



Consumer Data

New Research Opportunities

Guy Lansley



Consumer
Data
Research
Centre

An ESRC Data
Investment

Who we are

We are an academic led, multi-institution laboratory which discovers, mines, analyses and synthesises consumer-related datasets from around the UK. The CDRC is an ESRC Data Investment.

www.cdrc.ac.uk

maps.cdrc.ac.uk

data.cdrc.ac.uk



CDRC-Public

Access retail, consumer and contextual information through our free public data and mapping portal.



CDRC-Stakeholder/Archive

A download service for retail / consumer data for use in academic research.



CDRC-Secure

Access anonymised consumer / retail data from our secure on-site facilities.



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'Ladder of Engagement'

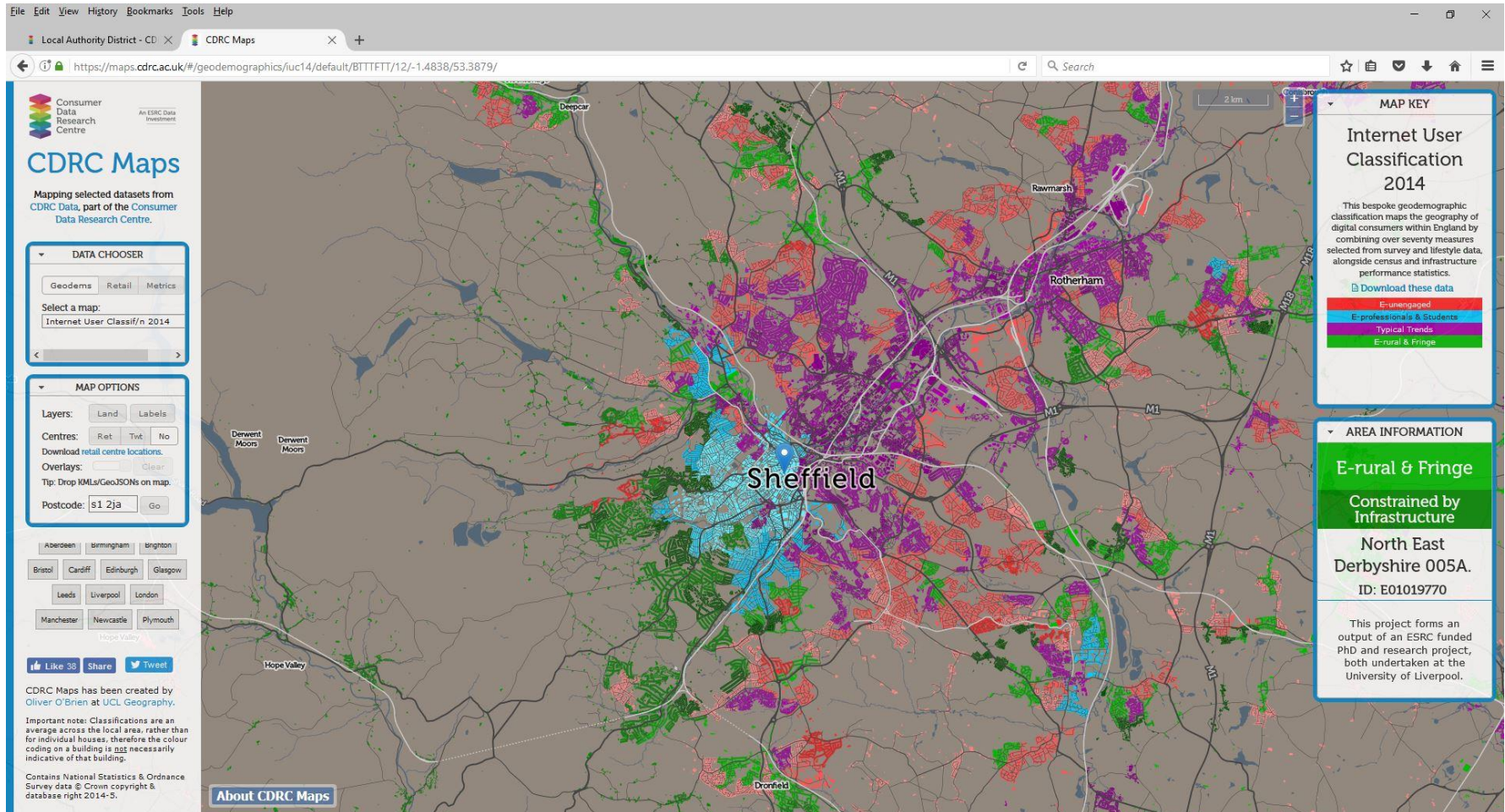
Co-
production
of data

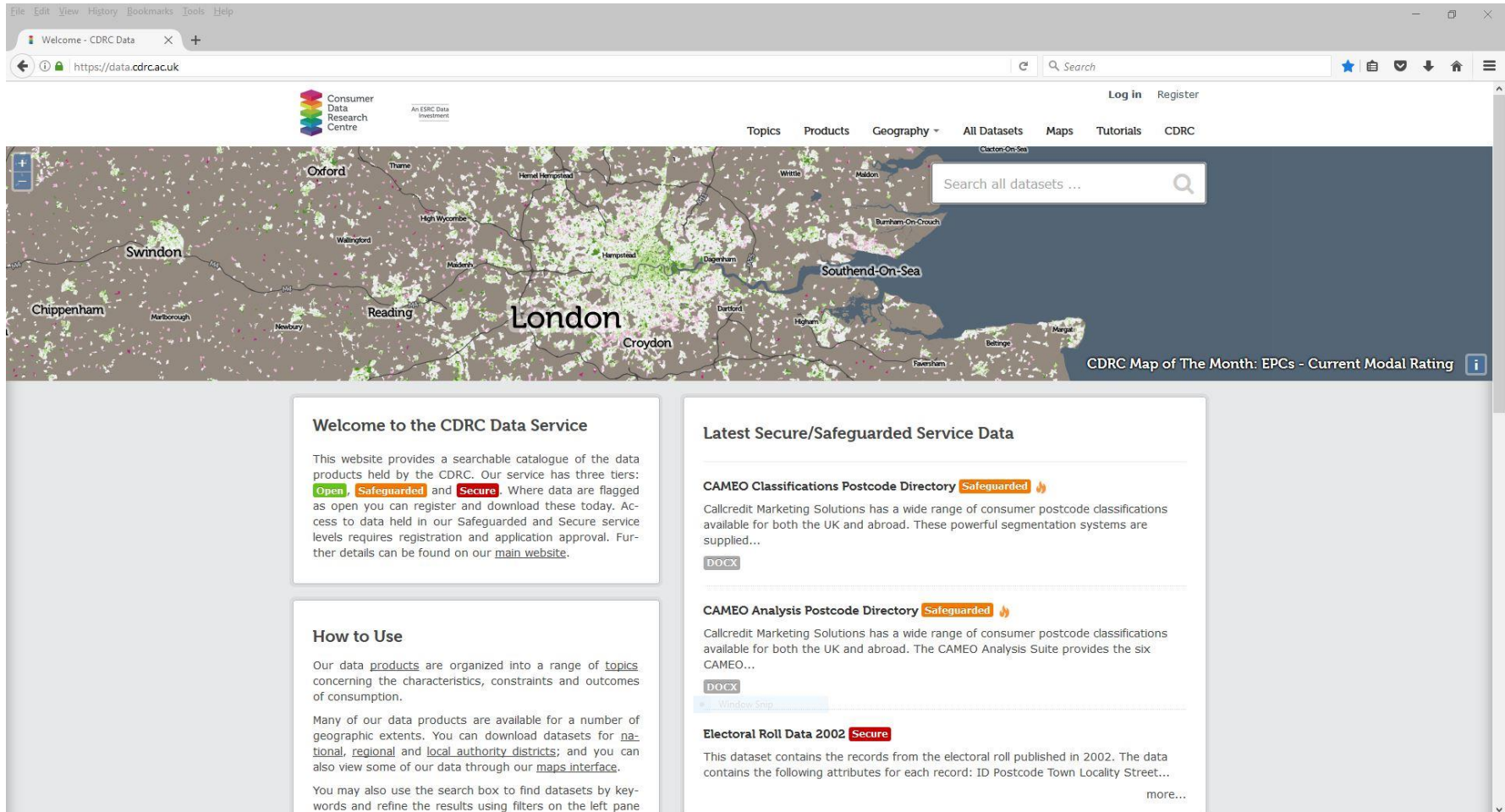
Data
Sharing
with CDRC

Partner
focused
research
projects

PhD
Research

Masters
Programmes





The screenshot shows the CDRC Data website interface. At the top, there's a navigation bar with links for 'Topics', 'Products', 'Geography', 'All Datasets', 'Maps', 'Tutorials', and 'CDRC'. A search bar is prominently displayed with the text 'Search all datasets ...'. Below the navigation bar, a large map of the South East of England is shown, with various locations labeled like Oxford, London, Reading, and Swindon. The map is titled 'CDRC Map of The Month: EPCs - Current Modal Rating'. Below the map, there are two main content areas. The left area is titled 'Welcome to the CDRC Data Service' and describes the data tiers: Open, Safeguarded, and Secure. The right area is titled 'Latest Secure/Safeguarded Service Data' and lists two datasets: 'CAMEO Classifications Postcode Directory' (Safeguarded) and 'CAMEO Analysis Postcode Directory' (Safeguarded). Below these, there's a section for 'Electoral Roll Data 2002' (Secure). The website has a clean, professional layout with a grey header and footer.

File Edit View History Bookmarks Tools Help

Welcome - CDRC Data

https://data.cdrc.ac.uk

Consumer Data Research Centre

An ESRC Data Investment

Log in Register

Topics Products Geography All Datasets Maps Tutorials CDRC

Search all datasets ...

CDRC Map of The Month: EPCs - Current Modal Rating

Welcome to the CDRC Data Service

This website provides a searchable catalogue of the data products held by the CDRC. Our service has three tiers: **Open**, **Safeguarded** and **Secure**. Where data are flagged as open you can register and download these today. Access to data held in our Safeguarded and Secure service levels requires registration and application approval. Further details can be found on our [main website](#).

How to Use

Our data [products](#) are organized into a range of [topics](#) concerning the characteristics, constraints and outcomes of consumption.

Many of our data products are available for a number of geographic extents. You can download datasets for [national](#), [regional](#) and [local authority districts](#); and you can also view some of our data through our [maps interface](#).

You may also use the search box to find datasets by keywords and refine the results using filters on the left pane

Latest Secure/Safeguarded Service Data

CAMEO Classifications Postcode Directory **Safeguarded**

Callcredit Marketing Solutions has a wide range of consumer postcode classifications available for both the UK and abroad. These powerful segmentation systems are supplied...

[DOCK](#)

CAMEO Analysis Postcode Directory **Safeguarded**

Callcredit Marketing Solutions has a wide range of consumer postcode classifications available for both the UK and abroad. The CAMEO Analysis Suite provides the six CAMEO...

[DOCK](#)

Windsor Smg

Electoral Roll Data 2002 **Secure**

This dataset contains the records from the electoral roll published in 2002. The data contains the following attributes for each record: ID Postcode Town Locality Street...

