An Estimation Method for Spatiotemporal Traffic States Based on Incomplete Traffic Observation

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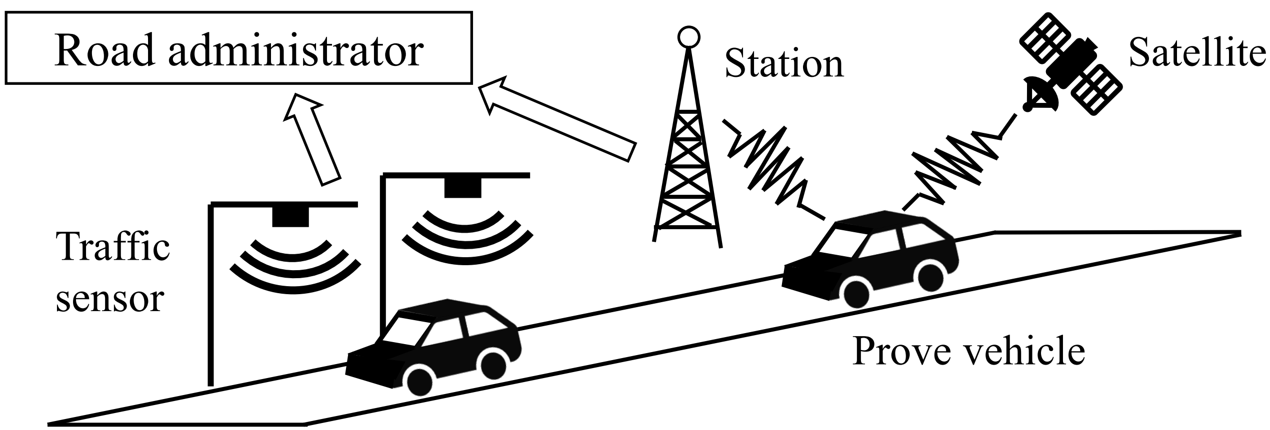
Background

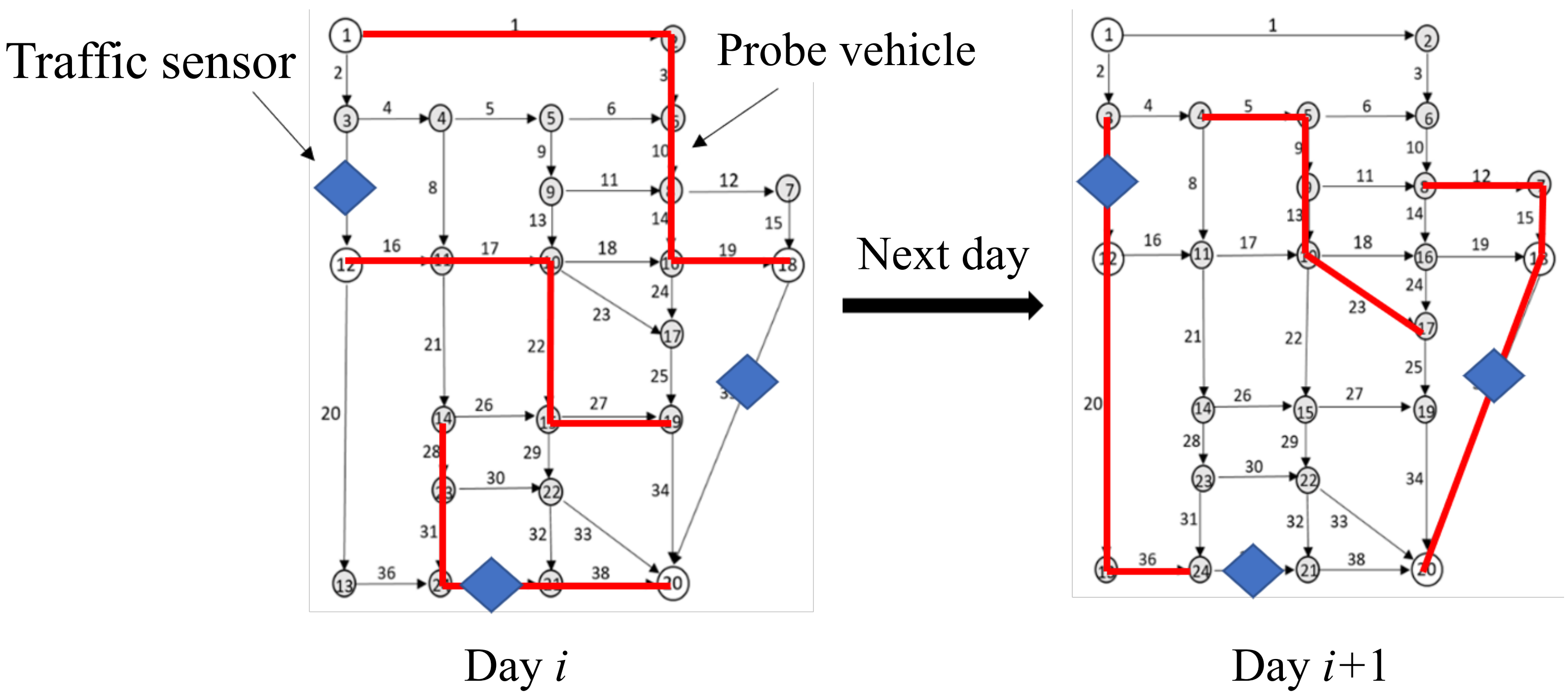
Network-based traffic state estimation with traffic sensor and probe car data

