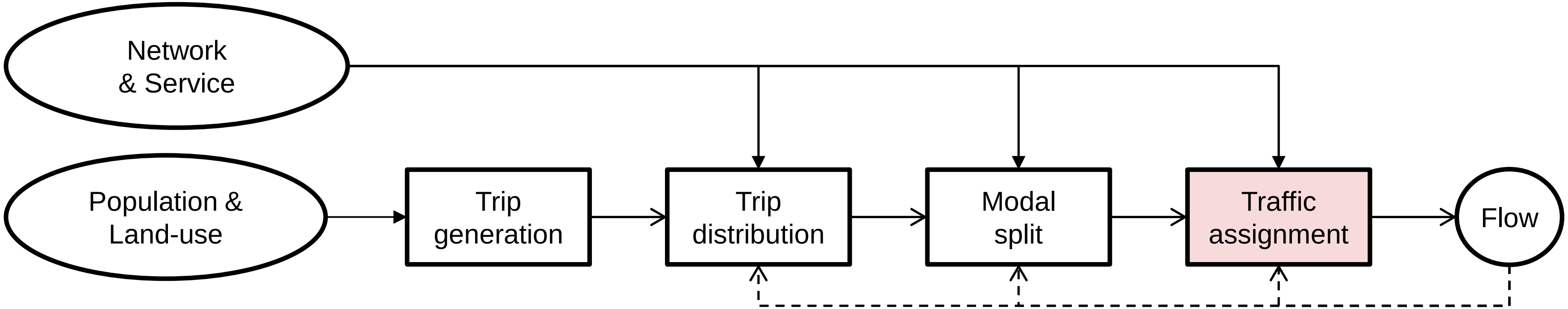
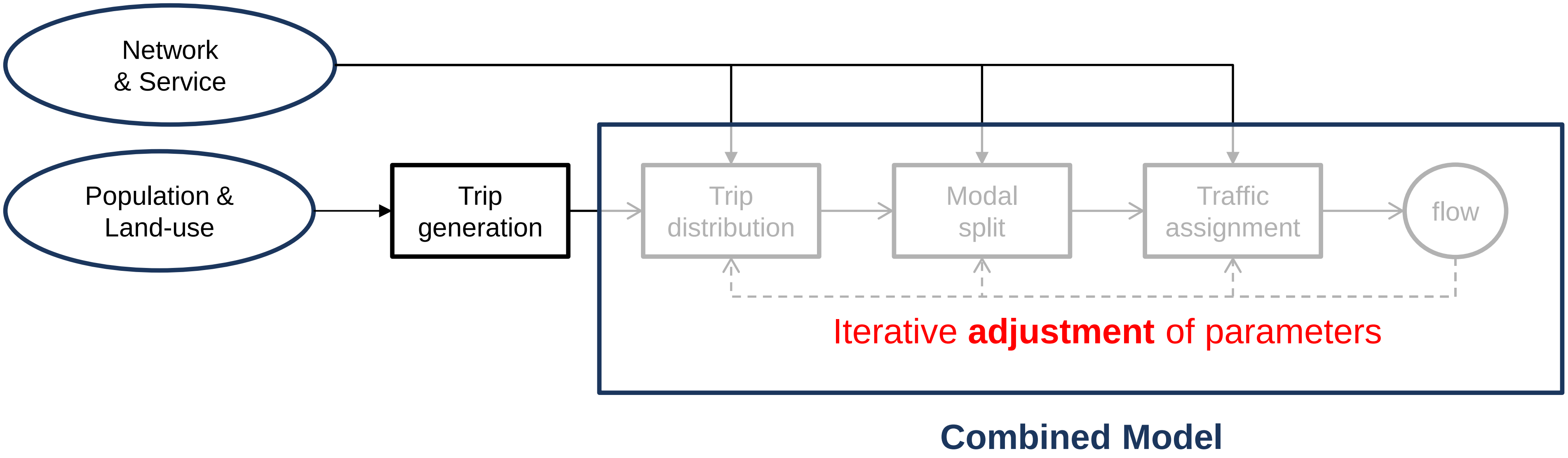


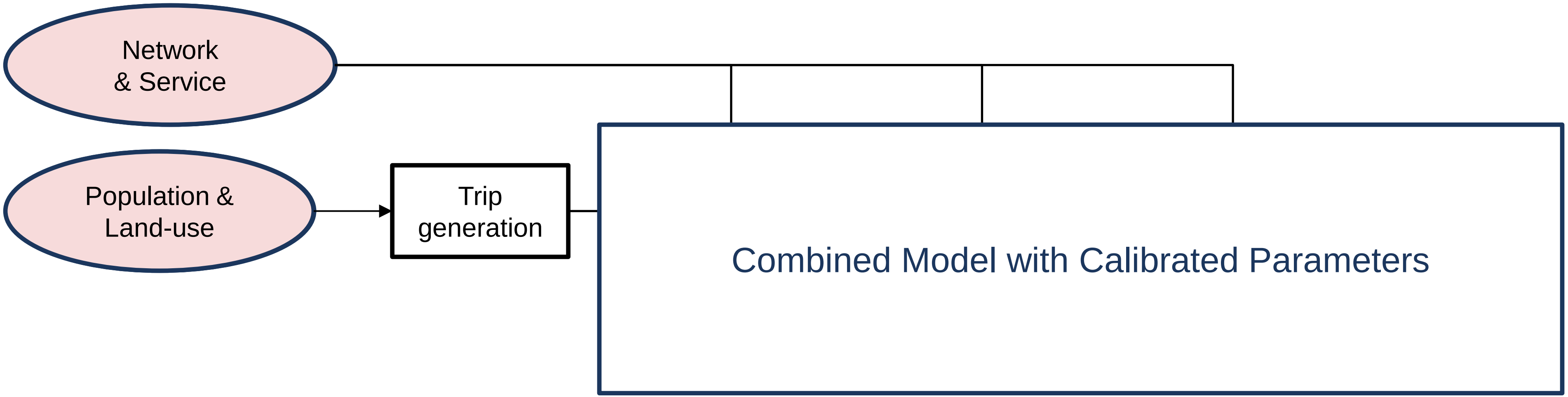
Iterative **adjustment** of parameters

Combined Model for One-Shot Calibration



Our model provides more **robust** parameter estimates with **automated** calibration.

Combined Model for One-Shot Calibration

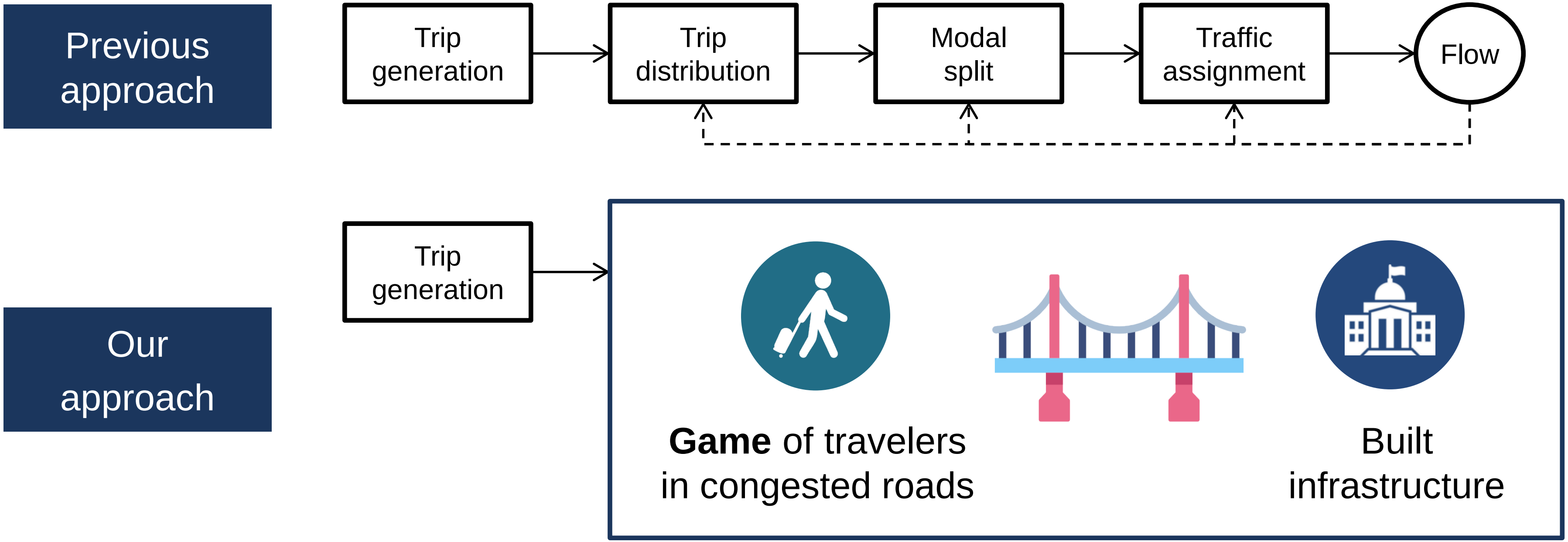


To predict **future** travel patterns after …

- construction
- adopting innovative mobility services
- changes in demographics

Novelty

Contribution: First model to **incorporate parameter calibration** in a convex program.



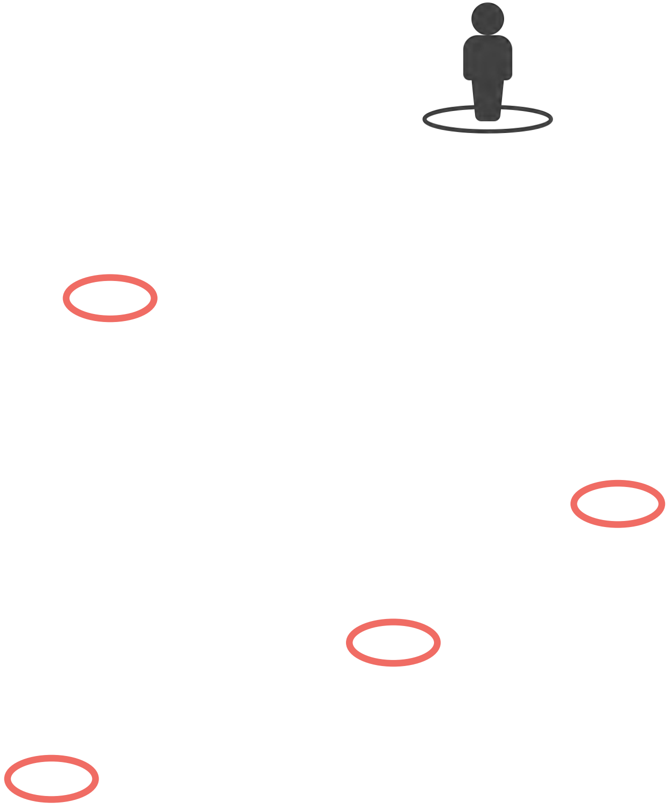
Our integrated model connects **urban planning** with analysis of **mobility patterns**.

