

An ESRC Data Investment

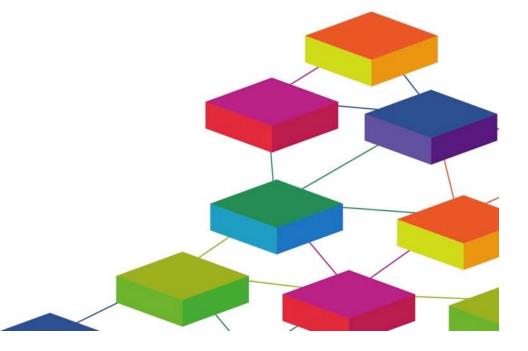






The Provenance of Consumer and Social Media Data

Paul Longley and colleagues



4th International Conference on Data Management Technologies and Applications, Colmar, 20-22 July



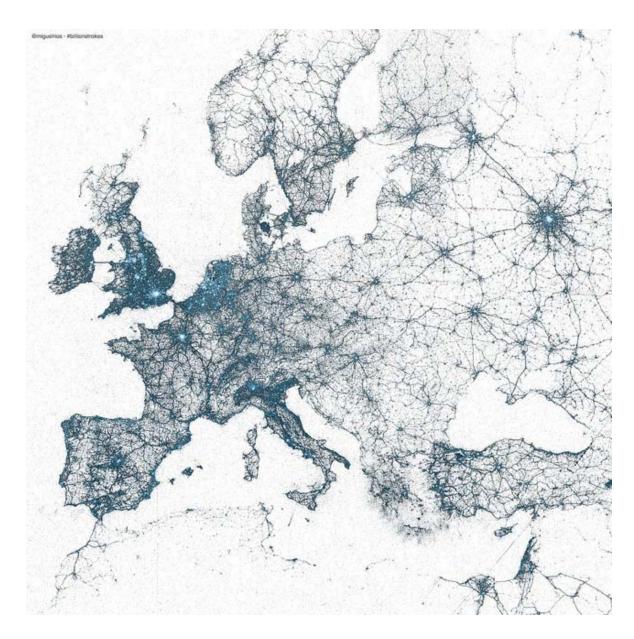
'Big' consumer data

- Real share of data: 'exhaust'
- Naïve empiricism?
- SDI?
 - Incompatible measures and units
 - Big (geotemporal) Data and the linear research design
 - Data linkage (but to which 'populations'?)
- Front loading of modelling assumptions to model individuals through space and time
 - Horses for courses approach to data creation and maintenance



Tweets – pretty but what value?

The European distribution of a billion global Tweets between 2011 and mid-2013.





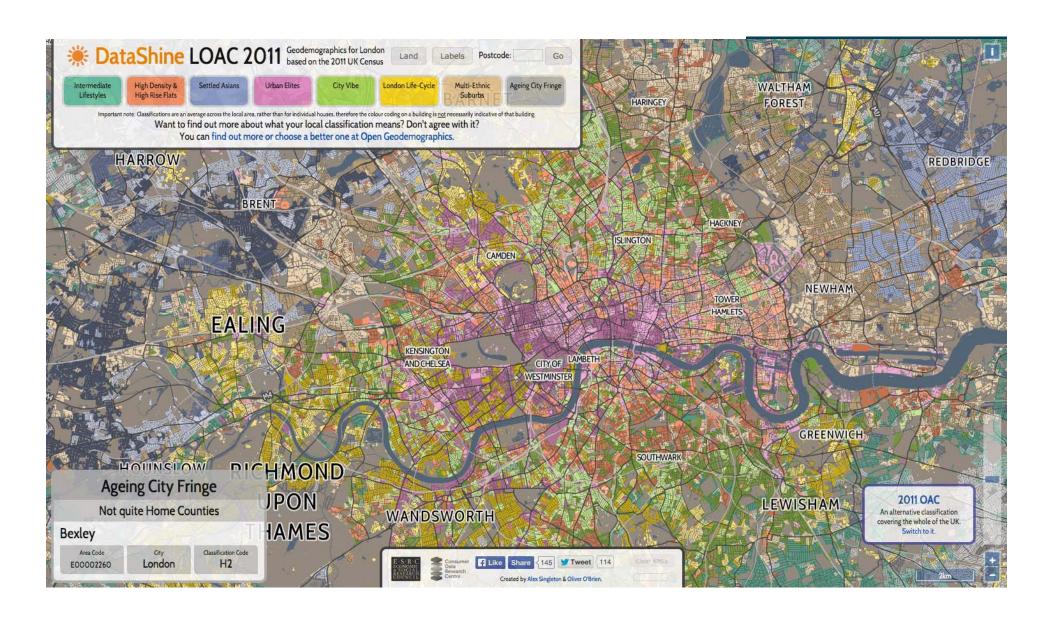
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Consumer Data Research Centre (CDRC)

