Statistical Methods in Transportation Research

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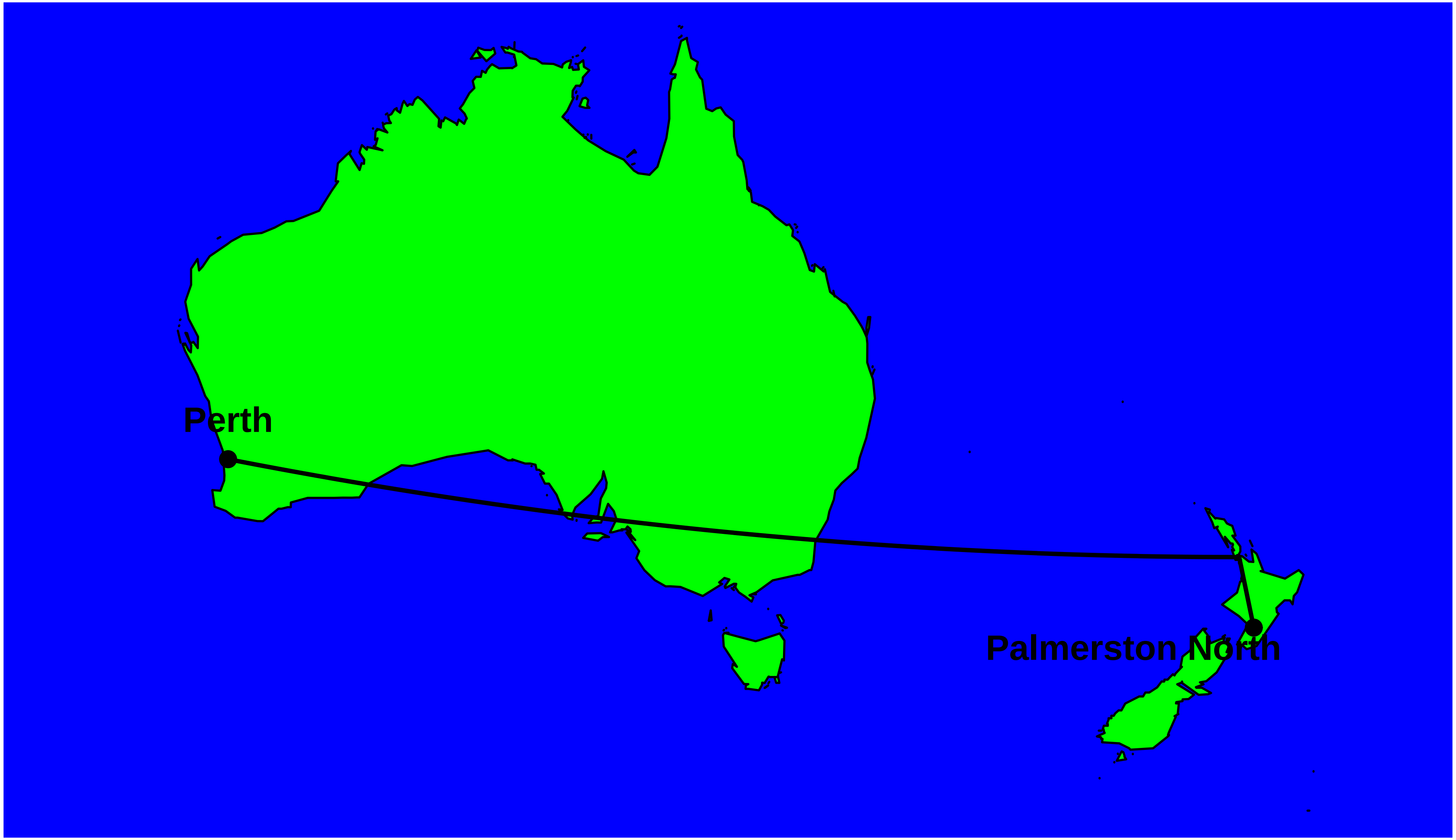
The Travelling Statistician Problem



The Problem

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Some Transport Statistics

- In developed countries, transportation typically accounts between 5% and 12% of GDP.
- Transport accounts for around 20% of global CO_2 emissions.
- Around 2000 Australian transport fatalities each year (90% road).
- Transport sector supplied 427000 jobs in Australia in 2003.
- In 2000, road traffic congestion in U.S. estimated to have caused:
  - 3.6 billion vehicle-hours of delay
  - 21.6 billion litres of wasted fuel
  - $67.5 billion in lost productivity
- Statisticians account for 0.1% of transportation research. (OK, that one's a guess!)

