University College London

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Session 3: Big Data, Network Data, Measuring Disruption in the 24 Hour City

Michael Batty

http://www.spatialcomplexity.info/

July 7, 2018

SHANGHAI UNIVERSITY OF FINANCE AND ECONOMICS

Let me point you at www.spatialcomplexity.info where I have now added the material under the menu item

Shanghai

There you will find

- **The Journal Publication: Big Data and the City The**
- **Shanghai Smart Cities Lecture 1, 2, 3, and 4**

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 Variants of the Data Sets**
- **991 million** Oyster Card taps over Summer 2012 – this is big data
- Quality of Data
- What Can We Use It For
- Missing Data and Noise

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

UCL ENGINEERING
Change the world

Menu +

Home – Projects – Oyster gives up pearls

OYSTER GIVES UP PEARLS

How studying millions of Oyster Card journeys reveals London's 'polycentres'

Researchers from UCL have analysed millions of Oyster Card journeys in a bid to understand how, why and where we travel in London.

Professor Michael Batty (UCL Centre for Advanced Spatial Analysis) and Dr Soong Kang (UCL Management Science and Innovation) applied the techniques of statistical physics to their mountain of raw data.

The pair joined forces with a computational social scientist and a physicist, both based in Paris, to explore patterns of commuting by tube into central London.

UCL Engineering - Oyster Gives up Pearls

0:00 / 3:32

They used Transport for London's database of 11 million records taken over one week from the Oyster Card electronic ticketing system.

Latest news from UCL Engineering

- New web privacy system could revolutionise the safety of surfing
- UCL host Google Girls Coding Programme with Generating Genius and University of West indies
- Professor Polina Bayvel to Give Royal Society Lecture

Twitter feed

RT @markmiodownik: Am giving a ENGins seminar today for @UCLEngineering @UCLENGins all UCL engineers welcome - Roberts G06, 6:30pm. http:/...
8:58am Thu 9th October 2014

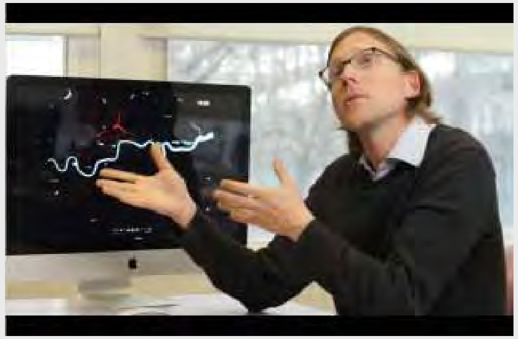
RT @Centre4EngEdu: We're hiring! Multi-talented Centre Administrator required to help us launch and expand! bit.ly/ZsERSM
10:54am Wed 8th October 2014

Join our mailing list

[redacted]

And how can we make sense of this

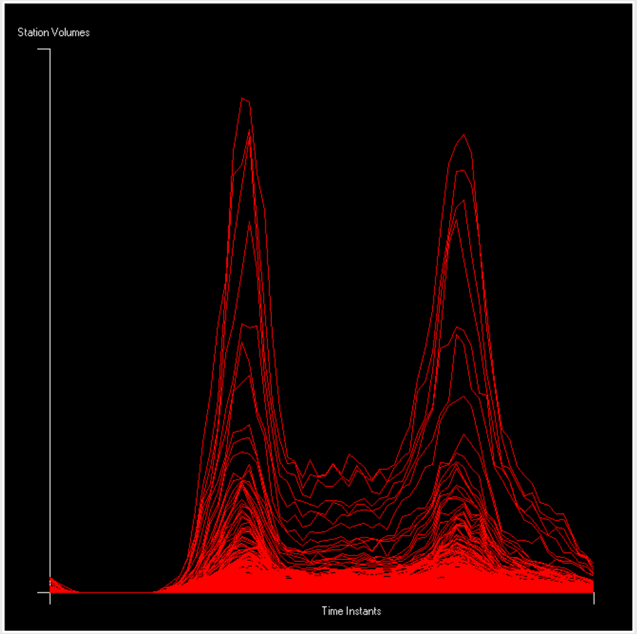
http://www.simulacra.info/

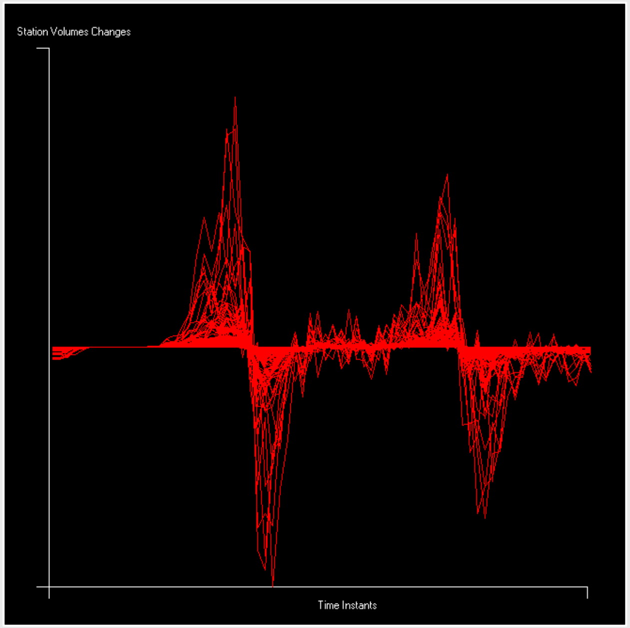


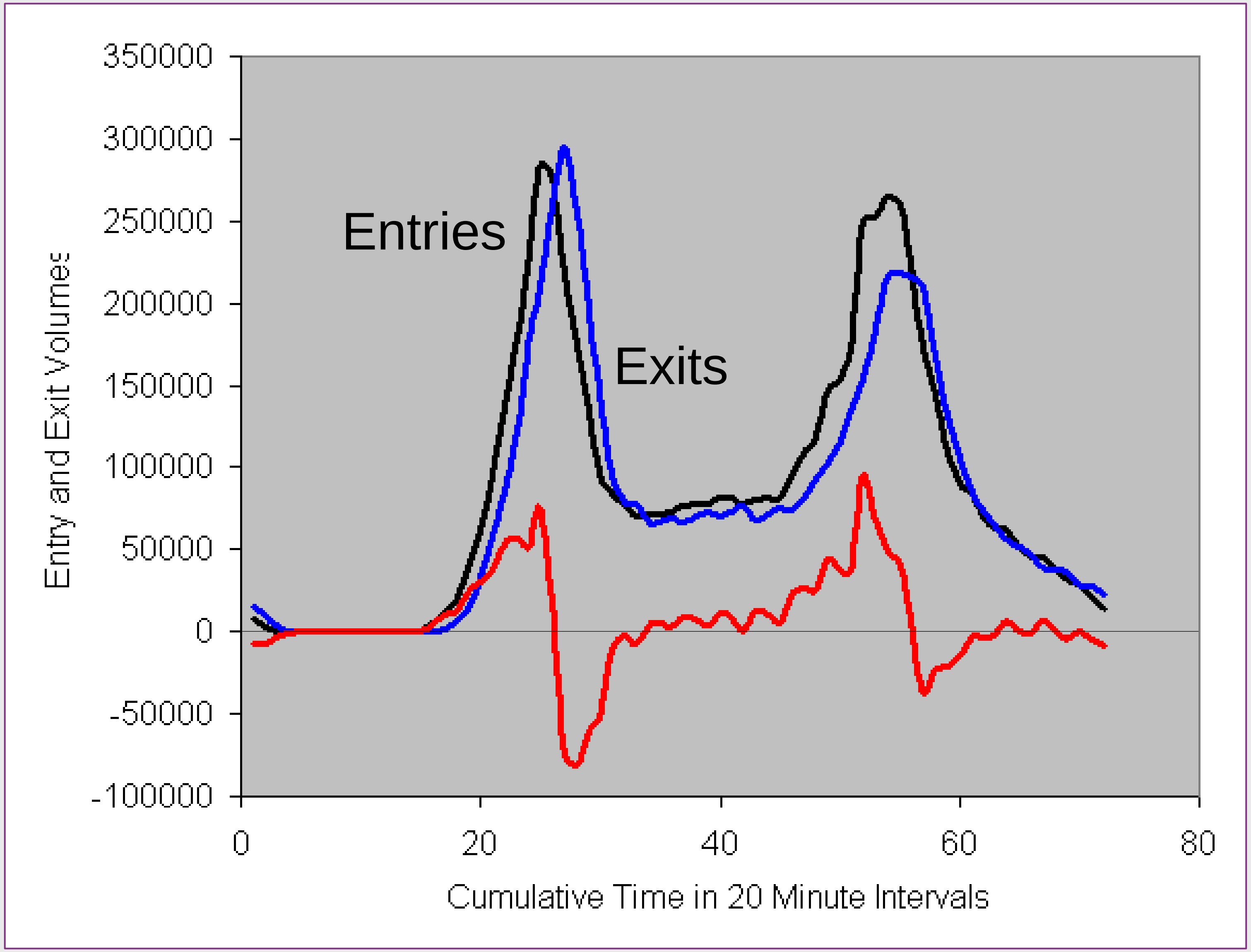
This of course was the thing that Lt Henry Harness did in Dublin in 1837 and what Minard et al. did a little later. In our LUTI models, this is an enormous problem as the scale of this assignment to networks is different

Variabilities – Heterogeneity and Travel Profiles

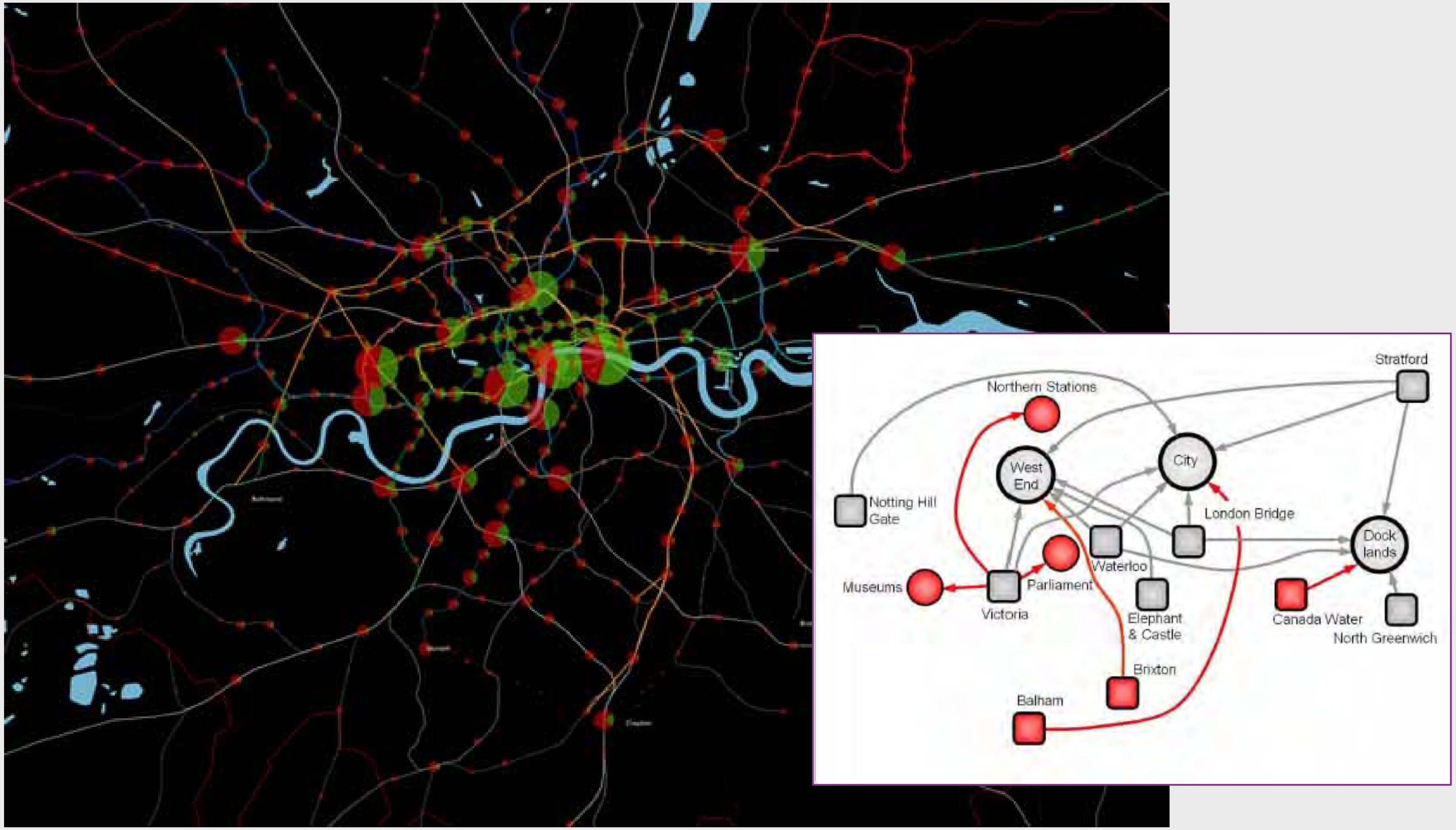
First we will look at some of the data and how it varies in terms of the diurnal flows usually morning and evening peaks, with a small blip (peak) around 10pm at night





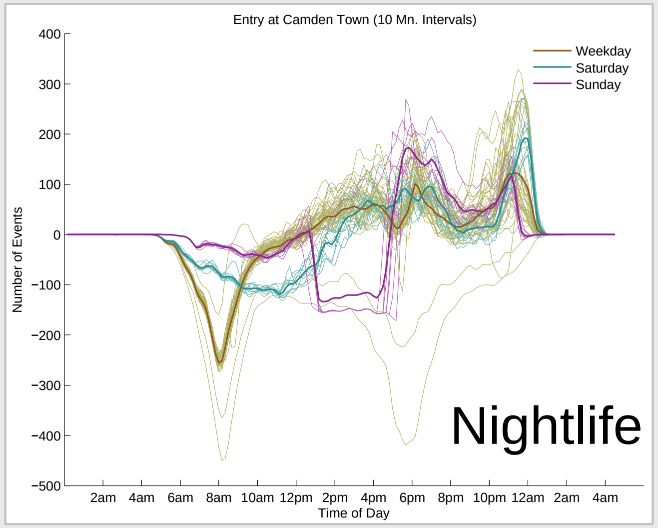

350000
300000
250000
200000
150000
100000
50000
0
-50000
-100000
0
20
40
60
80
Entries
Exits
Entry and Exit Volumes
Cumulative Time in 20 Minute Intervals

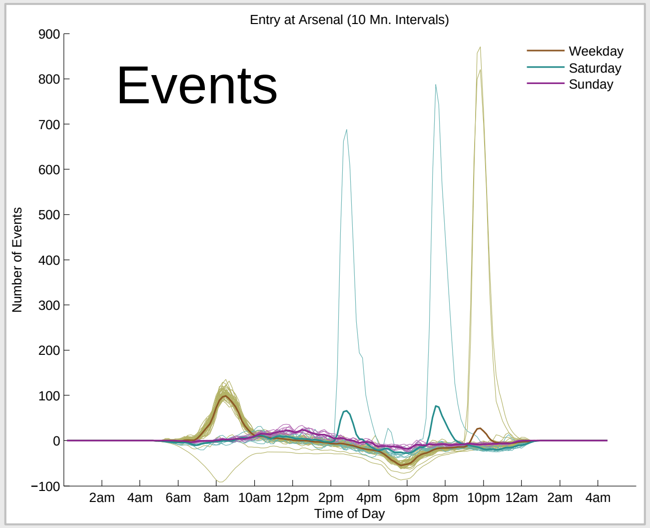
Oyster Card Data – interpreting urban structure, multitrips, etc.