[more...](#)

Visit www.cdrc.ac.uk

Review CDRC Data catalogue

Data identified and service selected

User Journey

Open Data Service

Register to download

Download open data

Undertake research

Safeguarded Data Service

Researcher registration

Proposal development,
assessment & approval

Safe Researcher Training

Safeguarded data available for
secure download

Create
summary of
findings

Publish &
archive as
appropriate

Send to CDRC

Inform CDRC

Secure Data Service

Researcher registration

Proposal development,
assessment & approval

Safe Researcher Training

Access to agreed controlled data
at secure CDRC sites

Perform analysis at secure site
and submit to CDRC approver
pool

CDRC review analysis and
confirm it is in line with project
approval

Analysis released to researcher

Create
summary of
findings

Publish as
appropriate

Send to CDRC

Inform CDRC

Safe Projects

Safe People

Safe Setting

Safe Outputs

Safe Data

Example Datasets

Smart Meter energy consumption data from a domestic energy supplier

Electoral Roll data (1998 – 2012) and Consumer Registers (2003 – 2017)

Active Inspiration – Activity Data

Debit card transactions from a Youth Banking Card Provider

WhenFresh/Zoopla Property Transactions and Associated Migration

Appliances Online Retail Data

YouGov Survey Data

Synthetic Population

Online retail transactions from Shop Direct

Store transactions (linked to customer loyalty accounts) from a high street retailer

Regional Transport Provider: Ticket counts; assets, travel demand, vehicle position & transport infrastructure data

Football sensor data from Local Data Company

Secure

Safeguarded

Acxiom – Income Data

British Population Survey



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CDRC Data Products

CDRC 2011 Census Data Packs

Internet User
Classification 2014

CDRC Wifi Hotspots

CDRC Council Tax
Bands

CDRC 2011 Residence-
Workplace Geodata Pack

CDRC Individual Income
Estimates (PAYE)

CDRC 2015 OS
Geodata Pack

CDRC 2011 OAC
Geodata Pack

Outstanding Residential
Mortgage Lending by Postcode
Lending by Postcode Sector

CDRC Price Paid Data per
Property Type at the LSOA scale

CDRC Access to Healthy
Assets & Hazards Index
(AHAH)

CDRC Fixed Broadband and
Network Infrastructure

CDRC 2015 Energy
Estimate Geodata Pack

Open Data

CDRC Estimated
Change in the
Rateable Value of
Retail Premises

London Workplace
Zone Classification
(LWZC)



CDRC Training

- **15th Jan:** Introduction to QGIS: Understanding and Presenting Spatial Data - University of Southampton (co-badged ADRC-E)
- **17th Jan:** Confident Spatial Analysis– University of Southampton (co-badged ADRC-E)
- **22nd Feb:** Tableau Workshop: University of Leeds
- **19th Mar:** Introduction to ArcGIS: University of Leeds
- **23rd Apr:** Introduction to spatial data and using R as a GIS - University of Liverpool in London (co-badged ADRC-E)
- **24th Apr:** Confident Spatial Analysis and Statistics in R & GeoDa – University of Liverpool in London (co-badged ADRC-E)
- **Date TBC:** Introduction to Data Linkage – Said Business School (co-badged ADRC-E)
- **Date TBC:** Advanced Data Linkage – Said Business School (co-badged ADRC-E)
- **13-15th June:** Retail Location and Customer Analysis – Said Business School
- **2 days Early summer:** Machine Learning and Social Science – University of Liverpool, University of Liverpool in London/UCL



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Big Data



An increasing share of
data on people are being
collected by commercial
organisations

Exhaust

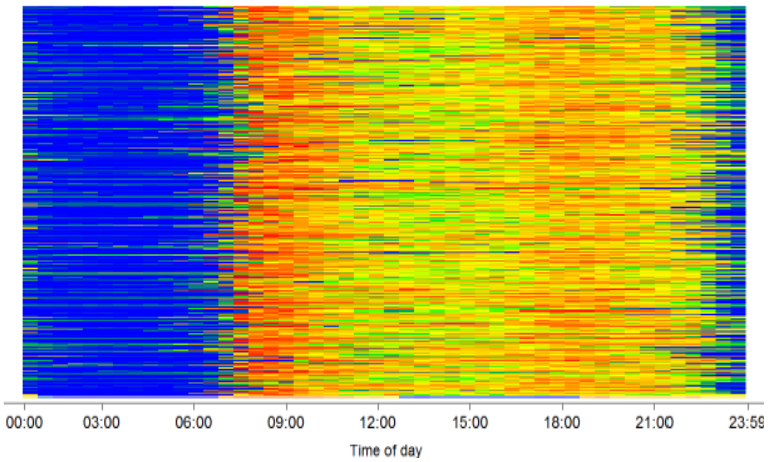
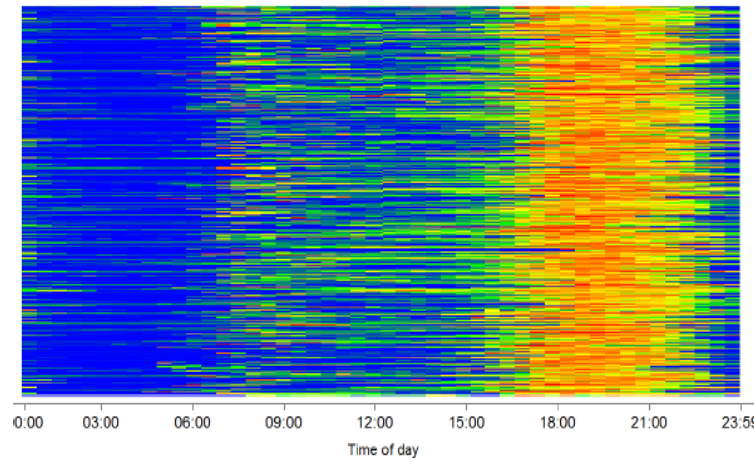
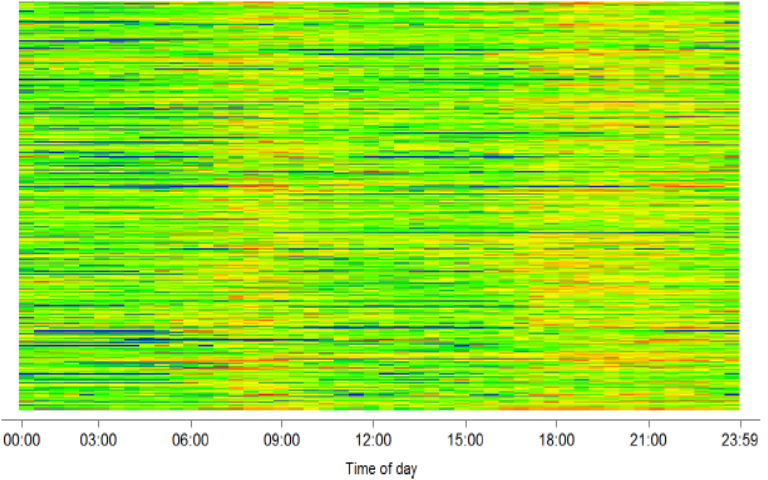
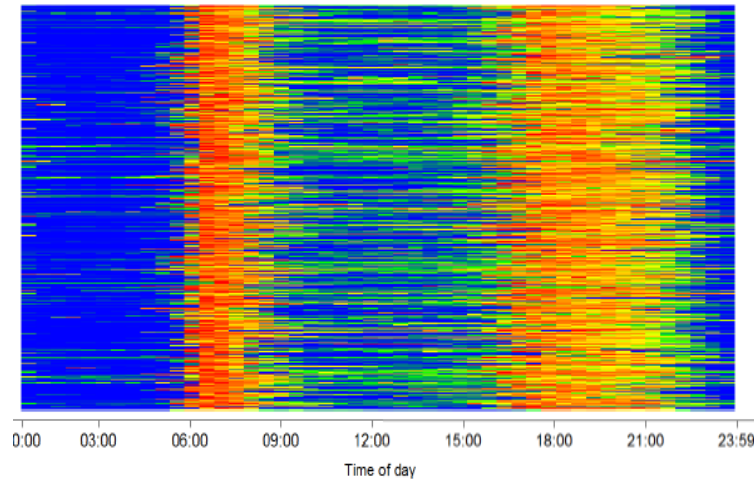




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Smart Meter Data



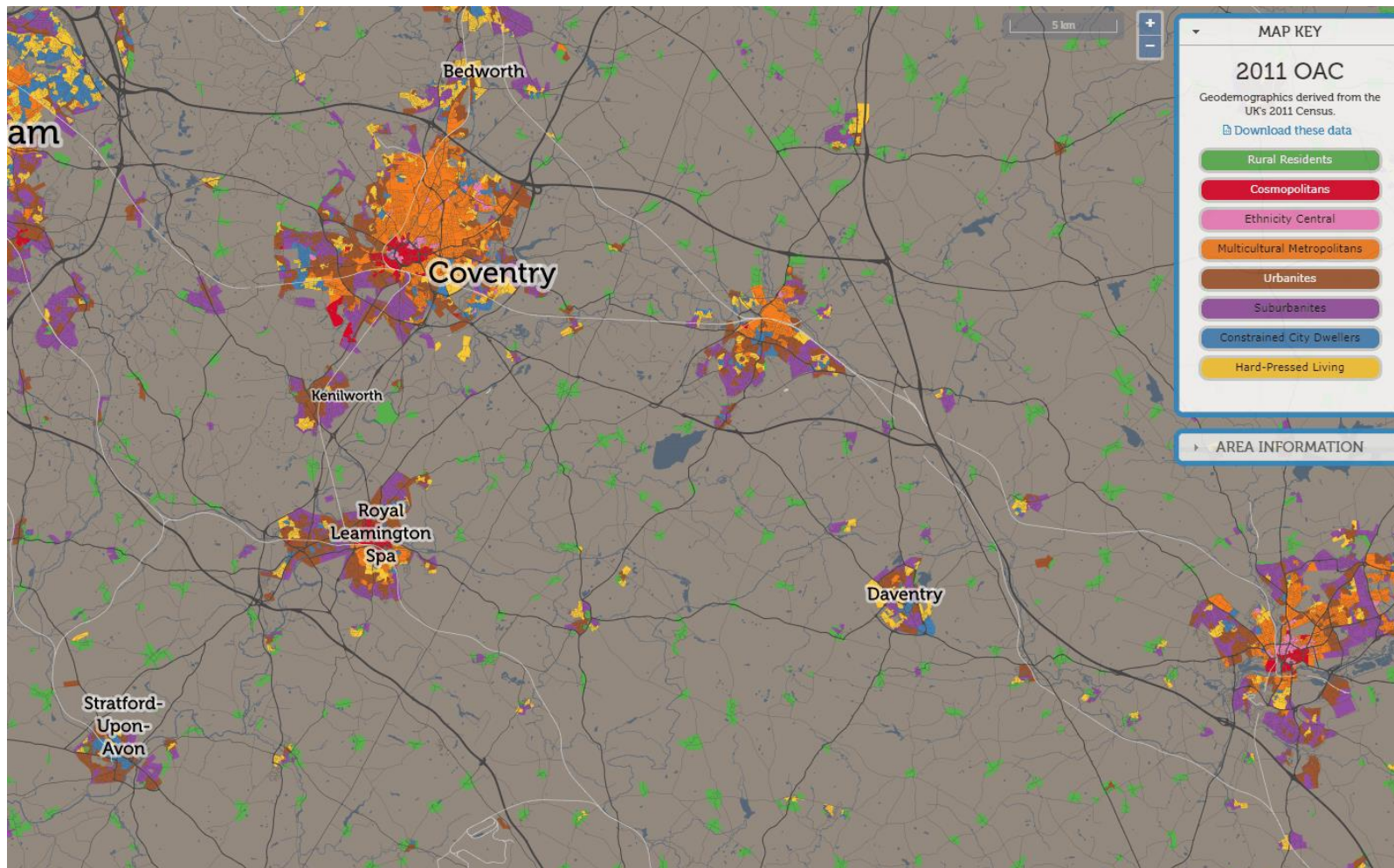
Samson, Lansley and Simpson (2014) *Can smart meters save consumers and British Gas money and carbon by pinpointing which consumers are most likely and best placed to install insulation in their homes?*