If the data observation is incomplete…
- low penetration of probe vehicles,
- privacy protection,
- less installation of traffic sensors

Impossible to collect perfect data set spatiotemporally



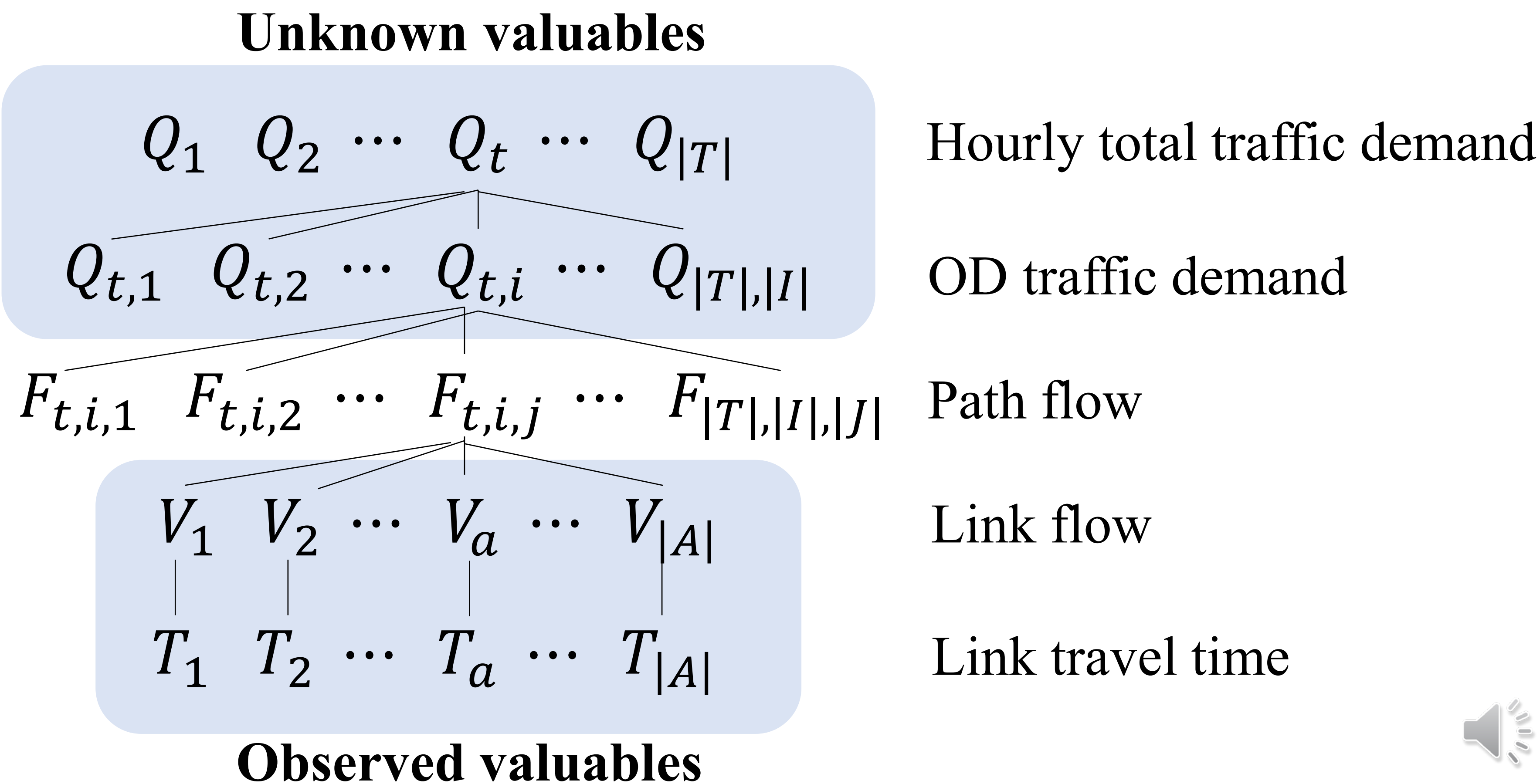
Background



- Day-to-day observation
- The number of traffic sensors and the scale of traffic demand are comparatively small than network size

Objectives

- to estimate traffic states as network-sized multivariate random variables
- to consider the missing data of the traffic observation



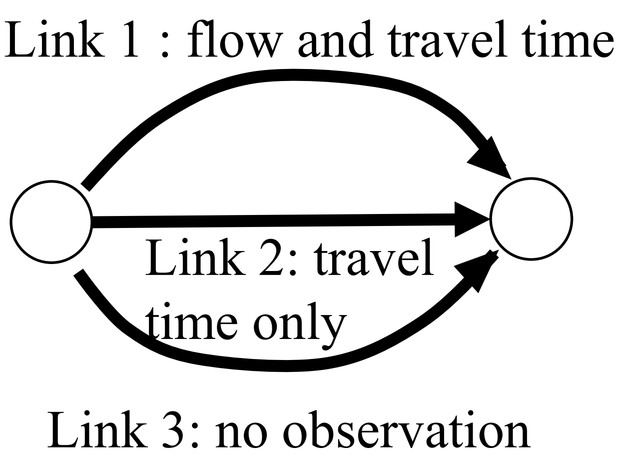
Methodology

Estimation target

Link flow : $\mathbf{V} \sim MVLN(\boldsymbol{\mu}_{\mathbf{V}}, \boldsymbol{\Sigma}_{\mathbf{V}})$

Link travel time (delay time): $\mathbf{T} \sim MVLN(\boldsymbol{\mu}_{\mathbf{T}}, \boldsymbol{\Sigma}_{\mathbf{T}})$

Data missing



Observed data set

$$\boldsymbol{d}_g = (\hat{v}_1, \hat{t}_1, -, \hat{t}_2, -, -) \quad \forall g \in \{1, \dots, G\}$$

Shrink the dimension

