

Automated and Adaptive Activity-Travel Survey using Online Interaction with Travelers

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Travel behavior survey

- Travel behavior data is essential for activity/travel behavior modeling

traveler id	trip id	origin	destination	mode	departure time	...
1	1	home	office	train	8:30	
1	2	office	shop	walk	17:00	
2	1	home	restaurant	car	11:30	
⋮						

- Actual activity/travel data is often collected by conducting a survey
 - realistic compared to stated preference (virtual) data

Conventional survey methods

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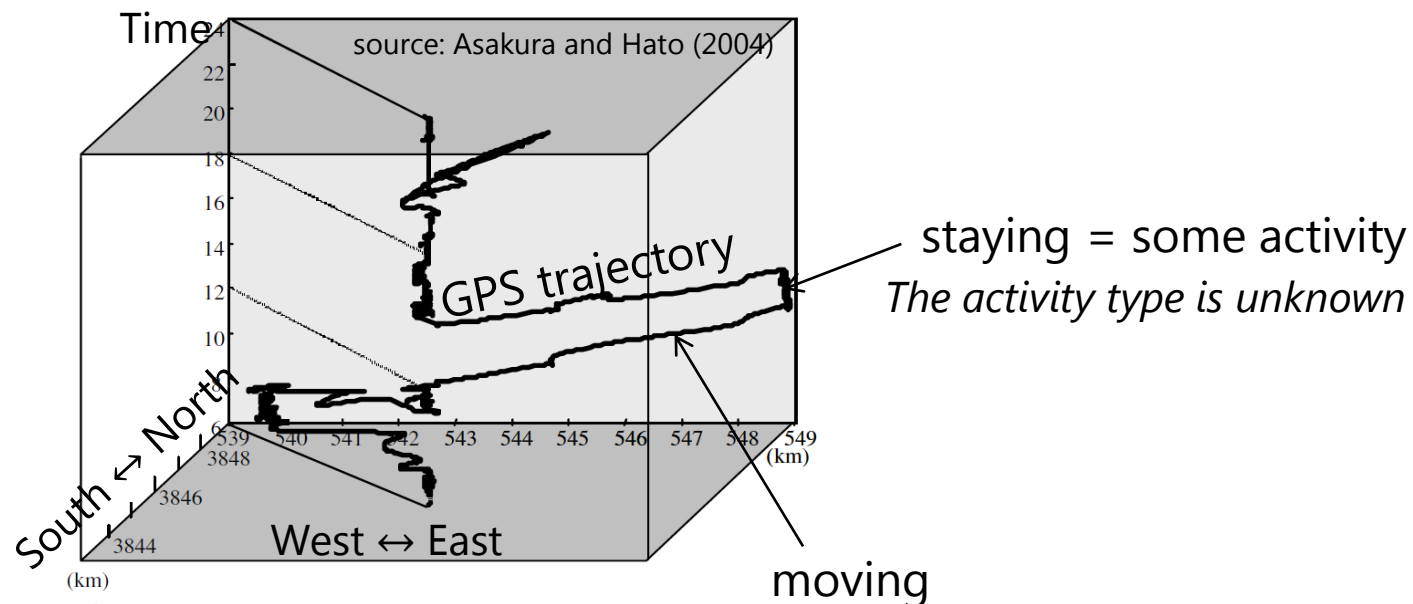
The image shows a complex Japanese questionnaire form. At the top, it includes a header with the survey title and a '個人票' (Individual Form) label. Below this, there are several numbered sections (1-4) for data entry, each with a grid of checkboxes and text boxes. The form also includes a 'はじめて' (First time) section with instructions and a '調査内容' (Survey Content) section with a list of questions. The bottom part of the form contains a '個人票' (Individual Form) section with a grid for recording responses to various questions.

Questionary survey

- Travel data is collected by paper- or web-based questionnaire
- Limitations:
 - **burden** for survey participants: *where did you go? when? how? why? with whom? etc.*
 - **inaccurate** due to incomplete memory
 - **Long-term, large-scale, and accurate** data collection is difficult (panel attrition, fatigue)

Conventional survey methods

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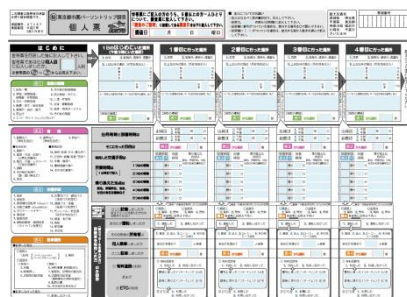


GPS data collection

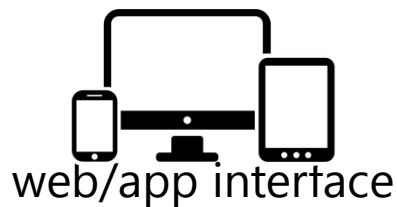
- **accurate** spatiotemporal data
- **Activity type** (trip purpose) **is missing**

Conventional survey methods

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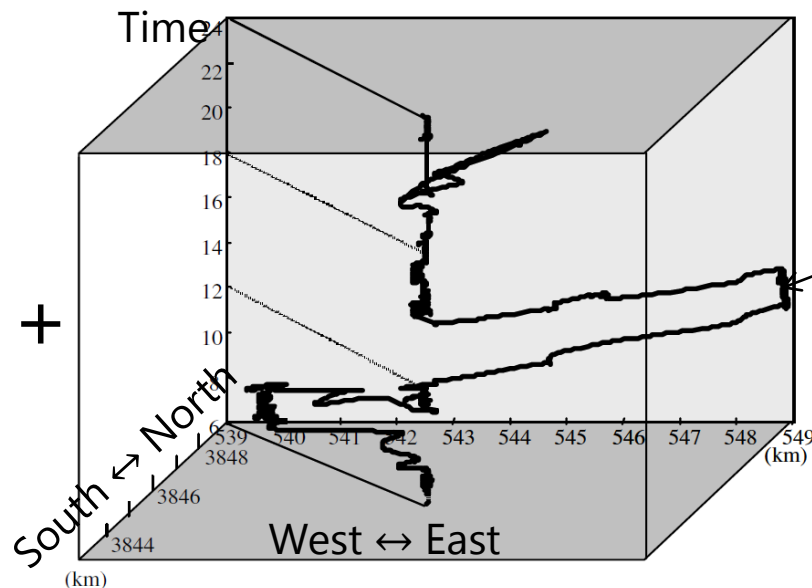


survey sheet



web/app interface

+



staying
The activity type is asked by
questionary survey

GPS data collection + questionnaire survey

- **accurate** spatiotemporal data
- relatively **accurate** activity data
 - GPS log can help memory recalling
- **burden** for participants
 - Extensive manual input is still mandatory

