DENSO
Crafting the Core

Route Optimization for Multimodal Transport Systems

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DENSO × QUANTUM 3

WASEDA University

DENSO Future direction

Crafting the Core— Crafting a new core with our technologies in anticipation of change

Due to companies from other industries entering the market and fierce technological competition, the automotive industry is currently approaching a paradigm shift, which is said to occur once every 100 years. Fully understanding the wave of changes that it faces, DENSO will clear the way for a new motorized society by enhancing and evolving its technologies.

DENSO Efficient Driving

DENSO envisions a future in which mobility is more efficient and driving is more fun. We are developing electrified technologies for a wide range of vehicles, from gasoline and diesel vehicles to HEV, PHEV, EV and FCV, to improve efficiency with better management of electric, kinetic and heat power. By predicting road conditions and charting the best course, our goal is to reduce energy loss, so people can drive as they wish while also being environmentally friendly.

DENSO Connected Driving

DENSO envisions a future in which mobility is connected inside and outside of the vehicle, including cars, people and infrastructure, as well as new services. It brings us new experiences for traveling, and helps us develop automated driving systems that are more convenient and comfortable yet extremely energy efficient. Of course, security issues have emerged from connectivity, such as hackers and data leaks, but with an unwavering focus on safety, DENSO will help protect people and cars.

DENSO Automated Driving

DENSO envisions a future in which everyone can travel freely and safely, regardless of their age or physical condition. That's why DENSO is deeply focused on advances in safety and security. Our goal is to evolve our sensing, information & communication and AI technologies to eliminate limitations to mobility.

Our direction

Quantum technology creates new era of
Mobility, Factory and Society IoT!!

Team & projects

Mobility IoT

This talk

Multi modal sharing service


WASEDA University

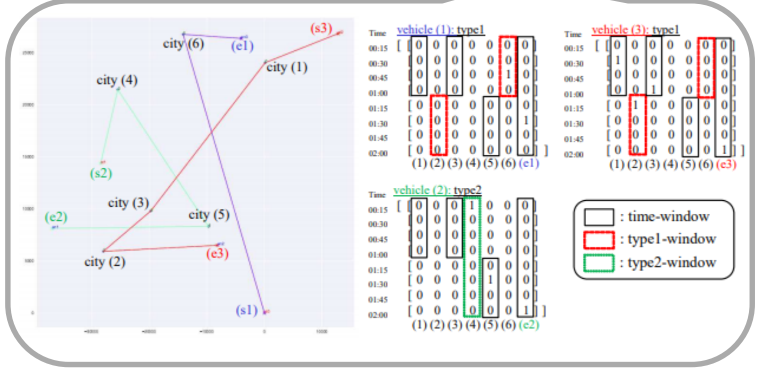
Akira Miki Shu Tanaka

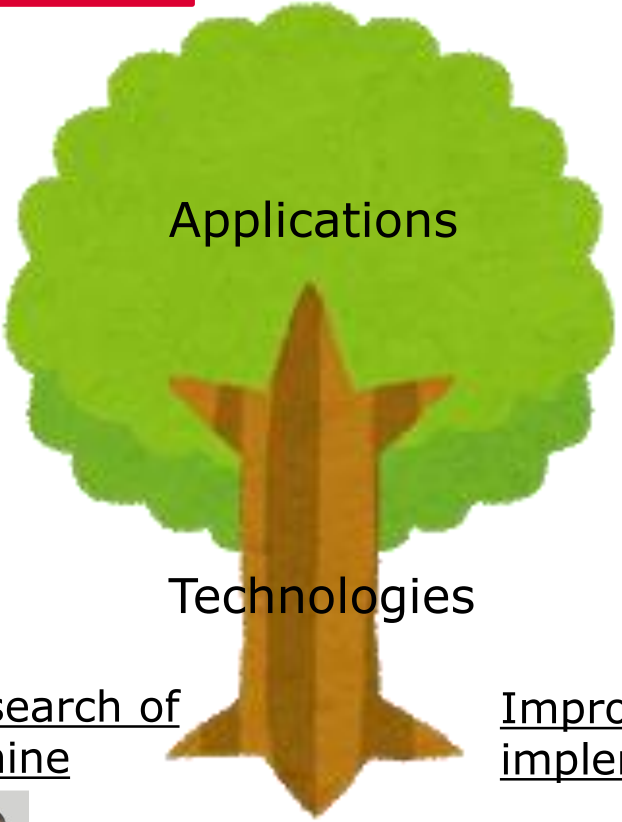
Delivery service etc. in Thailand


TOYOTA TSUSHO

Hirotaka Irie Toru Awashima

arXiv: 1903.06322





Factory IoT

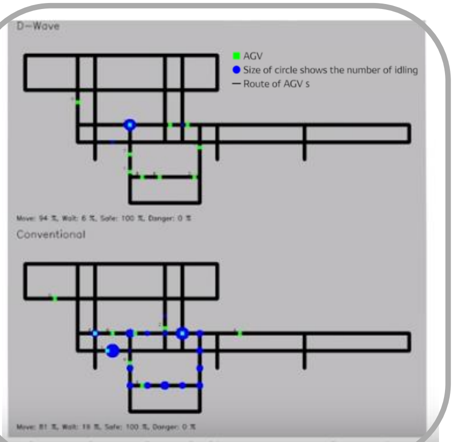
Multi robot control


TOHOKU UNIVERSITY

Akira Miki Masayuki Ohzeki

arXiv: 1812.01532

https://www.youtube.com/watch?v=4zW3_lhRYDc



Basic research of QA machine

Tadashi Kadowaki

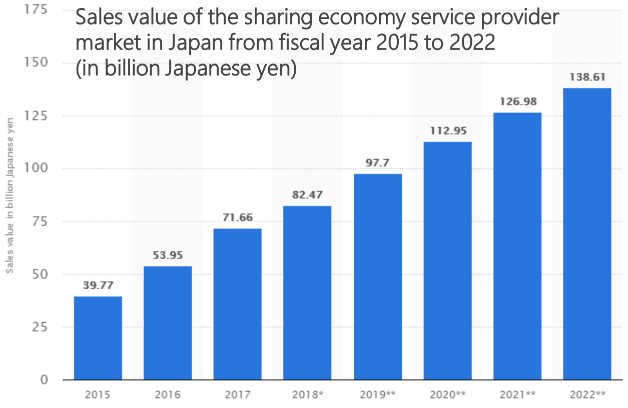
Improvement of implementation efficiency

Shuntaro Okada

Okada's talk (tomorrow)