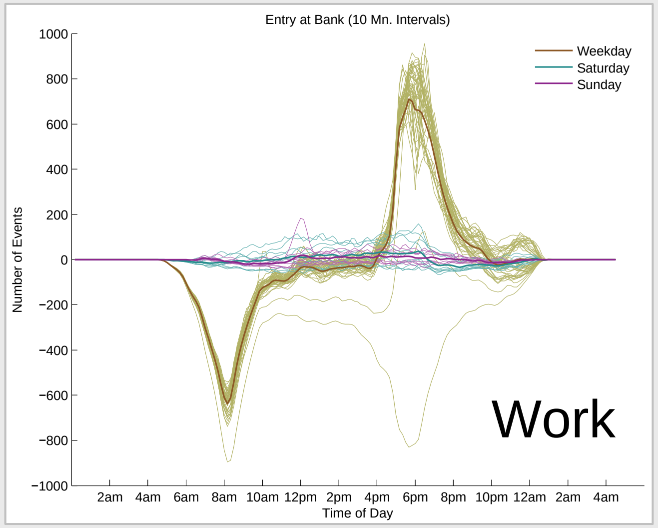


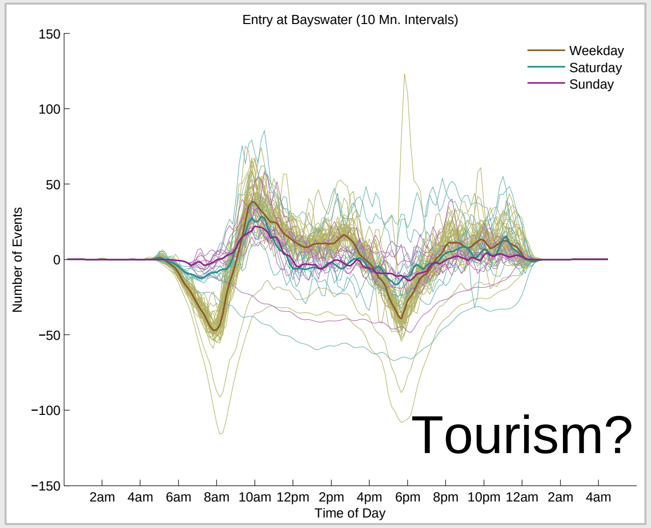
Roth C., Kang S. M., Batty, M., and Barthelemy, M. (2011) Structure of Urban Movements: Polycentric Activity and Entangled Hierarchical Flows. **PLoS ONE 6(1):** e15923. doi:10.1371/journal.pone.0015923

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

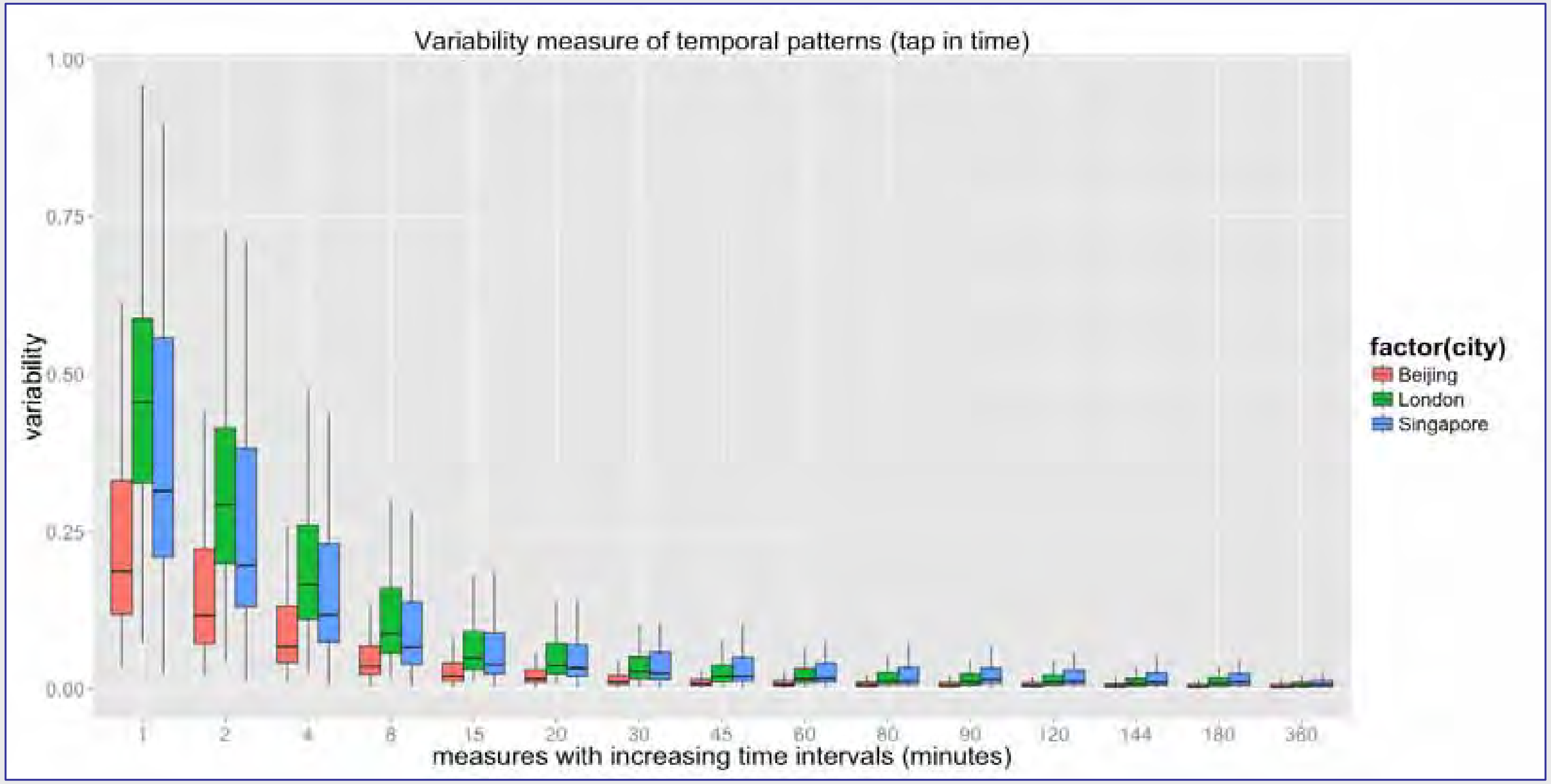
(1) Number of stations is the number of stations with smart-card records generated.

(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



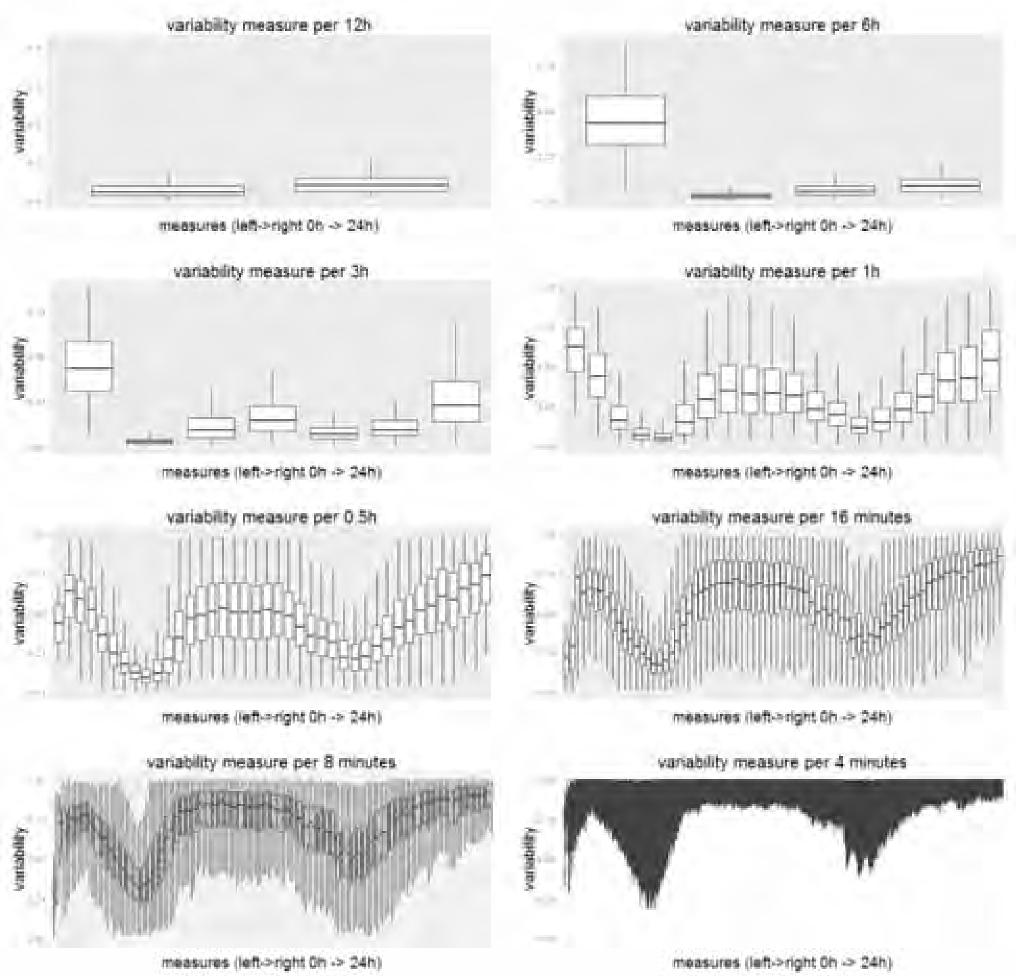
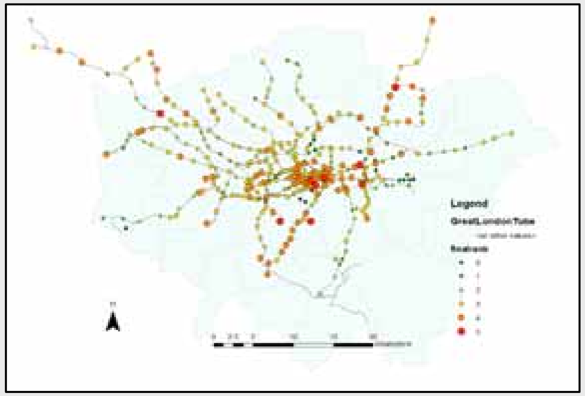


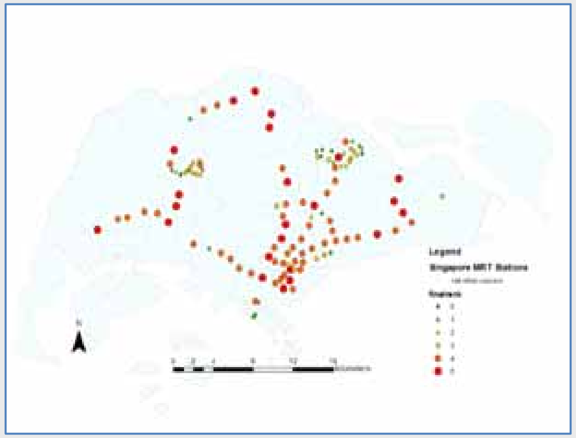
Figure 1. Variability of regularity in the trip matrix over time.

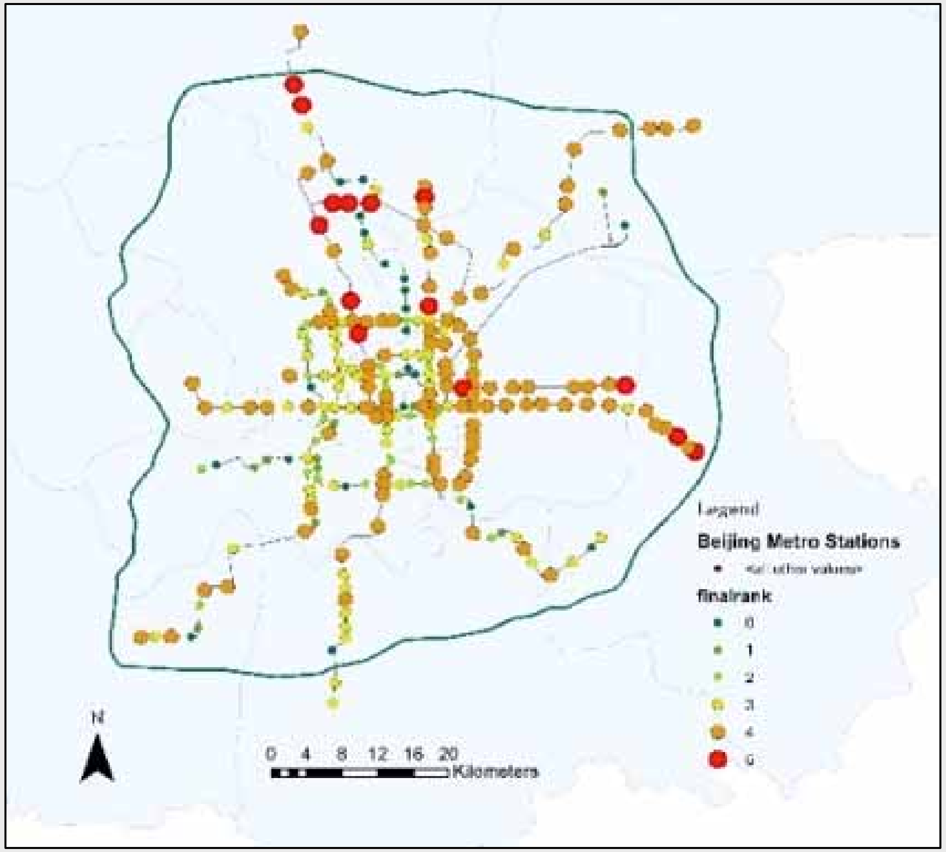
Note: Each box plot shows the variability of 400 stations over time measured at different temporal scales. Overall, eight subplots give a similar trend where lower variability appears during peak hours (around 9 am in the morning and 6pm in the evening). More details can be captured as differences of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

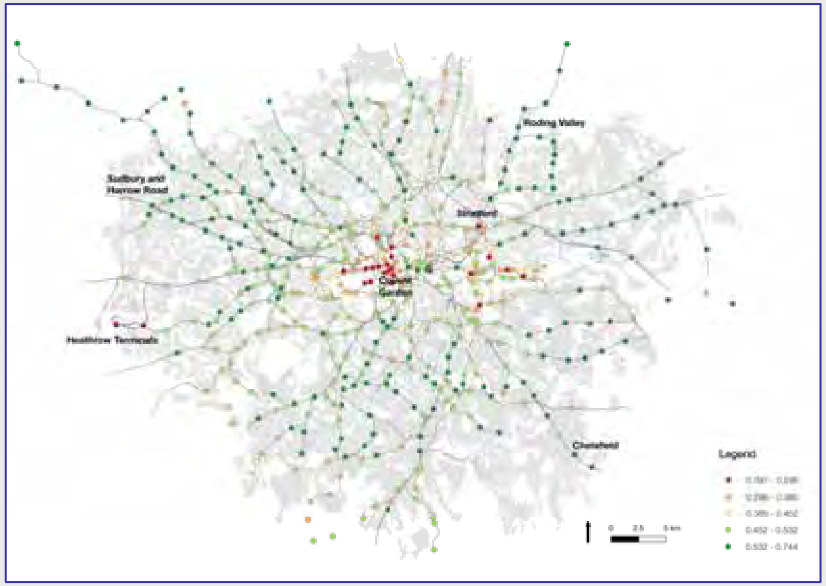
Comparing Variability for different time Intervals over the day

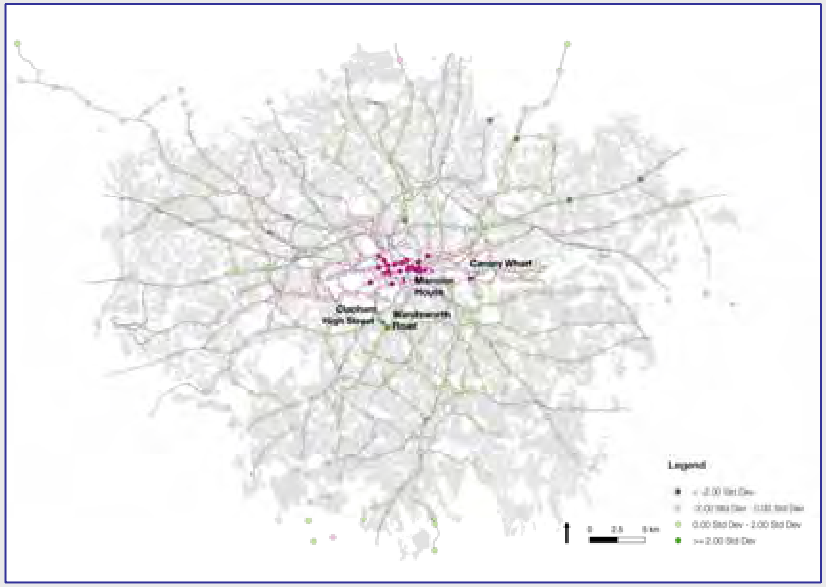
Comparing Variability for different time intervals for Three World Cities: London, Beijing and Singapore











Maps of Underground and Rail stations in London visualised by the proportion of regular trips

originating at each location

ending at each location

starting and ending at each location

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

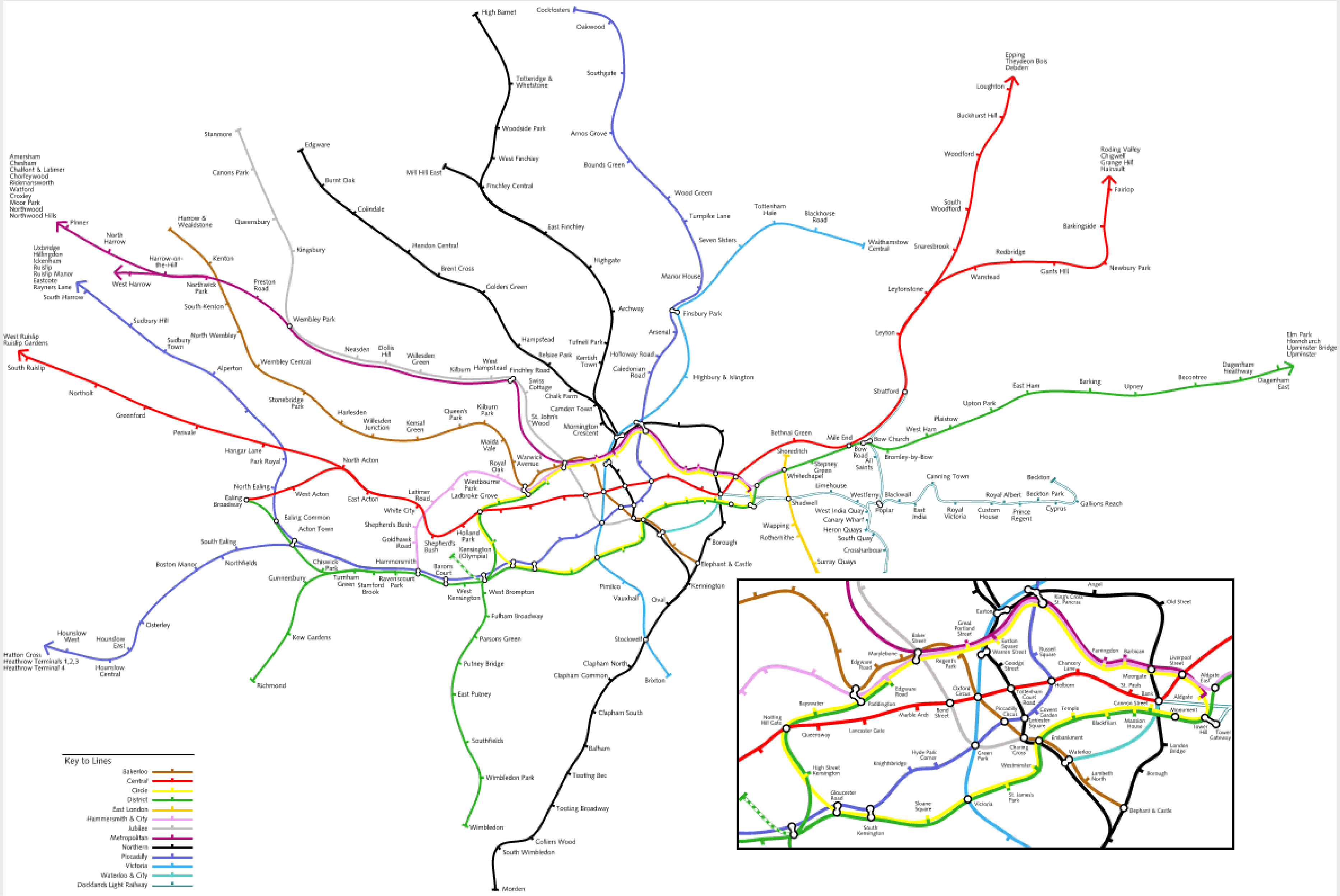
- Then an example of the Circle and District Lines which had a 4 hour stoppage on July 19th 2012