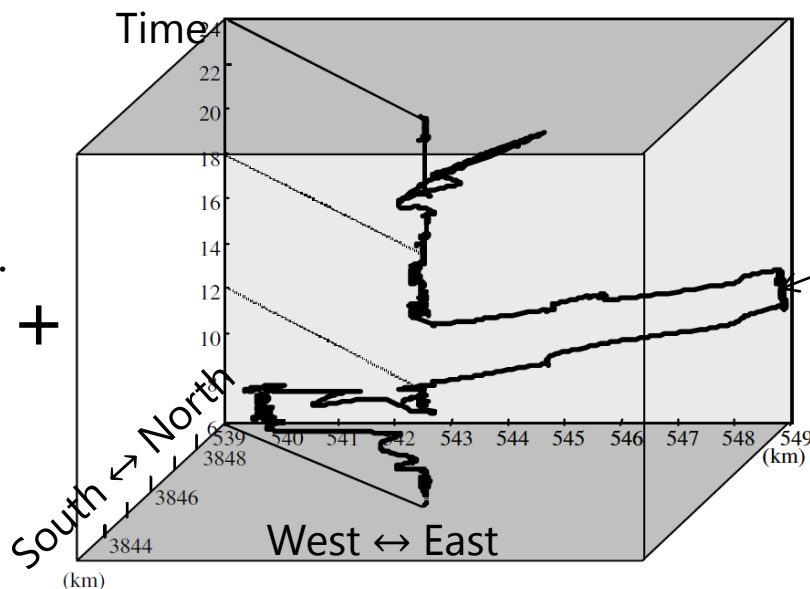
Existing advanced survey methods

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$$\frac{e^{V_i}}{\sum_j e^{V_j}}$$

calibrated model



The place is shop



The activity
must be shopping

staying

Existing behavior model predicts
that he will go shopping



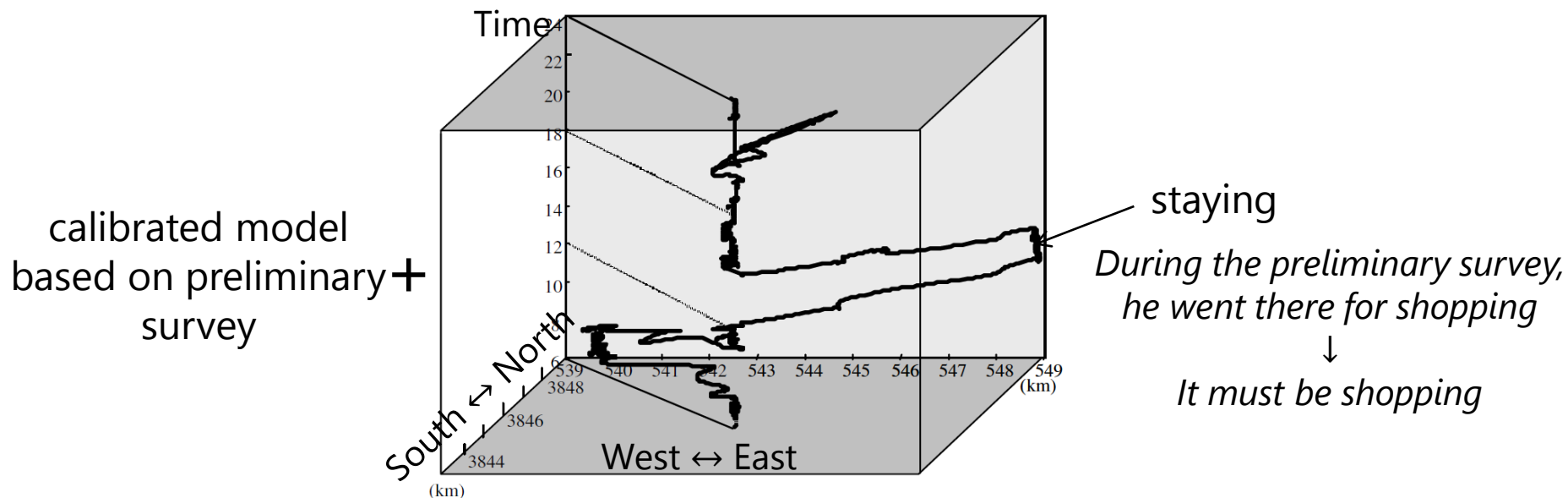
It must be shopping

GPS data collection + imputation based on *a priori* info.

- Automatic imputation based on a priori information (eg: Wolf et al., 2001; Shen and Stopher, 2013; Gong et al., 2013)
 - land use
 - behavior model calibrated by using existing data
- Collected data may have several limitation
 - Traveler **heterogeneity** is ignored
 - The data is not suitable for **behavior modeling** purposes