Outline

- Transportation research (and what’s currently wrong with it . . .)
- The audience buys a car
- Some problems for statisticians:
  - Speed estimation
  - Estimation of trip matrices
  - Modelling day-to-day dynamics of traffic flow
- Further statistical problems

Current State of Transport Research

- Variety of research fields:
  - Transport policy
  - Pyschology and transport
  - Transport and urban planning
  - Transport modelling

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- Most researchers transport modelling have an engineering or applied mathematics background
- Variability frequently gets ignored

Variation and Transport Research

Examples of (stochastic) variation:

- Traffic counts
- Vehicle speeds
- Route choice

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Ignore variation and:

- Extreme events may be missed (e.g. gridlock)
- Estimates and predictions may be biased
- Essential information may be lost

Statisticians and Transport Research

- Variability is a statistician’s trade
- Statisticians have the opportunity to play an important role in transportation research

The Audience Buys a Car

- **Aim**: to get best fuel efficiency
- *Dealer 1:*
  - Buy car that does 40 km per litre with prob. $1/2$
  - Buy car that does 10 km per litre with prob. $1/2$
- *Dealer 2:*
  - Buy car that does 20 km per litre

Which Dealer?

- The mean km per litre are:
  - *Dealer 1*: $1/2 \times 40 + 1/2 \times 10 = 25$.
  - *Dealer 2*: 20.
- So get more km per litre on average going to Dealer 1.

Look at Things the Other Way Up

- *Dealer 1:*
  - Buy car that needs 1/40 litre per km with prob. $1/2$
  - Buy car that needs 1/10 litre per km with prob. $1/2$
- *Dealer 2:*
  - Buy car that needs 1/20 litre per km

- The mean litres per km are:
  - *Dealer 1*: $1/2 \times 1/40 + 1/2 \times 1/10 = 1/16$.
  - *Dealer 2*: $1/20$.
- So need less litres per km on average from Dealer 2.

The Importance of Variation

- Answers are different because generally

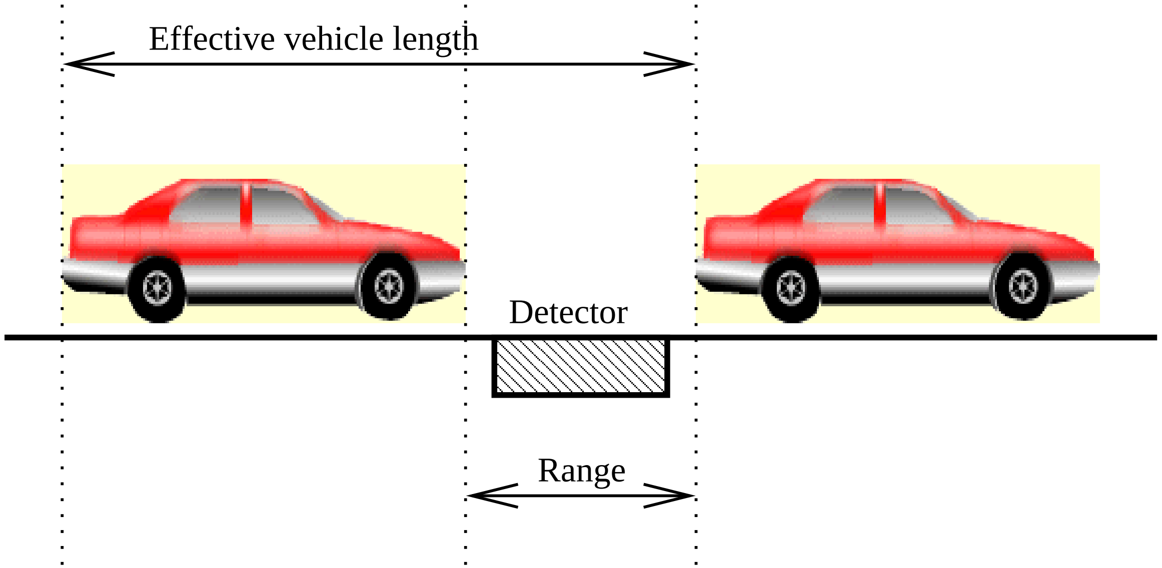
$$1/\mathbb{E}[X] \neq \mathbb{E}[1/X]$$

  for a random variable X.
- Car buying example illustrates importance of accounting for variation.

