



# Network Tomography

**Goal:** estimate origin-destination rates of traffic flow over a network.

**Data:** traffic counts at various network locations.

**Applications:** road networks, electronic communication networks.

# Network Tomography

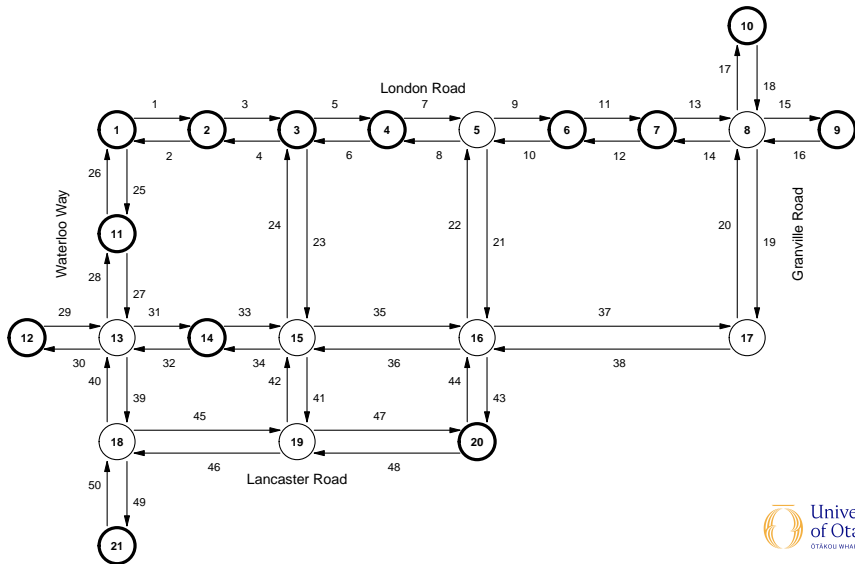
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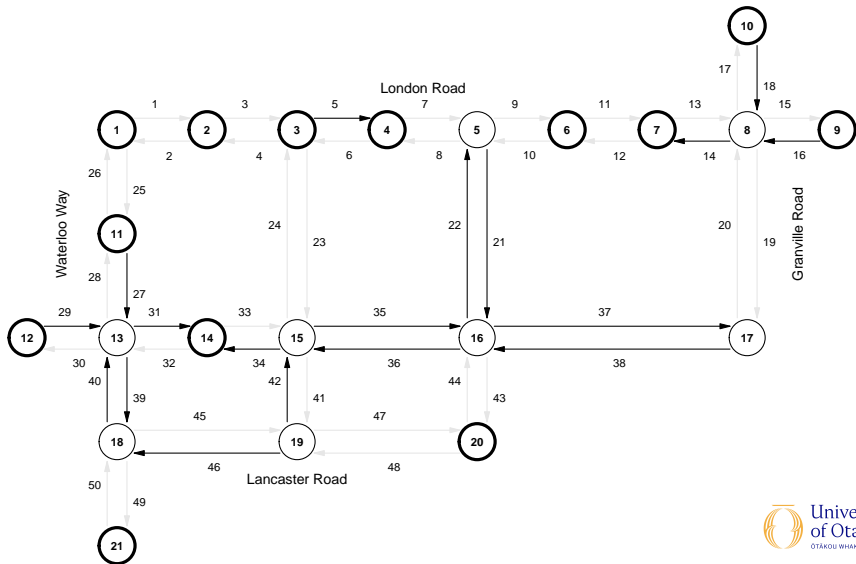
# Illustrative Example

Leicester, U.K.



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Leicester, U.K.



# More Questions Than Answers

Number of origin/destination nodes		13
Number of origin-destination pairs	$13 \times 12 =$	156
Number of traffic count sites		18