Existing advanced survey methods

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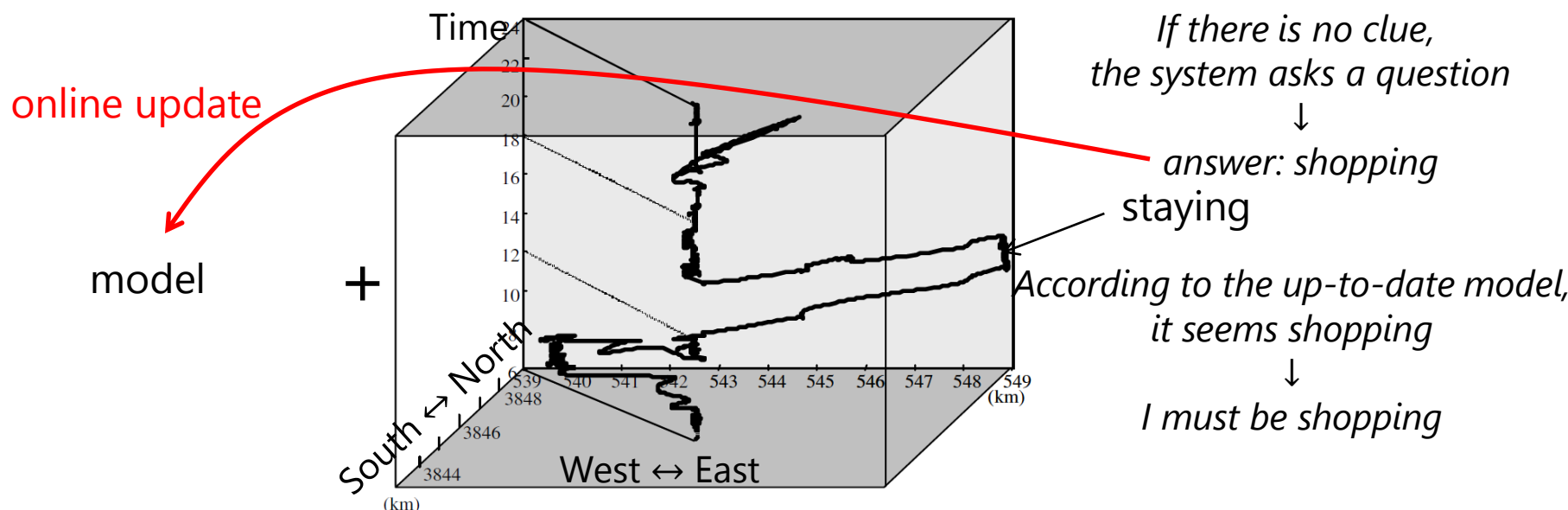
GPS data collection + imputation based on *offline* info.

(Kim, Ben-Akiva, et al., 2014, 2015)

- Automatic imputation based on preliminary survey
 - Data is collected by preliminary survey for the same participants
 - Traveler heterogeneity can be captured

Proposed survey method

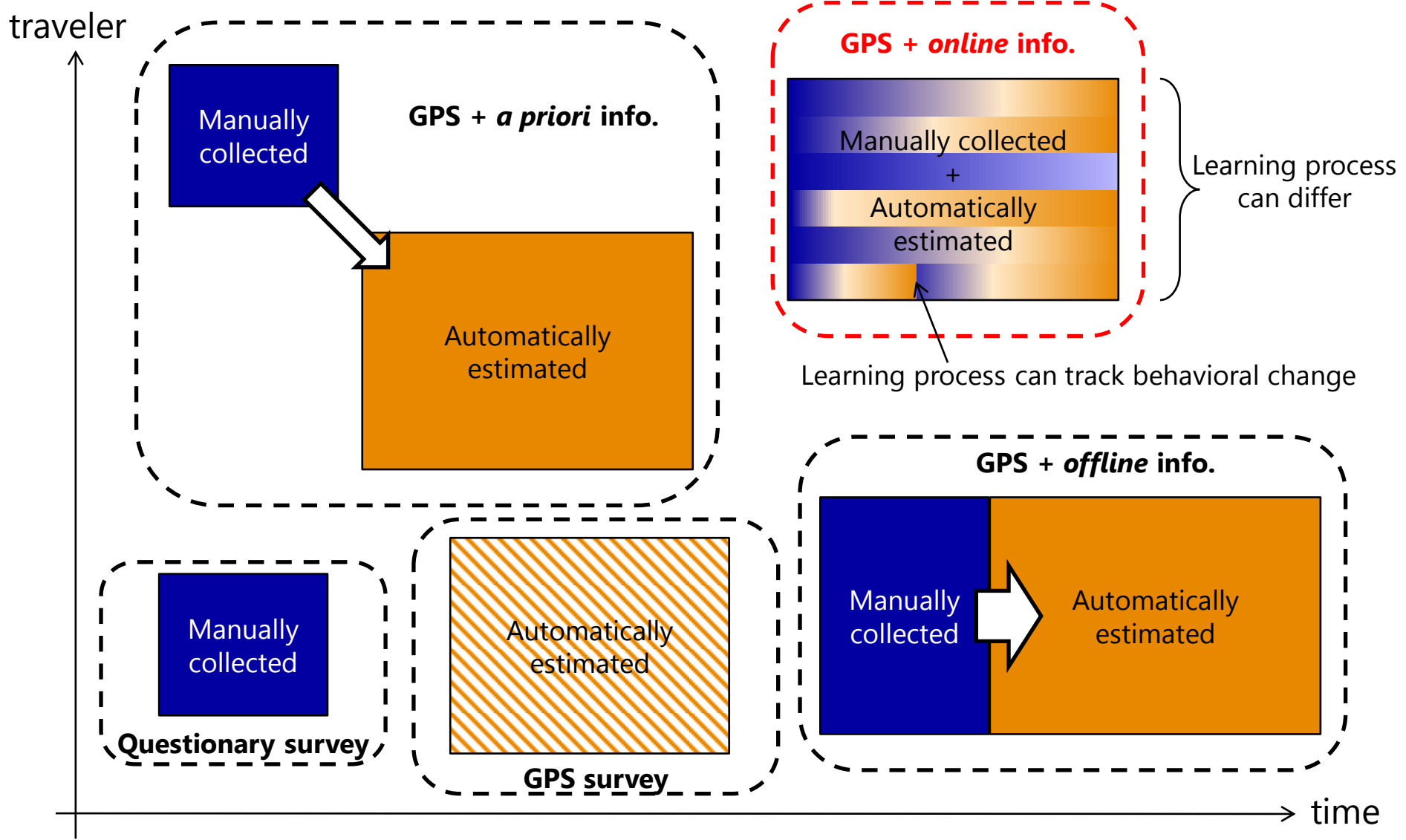
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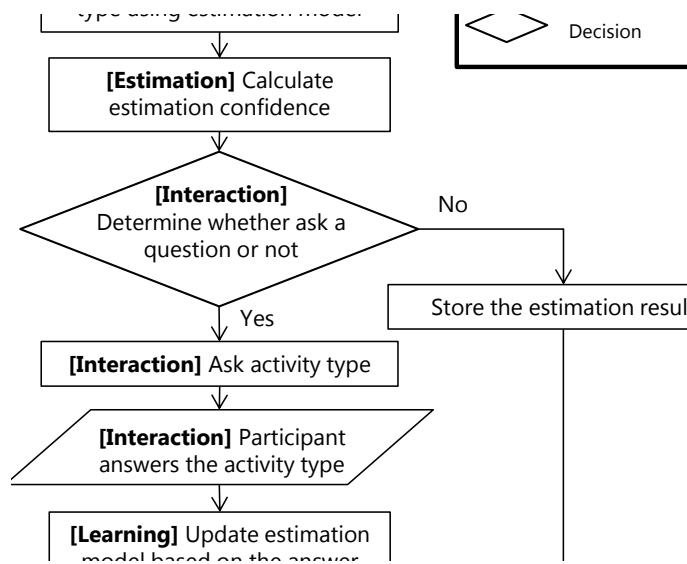