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Geodemographics



2011 Output Area Classification (UCL & ONS)

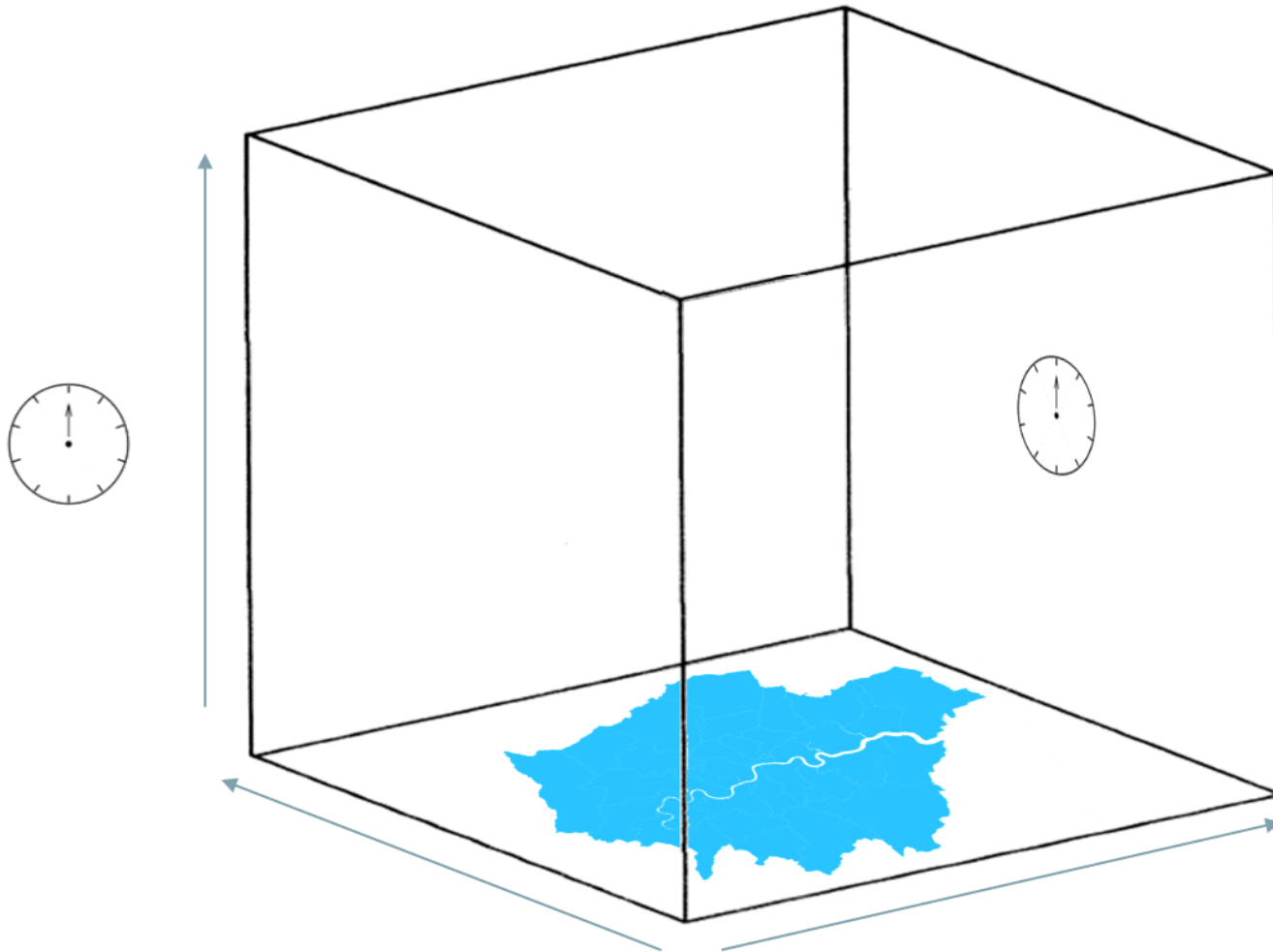
<https://maps.cdrc.ac.uk>



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Time and Space





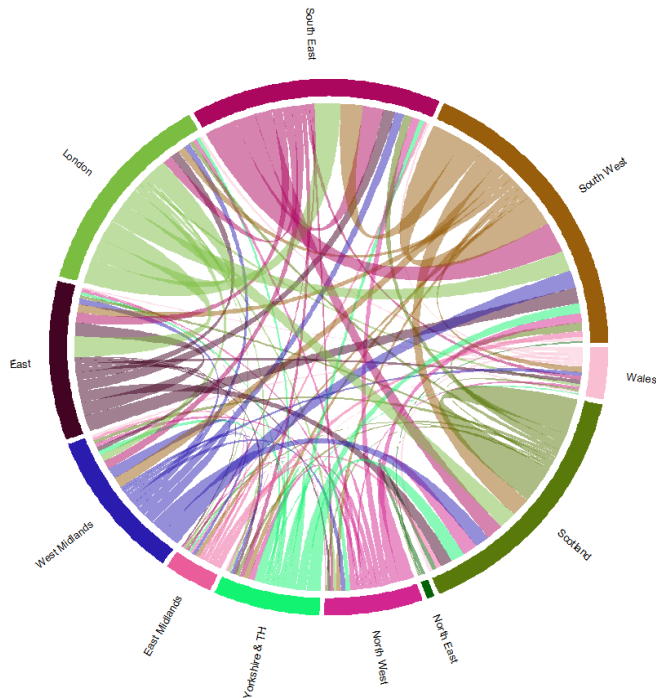
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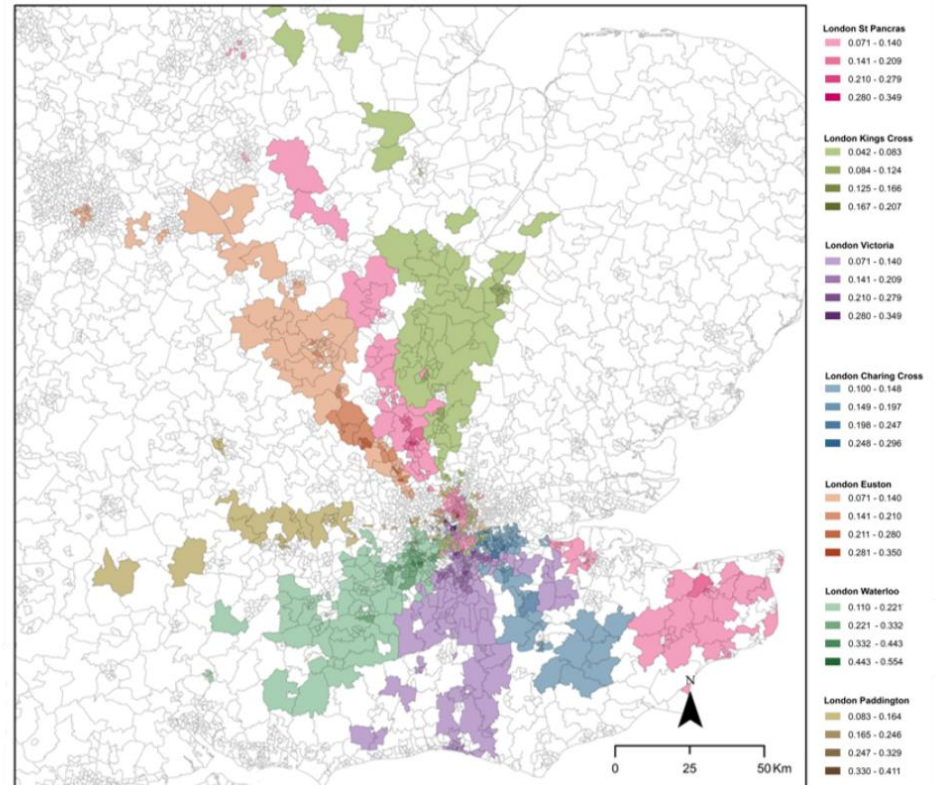
High Street Retailer

Estimating Relocations

Origin region > New store region



Stores located near transport hubs, Central London



Method Applications



High Street Retailer

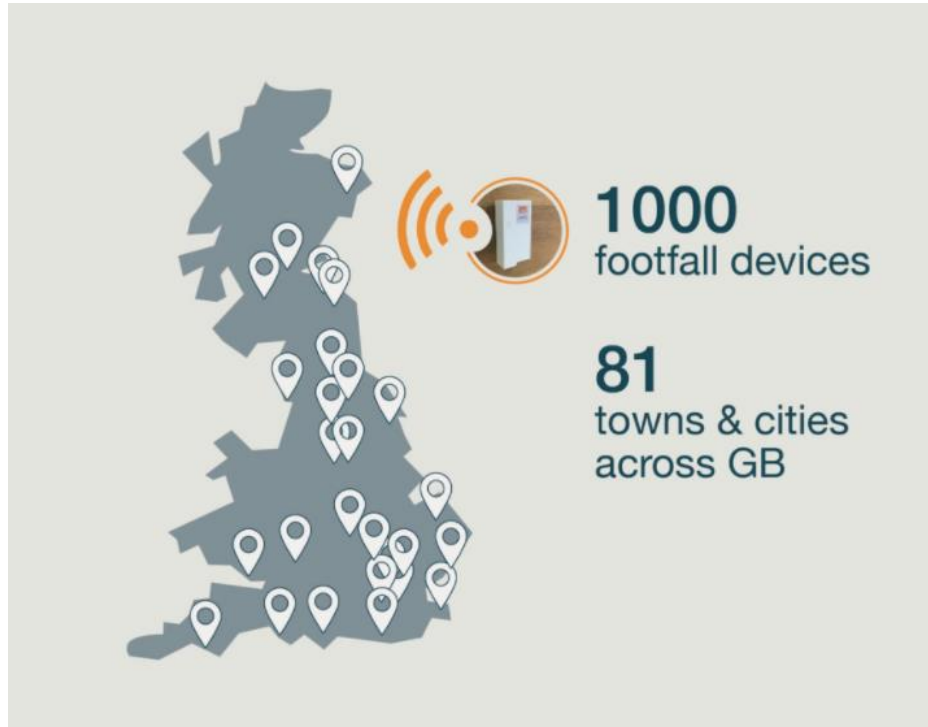




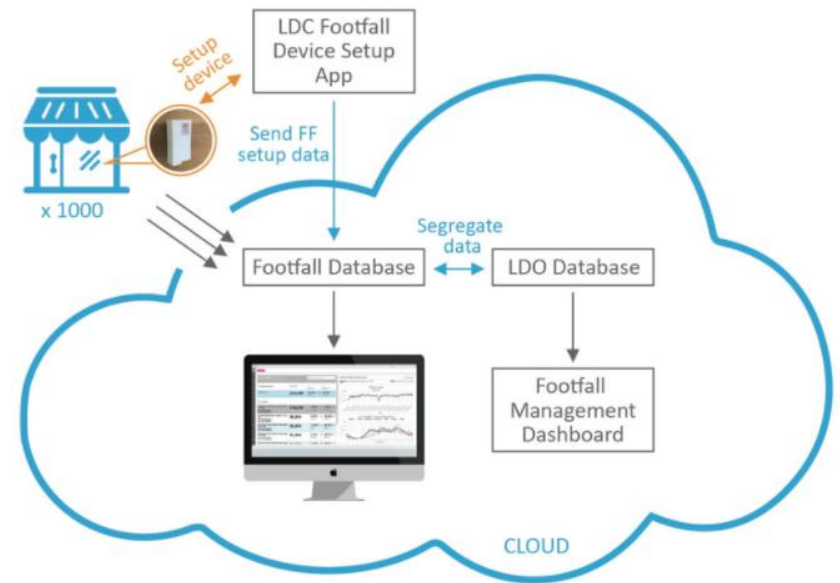
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SmartStreetSensors



How does it work?



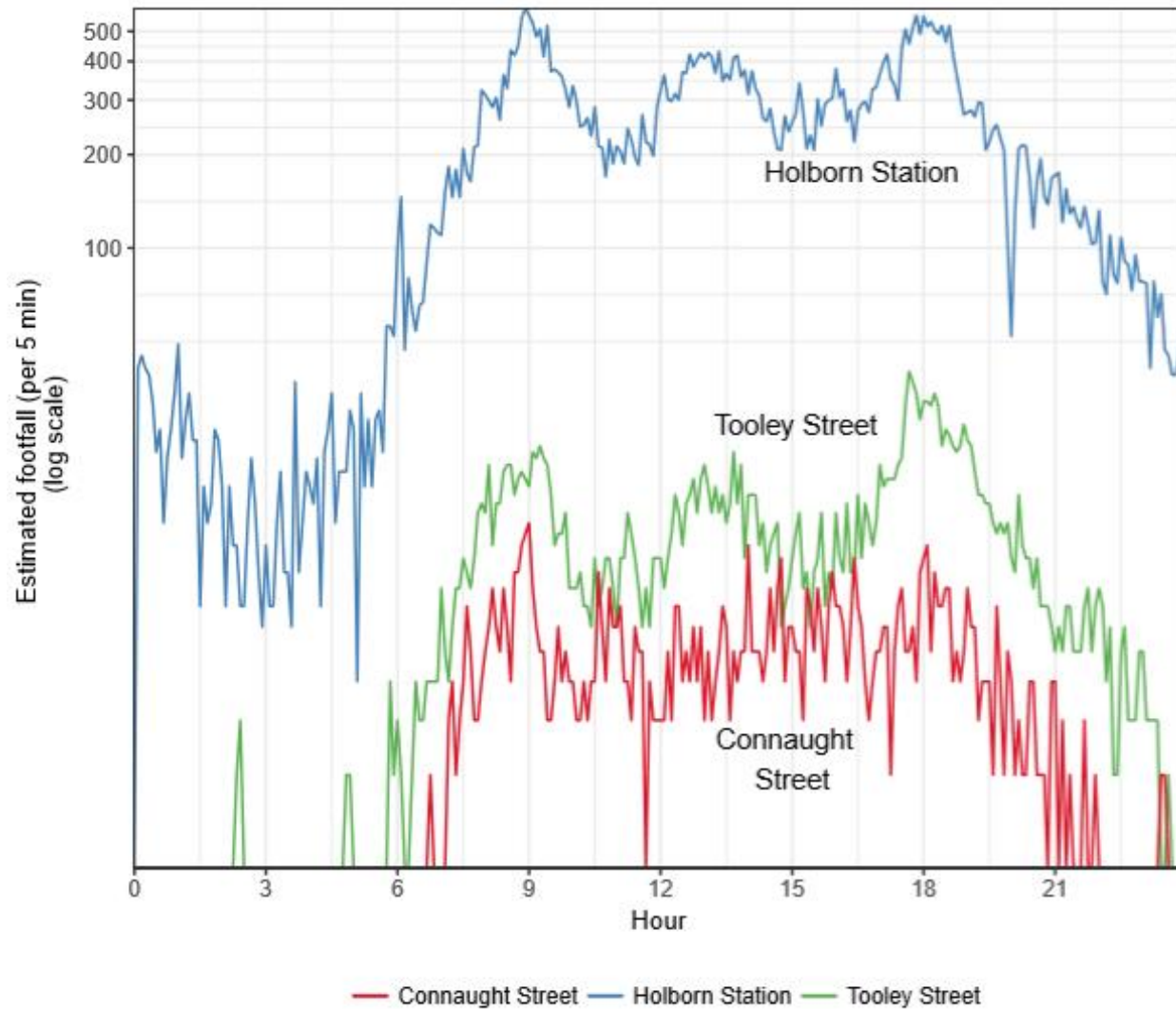
<http://blog.localdatacompany.com/the-story-of-the-smartstreetsensor-project>