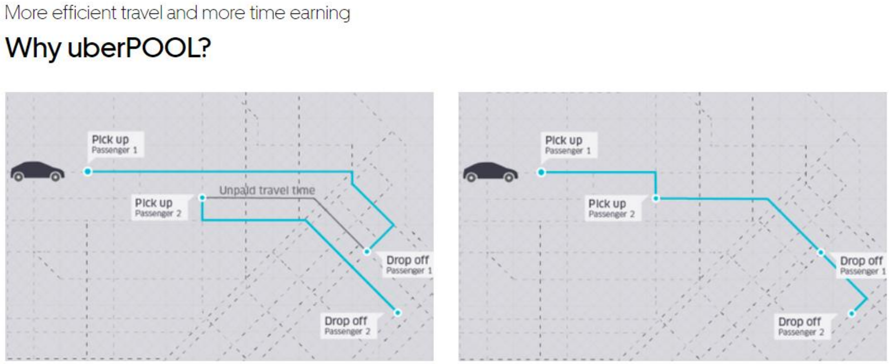
Motivation

Sharing economy is one of the market with growth potential



https://www.statista.com/statistics/795505/japan-sharing-economy-market-size/

Sharing economy with transport system like Uber becomes



https://www.uber.com/ride/express-pool/

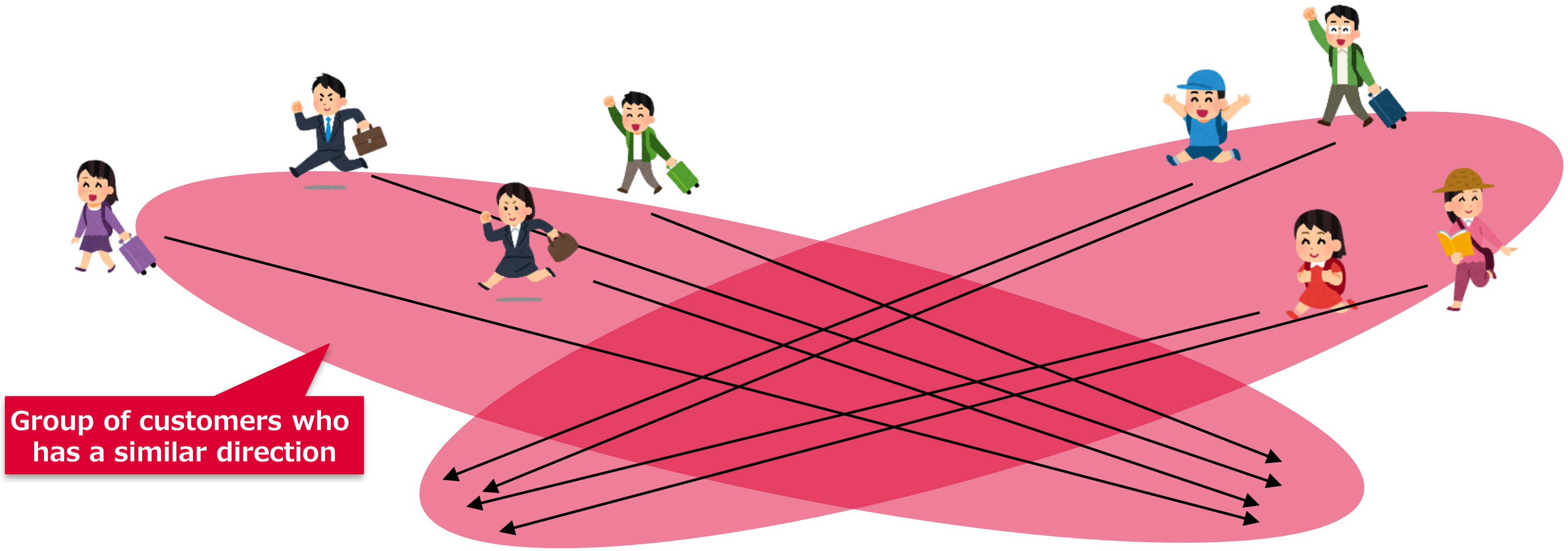
We would propose optimization of advanced transport system with sharing

Current : ride-sharing

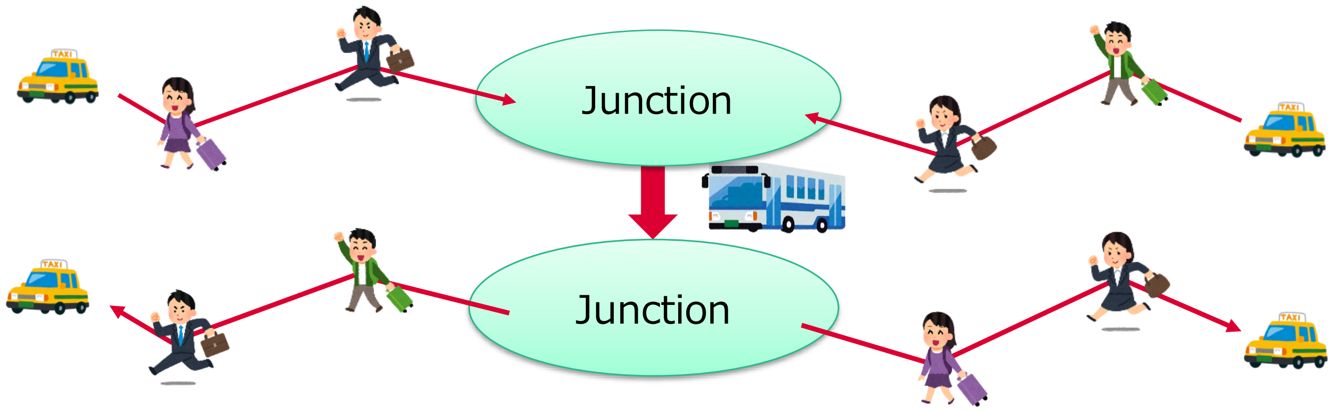
Future : multi modal sharing

System overview

1. Clustering group of customers by digital computer

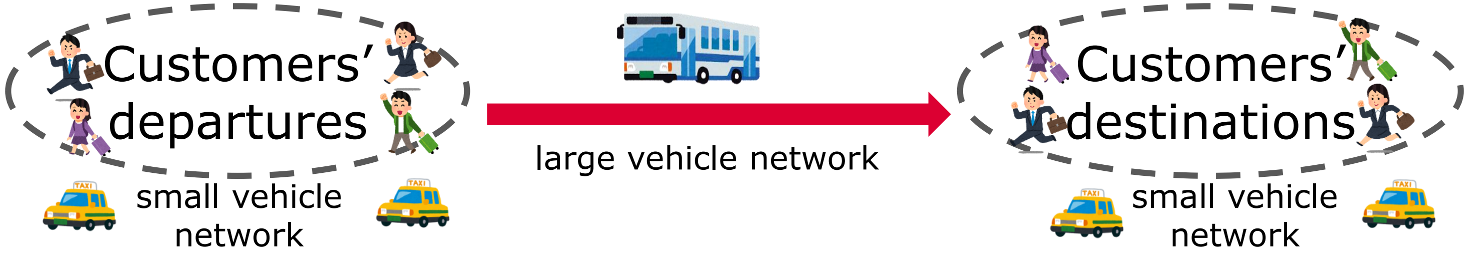


2. Route optimization of multimodal transport system

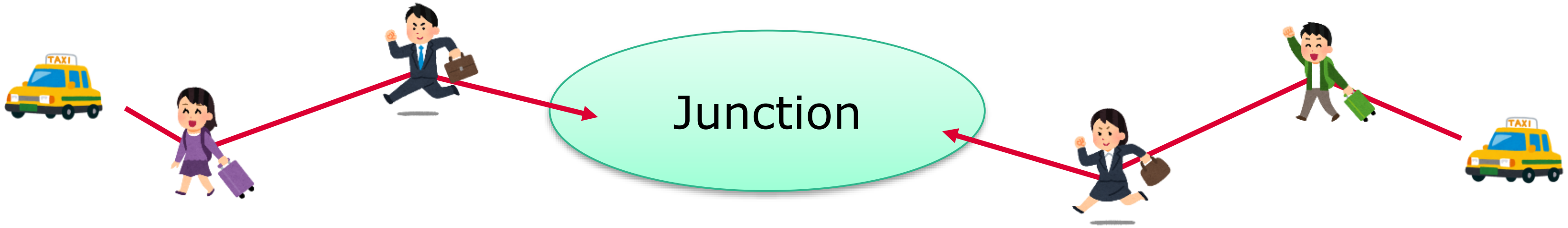


Optimization of multi modal sharing

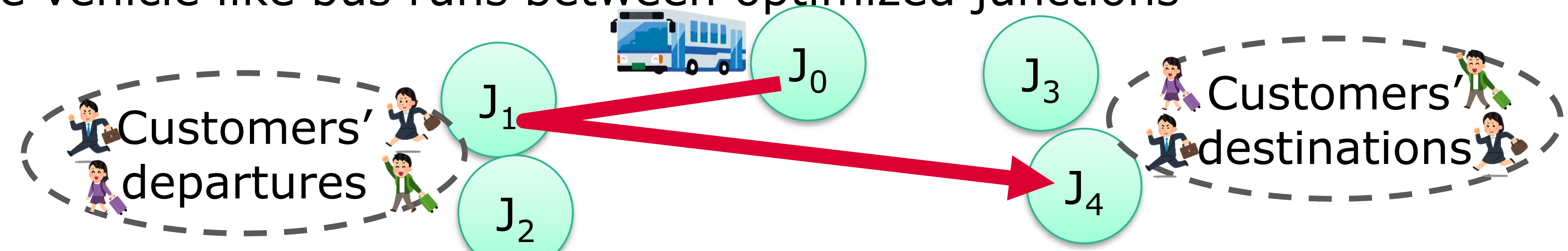
1. All customers have similar directions of departure and destination



2. Each small vehicle like taxi makes a route for customers and an optimized meeting point (junction) of large vehicle (VRP)