- 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

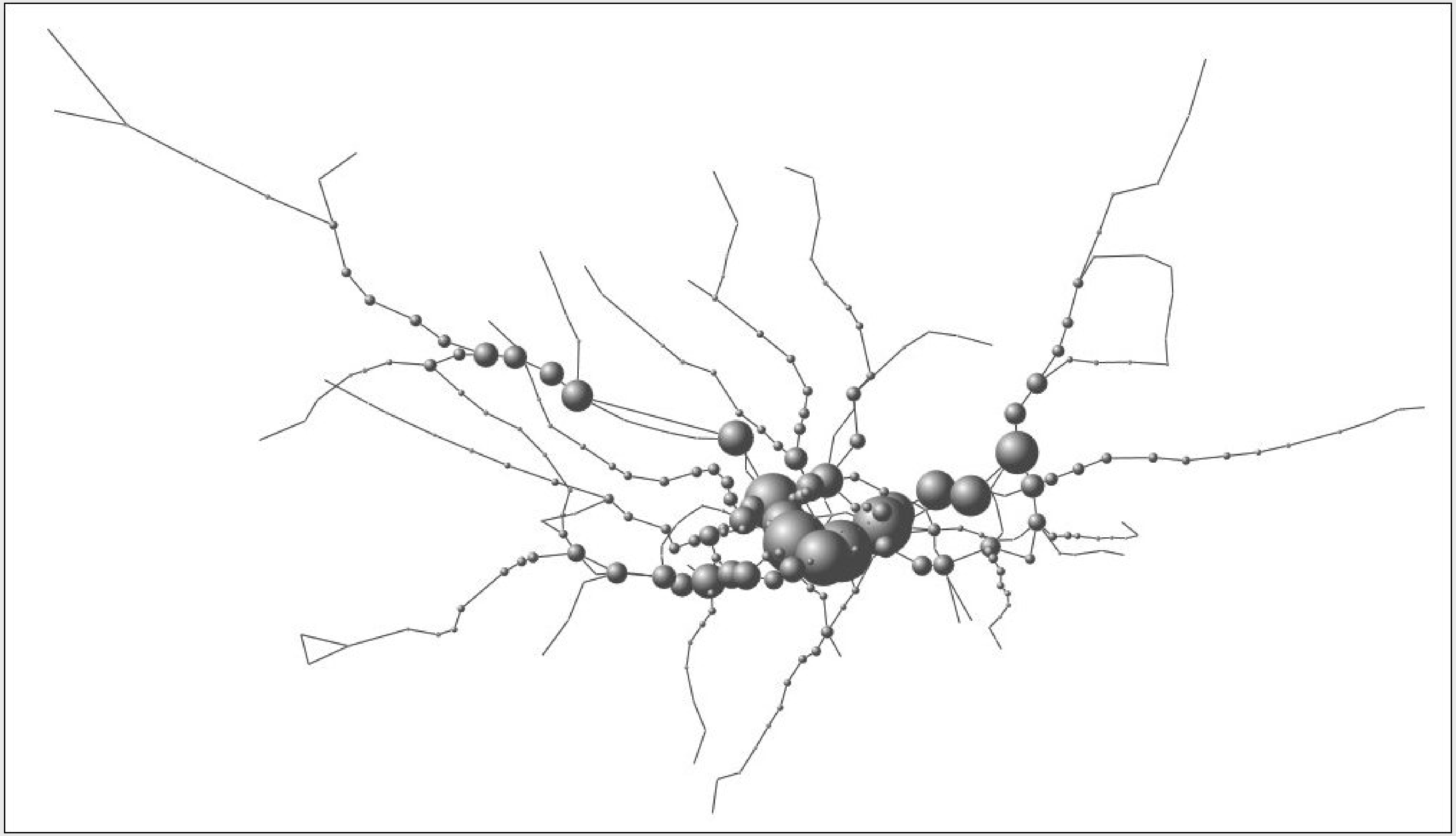
Service information
Date
Time
No Service On The Entire Line
And Kings Cross
And Edgware Road
District Line
Jubilee Line
And Stratford
Holloway Road Station Closed

UNDERGROUND


Key to Lines
Bakerloo
Central
Circle
District
East London
Hammersmith & City
Jubilee
Metropolitan
Northern
Piccadilly
Victoria
Waterloo & City
Docklands Light Railway
High Barnet
Cockfosters
Edgware
Stanmore
Epping
Morden
Wimbledon
Richmond
Upminster

Resilience and Disruption

Examining Network Disruption: Station and Line Closures



Representing the Tube Network

We use standard graph algebra to represent the network where we define three indices of centrality

Degrees of the graph

$$\left.\begin{aligned} \sigma_i &= \sum_j a_{ij} \\ \sigma_j &= \sum_i a_{ij} \end{aligned}\right\} \quad \sigma = \sum_i \sigma_i = \sum_j \sigma_j = \sum_i \sum_j a_{ij}$$

Betweenness Centrality $$C_k = \sum_i \sum_j \frac{\sigma_{ikj}}{\sigma_{ij}}$$

Closeness Centrality $$L_i = KD_i^{-1} = K\left(\sum_j d_{ij}\right)^{-1}$$

Representing Flows

Trip Volume

Entries and Exits

$$\left.\begin{aligned} T_i &= \sum_j T_{ij} \\ T_j &= \sum_i T_{ij} \end{aligned}\right\} \; T = \sum_i T_i = \sum_j T_j = \sum_i \sum_j T_{ij}$$

Changes in

Trip Volumes

$$\left.\begin{aligned} \Delta_i &= T_i - T_i' \\ \Delta_j &= T_j - T_j' \end{aligned}\right\} \; \sum_i \Delta_i = \sum_i \Delta_j = 0$$

Weighted Betweenness

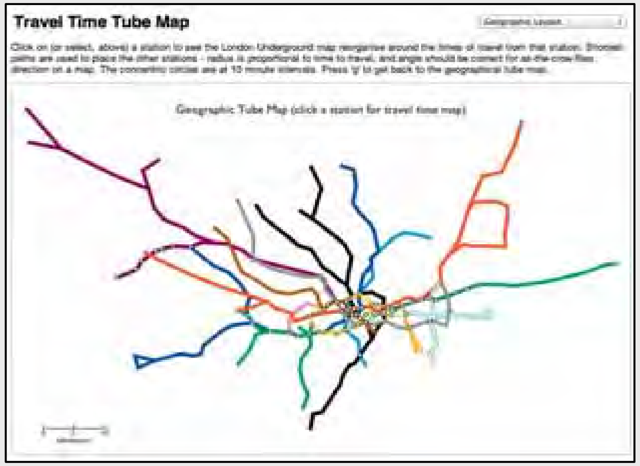
Centrality

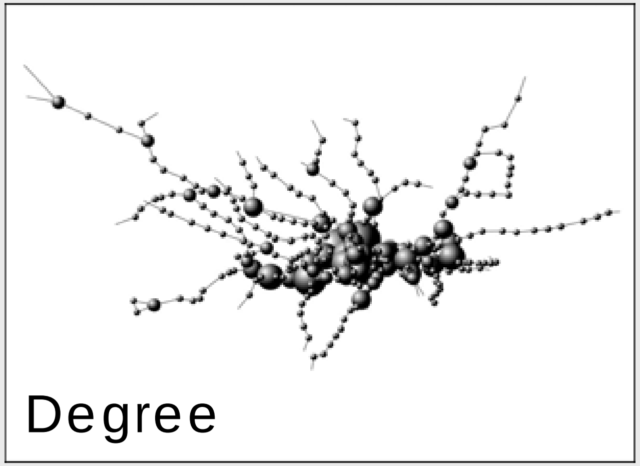
$$p_{ijk} = \frac{\sigma_{ikj}}{\sigma_{ij}} = \frac{\sigma_{ikj}}{\sum_\ell \sigma_{i\ell j}} \quad , \quad \sum_k p_{ikj} = 1$$

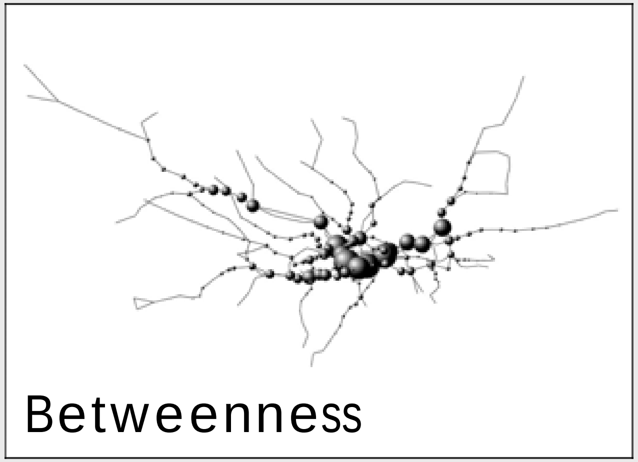
$$\tilde{C}_k = \sum_i \sum_j T_{ij}\, p_{ikj} = \sum_i \sum_j T_{ij} \frac{\sigma_{ikj}}{\sigma_{ij}}$$

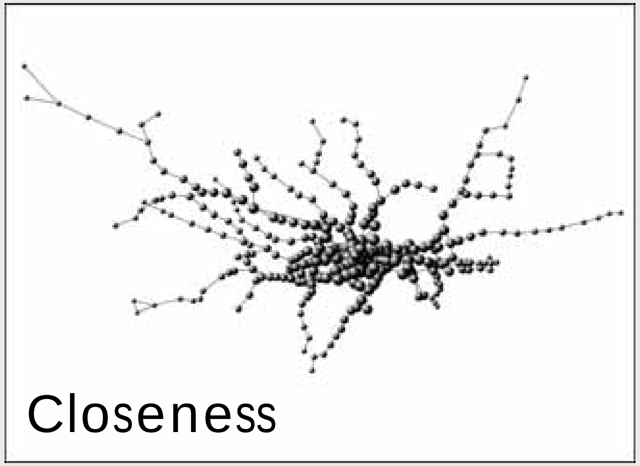
A Preliminary Analysis (1)

The Minimal Tube Network and the Three Centrality Indices









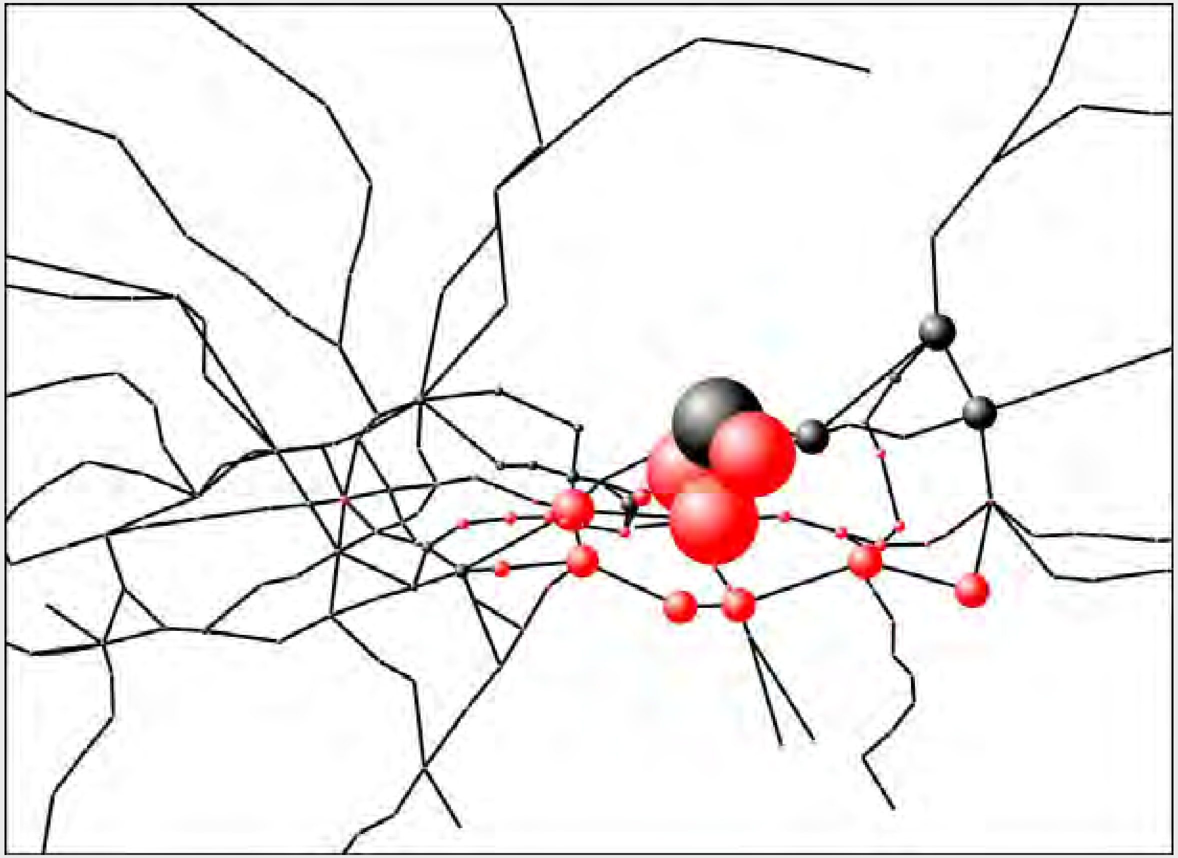
A Preliminary Analysis (2)

- Top Stations
- By Centrality

Station	d_i	Station	$\hat{C}_i$	Station	$\hat{L}_i$
Baker Street	7	*Green Park*	16399	*Green Park*	2.137
King's Cross	7	Waterloo	15644	Westminster	2.107
Bank	6	Bank	15008	Bond Street	2.101
Earl's Court	6	Baker Street	14441	Oxford Circus	2.089
Green Park	6	Westminster	14139	Waterloo	2.089
Oxford Circus	6	Bond Street	11429	Bank	2.074
Waterloo	6	***Liverpool Street***	11186	Baker Street	2.071
Canning Town	5	Stratford	10814	Victoria	2.065
Liverpool Street	5	Mile End	10302	Hyde Pk Corner	2.053
Paddington	5	Bethnal Green	10017	Embankment	2.041
Shadwell	5	Finchley Road	8905	Piccadilly Circus	2.041
Turnham Green	5	Earl's Court	8706	St. James's Park	2.035
Acton Town	4	King's Cross	8679	Regent's Park	2.032
Bond Street	4	Wembley Park	7968	King's Cross	2.029
Camden Town	4	South Ken	7182	***Liverpool Street***	2.026
Canada Water	4	Euston	7156	Marble Arch	2.026
Canary Wharf	4	Gloucester Rd	7042	Tottenham Ct Rd	2.026
Embankment	4	Paddington	7028	Moorgate	2.020
Euston	4	Victoria	6558	Charing Cross	2.017
Finchley Road	4	Harrow-o-t-Hill	6253	Great Portland St	2.017

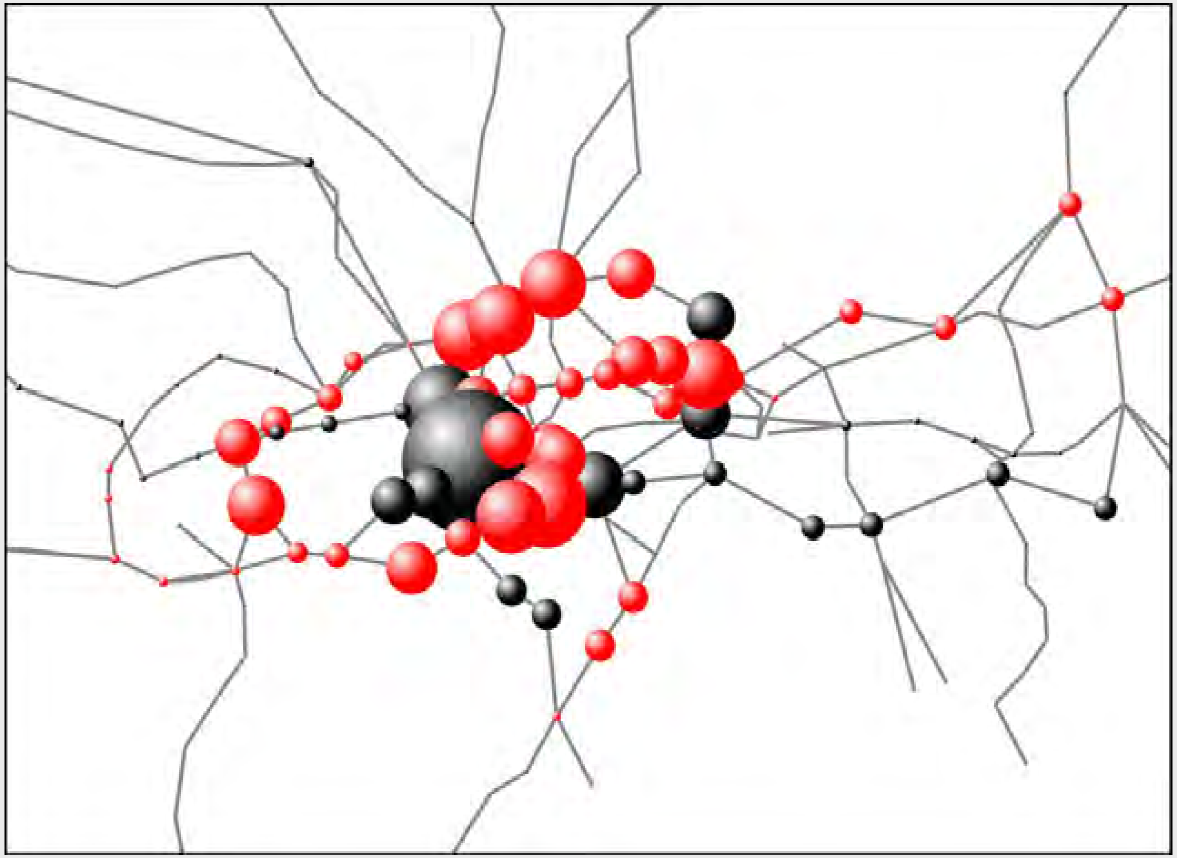
A Preliminary Analysis (3)