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SmartStreetSensors



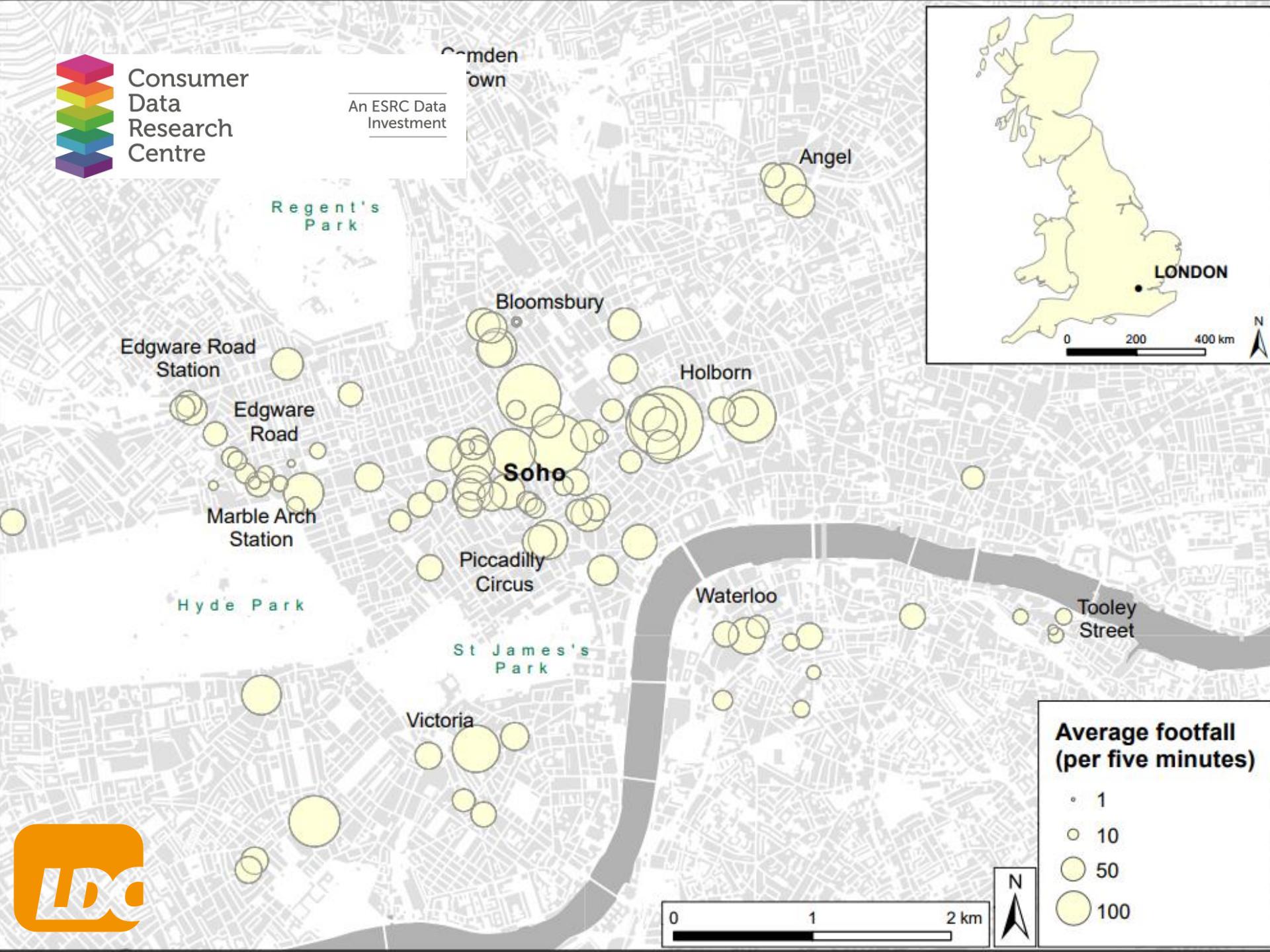
Murcio, Soundararaj and Lugomer (forthcoming)





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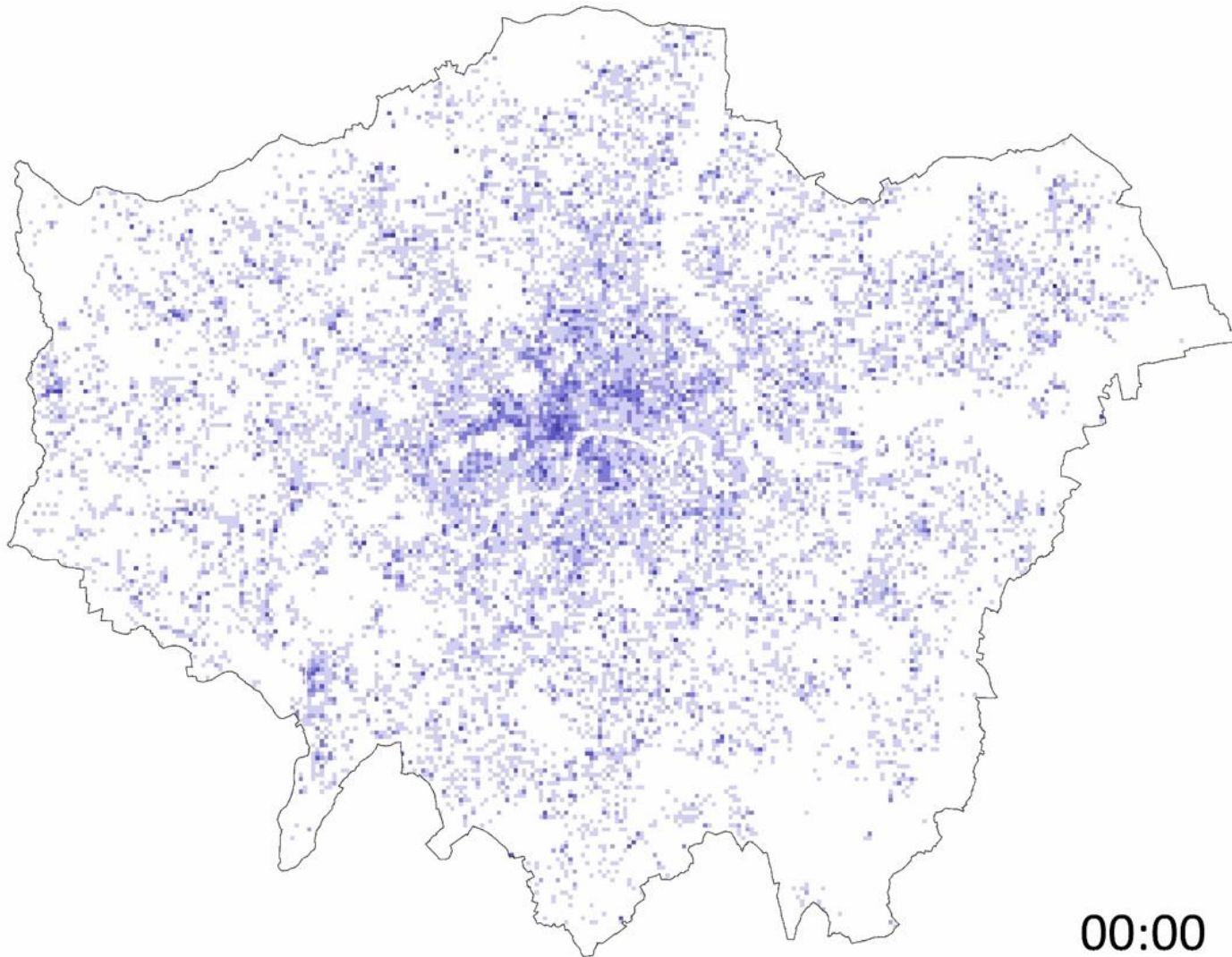




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Geotemporal Demographics



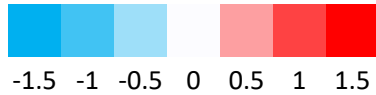
00:00

Longley, Lansley and Adnan (2015) The geotemporal demographics of Twitter usage. *Environment and Planning A*, 47 (2), 465-484



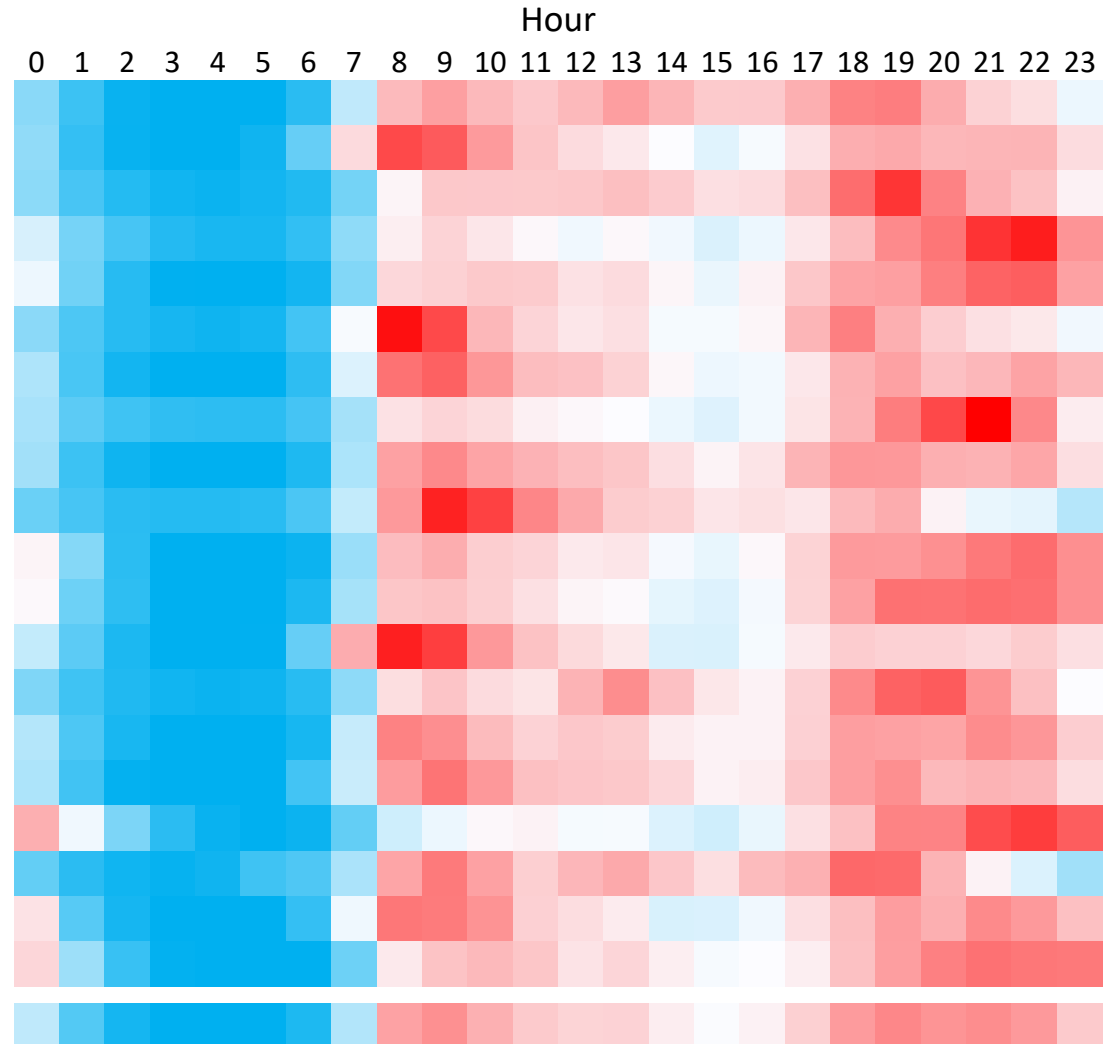
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Twitter Topics