Modeling Assumption: Hierarchical Logit Model

individual i

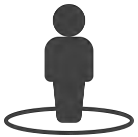
o_i

individual i

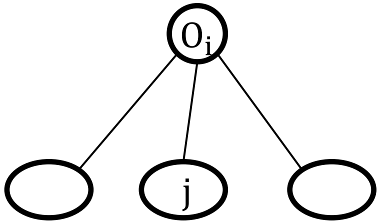


Modeling Assumption: Hierarchical Logit Model

individual i



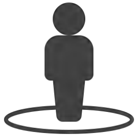
individual i



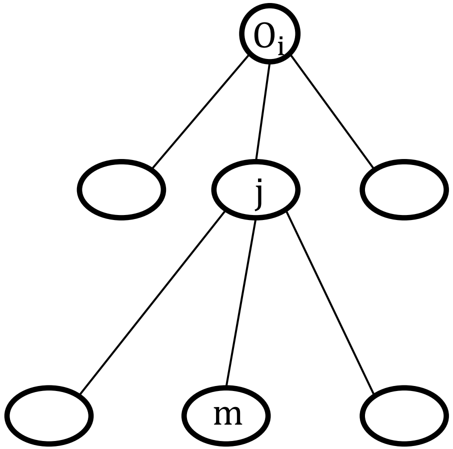
destination j

Modeling Assumption: Hierarchical Logit Model

individual i



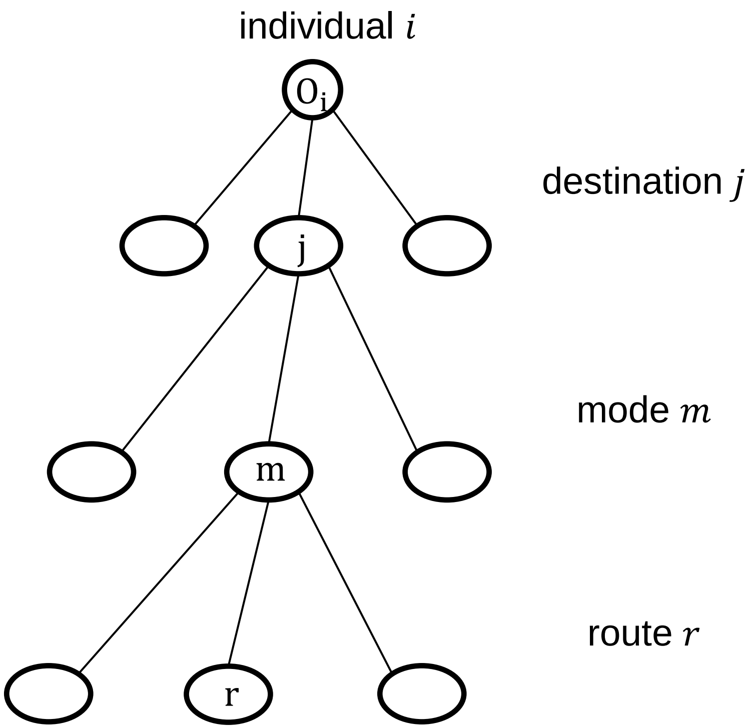
individual i

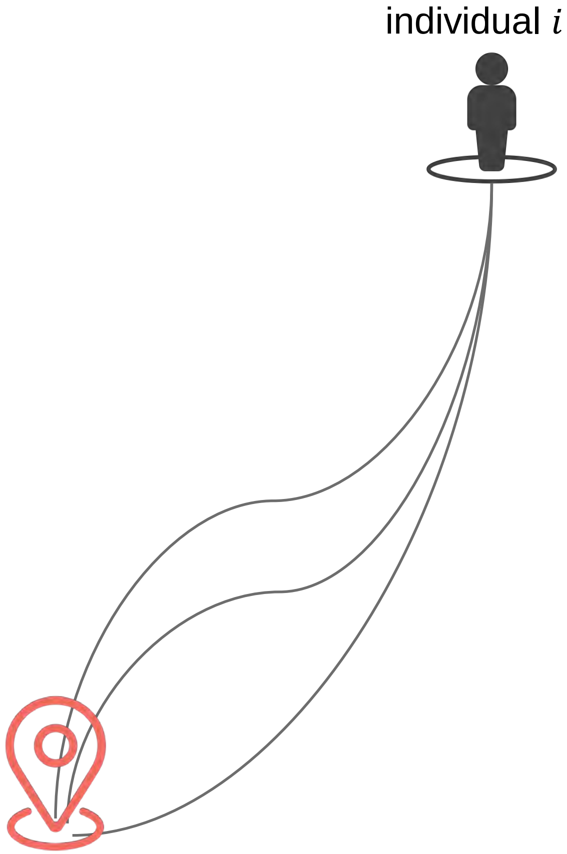


destination j

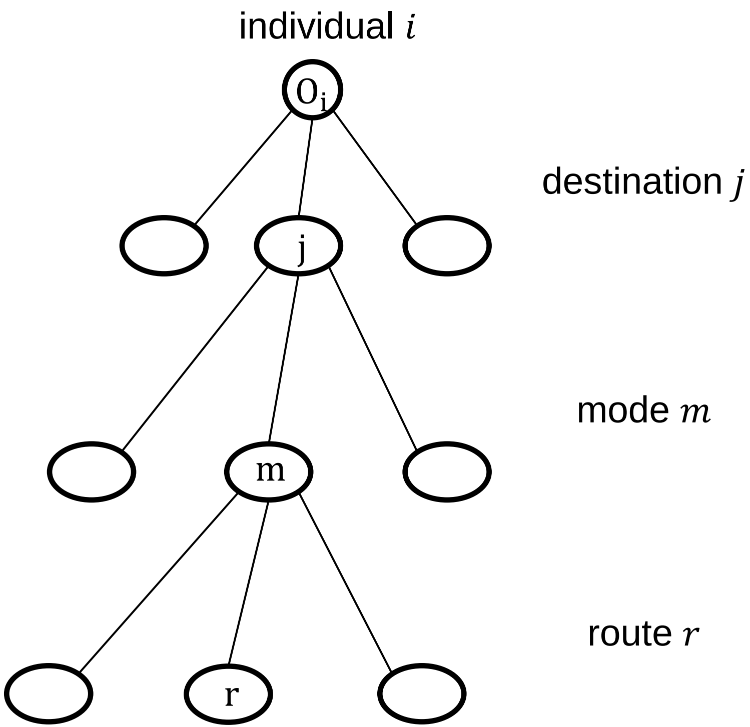
mode m

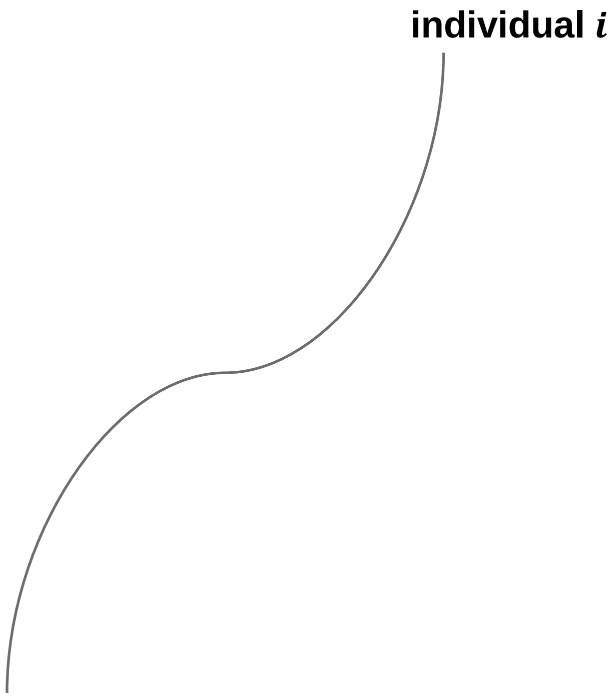
Modeling Assumption: Hierarchical Logit Model