$$\mathbf{M}_g = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix} \forall g \in \{1, \dots, G\}$$

- Each data set can be missed
- **Likelihood estimation considering data missing**

Full information maximum likelihood function

$$L(\boldsymbol{\mu}, \boldsymbol{\Sigma}) = \prod_{g=1}^{G} \frac{\exp\left(-\frac{1}{2}\left(\widehat{\boldsymbol{d}}_g - \boldsymbol{\mu}_g\right)^T \boldsymbol{\Sigma}_g^{-1}\left(\widehat{\boldsymbol{d}}_g - \boldsymbol{\mu}_g\right)\right)}{2\pi^{n(g)/2}\left|\boldsymbol{\Sigma}_g\right|^{1/2}}$$

where

$$\boldsymbol{\Sigma}_g = \mathbf{M}_g \boldsymbol{\Sigma} \mathbf{M}_g^T, \quad \boldsymbol{\mu}_g = \mathbf{M}_g \boldsymbol{\mu}^T, \quad \widehat{\boldsymbol{d}}_g = \mathbf{M}_g \boldsymbol{d}_g^T$$

With equilibrium constrain

Traffic assignment considering network uncertainty

$$E\left[F_{ij}\right] = p_{ij}\left(\mathbf{c}(\mathbf{F})\right) \cdot E[Q_i] \ \ \forall i \in \mathbf{I}, \forall j \in \mathbf{J}_i$$