Speed Estimation: The Problem

- Automated vehicle detector set in road.
- Detector is ‘occupied’ while vehicle passes over it.
- Aggregate data returned for 20 or 30 second intervals:
  - Vehicle count during interval, n
  - Total time that detector is occupied during interval, y.
- **Goal**: to estimate mean vehicle speed during interval.

Speed Estimation: Towards a Solution



- Each vehicle occupies detector for time it takes to travel the 'effective vehicle length' λ.
- 'Typical' effective vehicle length given by

$$\lambda = d + \bar{l}$$

where d is detector range, $\bar{l}$ is mean vehicle length.

Speed Estimation: Simple Solution

$$\text{Speed} = \frac{\text{Distance}}{\text{Time}}$$

Hence simple estimator of speed is

$$\hat{s} = \frac{n\lambda}{y} = \frac{\lambda}{\bar{y}}$$

where $\bar{y}$ is mean occupancy of each vehicle.

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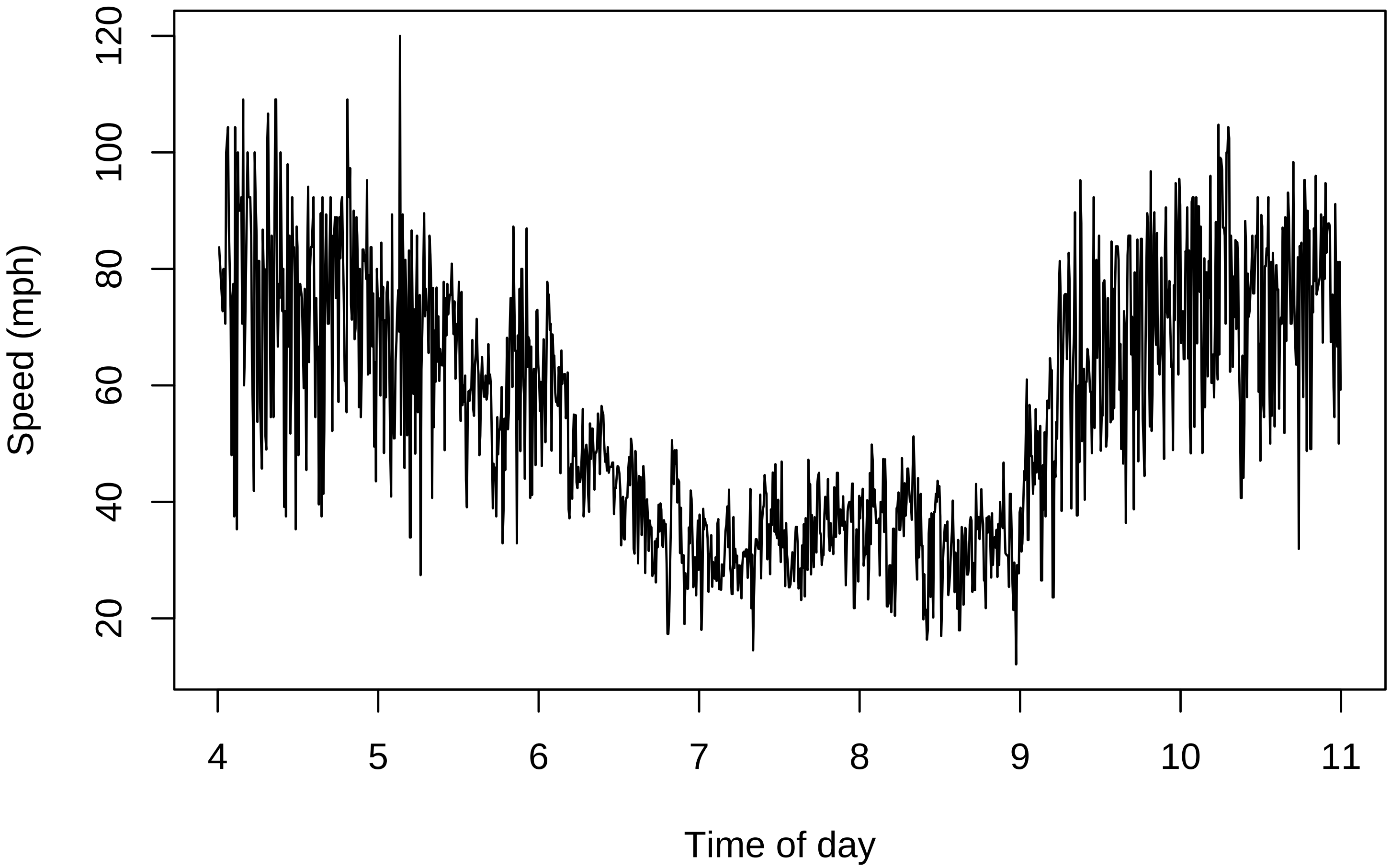
$$\hat{s} = \frac{\lambda}{\bar{y}} \neq \overline{\left[\frac{\lambda}{y}\right]} = \bar{s}$$