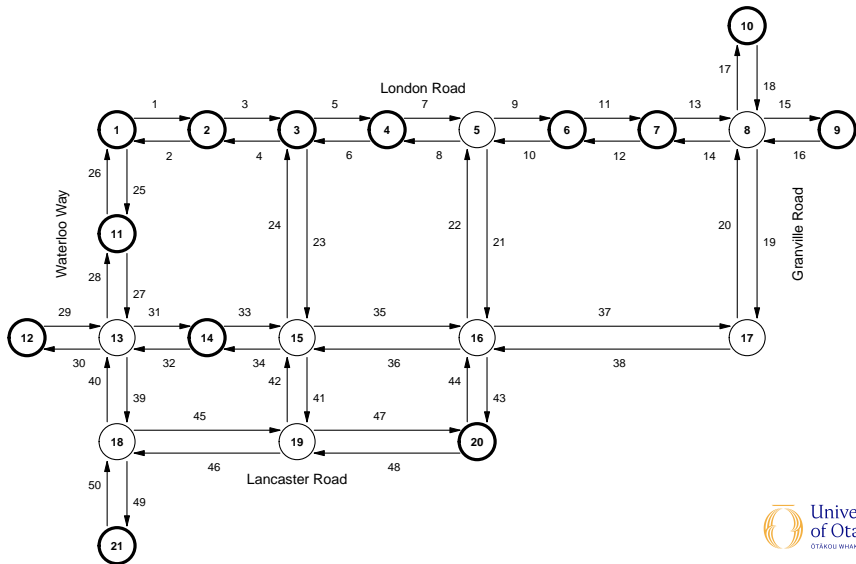
$d = 156$  parameters  $\theta = (\theta_1, \dots, \theta_d)^T$  to estimate.

$n = 18T$  traffic count data points  $\mathbf{y}$  available, over  $T$  periods.

Usually prior information on origin-destination rates  $\theta$  is available.

# Routed

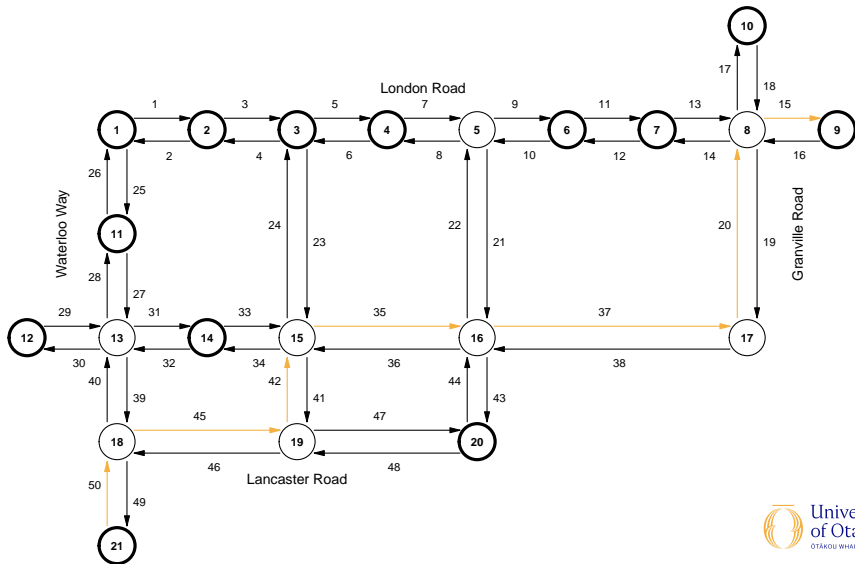
Leicester, U.K.