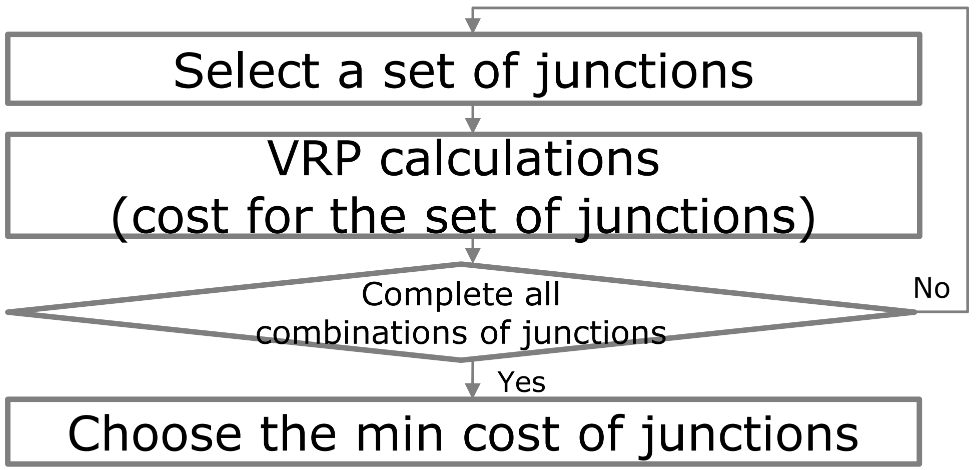
3. Large vehicle like bus runs between optimized junctions



4. Each small vehicle make a route from an optimized junction and customer destinations (VRP)

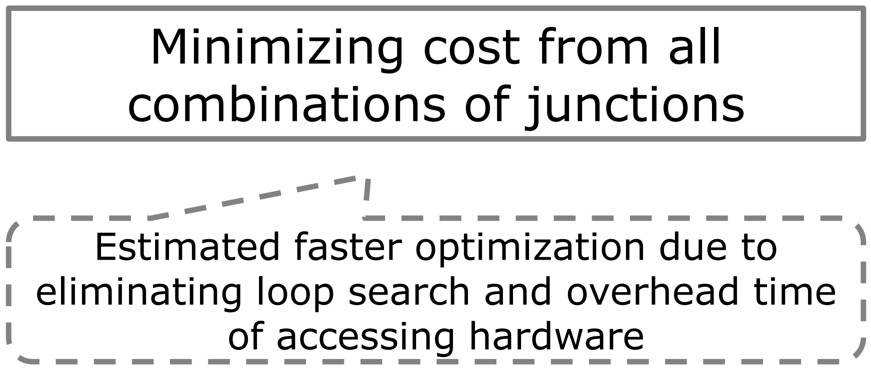
Our formulation of the optimization

- Conventional method (VRP iterations: linear programming (LP))



- Optimized by linear programming solver
  - Gurobi

- Proposed method (QUBO / quadratic programming (QP))



- Optimized by quadratic programming solver
  - Gurobi
- Ising model hardware
  - D-Wave

Benchmarking D-Wave with proprietary solver Gurobi

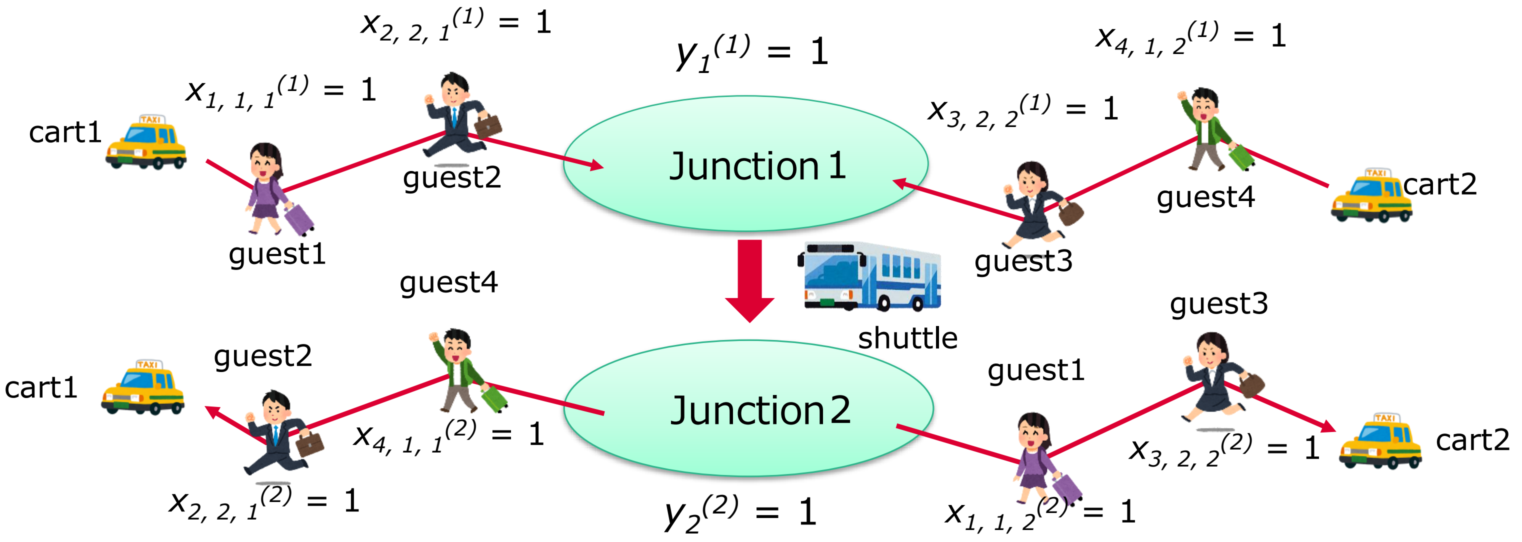
Decision Variables for QUBO formulation

- x variables for carts: $x_{g,t,c}^{(1)}$: pick up, $x_{g,t,c}^{(2)}$: drop off

$$x^{(1)}_{g,t,c} \begin{cases} 1\text{: pick up / drop off guest g at time t for cart c} \\ 0\text{: not pick up / drop off guest g at time t for cart c} \end{cases}$$

- y variables for shuttle: $y_j^{(1)}$: pick up, $y_j^{(2)}$: drop off

$$y_j^{(1)} \begin{cases} 1\text{: stop j junction for picking up / dropping off guests} \\ 0\text{: not stop j junction for picking up / dropping off guests} \end{cases}$$

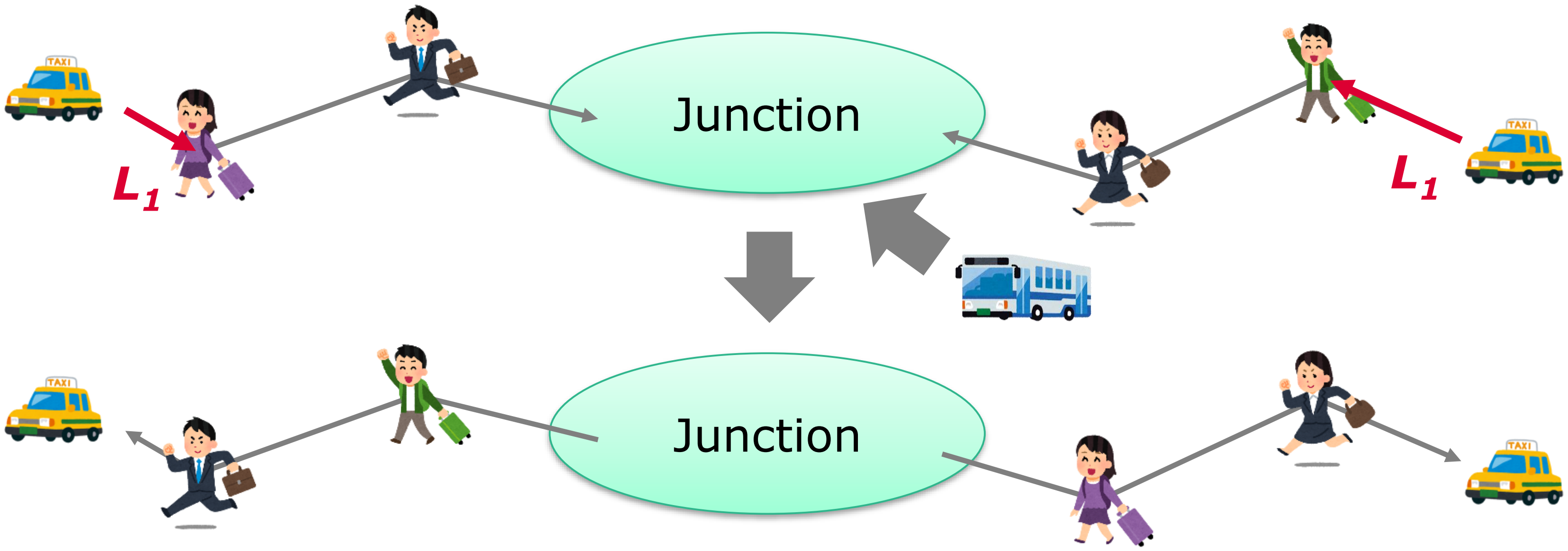


Objectives for QUBO formulation (1/6)