Speed Estimation: Simple Solution (cont.)

- Simple solution gives noisy estimation through time
- Fails to properly account for variation in vehicle lengths.



Speed Estimation: A Statistician's Approach

A statistician might:

- Try and apply smoothing through time.
- Model individual vehicle speeds and lengths as missing data.
- Not so hard to do post hoc, perhaps with MCMC for model fitting.
- But traffic control often needs real-time estimates.

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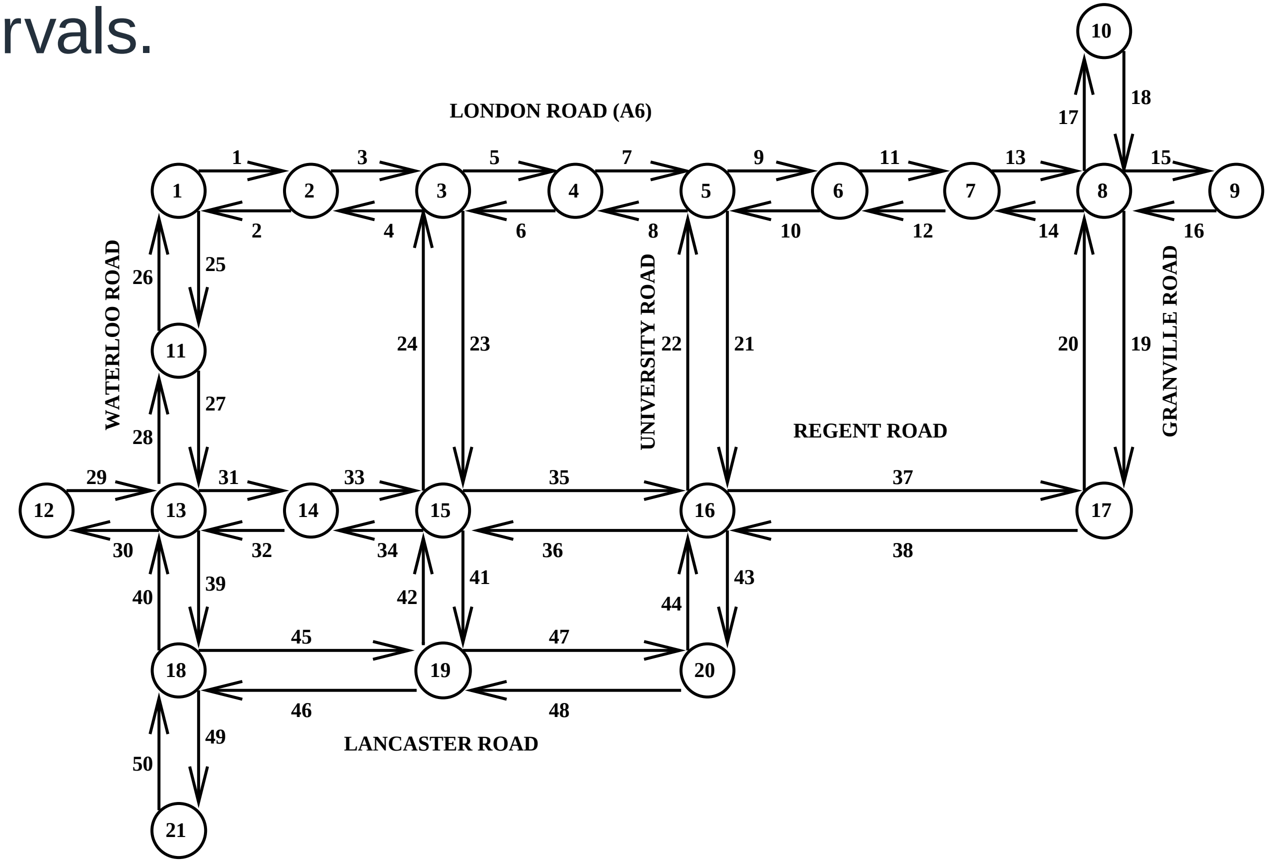
Research problem: develop real-time speed estimation methods that are computationally cheap.