Closing Liverpool Street

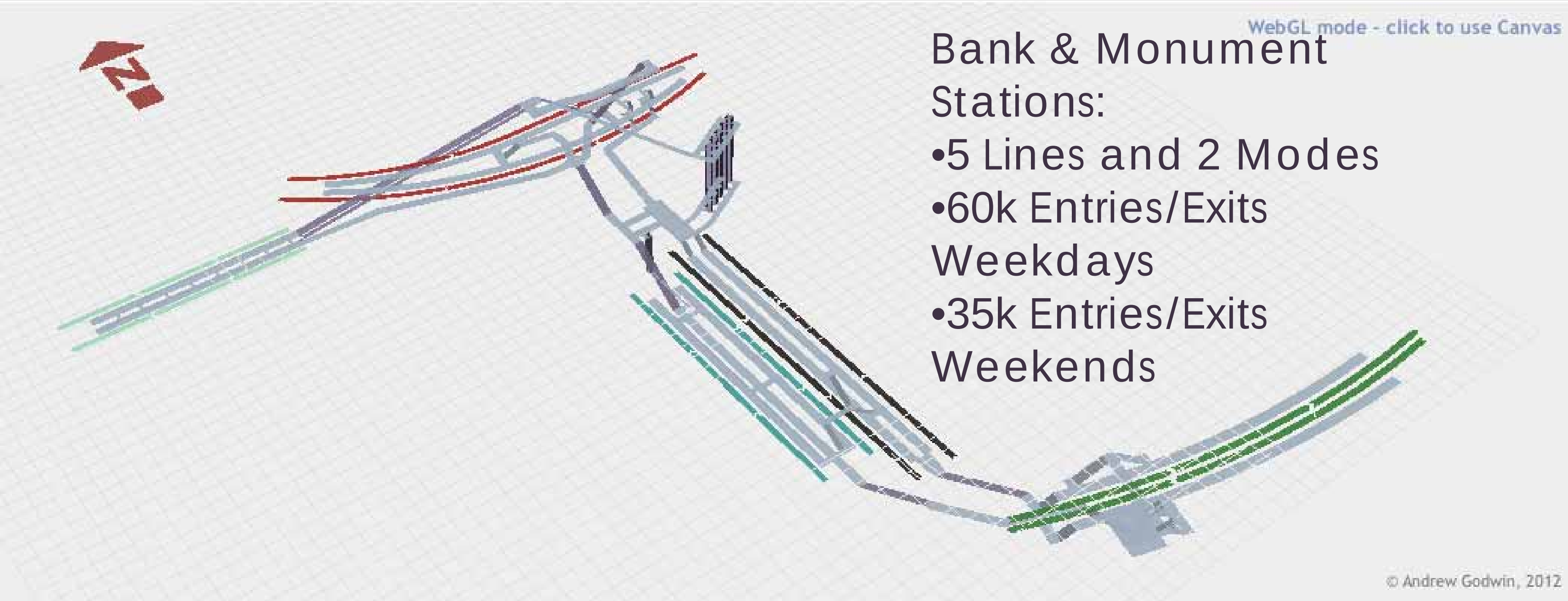


A Preliminary Analysis (3)

Closing Green Park

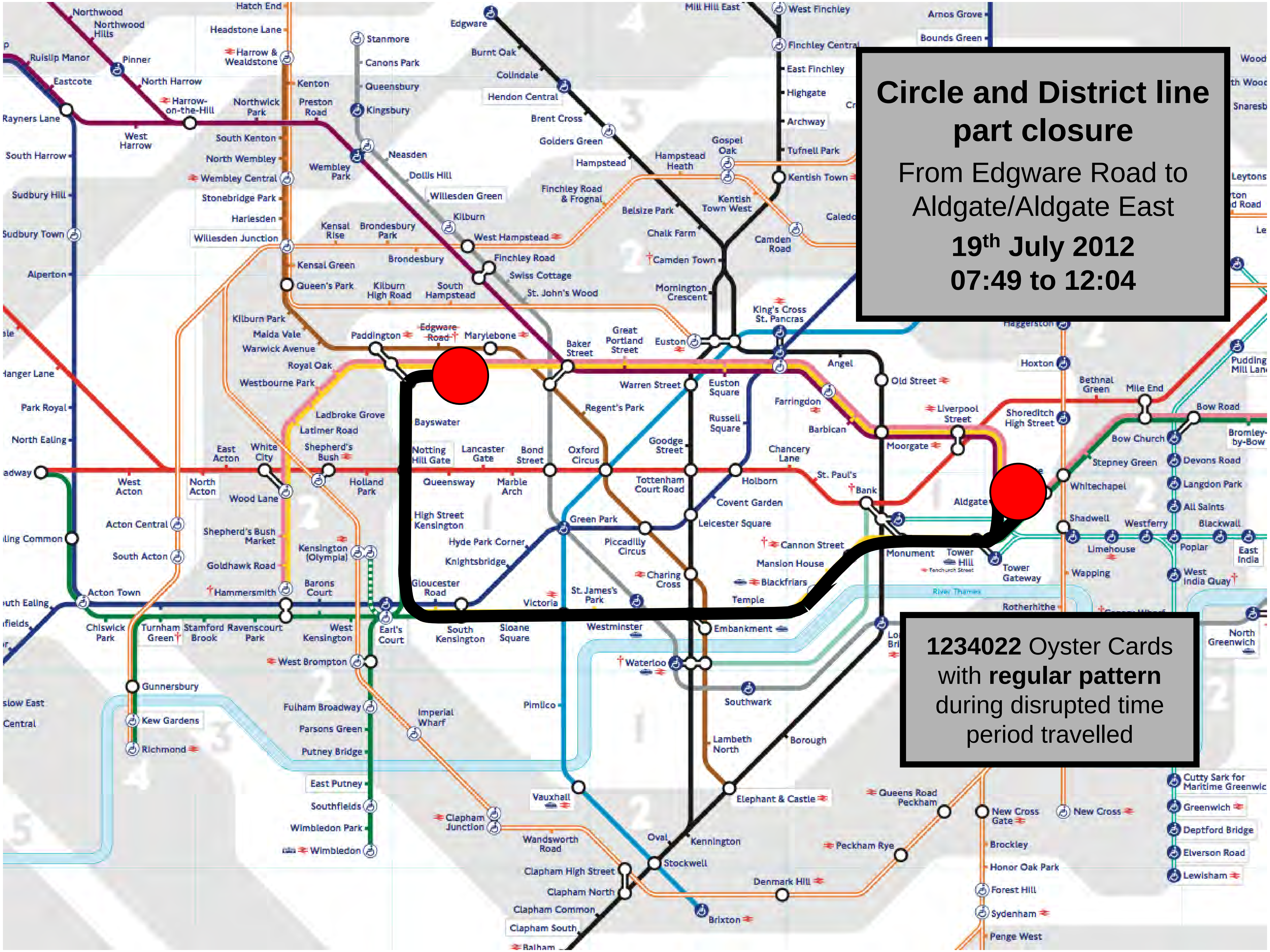


Looking at Station Closures and Shifts of Travellers Using The 'Shortest'-Paths



Bank & Monument Stations:
- 5 Lines and 2 Modes
- 60k Entries/Exits Weekdays
- 35k Entries/Exits Weekends

Although a simple station/line network may be sufficient for small cities, for 'Mega-Cities' such as London, New York, or Tokyo a much more detailed network is needed with interchanges measured down to the platform level. The 'penalties' for changing lines (and permitted Out-of-Station Interchanges) can be severe and should be included in a schematic network representation.



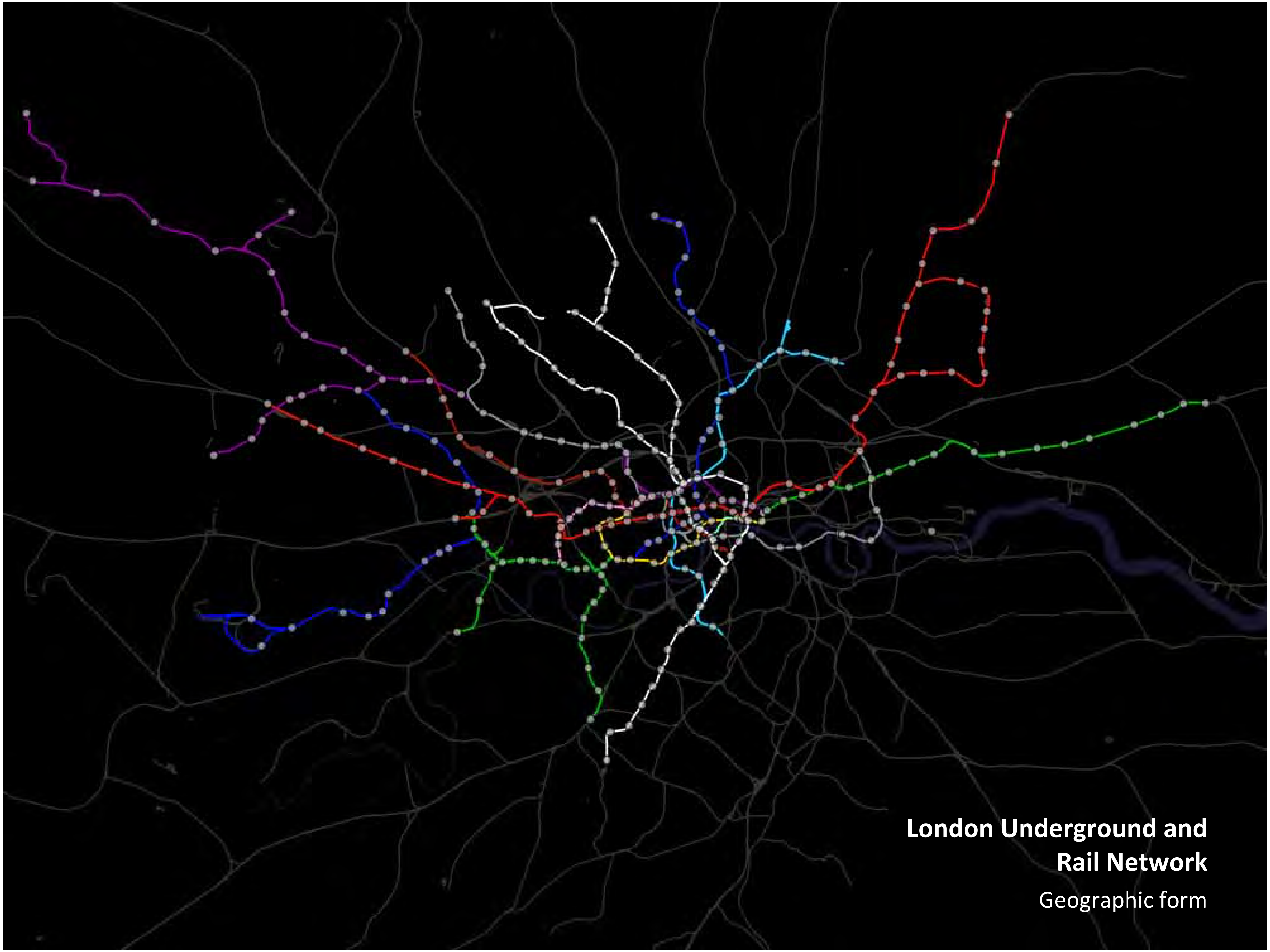
Circle and District line part closure

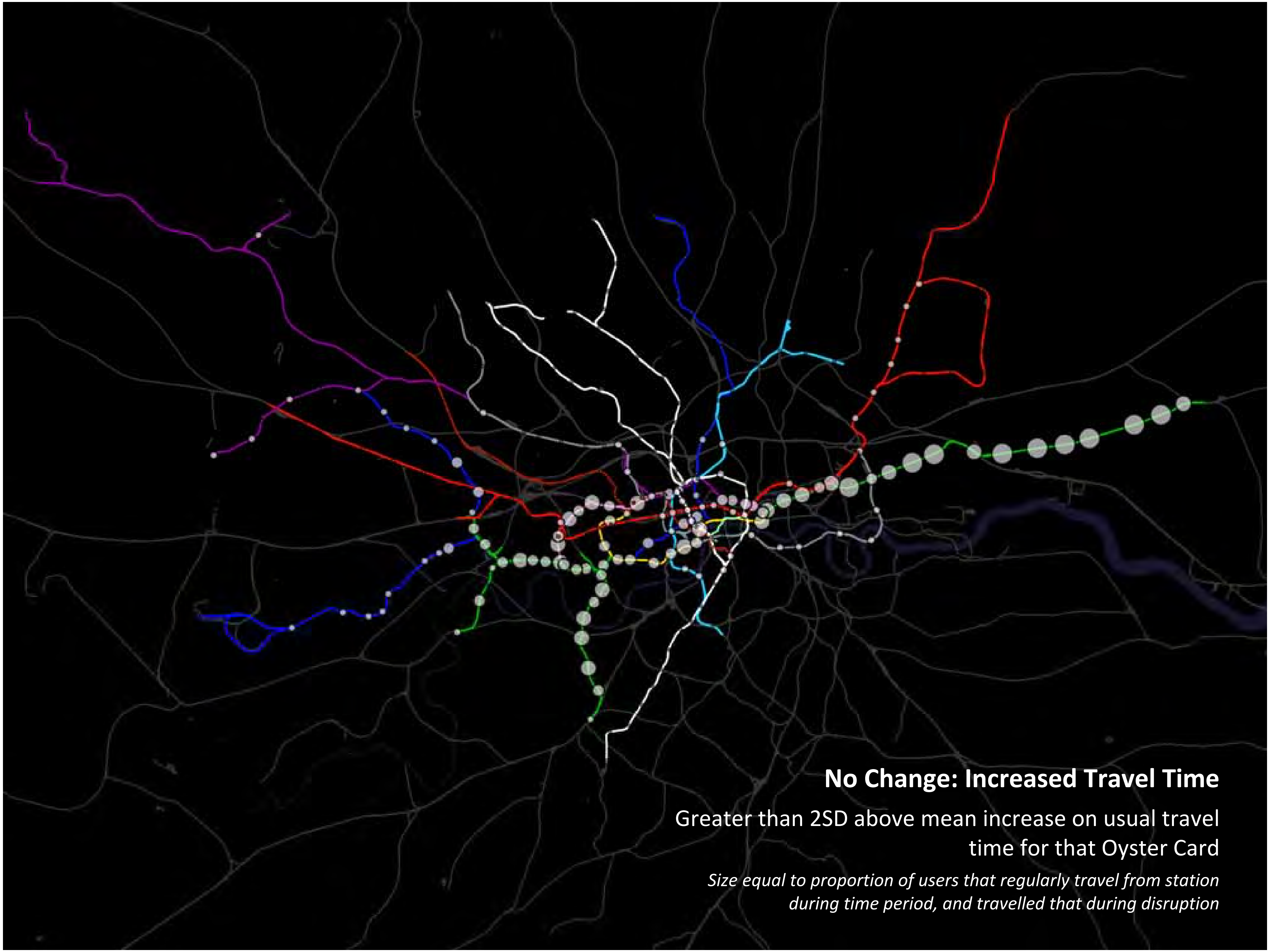
From Edgware Road to Aldgate/Aldgate East

