CITY SCIENCE
endless possibilities

Data for a Smart City

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Cities

- 1950: 746 million people lived in cities[1]
- 2014: 3.9 billion people lived in cities
- 2050: Over 2 in 3 people will live in cities(estimated)

This matters to (a) cities and (b) the whole world.

[1] Source: UN (2014) *World Urbanization Prospects* UN DESA Population Division

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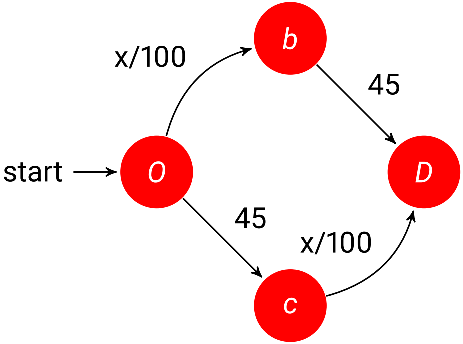
This matters to (a) cities and (b) the whole world.

- 70 cities are bigger than Wales, 38 bigger than Scotland.
- 37 are bigger (but not better) than Yorkshire.

It's cities, not administrative entities that *have* to compete globally

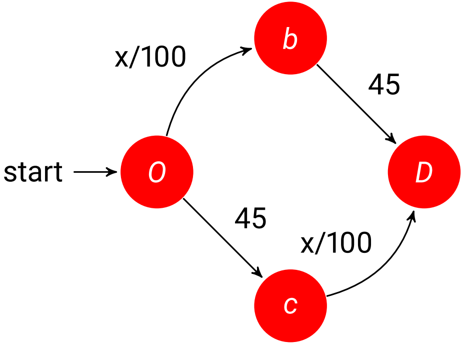
[1]Source: UN (2014) *World Urbanization Prospects* UN DESA Population Division

Optimising Cities



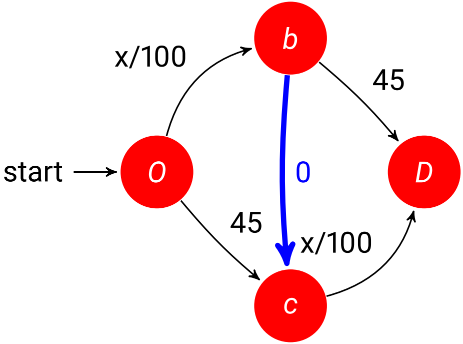
- 4000 vehicles
- Most efficient solution?

Optimising Cities



- 4000 vehicles
- Most efficient solution?
  - 2000 travel $O \to c \to D$,
  - 2000 travel $O \to b \to D$
- $\therefore$ optimal travel cost is $65 = 45 + \frac{2000}{100}$ (or $\frac{2000}{100} + 45$)

Optimising Cities



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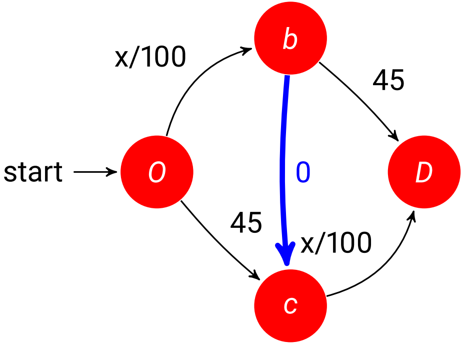
Optimising Cities



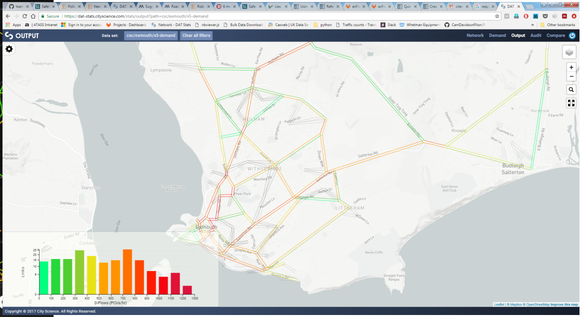
- 4000 vehicles
- Most efficient solution?
  - 4000 $O \to b \to c \to D$,
- Optimal travel cost: $80 = \frac{4000}{100} + \frac{4000}{100}$
- If *you* switch routes, $\frac{4000}{100} + 45$ or $45 + \frac{4000}{100} = 85$