- Multi- institution laboratory (c.£12m) that discovers, mines, analyses and synthesises consumer-related datasets from around the UK.
- Creates, supplies, maintains and delivers consumer-related data to a range of end users
 - CDRC-Public (Open, maps)
 - CDRC-Stakeholder / Archive
 - CDRC-Secure
- Programme of research and outreach activities.





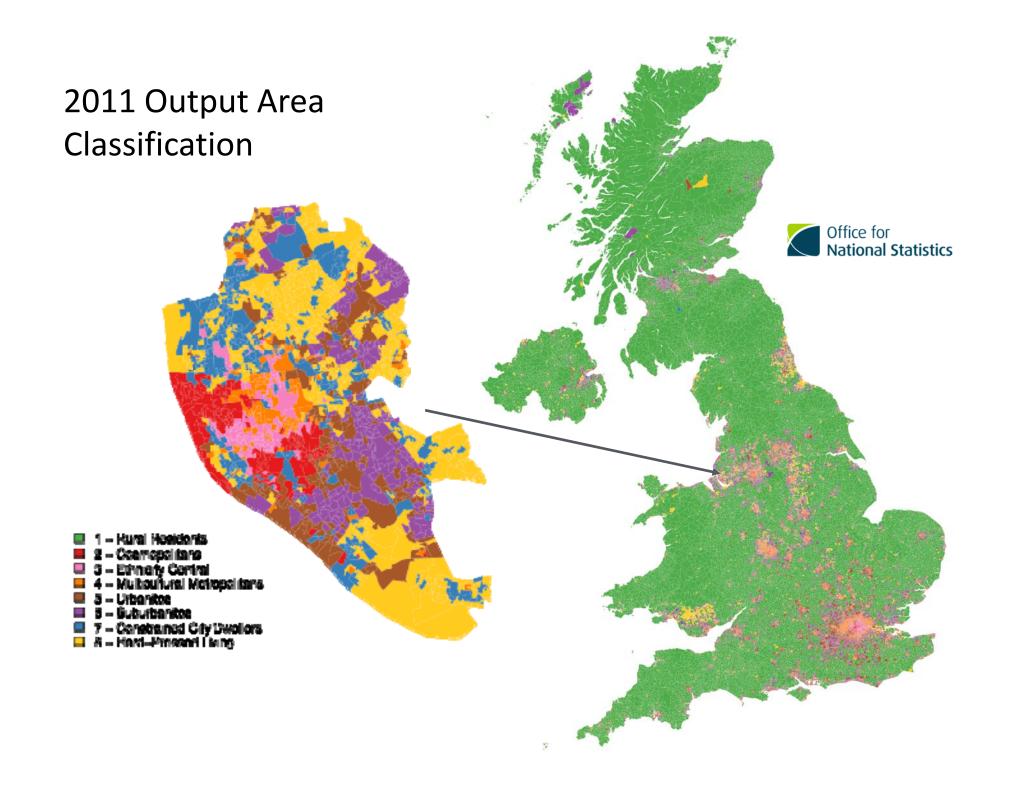


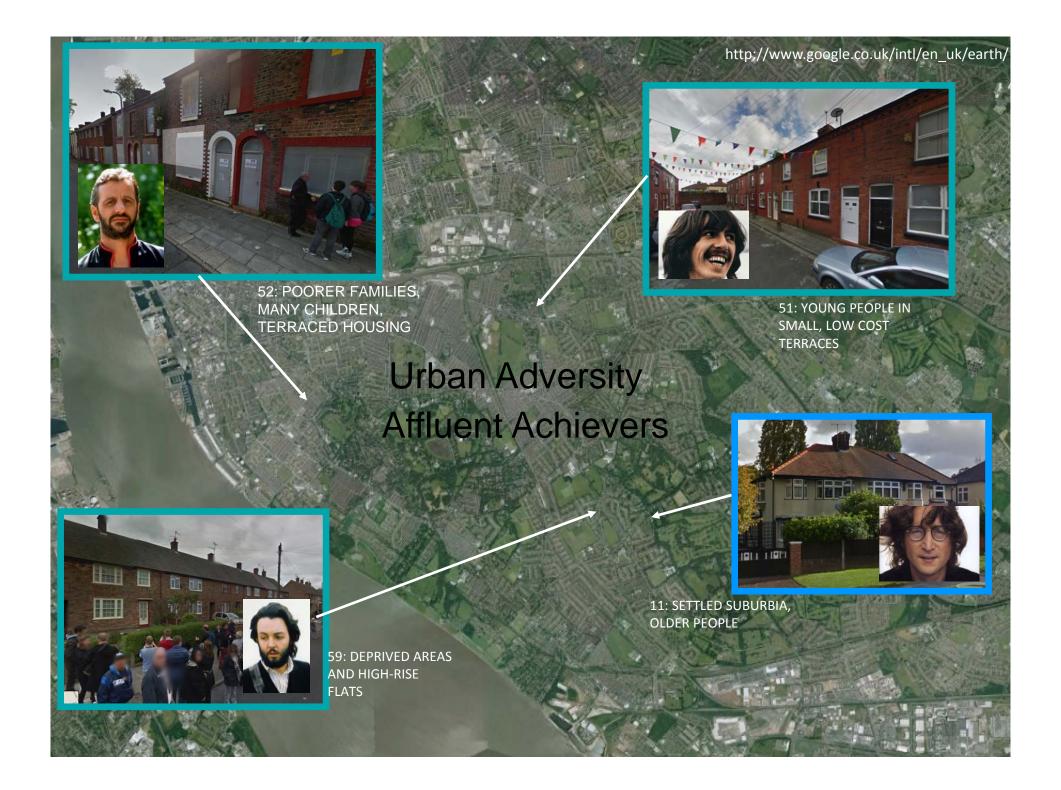
An ESRC Data



Geo-temporal demographics