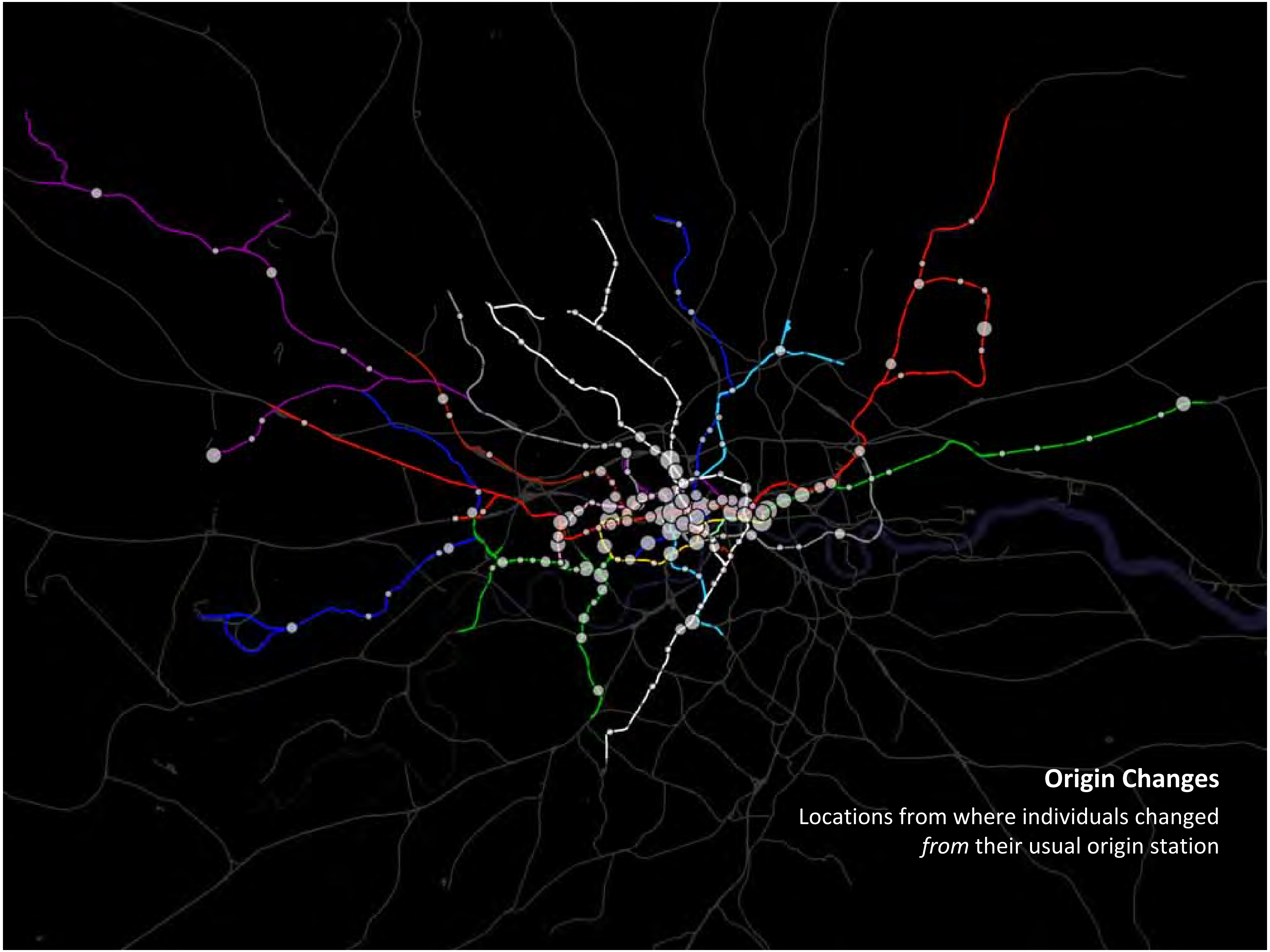
19th July 2012

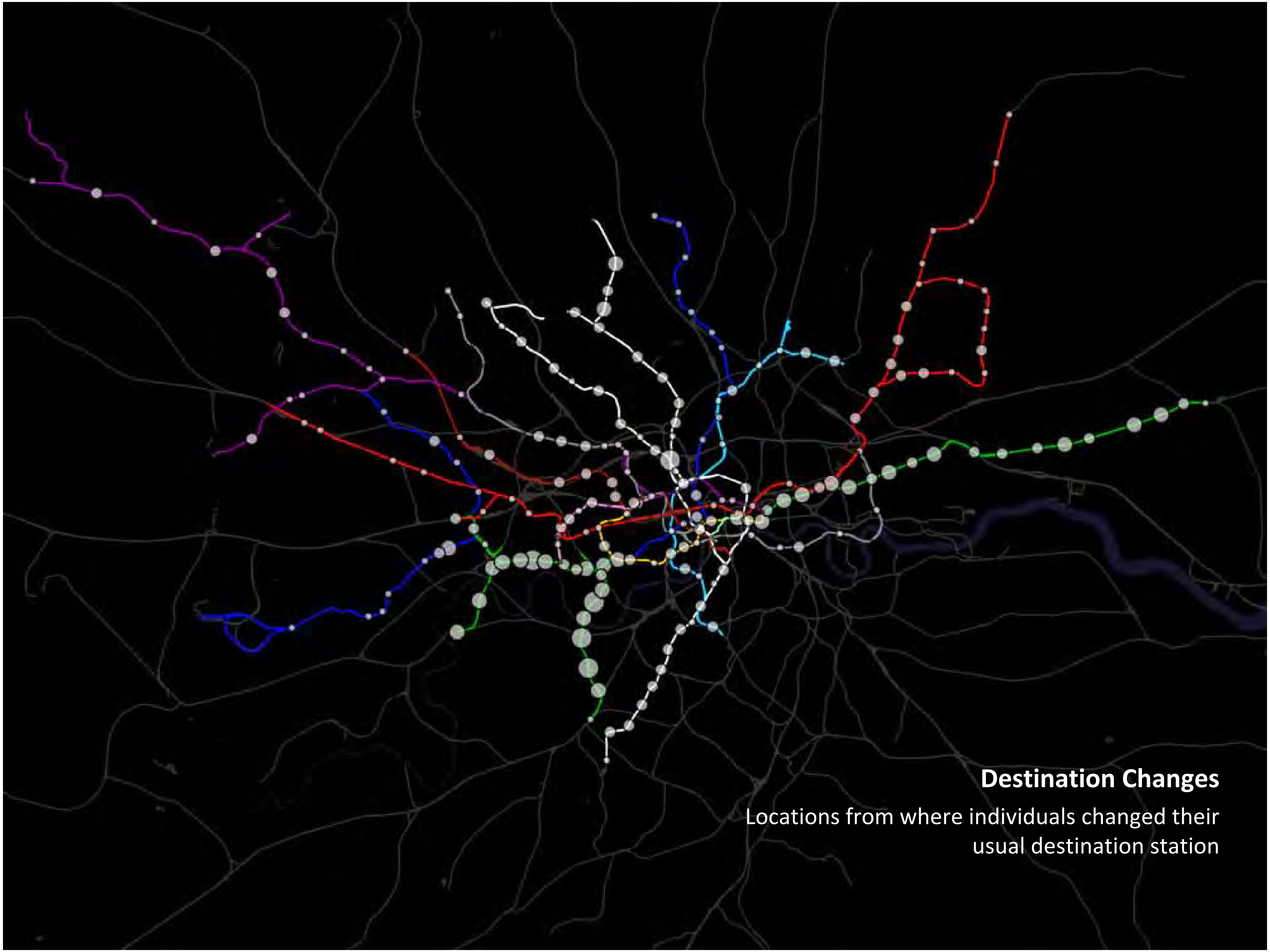
07:49 to 12:04

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


London Underground and
Rail Network
Geographic form

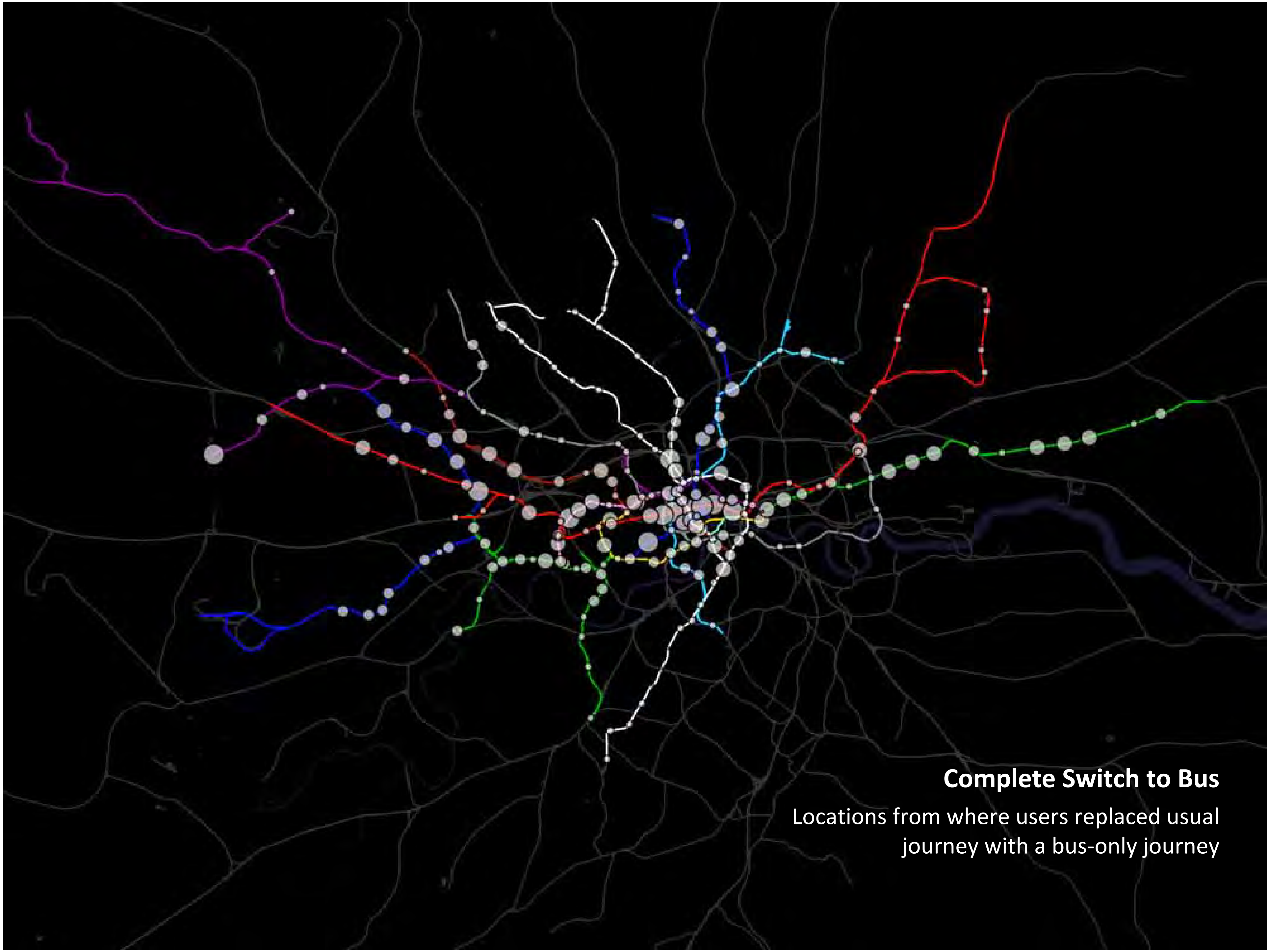

No Change: Increased Travel Time
Greater than 2SD above mean increase on usual travel time for that Oyster Card
Size equal to proportion of users that regularly travel from station during time period, and travelled that during disruption

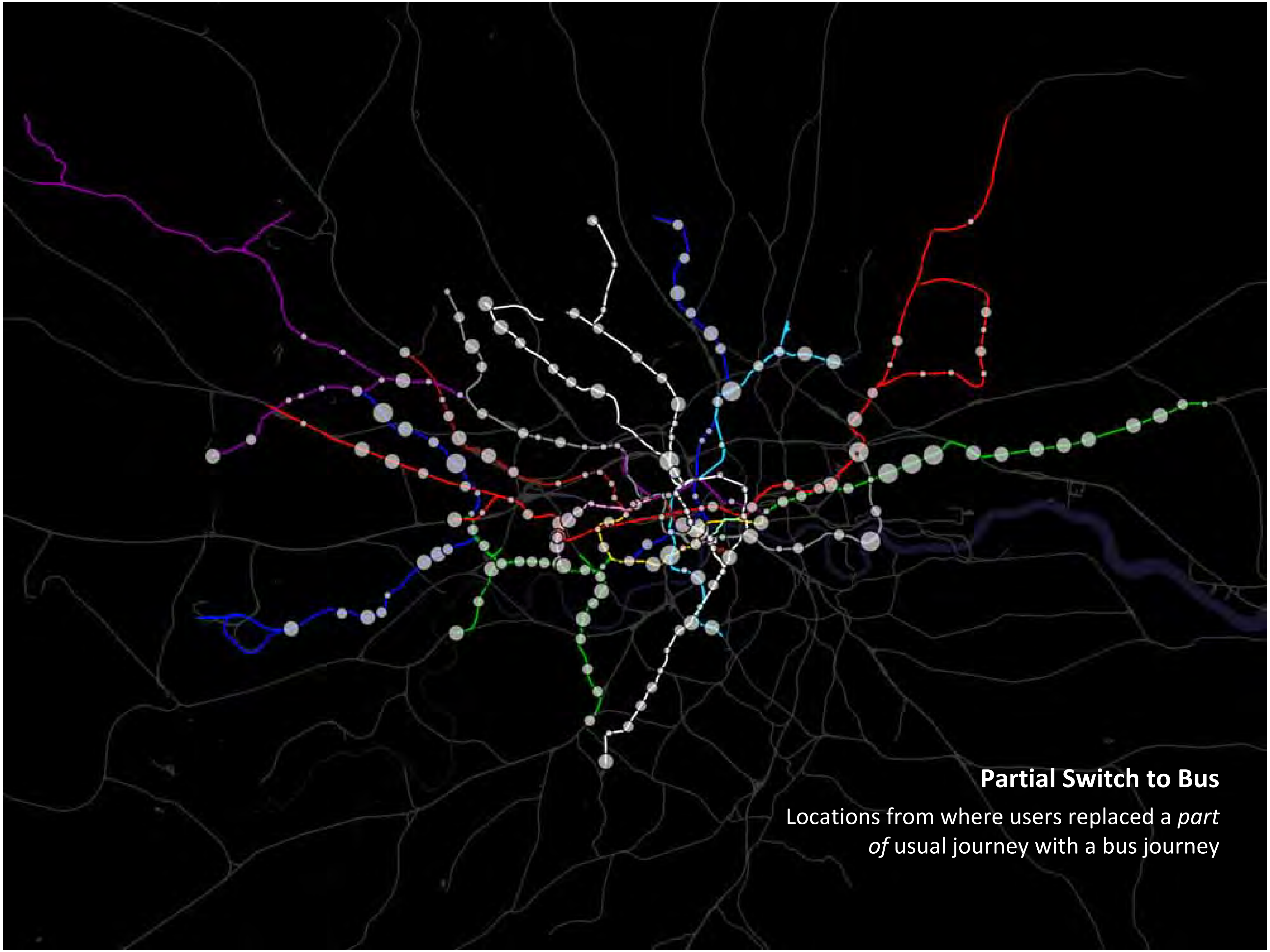

Origin Changes
Locations from where individuals changed
from their usual origin station

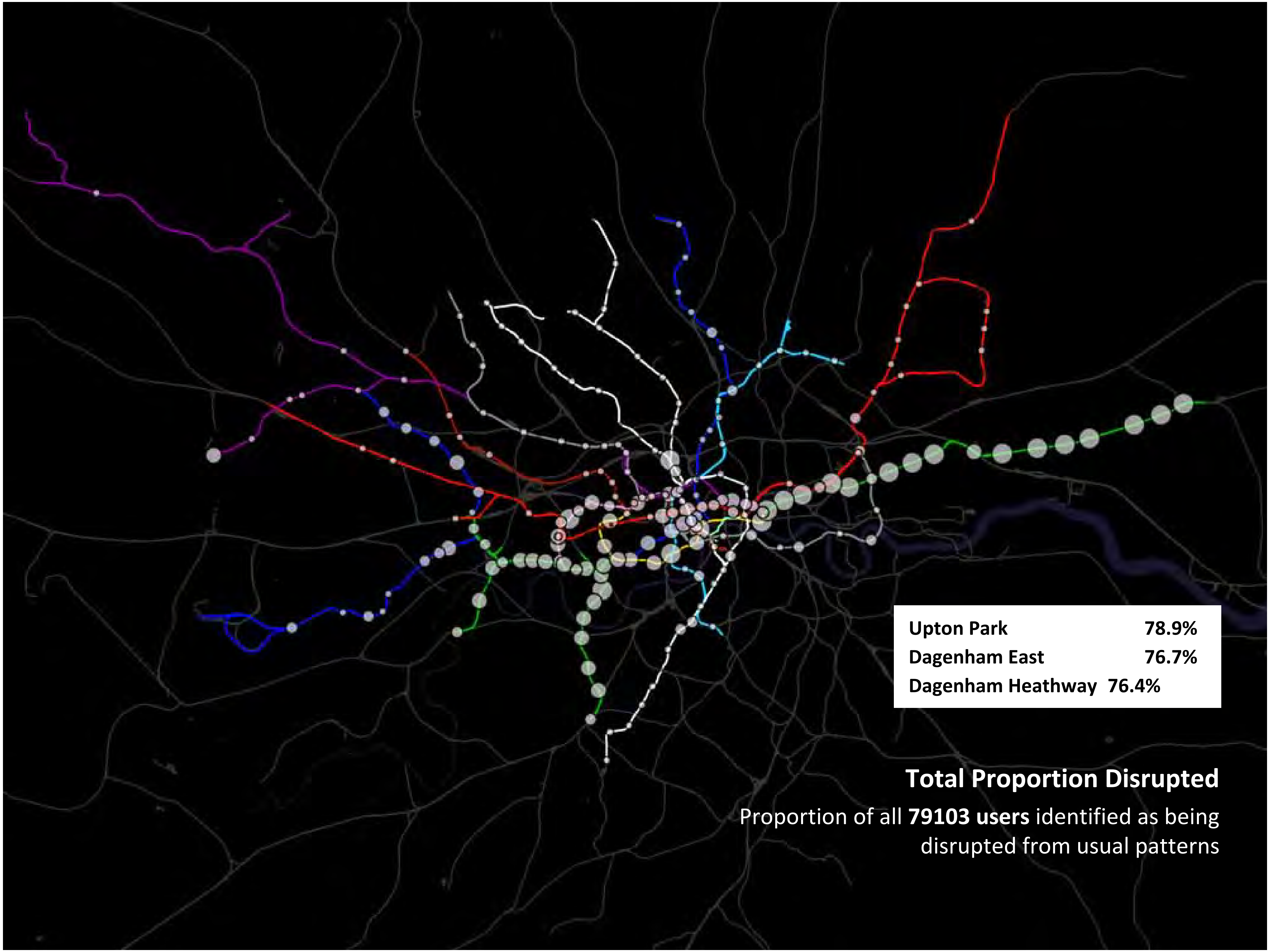


Destination Changes

Locations from where individuals changed their usual destination station


Complete Switch to Bus
Locations from where users replaced usual journey with a bus-only journey


Partial Switch to Bus
Locations from where users replaced a *part of* usual journey with a bus journey



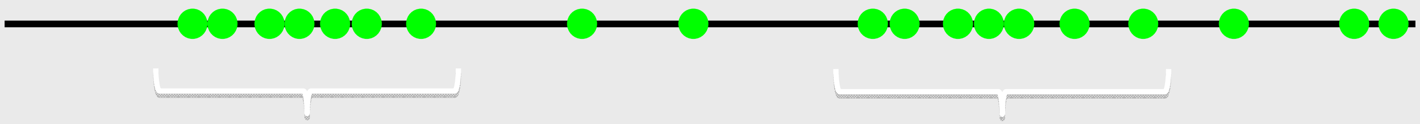
Total Proportion Disrupted

Proportion of all **79103 users** identified as being disrupted from usual patterns