$$L_1 = \sum_{c=1}^{C} \sum_{g=1}^{G} \ell_{j_g,g} x^{(1)}_{g,1,c}$$

j_g: nearest junction from guest g

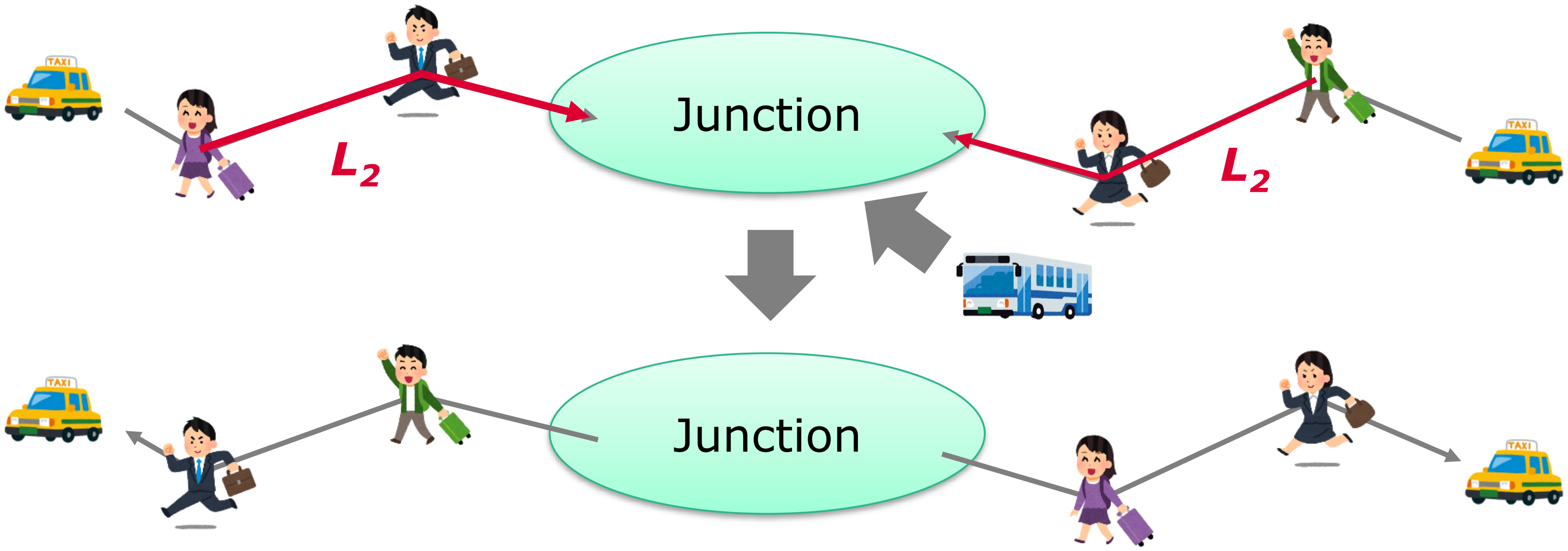
Cost (distance) from start position of cart to first guest position



Objectives for QUBO formulation (2/6)

$$L_2 = \sum_{c=1}^{C}\sum_{t=1}^{T-1}\sum_{g_2=1}^{G}\sum_{g_1=1}^{G} \ell_{g_1,g_2} x^{(1)}_{g_1,t,c} x^{(1)}_{g_2,t+1,c} + \sum_{c=1}^{C}\sum_{j=1}^{J}\sum_{g=1}^{G} \ell_{g,j} x^{(1)}_{g,T,c} y^{(1)}_{j}$$

Cost (distance) from first guest position to last guest position and from last guest position to junction of shuttle coming

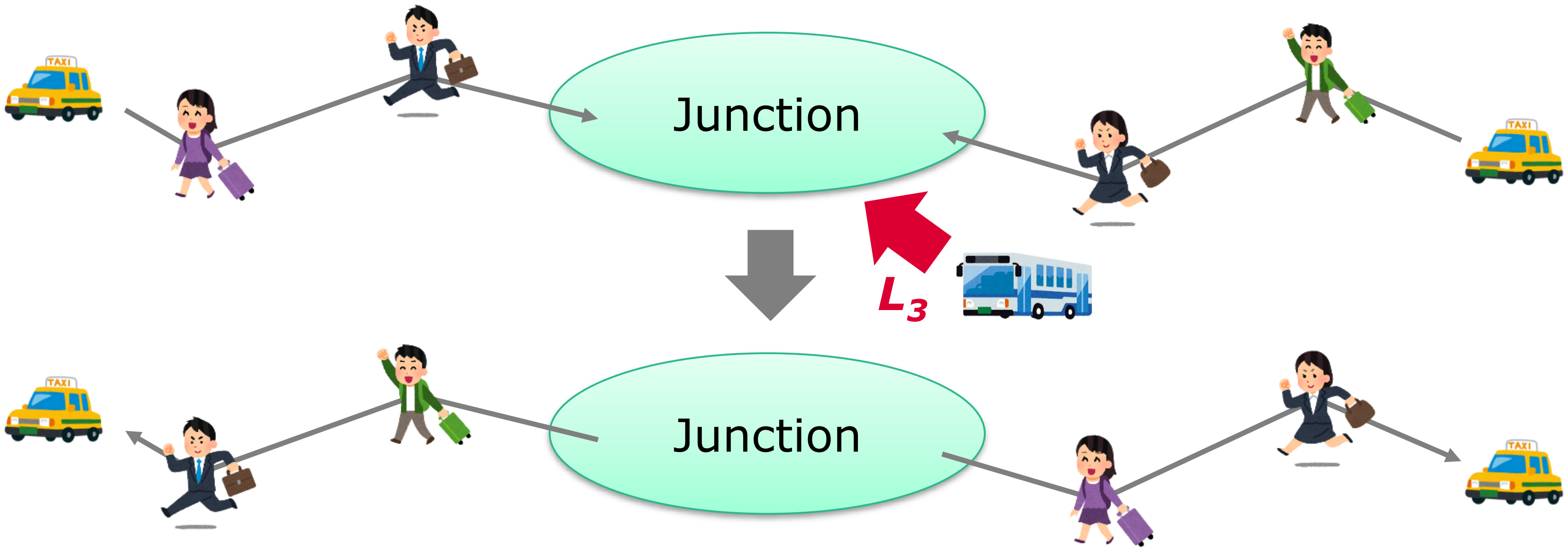


Objectives for QUBO formulation (3/6)