GPS data collection + imputation based on **online info**. (Kusakabe et al., 2015; Seo et al., 2016)

- Automatic imputation based on data collected from previous **online interaction**
 - online interaction: the survey system will ask a question **automatically** and **dynamically**
- Possible features of the proposed method:
 - Reducing frequency of questions
 - Keeping quality of data high
 - Considering traveler heterogeneity
 - Adaptive tracking of behavioral change
 - Automatic process (No need of manual control by survey administrator)

Illustration of methods





$$\hat{c} = \operatorname{argmax}_c P(c|Y)$$

$$\hat{c} = \operatorname{argmax}_c \prod_k P(x_k|c)P(c)$$

$$\{(c_1, Y_1), (c_2, Y_2), \dots (c_i, Y_i), \dots\}$$

$$P(\hat{c}|Y)$$

Methodology

Concept

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- The proposed method estimates activity type
- The system always measures activity situation using standard sensors
 - date, time, location
- The system detects occurrence of an activity
 - move-or-stay identification
- The system **can** ask a question about activity to the survey participants

- date
- time
- location



What are you doing now?

Are you working now?



Concept

- The system can ask a question, **if the system cannot estimate the activity**
- The system learns a traveler-specific behavior pattern
- The system runs automatically

Day 1, 9am, home to office

What are you doing?

Commuting!

Day 2, 9am,
home to office

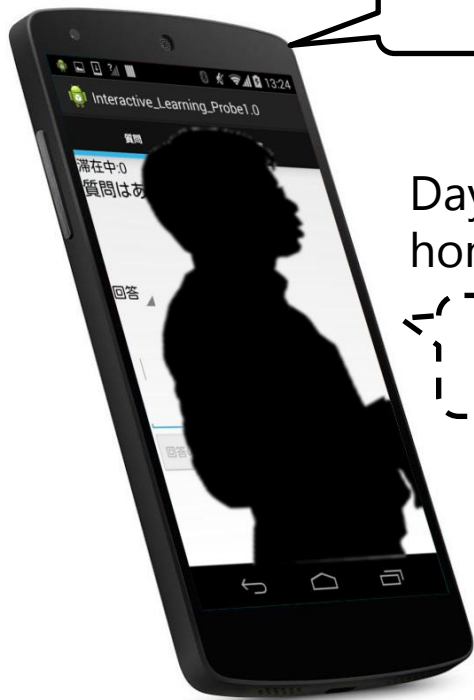
This must be
commuting.

Good. It stops
bothering me.

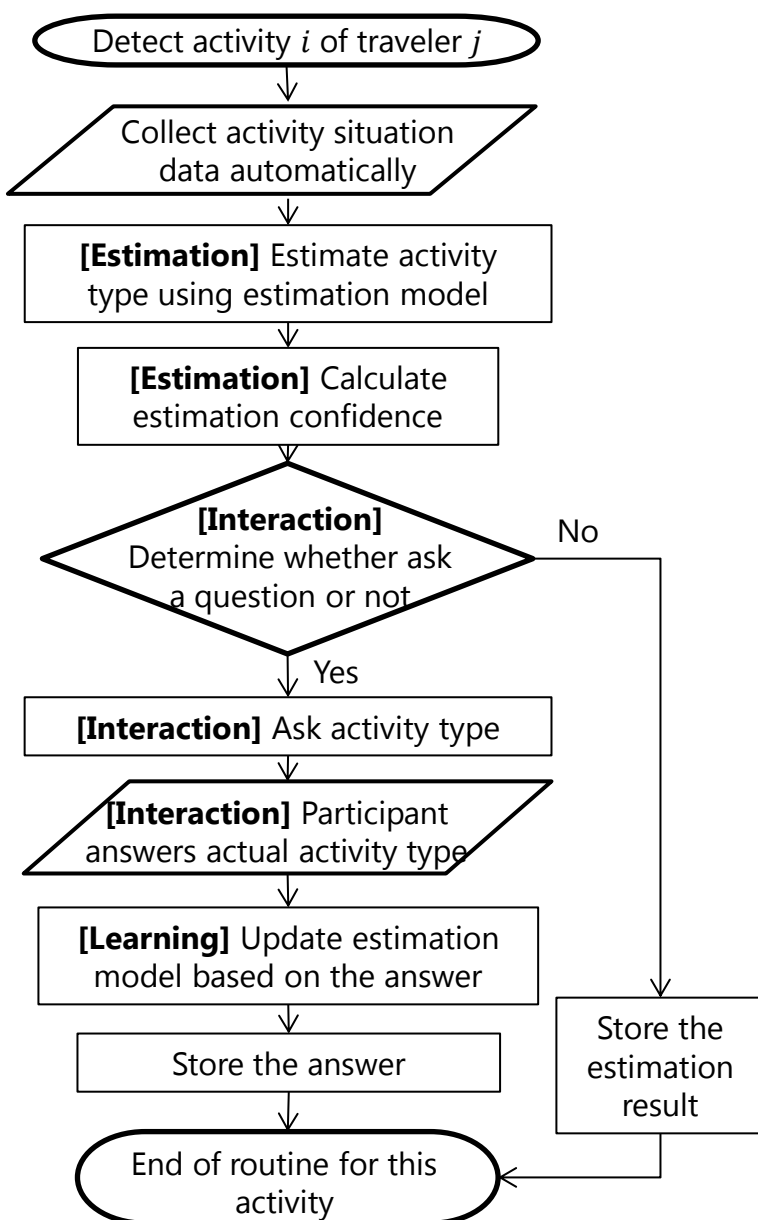
Day 3, 9am, home to **somewhere else**

What are you doing?

