14th Behavior Modeling in Transportation Networks, UT
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A context-dependent scheduling model considering measurement errors in pedestrian network

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Behavior in Networks Studies Unit

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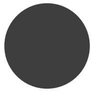
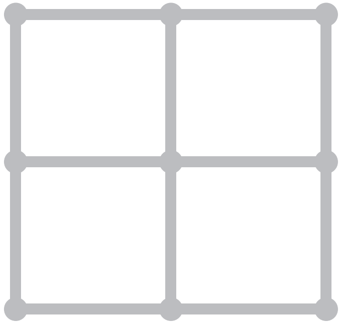
Time use pattern in pedestrian network

Development around station



Urban renovations



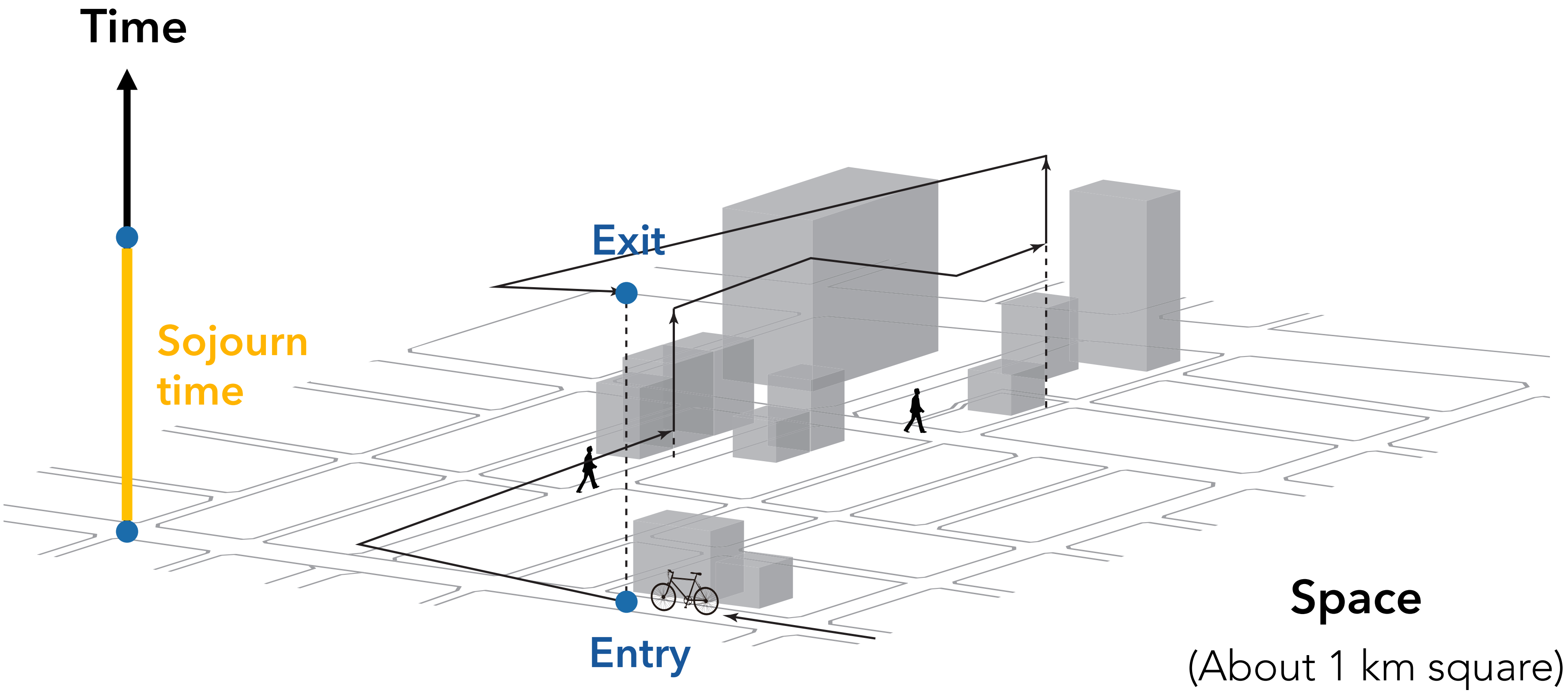
Large scale buildings
No. of visitors

Small scale projects
Frequency / Duration /…

How people spent their time in these districts?

Target | City Center Sojourn

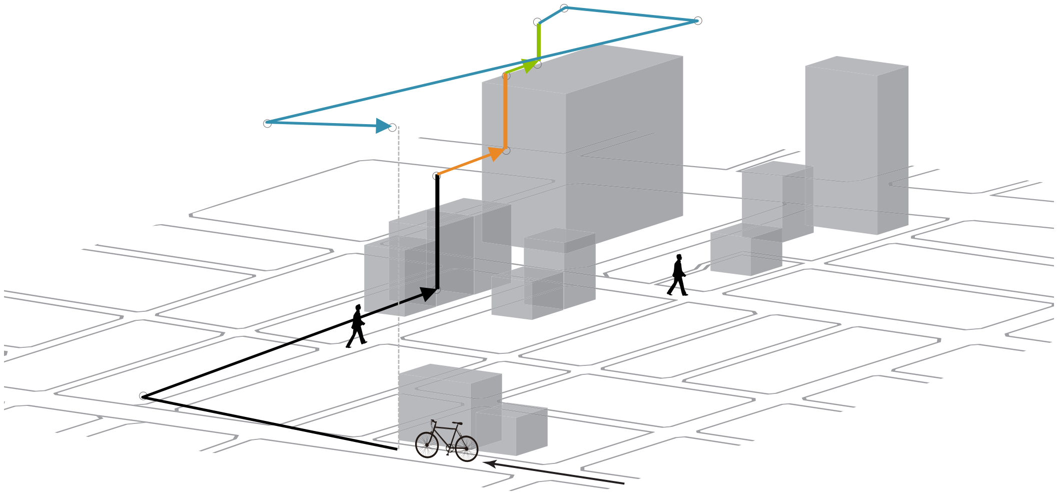
- **City Center Sojourn** refers to pedestrian scheduling behavior in city centers, which includes a sequence of moving (travel) and staying (activity) decisions.



