SHENYANG JIANZHU UNIVERSITY

casa

UCL University College London

New Tools for Understanding & Planning the Smart City

Big Data & Urban Analytics

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CASA-UCL

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Outline

- What Is the Smart City? What Is Big Data ?
- A Short History of Big Data: How Big is Big?
- Real-Time Streaming: Dash Boards & Portals
- Mobility, Transit, & Real-Time Streaming: The Oyster Card Data Set
- Learning about Mobility from the Data

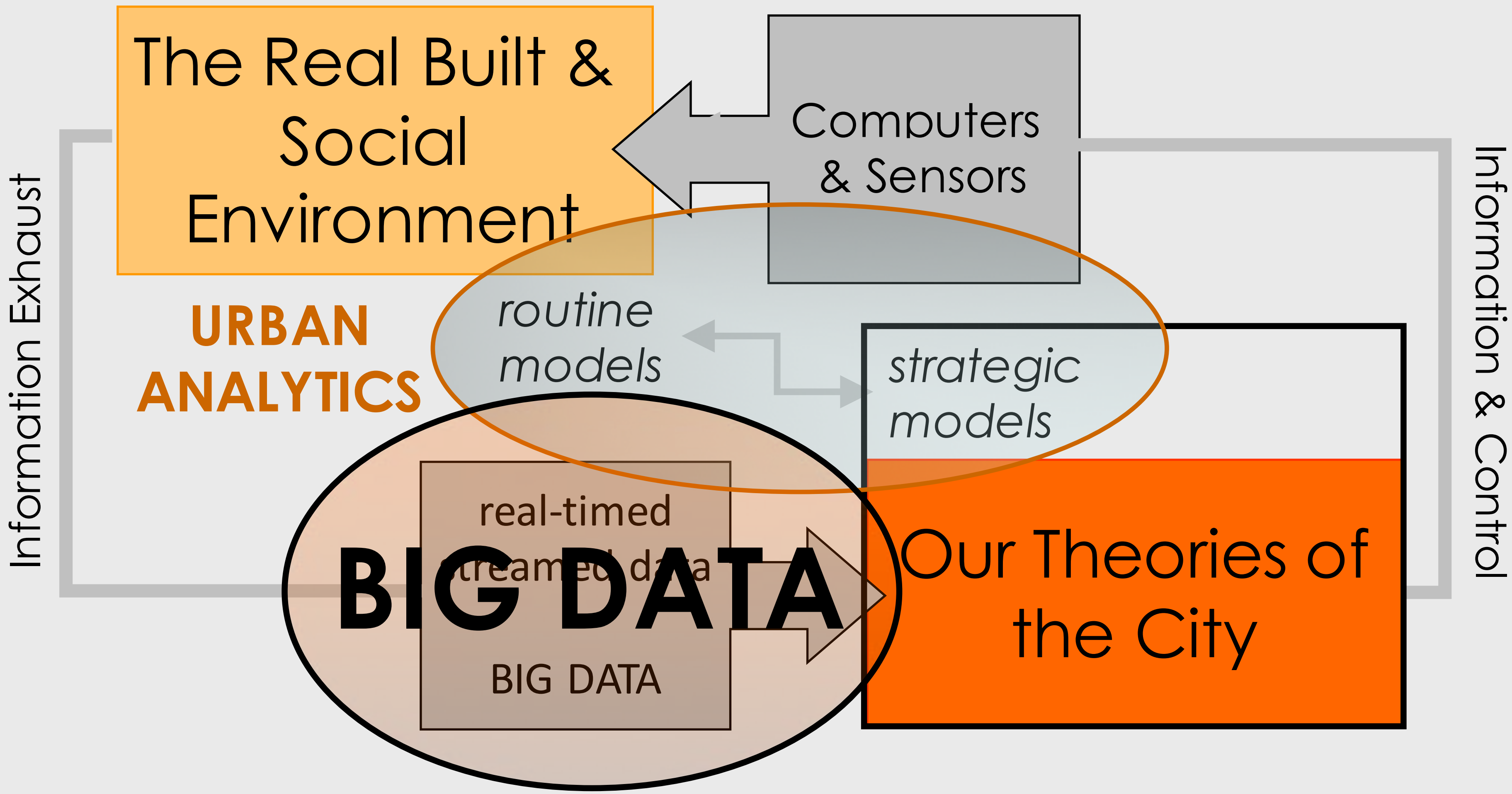
  Variabilities – Heterogeneity and Travel Profiles

  Disruptions – Signal Failures, Stalled Trains

  Variable Locational Dynamics of Demand
- Can Social Media Contribute to Smart City Planning
- What Can We Learn: The Limits to Big Data

What Is the Smart City?

The spreading out of computers into public places & the built environment and all their consequences



What Is Big Data ?

- Data is big with respect to its volume. I know there are other definitions – velocity, variety etc. but to me, data is big if it requires large use of computer memory implying volume. MB, TB, PB …..
- The conventional definition in business is the Five V's – volume, velocity, variety, veracity, value
- Too big to fit in an Excel Spreadsheet
- In cities, data usually implies numbers of locations and their attributes but locations imply interactions.
- Thus data are relations between locations and in essence if we have ***n locations***, we have ***n^2 interactions***. *Thus small data can become big*

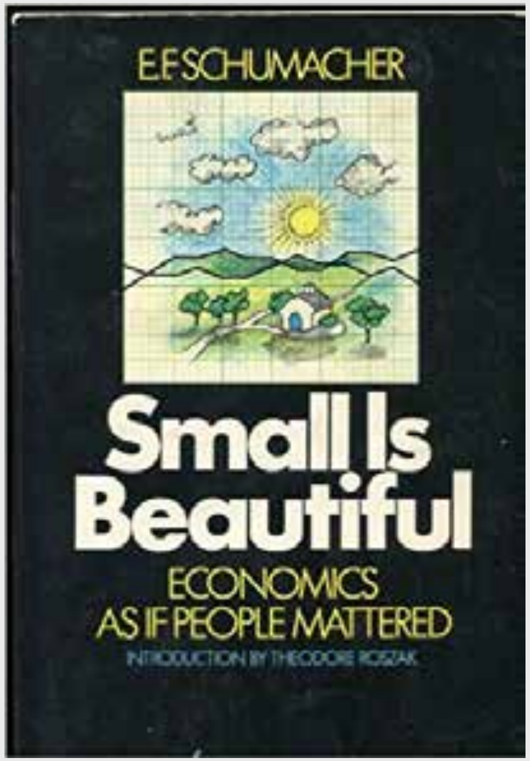
Planning the Smart City

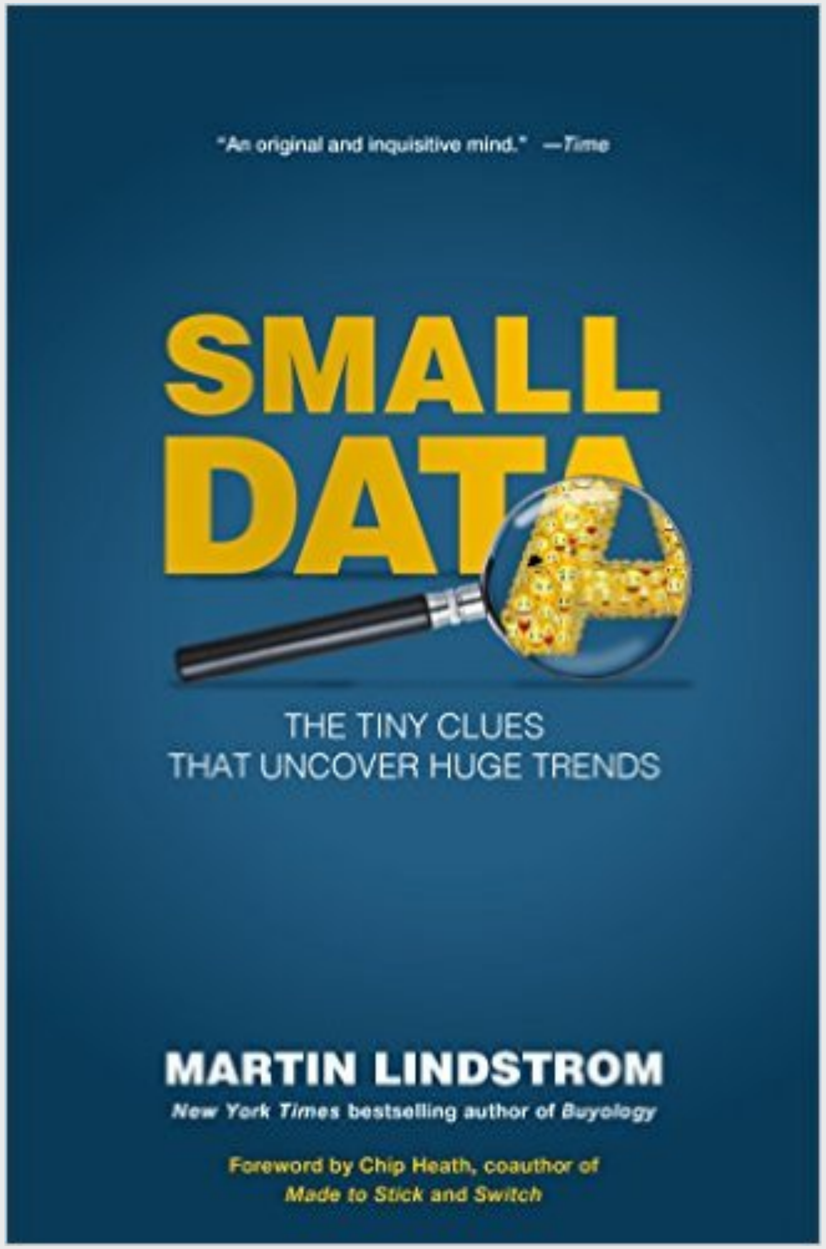
- The key issue is time scales – most of our planning is long term and this shifts the balance to short term
- The smart city is the high frequency city and most of our planning is for the very short term, for disruptions, emergencies, for local improvements without major infrastructural changes
- The short term can turn into the long term if sensed data is continuously collected
- We need to develop better models – analytics for the short term. Only then can we see how the short and long terms can be integrated
- This talk is thus about planning to counter disruptions

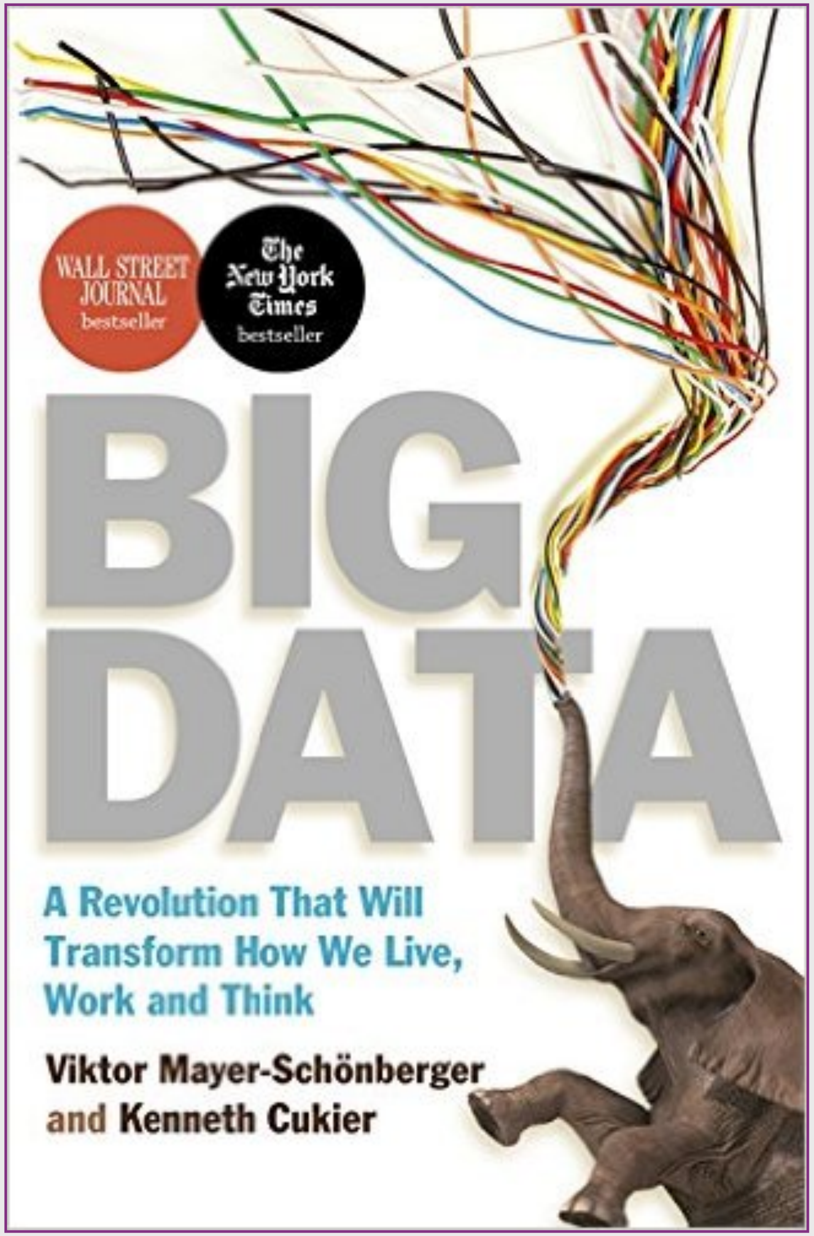
A Short History of Big Data

- But there is controversy about how big.
- Big is not necessarily beautiful – small is beautiful – this was the watch word of the 1970s
- So we need to be careful

We can still develop good ideas and good theory with small data. In fact the idea that the truth or even the path to progress lies in big data is problematic; **there are limits to machine learning**







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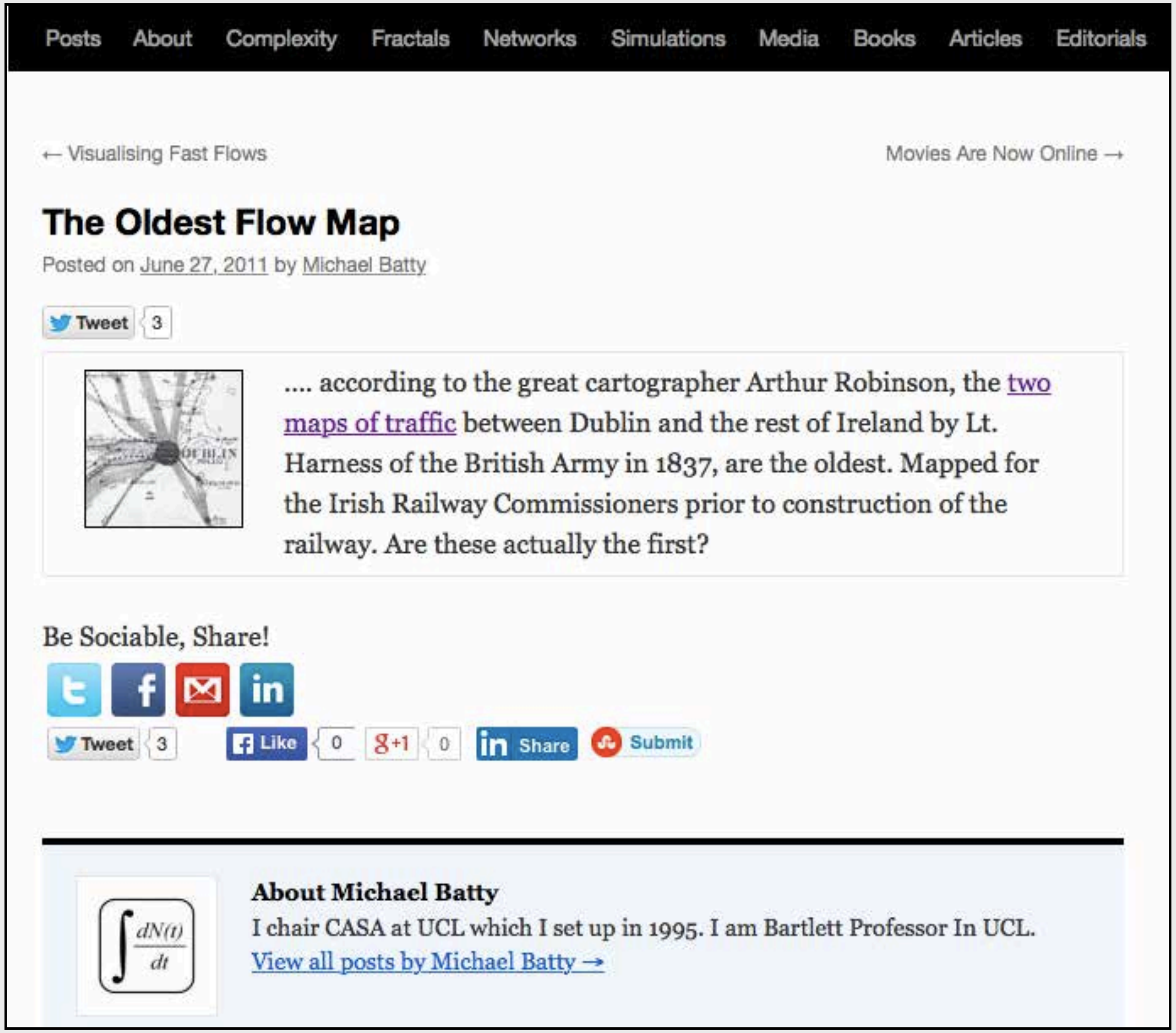
- Thus when we have data that contained relations, as we do in spatial analysis, the data can begin to blow up, It explodes
- This is true of flow and network data and arguably this is the most important data that we can get because all locations are really the product of flows
- That is the point I keep making in my various papers; data are relations between locations and in essence if we have ***n locations***, we have ***n^2 interactions***.
- Thus small data can become big as I implied a moment ago

Examples: Dublin 1837, Ireland 1888, London 1953



Posts About Complexity Fractals Networks Simulations Media Books Articles Editorials

← Visualising Fast Flows

Movies Are Now Online →

The Oldest Flow Map

Posted on June 27, 2011 by Michael Batty

Tweet 3

.... according to the great cartographer Arthur Robinson, the two maps of traffic between Dublin and the rest of Ireland by Lt. Harness of the British Army in 1837, are the oldest. Mapped for the Irish Railway Commissioners prior to construction of the railway. Are these actually the first?