Photography and Sights
Optimism, Kindness and Positivity
Leisure and Attractions
TV and Film
Humour and Informal Conversations
Transport and Travel
Politics, Beliefs and Current Affairs
Sport and Games
Anticipation and Socialising
Business, Information and Networking
Pessimism and Negativity
Music and Musicians
Routine Activities
Food and Drink
Body, Appearances and Clothes
Social Media and Apps
Slang and Profanities
Place and Check-Ins
Wishes and Gratitude
Foreign and Other
All Tweets

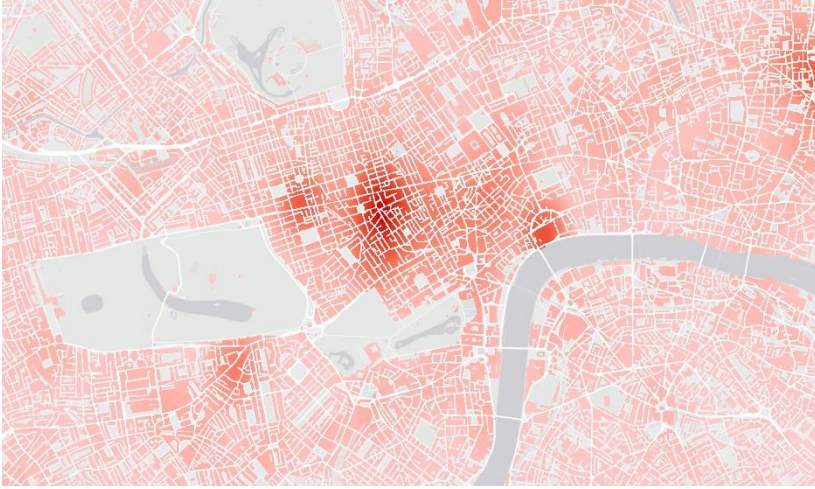




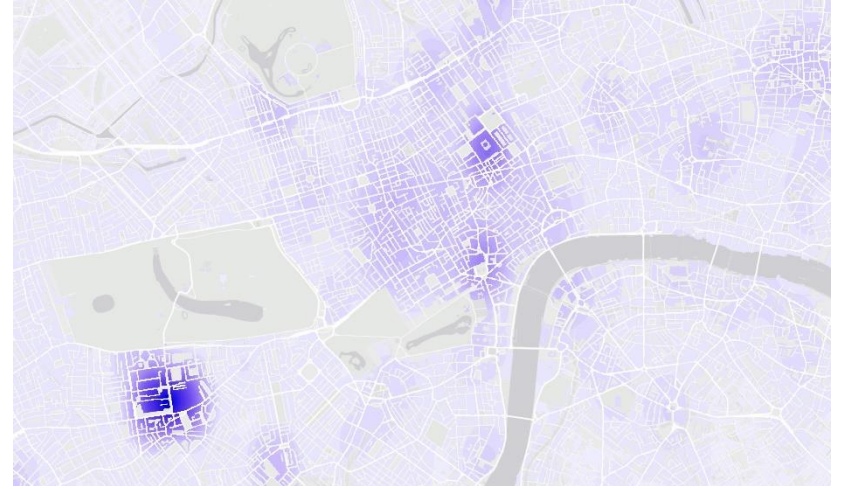
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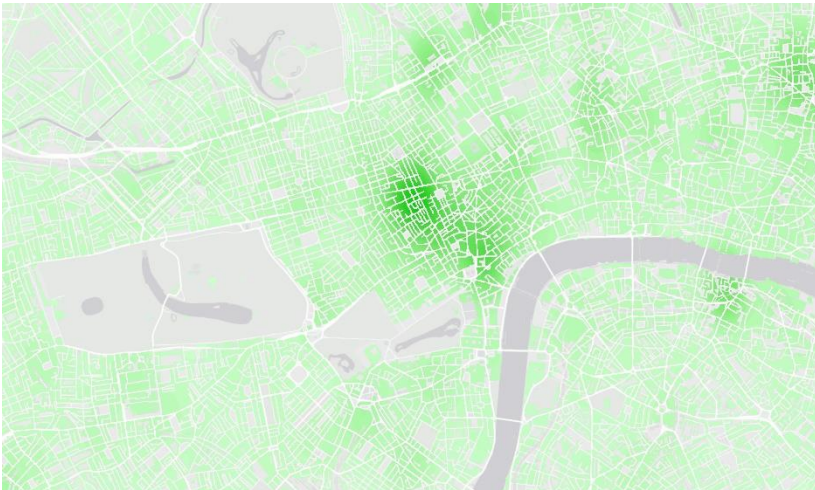
Twitter and Space



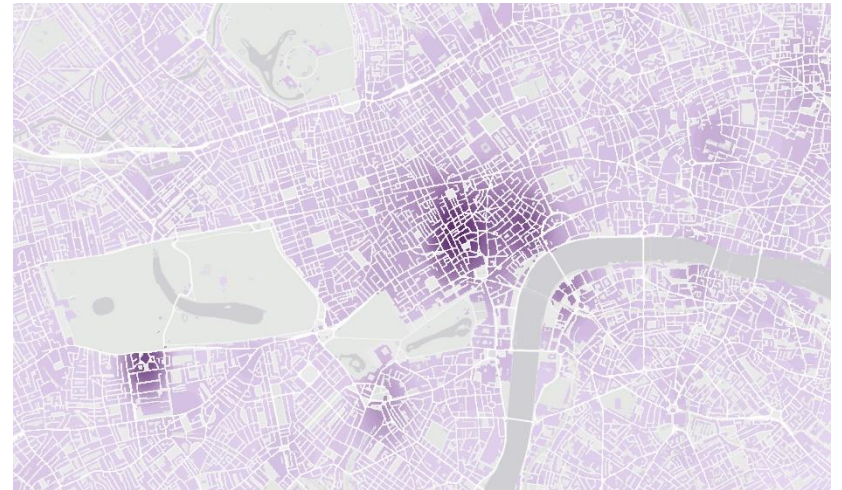
Fashion and Shopping



Museums and Galleries



Nightlife



Shows and Entertainments



Consumer Registers

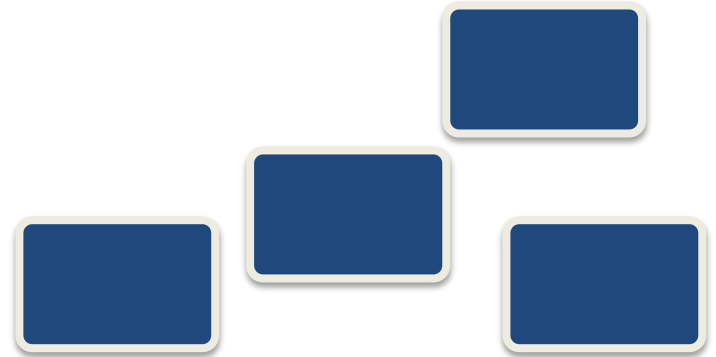
Public Version of the
Electoral Register