Target | Pedestrian scheduling

Activities can be generated (walking) context-dependently

- Spatial attributes (stumbling on an attractive shop,…)
- Activity history (finding next shop for goods she wants, …)
- Social interaction (a friend says he wants to drop in a café,…) …



Pattern is not alternative but result of dynamic scheduling process

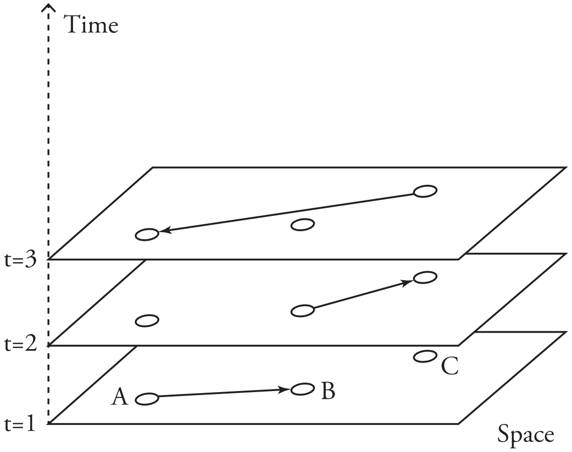
e.g.; Habib (2011)

Activities (staying) do not always decided to conduct before travels (moving)

Review | Scheduling models

1. Markov chain

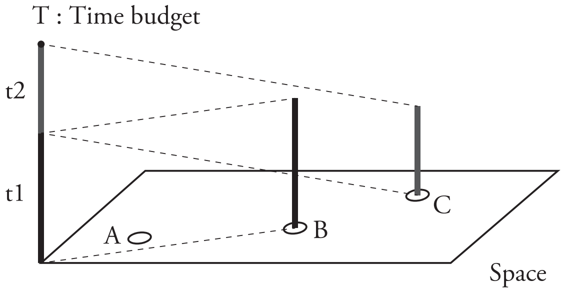
Lerman (1979),
Borgers and Timmermans (1986)



$$p_t(i,j)$$

2. Time allocation

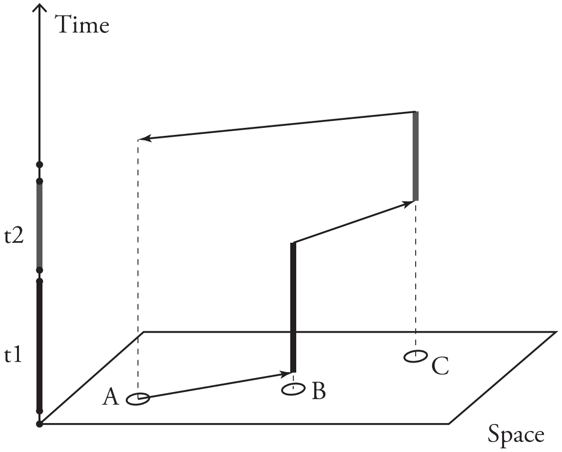
Bhat et al. (2005),
Fukuyama and Hato (2013)



$$\sum_{k=1}^{K} t_k = T$$

3. Utility maximization

Bowman and Ben-Akiva (2001),
Recker (1995)



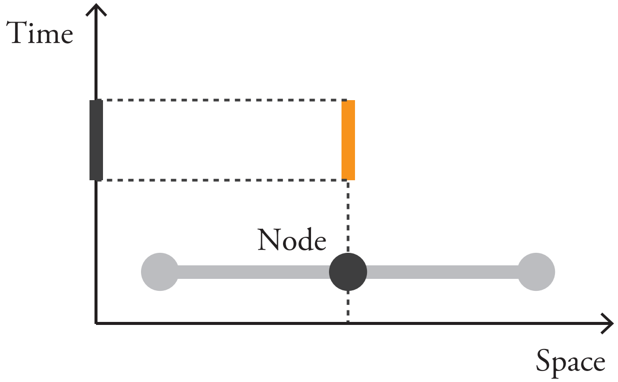
$$\max U$$

○ ordered	× random ordered	○ ordered
× separated	△ semi-separated	○ linked
○ context-dependent (but only at the time)	× independent (pre-trip)	× independent (pre-trip)

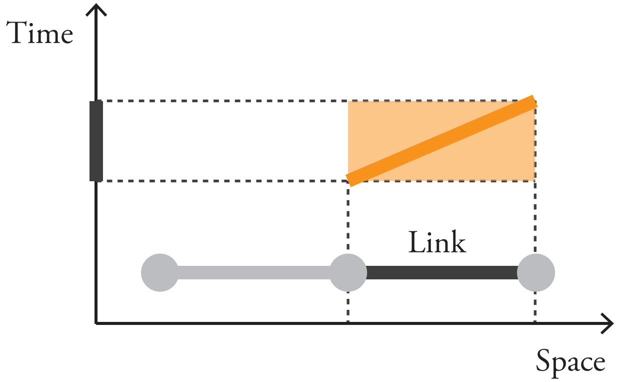
Model | Dynamic scheduling model

Activity = Time allocation behavior to a certain 'space'

- **Staying** : duration time choice in a certain **'node'** $n \in S$



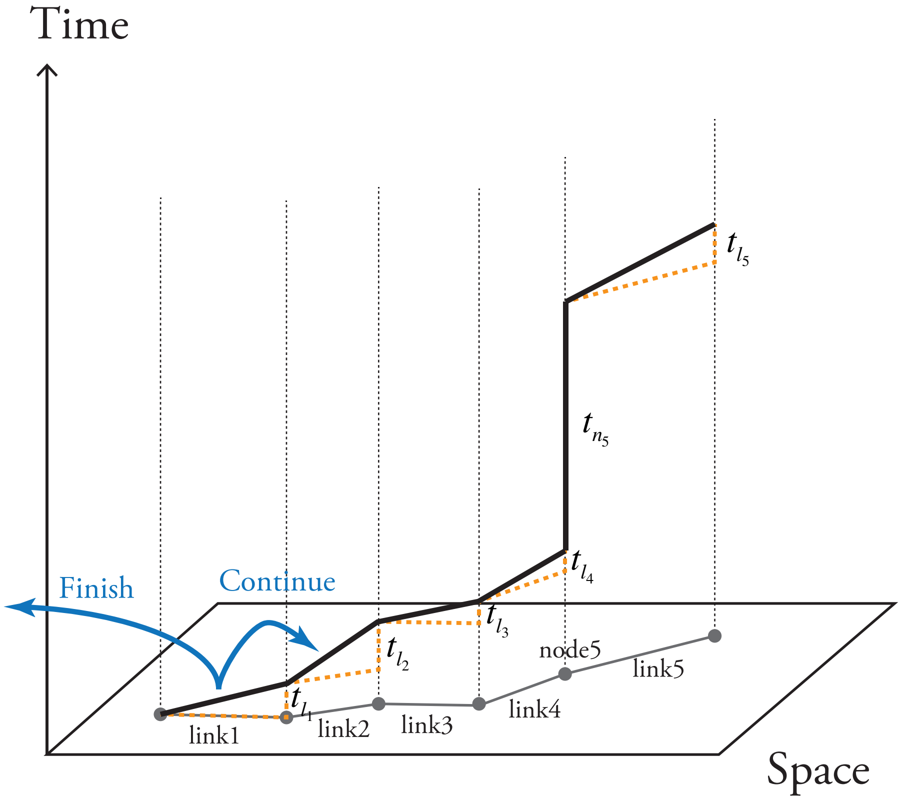
- **Moving** : duration time choice in a certain **'link'** $l \in S$



Model | Dynamic scheduling model

Activity = Time allocation behavior to a certain 'space'

- **Moving** : duration time choice in a certain **'link'** $l \in S$
- **Staying** : duration time choice in a certain **'node'** $n \in S$



Dynamic scheduling model in space

1. Activity generation model

***Continue* or *Finish* activities ?**

*'Continue' means moving next space
*'Finish' means moving out of district

What this decision is based on?