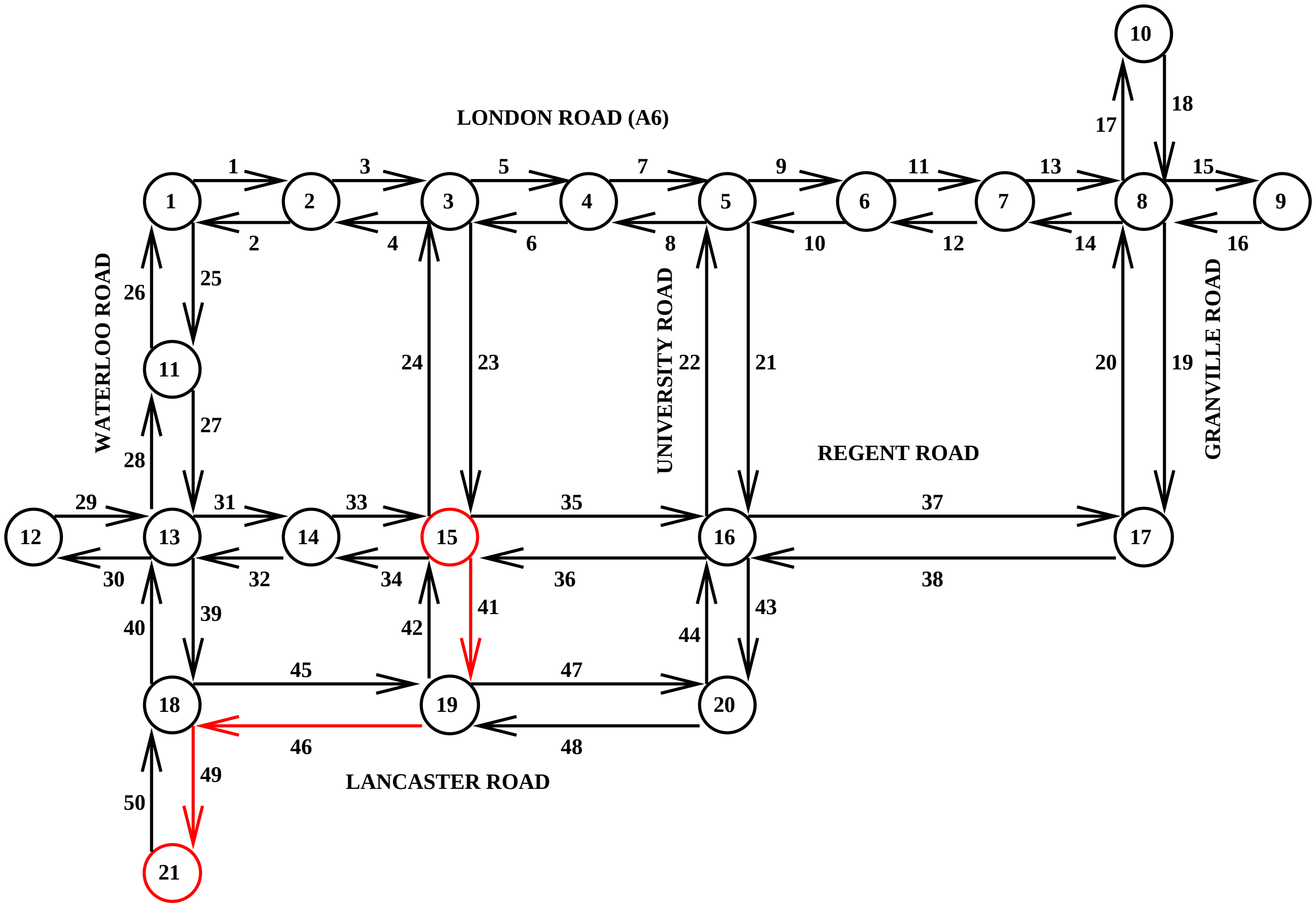
Trip Matrix Estimation: The Problem

- Estimate intensity of traffic flow between origins and destinations of travel on a network.
- Available data are traffic counts on certain road links over given time intervals.



