# Generalized Statistical Traffic Assignment (GESTA)

Methodology, Properties and Variance Analysis

# Wei Ma, Sean Qian

# Background

Classical traffic assignment plays a pivotal role in planning and operations

 $\phi: q \mapsto x, f$ 



Daily time-varying traffic counts on SR41 SB and NB

□ Statistical traffic assignment explores the statistical features of recurrent flow patterns

$$\phi \colon Q \longmapsto X$$
,  $F$ 

Stochastic process vs. Stationary distribution



### Literature review

□ Network variation ≈ Flow variation
□ Flow variation comes from different sources



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### OD demand variation

**OD** was first considered as a deterministic value

- Variance of OD was modelled but the covariance was not (e.g. Poisson distribution)
- Both variance and covariance was modelled (e.g. MVN)

#### Example:

 $q_1$ 

) 
$$\square$$
  $Q_i \sim Pois(\lambda_i)$ 

MVN: Multi-variate Normal Distribution



### Route choice variation

- $\Box$  Understand the route choice probability p
- In uncongested networks, the route choice can be pre-determined
- □ The fixed proportion *p* that travelers will select certain routes
- □ The probability *p* for an arbitrary traveller to choose certain route

#### Example:

100 travelers, 2 routes,  $p_1 = 0.3$ ,  $p_2 = 0.7$ 

$$f_1 = 30$$
  $F_1 \sim BN(100, 0.3)$ 





### Measurement error

- Measurement error is different from perception error, it exists physically
- □ Choice model may combine the perception error and measurement error (e.g. logit/probit)
- Explicitly considering the measurement error helps to calibrate the model





# Our study

OD demand	Route Choice	Measurement Error	Model
Deterministic	Pre-determined	Not consider	Trivial case
Deterministic	Fixed portion w/ route choice model	Implicitly considered in choice model	Logit/Probit model
Stochastic but independent	Pre-determined	Not consider	Vardi 1996, Hazelton 2008, Parry & Hazelton 2012, Hazelton et al. 2015
Stochastic but independent	Stochastic probability w/ route choice model	Implicitly considered in choice model	Nakayama &Watling 2014, Castillo et al. 2014
Stochastic but independent	Fixed portion w/ stochastic route choice model	Implicitly considered in choice model	Nakayama & ichi Takayama 2006, Nakayama & Takayama 2003
Stochastic and dependent	Fixed portion w/ route choice model	Implicitly considered in choice model	Shao, Lam & Tam 2006, Lam et al. 2008, Shao et al. 2014, 2015
Stochastic and dependent	Stochastic probability w/ route choice model	Explicitly considered	This study

# Model

OD OD

- MVN:  $Q \sim N(q, \Sigma_q)$
- Scalable, stable and consistent, Castillo et al. (2014)
- □ Route choice
  - *p* is deterministic for a recurrent traffic network
  - A generalized probability function:  $p = \psi(C; \Theta)$

□ Path flow

- Path flow follows multinomial distribution
- $F_{rs}|Q_{rs} \sim MN(Q_{rs}, p_{rs})$
- Normal approximation
- □ Link flow
  - $X = \Delta F$ , where  $\Delta$  is the path/link incidence matrix

□ Path cost

- A generalized path cost function:  $C \sim t(X; \Theta)$
- Normal approximation

### Model: Hierarchy

Level 1:		
	$X_m \sim N(X + e, \Sigma_x + \Sigma_e)$	Measurement error
Level 2:		
	$X \sim N(\Delta pQ, \Sigma_x) F \sim N(pQ, \Sigma_f)$	Route choice variation
Level 3:		
	$Q \sim N(q, \Sigma_q)$	OD variation

- □ Level i is conditional on level i+1
- Each level reflects one single source of the link flow variation



# Model: Property

- □ Existence and consistence of the solution
  - Fixed point problem



- If the path cost function is continuous, the solution  $(x, \Sigma_x, f, \Sigma_f, p)$  exists.
- Once the solution  $(x, \Sigma_x, f, \Sigma_f, p)$  is determined, then it's consistent.
- **Reducible** 
  - Model can be reduced to existing statistical assignment models
- Data driven
  - Friendly to model learning techniques for large scale networks
  - Dimension reduction, sparse regularization, model selection

# Model: Application

□ Marginal distribution

Marginal distribution of  $X_m$  can be written as:

$$X_m \sim N(x_m, \Delta p \Sigma_q p^T \Delta^T + \Delta \Sigma_{f|q} \Delta^T + \Sigma_e)$$

Three matrices represent the variance from OD, route choice and measurement error separately.

#### □ Variance ratio

- To measure the portion of each source of variance
- To help to reduce the system variance
- Trace norm, nuclear norm

□ MANOVA

- Hypnosis testing
- Calculate confidence interval (CI) of link flows

Solution algorithms

□ Path based: K-shortest paths

□ Alternating optimization: may not converge

□ MSA based algorithm: may not converge to global optimum

□ Computational complexity: quadratic to # of paths

# Experiment

□ Settings



- OD: 1 -> 3,  $q = 1000, \sigma^2 = 10000$
- Route choice model: Probit + Multinomial
- Link cost function: BPR function
- Measurement error: e = 0,  $\sigma_e^2 = 100$

# Experiment

□ Basic results







□ Varying OD variance





#### Change of link flow



**Carnegie Mellon University** Civil and Environmental Engineering Variance ratio: trace based

# Large Scale Network

- □ Settings
  - SR41 freeway network: 2413 links and 7110 OD pairs
  - OD demands were carefully calibrated
  - Assume the O-D demand variance is 20% of its mean
- □ Results
  - Terminated in 9 iterations and 467 seconds





- Using Rectangle CI approximation.
- Red represents volume/capacity>1, and green represents volume/capacity=0, other colors are smoothly transitioned from green to red as volume/capacity increases from 0 to 1)

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# Highlights

- To generalize and extend previous studies on statistical traffic assignment models
- □ To prove the existence and consistence of the network equilibrium
- □ To demonstrate the analytical application of GESTA: marginal distribution, variance decomposition, MANOVA
- □ To test the model on a large-scale networks and prove its computational efficiency

Future work

- □ Sensitivity analysis of GESTA
- Calibration of GESTA (OD estimation)

Dynamic-GESTA

# Thanks!

Contact Info: Carnegie Mellon University Mobility Data Analytics Center Wei Ma: <u>weima@cmu.edu</u> Sean Qian: <u>seanqian@cmu.edu</u>