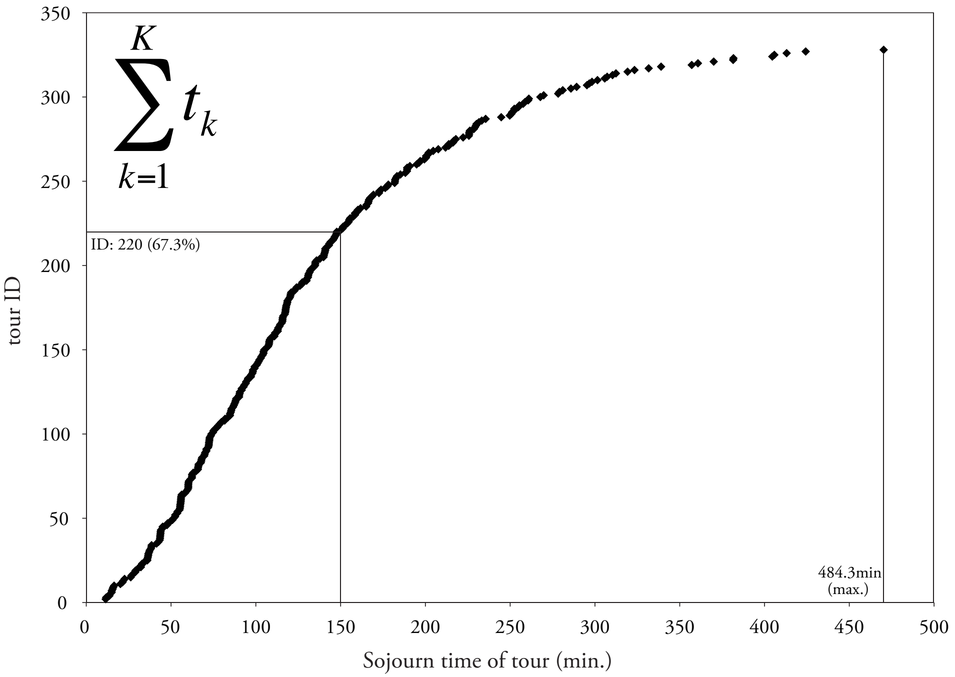
2. Time allocation model

Duration time **choice in the space**

$$\max u_k(t_k)$$

Model | Activity generation model

Is it enough with only time constraints ?



- **Non-mandatory tour** (shopping, eating, recreational, other activities are included).
- Sojourn time (cumulative duration) is **continuously distributed**.

- We **cannot explain** the sojourn time differences among tours **by only time constraint**.

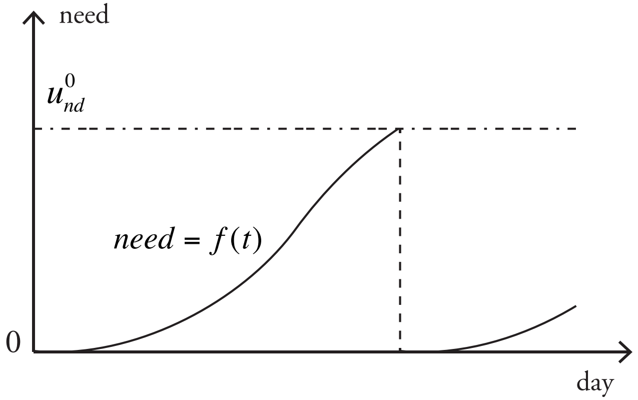
We have to consider:

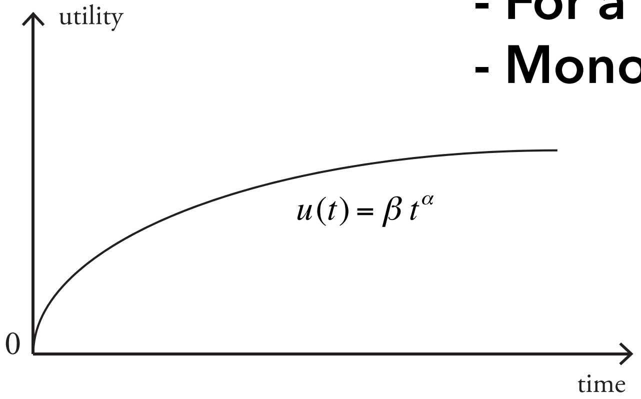
Psychological (personal) concept as resource

Model | Activity generation model

Psychological mechanisms in behavior modeling

- **Need** (Maslow, 1943; Arentze and Timmermans, 2004; Nijland et al., 2013)
- **Satisfaction** (Pattabhiraman et al., 2013)
- **Satiation** (MacAlister, 1982; Bhat et al., 2005)



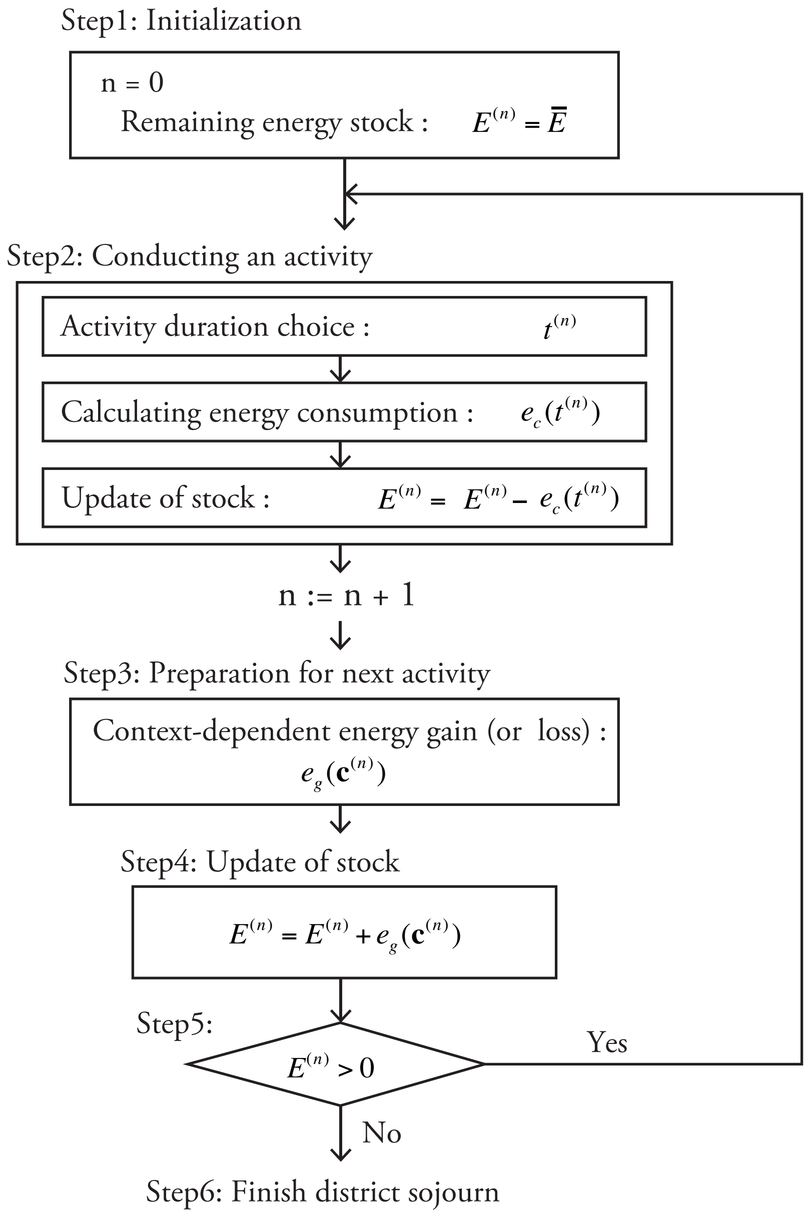


- **For a particular activity**
- **Monotonicity**

‘Energy’ : personal resource for engaging in activities.