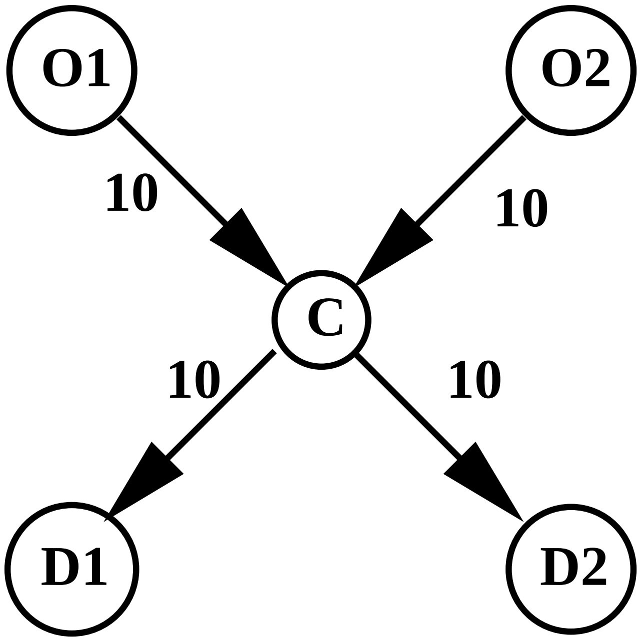
Trip Matrix Estimation: The Crux

- Trip matrix easy to estimate from *route* traffic counts.



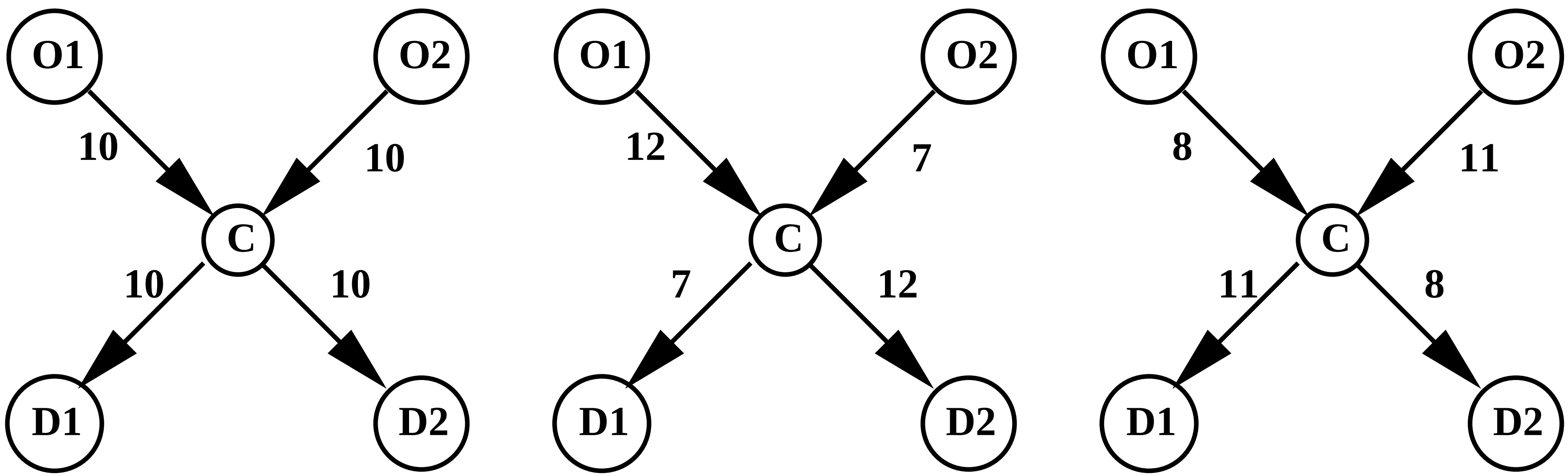
Trip Matrix Estimation: The Crux (cont.)

- But route flows generally not uniquely determined from a single set of link counts.
- Hence good trip matrix estimation impossible from aggregate link counts unless other information is available (e.g. informative prior).



Trip Matrix Estimation: Towards a Solution

- Sequence of set of link counts provides vital additional information.
- Trip matrix parameters are identifiable for e.g. Poisson model of trip generation.