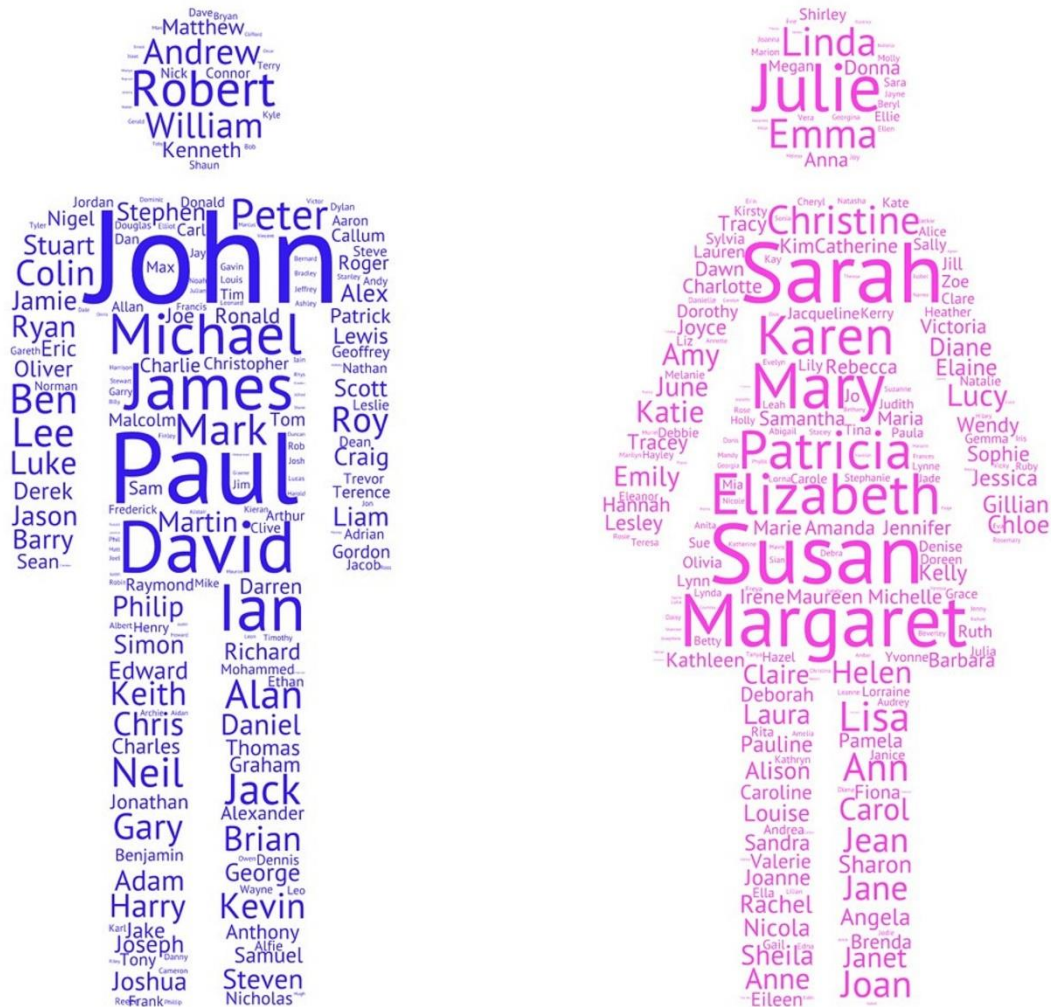
1998 - 2017

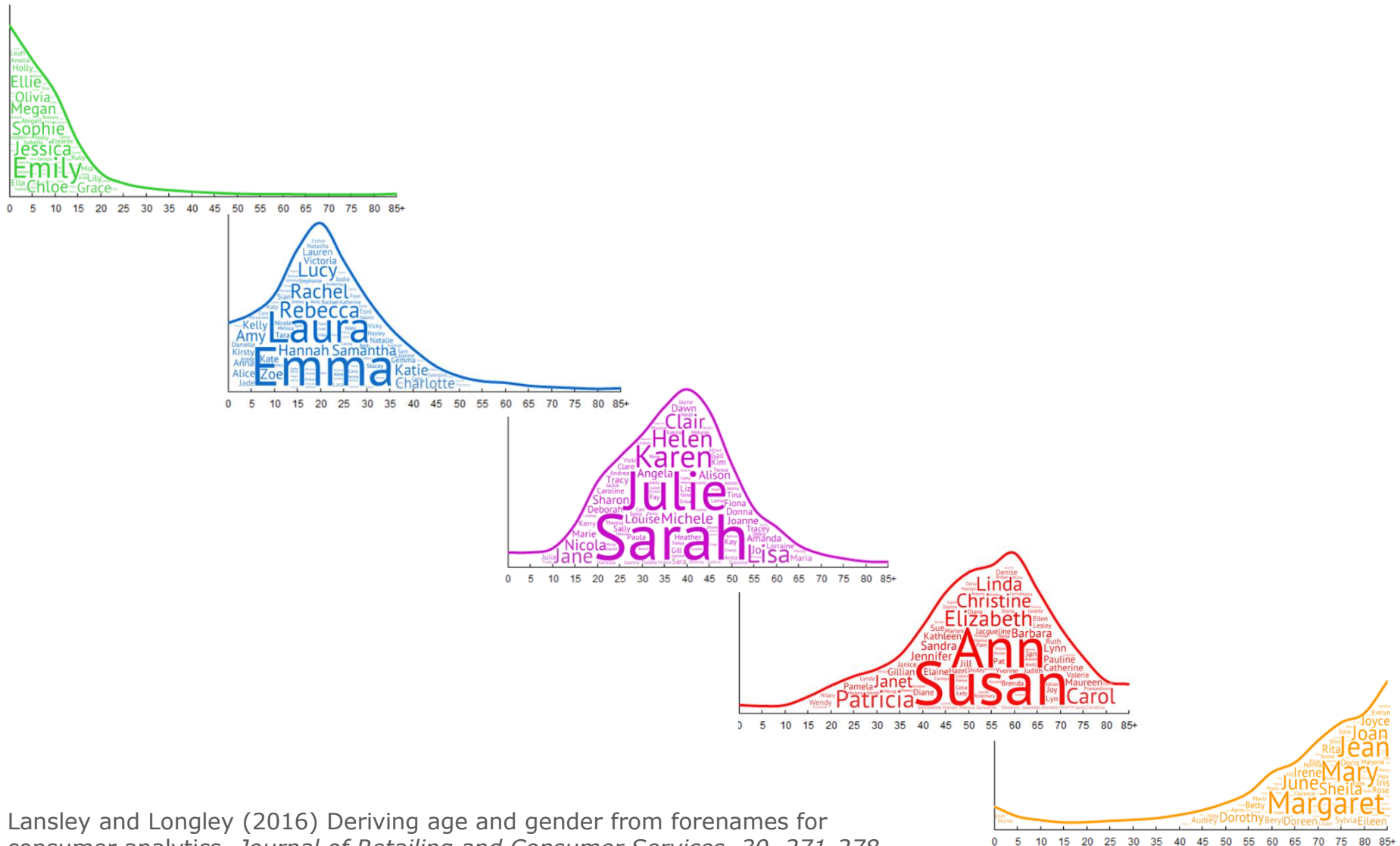


Consumer data from
several sources

2003 - 2017







Lansley and Longley (2016) Deriving age and gender from forenames for consumer analytics. *Journal of Retailing and Consumer Services*, 30, 271-278



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Ethnicity

Consumer Data Research Centre

CDRC Maps

Mapping selected datasets from CDRC Data, part of the Consumer Data Research Centre.

DATA CHOOSER

Classifs Indicators Metrics

Select a map:

- Ethnicity Estimator: Asian: Indian
- Health: AAHA Services
- Health: AAHA Physical Envir
- Health: Gambling
- Health: Fast Food
- Health: Pubs
- Health: Off-Licences
- Health: Tobacco
- Health: GPs
- Health: Hospitals
- Health: Dentists
- Health: Pharmacies
- Health: Leisure Services
- Health: NOs
- Health: PMUs
- Health: SOs
- Health: Green Space
- Ethnicity Estimator: White: British
- Ethnicity Estimator: White: Irish
- Ethnicity Estimator: White: Other
- Ethnicity Estimator: Asian: Indian

Comparison Twitter or

Download retail centre locations.

Bristol Cardiff Edinburgh Glasgow

Leeds Liverpool London

Manchester Newcastle Plymouth

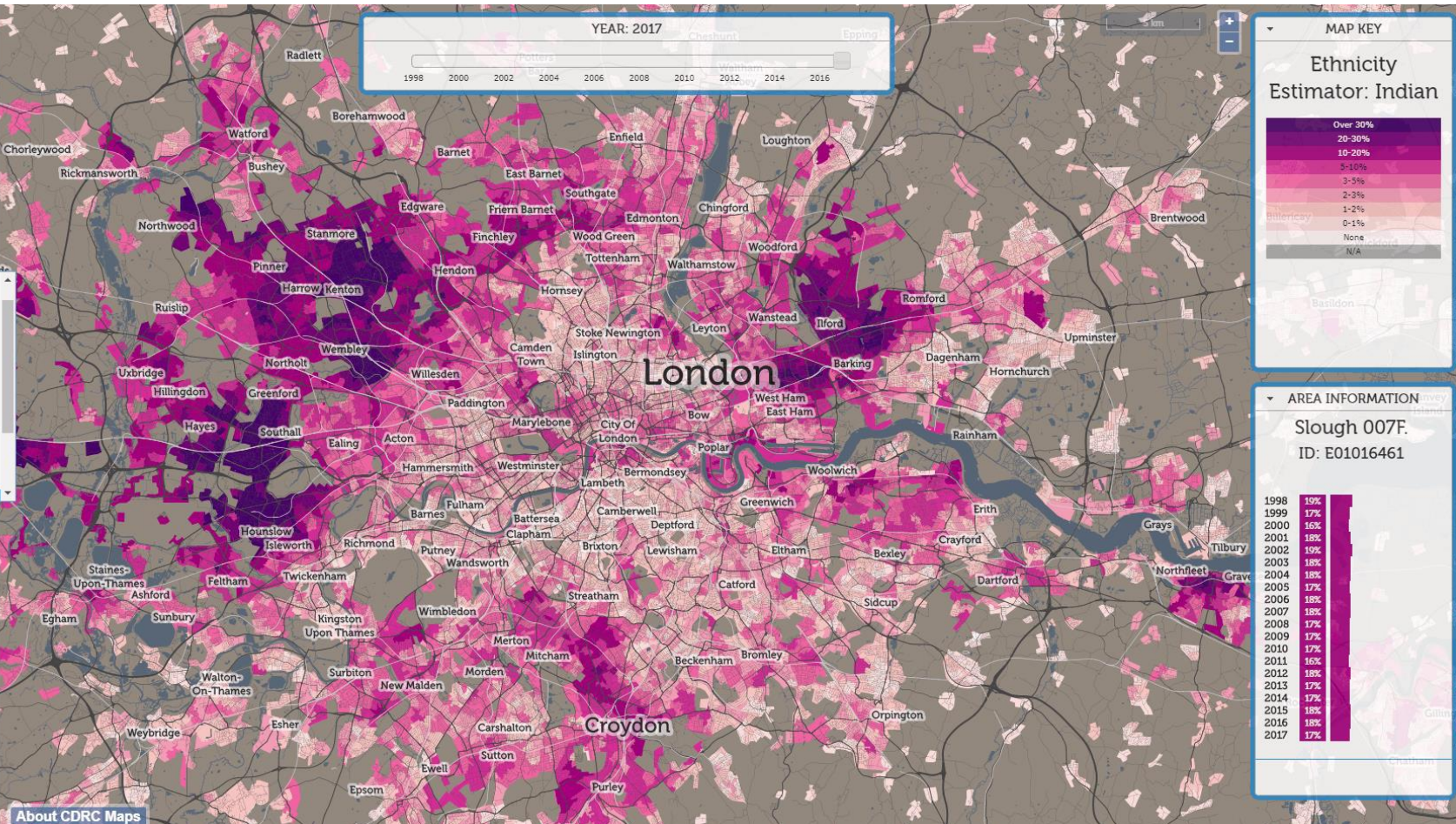
Like 157 Share Tweet

CDRC Maps has been created by Oliver O'Brien at UCL Geography.

Important note: Classifications are an average across the local area, rather than for individual houses, therefore the colour coding on a building is not necessarily indicative of that building.

Contains National Statistics and Ordnance Survey data © Crown copyright & database right 2014-7.