Enjoying my vacation!

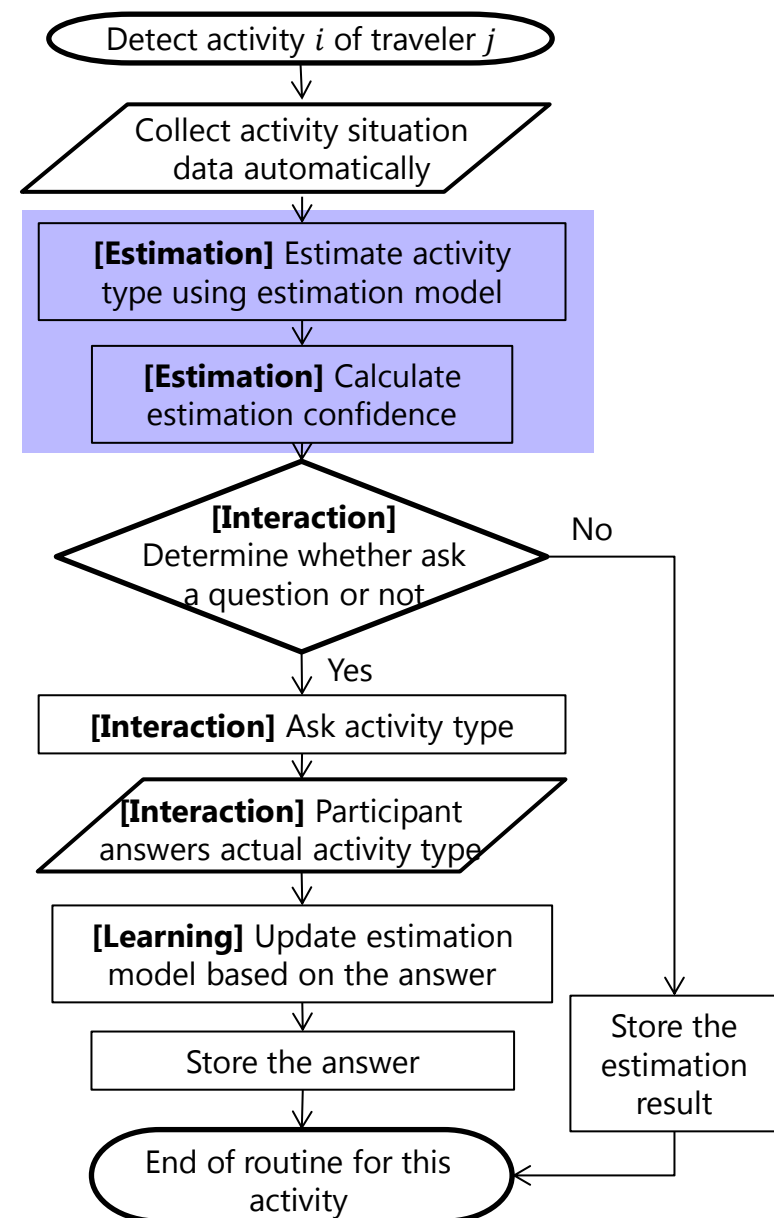


Overview



- Activity detection phase
 - Detects the survey participant staying somewhere to do unknown activity
 - out of scope of this study
- Estimation phase
 - Estimates the **activity type** using an traveler-specific estimation model
- Interaction phase
 - Will **ask activity type** to the survey participant, if the estimation is **not confident**
 - Will not ask the question, if the estimation is confident
- Learning phase
 - Updates the **estimation model** based on the participant's answer

Estimation phase



- Activity type estimation problem:

$$\hat{c} = \operatorname{argmax}_c P(c|Y)$$

where

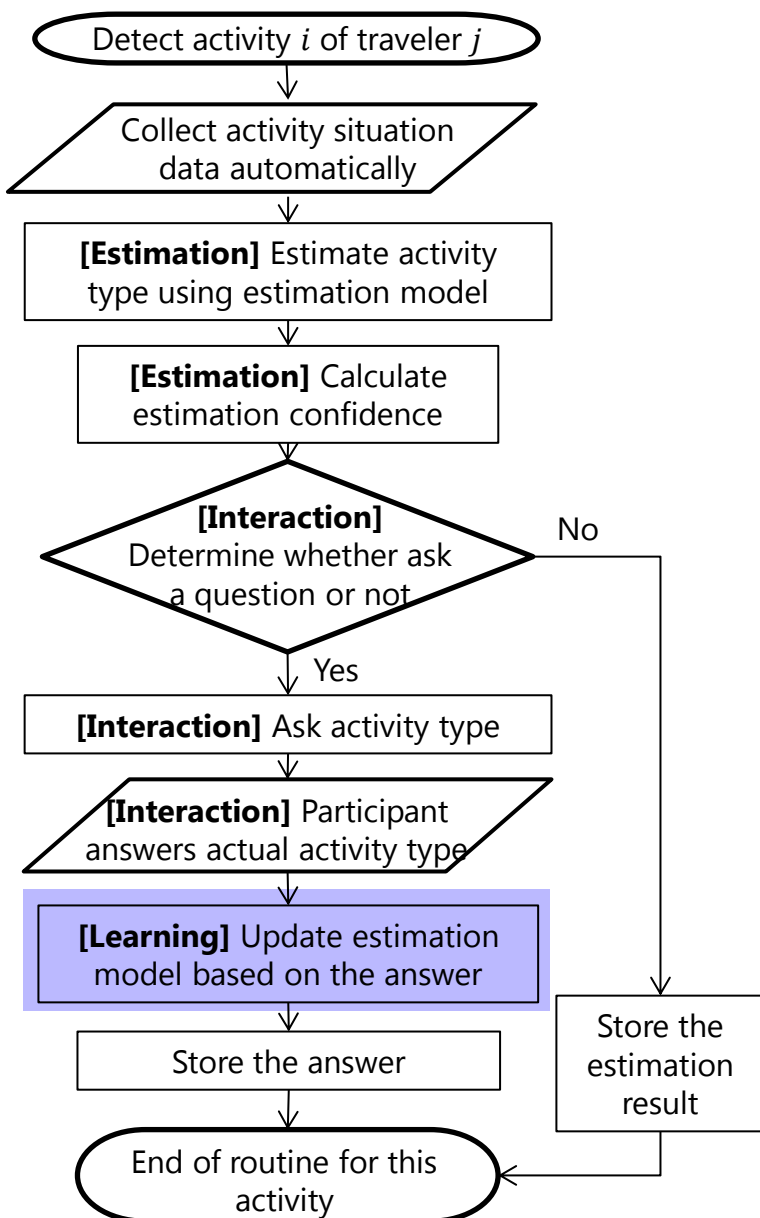
- activity type: c
eg: work, leisure
- activity situation: $Y = (x_1, x_2, \dots)$
eg: time: x_1 , location: x_2