Measuring Regularity

Version 2: DBSCAN Method

Oyster Card A – Origin 747



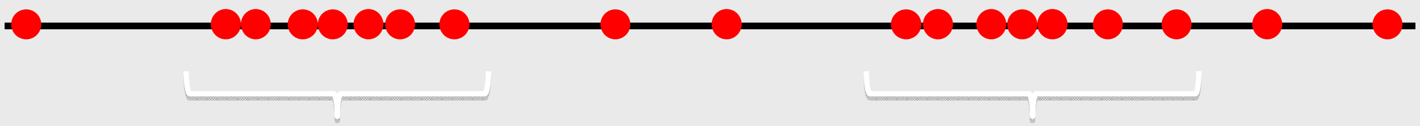
Cluster 1

Mean: 08:07; SD = 6.2
Max: 07:45; Min: 08:16
Proportion of Days = 0.8

Cluster 2

Mean: 17:34; SD = 17.1
Max: 16:58; Min: 18:57
Proportion of Days = 0.6

Oyster Card A – Destination 647

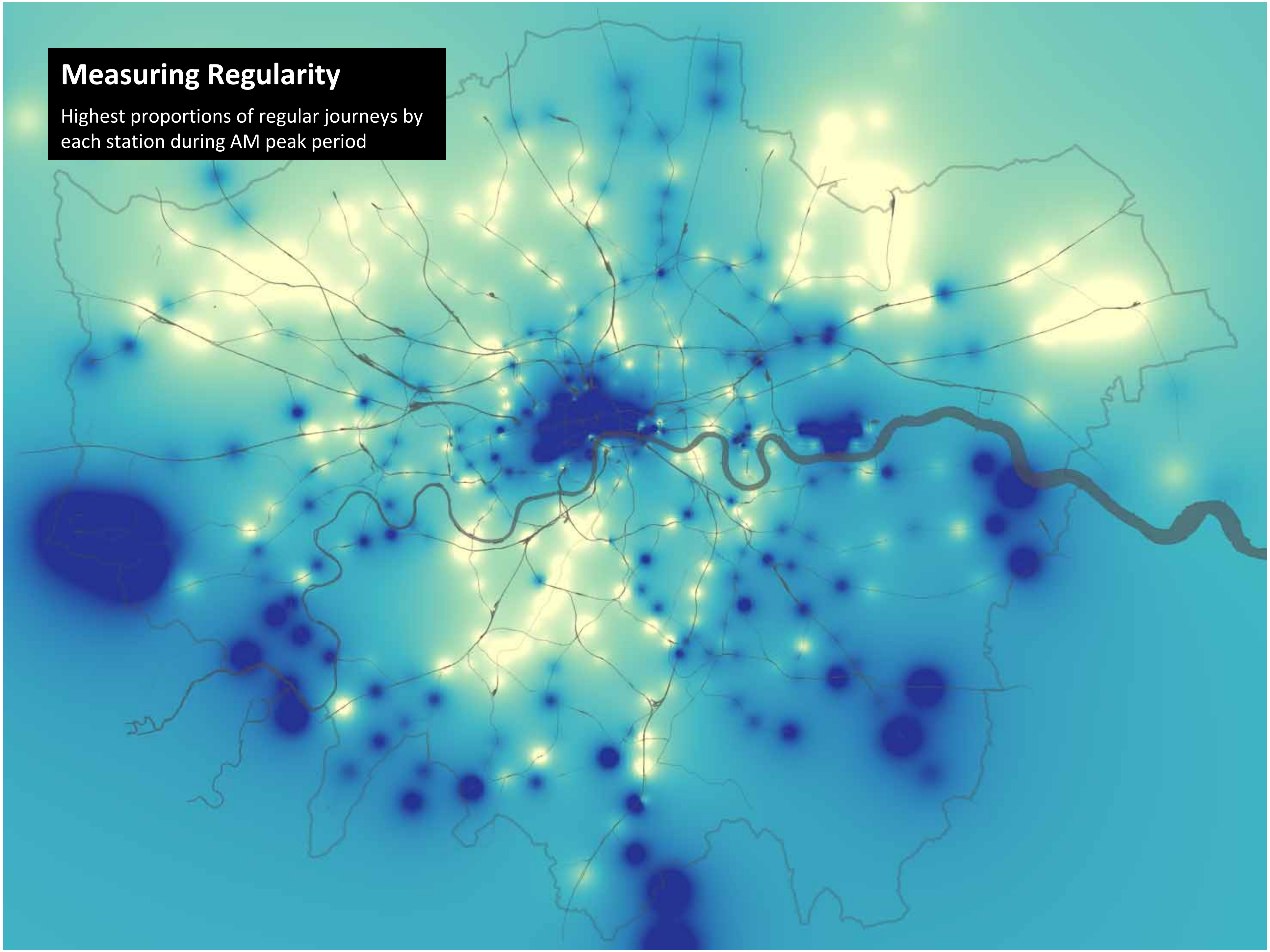


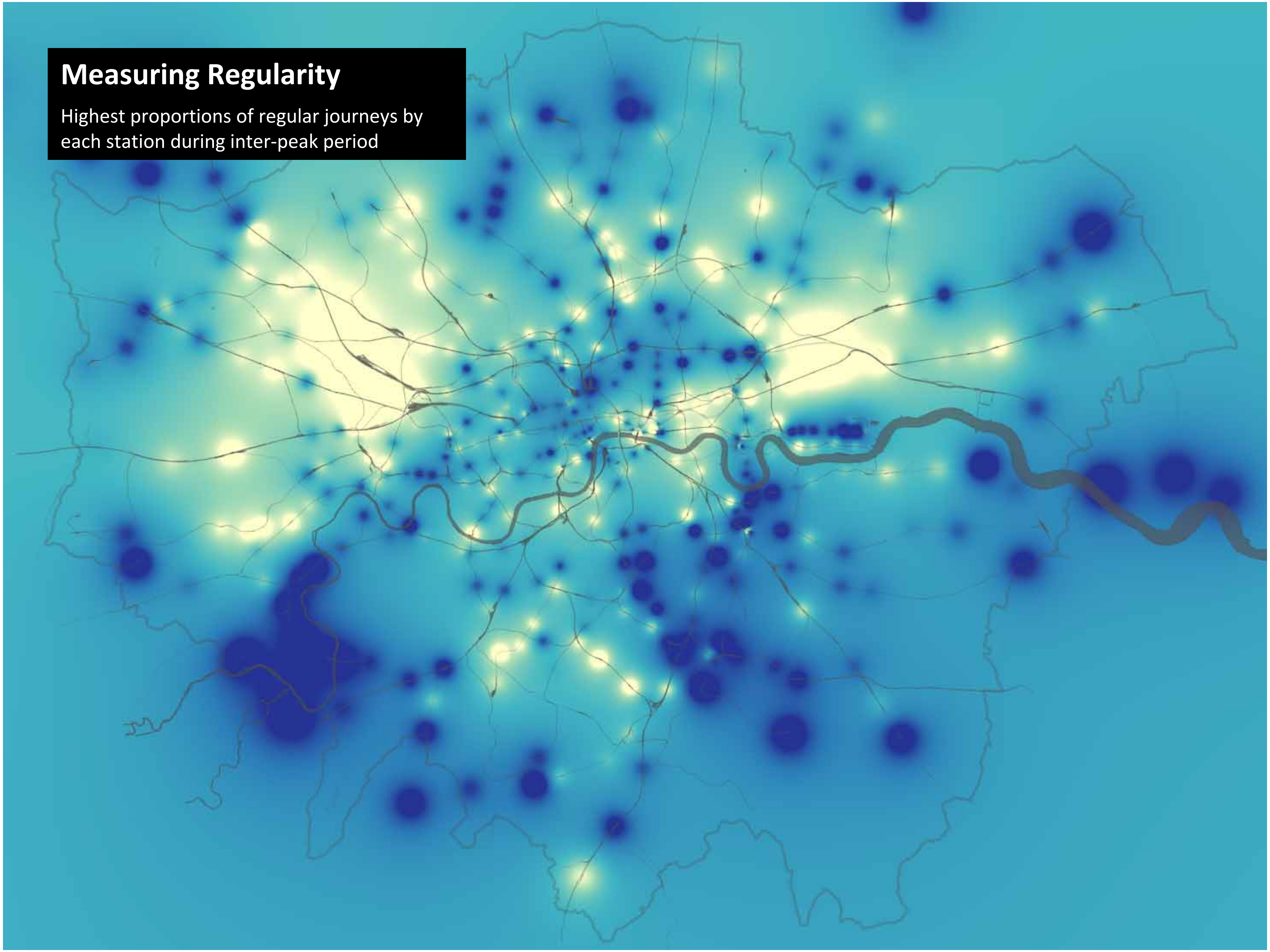
Cluster 3

Mean: 08:37; SD = 7.4
Max: 08:13; Min: 08:48
Proportion of Days = 0.8

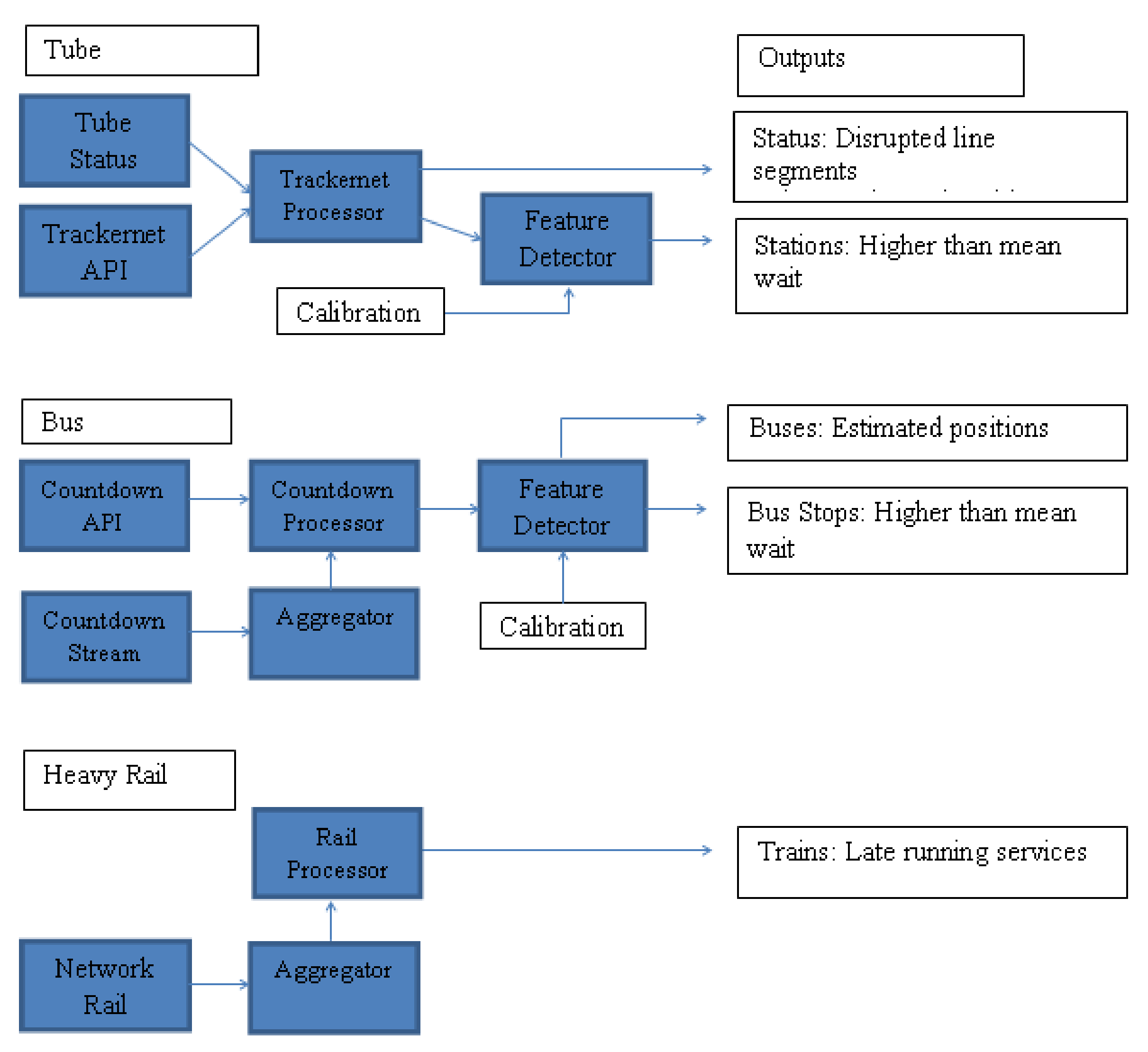
Cluster 4

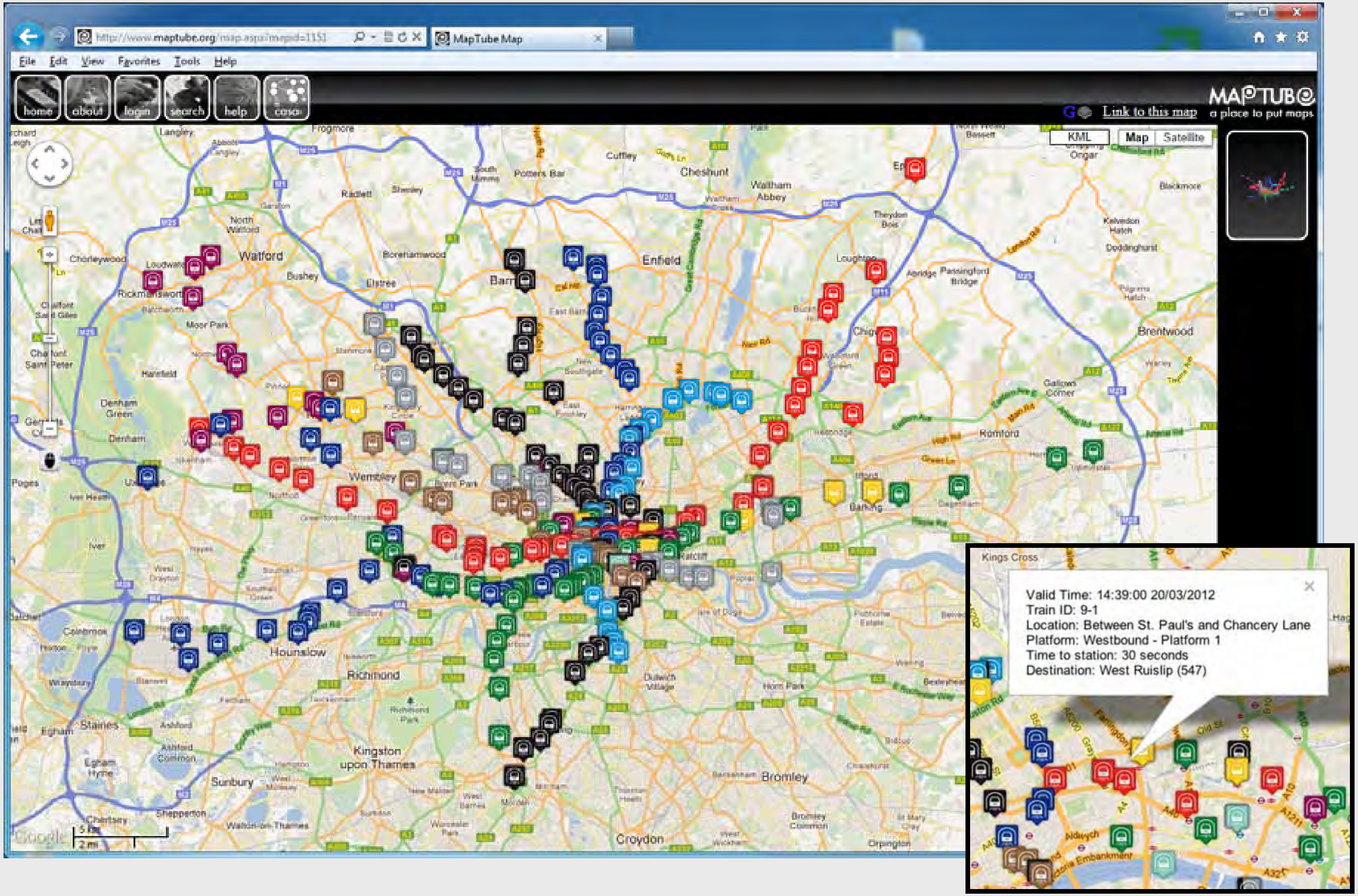
Mean: 18:06; SD = 18.1
Max: 17:26; Min: 19:28
Proportion of Days = 0.6


Measuring Regularity
Highest proportions of regular journeys by each station during AM peak period