- Kaleidoscope and mosaic
- Activities not night time residence (Alex Singleton)
- Process and dynamics known, but not generalised pattern that they fit



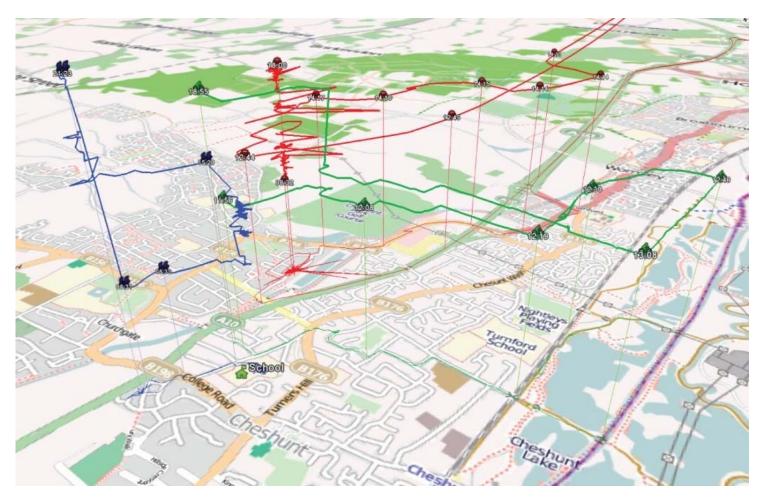






Geo-temporal demographics

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Schematic representation of weekend activities of three children in Cheshunt, UK.

(Reproduced with permission of Yi Gong: base image Courtesy www.openstreetmap.org)