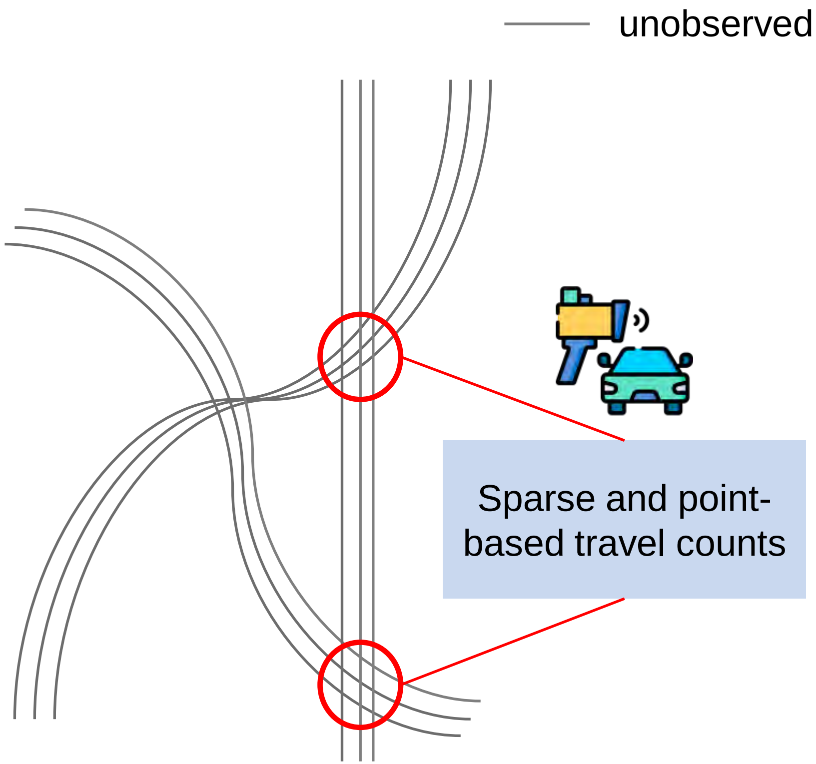


Modeling Assumption: Hierarchical Logit Model





Challenges: Incomplete Observation



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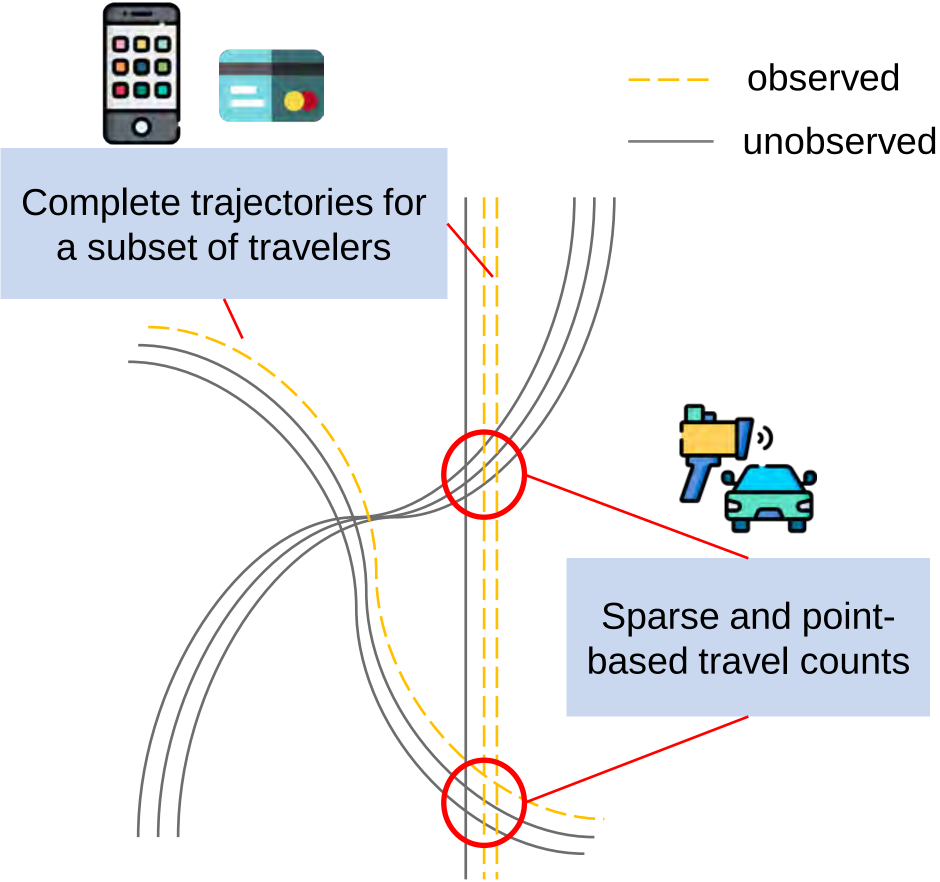
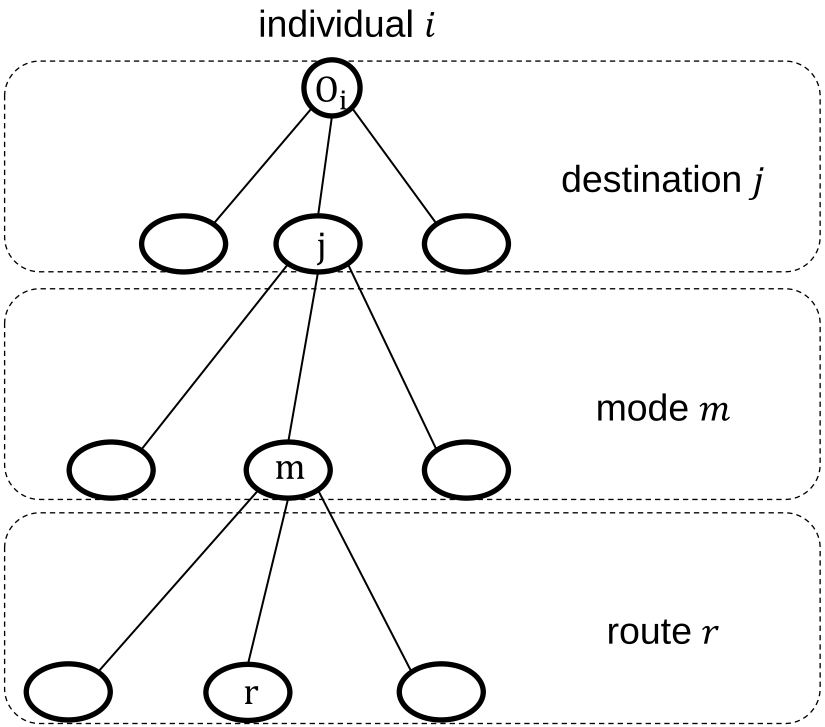
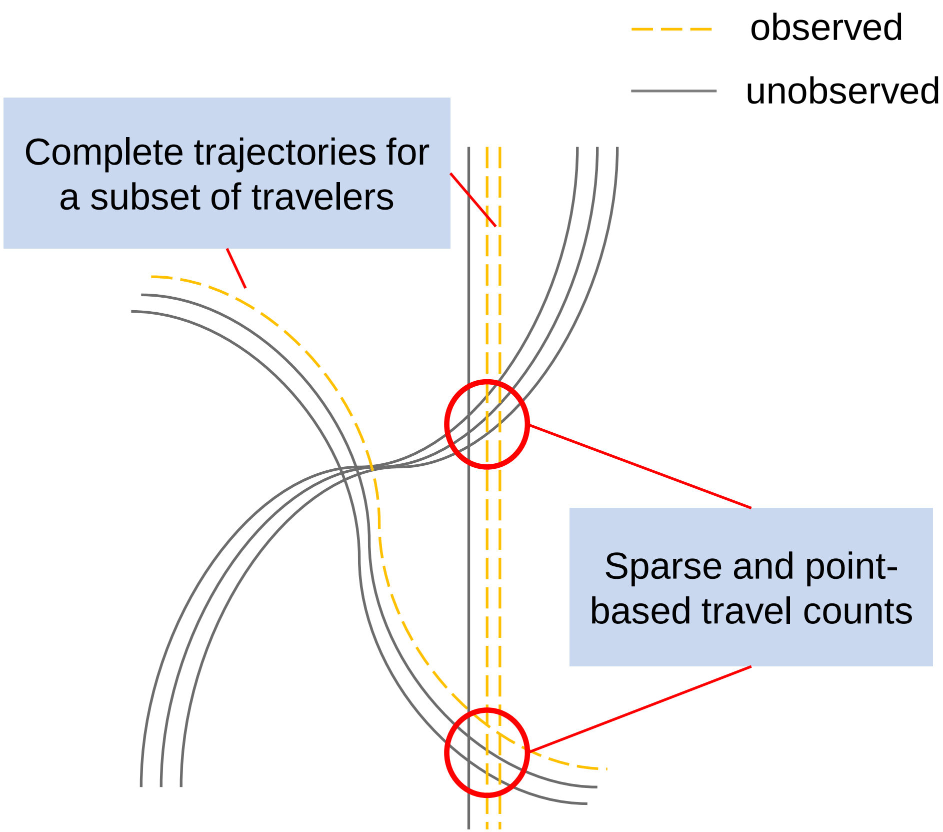


Complement Incomplete Observations with Theory-driven Model

Parametric, aggregated models

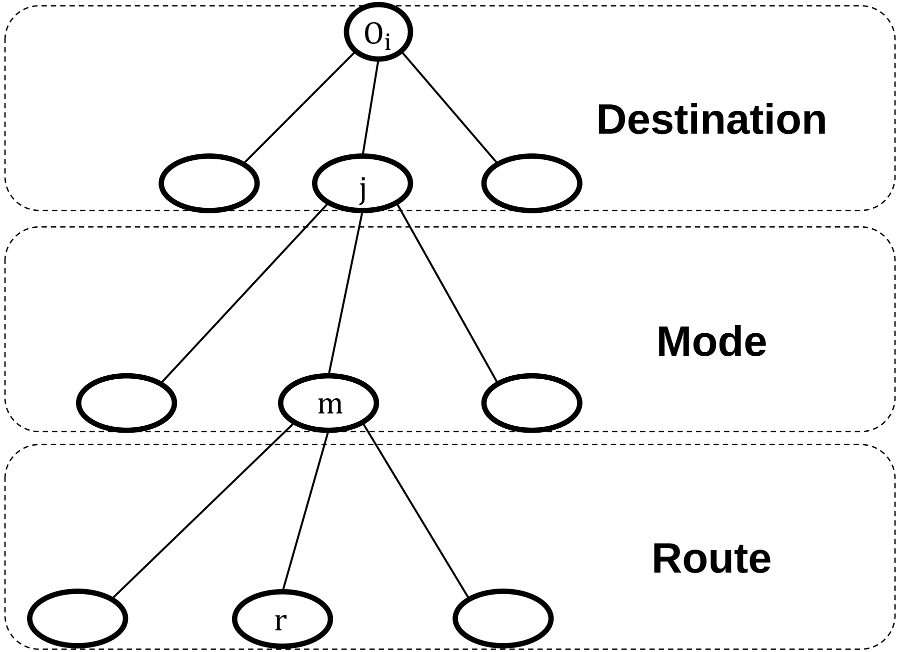


Hierarchical logit model



Modeling Assumption: Hierarchical Logit Model

Hierarchical logit model



Multinomial logit model
(Standard gravity model)

Nested logit model
(Correlation among modes)

Path size logit model
(Route overlapping)

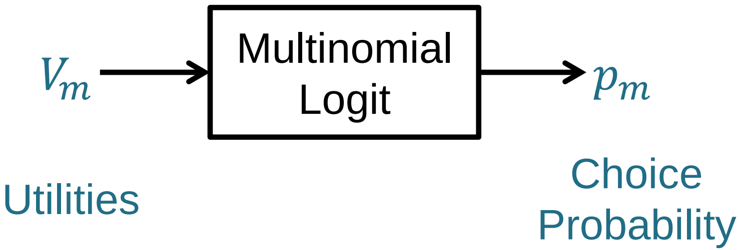
We incorporate **flexible** choice models with **rich behavioral details**.