The “Price of Anarchy”

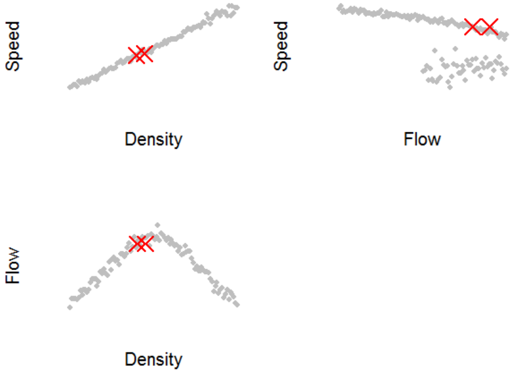
- This *specific* phenomena does exist [2]. Is it very common?
- We [3] individually pick the best route for ourselves.
- Our individual choice may make a city more congested than if we co-operated with a benevolent routing dictator
- This is just *one* example of how traffic on road networks behaves in very non-intuitive ways

[2] e.g., Cheonggyecheon, South Korea and 42nd Street, New York 1990
[3] according to economic theory

Speed and flow models

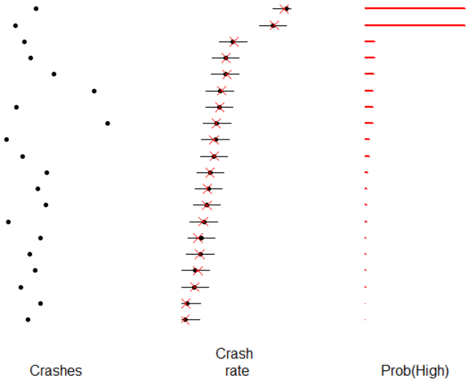


Speed flow relationships



- Flow models: traditional, well validated (Census, Loops and Counts etc., Mobile Phone)
- Speed models: machine learning + various (GPS tracker vehicles)
- Allows us:
  - Assess performance of road
  - Assess “stress”

Speed and flow and road injury

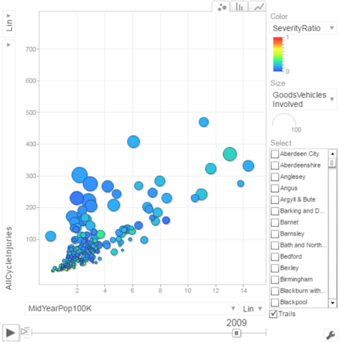


- Compute collisions / flow for most roads in a City *per* time period
- Fit point process models to investigate the effect of *actual* speed
- Look for gross anomalies . . . and assess the strength of evidence to claim them as such
- Generalise / predict elsewhere

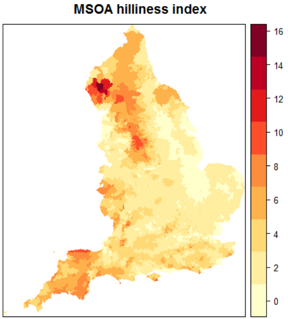
The more we condition on geographic and sociodemographic factors the more we can generalise the model. Generalisable models that make out of area predictions are *testable*