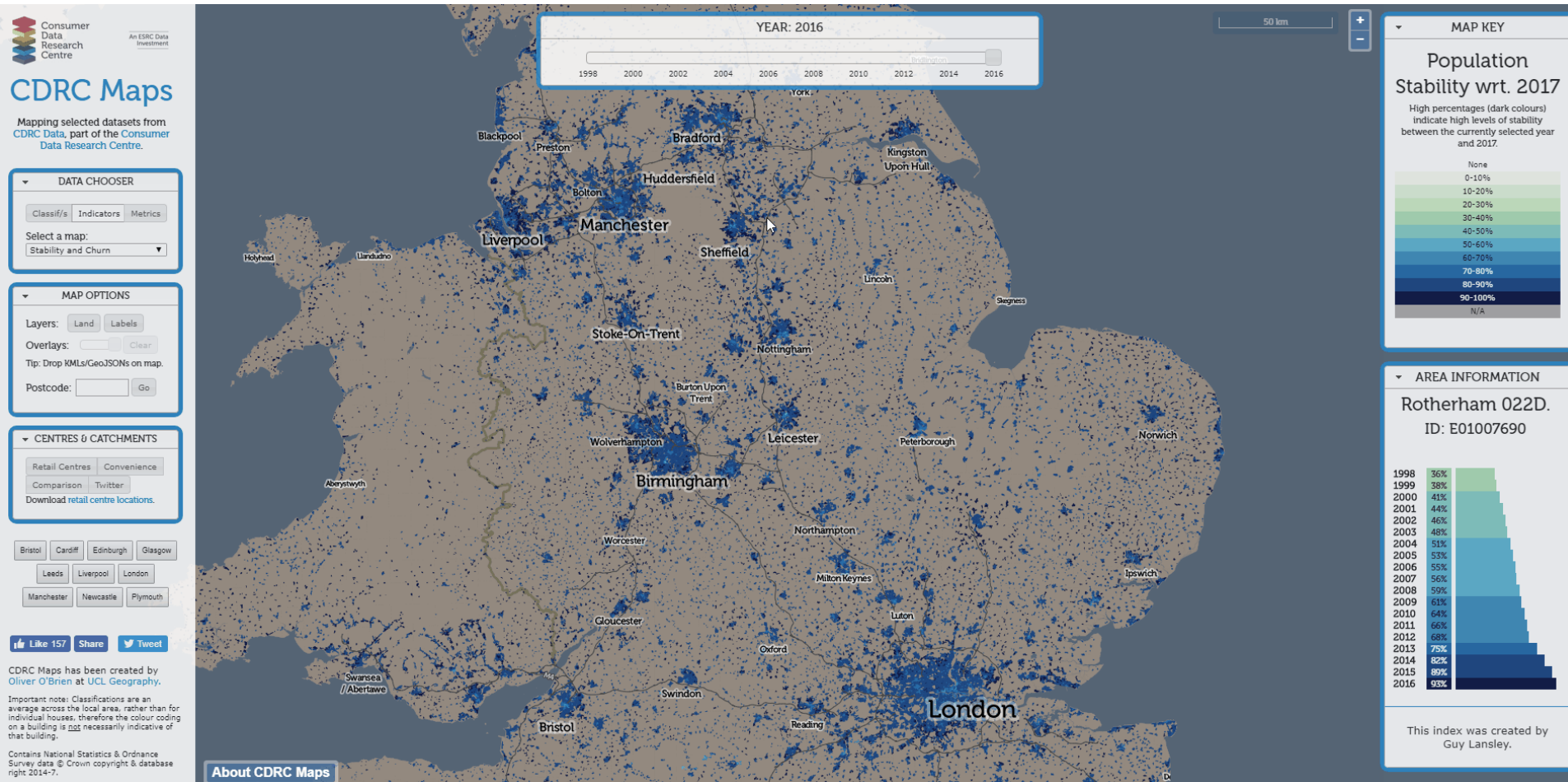
About CDRC Maps



CDRC Maps Beta

https://maps.cdrc.ac.uk/index_beta.php#/indicators/

Population Churn

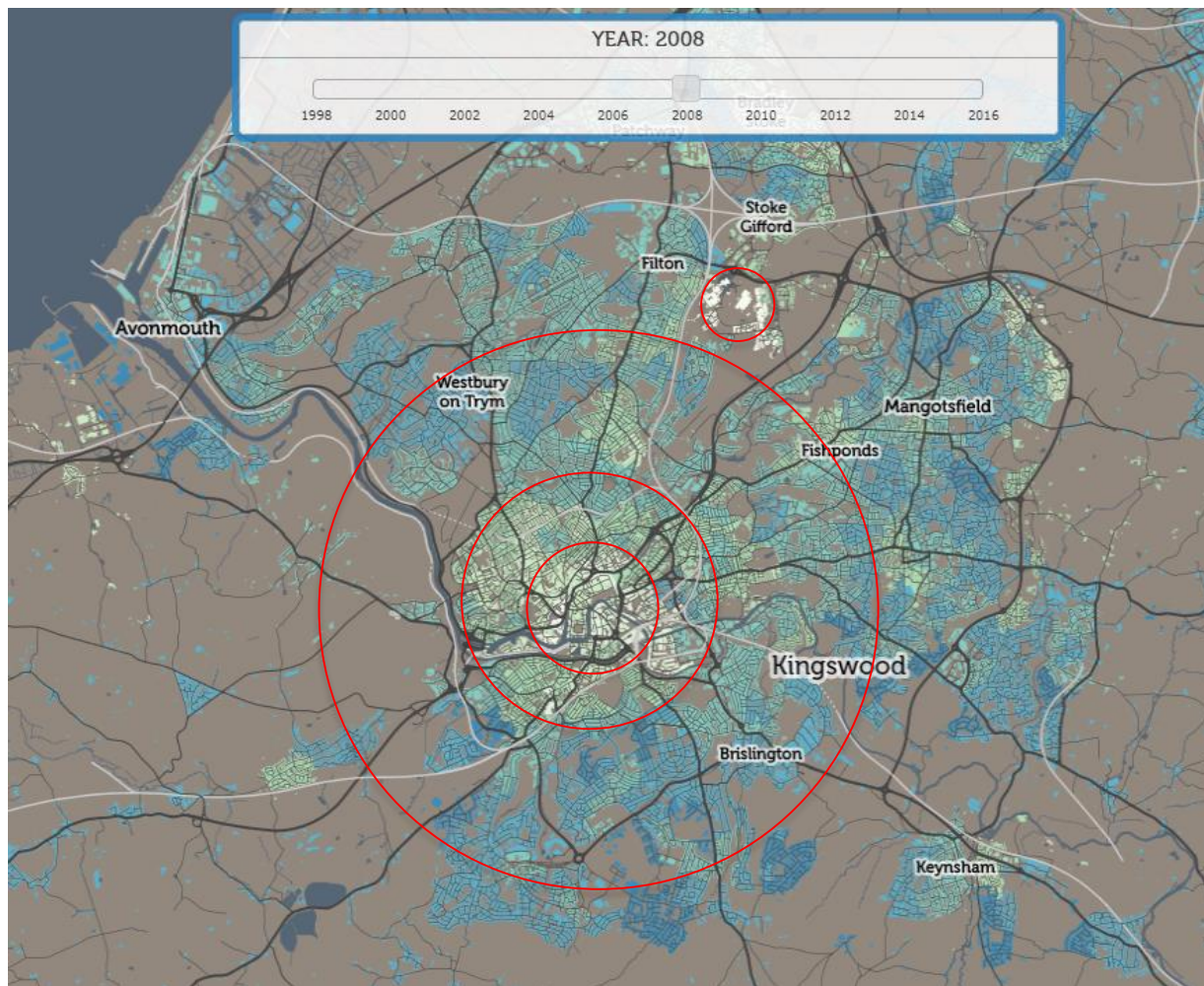




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Population Churn



CDRC Maps Beta

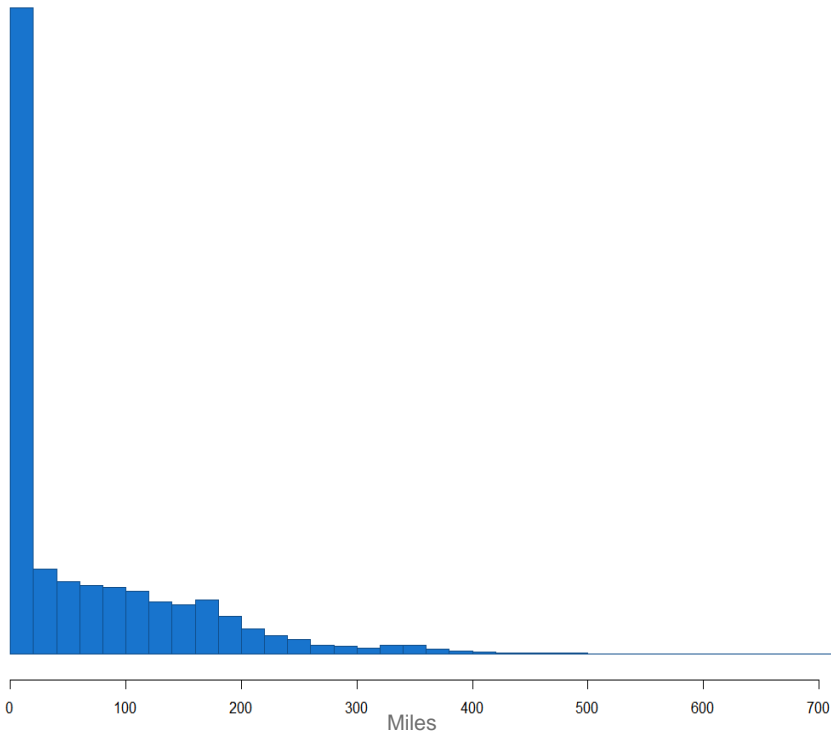
https://maps.cdrc.ac.uk/index_beta.php#/indicators/



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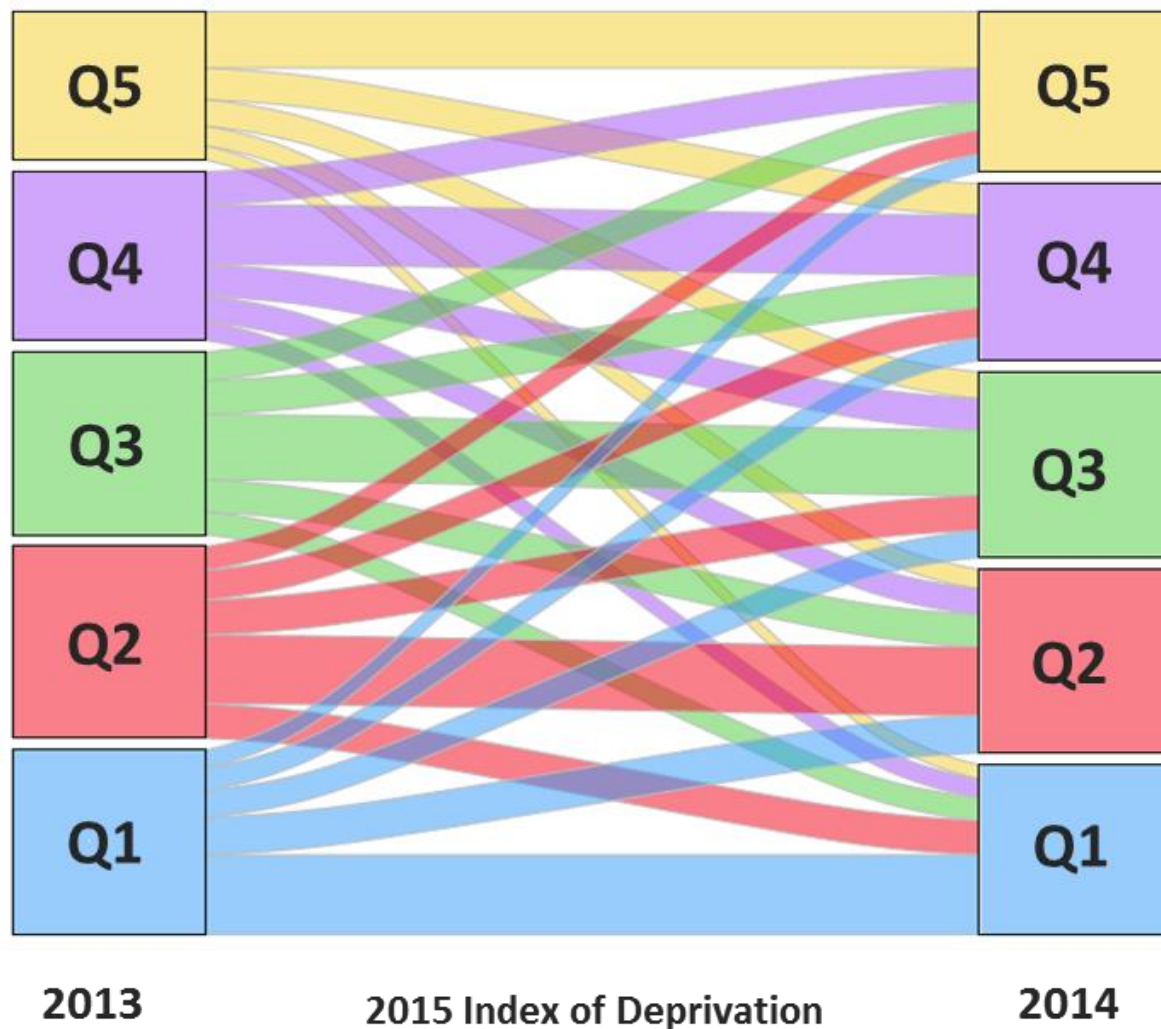
- Flows between large urban districts
- Flows between neighbouring districts
- Median move of 20.97 miles



Estimating Migration



Social Mobility



Lansley and Li (2018) Consumer registers as spatial data infrastructure and their use in migration and residential mobility research. *Forthcoming...*

The CDRC Masters Research Dissertation Programme





January

Projects are advertised on the CDRC website

Jan - Apr

The student application process is open. The CDRC will forward selected CVs and cover letters.

May - Aug

Research is undertaken either at the students own institution or on-site with the industry sponsor

September

Dissertations are submitted to the CDRC and industrial sponsors

October

Participants are invited to an Academic conference where the prizes are awarded

Sponsors (2012-17)

YOUR M&S

Sainsbury's



The co-operative

John Lewis

TESCO

WHITBREAD

DIXONS RETAIL
BRINGING LIFE TO TECHNOLOGY



British Gas

e-on



BARCLAYS



SHOP DIRECT

Knight
Frank

CLUTTONS



Ham
mer
smith
LONDON

City of Westminster

goHenry

easyJet



CACI

Barbour ABI

Thomas Cook

JAYWING

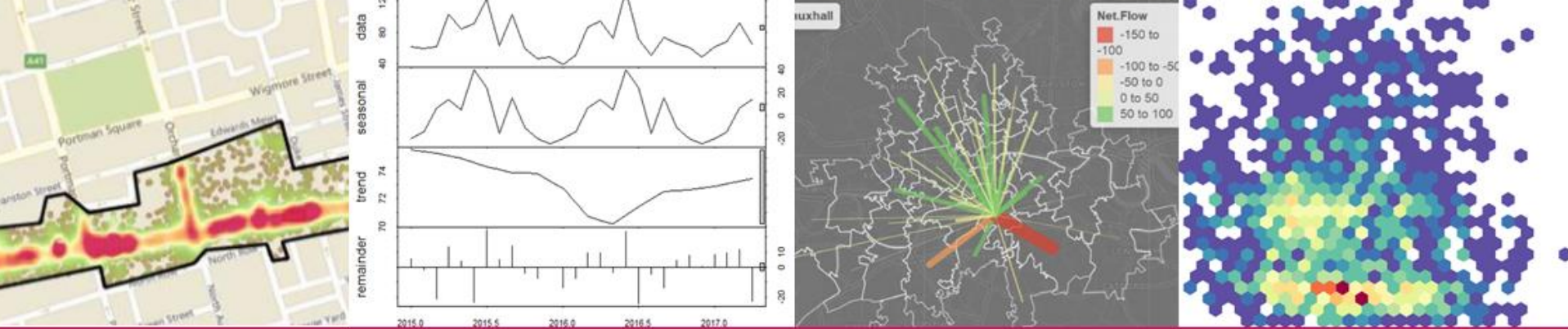
movement
strategies

Experian™



Students (2012-17)





The programme offers students a unique opportunity to apply their skills to **real-world problems** and to gain valuable experience working with **commercial datasets**



ALICE

Identifying fuel poverty characteristics through LON consumer records and geo-demographic segmentation data

Alexander Blane*, Andy Heywood, Ben Kooze*

*University of Leeds, UK, UK, UK

Project background

Fuel poverty is known to be a distinct social problem, which can occur across a wide array of household demographics. The labelling of households through the associated definition has been under recent review and new income-based levels of absence of fuel poverty, energy cost and stability of household income. The 1996 review definition (D10.2) provided a multi-measure update, to more accurately identify the fuel poor in the UK. E.ON wanted to deliver the review in effort to align their obligations set by the government to provide support to disadvantaged customers. As a distinct social problem the occurrence of fuel poverty across different demographics has been identified by many different studies, using a range of data sets. This dissertation presents a unique identification process, combining household residential data with commercial geo-demographic customer segmentation classification (CAMEO), not previously used in the identification of fuel poverty.

Data Methods

3.3 million E.ON customer data records were received with CAMEO classifications attached. Customers associated with selecting a viable customer samples reduced the data set to 2.1 million records. Record eligibility was selected by the following criteria: reasonable consumption values and being a dual fuel customer (reducing the data set approximately). Carrying out the filtering by use of the 20th software SPSS, enabled the justified selection to be made, allowing for subsequent fuel poverty analysis.