Solution Approach: Entropy Maximization Principle

Multinomial Logit

$$p_m = \frac{e^{V_m}}{\sum_{m' \in \mathcal{M}} e^{V_{m'}}}, \forall m$$

Non-linear constraints cause **intractability** in optimization problem



[Mogens Fosgerau et al., 2020]

Solution Approach: Entropy Maximization Principle

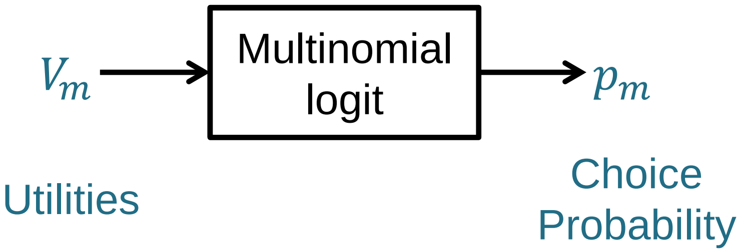
Multinomial Logit

$$p_m = \frac{e^{V_m}}{\sum_{m' \in \mathcal{M}} e^{V_{m'}}}, \forall m$$

Entropy Maximization

$$\max_{\mathbf{p}} \sum_{m \in \mathcal{M}} V_m p_m + H(p_m)$$

$$\text{s.t.} \sum_{m \in \mathcal{M}} p_m = 1$$



[Mogens Fosgerau et al., 2020]

Solution Approach: Entropy Maximization Principle

Multinomial Logit

$$p_m = \frac{e^{V_m}}{\sum_{m' \in \mathcal{M}} e^{V_{m'}}}, \forall m$$

- Travelers maximize utilities
- Error term follows Gumbel distribution

Entropy Maximization

Total utilities — Uncertainty

$$\max_{\mathbf{p}} \quad \sum_{m \in \mathcal{M}} V_m p_m + H(p_m)$$

$$\text{s.t.} \quad \sum_{m \in \mathcal{M}} p_m = 1$$

Probabilities are summed up to 1

[Mogens Fosgerau et al., 2020]

Solution Approach: Entropy Maximization Principle

Multinomial Logit

$$p_m = \frac{e^{V_m}}{\sum_{m' \in \mathcal{M}} e^{V_{m'}}}, \forall m$$

Entropy Maximization

Uncertainty

$$\max_{\mathbf{p}} \sum_{m \in \mathcal{M}} V_m p_m + \boxed{H(p_m)}$$

$$\text{s.t.} \sum_{m \in \mathcal{M}} p_m = 1$$

Proven to be a **convex** program

“Entropy” can be interpretable as (1) value of **choice variety** and (2) **information cost**.

[Mogens Fosgerau et al., 2020]

Advantages of Convex Programming

Existence of Solution
and **Global Optimality**

Tractability
(e.g., Gradient Descent,
Interior-point Methods)

Solution Approach: Entropy Maximization Principle

Multinomial Logit

$$p_m = \frac{e^{V_m}}{\sum_{m' \in \mathcal{M}} e^{V_{m'}}}, \forall m$$

Entropy Maximization

$$\max_{\mathbf{p}} \quad \sum_{m \in \mathcal{M}} V_m p_m + H(p_m)$$

$$\text{s.t.} \quad \sum_{m \in \mathcal{M}} p_m = 1$$

The transformation allows the **integration** of **discrete choice modeling** into **optimization.**

Two Stage Approach: Estimate and then Predict

Estimating Parameters and
Reconstructing Current Travel Pattern

Predicting
Future Travel Pattern

Two Stage Approach: Estimate and then Predict

Stage 1: Estimate

$$\max_{\mathcal{P}} \quad H_{\text{MNL}}(\mathbf{p}_{\mathcal{J}|\mathcal{I}}) + H_{\text{NL}}(\mathbf{p}_{\mathcal{M}|\mathcal{I}\mathcal{J}}) + H_{\text{PSL}}(\mathbf{p}_{\mathcal{R}|\mathcal{I}\mathcal{J}\mathcal{M}})$$

$$- \frac{1}{\widehat{T}} \sum_{i\in\mathcal{I}, j\in\mathcal{J}} \sum_{m\in\mathcal{M}, r\in\mathcal{R}} \sum_{a\in\mathcal{A}_{ijmr}} \int_0^{f_a^m} g_a^m(w)dw$$

s.t.

$$H_{\text{MNL}}(\mathbf{p}_{\mathcal{I}\mathcal{J}}|\widehat{\mathbf{p}}_{\mathcal{I}}) \geq H_{\text{MNL}}(\widehat{\mathbf{p}}_{\mathcal{I}\mathcal{J}}|\widehat{\mathbf{p}}_{\mathcal{I}}) \qquad [-1 + \frac{1}{\theta_{\text{dest}}}]$$

$$H_{\text{NL}_1}(\mathbf{p}_{\mathcal{I}\mathcal{J}\Pi(\mathcal{M})}|\mathbf{p}_{\mathcal{I}\mathcal{J}}) \geq H_{\text{NL}_1}(\widehat{\mathbf{p}}_{\mathcal{I}\mathcal{J}\Pi(\mathcal{M})}|\widehat{\mathbf{p}}_{\mathcal{I}\mathcal{J}}) \qquad [-1 + \frac{1}{\theta_{\text{mode}}}]$$

$$H_{\text{NL}_{\mathcal{N}}}(\mathbf{p}_{\mathcal{I}\mathcal{J}\mathcal{M}}|\mathbf{p}_{\mathcal{I}\mathcal{J}\mathcal{N}}) \geq H_{\text{NL}_{\mathcal{N}}}(\widehat{\mathbf{p}}_{\mathcal{I}\mathcal{J}\mathcal{M}}|\widehat{\mathbf{p}}_{\mathcal{I}\mathcal{J}\mathcal{N}}) \quad , \forall \mathcal{N} \in \Pi(\mathcal{M}) \qquad [-1 + \frac{\tau_{\mathcal{N}}}{\theta_{\text{mode}}}]$$

$$\sum_{i\in\mathcal{I}, j\in\mathcal{J}} p_{ij}\widehat{X}_{ij}^k = \sum_{i\in\mathcal{I}, j\in\mathcal{J}} \widehat{p}_{ij}\widehat{X}_{ij}^k \quad , \forall k \in \mathcal{K} \qquad [\beta_k]$$

$$\sum_{i\in\mathcal{I}, j\in\mathcal{J}} \sum_{m\in\mathcal{M}} p_{ijm}\widehat{X}_{ijm}^q = \sum_{i\in\mathcal{I}, j\in\mathcal{J}} \sum_{m\in\mathcal{M}} \widehat{p}_{ijm}\widehat{X}_{ijm}^q \quad , \forall q \in \mathcal{Q} \qquad [\beta_q]$$

Stage 2: Predict

$$\max_{\mathcal{P}} \sum_{i\in\mathcal{I}, j\in\mathcal{J}} p_{ij}V_{ij}(\widehat{\beta}_k, \widehat{X}_{ij}^k) + \sum_{i\in\mathcal{I}, j\in\mathcal{J}} \sum_{m\in\mathcal{M}} p_{ijm}V_{ijm}(\widehat{\beta}_q, \widehat{X}_{ijm}^q)$$

$$+ \frac{1}{\widehat{\theta}_{dest}} H_{\text{MNL}}(\mathbf{p}_{\mathcal{J}|\mathcal{I}})$$

$$+ \frac{1}{\widehat{\theta}_{mode}} H_{\text{NL}}(\mathbf{p}_{\mathcal{M}|\mathcal{I}\mathcal{J}})$$

$$+ H_{\text{PSL}}(\mathbf{p}_{\mathcal{R}|\mathcal{I}\mathcal{J}\mathcal{M}})$$

$$- \frac{\hat{\lambda}}{\widehat{N}} \sum_{i\in\mathcal{I}, j\in\mathcal{J}} \sum_{m\in\mathcal{M}, r\in\mathcal{R}} \sum_{a\in\mathcal{A}_{ijmr}} \int_0^{f_a^m} g_a^m(w)dw$$

Objective Function

$$\max_{p_{ijmr}}$$

Entropy Functions
Uncertainty of choice

$$+$$

Beckmann Equation
Traffic Equilibrium

Objective Function

$$\max_{p_{ijmr}} \; H_{\mathrm{MNL}}(\mathbf{p}_{\mathcal{J}|\mathcal{I}}) + H_{\mathrm{NL}}(\mathbf{p}_{\mathcal{M}|\mathcal{I}\mathcal{J}}) + H_{\mathrm{PSL}}(\mathbf{p}_{\mathcal{R}|\mathcal{I}\mathcal{J}\mathcal{M}})$$

Entropy Functions

p_{ijmr}
Probability
(Travel patterns)

$$-\frac{1}{\widehat{T}} \sum_{i\in\mathcal{I},j\in\mathcal{J}} \sum_{m\in\mathcal{M},r\in\mathcal{R}} \sum_{a\in\mathcal{A}_{ijmr}} \int_0^{f_a^m} g_a^m(w)dw$$

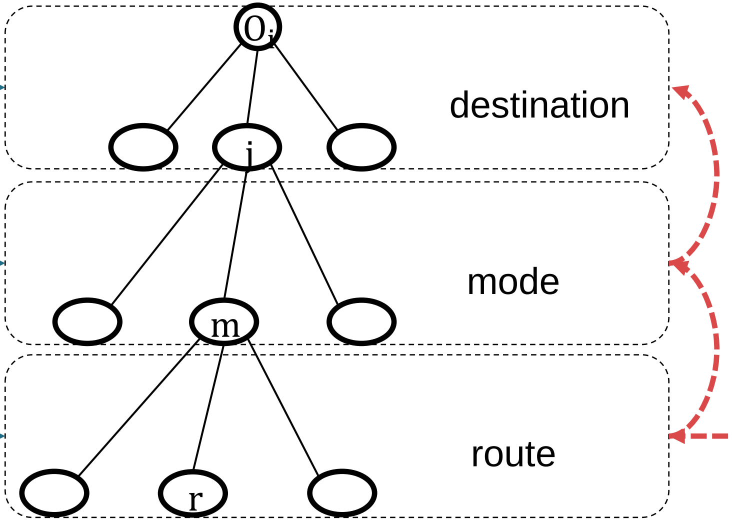
Beckmann Equation

f_a^m
Traffic count
(# of cars)

Objective Function Links Choice Models and User Equilibrium

Entropy Functions ≡ Choice Models | **Beckmann Equation for Equilibrium**

$$\max_{p_{ijmr}} H_{\text{MNL}}(\mathbf{p}_{\mathcal{J}|\mathcal{I}}) + H_{\text{NL}}(\mathbf{p}_{\mathcal{M}|\mathcal{I}\mathcal{J}}) + H_{\text{PSL}}(\mathbf{p}_{\mathcal{R}|\mathcal{I}\mathcal{J}\mathcal{M}}) - \frac{1}{\widehat{T}} \sum_{i\in\mathcal{I},j\in\mathcal{J}} \sum_{m\in\mathcal{M},r\in\mathcal{R}} \sum_{a\in\mathcal{A}_{ijmr}} \int_0^{f_a^m} g_a^m(w)dw$$



Tractable Convex Programming

$$\max_{p_{ijmr}}$$

Entropy + Beckmann

Travel Pattern Matches with Observations

Conditional entropies
(**Uncertainty** in predicting behavior)