- Naive Bayes assumption:

$$\hat{c} = \operatorname{argmax}_c \prod_k P(x_k|c)P(c)$$

- $P(x_k|c)$ and $P(c)$ are calculated based on historical data
= **learning**

Learning phase

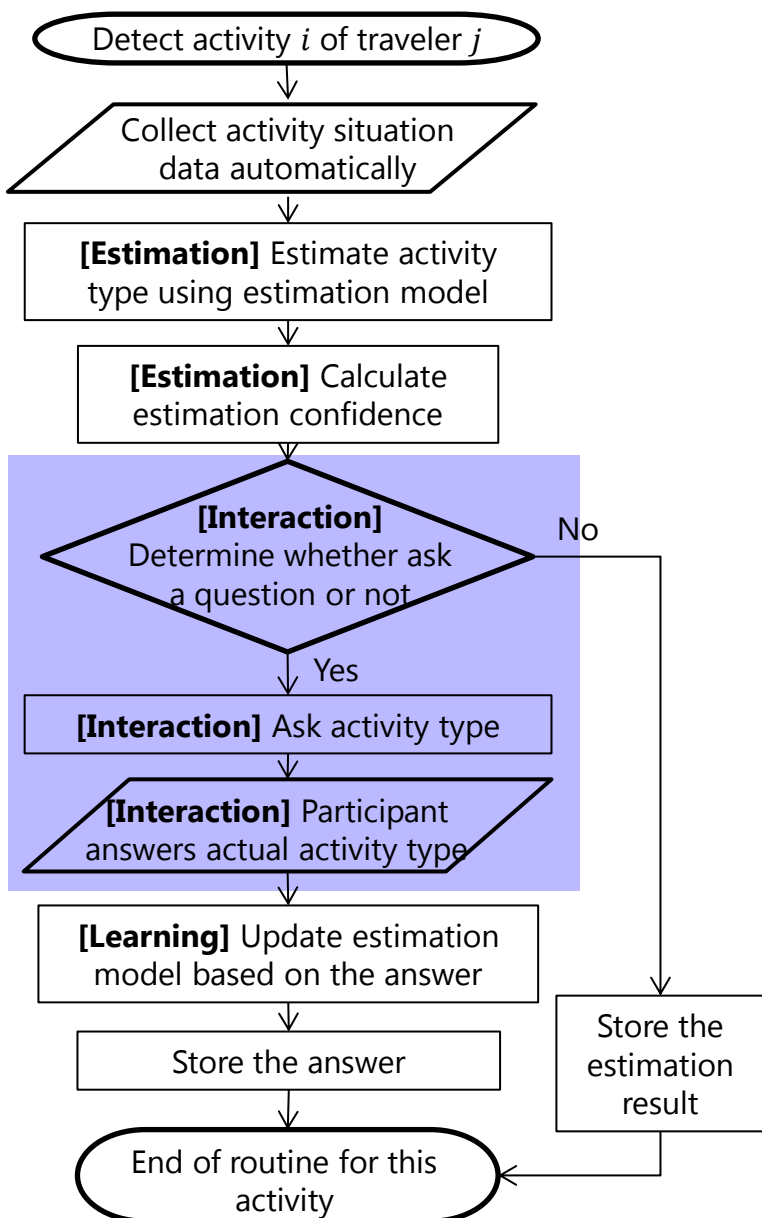


- Historical data:

$$H_{\text{traveler,time}} = \{(c_1, Y_1), (c_2, Y_2), \dots (c_i, Y_i), \dots\}$$
 - traveler-specific
 - dynamically updated
- $P(x_k | c)$ and $P(c)$ can be easily calculated based on the historical data
- How to collect the historical data?
 - **online interaction** between the system and participant

Interaction phase

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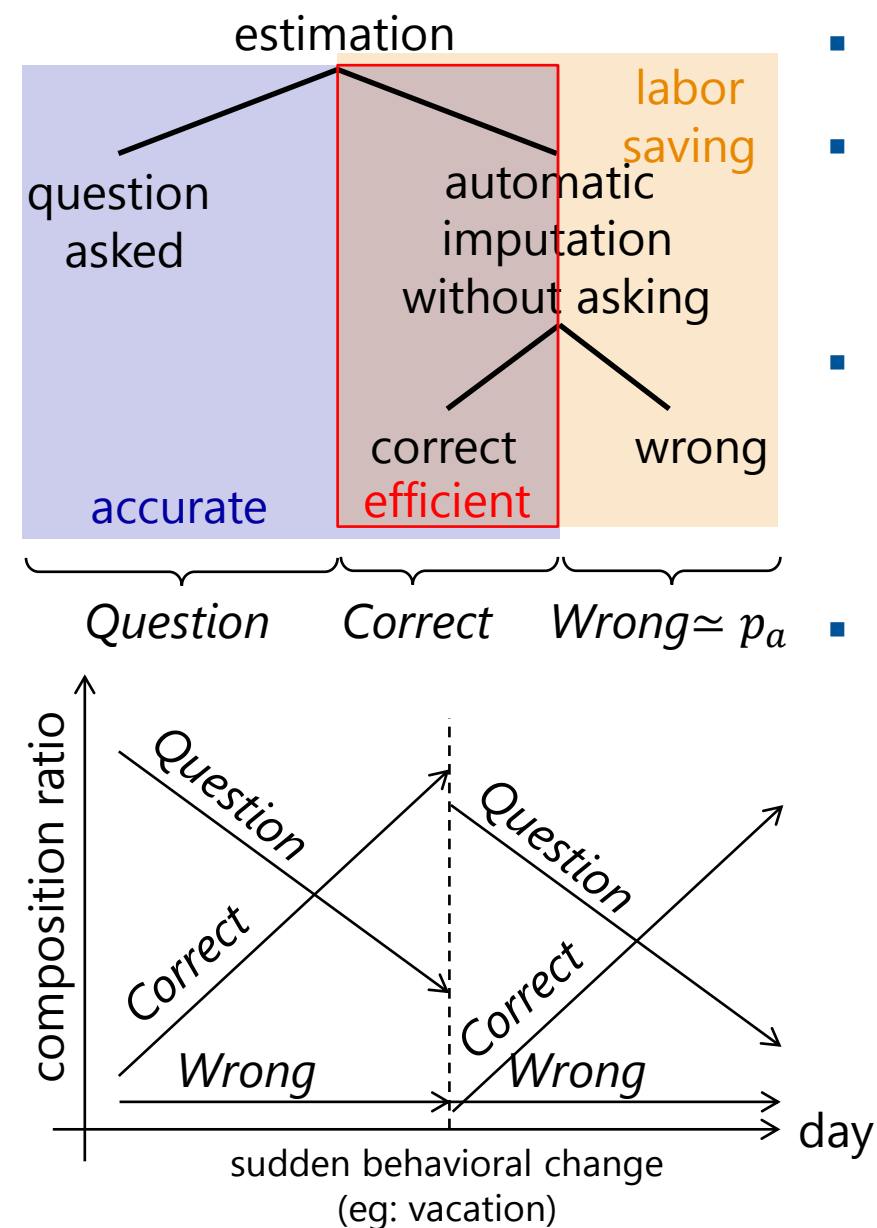