- All of activities in **a tour have** ‘energy’ **in common**.
- Energy decreases by engaging activities, and can **increase based on context**.

Model | Activity generation model



Step1: Initialization

n = 0
Remaining energy stock : $E^{(n)} = \bar{E}$

Step2: Conducting an activity

Activity duration choice : $t^{(n)}$

Calculating energy consumption : $e_c(t^{(n)})$

Update of stock : $E^{(n)} = E^{(n)} - e_c(t^{(n)})$

n := n + 1

Step3: Preparation for next activity

Context-dependent energy gain (or loss) : $e_g(\mathbf{c}^{(n)})$

Step4: Update of stock

$E^{(n)} = E^{(n)} + e_g(\mathbf{c}^{(n)})$

Step5:

$E^{(n)} > 0$

Yes

No

Step6: Finish district sojourn

Remaining energy :

$$E^{(n+1)} = \bar{E}_{i,d} \underline{- E_c^{(n)}} \underline{+ E_g^{(n+1)}} \qquad (1)$$

Energy consumption :

$$E_c^{(n)} = \sum_{k=1}^{n} e_c(t^{(k)}, x^{(k)}) \qquad (2)$$

Energy gain (or loss) :

$$E_g^{(n)} = \sum_{k=1}^{n} \sum_{i} \gamma_{ki} I_{ki} + \sum_{j} \delta_{nj} s_{nj} \qquad (3)$$

I_{ni} : Activity history variables

s_{nj} : Spatial attributes variables

Model | Pedestrian scheduling model

Activity generation model

$$E^{(n)} = \overline{E}_{i,d} - E_c^{(n-1)} + E_g^{(n)} + \varepsilon \qquad (1)'$$

ε : random error term (i.i.d. gumbel distribution)

If energy is greater than zero, the sojourn will be continued, otherwise finished.

$$\Pr(continue) = \Pr(E^{(n)} > 0)$$

Time allocation model (Habib, 2011)

*k=1: next activity, k=2: composite activities

$$\max U(t_k) = \sum_{k=1}^{2} \frac{1}{\alpha_k} \exp\left(\psi_k z_k + \varepsilon'_k\right)\left(t_k^{\alpha_k} - 1\right) \qquad (4)$$

$$\text{s.t.,} \quad t_1 + t_2 = T \qquad (5)$$

α_k : satiation parameter (< 1) z_k : vector of variables ψ_k : vector of weights

ε'_k : random error term (i.i.d. gumbel distribution)

Model | Pedestrian scheduling model

Joint probability : Habib(2011)*

$$\Pr(continue \cap Time = t_k)$$

$$= \left(\frac{1-\alpha_1}{t_k} + \frac{1-\alpha_2}{T-t_k} \right) \cdot \frac{1}{\sigma} \exp\left(\frac{-(V'_2 - V'_1)}{\sigma} \right) \cdot \left[1 + \exp\left(\frac{-(V'_2 - V'_1)}{\sigma} \right) \right]^{-2} \times \Phi\left(\frac{J_d(\varepsilon) - \rho J_c(\varepsilon'_k)}{\sqrt{1-\rho^2}} \right) \tag{6}$$

where,

$$V'_k = \psi_k z_k + (\alpha_k - 1)\ln\left(t_k\right)$$

$J(\varepsilon)$: the inverse of CDF of standard normal distribution (Lee, 1983)

MLE (Maximum Likelihood Estimates)

$$L = \prod_{i=1}^{I} \left[\prod_{k=1}^{n} \left(\Pr_i(continue \cap Time = t_k) \right)^{\delta_{ic}} \right] \tag{7}$$

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*Khandker M. Nurul Habib (2011). A random utility maximization (RUM) based dynamic activity scheduling model: Application in weekend activity scheduling, Transportation, Vol.38, pp.123-151.

Part 2 : Data processing

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1. **Introduction** :
   - City Center Sojourn of pedestrians
2. **Modeling** :
   - Pedestrian dynamic scheduling model
   - Context-dependent energy
3. **Measurement Model** :
   - Probe Person data with GPS technologies
   - Detection of pedestrian activity paths

Part 2

4. **Case study** :
   - Model Estimation and Results
5. **Conclusions**

Data | Probe Person survey

Methods :

GPS (automatic) $\hat{m} = (\hat{x}, \hat{t})$

- Latitude / Longitude (a coordinate)
- Timestamp (at the interval of 5~30 s)

+ Web diary $a = (x, t^{-}, t^{+})$

- Trip purpose
- Transportation mode

+ personal information

Personal day-to-day data

Measurements : $\hat{m}_{1:J_i^d} = (\hat{m}_1, \ldots, \hat{m}_{j_i^d}, \ldots, \hat{m}_{J_i^d})$

Reported activity episodes : $a_{1:R_i^d} = (a_1, \ldots, a_{r_i^d}, \ldots, a_{R_i^d})$

where, i : an individual, d : a day

Data | Probe Person survey

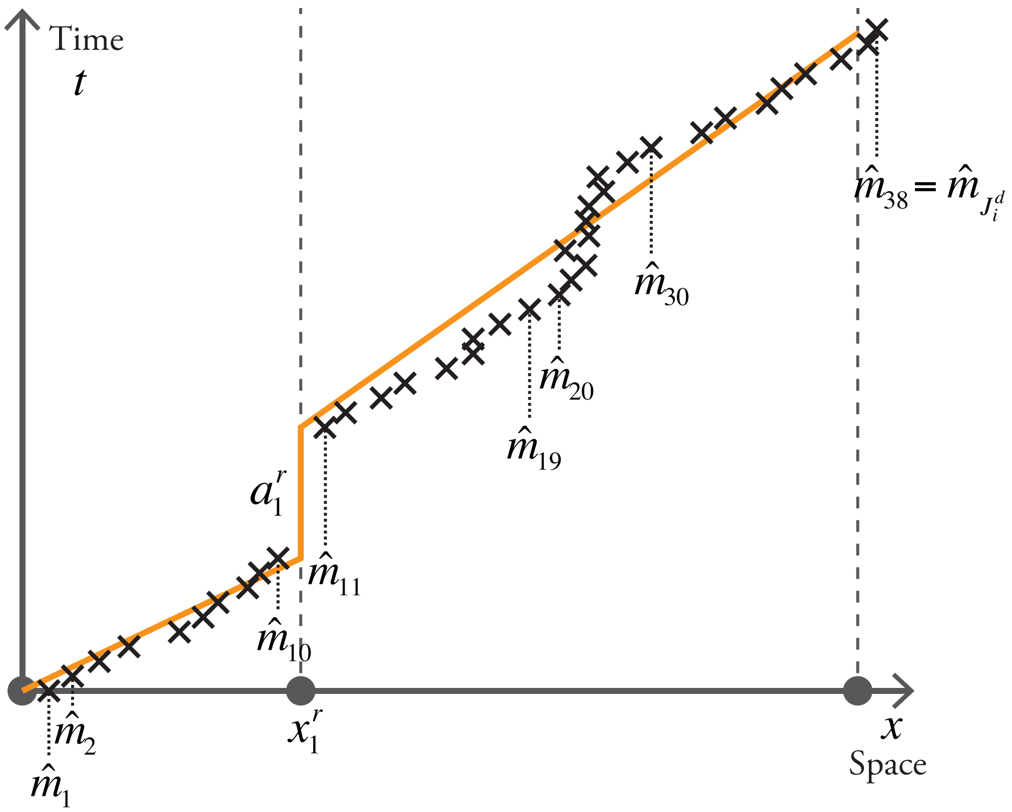
Reported path (—) :

$$\hat{m} = (\hat{x}, \hat{t})$$

$$a_r = (x, t^-, t^+)$$

- There can be dropped (non-reported) staying activity.
- Measurements have not connected with 'space' yet.