Momentum matching
(**Movement** of a population)

Tractable Convex Programming

Theorem 1

The first stage model is a convex program

$$\max_{p_{ijmr}}$$ Entropy + Beckmann — Convex objective function

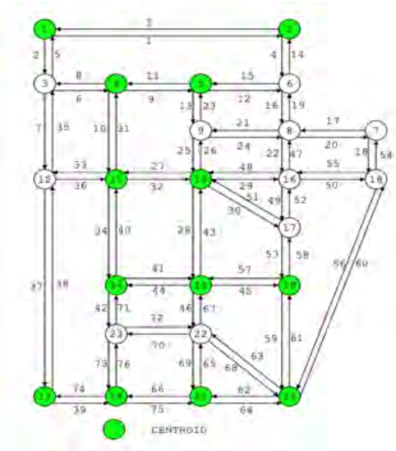
Travel Pattern Matches with Observations

Conditional entropies
(**Uncertainty** in predicting behavior) — Convex inequality constraints

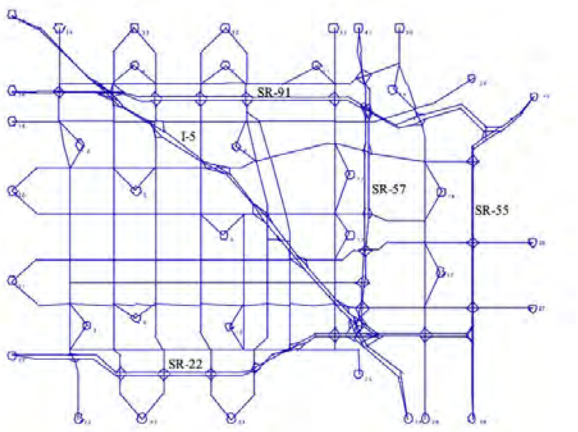
Momentum matching
(**Movement** of a population) — Linear equality constraints

Benchmark Networks

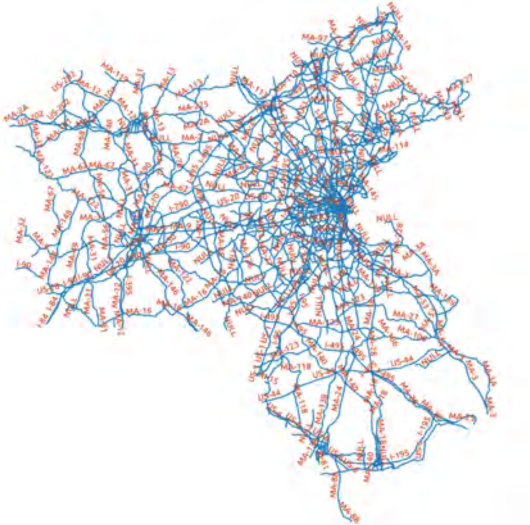
Sioux Falls



Anaheim



Eastern-Massachusetts



Benchmark Networks

	# of Nodes	# of Links	# of ODs	# of Routes	Time to Build Model (sec)	Solution Time (sec)
SiouxFalls	24	76	528	644	11.0	0.7
EMA	74	258	1,113	1,797	14.4	1.3
Berlin Friedrichshain	224	523	506	656	16.6	0.7
Berlin Mitte	398	871	1,260	1,706	18.0	0.9
Anaheim	416	914	1,406	2,700	55.4	3.7
Barcelona	1,020	2,522	7,922	16,570	583.9	18.8
Winnipeg	1,057	2,535	4,345	8,000	294.5	16.2
Munich	742	1,872	67,122	108,012	2608.2	115.6
Chicago Sketch	933	2,950	93,513	225,507	1799.6	123.1

One-Shot Approach for Calibration

Theorem 2

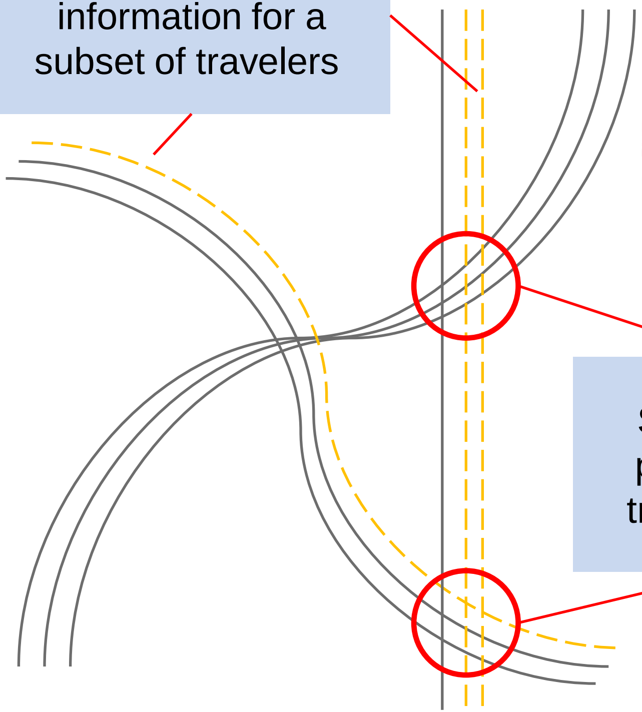
The optimal **primal** and **dual** solutions satisfy the hierarchical logit model.

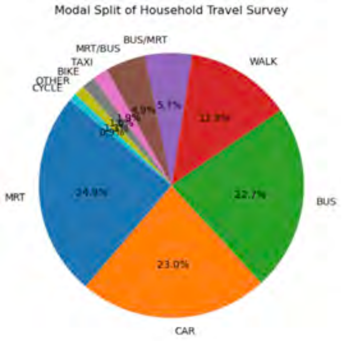
Primal
→ Travel equilibrium

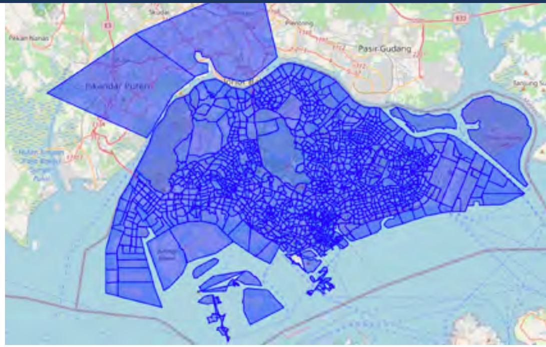
Dual
→ **Parameter estimation**

The dual problem resembles maximum likelihood estimation
but uniquely incorporates **constraints for observations**.

Future: Deployment in the Real-world







- Cell phone location
- Smart card
- Taxi data
- Household travel survey

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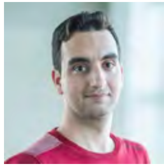
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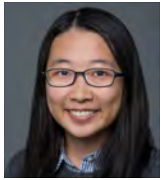
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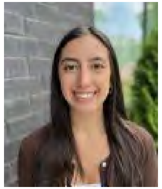
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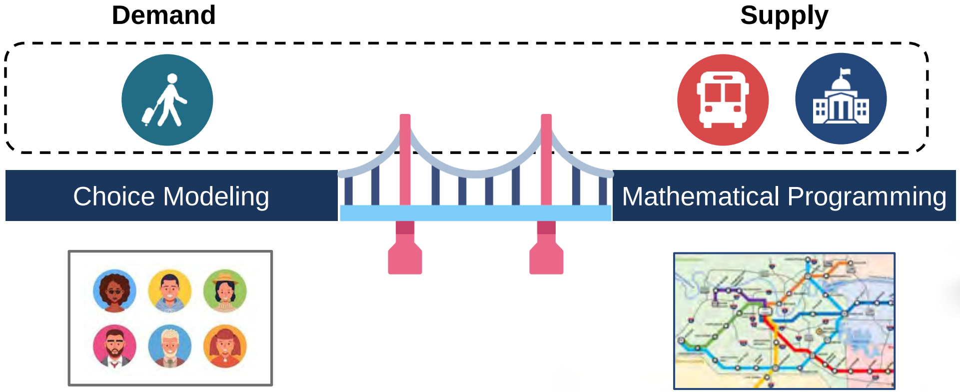
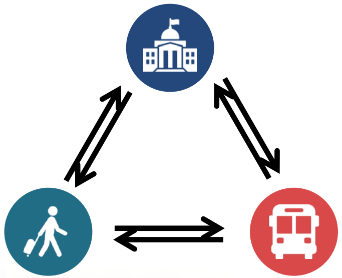
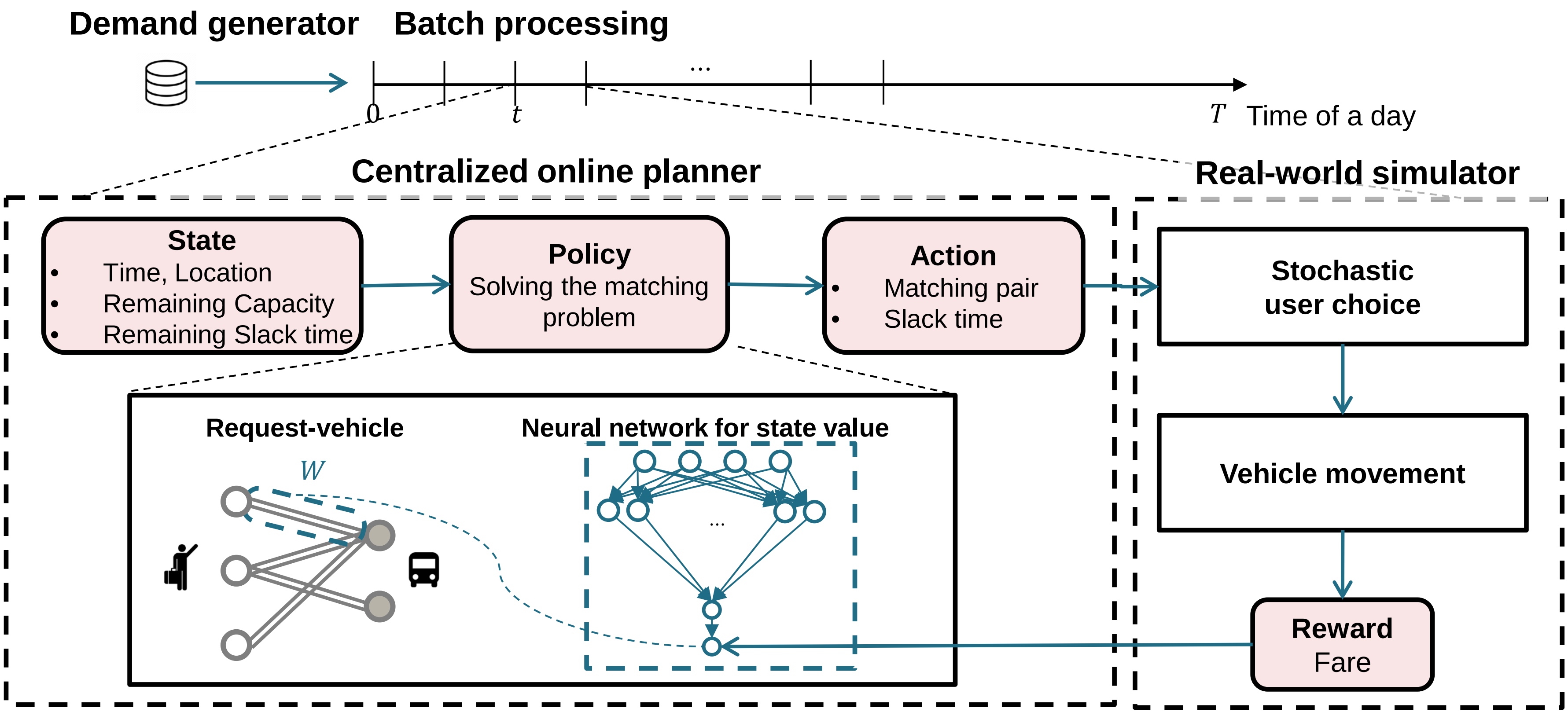