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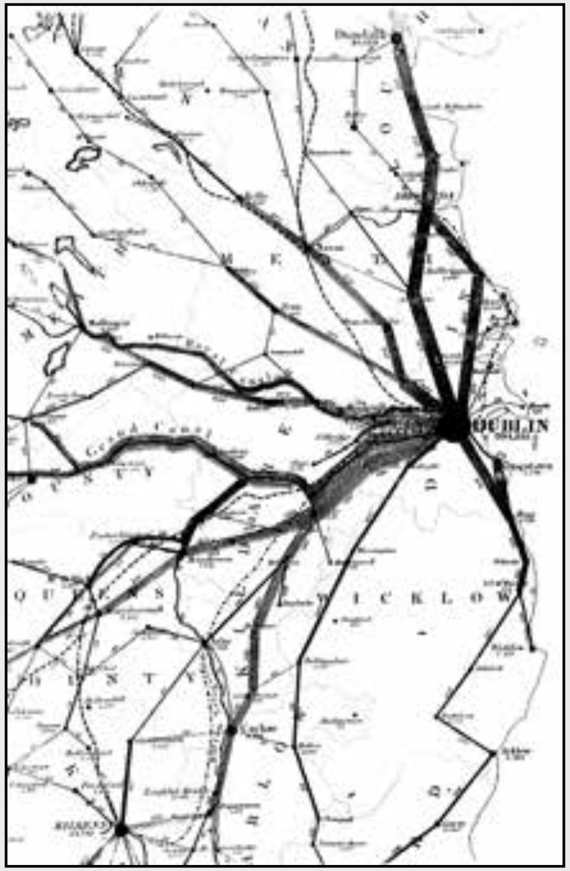
About Michael Batty

I chair CASA at UCL which I set up in 1995. I am Bartlett Professor In UCL.

View all posts by Michael Batty →

Examples: Dublin 1837, Ireland 1888, London 1955



Harness, 1837

Ravenstein 1888

- So big data can derive from small if we think of it as relations.
- But also big data is relative to our ability to process it – the machines or ‘brains; we have to crunch it
- If I have a big box of punched cards, say several hundred then I can reduce the physical size by putting on another media – punched tape for example, or magnetic tape
- But the size of the machine to process it is a limit – the computer may only be able to process so much in core memory and the problem may be too big for the machine. There is a great example ….

https://www.youtube.com/watch?v=pcBJfkE5UwU

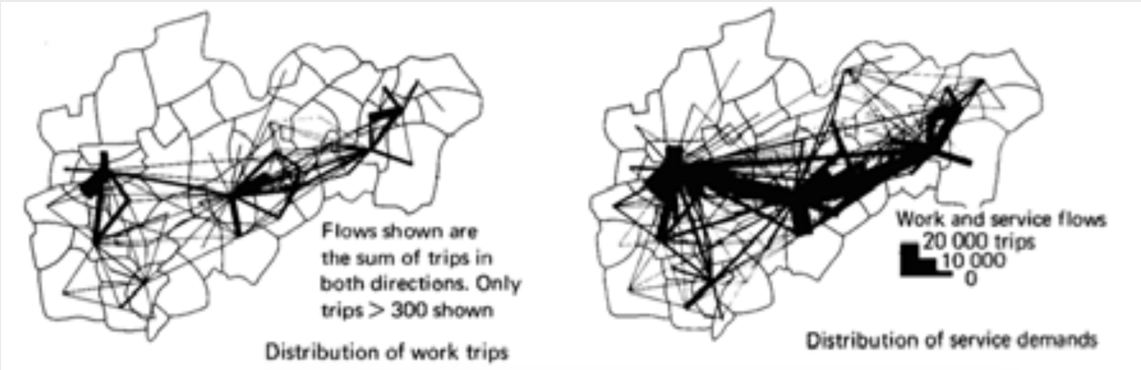
Locations and Interactions: Flow Systems in Cities

Elsewhere I have argued that we should treat cities as flow systems – as networks. This has been a focus for a long time in transport and land use and we have always been up against the problem of big data.

So let me begin my illustration of this dilemma and how we are thinking about it with some problems that have very small data. Problems of spatial interaction where our numbers of locations is small < 100, ~ 50

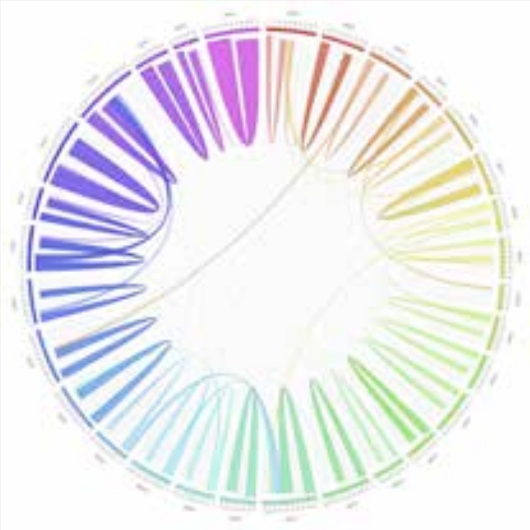
Understanding and Visualising Flows

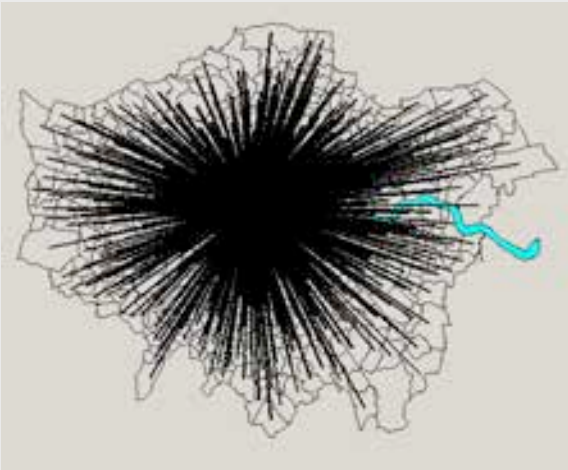
An early model circa 1967-8 Central and NE Lancs



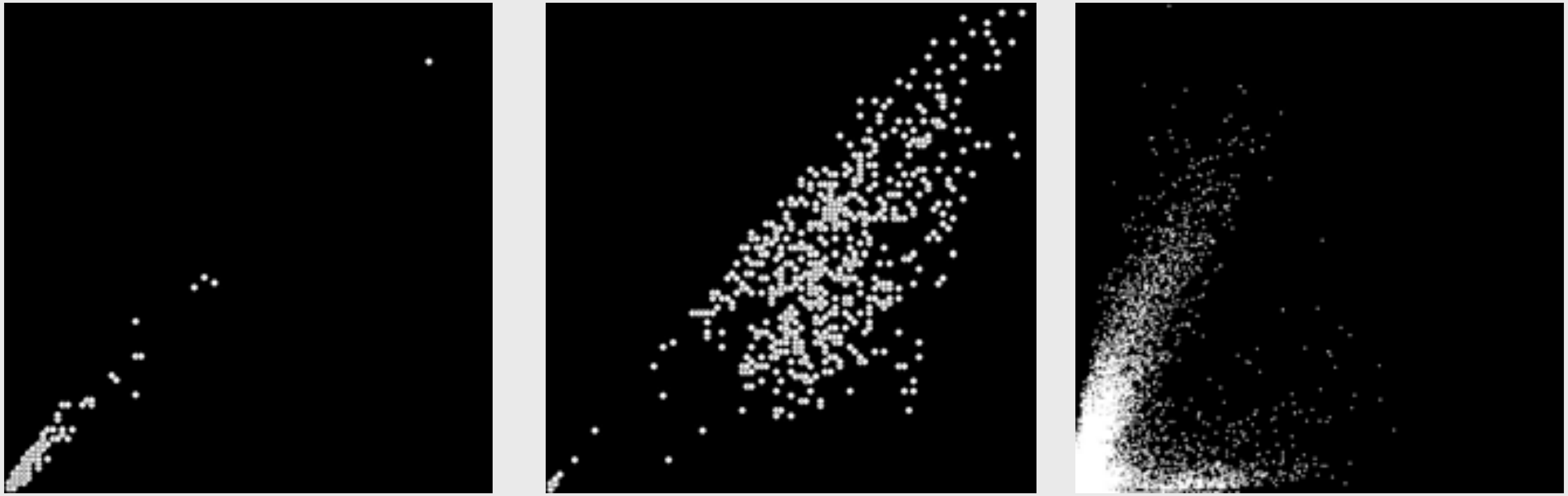
M. Batty (1976)
Urban Modelling
Cambridge UP

$n^2=33^2=1089$, not so big but hard to visualise





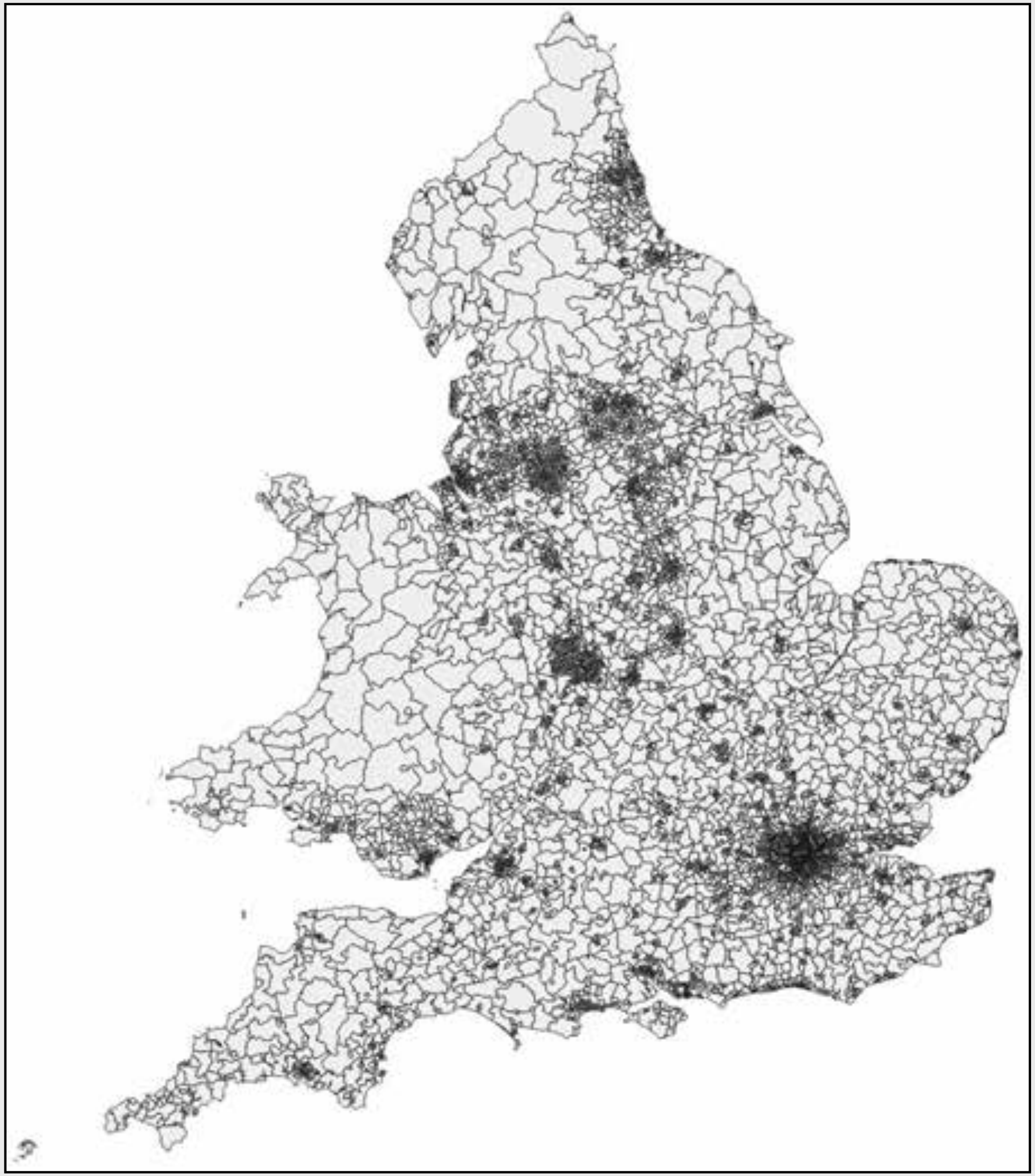
$n^2=633^2=400{,}689$, bigger but impossible to visualise



Even our statistics breaks down when we get large numbers like over several thousand as you can see on the left and above right for 400K data points where the pattern is highly convoluted. This is from a gravity model.

Now what happens when we really do scale up to the level of MSOAs of which there are 7201 in the UK – do we partition and argue we don't need to scale up to $n^2=7201^2=51{,}854{,}401$.

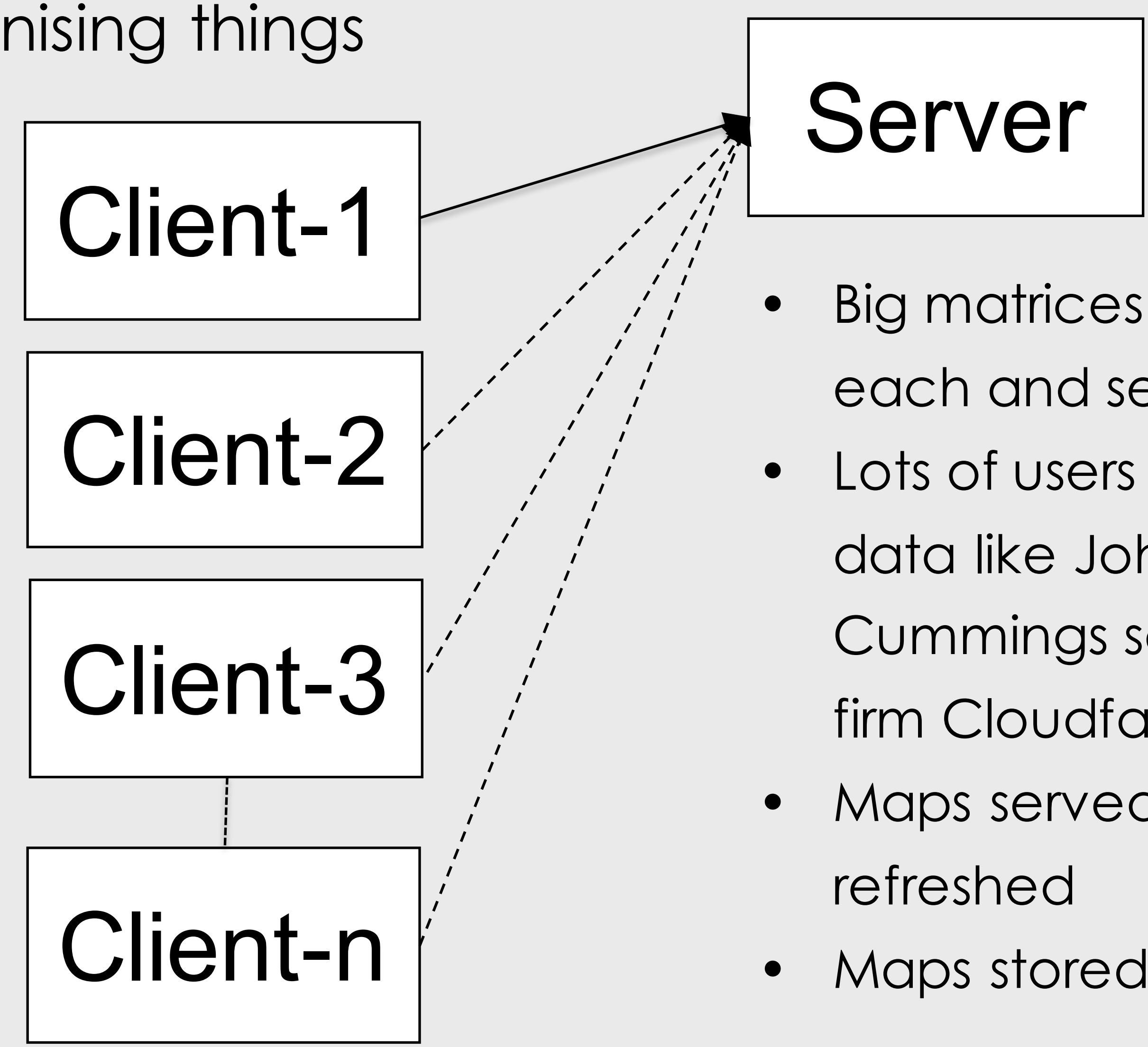
Circa 52 million points is an issue but our models run in a matter of seconds but that is a lot of data to store – ok it is sparse but sparsity isn't structured so we can't easily partition and in any case we want to compute any possible flows between central London say and Newcastle. Here is the problems scaled up and this is what we are grappling with at present.