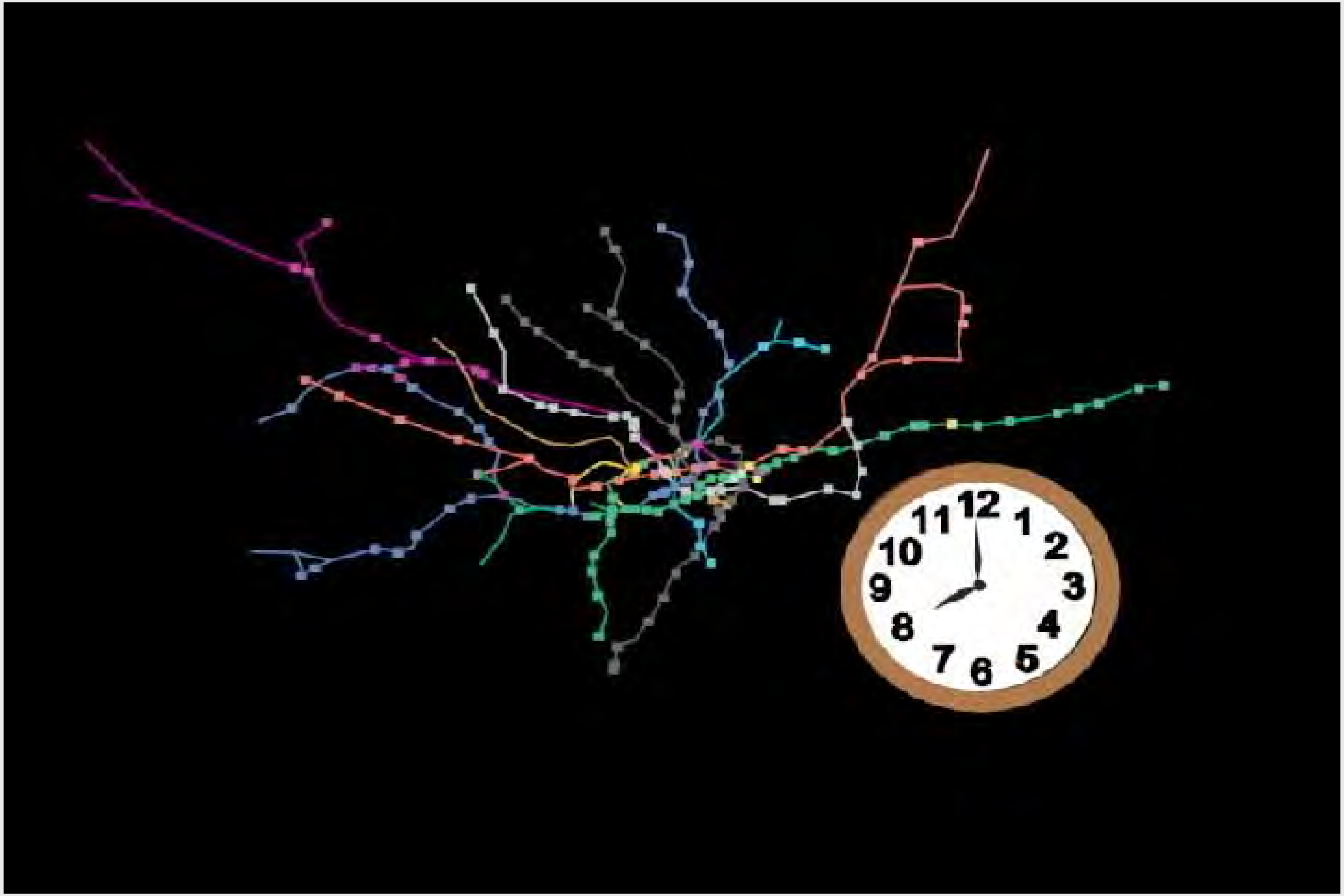

Measuring Regularity
Highest proportions of regular journeys by each station during inter-peak period

The Public Transport System in Terms of Vehicle Flows

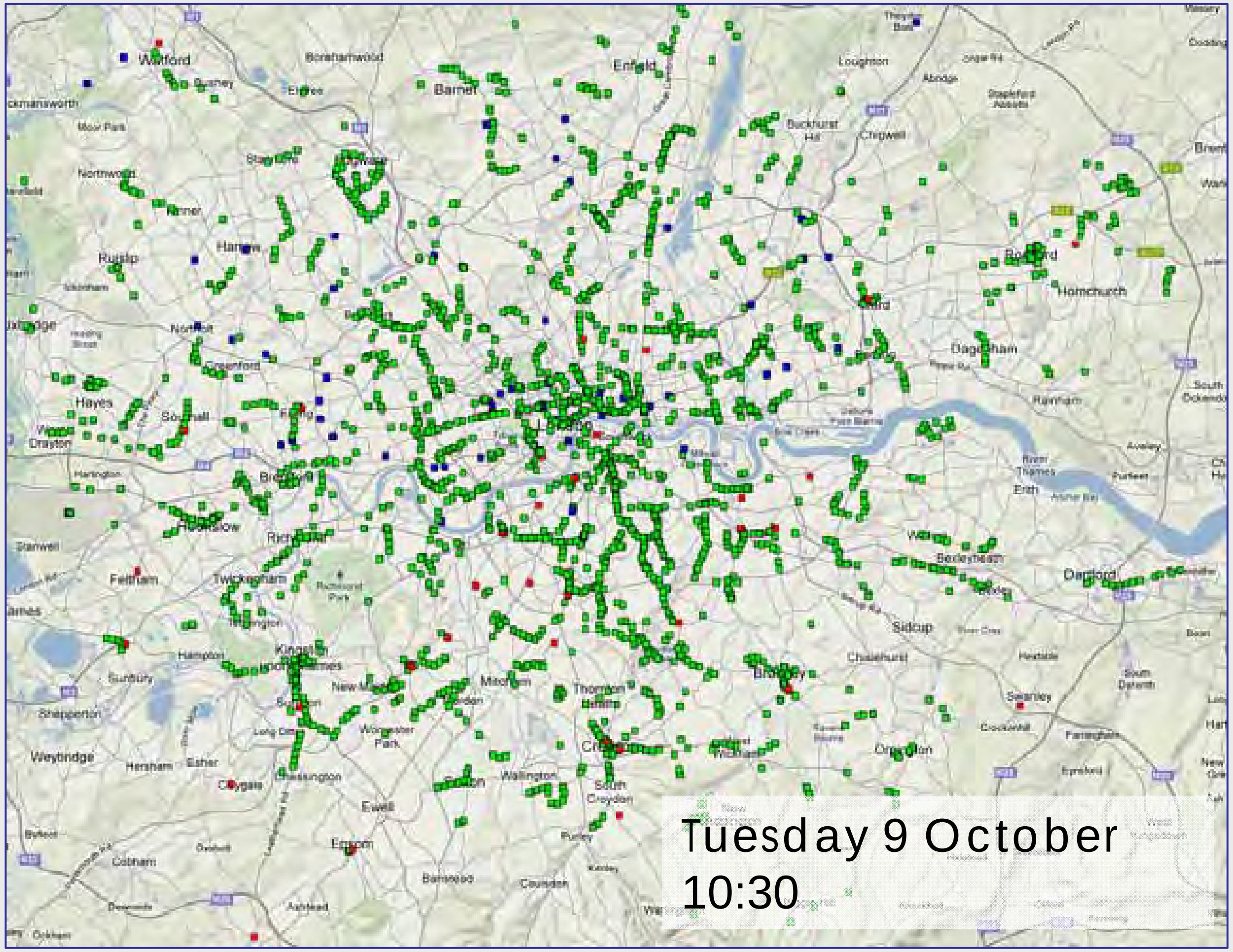




MapTube Map
File Edit View Favorites Tools Help
home
about
login
search
help
casa
Link to this map
MAPTUBE
a place to put maps
KML
Map
Satellite
Watford
Enfield
Cheshunt
Brentwood
Romford
Wembley
Hounslow
Richmond
Kingston upon Thames
Bromley
Croydon
Kings Cross
Valid Time: 14:39:00 20/03/2012
Train ID: 9-1
Location: Between St. Paul's and Chancery Lane
Platform: Westbound - Platform 1
Time to station: 30 seconds
Destination: West Ruislip (547)


12
1
2
3
4
5
6
7
8
9
10
11

Delays from Tube, National Rail and Bus Fused



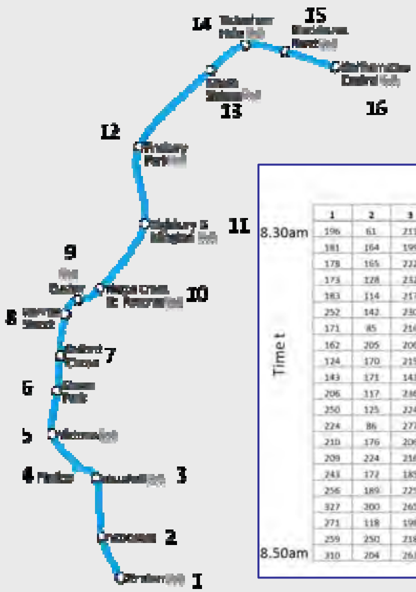
Key

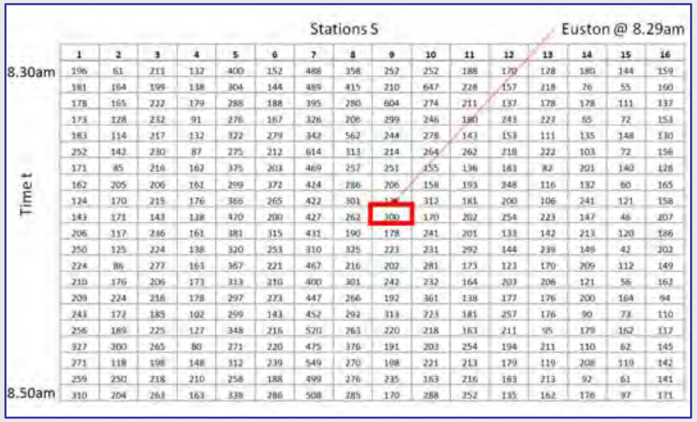
- National Rail more than 5 minutes late
- Tube stations showing a wait time 15% above expected
- Bus stops showing a wait time 20% above expected

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

Locational Dynamics of Demand

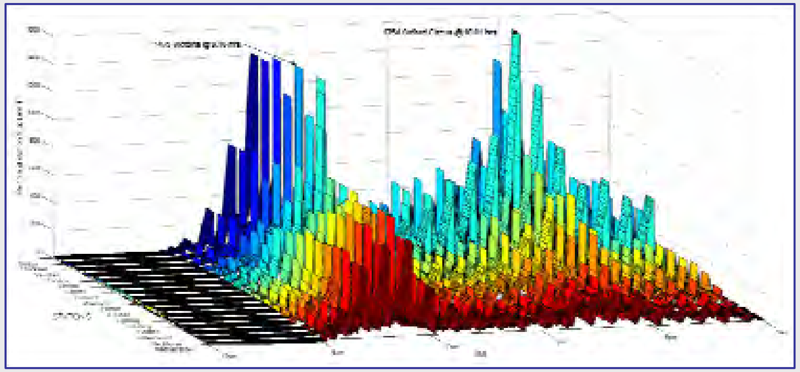
We are currently using information theory to figure out how much information from trips is transmitted from station to station through time by working out how many passengers are in stations or on trains in stations over time. We are using the concept of **transfer entropy** to do this. I don't have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





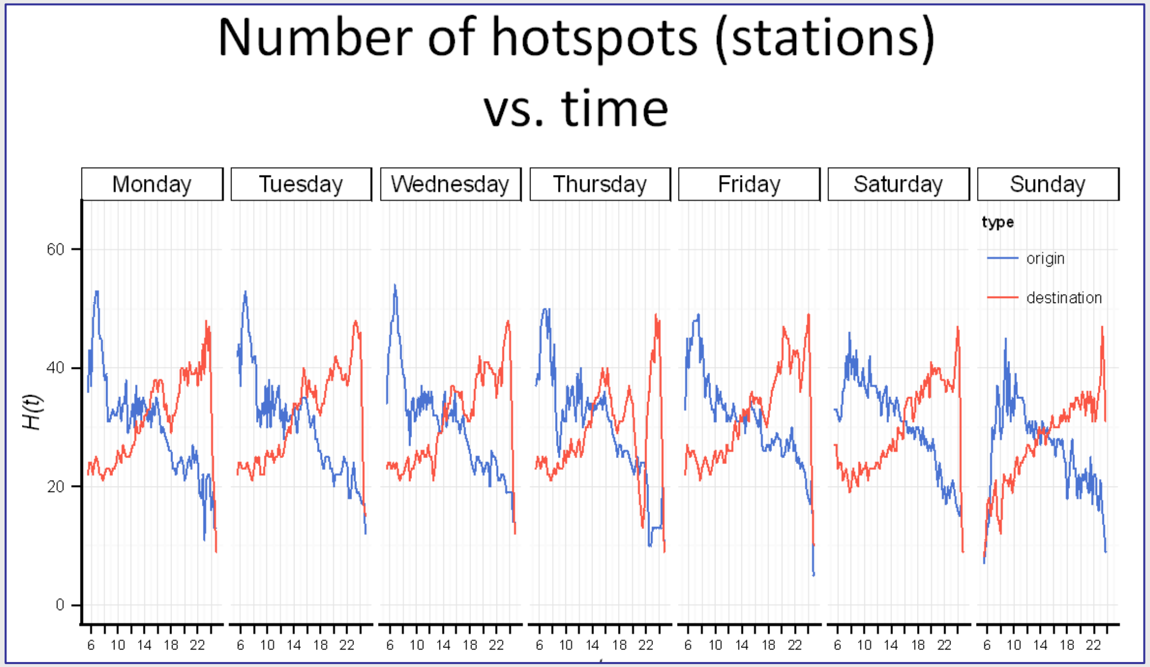
Stations S — Euston @ 8.29am

Time t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
8.30am	196	61	211	132	400	152	488	358	252	252	188	170	128	180	144	159
	181	164	199	138	304	144	489	415	210	647	228	157	218	76	55	160
	178	165	222	179	288	188	395	280	604	274	211	137	178	178	111	137
	173	128	232	91	276	167	326	206	299	246	180	243	227	65	72	153
	183	114	217	132	322	279	342	562	244	278	143	153	111	135	148	130
	252	142	230	87	275	212	614	313	214	264	262	218	222	103	72	156
	171	85	216	162	375	203	469	257	251	155	136	183	82	201	140	128
	162	205	206	161	299	372	424	286	206	158	193	248	116	132	60	165
	124	170	215	176	366	265	422	301	[illegible]	312	181	200	106	241	121	158
	143	171	143	138	470	200	427	262	300	170	202	254	223	147	46	207
	206	117	236	161	381	315	431	190	178	241	201	133	142	213	120	186
	250	125	224	138	320	253	310	325	223	231	292	144	239	149	42	202
	224	86	277	161	367	221	467	216	202	281	173	123	170	209	112	149
	210	176	206	173	313	216	400	301	242	232	164	203	206	121	56	162
	209	224	216	178	297	273	447	266	192	361	138	177	176	200	164	94
	243	172	185	102	299	143	452	292	313	223	181	257	176	90	73	110
	256	189	225	127	348	216	520	263	220	218	163	211	95	179	162	117
	327	200	265	80	271	220	475	376	191	203	254	194	211	110	62	145
	271	118	198	148	312	239	549	270	198	221	213	179	119	208	110	142
	259	250	218	210	258	188	499	276	235	163	216	163	213	92	61	141
8.50am	310	204	263	163	338	286	508	285	170	288	252	135	162	176	97	171



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

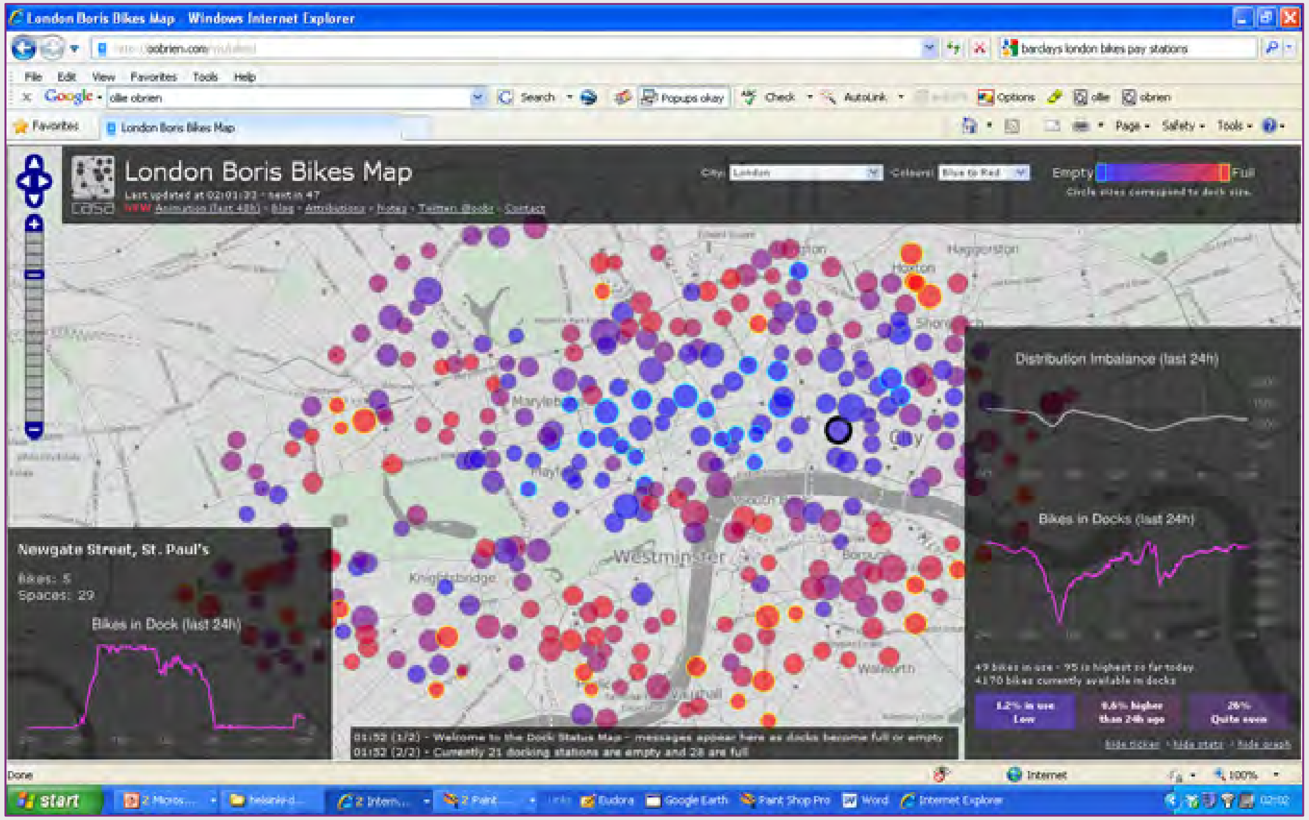
Second we are working with the Oyster data again with Melanie Bosredon in out group and Marc Barthelemy in Paris on extracting clusters from the travel data using a new method of defining intensity. I will show this as a simple movie of origin and destination intensities as they change over time of day.