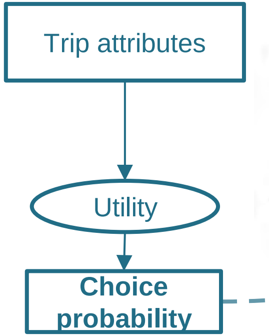


Questions?

Appendix: Markov Decision Process



Appendix A1. Formulation for Matching Problem

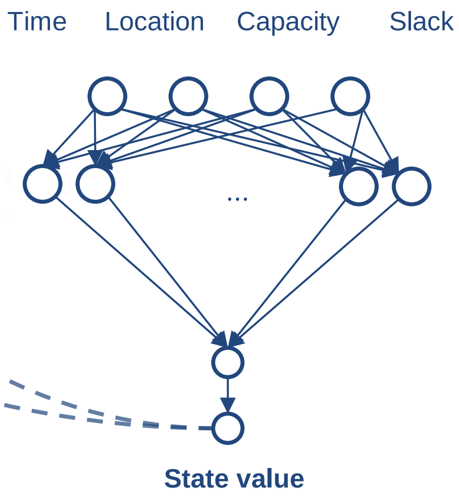


Calculate the **value of matching W**

$$\underset{e_{ijd}}{\text{argmax}} \sum_{d\in\mathcal{D}}\sum_{i\in\hat{\mathcal{R}}_t,}\sum_{j\in\mathcal{V}_t}\Big[\overbrace{\underbrace{P_i(j,d)\times r_i}_{\text{expected immediate gain}} + \underbrace{\mathbb{E}_\pi[V_\pi(s^j_{t+1})]}_{\text{expected value of next state}} - \underbrace{V_\pi(s^j_t)}_{\text{current state}}}^{\text{Advantages of matching over doing nothing}}\Big] e_{ijd}$$

$$\text{s.t.} \quad \sum_{d\in\mathcal{D}}\sum_{i\in\hat{\mathcal{R}}_t} e_{ijd} \leq 1, \forall j\in\mathcal{V}_t, \quad \sum_{d\in\mathcal{D}}\sum_{j\in\mathcal{V}_t} e_{ijd} \leq 1, \forall i\in\hat{\mathcal{R}}_t$$

$e_{ijd} \in \{0,1\}$: request-vehicle-maximum detour pair



Choice modeling

Discrete optimization

Reinforcement learning

Appendix A2. Problem Complexity

Scale in New York City

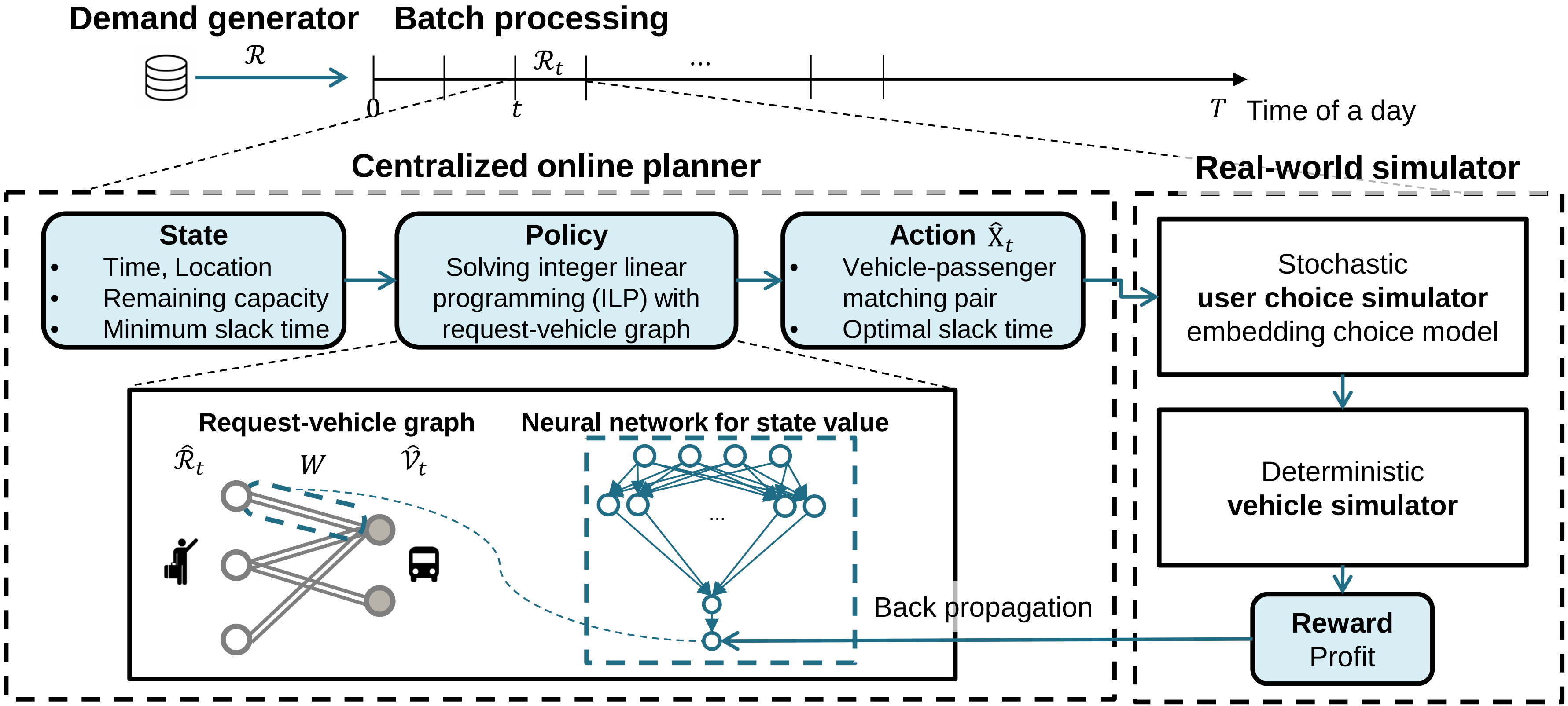
- ✓ 220,000 – 880,000 requests per day
- ✓ 100 – 300 requests per batch
- ✓ 1,000 – 3,000 vehicles
- ✓ Vehicle capacities 1 – 10

Effectiveness of algorithm

- ✓ The number of requests n
- ✓ The number of vehicles m
- ✓ Vehicle capacity c
- ✓ The number of variables: $O(mn^c)$ but much lower in practice
- ✓ The number of constraints: $O(n+m)$

[Alonso-Mora et al., 2017]

Appendix A3. Reinforcement Learning



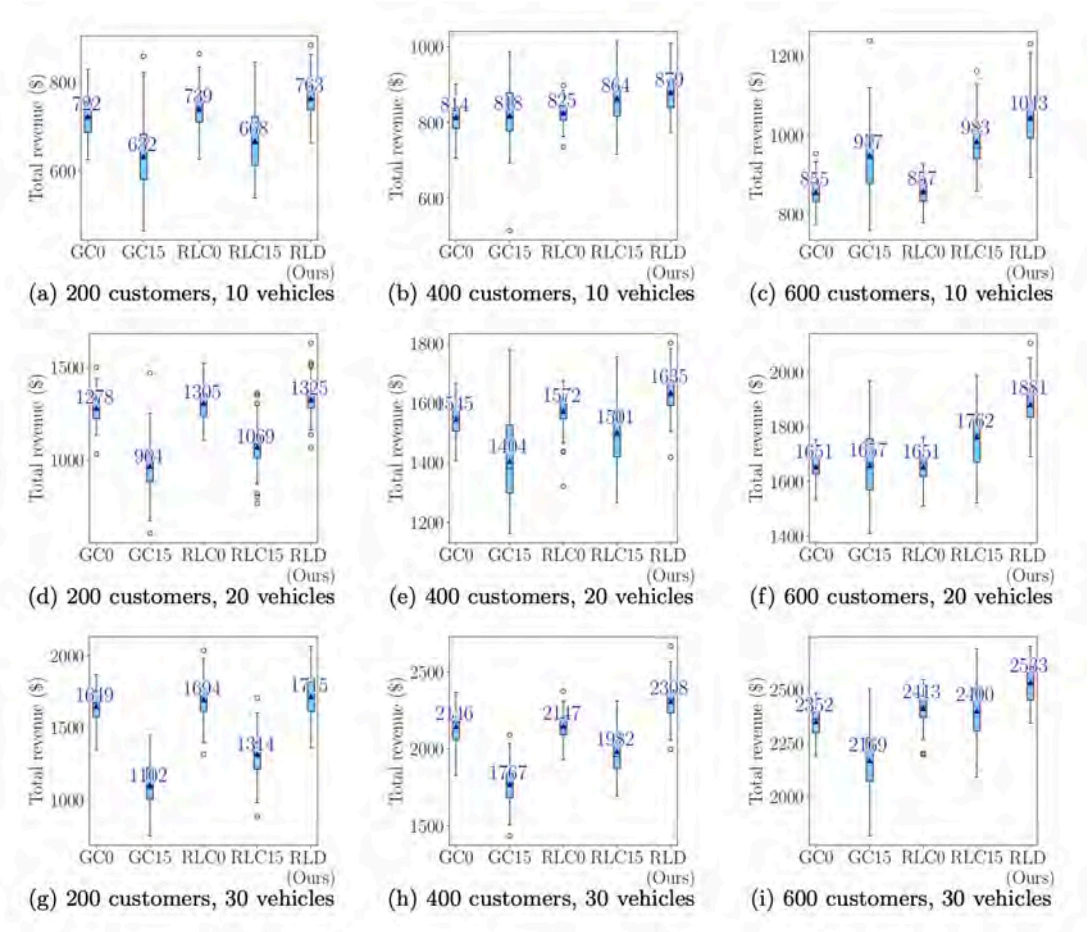
Appendix A4. Choice Model

Binary choice model to measure the willingness to adopt a service

$$P_i = P(U_i^{pooling} \geq U_i^{taxi}) = P(V_i^{pooling} - V_i^{taxi} \geq \varepsilon)$$
$$= \frac{\exp((t_i^{pooling} - t_i^{taxi})\beta^{vot} + (r_i^{pooling} - r_i^{taxi}))}{1 + \exp((t_i^{pooling} - t_i^{taxi})\beta^{vot} + (r_i^{pooling} - r_i^{taxi}))}$$