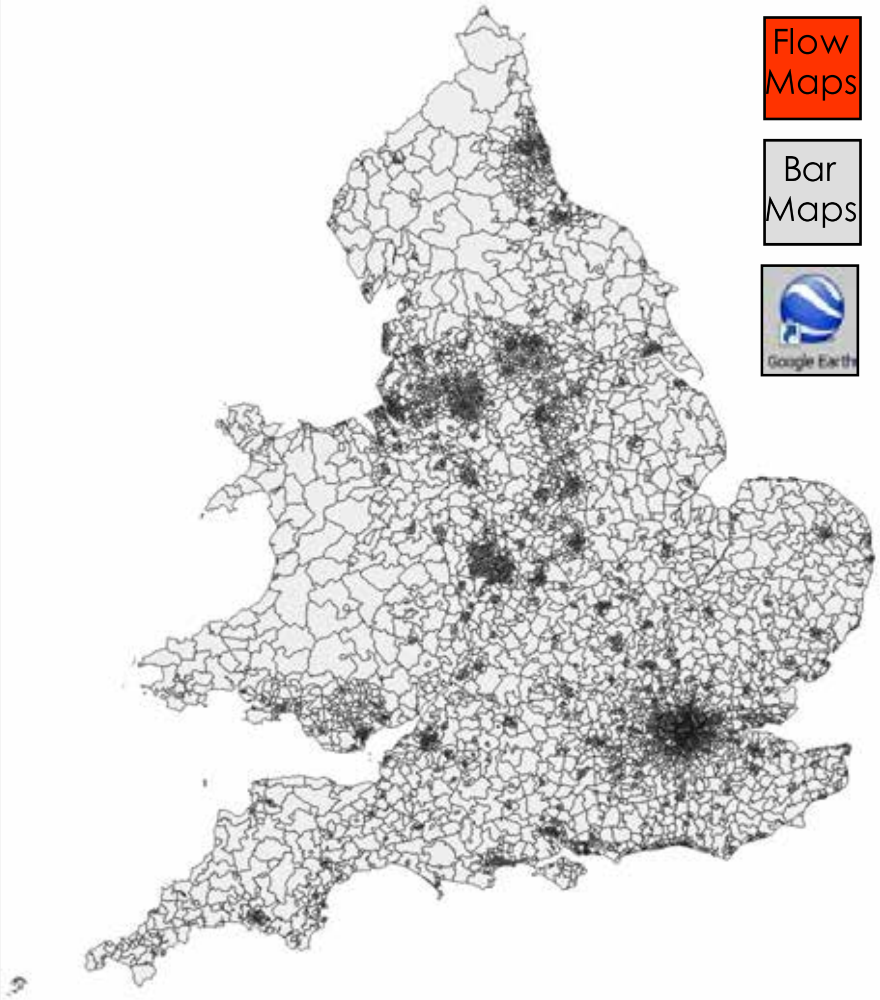
(a) MSOA (A=7201) (b) LSOA (A=34753) (c) OA (A=181408)

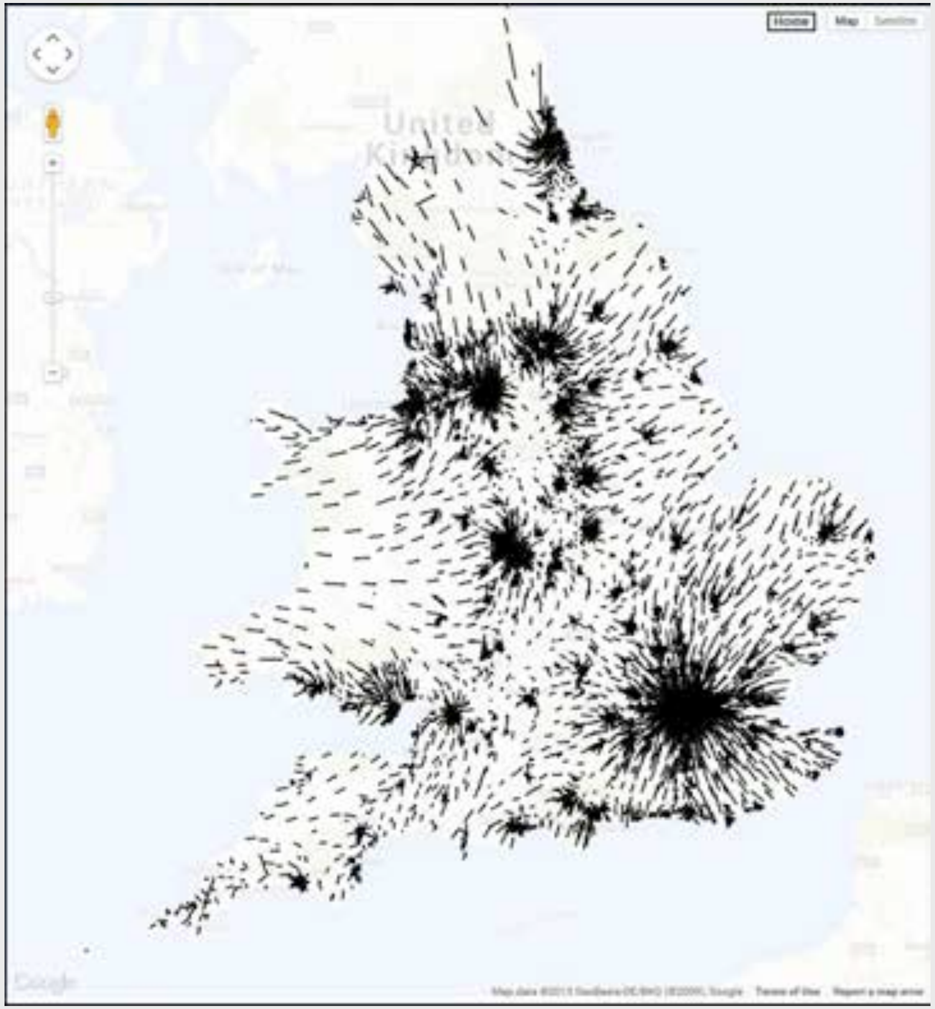
Figure 8.2: ONS Geographies for MSOA, LSOA and OA levels.

Here is a block diagram of how we are currently organising things

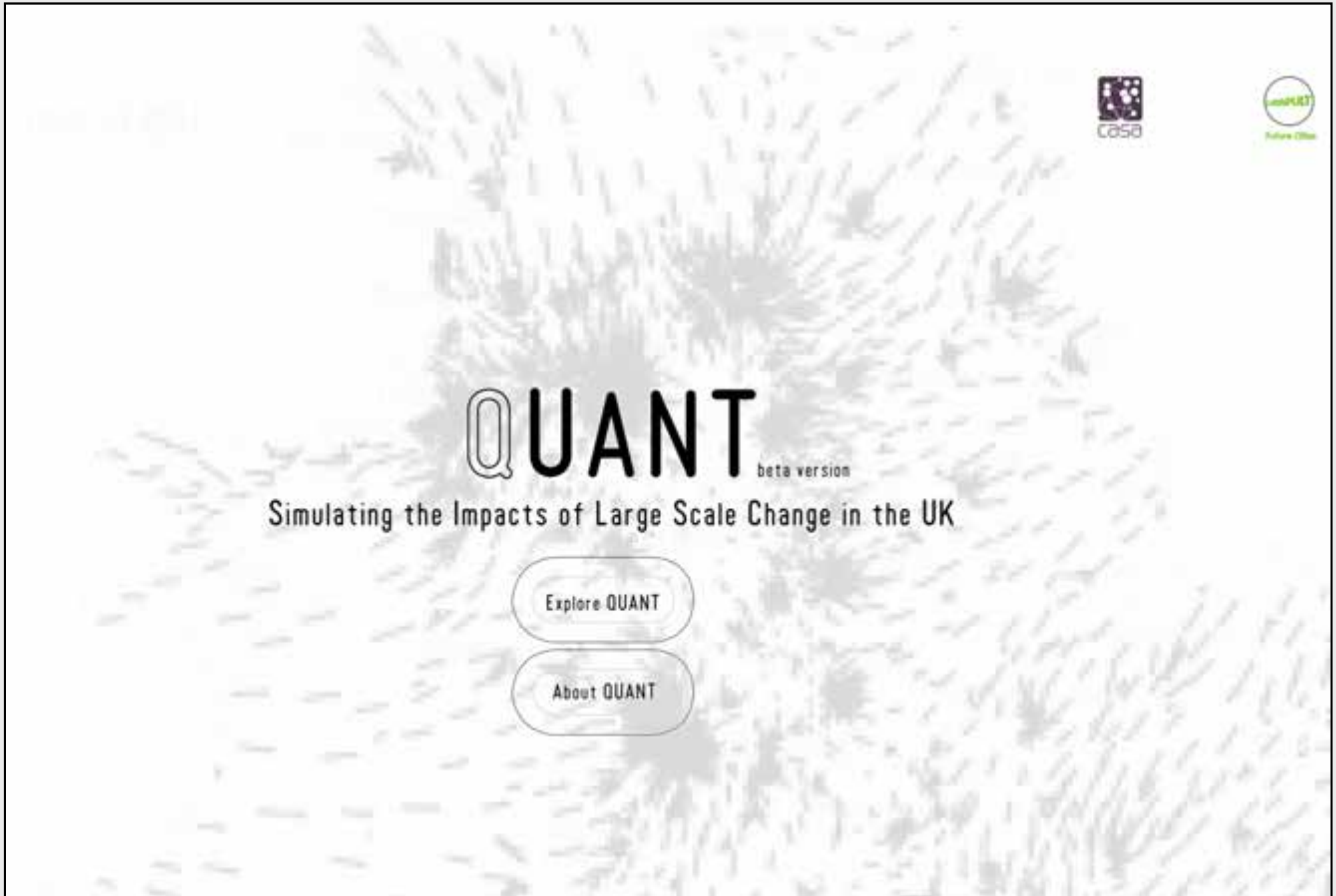


- Big matrices 52 million cells each and several in core
- Lots of users – all generating data like John Graham-Cummings said about his firm Cloudfare
- Maps served as tiles and refreshed
- Maps stored on server side

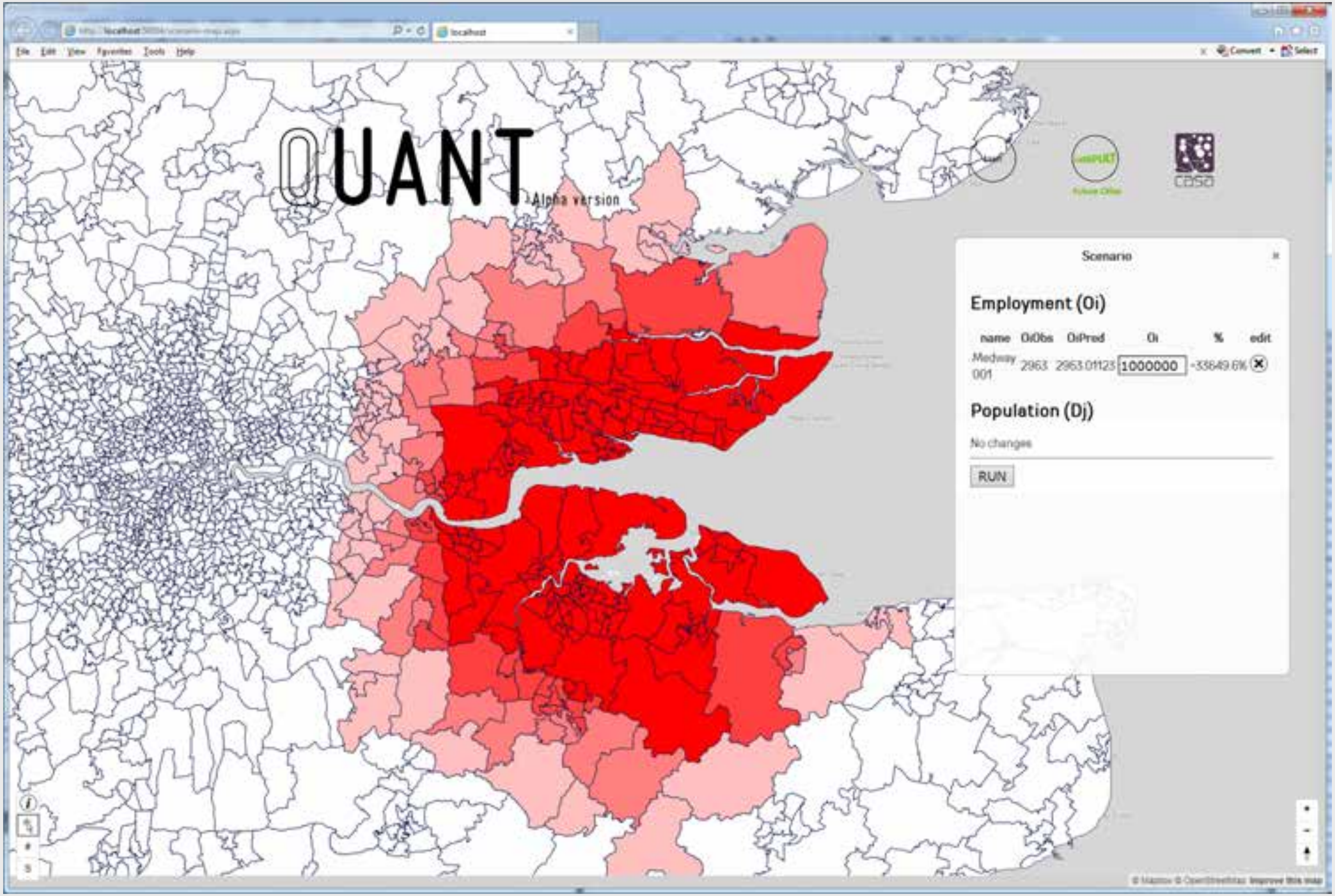




$$[x_i, y_i] = [[x_i, y_i], \left[\left[x_i + \frac{\sum_j T_{ij}\,[x_i - x_j]}{n}\right], \left[y_i + \frac{\sum_j T_{ij}\,[y_i - yy_j]}{n}\right]\right]]$$



http://quant.casa.ucl.ac.uk/



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Real-Time Streaming: Dash Boards & Portals

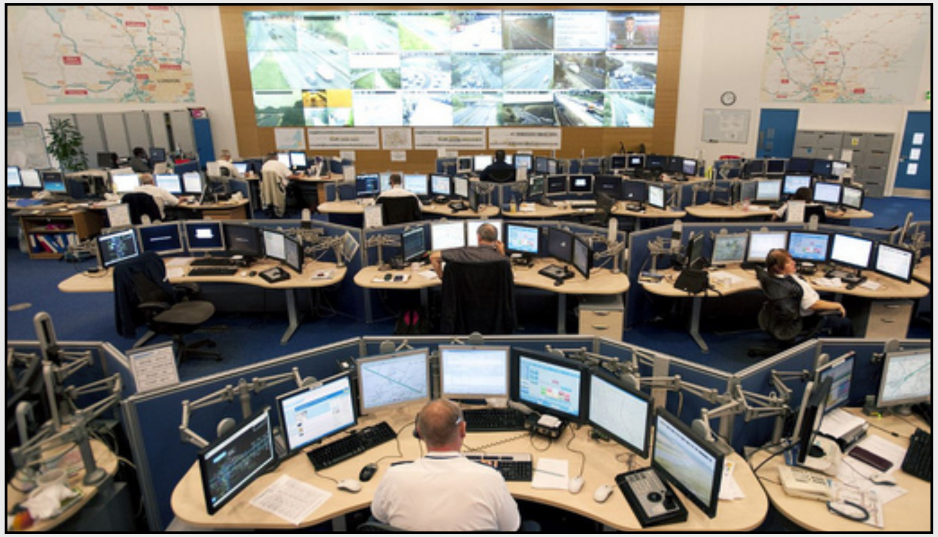
www.citydashboard.org

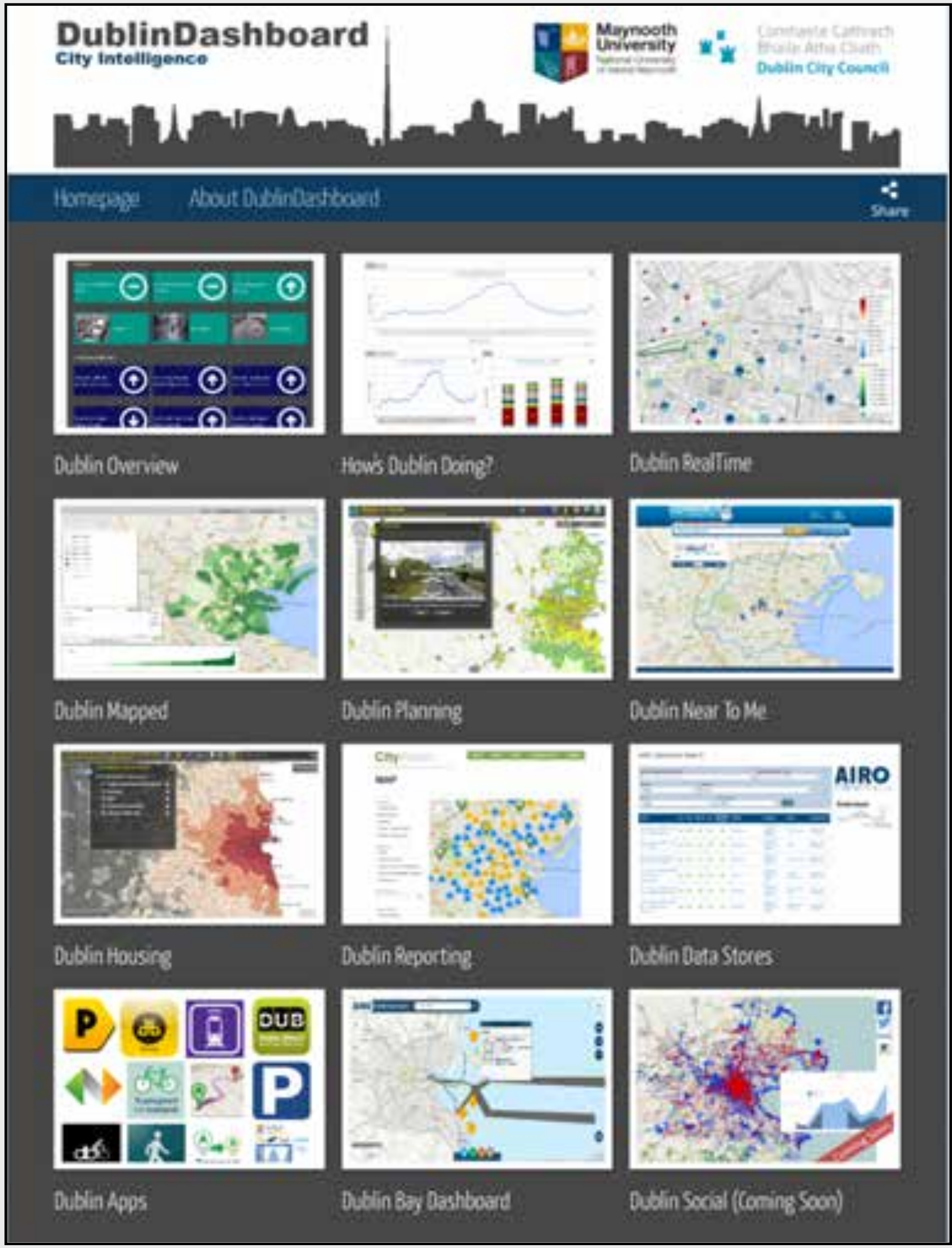
[redacted]

[redacted]

http://vis.oobrien.com/panopticon/


CENTRO DE OPERAÇÕES
PREFEITURA DO RIO





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- We are building a 3D version of London which captures real time data in real time and displays it almost immediately – this kind of application is moving very fast at present and there are countless variants on the web

- Let me show this movie instead as it has some good real time content – no I can't show this one as I have to load Quick Time and we don't have time

Intelligent Transit: Mobility from Big Data

- It is in the area of transit – fixed transport systems like that greatest progress is being made – largely because we have data from smart cards.
- These are for ***passenger demand for travel*** by time and place, and we also have ***supply of vehicles/trains*** (and buses) which relate to demand
- This is generating big data – without much attribute data of course but excellent portraits of what happens in time and space
- In London we have a very complex system which is accessed by Oyster Card.