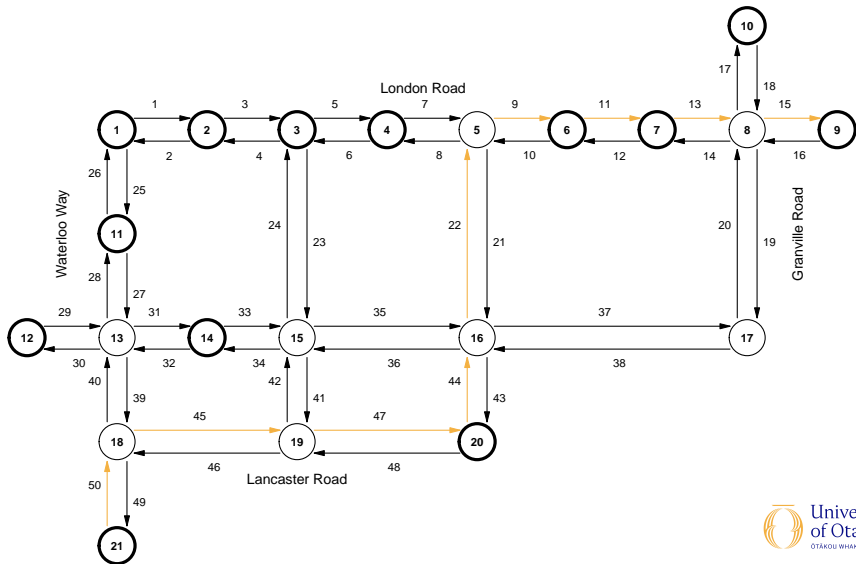
# Routed

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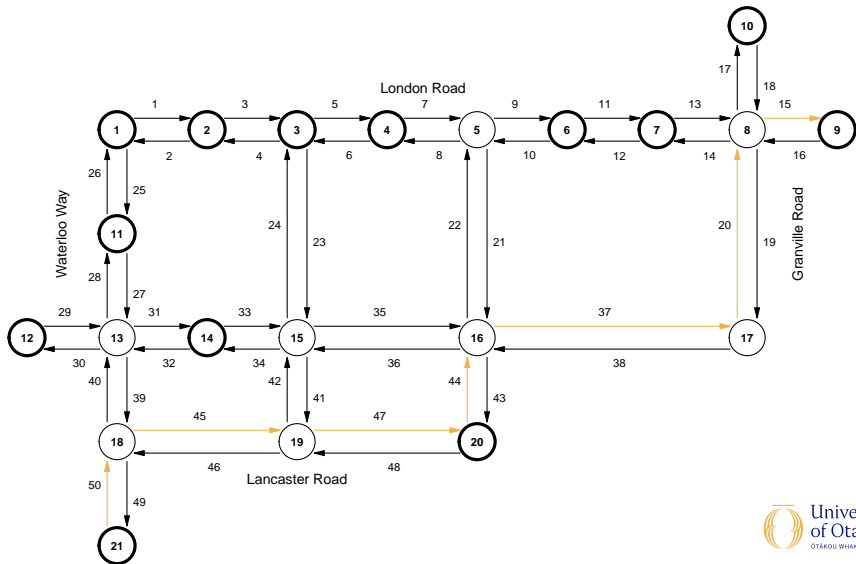
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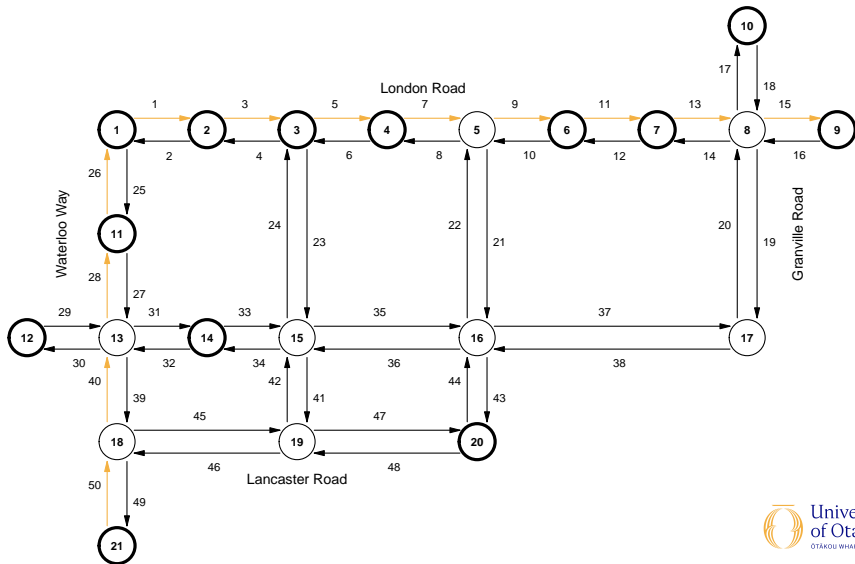
# Routed