$$L_3 = \sum_{j=1}^{J} \ell_{j_s,j} y_j^{(1)}$$

j_s: junction of initial shuttle position

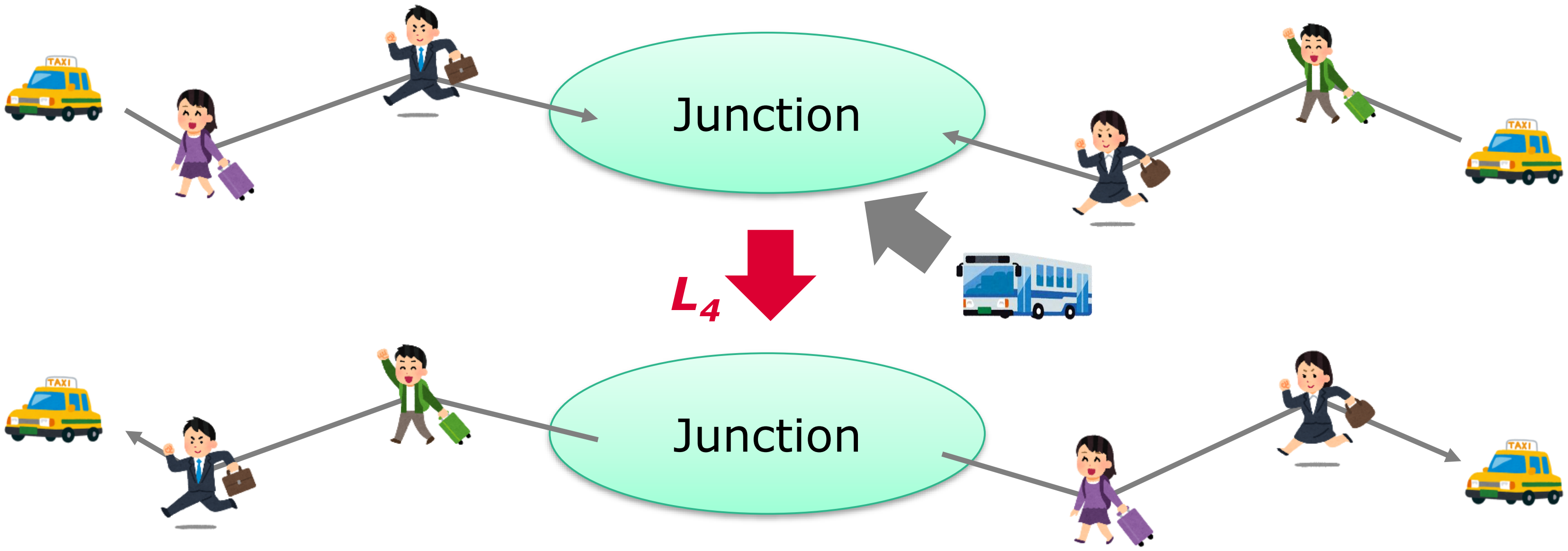
Cost (distance) from start position of shuttle to junction of cart coming



Objectives for QUBO formulation (4/6)

$$L_4 = \sum_{j_1=1}^{J} \sum_{j_2=1}^{J} \ell_{j_1,j_2} y_{j_1}^{(1)} y_{j_2}^{(2)}$$

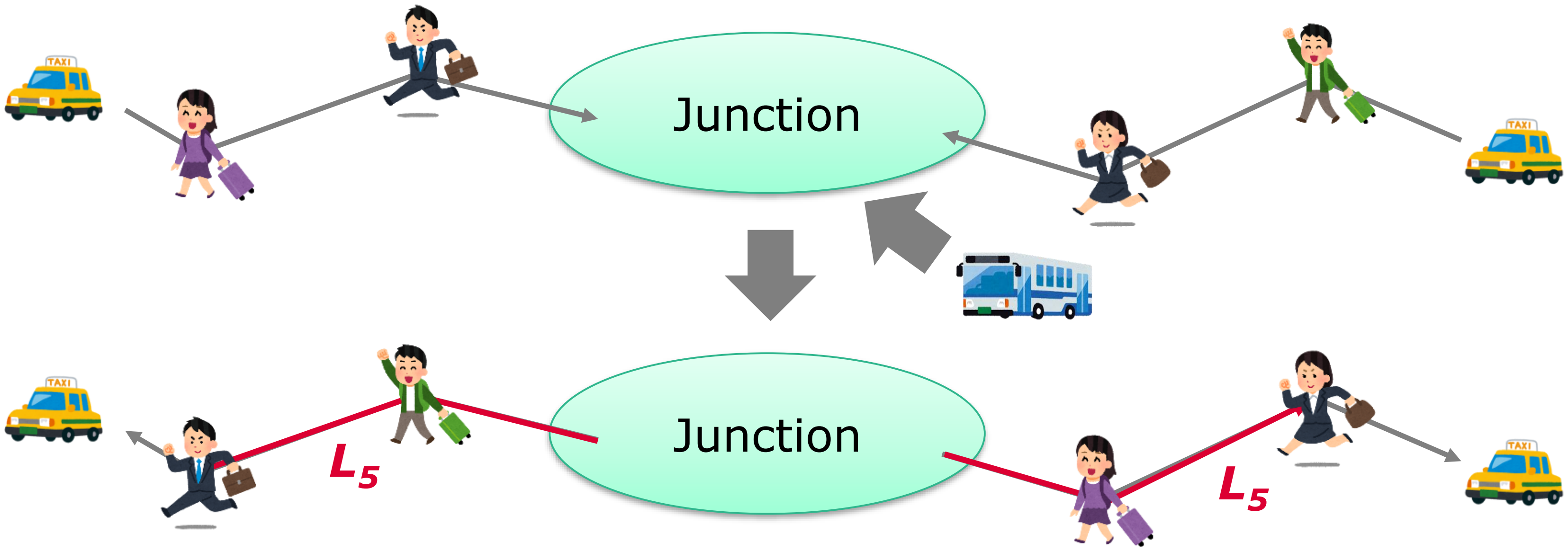
Cost (distance) between junctions of shuttle running



Objectives for QUBO formulation (5/6)

$$L_5 = \sum_{c=1}^{C}\sum_{j=1}^{J}\sum_{g=1}^{G} \ell_{j,g}\, y_j^{(2)} x_{g,1,c}^{(2)} + \sum_{c=1}^{C}\sum_{t=1}^{T-1}\sum_{g_2=1}^{G}\sum_{g_1=1}^{G} \ell_{g_1,g_2}\, x_{g_1,t,c}^{(2)} x_{g_2,t+1,c}^{(2)}$$

Cost (distance) from junction to first guest position and from first guest position to last guest position

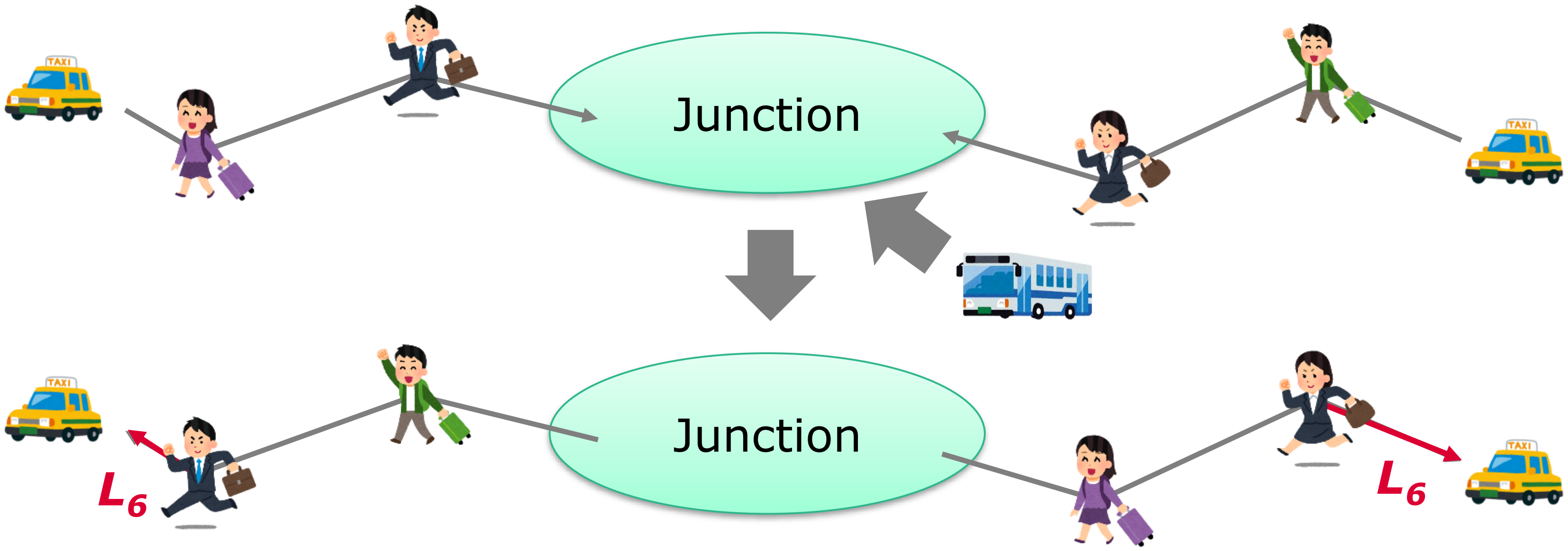


Objectives for QUBO formulation (6/6)