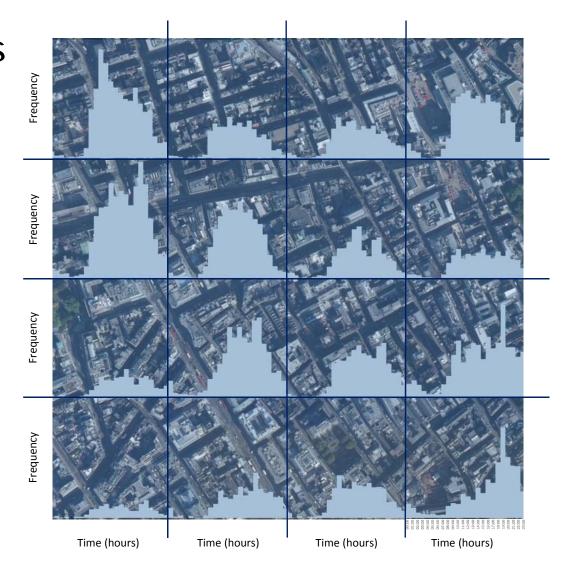
Case Study (1): Twitter demographics





Twitter estimated footfall in Soho

 The frequency of geotagged Tweets across space and time can tell us about the dynamics of a city (courtesy Guy Lansley) The average weekday activity in 2013



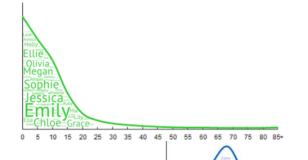
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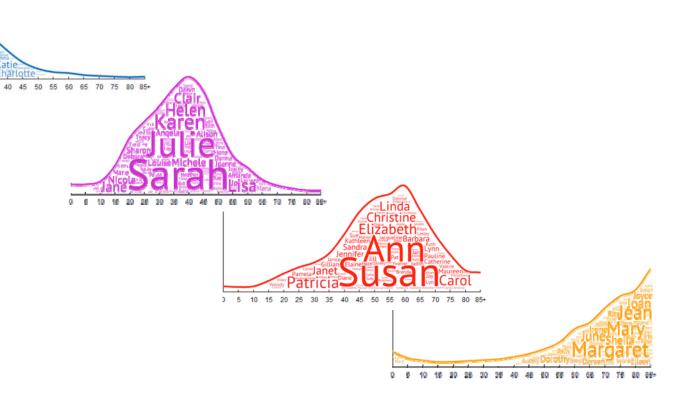