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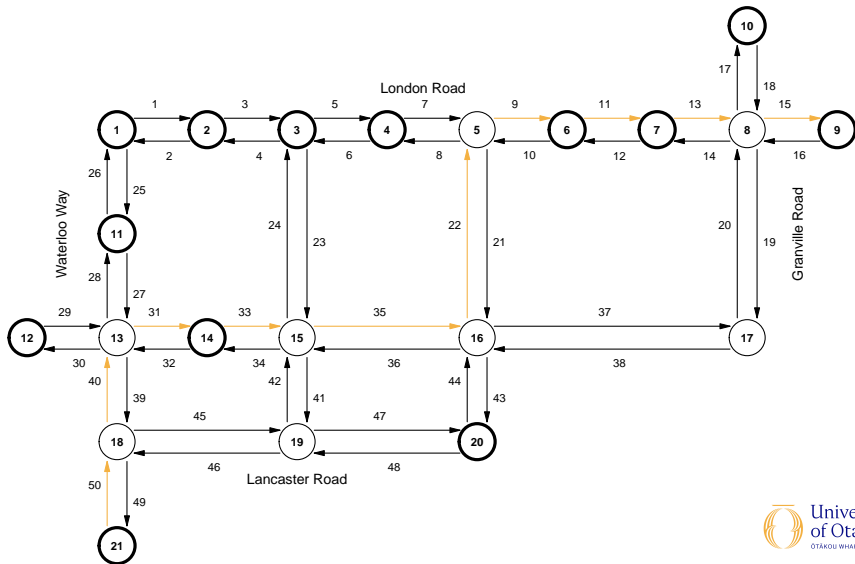
# Routed

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# Routed

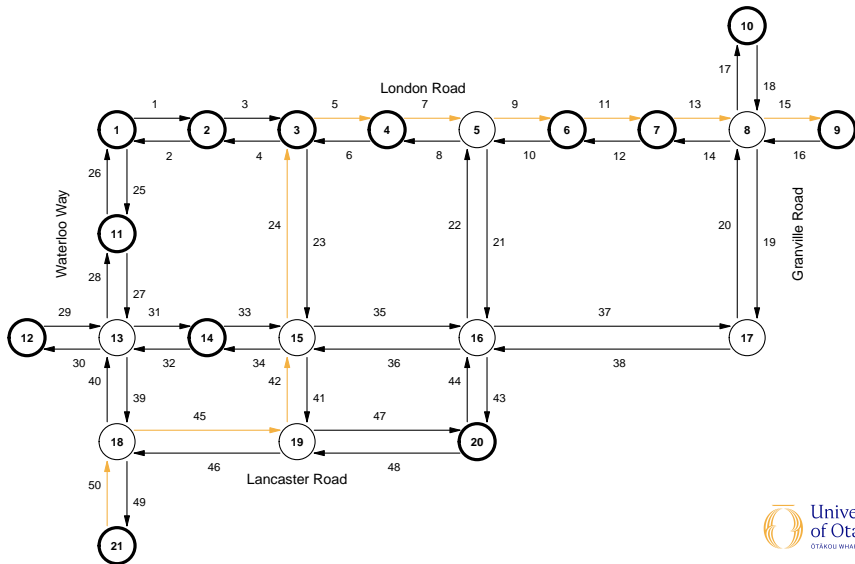
Leicester, U.K.





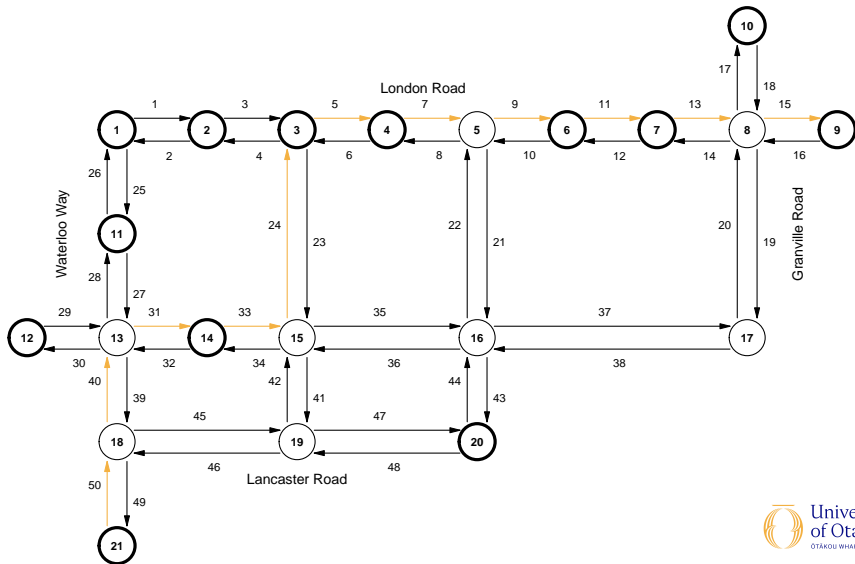
# Routed

Leicester, U.K.