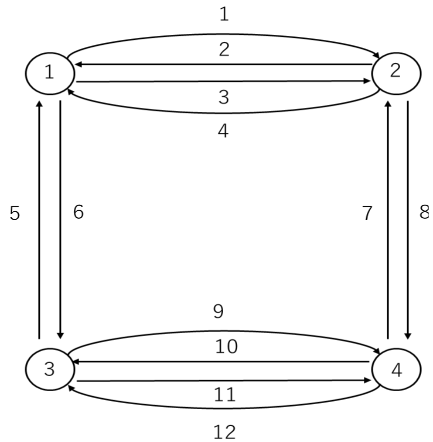
where

$$p_{ij} = \frac{\exp\left(-\phi \cdot c_{ij}(\mathbf{F})\right)}{\sum_{j=1}^{|J_i|} \exp\left(-\phi \cdot c_{ij}(\mathbf{F})\right)} \forall i \in \mathbf{I}, \forall j \in \mathbf{J}_i$$

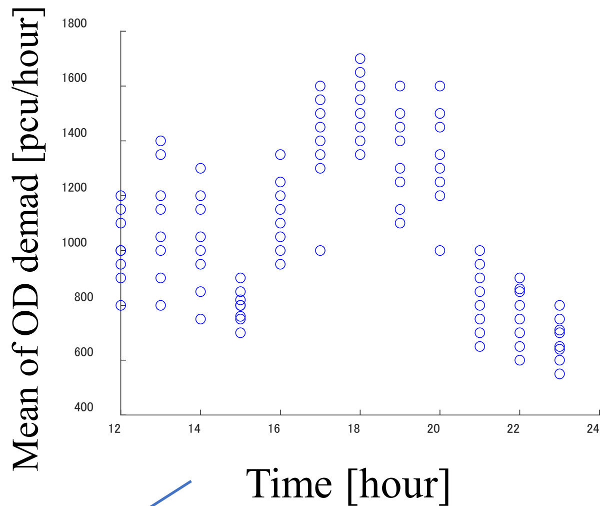
$$\mathbf{c} = \left(c_{11}(\mathbf{F}), \cdots, c_{i|I|\cdot|J_{|I|}|}(\mathbf{F})\right), \mathbf{F} = \left(F_{11}, \cdots, F_{|I|\cdot|J_{|I|}|}\right)$$

Fixed point problem
Logit-type SUE

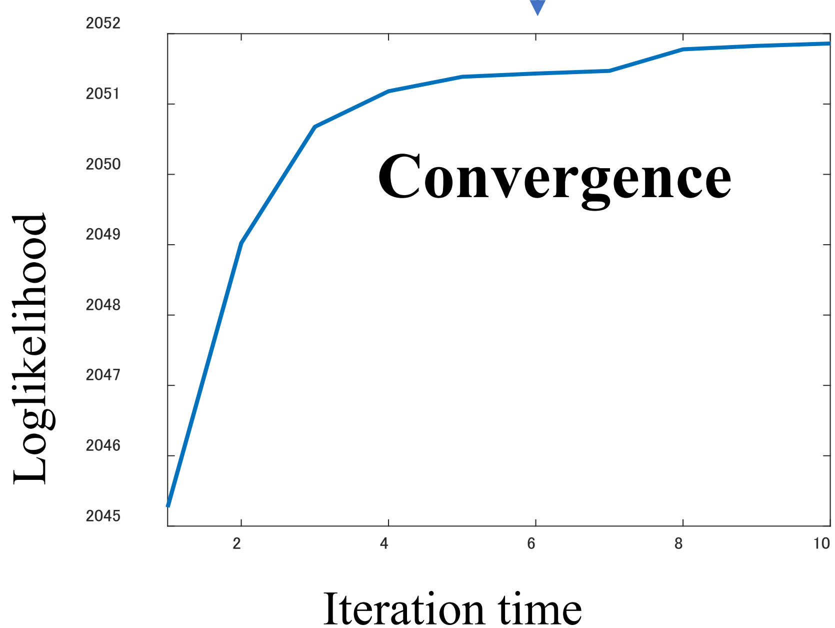
Numerical experiment



Test network



Traffic state estimation



Major settings

- 12 time intervals
- Probe ratio: 30%
- Sample size: 300

- Solved two auxiliary problems iteratively
- Estimated mean and variance-covariance of traffic demands

Conclusion

- Network-based traffic states estimation for several time intervals
- With missing spatiotemporal data
    - traffic sensor; probe vehicle
- Numerical test showed the solution conversion

Next step

- Realtime prediction of the traffic states from the latest observation
    - Bayesian estimation considering data missing