[redacted]

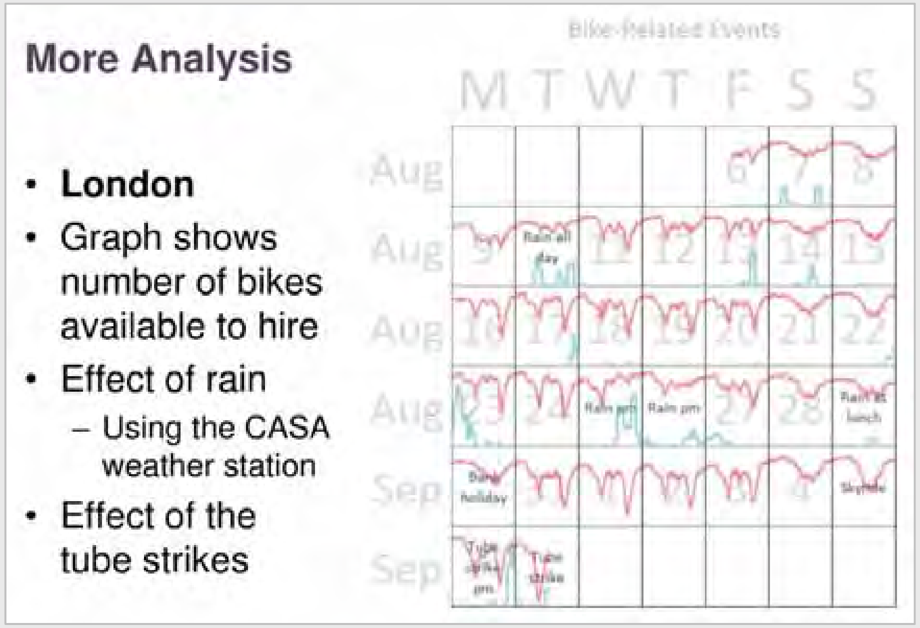
Related Real-Time Data: Bikes, Social Media

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



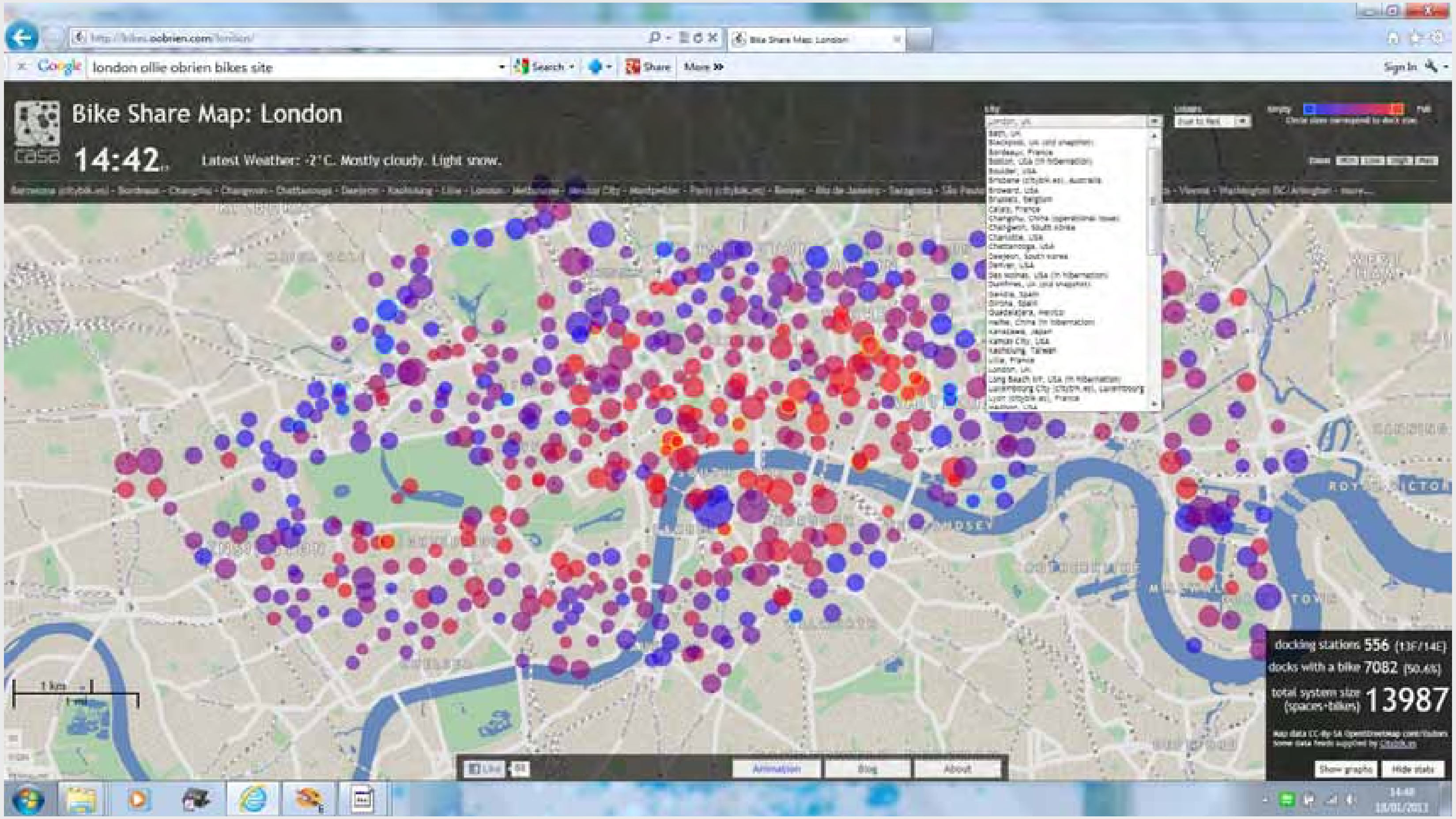
Animations of Public Bike Movements

Animations of Changes in the Bike Nodes: Docking

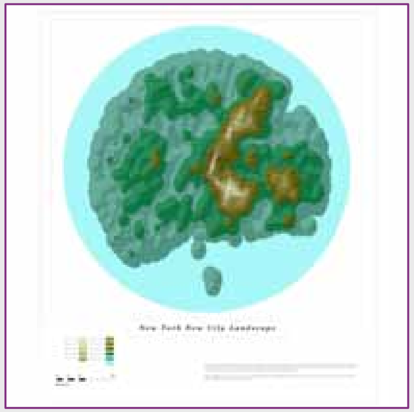


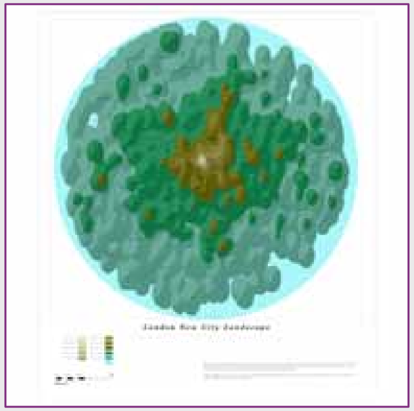
The Website: Real Time Visualisation of Origins and Destinations Activity

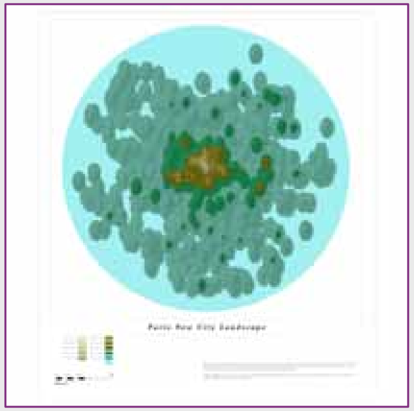
http://bikes.oobrien.com/london/

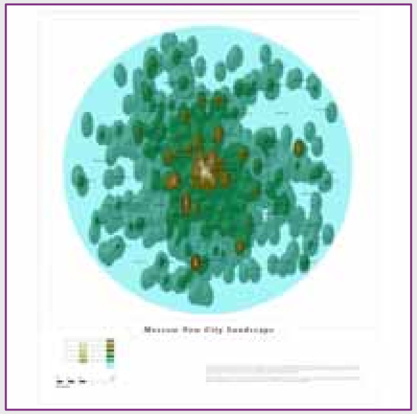


[redacted]







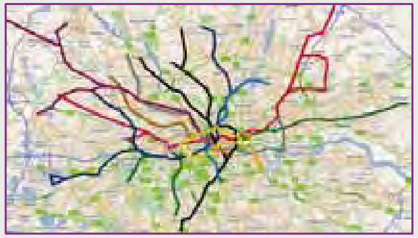


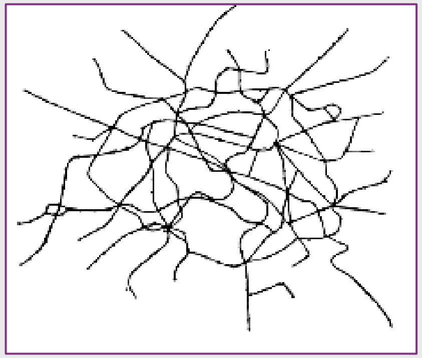
New York

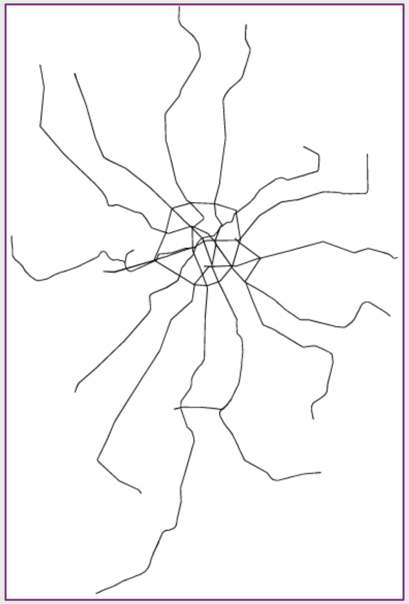
London

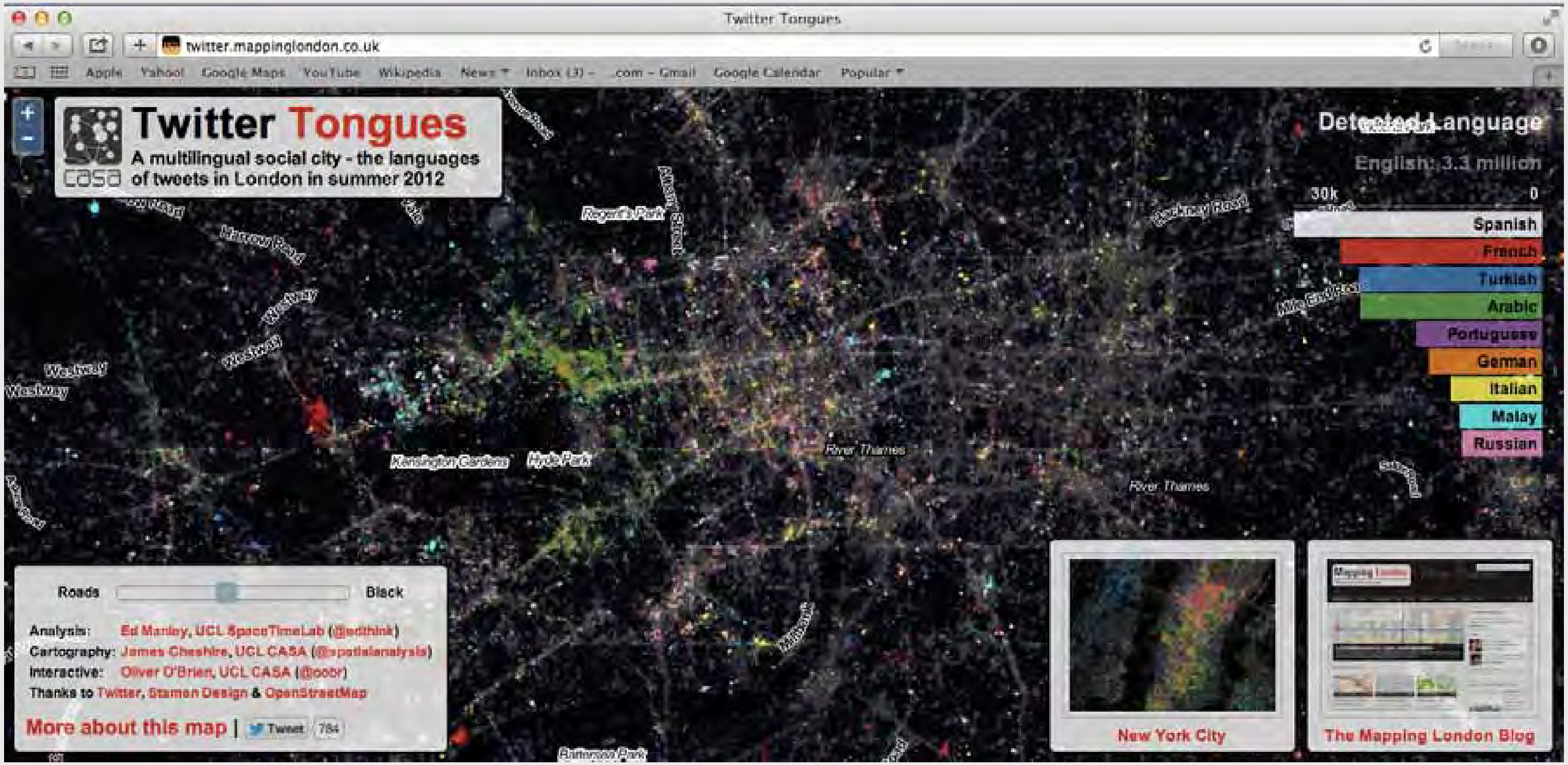
Paris

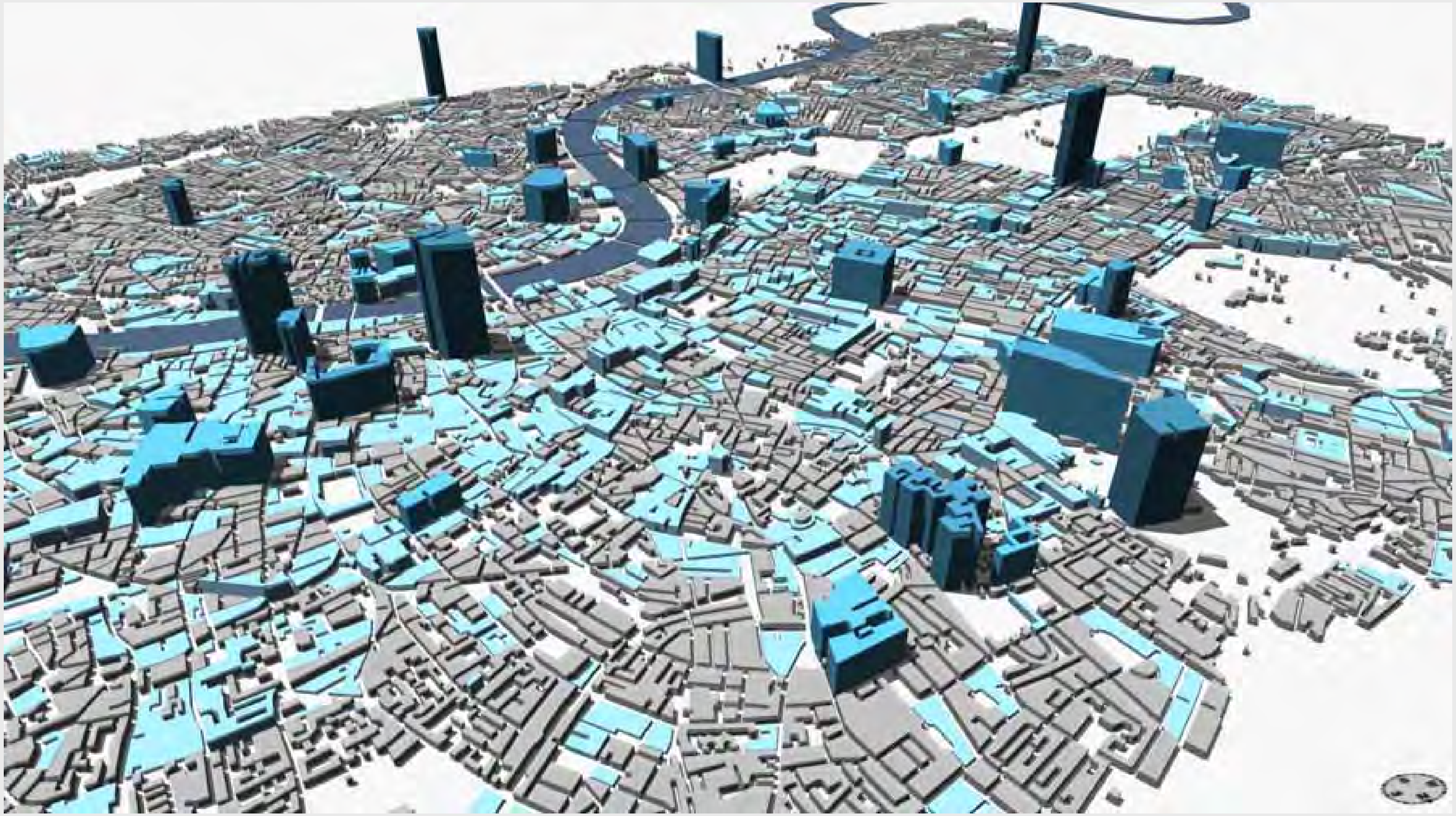
Moscow








Twitter Tongues
twitter.mappinglondon.co.uk
Twitter Tongues
A multilingual social city - the languages of tweets in London in summer 2012
Detected Language
English: 3.3 million
30k
0
Spanish
French
Turkish
Arabic
Portuguese
German
Italian
Malay
Russian
Regent's Park
Harrow Road
Westway
Kensington Gardens
Hyde Park
River Thames
Hackney Road
Mile End Road
Battersea Park
Roads
Black
Analysis: Ed Manley, UCL SpaceTimeLab (@edthink)
Cartography: James Cheshire, UCL CASA (@spatialanalysis)
Interactive: Oliver O'Brien, UCL CASA (@oobr)
Thanks to Twitter, Stamen Design & OpenStreetMap
More about this map
New York City
The Mapping London Blog



[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 producing synthetic results –a paper in IJGIS

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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Roth C., Kang S. M., Batty, M., and Barthelemy, M. (2011) Structure of Urban Movements: Polycentric Activity and Entangled Hierarchical Flows. **PLoS ONE 6(1):** e15923. doi:10.1371/journal.pone.0015923

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

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Funding: This work was co-funded by the European Research Council (https://erc.europa.eu/) under 249393-ERC-2009-AdG (PI: Michael Batty) and the National Natural Science Foundation of China(http://www.nsfc.gov.cn/) under grant number: 51408029 (PI: Feng Chen). The funders had no role in study

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.