Real-Time Streaming: The Oyster Card Data Set

Tap at start and end of train journeys

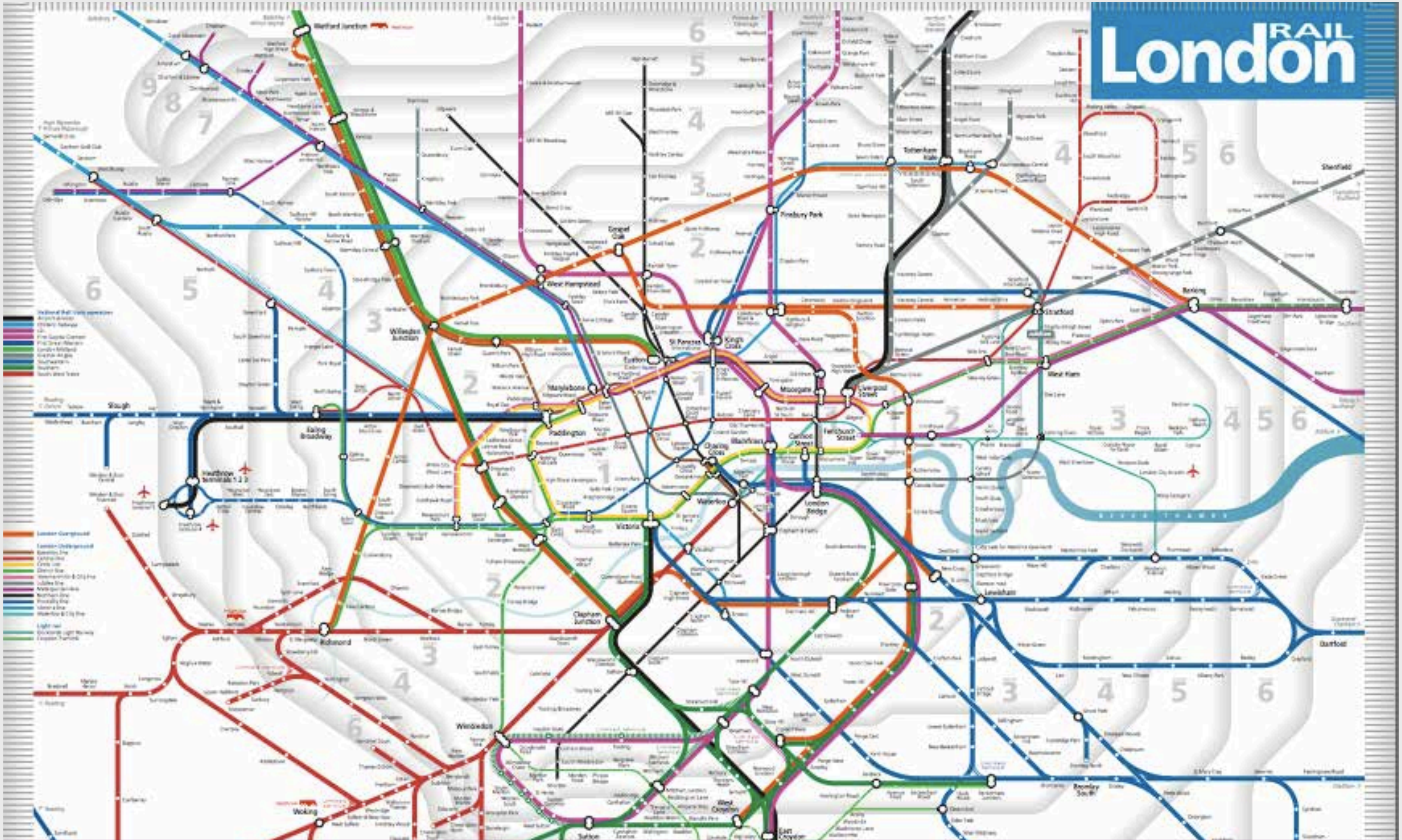
Tap at start only on buses

Accepted at 695 Underground and rail stations, and on thousands of buses

Many Data Variants

991 million Oyster Card taps over Summer 2012 – this is big data by any standards – it won't fit in an Excel spreadsheet

The Complexity of London's Rail Network



Tube, Overground and National Rail Networks in London where Oyster cards can be used

Let me show you a little movie to get a sense of how our tubes are different from yours

New Tools for Understanding & Planning the Smart City

[redacted]

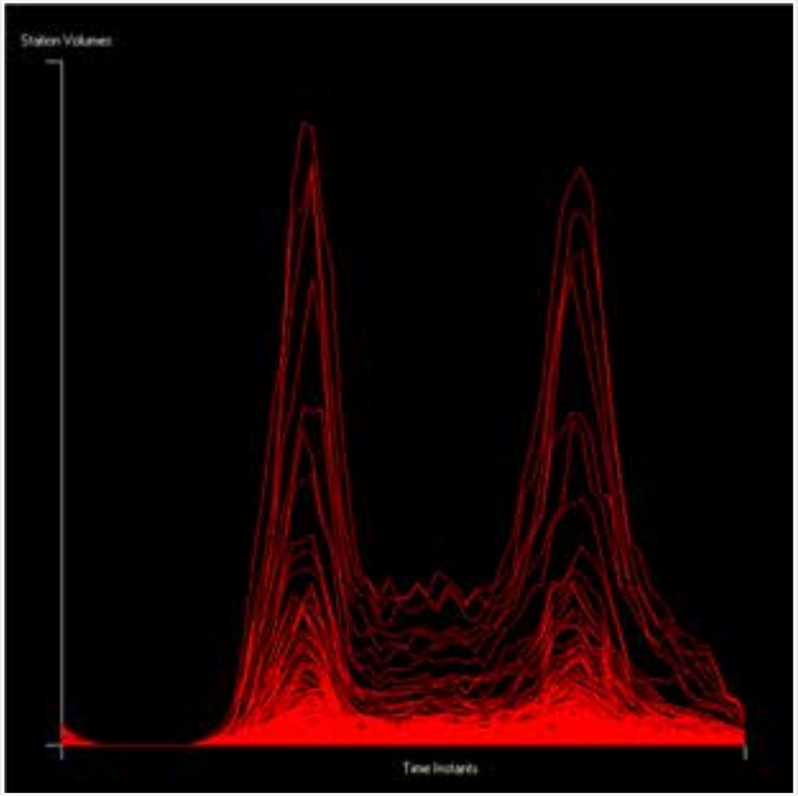
I have shown this many times before but it gives a sense of how we piece the data together

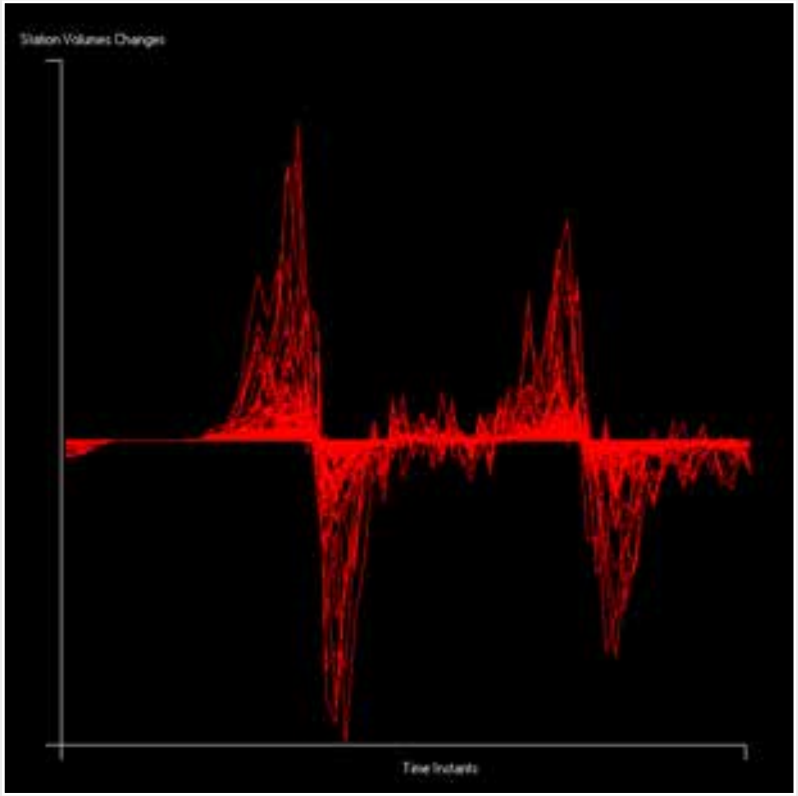
Jon Reades' movie at https://vimeo.com/41760845

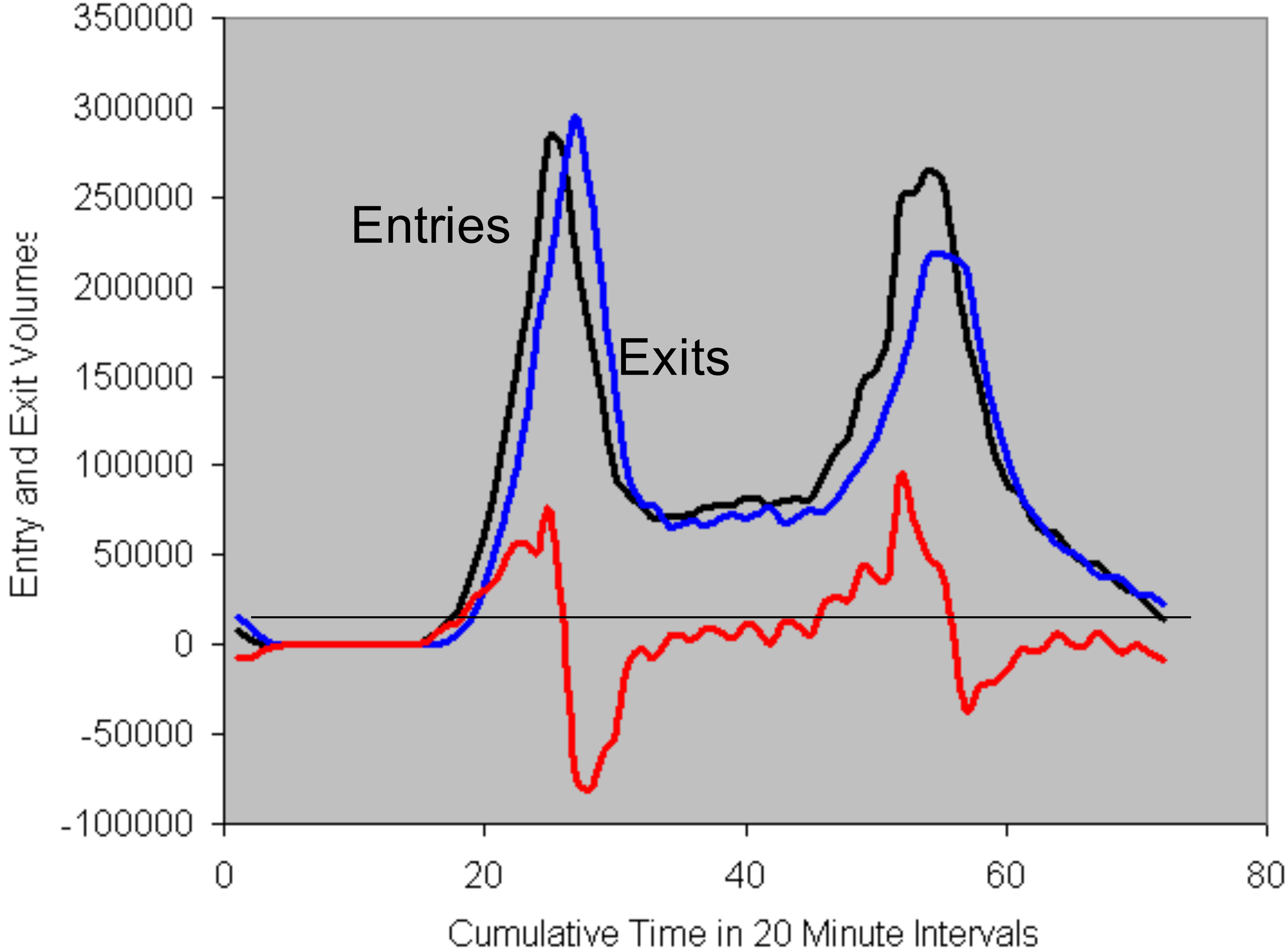
[redacted]

Variabilities – Heterogeneity and Travel Profiles

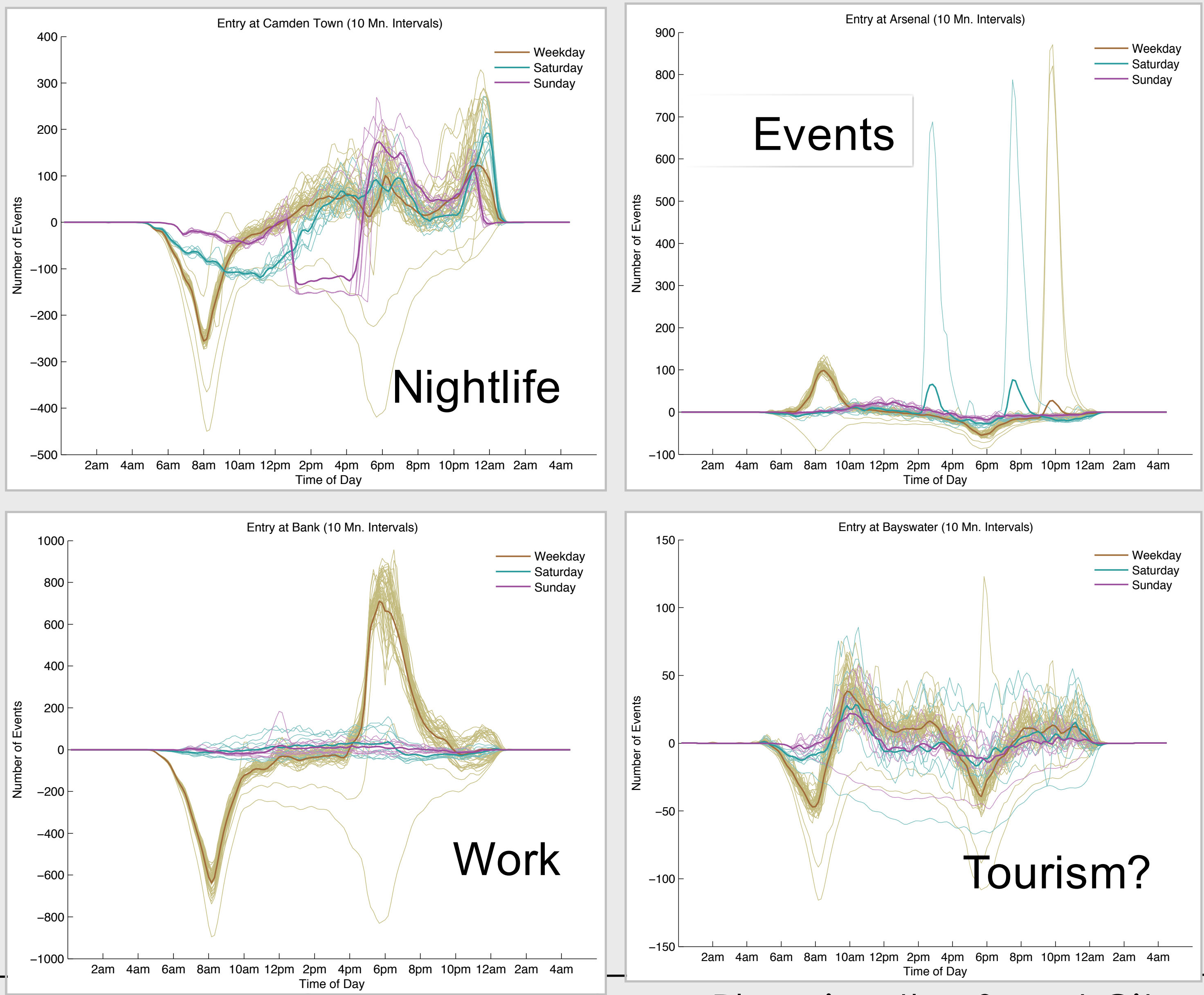
First we will look at some of the data and how it varies in terms of the diurnal flows usually morning and evening peaks, with a small blip (peak) around 10pm at night






350000
300000
250000
200000
150000
100000
50000
0
-50000
-100000
Entry and Exit Volumes
Entries
Exits
0
20
40
60
80
Cumulative Time in 20 Minute Intervals

And for Particular Events: Weekdays, Saturdays and Sundays



Comparing Variability for different time intervals for Three World Cities: London, Beijing and Singapore

Table 1. Summary statistics of one-week of smart-card data (metro trips only)

	London	Singapore	Beijing
Monday	3,457,234	2,208,173	4,577,500
Tuesday	3,621,983	2,250,597	4,421,737
Wednesday	3,677,807	2,277,850	4,564,335
Thursday	3,667,126	2,276,408	4,582,144
Friday	3,762,336	2,409,600	4,880,267
Number of stations (1)	400	130	233
Number of tube line	13	4	17
Area (2)	1,572 km^2	718.3 km^2	2267 km^2
Total population (3)	8.63 million	5.3 million	21.15 million
Ridership of Metro	20%	35%	21%
Length of metro lines	402km	182km (MRT+LRT)	465 km