(and it has measurement error)

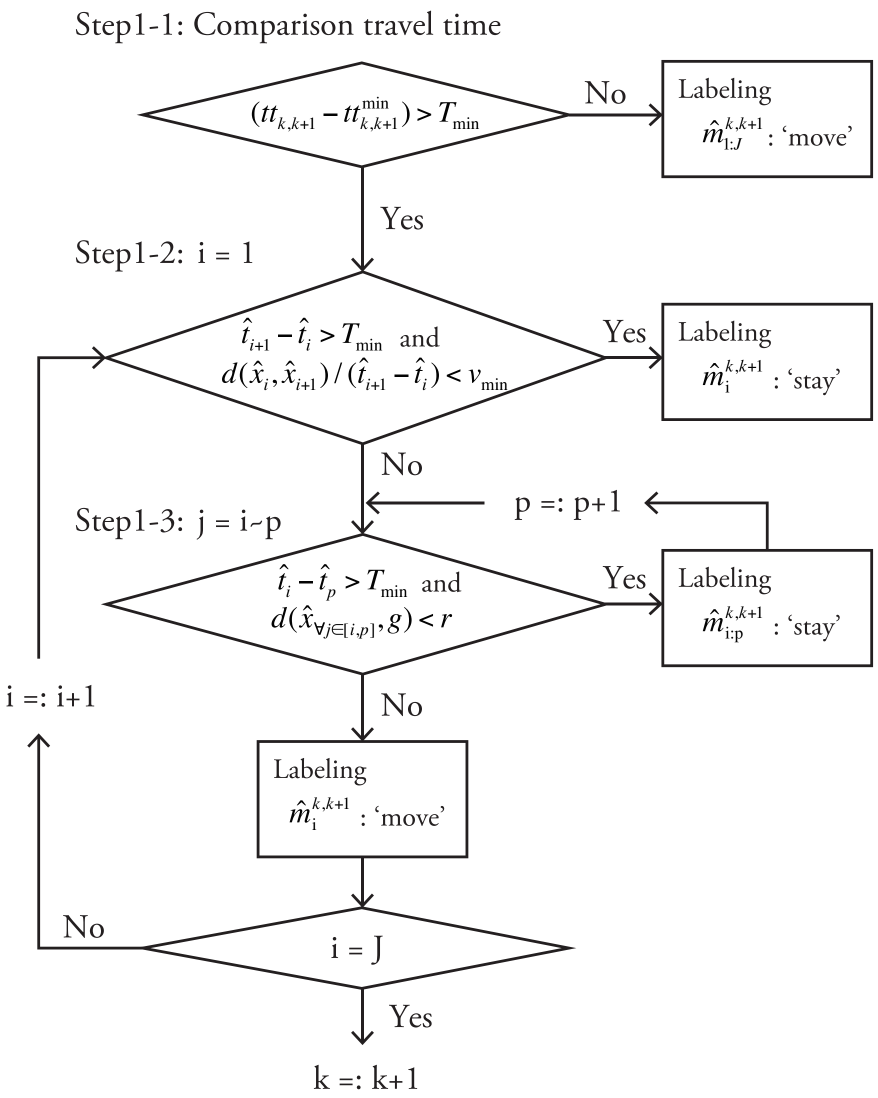


We need to

1. **Label measurements ('moving' or 'staying')**
2. **Connect measurements with 'space' (node / link)**

Data | Detection of activity paths

Step1: Classification of moving or staying



Step1-1: Comparison travel time

$(tt_{k,k+1} - tt^{\min}_{k,k+1}) > T_{\min}$

No

Labeling $\hat{m}^{k,k+1}_{1:J}$: 'move'

Yes

Step1-2: i = 1

$\hat{t}_{i+1} - \hat{t}_i > T_{\min}$ and $d(\hat{x}_i, \hat{x}_{i+1}) / (\hat{t}_{i+1} - \hat{t}_i) < v_{\min}$

Yes

Labeling $\hat{m}^{k,k+1}_{i}$: 'stay'

No

p =: p+1

Step1-3: j = i~p

$\hat{t}_i - \hat{t}_p > T_{\min}$ and $d(\hat{x}_{\forall j \in [i,p]}, g) < r$

Yes

Labeling $\hat{m}^{k,k+1}_{i:p}$: 'stay'

No

Labeling $\hat{m}^{k,k+1}_{i}$: 'move'