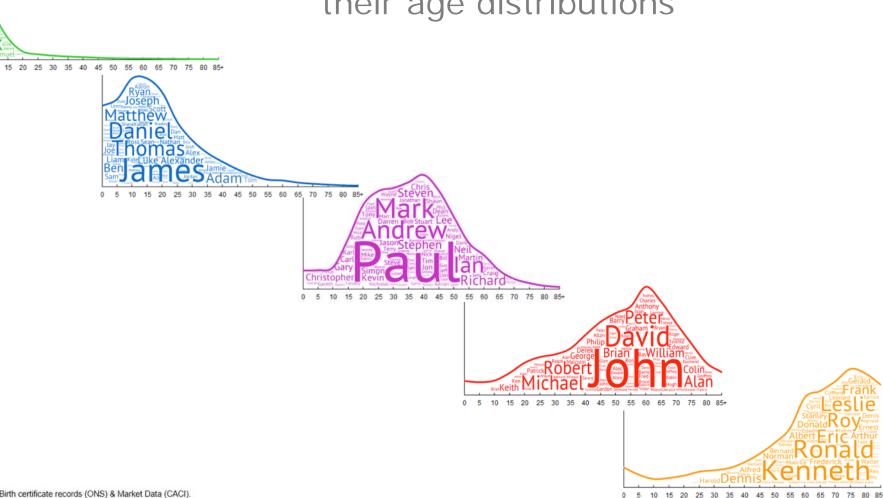


5 clusters of forenames based or their age distributions















Inferred demographic structure of Tweeters







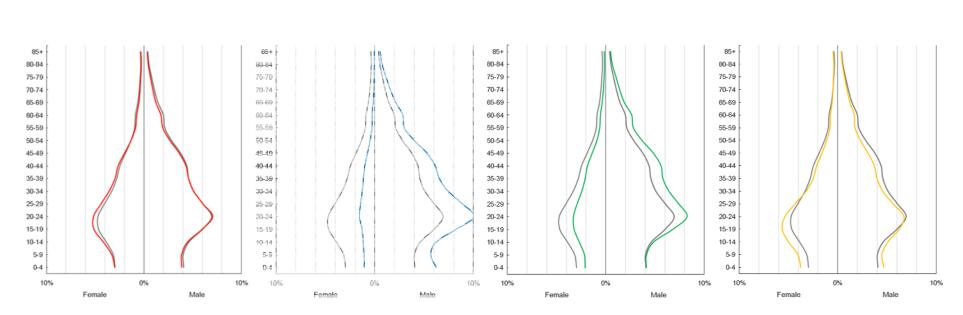


The O2 Arena

The Emirates stadium

Canary Wharf

Westfield Stratford





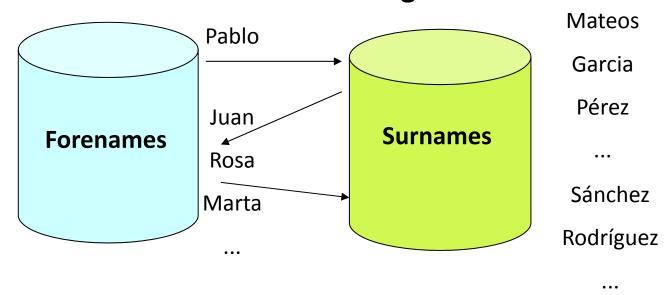




Onomap classification

Forename-Surname clustering (based on Hanks and Tucker, 2000)

Global names registers

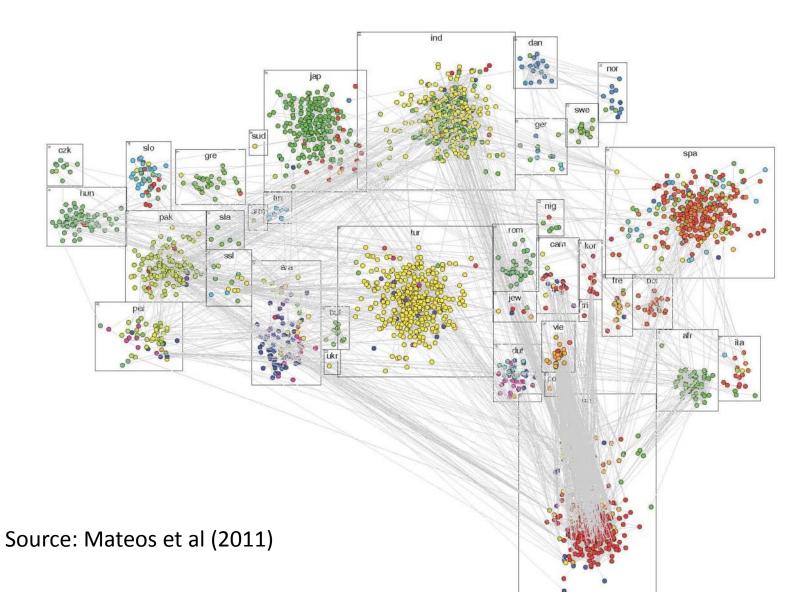


- Several iterations until self-contained cluster is exhausted
- Cluster assigned a cultural, ethnic & linguistic Onomap type
- Probability of ethnicity assigned to each name





WorldNames CEL clusters





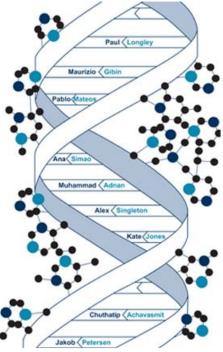
Cultural, Ethnic and Linguistic roots of names

OnoMAP is a new way of classifying people and the places they live, based on our common cultural, ethnic and linguistic roots.

OnoMAP analyses common patterns of forenames and surnames using one of the world's largest databases of people drawn from 28 countries. The OnoMAP classification covers over 500,000 forenames and 1 million surnames, and most exhibit distinctive geographic patterning.







Guy Lansley – English
Alyson Lloyd – Welsh
Kira Kowalski - Polish
Wen Li – Chinese
Jens Kandt – Danish
Muhammad Adnan – Pakistani
Syed Uddin - Bangladeshi



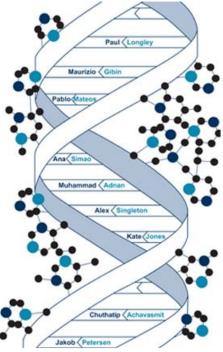
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What's in a Surname (NGM, 2011)