$$L_6 = \sum_{c=1}^{C} \sum_{g=1}^{G} \ell_{j_g,g} x^{(2)}_{g,T,c}$$

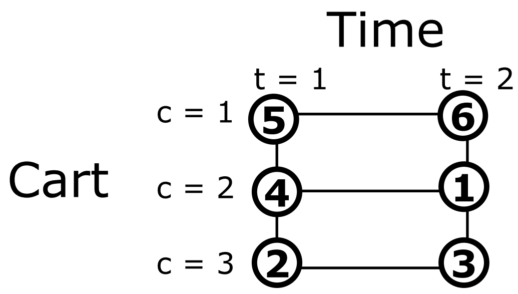
j_g: nearest junction from guest g

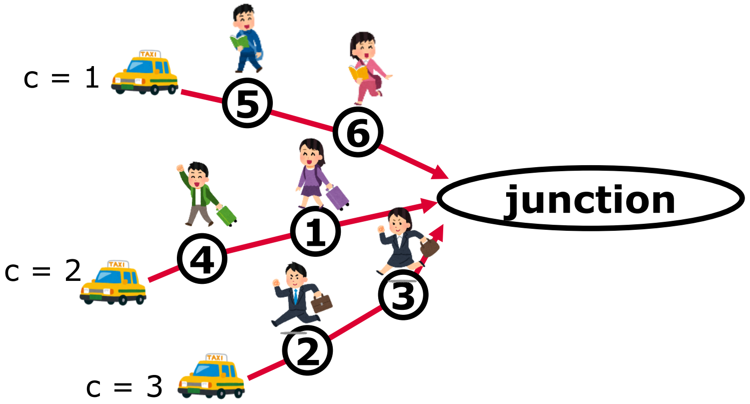
Cost (distance) from last guest position to end position of cart



Constraints for QUBO formulation (1/3)

Constraint rule 1: each time and cart have each one guest pick up or drop off by cart





For pick up

$$\lambda_g \sum_{c=1}^{C} \sum_{t=1}^{T} \left(\sum_{g=1}^{G} x_{g,t,c}^{(1)} - 1 \right)^2$$

For drop off

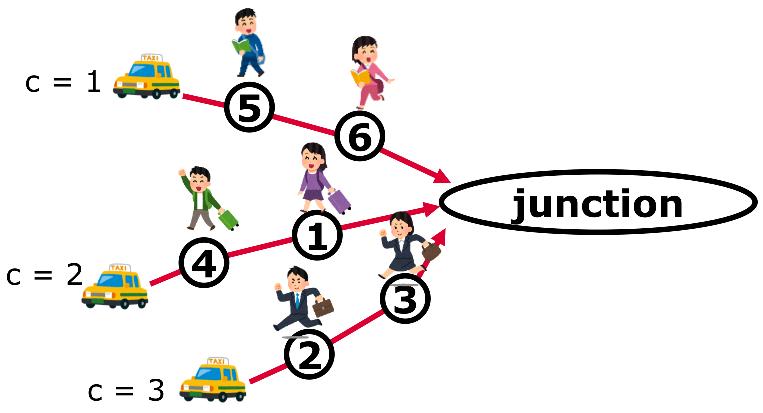
$$\lambda_g \sum_{c=1}^{C} \sum_{t=1}^{T} \left(\sum_{g=1}^{G} x_{g,t,c}^{(2)} - 1 \right)^2$$

Constraints for QUBO formulation (2/3)

Constraint rule 2: each guest has each one condition of pick up or drop off

Condition

Guest	Condition
①	c=1, t=2
②	c=3, t=1
③	c=3, t=2
④	c=2, t=1
⑤	c=1, t=1
⑥	c=1, t=2



For pick up

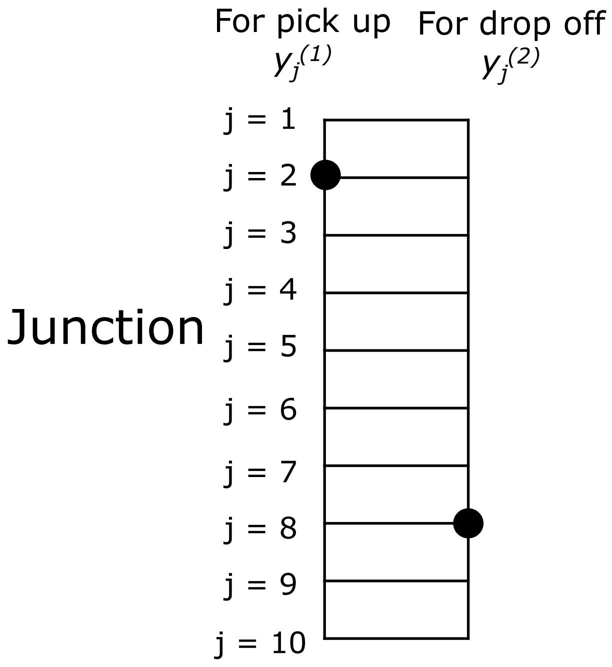
$$\lambda_{tc} \sum_{g=1}^{G} \left(\sum_{c=1}^{C} \sum_{t=1}^{T} x_{g,t,c}^{(1)} - 1 \right)^2$$

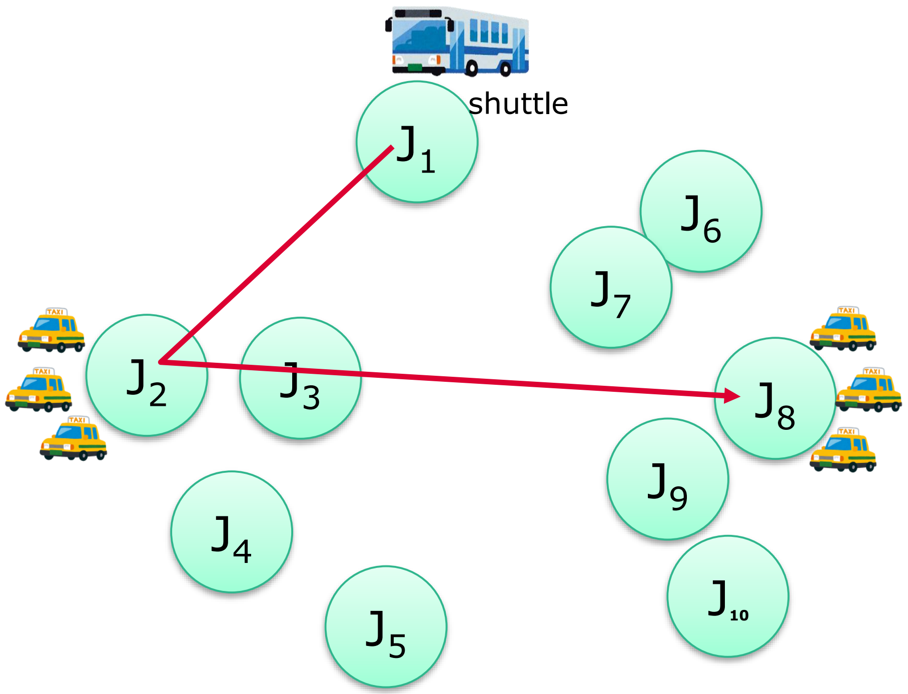
For drop off

$$\lambda_{tc} \sum_{g=1}^{G} \left(\sum_{c=1}^{C} \sum_{t=1}^{T} x_{g,t,c}^{(2)} - 1 \right)^2$$

Constraints for QUBO formulation (3/3)