i = J

No

i =: i+1

Yes

k =: k+1

$tt_{k,k+1} = t^{-}_{k+1} - t^{+}_{k}$: Reported travel time

$$tt^{\min}_{k,k+1} = d(x_k, x_{k+1}) / v_w \qquad (8)$$

: Shortest path travel time

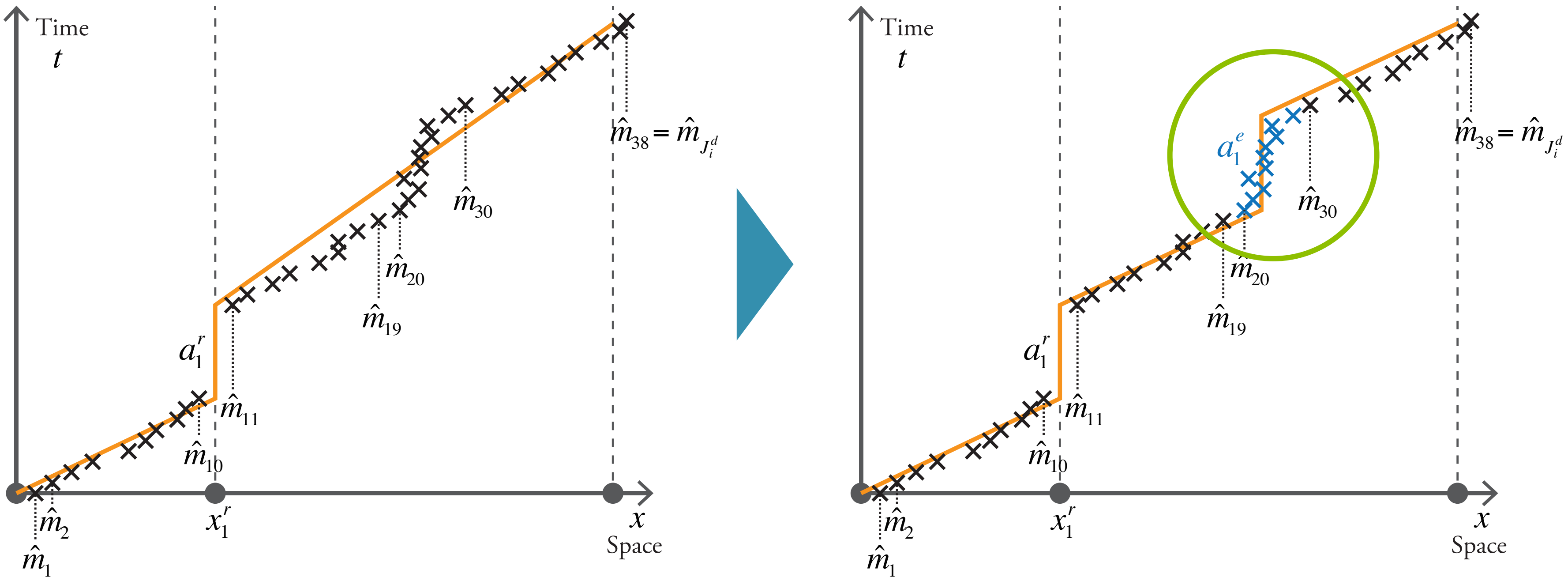
Centroid of $\hat{m}^{k,k+1}_{i:p}$

$$g_{i:p} = \frac{1}{p-i+1}\left(\sum_{j=i}^{p} \hat{x}_{jlat}, \sum_{j=i}^{p} \hat{x}_{jlon}\right) \qquad (9)$$

*$T_{\min} = 180s,\ v_w = 1.4m/s,\ r = 50m$

Data | Detection of activity paths

Step1: Classification of moving or staying



× $\hat{m} = (\hat{x}, \hat{t}, '\mathit{move}')$

× $\hat{m} = (\hat{x}, \hat{t}, '\mathit{stay}')$

Next: **Connect activities with 'space'** (move - link / stay - node)

Data | Detection of activity paths

Step2: Estimation of activity space for 'stay' data

Step2-1: Candidate set generation

Universal set: $\mathcal{U}_N = \{n : n \in S\}$

Space frequency score from day-to-day data:

$$f_{ni} = \sum_d \sum_k \delta_{k,n}^{i,d}, \quad f_n = \sum_i \sum_d \sum_k \delta_{k,n}^{i,d} \tag{10}$$

$\delta_{k,n}^{i,d}$: 1 if individual *i* stay *n* for activity *k* on day *d*, otherwise 0.

Importance Sampling using MCMC method

Adoption rate of *i* :

$$r_i = P_i / P_j = \exp(V_{in}) / \exp(V_{jn}), \quad V_{in} = \sum_j \beta_{nj} X_{nj} + w_1 f_{ni} + w_2 f_n \tag{11}$$

Finally we get a subset: $C_{iN} \subset \mathcal{U}_N$

Data | Detection of activity paths

Step2: Estimation of activity space for 'stay' data

Step2-2: Probability calculation

e.g.; Danalet et al. (2014)

Prior probability:
$$P_i(n) = \exp(V_{in}) / \sum_{m \in C_{iN}} \exp(V_{im}) \tag{12}$$

Measurement probability:

$$P(\hat{m}_{p:q} \mid n) = P(\hat{x}_{p:q} \mid x_n) = \Pi_{j=p}^{q} P(\hat{x}_j \mid x_n)$$
$$P(\hat{x}_j \mid x_n) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(- \frac{(\hat{x}_j - x_n)^2}{2\sigma^2} \right) \tag{13}$$

* We assume that measurement error is only localization σ

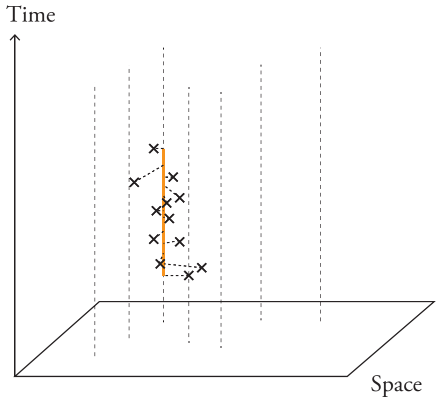
Probability of space *n* for 'stay' measurement set $\hat{m}_{p:q}$:

$$P(n \mid \hat{m}_{p:q}) = a \cdot P(\hat{m}_{p:q} \mid n) \cdot P_i(n) \tag{14}$$

Data | Detection of activity paths

Detected activity path:

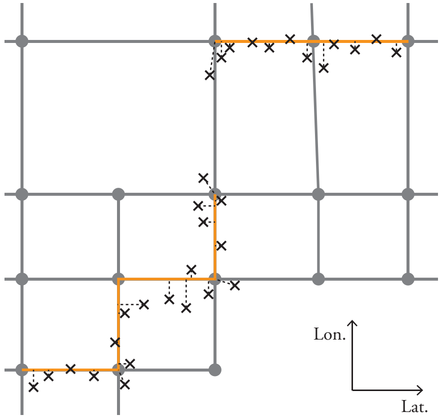
Step2: Estimation of 'stay' space



$$\hat{m} = (\hat{x}, \hat{t}, '\mathit{stay}')$$

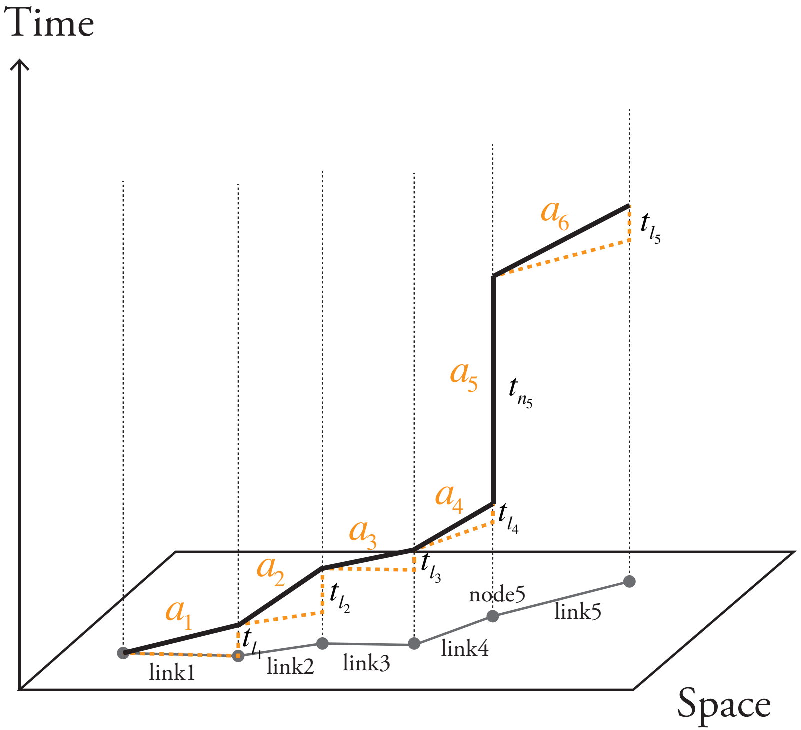
$$a = (n, t^-, t^+)$$

Step3: Estimation of 'move' space
(Map-matching)