GEOGRAPHY



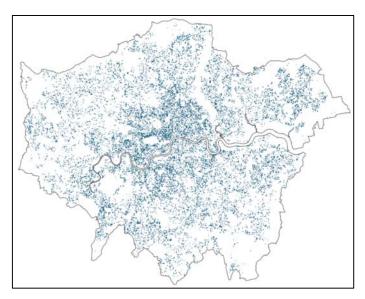
© London Media

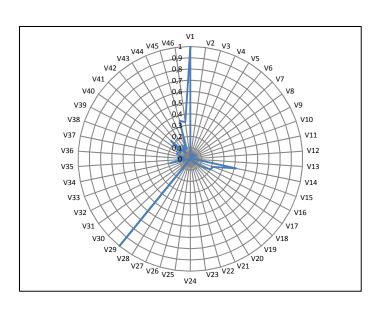
MAP MINA LIU, DUVER LIBERTI, NOM STAFF SOURCE: JAMES CHESHIRE, FAUL LONGLEY, AND FABLO MATEOS, UNIVERSITY DOLLEGE LONDON



Geo-temporal Demographics of Social Media

- Group A: London Residents
- Tweets made near residential locations.
- Tweets made on weeknights or weekends.

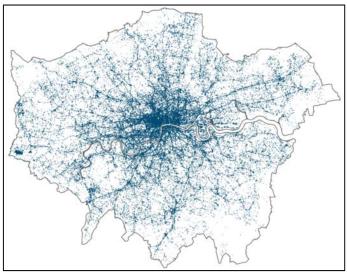


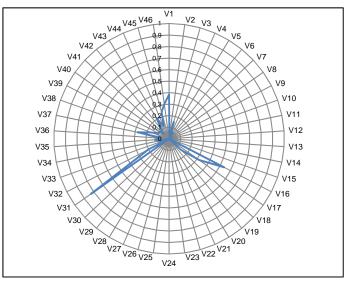




Geo-temporal Demographics of Social Media

- Group D: The Daily Grind
- Tweets made during peak weekdays and nights.
- Sent from residential locations or in transit.

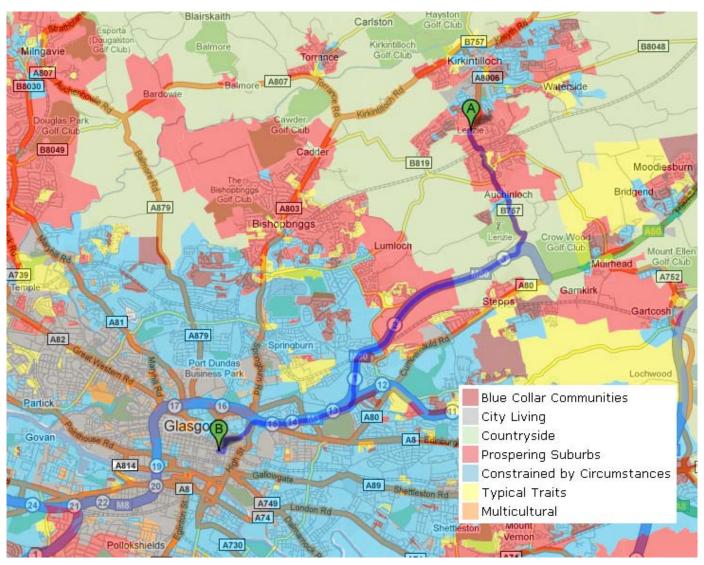






Case study (2): Social mobility and life chances

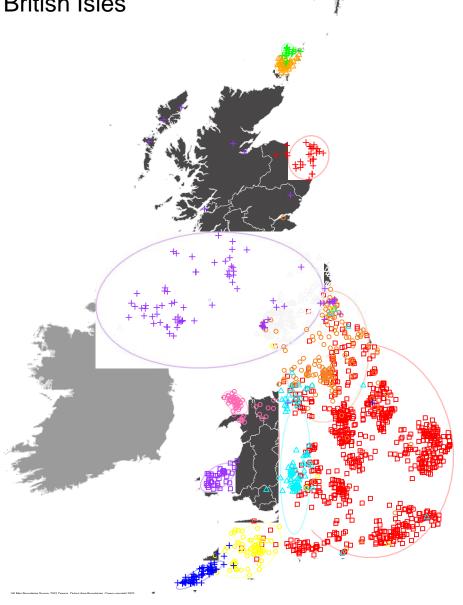




The local geodemography of Glasgow, showing the 7.8 mile route that links communities with life expectancies of 54 and 82