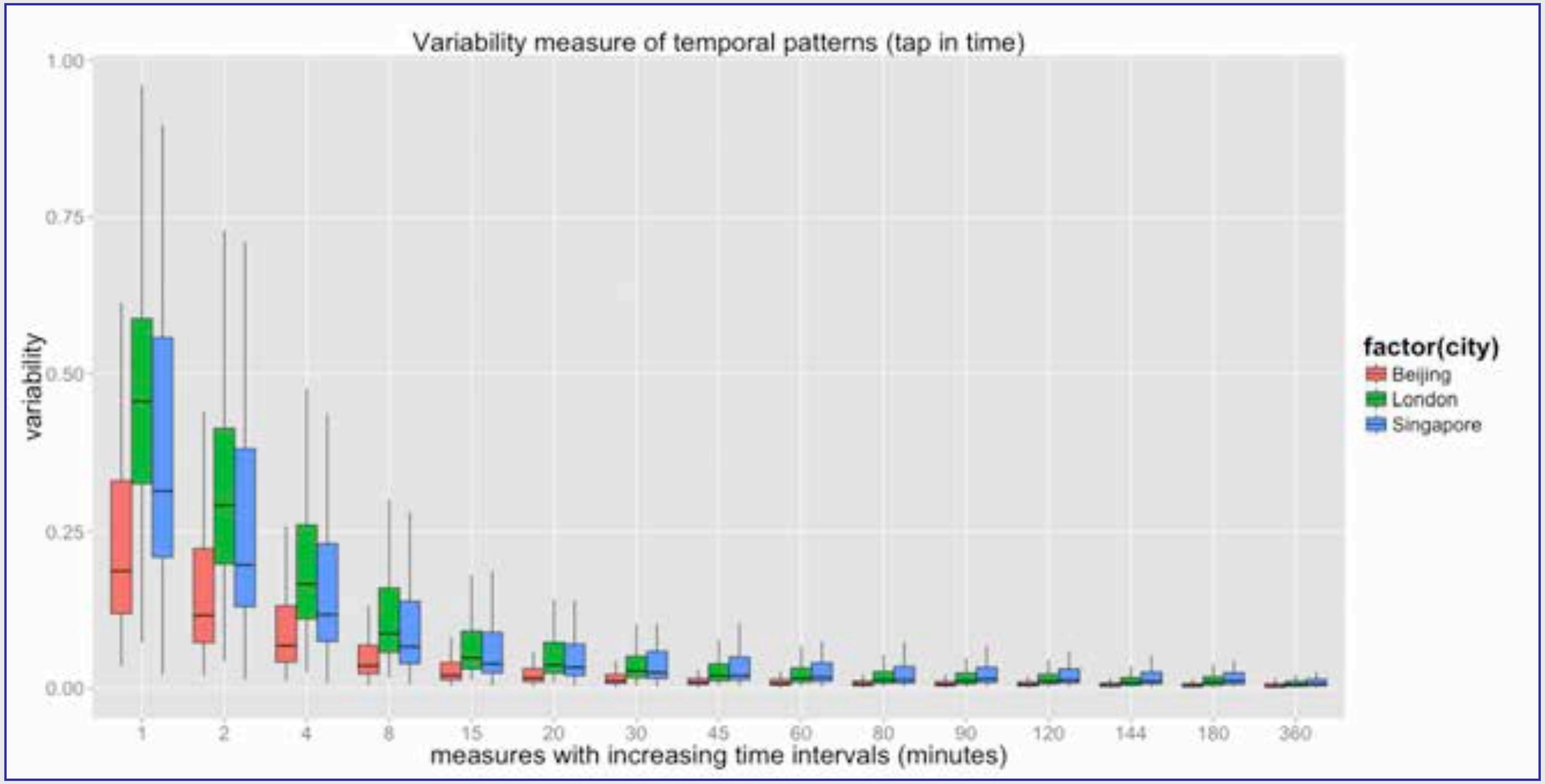
(1) Number of stations is the number of stations with smart-card records generated.

(2) The area of Beijing only counts the area enclosed by the 6th ring road for a fair comparison.

(3) From the World Population Review, http://worldpopulationreview.com/world-cities/ accessed 17 January 2016

Zhong, C., Batty, M., Manley, E., Wan, J., Wang, Z., Che, F., and Schmitt, G. (2016) Variability in Regularity: Mining Temporal Mobility Patterns in London, Singapore and Beijing using Smart-Card Data., **PLOS One**, http://dx.doi.org/10.1371/journal.pone.0149222

From 1 minute intervals to the whole day



Comparing variability for different time Intervals over the whole day

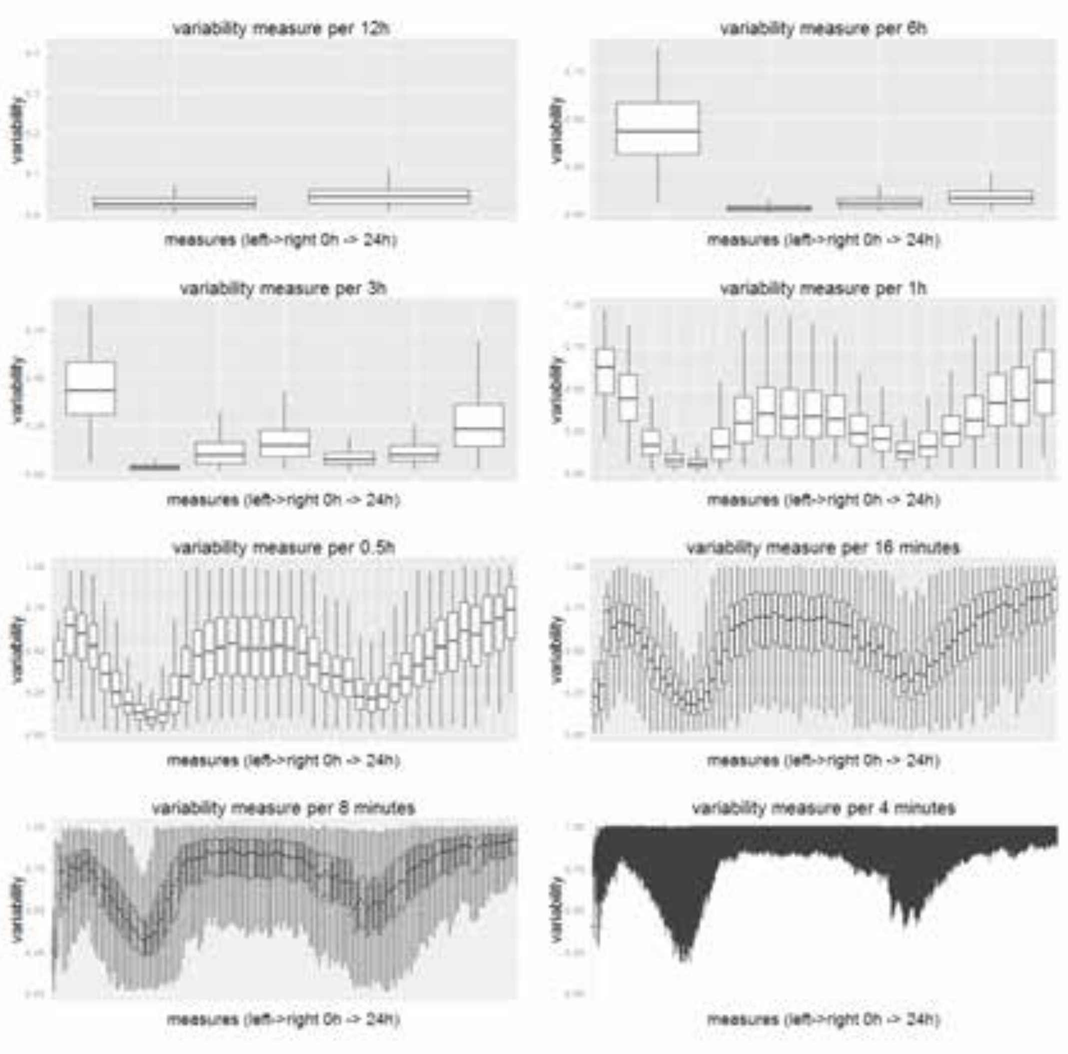
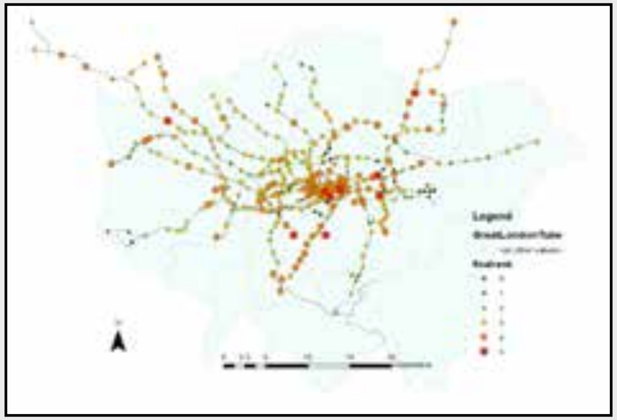
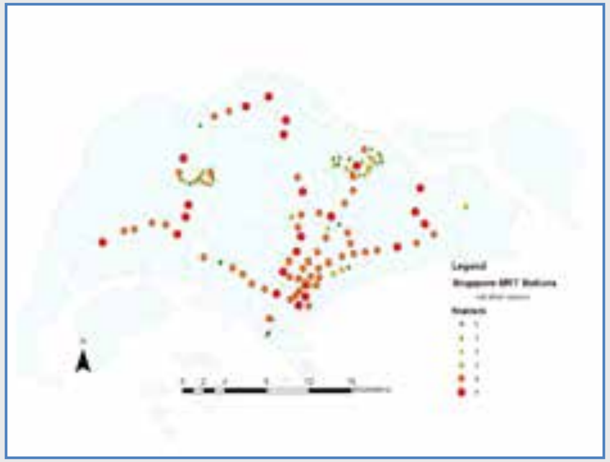


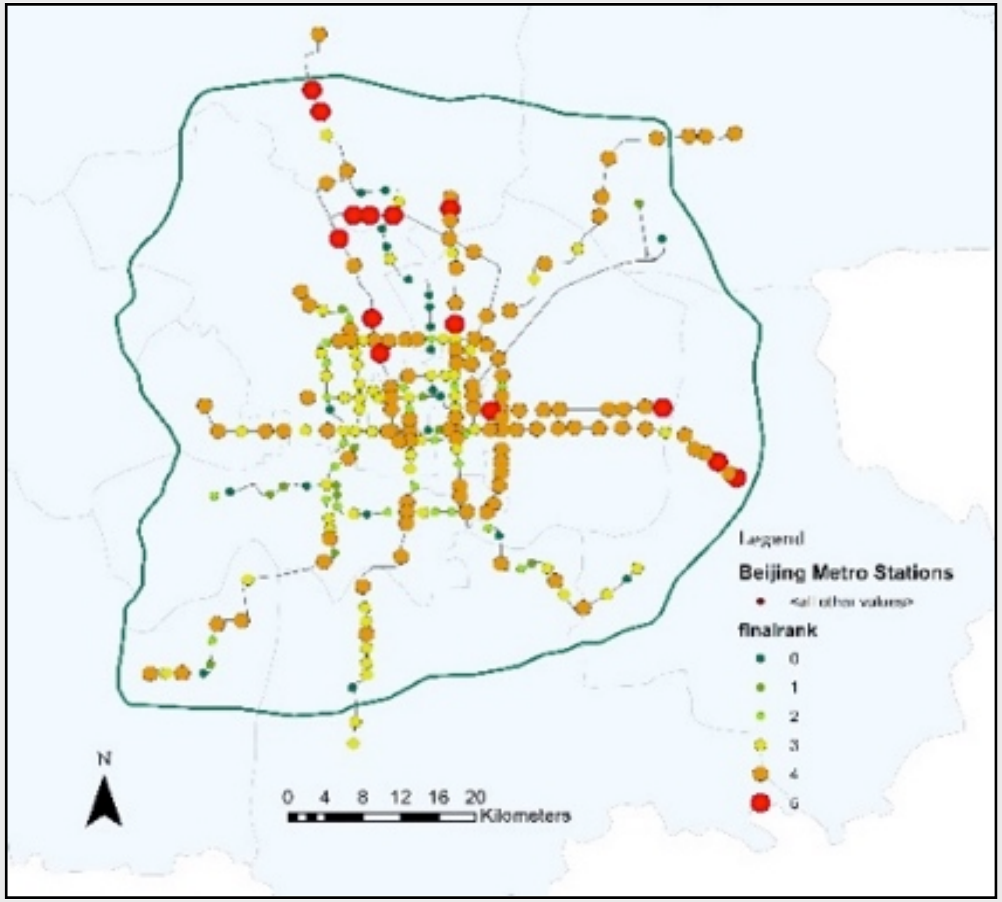
Figure 1. Variability of regularity in the trip matrix over time.

Note: Each box plot shows the variability of 400 stations over time measured at different temporal scales. Overall, eight subplots give a similar trend where lower variability appears during peak hours (around 9 am in the morning and 6pm in the evening). More details can be captured as differences of variability between each time unit are magnified as we decrease the temporal scale from 12h to 4 minutes.

Comparing variability for different time intervals and spatially by stations for Three World Cities: London, Beijing and Singapore







Disruptions – Routine Analysis of Daily Events

- Behaviours vary across network
- Different areas of network more resilient to disruption, due to available infrastructure and individual ability to change
- But areas of network are naturally closely tied through established usage patterns
- Individual-based analyses provide insight into behaviours underlying macroscopic flows

We will look at several kinds of disruption

- First hypothetical disruptions simply by examining breaks in the network

- Then an example of the Circle and District Lines which had a 4 hour stoppage on July 19th 2012

- And a Bus Strike in East London and how this shows up in the data

- And typical pattern of delay on all modes visualised for Greater London

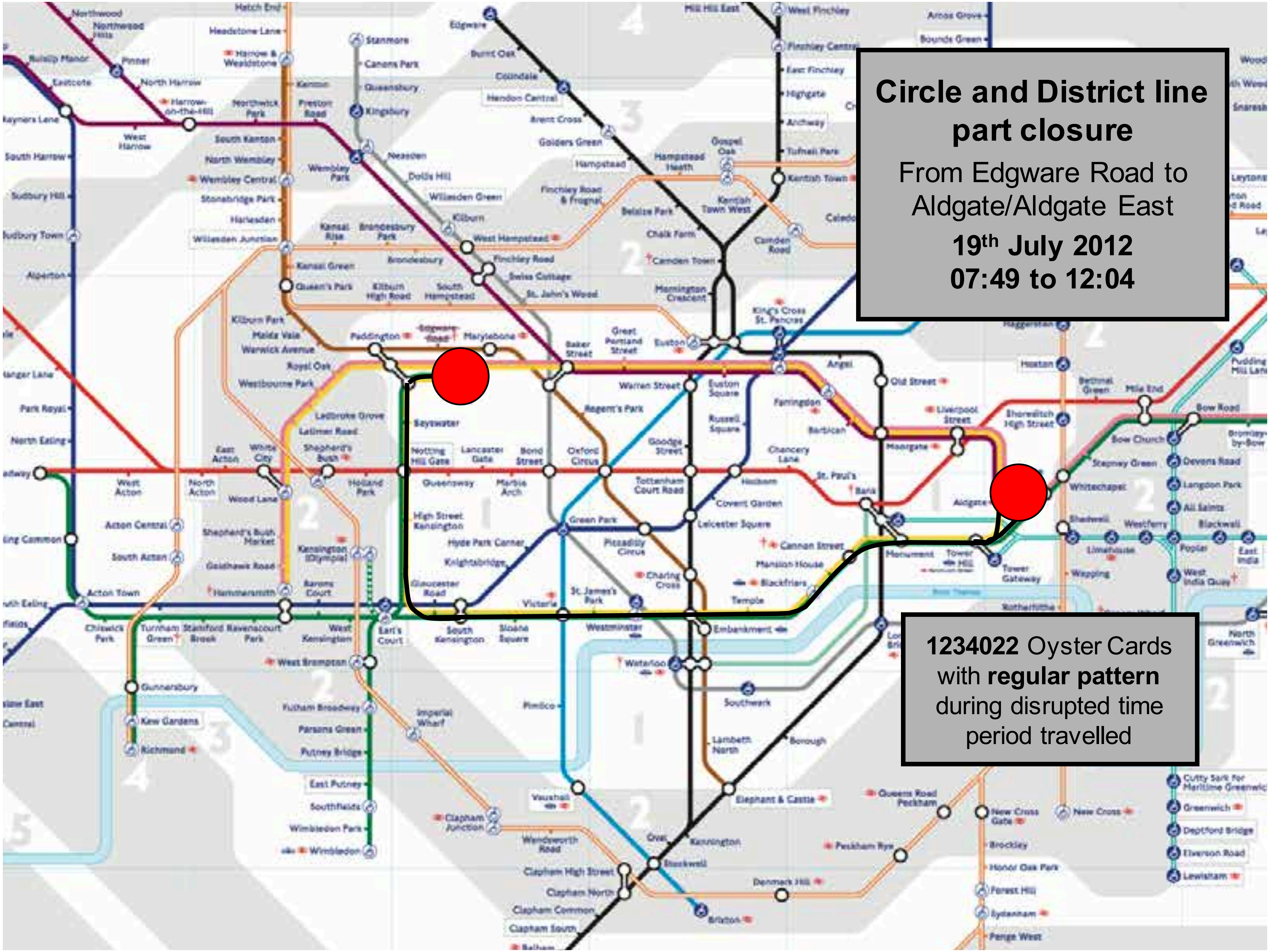

Service information
No Service On The Entire Line
And Kings Cross
And Edgware Road
And Stratford
Holloway Road Station Closed