$$\hat{m} = (\hat{x}, \hat{t}, '\mathit{move}')$$

$$a = (l, t^-, t^+)$$



Activity sequence with space

$$a_{1:M_i^d} = (a_1, \ldots, a_{m_i^d}, \ldots, a_{M_i^d})$$

Part 3 : Case study in Matsuyama city

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1. **Introduction** :
   - City Center Sojourn of pedestrians
2. **Behavior Model** :
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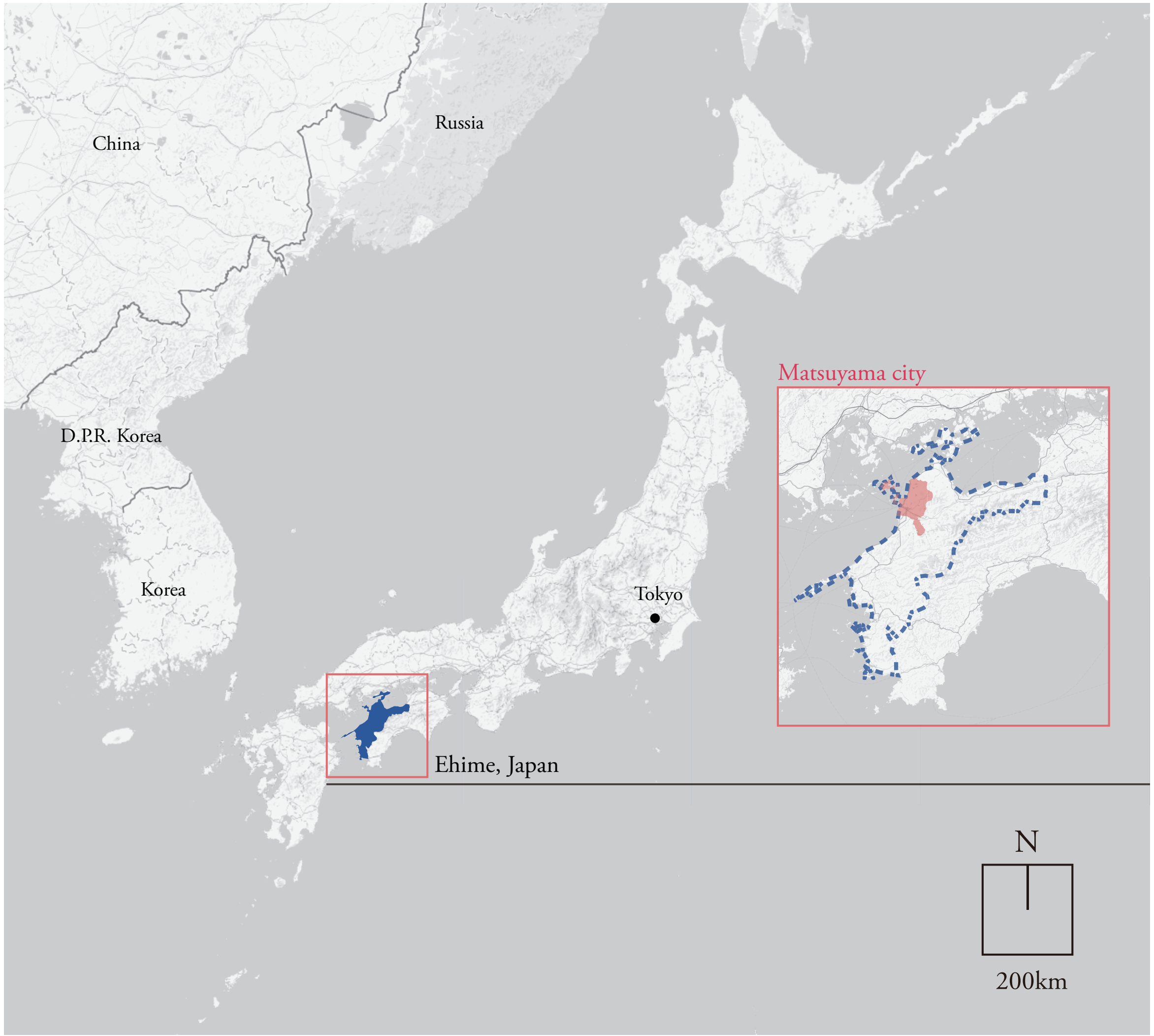
Part 3

Case study | City center of Matsuyama

Matsuyama city :