Geographic and demographic

4d plot collisions / predictors



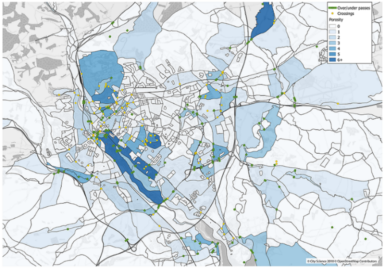
Hilliness level



Implications

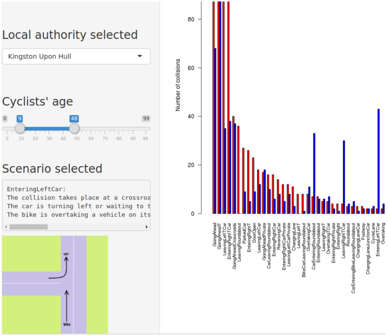
Average cyclist: 30 minutes

A measure of "porosity"



www.cityscience.com/blog/analytics-for-healthy-streets-part-1

Junctions 1: crash profile

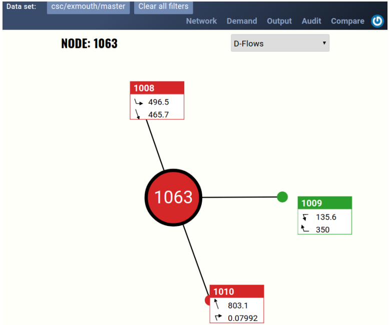


Not an exact science (but what is?)

- For each crash, assess type[1]
- We also assign a reliability score
- Build predictive models for junction profiles on reliability weighted crash data

[1] e.g. M. Stone, J. Broughton (2003) “Getting off your bike: Cycling accidents in Great Britain in 1990-1999” *Accident Analysis & Prevention* **35**:549-56

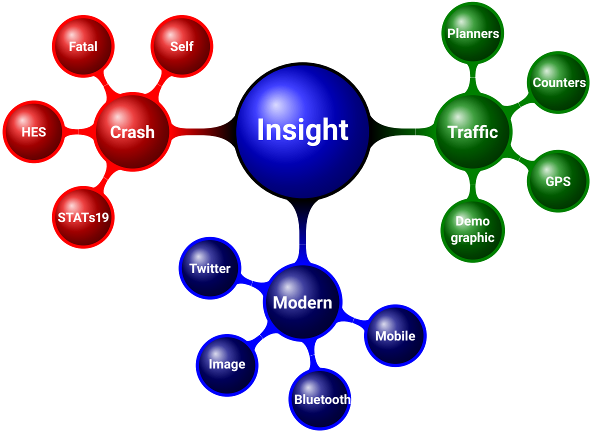
Junctions 2: flow profiles



- Junction profiles are complex
  - How many people are making opposed right turns?
  - How much opposing traffic exists?
  - What are the demographics of the road users
- We can estimate association between injury risk[a] and junction profiles
- Are some "routes" higher risk than others?

[a] Have to use probabilistic models

Data Fusion



Z. Zhang, Q. He Q, J. Gao and M. Ni (2018) “A deep learning approach for detecting traffic accidents from social media data” *Transportation Research Part C: Emerging Technologies*. **86**:580-96

Data Fusion

- Data = (1, 3, 2, 4, 5).
- Arithmetic mean = $\frac{1}{5}(1+3+2+4+5)=3$

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- Why not use $(\frac{1}{20}1 + \frac{2}{20}3 + \frac{4}{20}2 + \frac{5}{20}4 + \frac{8}{20}5) = 3.75$

(Almost) a.k.a. **E**xponentially **W**eighted **M**oving **A**verage, used routinely![4]

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- Or instead of recency, give more weight to data you trust more (this idea is as old as Gauss)
- Or give weight to data that is more important
- Sometimes data cannot be compared directly, but we can imagine that it is correlated with a “latent” variable (psychologists do this all the time)

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Conclusion

- A lot of data exists already but are not used
- Why don't more UK cities have detailed crash rate maps?
- Pollution = f(Flow/Speed); ∴ we already have pollution models! (and we have pretty maps of them!)
- Is there an unwillingness to use statistical models to do the fusion?
  - No data are perfect
  - Statistical models let you carry uncertainty from one dataset to another
- Doing data fusion is very powerful - don't necessarily need super-trendy datasets to add value!