Trip Matrix Estimation: Challenges

- What is a good stochastic model for trip generation?
- Well founded statistical approaches largely restricted to estimation of static trip matrices.
- Traffic control can require dynamic updating of trip matrices.

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Research problem: develop sound method of dynamic estimation for trip matrices.

Modelling and Inference for Day-to-Day System Dynamics

- **Aim**: to model time series of day-to-day traffic counts on network.

- Model can be:
  - *Descriptive*: used to understand properties of traffic system.
  - *Predictive*
- Example applications:
  - estimate flow patterns after road closure;
  - assess effect of proposed bypass.

Elements of Day-to-Day Model

- **Travel demand model**
  - trip matrix;
  - may be adjusted for seasonality, day of week etc.
- **Traffic assignment model**
  - describes how given demand will distributed itself over the network;
  - based on aggregation of route choices for all travellers.

Modelling Traveller Route Choice

- Route choice modelling pivotal.
- Natural to define model at microscopic (individual traveller) level.
- Travellers will select ‘cheap’ routes:
  - minimum travel time
  - short distance
  - easy drive
- (Random) variation in perceptions of costs between travellers.
- Properties of model required at macroscopic level (aggregate traffic flows).

Markov Models

- Travellers base route choice on combination of travel costs experienced over finite history.
- Inertia may suggest behaviour change only in case of clearly superior alternative.
- *Pro:* model properties relatively well understood.
- *Con:* no attempt to represent contemporaneous traveller interaction.

Inference for Behavioural Parameters

- Parameters can represent:
  - sensitivity to cost differences
  - length of memory
  - weighting of historical costs
- Inference may be based on:
  - traffic counts (very indirect information)
  - stated preference surveys (believable?)
  - travel diaries
- Inference is far from straightforward in all cases.

Inference from Traffic Counts

- Route flow evolve as Markov process.
- Observed link flows linear combination of route flows, plus measurement error.
- Hidden Markov model technology applicable, but:
  - Model has peculiar structure;
  - Practical problems may have huge size (e.g. thousands of road links, even more routes, for urban network model).

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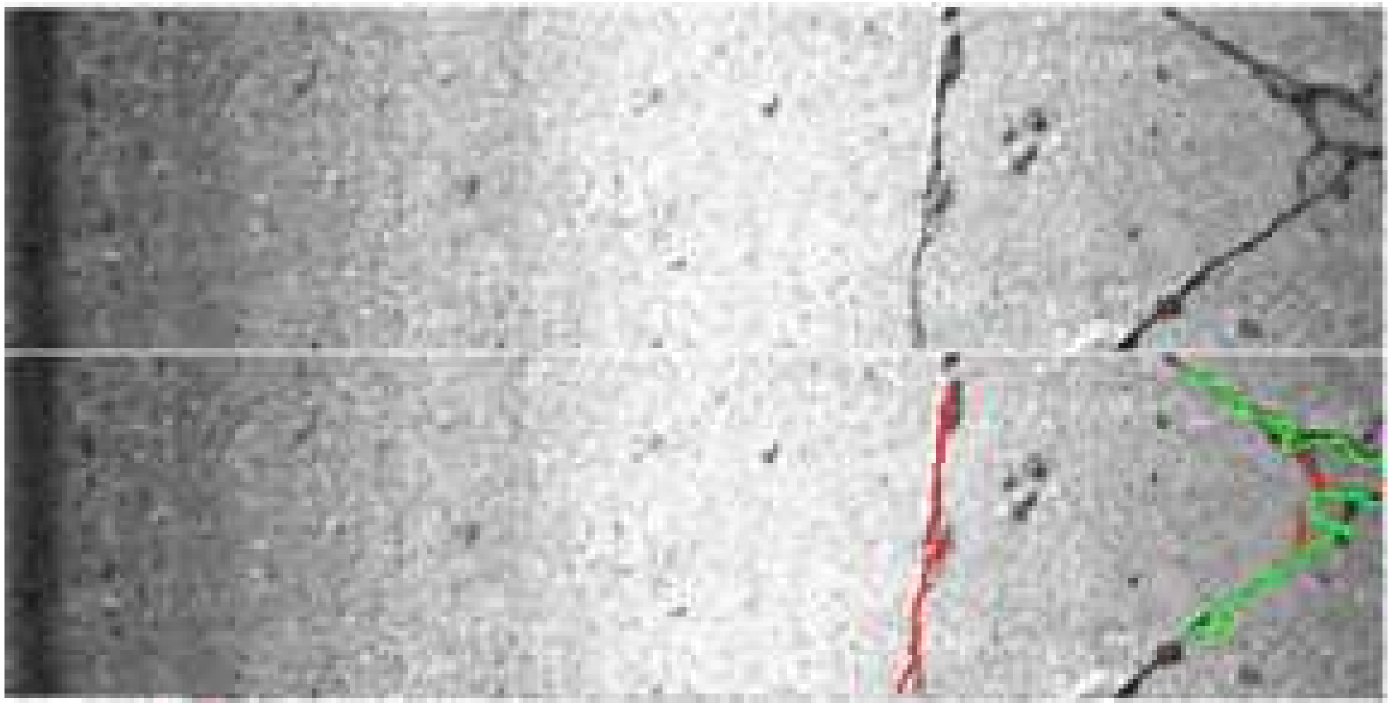
Research problem: develop methodology for inference for route choice models from readily available data.