UNDERGROUND

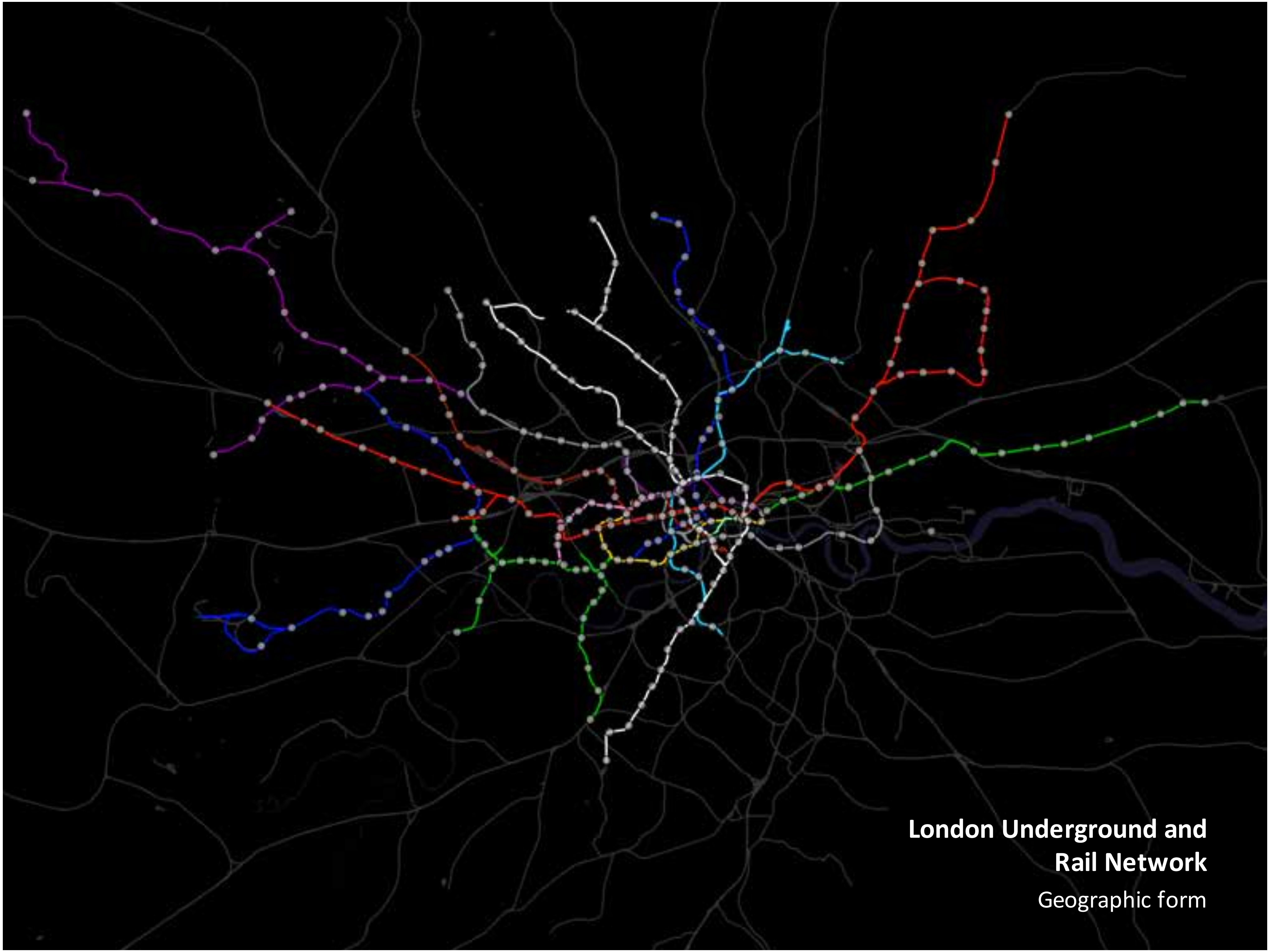
Circle and District line part closure

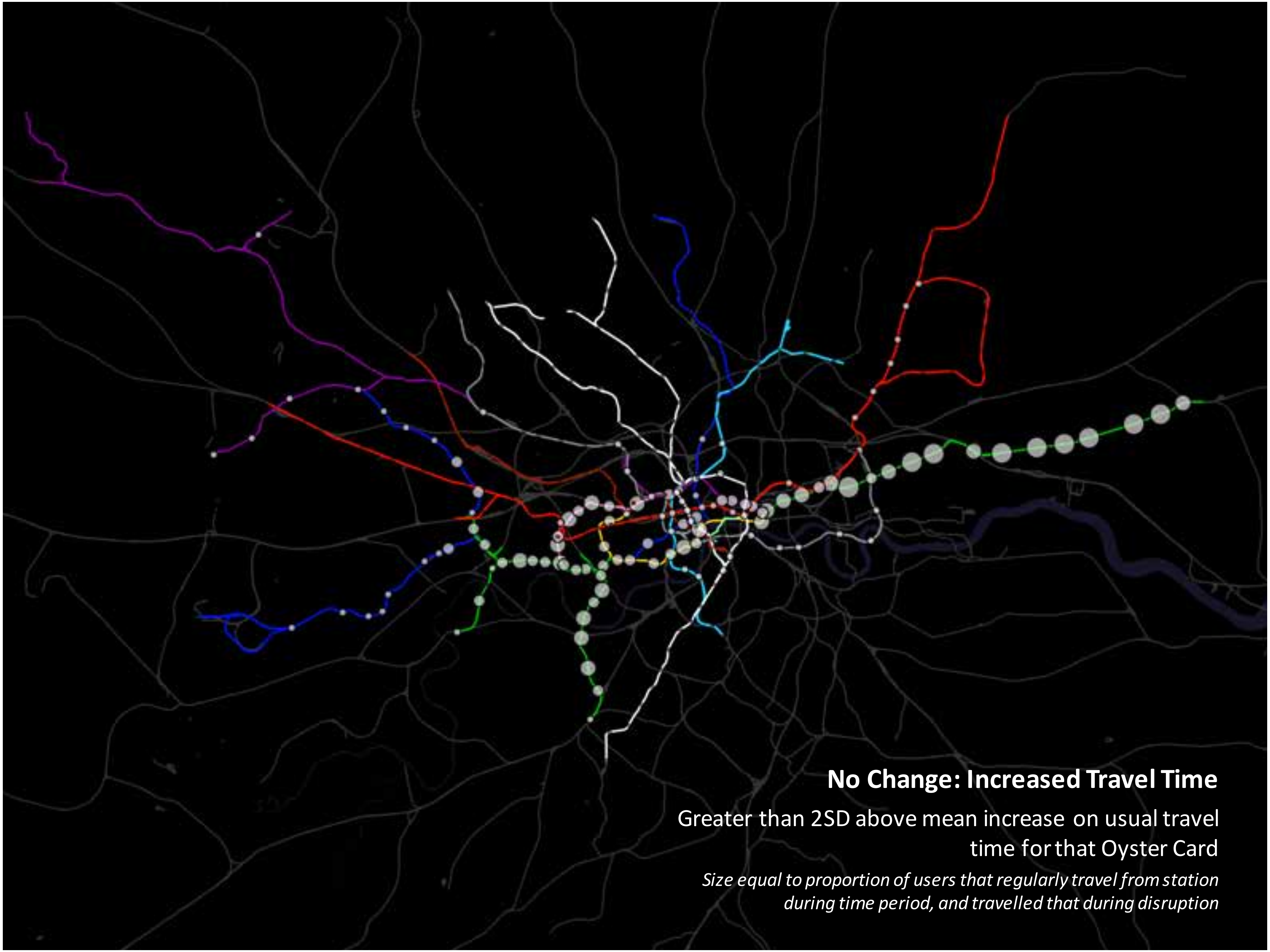
From Edgware Road to Aldgate/Aldgate East

19th July 2012
07:49 to 12:04



1234022 Oyster Cards with **regular pattern** during disrupted time period travelled


London Underground and
Rail Network
Geographic form

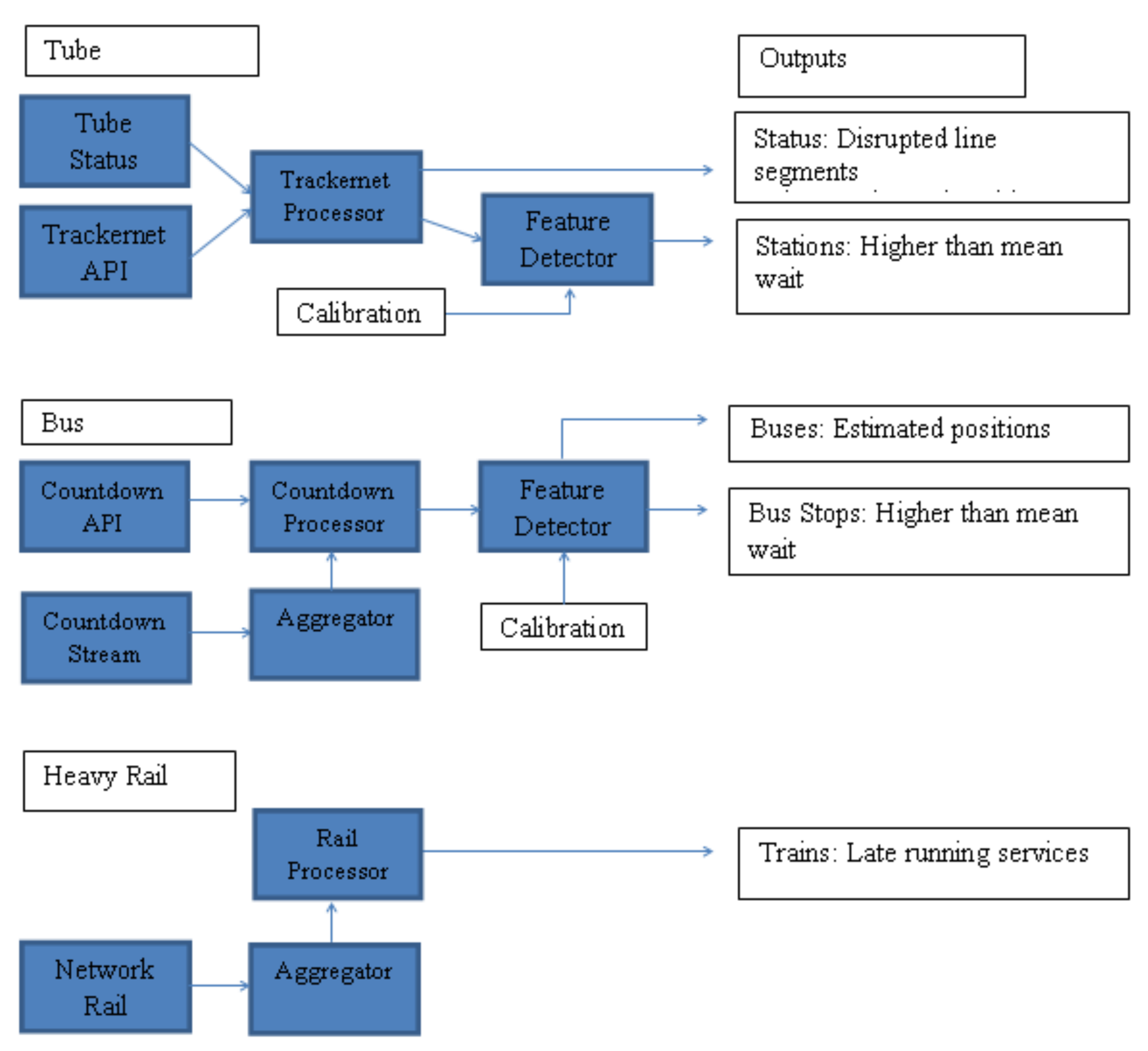


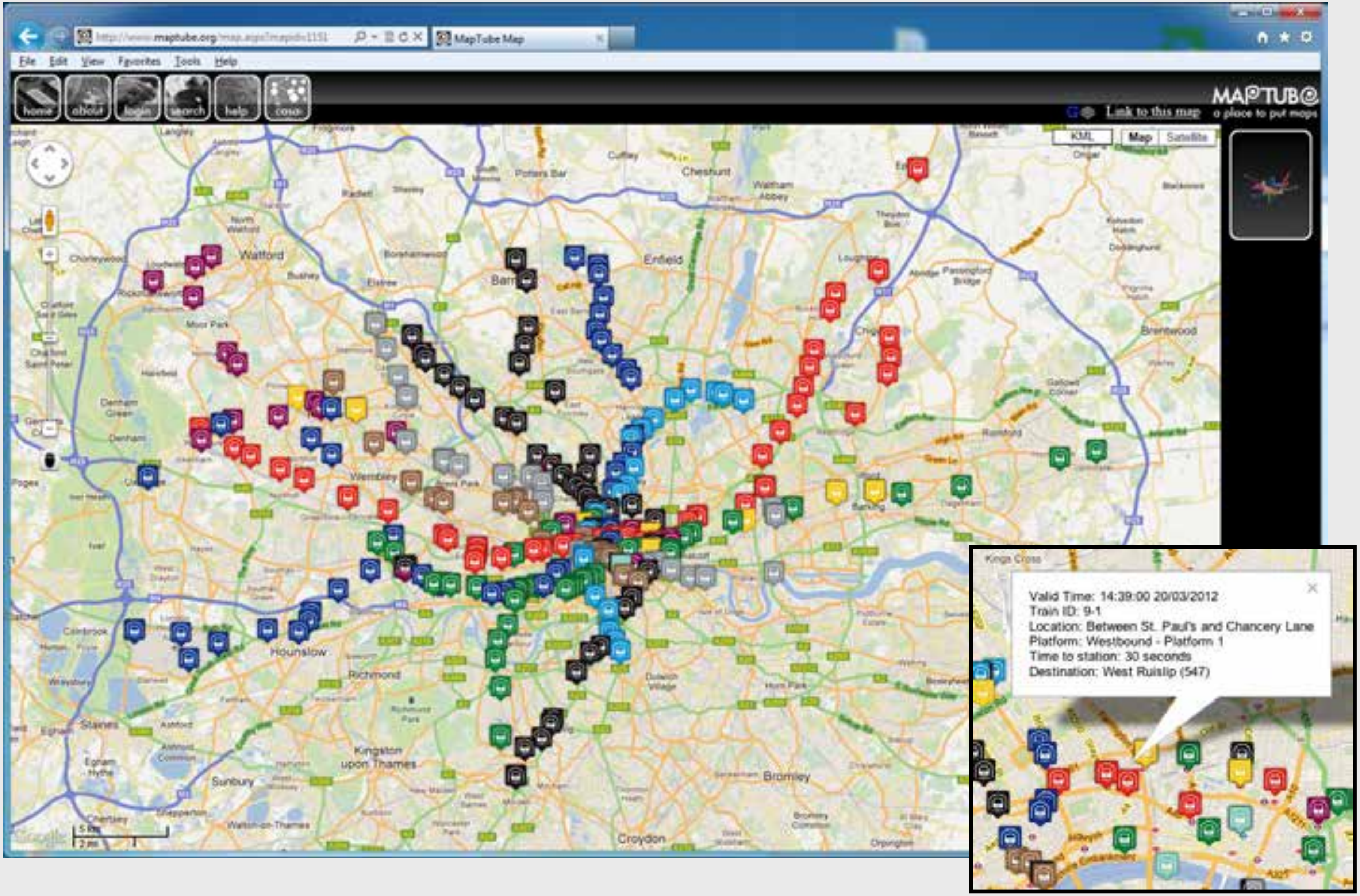
No Change: Increased Travel Time

Greater than 2SD above mean increase on usual travel time for that Oyster Card

Size equal to proportion of users that regularly travel from station during time period, and travelled that during disruption