# Routed

Leicester, U.K.



# Route Choice probabilities

## Nuisance Parameters

Number of origin-destination pairs	156
Number of plausible routes (paths)	355
Number of nuisance parameters	199

$r - d = 355 - 156 = 199$  free route choice probabilities

Limited explicit prior information.

Route choice will depend on traffic congestion.

# Modelling Route Choice Probability

## Traffic Equilibrium Models

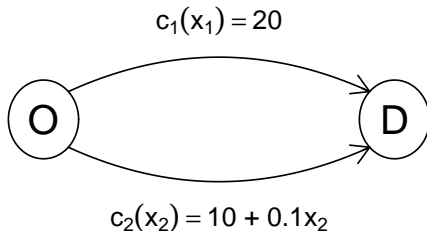
Long history of modelling route choice in transportation research

Deterministic equilibrium models, based on game theory, dominated historically.

- Premise is that route choices depend on travel times ...
- ... which depend on levels of congestion ...
- ... which depend on route choices.

# Stochastic User Equilibrium (Daganzo & Sheffi, 1977)

## Illustrative Example



Travel demand  $\theta = 100$ .

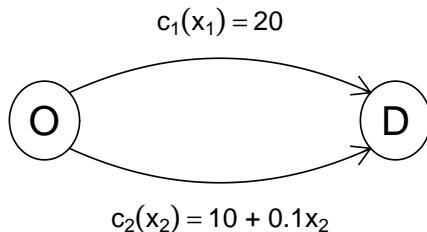
Stochastic User Equilibrium (SUE) is  $x_1 = 16.3$ ,  $x_2 = 83.7$ , since

$$P(\text{route 1}) = \frac{e^{-c_1(16.3)}}{e^{-c_1(16.3)} + e^{-c_2(83.7)}} = \frac{e^{-20}}{e^{-20} + e^{-18.4}} = 0.163$$

Daganzo, C. F., & Sheffi, Y. (1977). On stochastic models of traffic assignment. *Transportation science*, **11**(3), 253–274.

# Stochastic User Equilibrium

## Incorporating Cost Sensitivity



Introduce cost sensitivity parameter  $\omega$ :

$$P(\text{route 1}) = \frac{e^{-\omega c_1}}{e^{-\omega c_1} + e^{-\omega c_2}}$$

# Stochastic User Equilibrium

## Applied to Mean Traffic Flows

Stochastic User Equilibrium (SUE) route probabilities  $\mathbf{p}$  satisfy fixed point equation:

$$\mathbf{p} = \mathbf{q}(A^T \mathbf{c} (A \text{diag}(\boldsymbol{\theta}) \mathbf{p}))$$

- $A$  is link-path incidence matrix;
- $\mathbf{c}$  is (vector-valued) link cost (travel-time) function;
- $\mathbf{q}$  is probability model, e.g. logit.
- Recall  $\boldsymbol{\theta}$  is mean vector for origin-destination traffic volumes.

**Critical idea:** employ SUE model to implicitly define prior for route choice probabilities as function of  $\boldsymbol{\theta}$ .

# MCMC for Bayesian Inference

Define  $\mathbf{x}$  to be vector of latent route traffic volumes.

Then  $\mathbf{y} = A\mathbf{x}$ .

Model origin-destination volumes as  $\text{Pois}(\boldsymbol{\theta})$ , so  $\mathbf{x} \sim \text{Pois}(\text{diag}(\boldsymbol{\theta}_{ext})\boldsymbol{p})$ .

Outline of algorithm:

- 1 Sample latent  $\mathbf{x}$  given  $\mathbf{y}$ ,  $\boldsymbol{\theta}$ .
  - ▶ Possible by dynamic Markov basis fibre sampling (H. et al., 2021).
- 2 Sample  $\boldsymbol{\theta}$  given  $\mathbf{x}$ .
  - ▶ Requires evaluation of acceptance probability  $\propto [\mathbf{x} \mid \boldsymbol{\theta}][\boldsymbol{\theta}]$ .
  - ▶ Requires evaluation of SUE to compute  $\boldsymbol{p}(\boldsymbol{\theta})$

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Hazelton, M., McVeagh, M., & Van Brunt, B. (2021). Geometrically aware dynamic Markov bases for statistical linear inverse problems. *Biometrika*, **108**(3), 609–626.