Image Analysis in Transportation Research

Applications include:

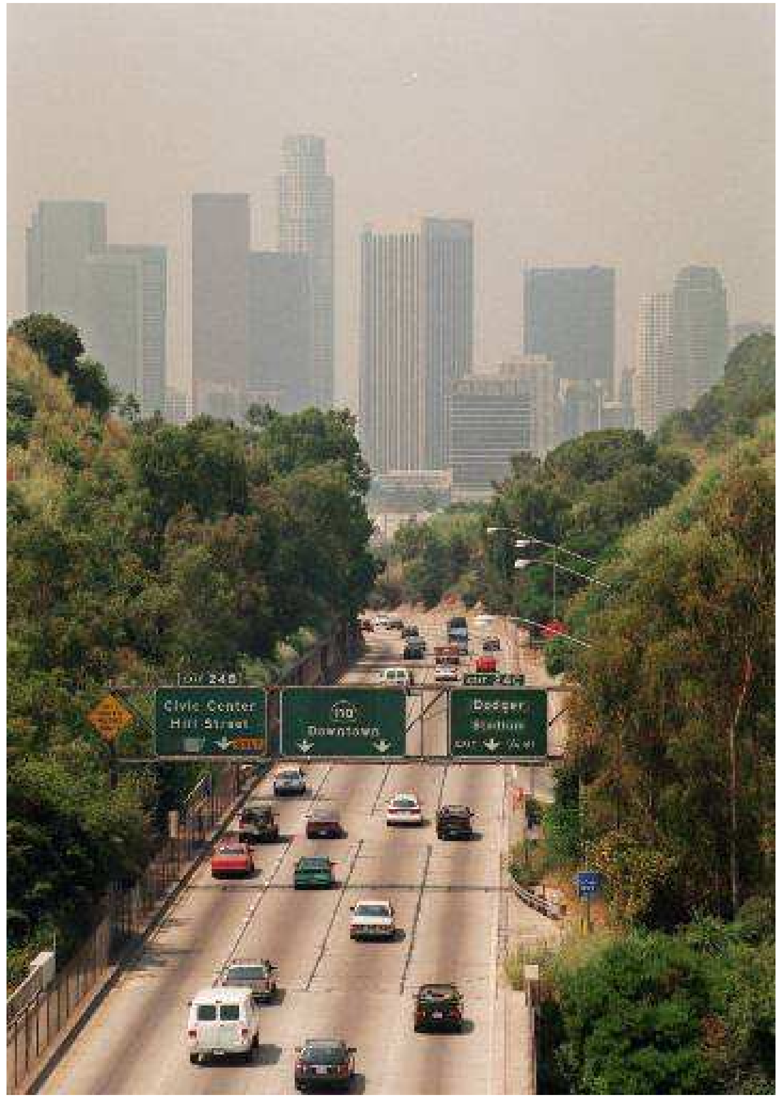
- number plate identification;
- automatic evaluation of road surface cracks.



Environmental Statistics in Transportation

Spatial statistics applied to:

- modelling road vehicle emissions in space and time;
- modelling health impacts (both globally and locally);
- modelling impact of road accidents with hazardous substances.



Further Statistical Problems in Transportation

- Survey design and analysis
- Random utility modelling and inference
- Stochastic operations research and system optimization
- Road accident modelling

Summary

- Transportation research likely to receive increasing attention as fuel prices and environmental costs spiral.
- Transportation science traditionally dominated by deterministic models and methods.
- Lots of opportunities for statisticians to make major contributions.