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The People of the British Isles



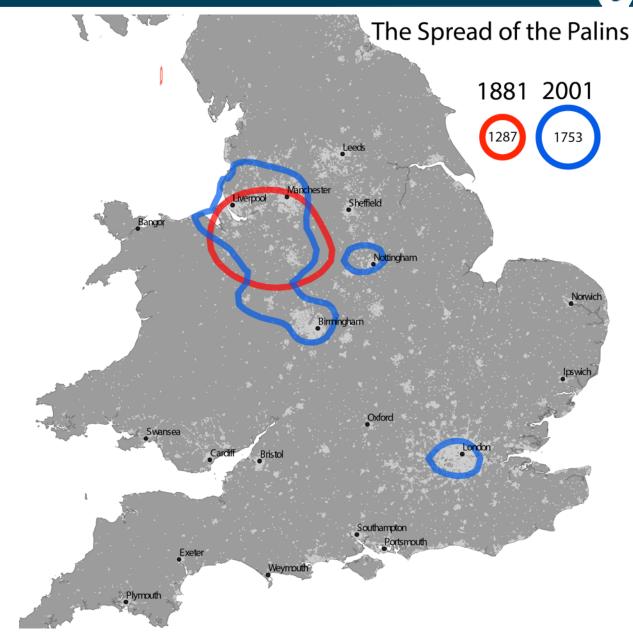


Names in Great Britain

TABLE 1: A CATEGORISATION OF BRITISH SURNAMES. ADAPTED FROM BARKER ET AL., 2007.

		W-1			
Category	Example	Explanation			
Occupational (Metonyms)					
Profession	Smith	Blacksmith/ metal worker			
Office/ Trade	Reeve	Chief magistrate/ overseer			
Rank/Status	Knight	A knighted person			
Occupation Features	Falconer	One who kept/trained Falcons			
Local Surnames (50% of surnames)					
Toponymic (from landscape)	Rivers	Dweller near river			
Toponymic (from village/ region)	Cornwall	Man from Cornwall			
Habitation (residence)	Gate	Habitation at/near a gate			
Habitation (work)	Hall	A worker at the hall.			
Surnames of Relationship					
From personal name (patronymic)	Johnson/ Jones	Son of John			
From personal name (metronymic)	Margaretson	Son of Margaret			
Personal name from other relative	Also: Johnson	Related to John			
Personal name from diminutive	Dickens	Son of Dick (Richard)			
Clan or tribal names	MacBain	Related to the MacBain clan.			
Nicknames					
From animals	Fox	Slyness or other attributes			
From characteristic traits	Careless	Free from care/ responsibility			
From objects	Shorthose	Someone who wore short boots			
From physical features	Little	A small person			
From times and seasons	Pasque	Person born at Easter			
From iconic description	Drinkwater	Heavy drinker			





Courtesy: James Cheshire



gbnames.publicprofiler.org

Social Demographics

Social Demographics	Statistics
Category of surname	Celtic; Irish; Starting with O-
Mosaic type with highest index #	Counter Cultural Mix
Index of top Mosaic type *	227
% of people with a more rural name	94
% of people with a more high-status name	92
Cultural, Ethnic, Linguistic categories of surname	British, Irish

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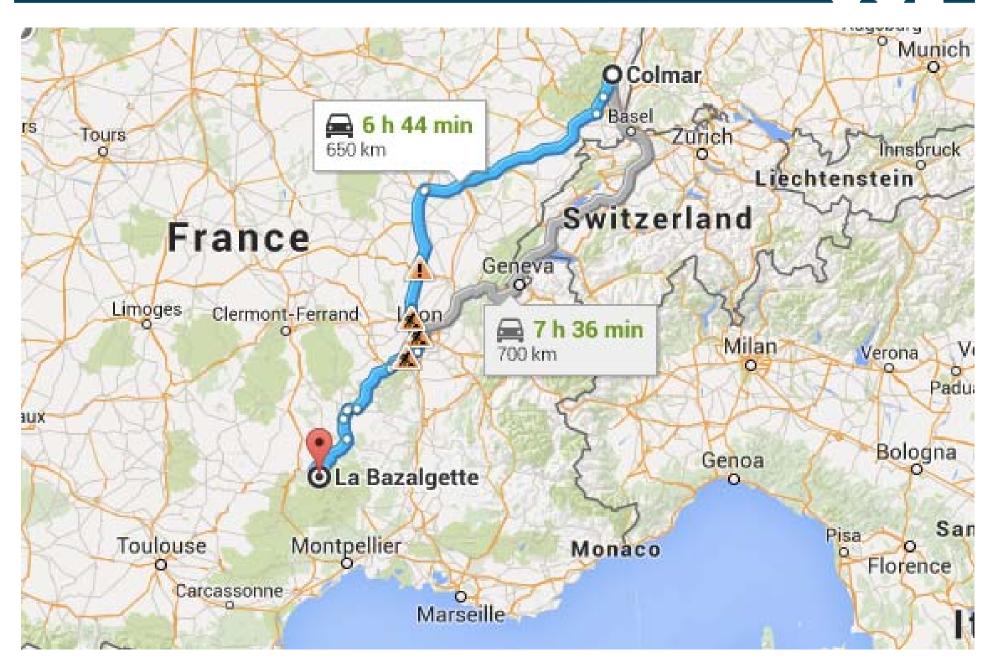