# SUE Emulation

Need to evaluate SUE probabilities at each iteration of sampler.

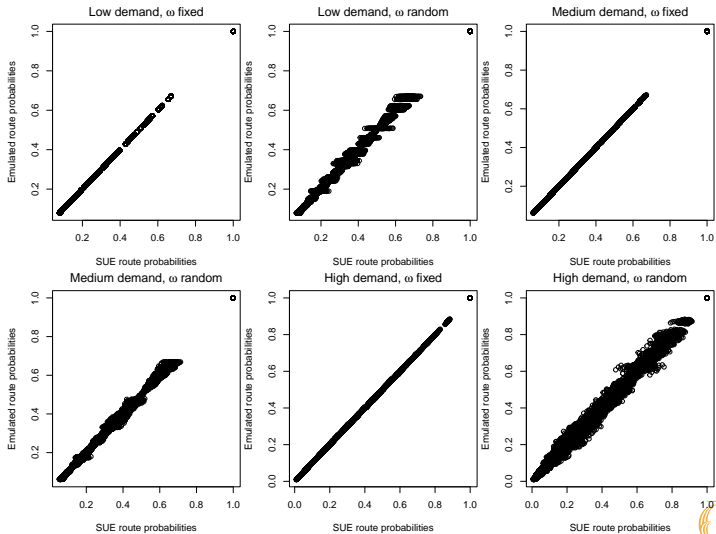
Solving fixed point equation for  $\mathbf{p}(\theta)$  is computationally intensive.

Employ regression-based emulator, working on scale of travel-times.

- Linearizes SUE costs as function of  $\theta$ .
- Uses training set with  $\theta$  sampled from prior.

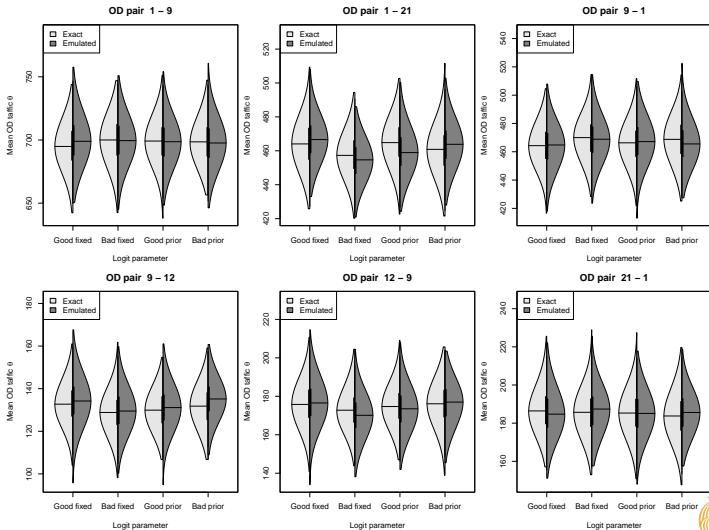
# Numerical testing

## Exact SUE Versus Emulated



# Numerical testing

## Impact of Emulation on Demand Estimation



# Conclusions

- Models from transportation science can provide useful prior information for network tomography.
- Implementation using emulation necessary to control computational expense.
- Linear inverse nature of problem makes inference challenging:
  - ▶ How much information do data provide about sensitivity parameter(s)?
  - ▶ Reliability of travel time (cost) function specification?
  - ▶ How to conduct useful assessment of model fit?

# Funding

Thanks to ...

MARSDEN FUND

TE PŪTEA RANGAHAU  
A MARSDEN

ROYAL  
SOCIETY  
TE APĀRANGI

## To Learn More ...

Hazelton, M. L., & Najim, L. (2024). Using traffic assignment models to assist Bayesian inference for origin-destination matrices.

*Transportation Research Part B: Methodological*, **186**, 103019.

### R packages

`https://github.com/MartinLHazelton/Leicester`

`https://github.com/MartinLHazelton/LinInvCount`

`https://github.com/MartinLHazelton/transportation`