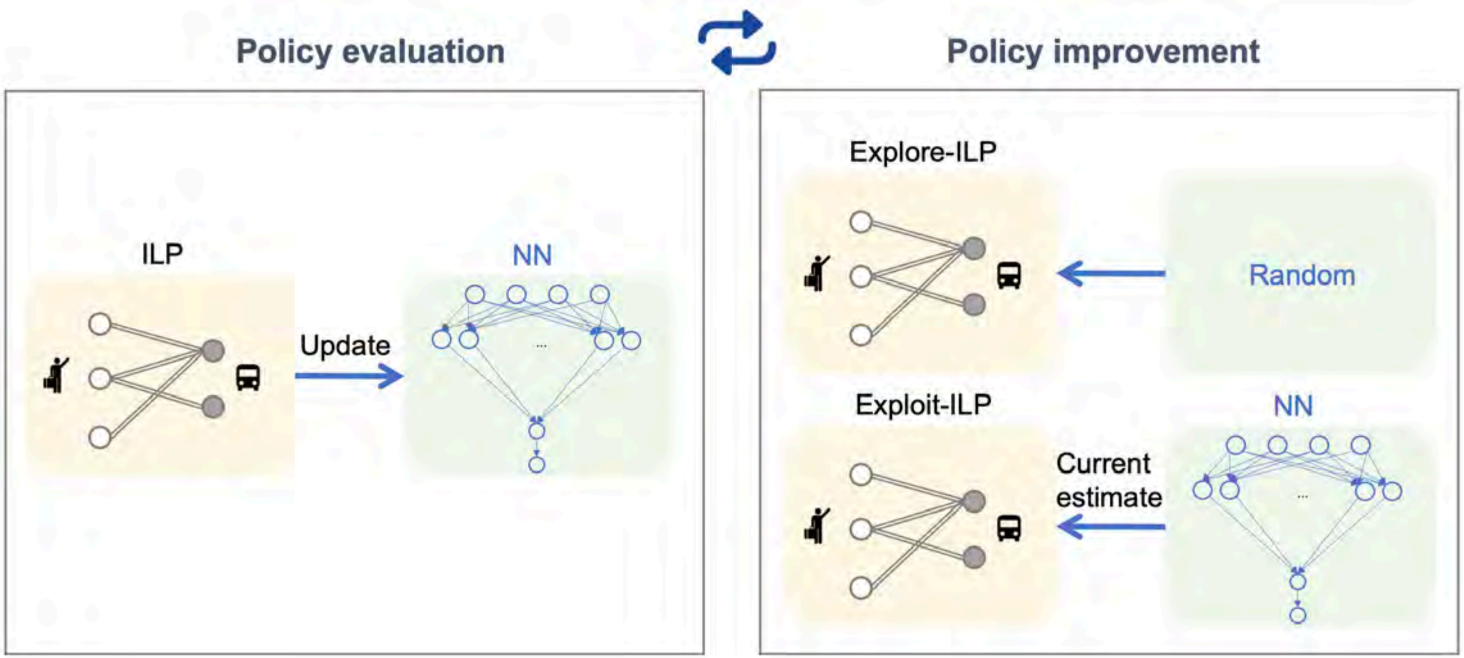
$$y_i = \begin{cases} 1 & \text{with probability } P_i \\ 0 & \text{with probability } P_i - 1 \end{cases}$$

Appendix A5. Experiment Results



(a) 200 customers, 10 vehicles
(b) 400 customers, 10 vehicles
(c) 600 customers, 10 vehicles
(d) 200 customers, 20 vehicles
(e) 400 customers, 20 vehicles
(f) 600 customers, 20 vehicles
(g) 200 customers, 30 vehicles
(h) 400 customers, 30 vehicles
(i) 600 customers, 30 vehicles

Appendix A6. Policy Iteration



Appendix B1. Equivalent Transformation

(P)

$$\max_{[\pi^j_{st}]_{j\in J, st\in\Omega}} \sum_{st\in\Omega}\sum_{j\in J} d_{st}\theta^j_{st}\pi^j_{st} - q^j_{st}$$

Price

$$\text{s.t.} \quad \theta^j_{st} = f([\pi^j_{st}]_{j\in J}), \forall st \in \Omega$$

Non-linear function

Flow conservation

(Q)

$$\max_{[\theta^j_{st}]_{j\in J, st\in\Omega}} \sum_{st\in\Omega}\sum_{j\in J} d_{st}\theta^j_{st} f^{-1}([\theta^j_{st}]_{j\in J}) - q^j_{st}$$

Choice Prob

Convex

s.t. Flow conservation

Decision variables

π^j_{st}: Price of mode j from st pair

θ^j_{st}: Probability of traveler in st pair choosing mode j

Appendix B2. Convex Program

The equivalent problem is a convex program

$$(Q) = \min_{\theta^j_{st}, z^j_{r,st}, y^j_{a,st}} \sum_{s,t\in N}\sum_{j\in J}\left(\frac{d_{st}}{p}\left[\underbrace{\theta^j_{st}\left(-ASC^j_{st}+T^j_{st}+V^n_{st}\right)}_{(\mathrm{A})^j_{st}} \right.\right.$$
$$\underbrace{+\sum_{r\in\mathcal{R}_{st}}\sum_{a\in A} z^j_{r,st}F_a(f_a)\delta_{ar}}_{(\mathrm{A})^j_{st}}$$
$$\left.\underbrace{+\theta^j_{st}\ln\theta^j_{st}}_{(\mathrm{B})^j_{st}} \underbrace{-\theta^j_{st}\ln\left(1-\sum_{j'\in J}\theta^{j'}_{st}\right)}_{(\mathrm{C})^j_{st}}\right]$$
$$\left.\underbrace{+\sum_{a\in A}[G_a(f_a)+c^j_a]y^j_{a,st}}_{(\mathrm{D})^j_{st}}\right)$$

subject to

$$[o^j_{st}]: \sum_{r\in\mathcal{R}_{st}} z^j_{r,st} = \theta^j_{st} \quad \forall j\in J\ \forall s,t\in N$$
$$[m_{st}]: \sum_{j\in J}\theta^j_{st} \le 1 \quad \forall s,t\in N$$
$$[\alpha^j_{a,st}]: \sum_{r\in\mathcal{R}_{st}} d_{st}\delta_{ar}z^j_{r,st} \le y^j_{a,st} \quad \forall a\in A\ \forall j\in J\ \forall s,t\in N$$
$$f_a = \sum_{s,t\in N}\sum_{j\in J} y^j_{a,st} \quad \forall a\in A$$
$$[\beta^j_u]: \sum_{a\in\delta^+(u)}\sum_{s,t\in N} y^j_{a,st} = \sum_{a\in\delta^-(u)}\sum_{s,t\in N} y^j_{a,st} \quad \forall u\in N\ \forall j\in J$$
$$[\rho^j_{r,st}]: z^j_{r,st}\ge 0 \quad \forall j\in J\ \forall s,t\in N\ \forall r\in\mathcal{R}_{st}$$
$$\theta^j_{st}\ free \quad \forall j\in J\ \forall s,t\in N$$
$$y^j_{a,st}\ free \quad \forall a\in A\ \forall j\in J\ \forall s,t\in N.$$

Convex objective function

Linear constraints

Appendix C1. Literature for Convex Combine Models

	Trip generation	Trip distribution (Gravity model)	Modal split (Multinomial logit model)	Traffic assignment (Wardrop user equilibrium)
Framework	**Utility**	**Entropy**	**Satisfaction**	**Beckmann**
Wilson (*10*)		O		
Anas (*14*)			O	
Beckmann et al. (*15*)				O
Evans (*16*)		O		O
Florian et al. (*17*)		O		O
Oppenheim (*18*)		O		O
Florian (*19*)			O	O
Abdulaal and LeBlanc (*20*)			O	O
Fernández et al. (*21*)			O	O
García and Marín (*22*)			O	O
Florian and Nguyen (*23*)		O	O	O
Friesz (*24*)		O	O	O
Safwat and Magnanti (*25*)	O	O	O	O
Framework	**Utility maximization**			
Oppenheim et al. (*5*)	O	O	O	O
Yao et al. (*6*)	O	O		O
Zhou et al. (*7*)	O	O	O	O
Ours	**O**	**O**	**O**	**O**

Gaps

Parameter estimation

Tractability & scalability

Assumption 1.

The road latency function g_a^m is an increasing power function.