- Interaction:
 - If **estimation confidence** is high enough, the estimation result will be stored as a survey result
 - Otherwise, the system will **ask** the actual activity to the survey participant
 - The answer is stored to **historical data for learning**, as well as a survey result
- Estimation confidence:

$$P(\hat{c}|Y)$$
 - probability of performing activity \hat{c} under situation Y
 - easily calculated based on historical data
- The system will ask question with certain probability p_q so that **expected error rate** will be equal to a given **acceptable error rate** p_a
 - p_a is given by the survey planner
eg: 5%

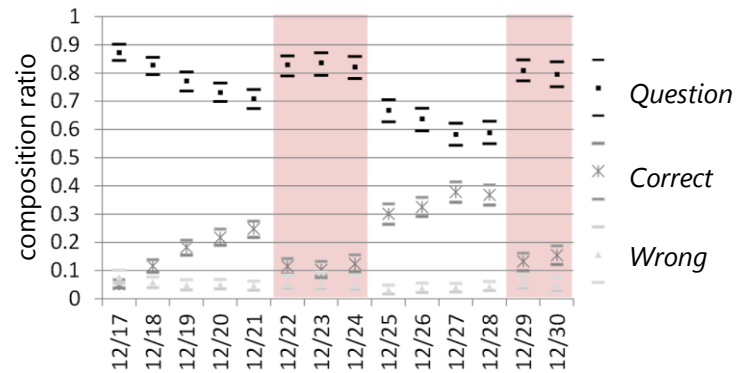
Summary

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- The survey admin will be happy if *Wrong* is small
- The survey participants will be happy if *Question* is small
 - It makes long-term survey easier
- The acceptable error rate p_a is given by admin
 - quality control
 - trade-off: $Wrong \downarrow \Leftrightarrow Question \uparrow$
- Estimation model keeps being updated during the entire survey period, for each travelers (=online)
 - At the initial stage, the estimation model is dumb
 - *Question* will be frequent
 - As the survey progresses, the estimation model will become accurate
 - *Question* will decrease; *Correct* will increase
 - Long-term behavioral change can be tracked
 - Traveler heterogeneity can be captured

2007/11/7	142	1000	0.666667	0.7916
2007/11/8	146	1000	0.641026	
2007/11/9	131	1000	0.625	0
2007/11/10	154	1000	0.818182	0.8260
2007/11/11	97	1000	0.75	0
2007/12/17	315	1000	0.785714	0.8928
2007/12/18	361	1000	0.833333	0.8571
2007/12/19	356	1000	0.818182	0.838
2007/12/20	369	1000	0.787879	0.8
2007/12/21	368	1000	0.75	0.718
2007/12/22	252	1000	0.837838	0.8333
2007/12/23	228	1000	0.851852	0.8148