The Public Transport System in Terms of Vehicle Flows





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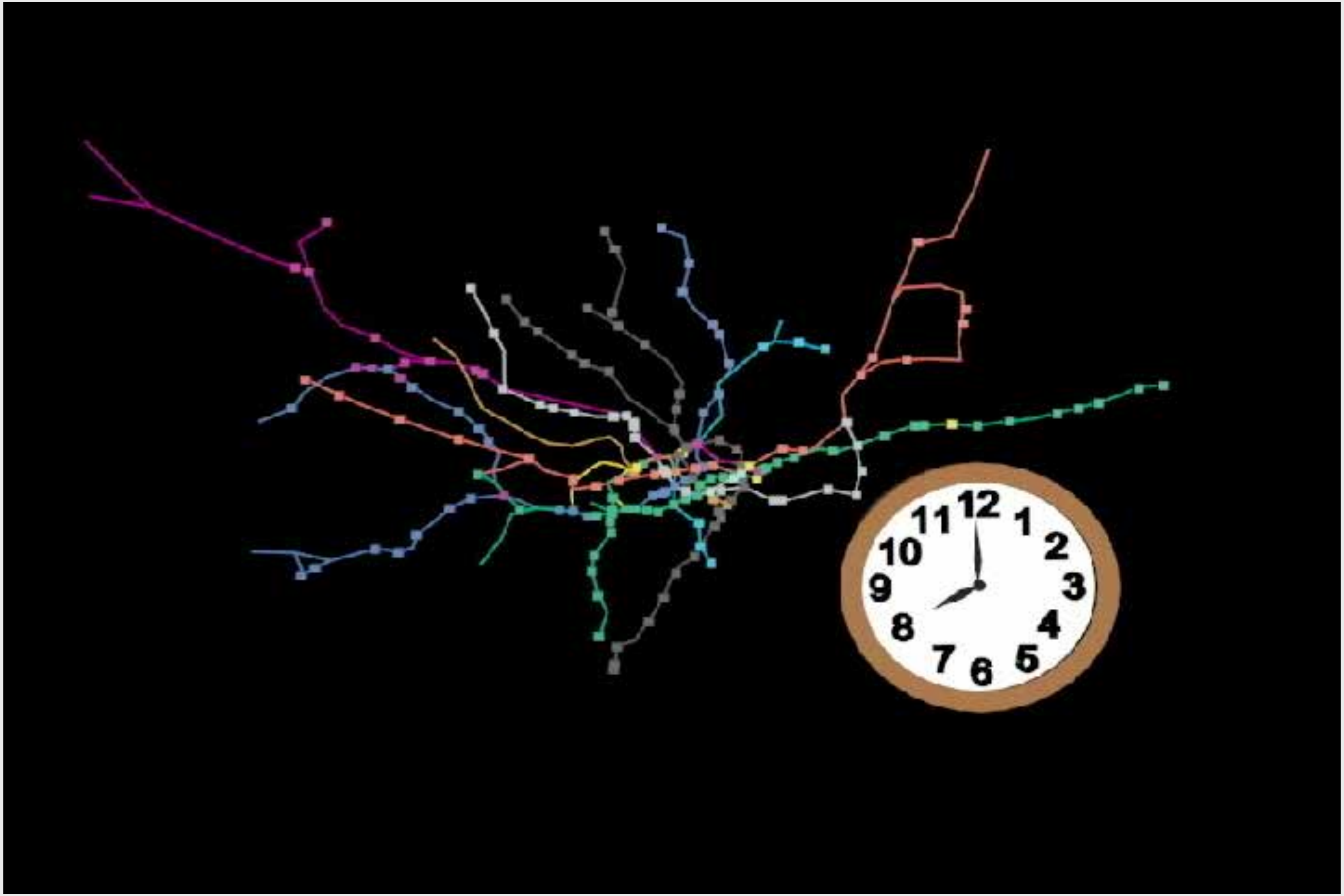
12
1
2
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4
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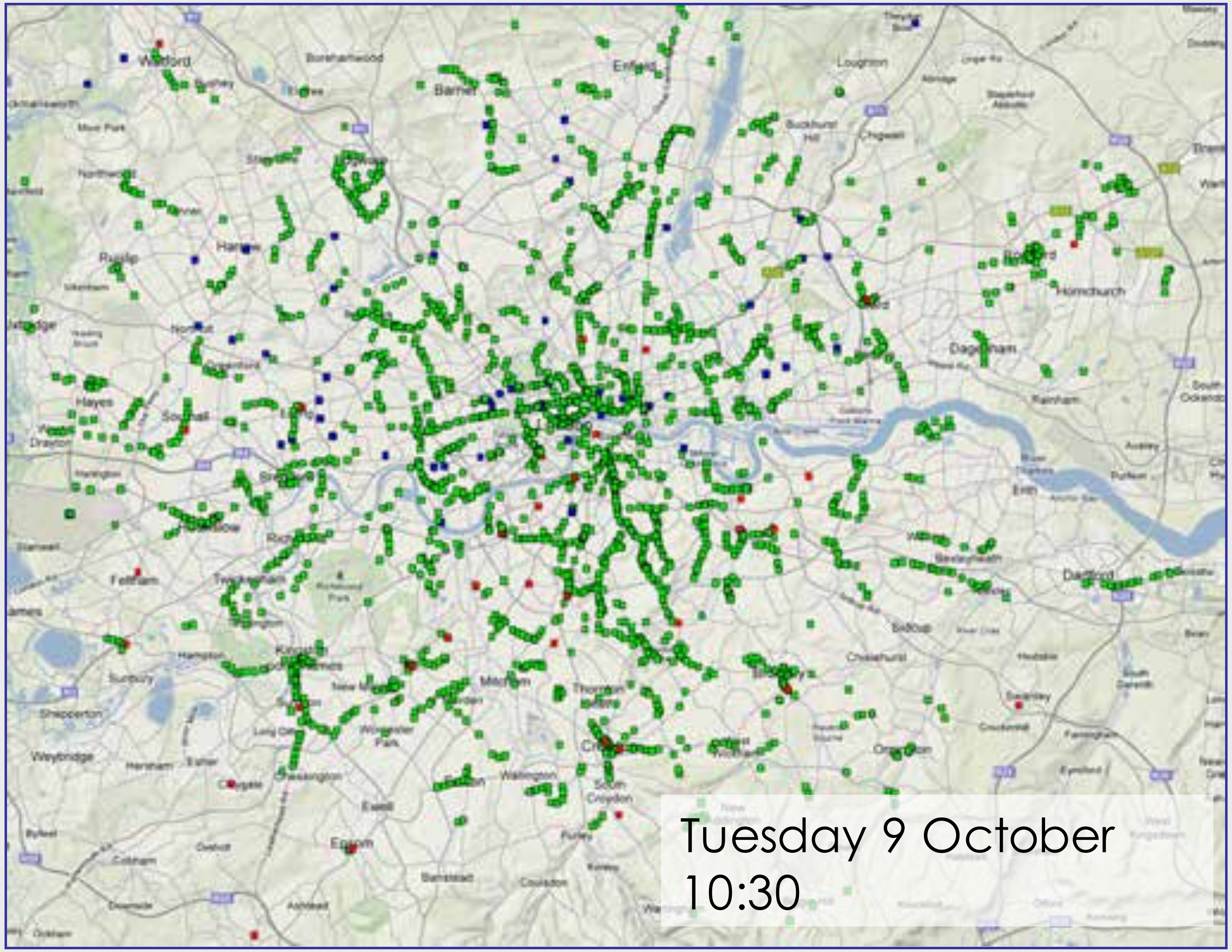
6
7
8
9
10
11

Delays from Tube, National Rail and Bus Fused



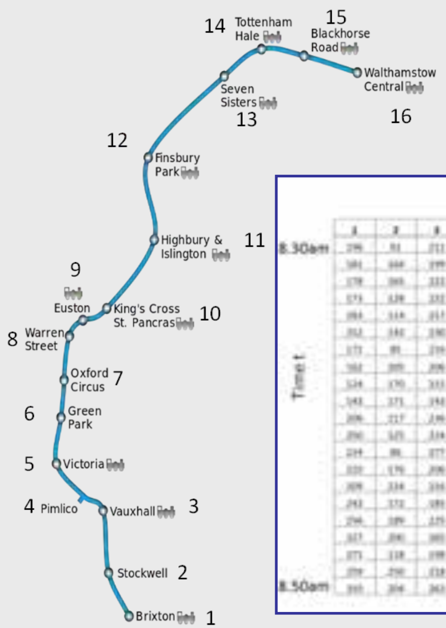
Key

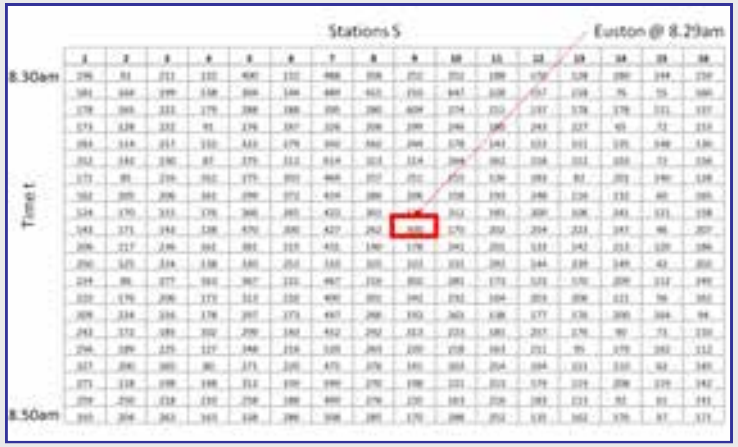
- National Rail more than 5 minutes late
- Tube stations showing a wait time 15% above expected
- Bus stops showing a wait time 20% above expected

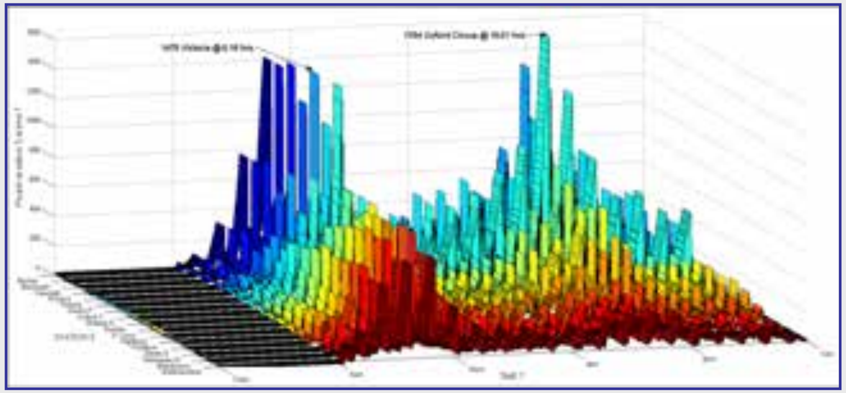
Tube delays from the TfL status feed are also plotted as lines

Locational Dynamics of Demand

We are currently using information theory to figure out how much information from trips is transmitted from station to station through time by working out how many passengers are in stations or on trains in stations over time. We are using the concept of **<u>transfer entropy</u>** to do this. I don't have time to say much about this but here is a picture about this for one line

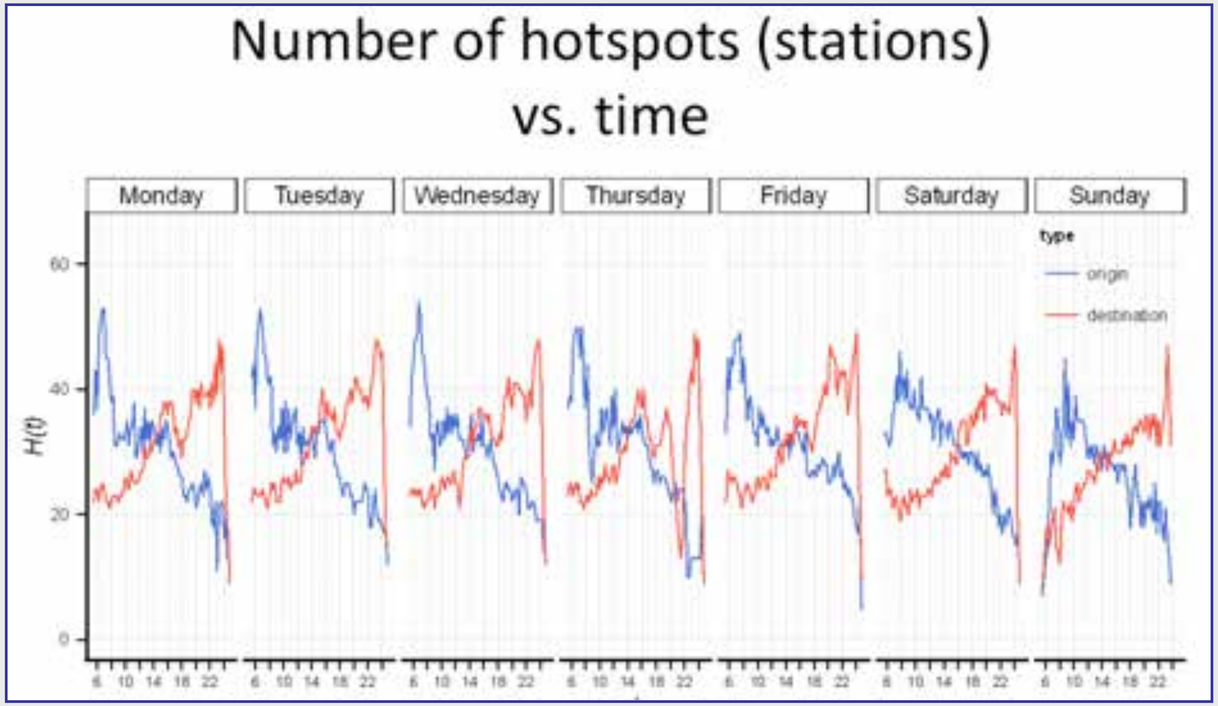






$$T_{YX} = \sum_{t=1} p(y_{t+1}, y_t, x_t) \log \frac{p(y_{t+1}|y_t, x_t)}{p(y_{t+1}|y_t)}$$

Second we are working with the Oyster data again with Melanie Bosredon in out group and Marc Barthelemy in Paris on extracting clusters from the travel data using a new method of defining intensity. I will show this as a simple movie of origin and destination intensities as they change over time of day.



[redacted]

Can Social Media Contribute to Smart City Planning?

I am going to look briefly at data on bikes – this is hardly social media but it is instructive.

And then I will look at some ideas from Twitter and building up data bases.

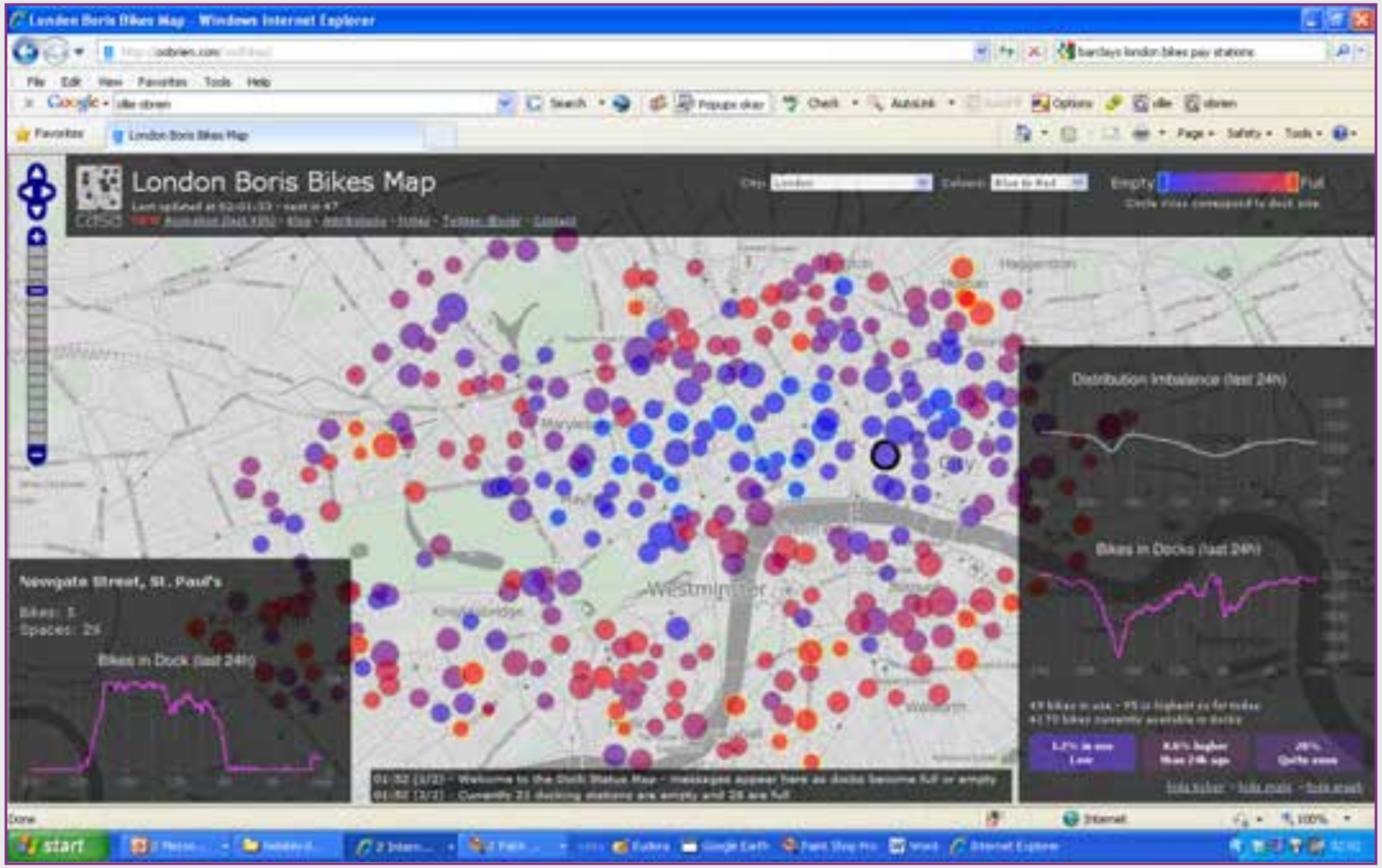
Key Issue is how good are these data sets?

And how good is big data in absolute terms?

By social media we mean data generated from smart phones, crowd-sourcing and even bikes data which is all online from the time one takes out the bike until it is dropped off. I will start with bikes.

Related Real -Time Data: Social Media

A lot of data is now coming online for travel and one of our group Oliver O'Brien has some 97 bike schemes world wide for which he has online data in real time - Bikes Data – 4200 bikes, started Nov 2010, all the data– everything – all trips, all times, all stations/docks

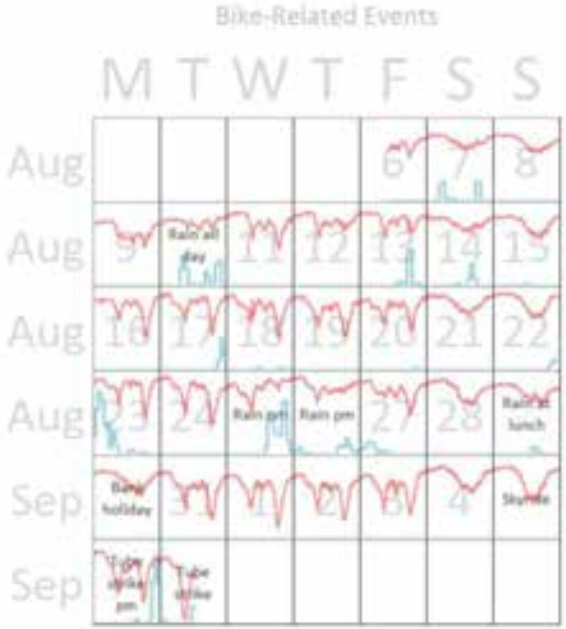


Animations of Public Bike Movements

Animations of Changes in the Bike Nodes: Docking

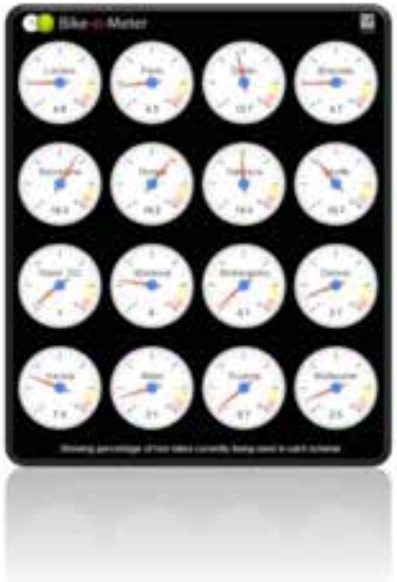
More Analysis

- **London**
- Graph shows number of bikes available to hire
- Effect of rain
  - Using the CASA weather station
- Effect of the tube strikes