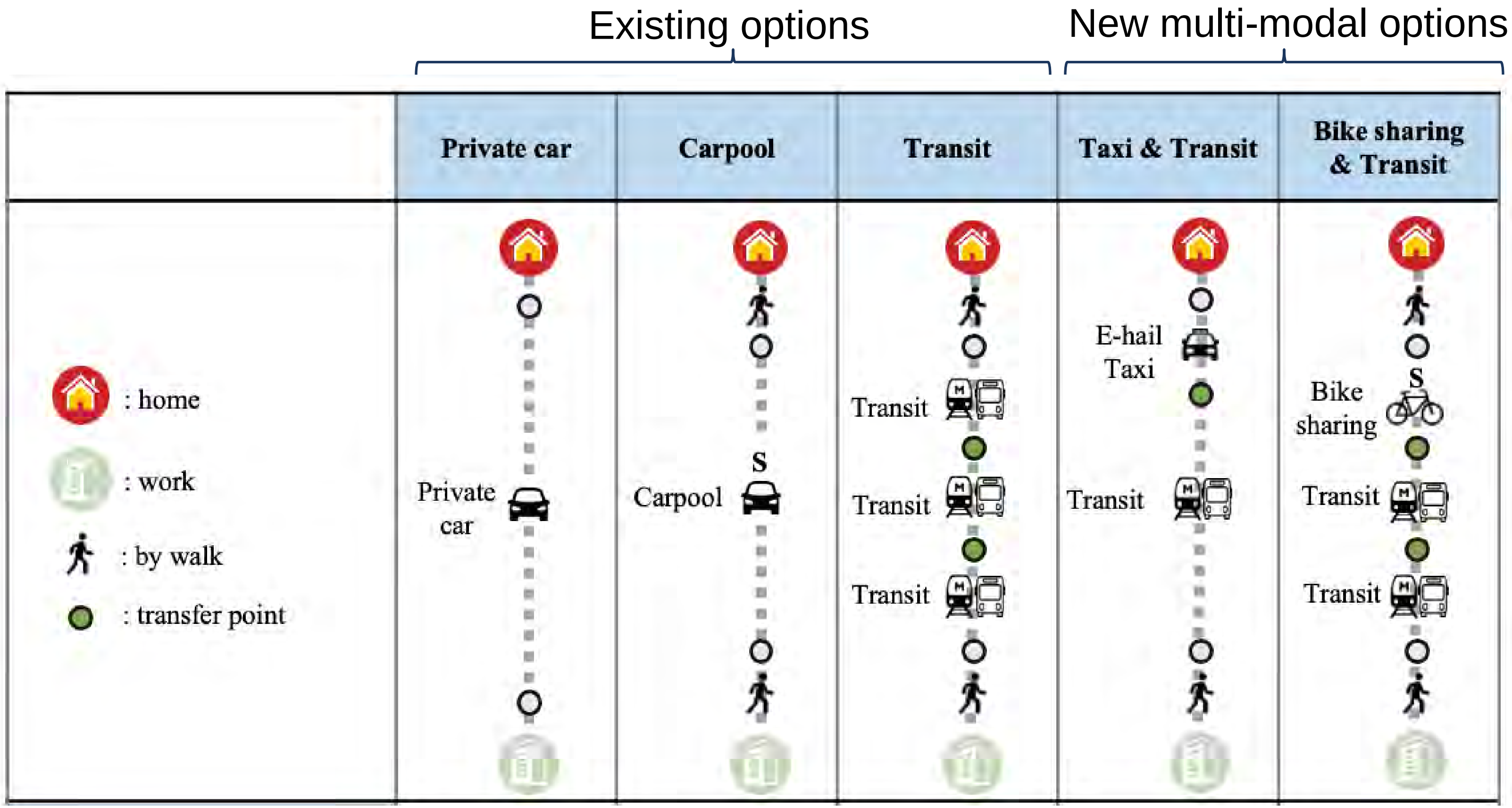
e.g., BPR function $$g_a^m(f_a^m) = T_a^{m,0}\left[1 + \alpha^m \left(\frac{f_a^m}{c_a^m}\right)^{\beta^m}\right]$$

$$H_{\text{MNL}}(\mathbf{p}_{\mathcal{J}|\mathcal{I}}) = -\sum_{i\in\mathcal{I},j\in\mathcal{J}} p_{ij}\ln\left(\frac{p_{ij}}{\widehat{p}_i}\right)$$

$$\begin{aligned} H_{\text{NL}}(\mathbf{p}_{\mathcal{M}|\mathcal{I}\mathcal{J}}) &= H_{\text{NL}_1}(\mathbf{p}_{\mathcal{I}\mathcal{J}\Pi(\mathcal{M})}|\mathbf{p}_{\mathcal{I}\mathcal{J}}) + \sum_{\mathcal{N}\in\Pi(\mathcal{M})} H_{\text{NL}_\mathcal{N}}(\mathbf{p}_{\mathcal{I}\mathcal{J}\mathcal{M}}|\mathbf{p}_{\mathcal{I}\mathcal{J}\mathcal{N}}) \\ &= -\sum_{i\in\mathcal{I},j\in\mathcal{J}}\sum_{\mathcal{N}\in\Pi(\mathcal{M})} p_{ij\mathcal{N}}\ln\left(\frac{p_{ij\mathcal{N}}}{p_{ij}}\right) - \sum_{\mathcal{N}\in\Pi(\mathcal{M})}\sum_{i\in\mathcal{I},j\in\mathcal{J}}\sum_{m\in\mathcal{N}} p_{ijm}\ln\left(\frac{p_{ijm}}{p_{ij\mathcal{N}}}\right) \end{aligned}$$

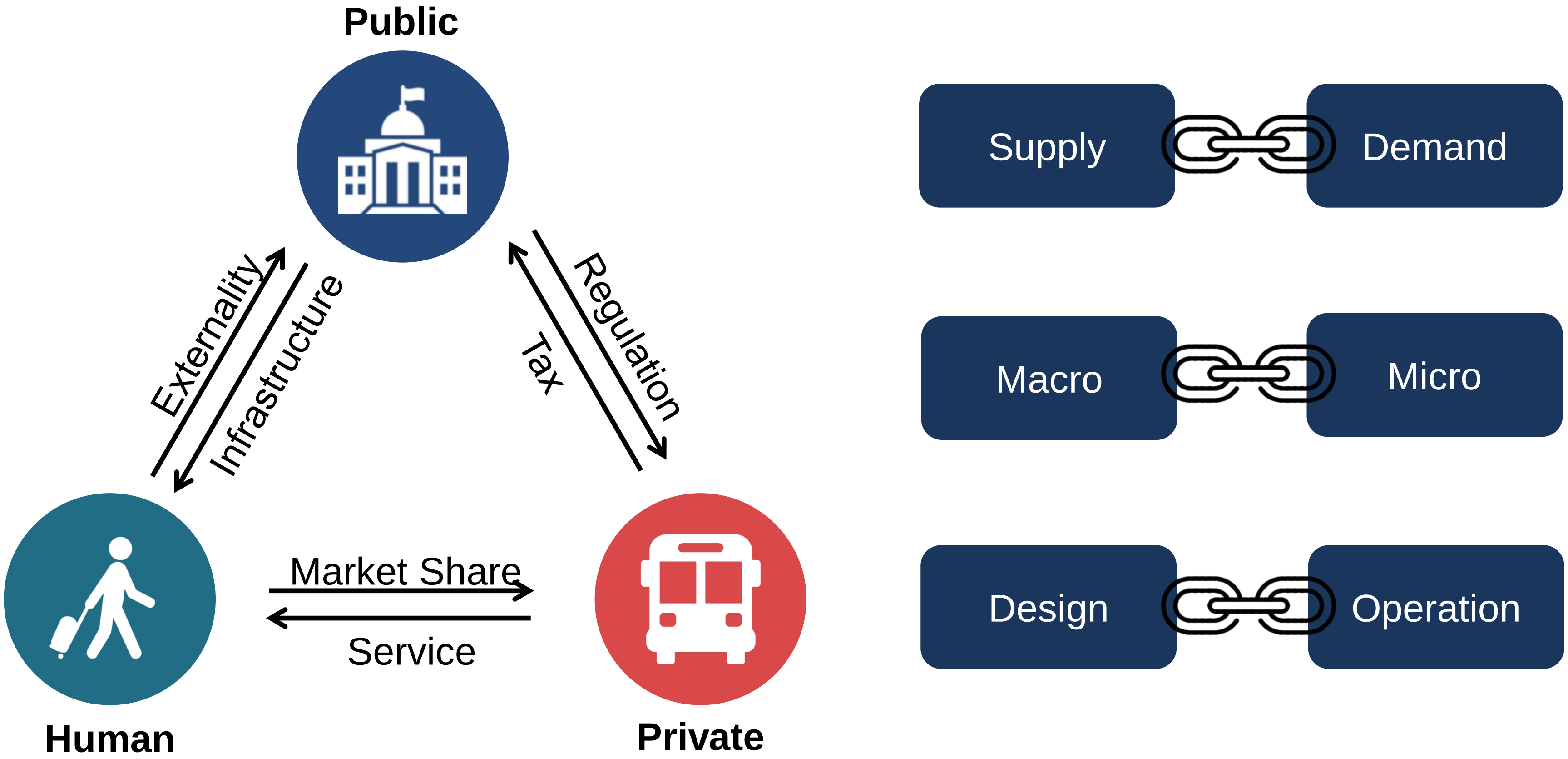
$$H_{\text{PSL}}(\mathbf{p}_{\mathcal{R}|\mathcal{I}\mathcal{J}\mathcal{M}}) = -\sum_{i\in\mathcal{I},j\in\mathcal{J}}\sum_{m\in\mathcal{M},r\in\mathcal{R}} p_{ijmr}\ln\left(\frac{p_{ijmr}}{p_{ijm}}\cdot\frac{1}{\overline{\psi}_{ijmr}}\right)$$

Appendix D1. Survey Design



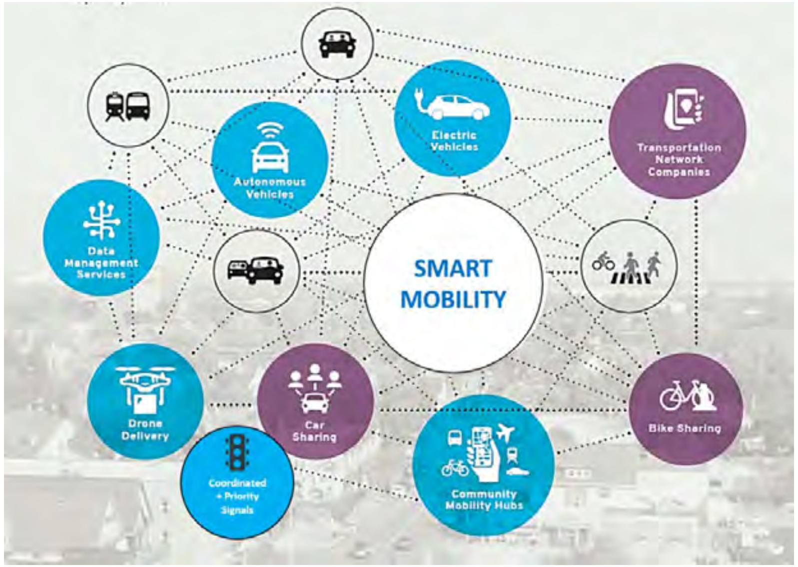
YK et al., 2021 E. Kim, **YK** et al., 2021

Ultimate Goal: Integrated and Automated Decision Making



Automated Decision Making Beyond Smart Mobility

Smart Mobility System



…and Beyond!

Supply chain management

Energy grids

Water resources

Urban infrastructure