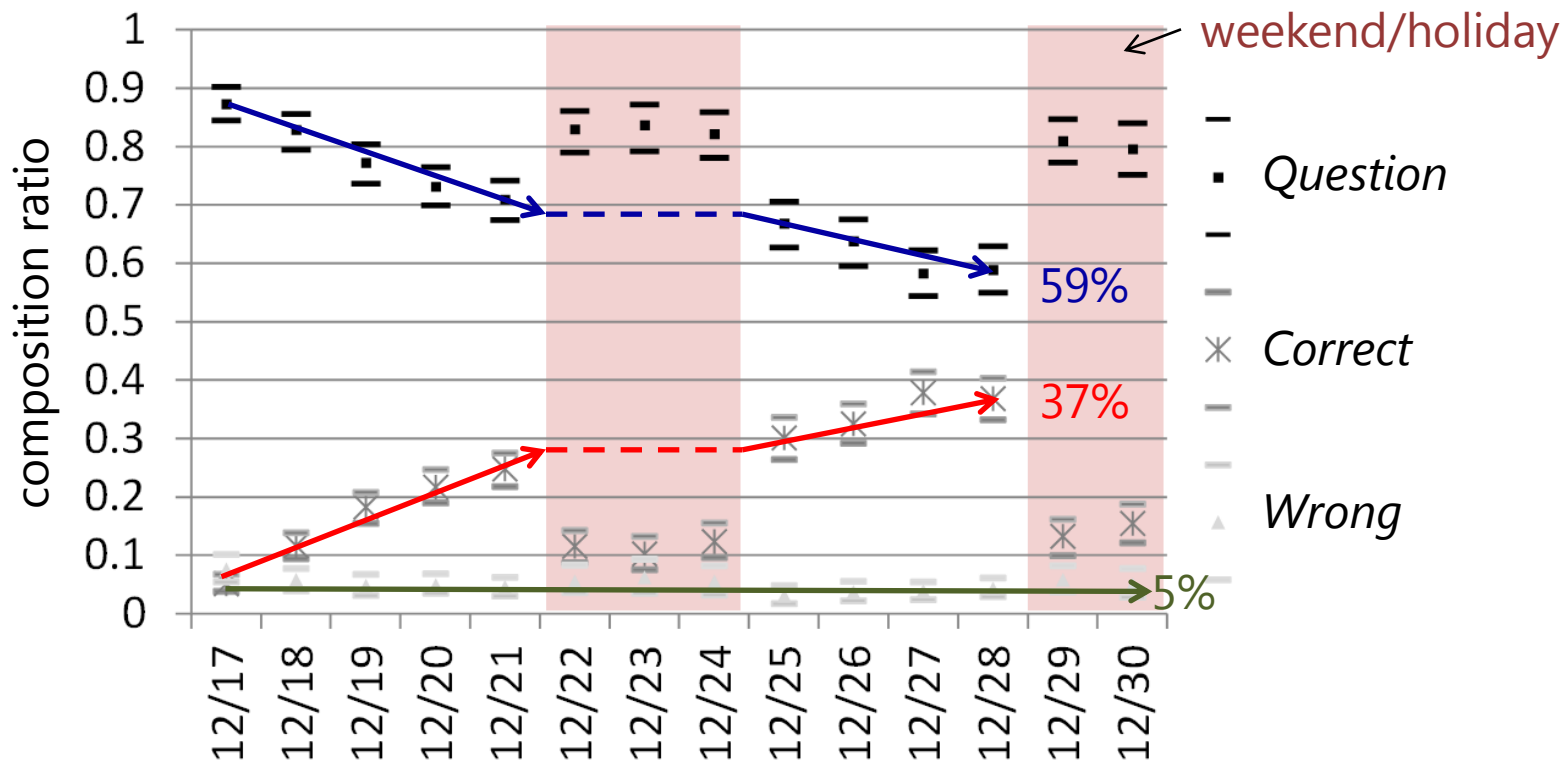
Empirical Validation

- The proposed method is validated by using existing travel survey data
 - collected by GPS + questionnaire survey
- Validation procedure
 1. Suppose that the survey data is true (ground truth)
 2. Emulate the proposed method
 3. Compare the estimation result with the ground truth

Date	Dec 17-30, 2007 <ul style="list-style-type: none">• duration: 2 weeks
Location	Matsuyama city, Japan
Number of participants	92
Number of trips	4120 <ul style="list-style-type: none">• 3.5 trips/person/day
Activity type (trip purpose)	commuting, returning home, business, shopping, food/leisure, others
Activity situation	weekday dummy, arrival time, location

Result

- For weekdays, *Question* decreases and *Correct* increases as time progresses
 - 37% *Correct* on the 12th day
 - Number of *Question* was almost halved
- Wrong* is almost constant at 5%
 - equal to the given acceptable error rate p_a
- Commuting and returning home trips were easier to be estimated



Proposed survey method

- GPS data collection = interpolation based on **online info** (location, time, etc. via web)
- Automatic interpolation based on data collected from previous **online interaction**
 - online interaction the survey system will ask a question **automatically** and **dynamically**
- Possible features of the proposed method
 - Reducing frequency of questions
 - Improving quality of data
 - Considering traveler heterogeneity
 - Adaptive tracking of behavioral change
 - Automatic process (no need of manual control by survey administrator)

Illustration of methods

Methodology

Estimation phase

- Activity type estimation problem: $Z = \arg \max_c P(c|Y)$
 - where
 - activity type: c
 - eg. work, leisure
 - activity situation: $Y = (x_i, t_i, \dots)$
 - eg. time x_i , location x_i
- Naive Bayes assumption: $Z = \arg \max_c \prod_i P(x_i|c) P(c)$
 - $P(x_i|c)$ and $P(c)$ are calculated based on historical data
 - = **learning**

Learning phase

- Historical data: $H_{i=1:n} = \{(x_1, Y_1), (x_2, Y_2), \dots, (x_n, Y_n), \dots\}$
 - traveler-specific
 - dynamically updated
- $P(x_i|c)$ and $P(c)$ can be easily calculated based on the historical data
 - **online interaction** between the system and participant

Interaction phase

- Interaction
 - If **estimation confidence** is high enough, the estimation result will be stored as a output result
 - Otherwise, the system will ask the actual activity to the survey participant
 - The actual answer is **used as learning** data
- Estimation confidence: $P(Z|Y)$
 - probability of performing activity c under situation Y
 - easily calculated based on historical data
- The system will ask question with certain probability, so that estimated error result will be equal to a given **acceptable error rate** ϵ , ϵ is given by the survey parameter ϵ , ϵ is given by the survey parameter ϵ , ϵ is given by the survey parameter ϵ .

Result

- For weekdays, Question decreases and Correct increases as time progresses
 - 27% Correct on the 12th day
 - Number of Question has diminished
 - Wrong is almost constant at 2%
 - equal to the given acceptable error rate, ϵ
- Computing and returning home trips were easier to be estimated

Conclusion

Achievements

- Travel behavior data collection method is proposed
 - for long-term and large-scale survey
- Features:
 - reduced frequency of questions
 - guaranteed quality of data
 - considered traveler heterogeneity
 - adaptive tracking of behavioral change
 - automatic process (no need of manual control by survey administrator)
- Methodology:
 - machine learning based on online interaction between the survey system and participant
- The proposed method is validated using existing travel data
 - it improved the frequency of questions on the 12th day
 - it helps to reduce further the acceptable error rate
 - the acceptable error rate was almost reached

Conclusion

Achievements

- Travel behavior data collection method is proposed
 - for long-term and large-scale survey
- Features:
 - reduced frequency of questions
 - guaranteed quality of data
 - considers traveler heterogeneity
 - adaptive tracking of behavioral change
 - automatic process (no need of manual control by survey administrator)
- Methodology:
 - machine learning based on online interaction between the survey system and participant
- The proposed method is validated using existing travel data
 - It almost halved the frequency of questions on the 12th day
 - It may be reduced further if the survey period is longer
 - The error ratio was 5% as intended

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