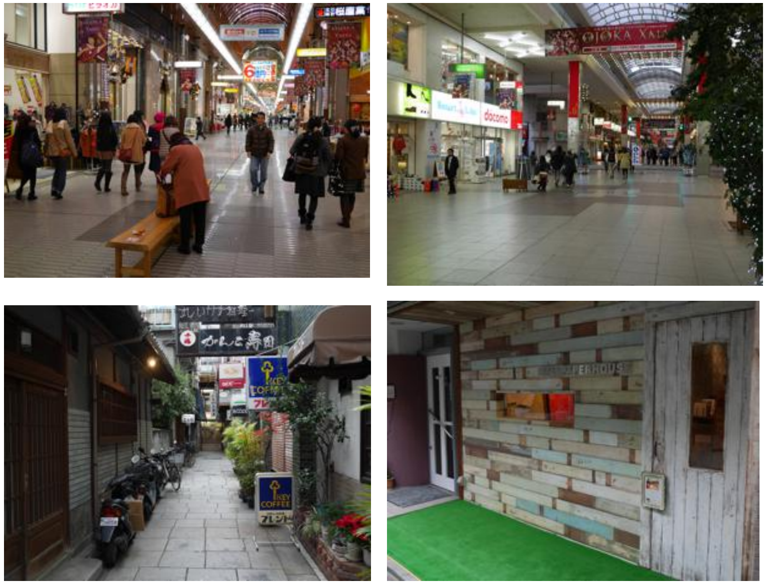
Data

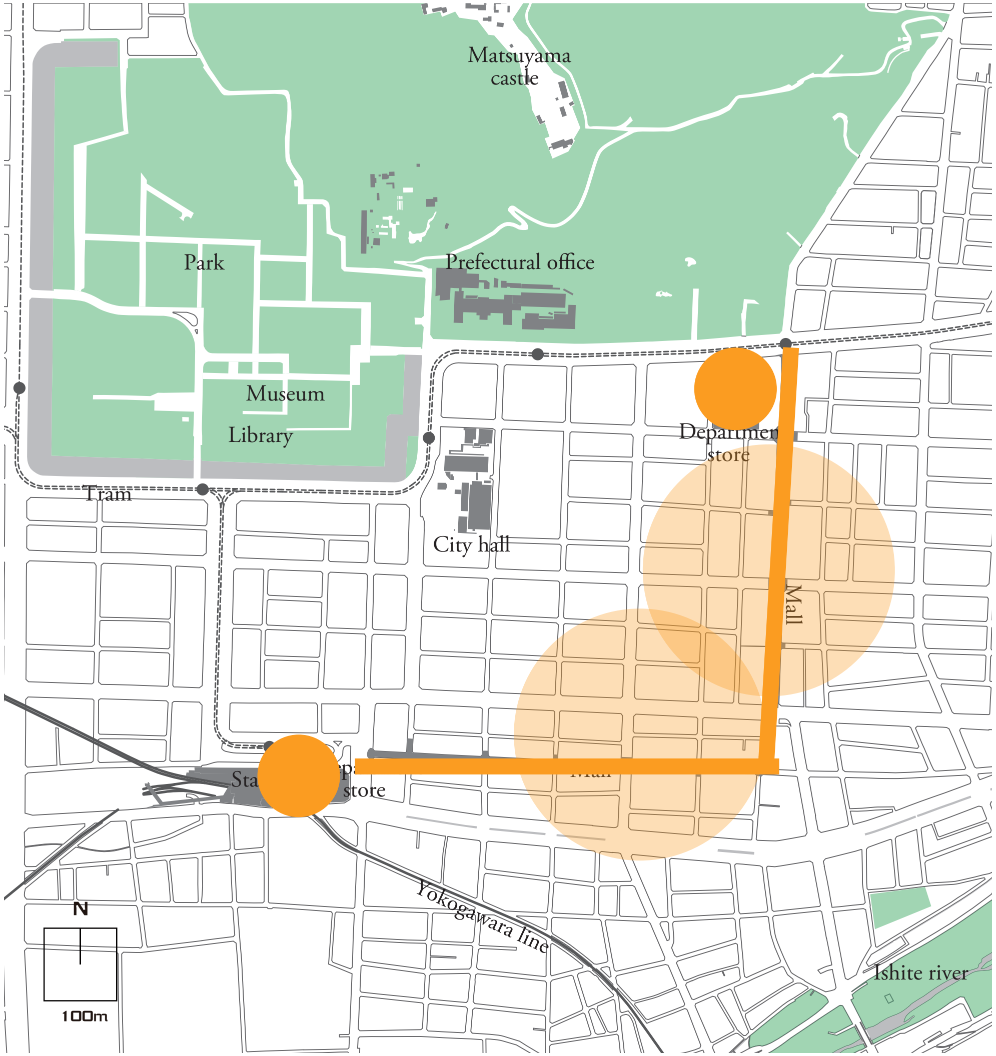
- Ehime prefecture, Shikoku region
- Population: 516,637 (December 1, 2010)
- Area: 428.86 sq. km
- Density: 1,204.68/sq. km

Case study | City center of Matsuyama

City center of Matsuyama :

- 2 department stores / 2 malls
- Various retails and restaurants are located around the streets.





About 1.5 km square

Case study | PP survey in Matsuyama

Data collection :

Survey	Period	Weeks	No. of monitors	Data (trip)
CityCenterPP2007	2007/02/19~2007/03/22	4	84	7,810
PP survey 2007A	2007/10/29~2008/01/21	12	508	17,697
PP survey 2007B	2007/10/29~2008/01/21	12	205	14,706
Bike sharing PP	2009/02/21~2009/03/07	2	15	668
Elderly PP 2010	2010/11/18~2011/01/31	12	30	1.380
Total		42	842	42,261

-> 1582 sojourn tours (non-mandatory) were observed

Estimation | Variables of Energy

Remaining energy $E^{(n+1)} = \bar{E}_{i,d} - E_c^{(n)} + E_g^{(n+1)}$

Initial stock of energy

$$\bar{E}_{i,d} = \sum_k \alpha_k x_k$$

- Female dummy (sex)
- Car inflow dummy (mode)
- Dist. between Entry point and Main (Location of entry point)

Energy consumption $E_c^{(n)} = \sum_{k=1}^{n} e_c(t^{(k)}, x^{(k)})$

By staying : $e_c^s = (\beta_{time}^s + \sum_k \beta_k^s x_k^s) \cdot t$

- Shopping purpose dummy
- How many times

By moving: $e_c^m = (\beta_{time}^m + \beta_{speed}^m s + \sum_k \beta_k^m x_k^m) \cdot t$

- Sidewalk width
- Shooing street dummy

Energy gain (or loss)

$$E_g^{(n)} = \sum_i \gamma_{ki} I_{ki} + \sum_j \delta_{nj} s_{nj}$$

- Cumulative number of activities
- Previous trip purpose

- Dist. from EP or Main facilities
- Shopping street dummy

Estimation | Results

	Variable	Parameter	t-value
ϱ	Correlation	0.048	0.90
α_c	Satiation Parameter of composite	0.594	12.98**
α_m	Satiation Parameter of moving	-3.196	-93.23**
α_s	Satiation Parameter of staying	-0.176	-8.92**
	Discrete choice		
α_1	Constant	5.354	26.03**
α_2	Female dummy	-0.170	-1.52
α_4	Log(EP-Main dist.(km) + 1)	0.164	11.07**
α_5	Car inflow dummy	0.632	5.06**
β_1	Basic parameter of time (min.)	-0.004	-6.75**
β_2	A Number of trips	0.002	6.74**
β_3	Shopping dummy	-0.003	-2.60**
β_4	Basic parameter of time (min.)	-0.264	-7.15**
β_5	Walking speed (m/s)	-0.063	-8.49**
β_6	Sidewalk width (m)	0.070	6.42**
β_7	Shopping street dummy	-0.240	-3.72**
γ_1	Cumulative stay activities	-0.986	-17.65**
γ_1	Cumulative move activities	0.638	10.78**
γ_2	Cumulative shopping stays	0.246	3.67**
γ_4	Previous activity : eating	0.364	1.82
γ_5	Previous activity : Main	-1.957	-14.24**
γ_4	Dist. from EP	-0.040	-2.60**
γ_5	Dist. from Main	-0.230	-14.52**

	Variable	Parameter	t-value
	Continuous choice (move)		
β_{mc}	Constant	-1.054	-5.17**
β_{time1}	Elapsed time (min./10)	0.006	2.55**
β_{time2}	Cumulative stay activities	-0.004	-0.16
β_{time3}	Cumulative move activities	-0.006	-1.13
β_{time4}	Link length (m)	0.024	21.56**
β_{time5}	No. of lanes	0.104	2.98**
β_{time6}	Sidewalk width (m)	-0.067	-2.49**
β_{time7}	Shopping street	0.665	2.99**
β_{time8}	Street trees	-0.057	-0.56
	Continuous choice (stay)		
β_{ms}	Constant	2.368	10.89**
β_{time9}	Elapsed time (min./10)	-0.004	-0.86
β_{time10}	Cumulative stays	-0.175	-4.87**
β_{time11}	Cumulative moves	-0.042	-4.45**
β_{time12}	Public facilities	0.113	0.99
β_{time13}	Department store	-0.564	-4.78**
β_{time14}	Shopping street	-0.606	-3.86**
β_{time15}	No. of retails	-0.029	-2.48**
	Observations		7247
	Initial Likelihood		-24949.15
	Final Likelihood		-18855.90
	Rho square (adj.)		0.243

Conclusions

- To capture **context-dependent activity generation** and **scheduling process** in pedestrian behavior,
- we incorporated "**energy**" into the scheduling model and described **a sequential time-allocation behavior to spaces**.
- And using PP data, **we detected activity paths with space**.

- As a result, it was clarified that the energy consumption and gain process are dependent on some **behavioral and spatial context variables**.

Thank you for your attentions!!
Questions?

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or oymyk.dom@gmail.com