Constraint rule 3: shuttle has each one junction stop for pick up or drop off





For pick up

$$\lambda_{sh}\left(\sum_{j=1}^{J} y_j^{(1)} - 1\right)^2$$

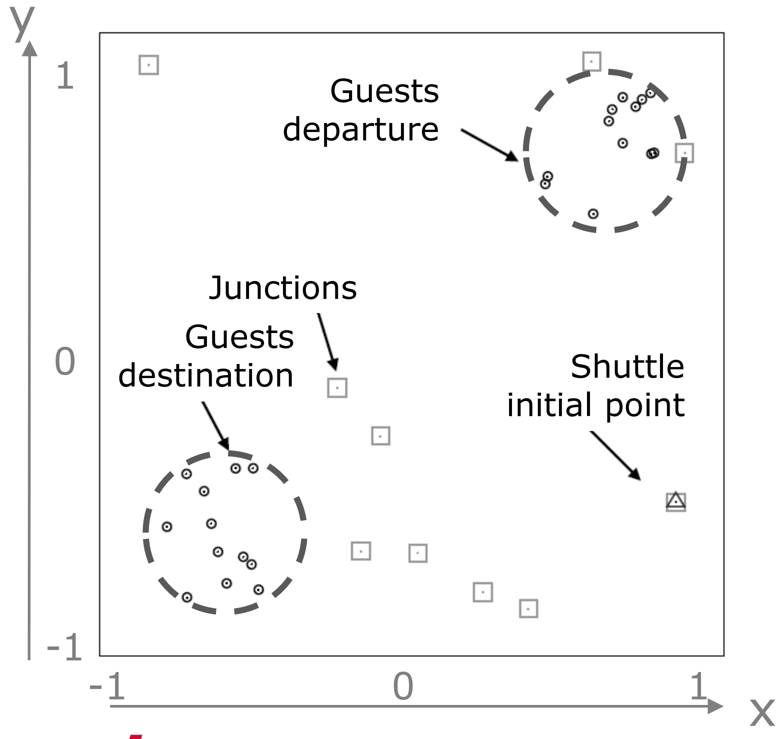
For drop off

$$\lambda_{sh}\left(\sum_{j=1}^{J} y_j^{(2)} - 1\right)^2$$

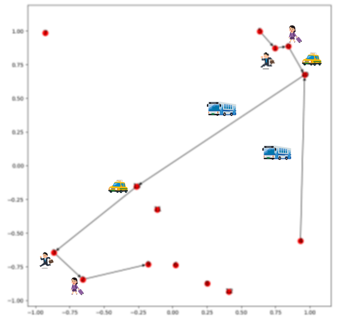
QUBO formulation and problem settings

$$H = \sum_{i=1}^{6} L_i + \lambda_g \sum_{c=1}^{C} \sum_{t=1}^{T} \left(\sum_{g=1}^{G} x_{g,t,c}^{(1)} - 1 \right)^2 + \lambda_g \sum_{c=1}^{C} \sum_{t=1}^{T} \left(\sum_{g=1}^{G} x_{g,t,c}^{(2)} - 1 \right)^2 + \lambda_{tc} \sum_{g=1}^{G} \left(\sum_{c=1}^{C} \sum_{t=1}^{T} x_{g,t,c}^{(1)} - 1 \right)^2 + \lambda_{tc} \sum_{g=1}^{G} \left(\sum_{c=1}^{C} \sum_{t=1}^{T} x_{g,t,c}^{(2)} - 1 \right)^2 + \lambda_{sh} \left(\sum_{j=1}^{J} y_j^{(1)} - 1 \right)^2 + \lambda_{sh} \left(\sum_{j=1}^{J} y_j^{(2)} - 1 \right)^2$$

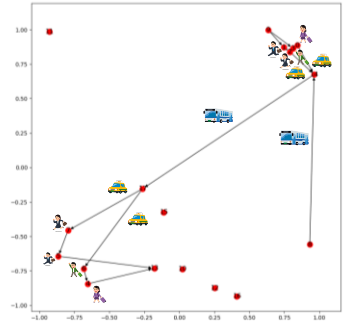
G: Num. of guests
C: Num. of carts
T: Num. of time
J: Num. of junctions



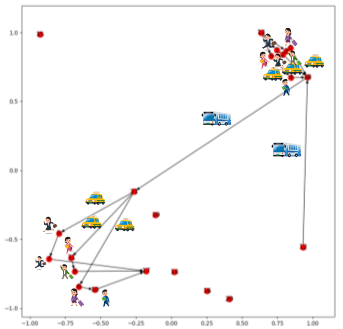
Exact solutions (G = 2, 4, 6)



G=2, C=1, T=2, J=10
Cost = 4.289,
Num. of variables = 28,
234 embedded qubits



G=4, C=2, T=2, J=10
Cost = 6.489,
Num. of variables = 52,
406 embedded qubits



G=6, C=3, T=2, J=10
Cost = 8.156,
Num. of variables = 92,
1488 embedded qubits

Gurobi : optimized within constraints space
(Gurobi version 8.10, Intel i7 4770K 32GB RAM)
D-Wave: $\lambda_g = 1.0$, $\lambda_{tc} = 1.0$, $\lambda_{sh} = 4.0$
(QUBO generation was greatly supported by PyQUBO)

Embedded h_0 normalization

Without h_0 normalization

$$H = \sum_{i=1}^{N}\sum_{j=1}^{N} Q_{ij}x_i x_j$$

$$Q_{ij} = 4 * Q_{ij}/max(abs(Q_{ij}))$$

With h_0 normalization

$$H = \sum_{i=1}^{N}\sum_{j=1}^{N} Q_{ij}x_i x_j$$

$$Q_{ij} = 4 * Q_{ij}/max(abs(Q_{ij}))$$

$$h_{0_i} = 2 * h_{0_i}/max(abs(h_i))$$

$$j_{0_{ij}} = 1 * j_{0_{ij}}/max(abs(J_{0_{ij}}))$$

h_0: embedded linear Ising coefficients.
j_0: embedded quadratic Ising coefficients

Num. of guests = 2, Num. of variables = 28

	Without h_0 normalization		With h_0 normalization	
	auto_scale=True	auto_scale=False	auto_scale=True	auto_scale=False
Percentage of exact [%]	0.95 ± 0.78	0.95 ± 0.47	29.9 ± 10.3	27.1 ± 8.95
Percentage of valid [%]	74.8 ± 6.74	64.73 ± 9.95	42.5 ± 11.9	40.3 ± 10.8

Num. of guests = 4, Num. of variables = 52, Exact: 0.69 ± 0.52 (without), Exact: 0.0 (with)
Num. of guests = 6, Num. of variables = 92, Exact: ~ 0.003 (without), Exact: 0.0 (with)

For small-case (28 variables), embedded h_0 normalization helps to adjust parameters for D-Wave

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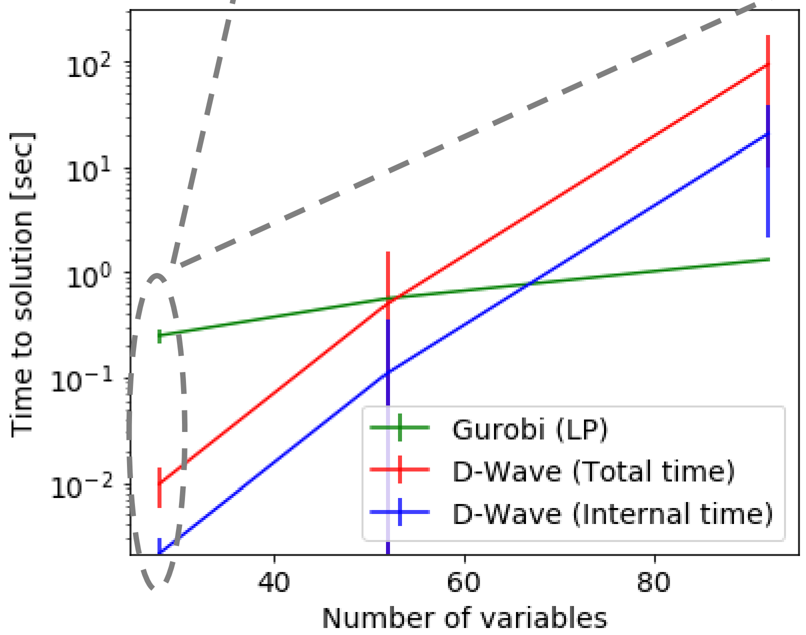
Results of D-Wave and Gurobi

Num. of guests = 2, Num. of variables = 28

	D-Wave	Gurobi	
	Quadratic	Quadratic	Linear
Run time [sec]	7.6 ± 3.9 (internal 1.6)	0.02 ± 0.002	0.31 ± 0.03
Num. of solutions	10000	1	1
Percentage of exact solution [%]	29.9	0	100
Best solution	4.289	4.306 (+0.4%)	4.289
Time to solution [sec]	0.0099 (internal 0.0021)	-	0.31



$$TTS(p) = t_c \frac{log(1-p)}{log(1-P_0)}$$

p = 0.99
t_c = run time / num. of sol.
P_0 = Percentage of exact sol.

