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Data

 From Sustrans, a charity that promotes sustainable transport in the UK

 Responsible for planning and delivering the National Cycle Network

• Counters count bikes!

Counters





Usage profiles

• What proportion of daily count per hour?

Usage profiles



Hours

Usage profiles

- What proportion of daily count per hour?
- What proportion of year count per month?

Usage profiles



Month

Usage profiles

- What proportion of daily count per hour?
- What proportion of year count per month?
- What shape do these profiles take?

Clustering

- Try to find common shapes.
- How do we assess dissimilarity? – Euclidean Manhattan Minkowski $d(x, y) = \left(\sum_{i=1}^{n} (x_i - y_i)^2\right)^{1/2} \qquad d(x, y) = \sum_{i=1}^{n} |x_i - y_i| \qquad d(x, y) = \left(\sum_{i=1}^{n} (x_i - y_i)^p\right)^{1/p}$

• K-means clustering on daily profiles.

Result



Hours

Result!



Result!

• 4 shapes!

Schools



Result!

- Schools
- Commuter



Result!

- Schools
- Commuter
- Leisure



Result!

- Schools
- Commuter
- Leisure
- Hybrid (shopping?)



Relate to explanatory variables

- Responses to Sustrans counter location information
- Try to fit a multinomial logit model (MLM) to "predict" classification.
 - A multivariate generalised linear model

$$\boldsymbol{\mu}_{i} = E[\mathbf{Y}_{i}] = (\pi_{1}(\mathbf{x}_{i}), \dots, \pi_{J-1}(\mathbf{x}_{i}))$$
$$\mathbf{g}(\boldsymbol{\mu}_{i}) = \alpha_{i} + \mathbf{X}_{i}\boldsymbol{\beta}$$

$$g_{j}(\mathbf{\mu}_{i}) = \log \frac{\mu_{ij}}{1 - (\mu_{i1} + \ldots + \mu_{i,J-1})}$$

Relate to explanatory variables

- Specifically baseline category logit models
- Choose one category as a baseline
 Modal category, or just the first/last one
- We compare other categories to the baseline
- Fit $\boldsymbol{\beta}$ using maximum likelihood estimation

Relate to explanatory variables

Response probabilities

$$\pi_{j}(\mathbf{x}) = \frac{\exp(\alpha_{j} + \boldsymbol{\beta}_{j}^{T} \mathbf{x})}{1 + \sum_{k=1}^{J-1} \exp(\alpha_{k} + \boldsymbol{\beta}_{k}^{T} \mathbf{x})}$$
$$\alpha_{J} = 0$$
$$\boldsymbol{\beta}_{L} = 0$$

Relate to explanatory variables

• Fit the following model

classification ~ Trafficfreeroute + region

Table of observed responses

region	midla	ands	no	rth	SO	uth
Trafficfreeroute	e 0	1	0	1	0	1
classification						
commuter	1	0	0	8	13	5
hybrid	12	12	2	14	2	1
leisure	0	7	2	16	1	6
schools	1	0	0	2	0	2

Relate to explanatory variables

 Response probabilities, say we wanted to know how we might classify a counter in the North that is traffic free.

commuter hybrid leisure schools 0.16622310 0.34772490 0.43838972 0.04766228

Problems

- If there is a zero in the table of observed responses, then parameter estimation sometimes breaks down.
- Limited data
- Schools result is not explained by any of the explanatory variables

Questions?

If you worried about falling off the bike, you'd never get on. Lance Armstrong

Example of parameter estimation failing

• Route adjacent to road table

	commuter	hybrid	leisure	schools
0	17	28	32	4
1	10	15	0	1

• Traffic free route table

	commuter	hybrid	leisure	schools
0	14	16	3	1
1	13	27	29	4

Example of parameter estimation failing

```
multinom(formula = classification ~
route, data = newClassRoute)
```

Coefficients:

	(Intercept)	route
hybrid	0.4989866	-0.09345878
leisure	0.6324810	-10.71041396
schools	-1.4469457	-0.85564786

Std. Errors:

	(Intercept)	route
hybrid	0.3074673	0.5110844
leisure	0.3001218	48.8004645
schools	0.5557196	1.1869667

multinom(formula = classification ~
Trafficfreeroute, data = newClassAll)

Coefficients:

	(Intercept)	Trafficfreeroute
hybrid	0.1335310	0.5973803
leisure	-1.5404378	2.3427939
schools	-2.6390253	1.4603639

```
      Std. Errors:
      (Intercept) Trafficfreeroute

      hybrid
      0.3659628
      0.4978849

      leisure
      0.6362076
      0.7184476

      schools
      1.0350836
      1.1825086
```