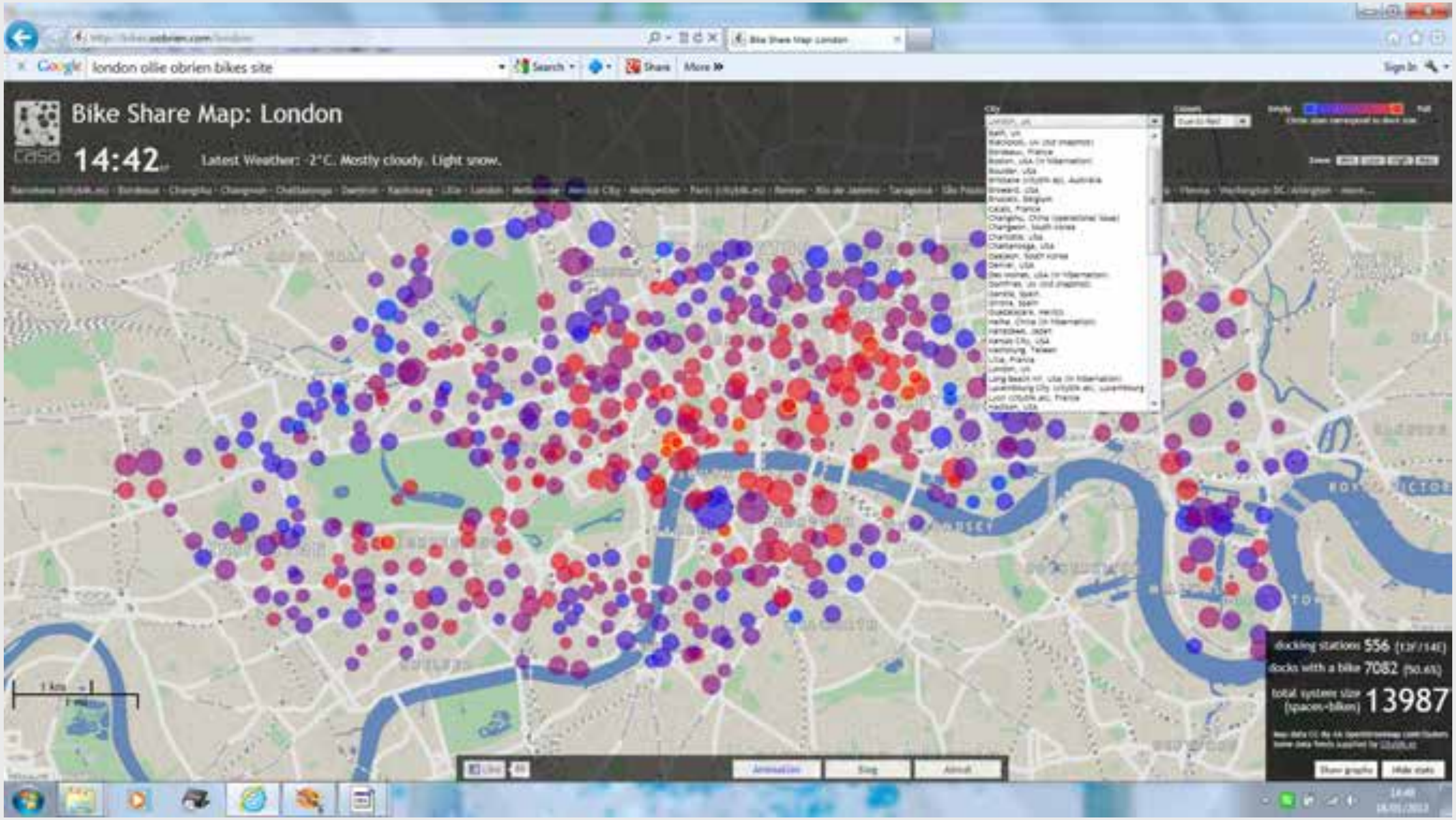
Bike-o-Meter
casa.ucl.ac.uk/bom

- Tweet-o-Meter for bikes
  - Steven Gray (@frogo)
  - Using Google Gauges
- See the real life Tweet-o-Meters at the new British Library “Growing Knowledge” exhibition
  - Should be easy to hack to show the Bike-o-Meters instead ☺

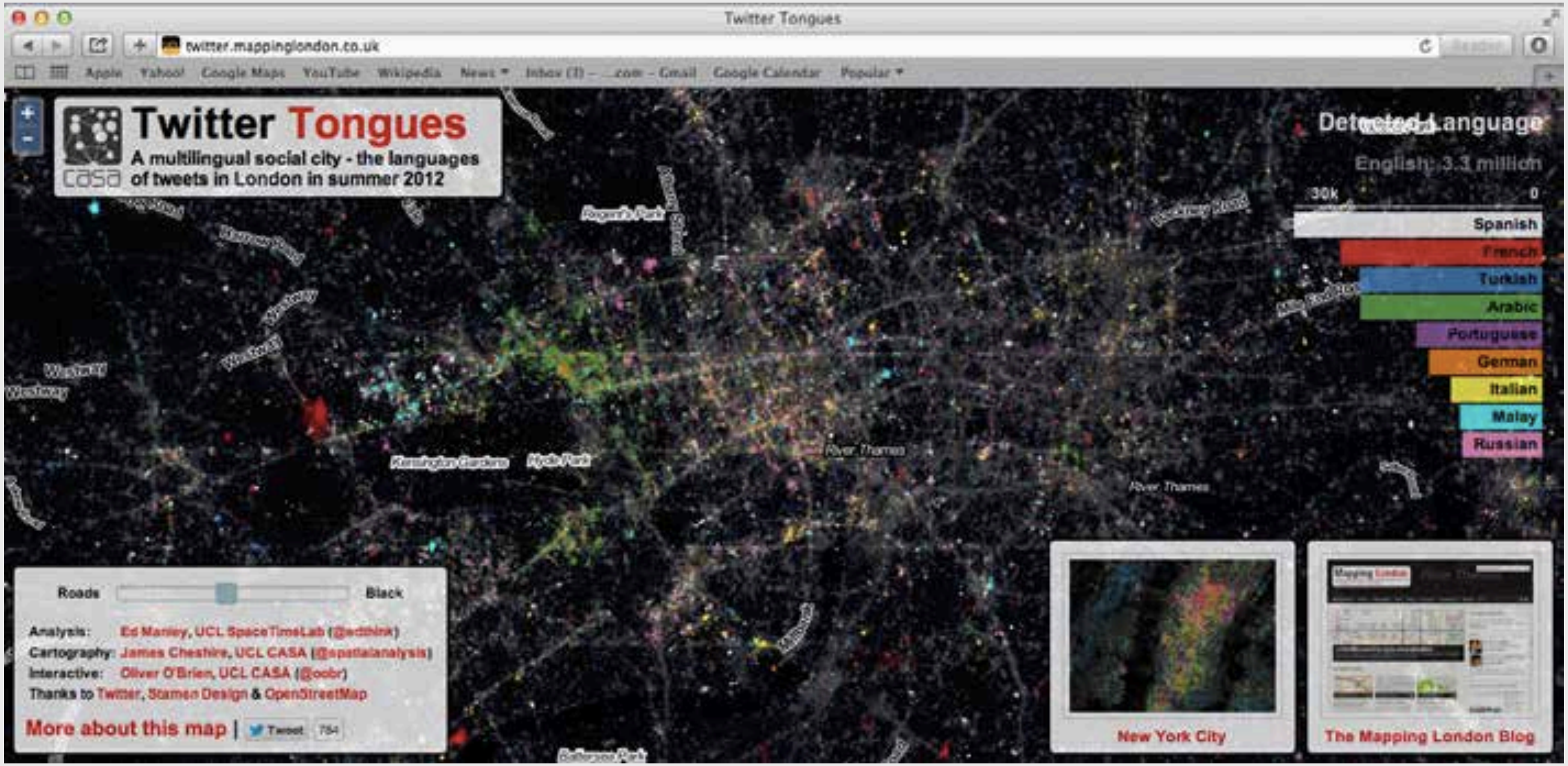


The Website: Real Time Visualisation of Origins and Destinations Activity

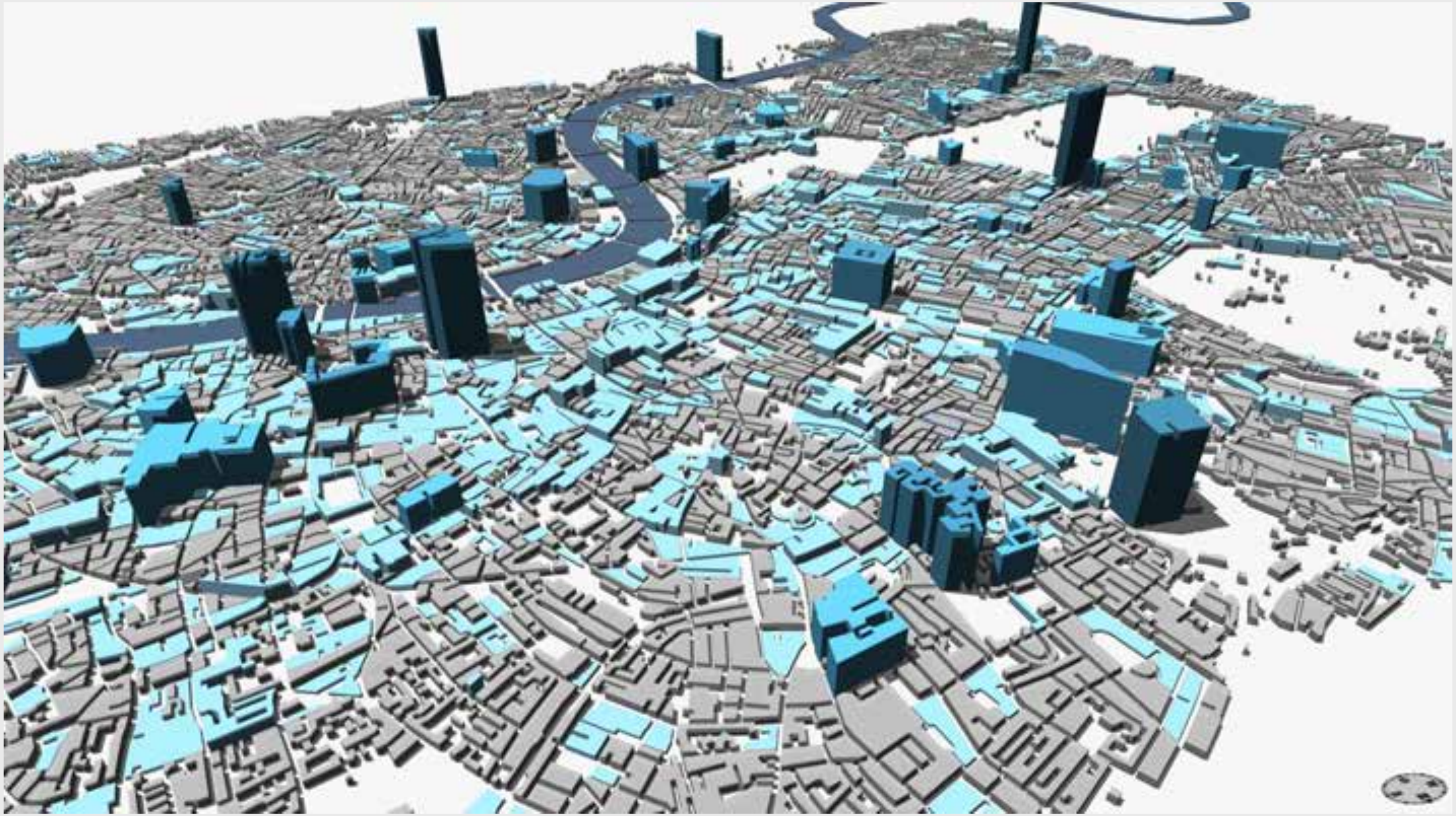
http://bikes.oobrien.com/london/



Ethnic Diversity from Twitter Feeds: The Challenge of Adding/Integrating New Data and Value to Real Time Data



Visualising Real Time Data in 3D: Twitter Feeds in Proportion to Building Heights



[redacted]

What Can We Learn: The Limits to Big Data

We need to add geo-demographics to this data – how – we barely have any possibility of doing this because of confidentiality

We only have a difference between young and old in terms of the card data

Chen Zhong my post doc, now a lecturer at Kings (KCL) has done a lot of work on this relating to extracting such data from related data sets

International Journal of Geographical Information Science, 2014
http://dx.doi.org/10.1080/13658816.2014.914521

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Detecting the dynamics of urban structure through spatial network analysis

Chen Zhong[a*], Stefan Müller Arisona[a,b], Xianfeng Huang[c], Michael Batty[d] and Gerhard Schmitt[a]

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Zhong, C., Arisona, S. M., Huang, X., Schmitt, G. and Batty, M. (2014)) Detecting the Dynamics of Urban Structure through Spatial Network Analysis, **International Journal of Geographical Information Science**, http://dx.doi.org/10.1080/13658816.2014.914521

Zhong, C., Batty, M., Manley, E., Wan, J., Wang, Z., Che, F., and Schmitt, G. (2016) Variability in Regularity: Mining Temporal Mobility Patterns in London, Singapore and Beijing using Smart-Card Data., **PLOS One**, http://dx.doi.org/10.1371/journal.pone.0149222

Zhong, C., Huang, X., Arisona, S. M., Schmitt, G., and Batty, M. (2014) Inferring building functions from a probabilistic model using public transportation data, **Computers, Environment and Urban Systems, 48**, 124–137

Zhong, C., Manley, E., Stefan Muller Arisona, S., Batty, M.,and Schmitt, G. (2015) Measuring Variability of Mobility Patterns from Multiday Smart-card Data, **Journal of Computational Science**, doi.org/doi:10.1016/j.jocs.2015.04.021

Finding Pearls in London's Oysters

JONATHAN READES, CHEN ZHONG, ED MANLEY,
RICHARD MILTON and MICHAEL BATTY

Public transport is perhaps the most significant component of the contemporary smart city currently being automated using sensor technologies that generate data about human behaviour. This is largely due to the fact that the travel associated with such transport is highly ordered. Travellers move collectively in closed vehicles between fixed stops and their entry into and from the system is unambiguous and easy to automate using smart cards. Flows can thus be easily calculated at specific station locations and bus stops and within fine temporal intervals. Here we outline work we have been doing using a remarkable big data set for public transport in Greater London generated from the Oyster Card, the smart card which has been in use for over 13 years. We explore the generic properties of the Tube and Overground rail system focusing first on the scale and distribution of the flow volumes at stations, then engaging in an analysis of temporal flows that can be decomposed into various patterns using principal components analysis (PCA) which smoothes out normal fluctuations and leaves a residual in which significant deviations can be tracked and explained. We then explore the heterogeneity in the data set with respect to how travel behaviour varies over different time intervals and suggest how we can use these ideas to detect and manage disruptions in the system.

Big Data, Automation and Smart Transit

Automation in transit systems is the most visible sign of how the city is being transformed to enhance the travel experience and efficiency of movement (Batty *et al.*, 2012). There are many ways of achieving this but one of the most significant is the use of smart cards for 'fully automatic fare collection'. These smart cards usually contain the value that the consumer has agreed to load onto the card; they meet stringent requirements for anonymity and security; and their use is such that by tapping in and out of an automated system, correct payments are ensured. Smart cards like this, in fact, go back to the late 1960s and rapid progress in their development was achieved in the 1970s and 1980s when they first made their appearance as phone cards in France. Different varieties of credit card were then emerging too, and by 1984 in places like Hong Kong, stored value cards for use on their new Mass Transit Railway (MTR) had been introduced. By the mid-1990s, contactless cards came onto the scene, first in Seoul with the UPass card, and then in Hong Kong where they introduced the Octopus card, which was then extended to other purchases in the local retail system.

Several other cities followed, but one of the most comprehensive rollouts was in London where, in 2003, the first cards were introduced on the underground ('Tube') system. These are called 'Oyster' cards – partly in tribute, it would seem, to Hong Kong's Octopus card – but the official reason is that the Oyster Card protects its 'pearl' – the stored value – in a 'hard shell'; hence, the name which we have used in the title to this paper. Our particular interest in these 'pearls' is not in their value but in the raw data that can be extracted which covers 'where' the owner of

PLOS ONE

RESEARCH ARTICLE

Variability in Regularity: Mining Temporal Mobility Patterns in London, Singapore and Beijing Using Smart-Card Data

Chen Zhong[1]*, Michael Batty[1], Ed Manley[1], Jiaqiu Wang[1], Zijia Wang[2,3], Feng Chen[2,3], Gerhard Schmitt[4]

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OPEN ACCESS

Abstract

To discover regularities in human mobility is of fundamental importance to our understanding of urban dynamics, and essential to city and transport planning, urban management and policymaking. Previous research has revealed universal regularities at mainly aggregated spatio-temporal scales but when we zoom into finer scales, considerable heterogeneity and diversity is observed instead. The fundamental question we address in this paper is at what scales are the regularities we detect stable, explicable, and sustainable. This paper thus proposes a basic measure of variability to assess the stability of such regularities focusing mainly on changes over a range of temporal scales. We demonstrate this by comparing regularities in the urban mobility patterns in three world cities, namely London, Singapore and Beijing using one-week of smart-card data. The results show that variations in regularity scale as non-linear functions of the temporal resolution, which we measure over a scale from 1 minute to 24 hours thus reflecting the diurnal cycle of human mobility. A particularly dramatic increase in variability occurs up to the temporal scale of about 15 minutes in all three cities and this implies that limits exist when we look forward or backward with respect to making short-term predictions. The degree of regularity varies in fact from city to city with Beijing and Singapore showing higher regularity in comparison to London across all temporal scales. A detailed discussion is provided, which relates the analysis to various characteristics of the three cities. In summary, this work contributes to a deeper understanding of regularities in patterns of transit use from variations in volumes of travellers entering subway stations, it establishes a generic analytical framework for comparative studies using urban mobility data, and it provides key points for the management of variability by policy-makers intent on for making the travel experience more amenable.

New Tools for Understanding & Planning the Smart City

Let me point you to some more material: there is a special issue of **Built Environment** from last year

Big Data and the City

Editor: Michael Batty
Centre for Advanced Spatial Analysis, University College London

Built Environment

Volume 42, number 3, September 2016

Big data is everywhere, largely generated by automated systems operating in real time that potentially tell us how cities are performing and changing. A product of the smart city, it is providing us with novel data sets that suggest ways in which we might plan better,anddesignmore sustainable environments. The articles in this issue tell us how scientists and planners are using big data to better understand everything from new forms of mobility in transport systems to new uses of social media. Together, they reveal how visualization is fast becoming an integral part of developing a thorough understanding of our cities.

http://www.spatialcomplexity.info/archives/3026

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http://www.complexcity.info/
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