Key findings

From the 2.1 million dual fuel customers, the fuel poor was identified using the fuel definition (D10.2). This presented 211,441 households who were regarded as being below the fuel poverty threshold, a population representing 9.7% of the E.ON customer sample. This record provided the high-resolution data sample displaying the characteristics of the fuel poor population as a whole. Figure 1 shows the distribution of the fuel poor population across England and Wales, with the highest concentrations appearing high levels of fuel poverty in the regions of Liverpool, Manchester and the West Midlands.

Proportionately the fuel poor record possesses larger quantities of dual-fuel heating, whilst more recently built residences, particularly detached and

semi-detached are less likely to house the fuel poor (Figure 2).

The associated depth of fuel poverty has been examined, presenting evidence that the composition of the fuel poor population is diverse within itself. Most notably the increase in the proportion of council tax-band A households, the highest disparity being over 6,000 households.

To validate the selection of fuel poor made statistical comparison to a previous study was made. A Pearson's correlation coefficient of 0.584 ($p < 0.005$) with an independent study by the Centre for Sustainable Energy, on the same geographic resolution was found. Predictive modelling presented no statistically significant correlations between variables in predicting fuel poverty, reassuring the complexity of the social issue whereby variables can require one another.

Attempts to generate a predictive model from the most influential characteristics in determining fuel poverty were conducted.



Figure 1: Kernel density map of fuel poor customers across England and Wales

Value of Research

Results presented in the study can be utilised by E.ON through prediction of customer-specific marketing strategies aiming to alleviate fuel poverty amongst its customer base. Information produced will also enhance the understanding of the distribution of the fuel poor by displaying the distribution of the fuel poor and highlighting the most prevalent characteristics, supporting previously published literature.

Neural network model prediction was designed and trained for both January and February to recognise associations with vulnerability on new unseen data.

e-on

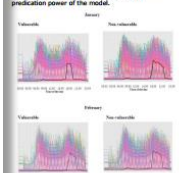
British Gas

Customers from smart meter data?

[H]eywood, Andy Simpson*

British Gas

Results have shown that model has prediction power yet it may depend on number of hidden nodes that are selected. The model has a prediction accuracy of 0.5 as zero and above as 1 gave a prediction accuracy of 70% on average regardless of the number of nodes. Further research may consider inclusion of variables on energy and geographic characteristics that may well contribute to prediction power of the model.



Average daily energy profiles of vulnerable and non-vulnerable households in January and February

Value of the Research

The extent to which analysis of gas consumption from smart meters was analysed in current academic literature is quite limited and for British Gas, it is also the first time that gas consumption data has been attempted for predictive analysis. Thus, the paper opens up a clear possibility to use machine learning techniques not just for operational research but also for public policy research that aims at informing policy interventions in the energy sector. As a student, I greatly appreciated the opportunity as I was shown not just how retail analysis can contribute to social science but also had a great chance to get a real insight into operational research through learning from British Gas experts and being a part of a large retailer.

Against official social comparison, the buffer and comparison area that represented the largest losses was a 10km buffer with a 10,000+ square foot footprint intersect. National turnover losses to the Co-Operative convenience stores were forecasted as

British Gas

The co-operative food

Location of the current Sunday Trading areas' convenience stores

Steve* Mark Coleman*

The Co-operative

£33,294. Following the geospatial analysis it was decided a more in-depth statistical review was needed in order to make forecasts for individual stores. Multi-linear regression Model: This model provided accurate store by store forecasts. The national forecasts were very similar to the first model further validating both forecasts. The forecasted annual losses for the Co-Operative stores over 280 square metres were £21,790, however when the model was applied to the Co-Operative stores over 280 square metres there were forecasted gains in turnover of £90,649. The forecast is likely to be an overestimation due to the model not being purpose built for forecasting for stores over 280 square metres. Although possibly inaccurate the predicted gains for the stores over 280 square metres highlights one of a number of ways the impact of the changes can be mitigated against.

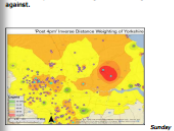


Figure 1: Kernel density map of fuel poor customers across England and Wales

Value of the Research

The results effectively forecast the potential losses to the Co-Operative convenience stores of £31-£33K. The possible gains have also been demonstrated with a forecast for stores over the size of 280 square metres. The method to mitigate against such losses were fully examined to form the advice given to the Co-Operative as a result of the potential changes in the Sunday Trading Laws. Whilst a forecast of new lines will not be a deviation, the multi-linear regression model brought a store by store forecast that will enable the Co-Operative to assess the impact on the individual stores where the lines are brought in to place.

Furthermore, customer comparison used data, segments or sufficiency of processes. Further, the handling of cabin layouts seemed to cause dissatisfaction and as did the information/communication on delivery. Service encounters seem to be one of the most important drivers for customer satisfaction. A friendly

easyJet

satisfaction and dissatisfaction by mining cabin feedback

Choussat* Maria Streuf*

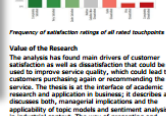
easyJet

and helpful crew drives customer satisfaction, whereas a crew that is rude, does not smile or does not take dress disqualification. Announcements of the cabin crew have room for improvement. In case of delays or changes, customers are not satisfied with the information they get and the style of communication of the crew. The cabin crew plays an important role in safety and security.

The cabin bag guarantee policy seems to be one of the main drivers of customer dissatisfaction, as it is discussed mostly in negative sentiment context.

Customers appreciate processes that run smoothly and efficiently and dislike disruptions, delays and waiting times. The longer customers have to wait, the less satisfied they are. The facilities at the boarding gate seem to be very important. Customers complain if they are in the wrong terminal or have to go long ways.

Many customers state that they are neither interested in food and drink, nor did they pay attention to the menu or purchase anything. This means that cross-selling potential is not realised. The selection and the quality of the food are discussed controversially. Customer segmentation might give more insights.



Frequency of satisfaction ratings of all retail households

Value of the Research

The analysis has found main drivers of customer satisfaction. The analysis of retail households can be used to improve service quality, which could lead to customers purchasing again. This paper opens up a clear possibility to use machine learning techniques not just for operational research but also for public policy research that aims at informing policy interventions in the energy sector. As a student, I greatly appreciated the opportunity as I was shown not just how retail analysis can contribute to social science but also had a great chance to get a real insight into operational research through learning from British Gas experts and being a part of a large retailer.

Neural network model prediction was designed and trained for both January and February to recognise associations with vulnerability on new unseen data.

Location of retail centres in England and Wales

Steve* Mark Coleman*

The Co-operative

£33,294. Following the geospatial analysis it was decided a more in-depth statistical review was needed in order to make forecasts for individual stores. Multi-linear regression Model: This model provided accurate store by store forecasts. The national forecasts were very similar to the first model further validating both forecasts. The forecasted annual losses for the Co-Operative stores over 280 square metres were £21,790, however when the model was applied to the Co-Operative stores over 280 square metres there were forecasted gains in turnover of £90,649. The forecast is likely to be an overestimation due to the model not being purpose built for forecasting for stores over 280 square metres. Although possibly inaccurate the predicted gains for the stores over 280 square metres highlights one of a number of ways the impact of the changes can be mitigated against.

negatively to health condition of the retail environments. Residential and workplace groups of variables are similarly important predictors and while considering them requires greater portion of the variance of the retail performance, this difference is not significant in view of them both used due to simplicity. The most important predictors were found to be percentages of non-retailers, workplace population with no qualifications, workplace population with low qualifications, population employed in manufacturing sector and population employed in intermediate/tertiary/retail/professional sector, together accounting for 21.8% of the variance of the retail performance. This might vary depending on the underlying data, but in general, socioeconomic (SES), industry (employment) and educational variables (qualifications) are the most important (Table 1). While age, family composition and ethnicity structure proved to be of a minor importance.



Figure 1: Kernel density map of fuel poor customers across England and Wales

Value of the Research

The results effectively forecast the potential losses to the Co-Operative convenience stores of £31-£33K. The possible gains have also been demonstrated with a forecast for stores over the size of 280 square metres. The method to mitigate against such losses were fully examined to form the advice given to the Co-Operative as a result of the potential changes in the Sunday Trading Laws. Whilst a forecast of new lines will not be a deviation, the multi-linear regression model brought a store by store forecast that will enable the Co-Operative to assess the impact on the individual stores where the lines are brought in to place.

Furthermore, customer comparison used data, segments or sufficiency of processes. Further, the handling of cabin layouts seemed to cause dissatisfaction and as did the information/communication on delivery. Service encounters seem to be one of the most important drivers for customer satisfaction. A friendly

LDC

customer reviews

Choussat* Maria Streuf*

easyJet

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Argos

the co-operative food

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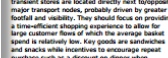
Location Statistics to help Co-Op better

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Accuracy of tests (%) depending on the number of items generated by an LDC team member

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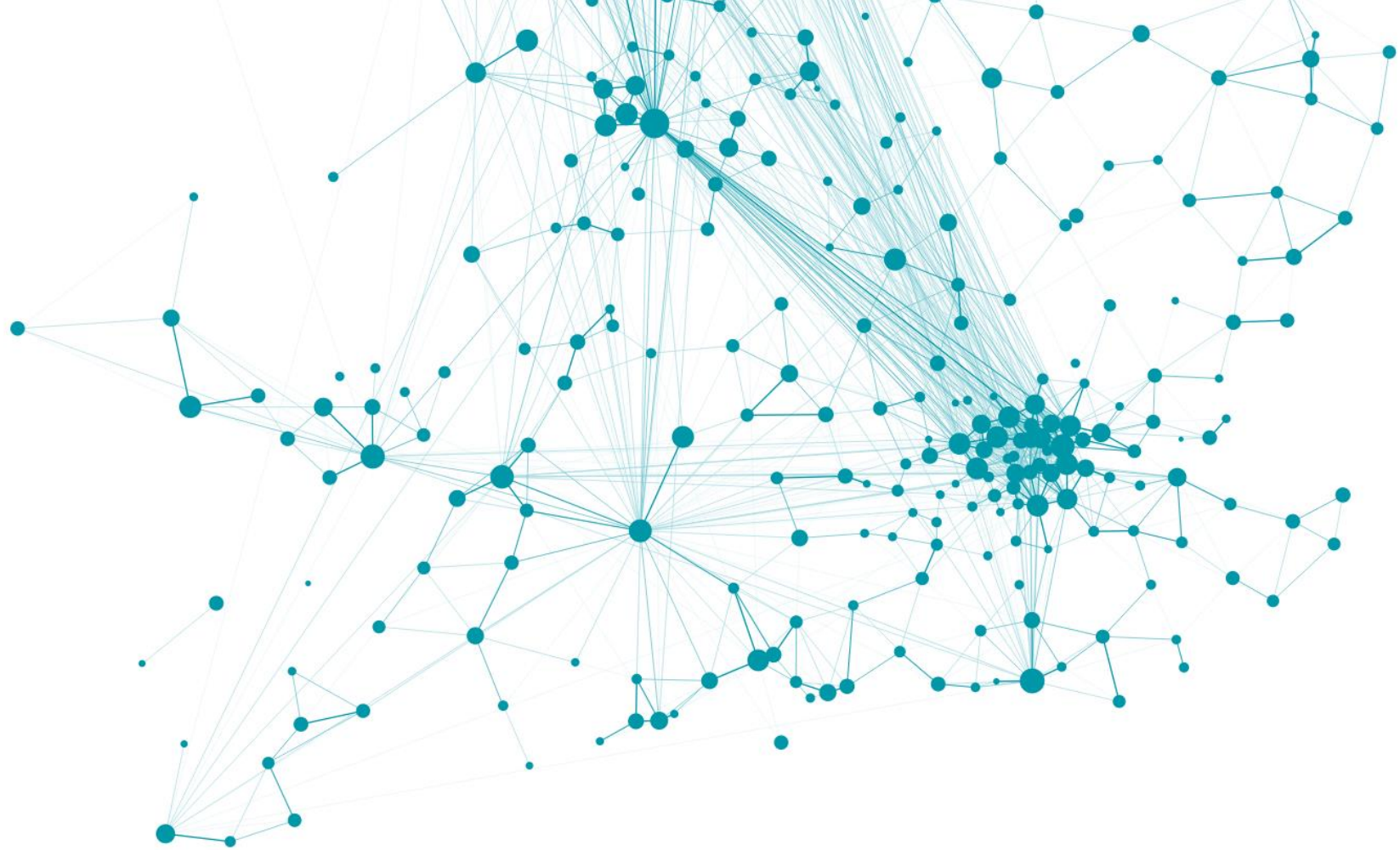
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Guy Lansley
g.lansley@ucl.ac.uk
@GuyLansley

www.cdrc.ac.uk/retail-masters