- Gurobi (QP) is faster than Gurobi (LP) but not reached exact solution
- D-Wave is faster than Gurobi on time to solution under 52 variables due to exact percentage decrease (next slide)

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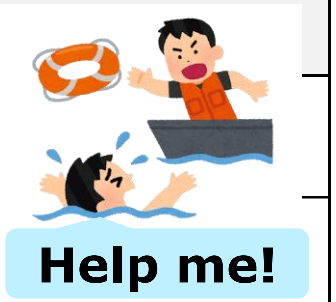
D-Wave exact solution details

Num. of guests = 2, Num. of variables = 28

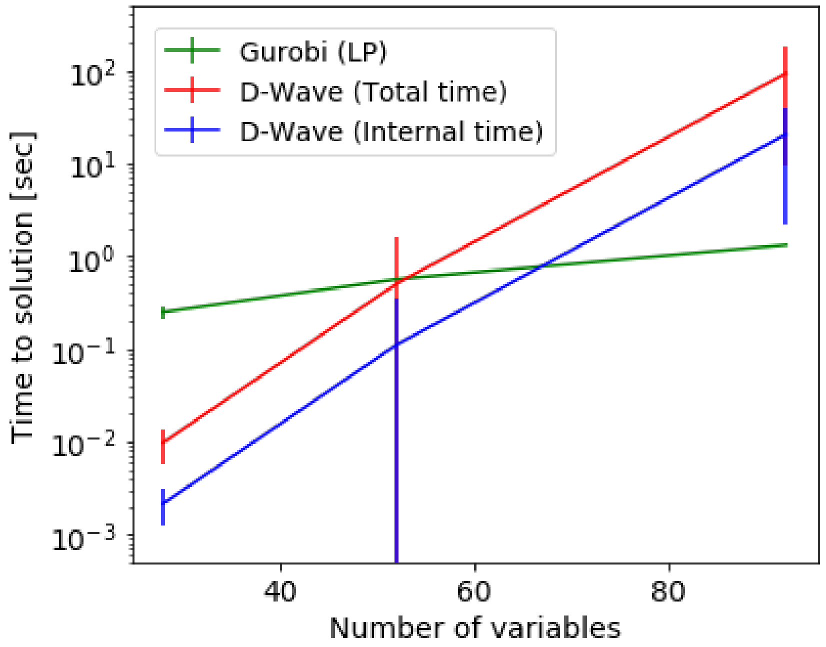
API	dwave_sapi2					Ocean				
Virtual Graph	False					False		True		
Post-process	None	Sampling	Optimization			Optimization				
Broken Chain	Minimize Energy			Vote	Weighted Random	Vote	Weighted Random	Vote	Weighted Random	Minimize Energy
Exact [%]	9.8 ± 2.1	0.0	29.9 ± 10.3	0.0	1.06 ± 0.33	0.0	0.0	0.0	0.0	Not work
Valid [%]	43.5 ± 5.68	7.28 ± 0.24	42.5 ± 11.9	0.0	9.8 ± 1.5	0.30 ± 0.10	7.91 ± 12.3	0.044 ± 0.07	0.00071 ± 0.00063	Not work

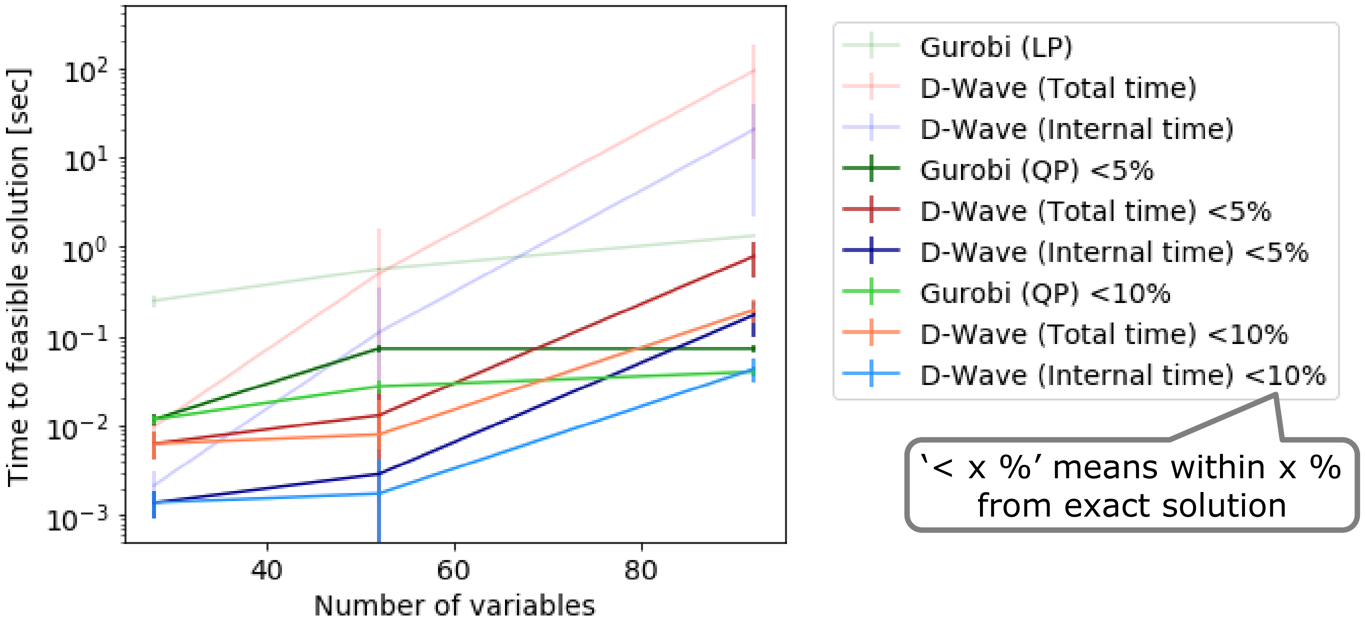


Num. of guests = 4, Num. of variables = 52, Exact: 0.69 ± 0.52, Valid: 35 ± 9.7 (opt. & min. energy)
Num. of guests = 6, Num. of variables = 92, Exact: ~ 0.003, Valid: 1.8 ± 0.34 (opt. & min. energy)

- Post-process and broken chain works well for the problem but virtual graph not work efficiently
- For large-cases (> 28 variables), the way to improve exact percentage become more important

D-Wave feasible solution details





$$TTS(p) = t_c \frac{log(1-p)}{log(1-P_0)}$$

p = 0.99
t_c = run time / num. of sol.
P_0 = Percentage of exact sol.

$$TTFS(p) = t_c \frac{log(1-p)}{log(1-P_0)}$$

p = 0.99
t_c = run time / num. of sol.
P_0 = Percentage of feasible sol.

- Time to feasible solution increase dependence on variables suppressed compared to time to solution (suppressed percentage decrease)
- Most feasible solutions of D-Wave were within 10%
- Embedding would be an issue to get better results

Summary

1. We propose QUBO formulation of multi modal transportation with selective junctions of small vehicles and large vehicles
2. Until 6 guests, exact solutions found by D-Wave
3. For small-case (2 guests), embedded h_0 normalization helps to increase exact solutions
4. For small-cases (2 guests), D-Wave is faster than Gurobi on time to solution, but large-case (>2 guests) slower due to exact solution decrease
5. Most feasible solutions of D-Wave were within 10%

Future work

1. Optimizing real examples of multi modal transportation
2. Benchmarking (Digital Ising machines, heuristic algorithms)
3. Better embedding methods for improving large-case problems

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VRP formulation for linear programming

$$\min \quad \sum_{i=0}^{n+1} \sum_{j=0}^{n+1} c_{ij} x_{ij} \tag{2.1}$$

$$\text{s.t.} \quad \sum_{\substack{j=1 \\ j \neq i}}^{n+1} x_{ij} = 1, \qquad i = 1, \dots, n, \tag{2.2}$$

$$\sum_{\substack{i=0 \\ i \neq h}}^{n} x_{ih} - \sum_{\substack{j=1 \\ j \neq h}}^{n+1} x_{hj} = 0, \qquad h = 1, \dots, n, \tag{2.3}$$

$$\sum_{j=1}^{n} x_{0j} \leq K, \tag{2.4}$$

$$y_j \geq y_i + q_j x_{ij} - Q(1 - x_{ij}), \qquad i, j = 0, \dots, n+1, \tag{2.5}$$

$$d_i \leq y_i \leq Q, \qquad i = 0, \dots, n+1, \tag{2.6}$$

$$x_{ij} \in \{0, 1\}, \qquad i, j = 0, \dots, n+1. \tag{2.7}$$

Pedro Munaria et. al., A generalized formulation for vehicle routing problems, arXiv:1606.01935