Table S2: Rare Oxbridge versus non-Oxbridge Surnames, 1800-29

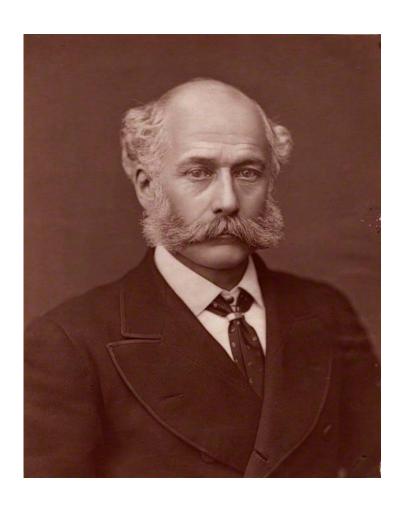
Oxbridge		Non-Oxbridge	
Agassiz	Brickdale	Agnerv	Bodgett
Anquetil	Brooshooft	Allbert	Boolman
Atthill	Bunduck	Arfman	Bradsey
Baitson	Buttanshaw	Bainchley	Breckill
Barnardiston	Cantis	Bante	Callaly
Bazalgette	Casamajor	Barthorn	Capildi
Belfour	Chabot	Bavey	Carville
Beridge	Charretie	Bedborne	Cavet
Bleeck	Cheslyn	Bemond	Chanterfield
Boinville	Clarina	Berrton	Chesslow
Boscawen	Coham	Bideford	Chubham
Bramston	Conyngham	Bisace	Clemishaw

Source: 'Surnames and Social Mobility', Gregory Clark and Neil Cummins

http://www.econ.ucdavis.edu/faculty/gclark/ecn110a/readings/Surname%20Mobilit y%202013.pdf



Bazalgette



Surname: 'BAZALGETTE'

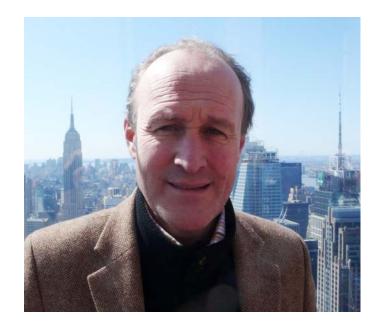
Forename	Surname	Address	Postcode
LANE	DAZALOSTTS		D114***
JANE	BAZALGETTE		BH1***
GUY	BAZALGETTE		BH1***
EMMA	BAZALGETTE		BH1***
ELIZABETH	BAZALGETTE		TW9***
VICTORIA	BAZALGETTE		LS1***
MARK	BAZALGETTE		DT1***
LUKE	BAZALGETTE		DT1***
MARIE	BAZALGETTE		DT1***
ELEANOR	BAZALGETTE		SW8***
LEE	BAZALGETTE		SA3***
ROBERT	BAZALGETTE		SA3***
ROBIN	BAZALGETTE		SA3***
RUTH	BAZALGETTE		PL1***
EMILY	BAZALGETTE		N15***
MARY	BAZALGETTE		BH1***
RICHARD	BAZALGETTE		BH1***

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http://www.econ.ucdavis.edu/faculty/gclark/ecn110a/readings/Surname%20 Mobility%202013.pdf

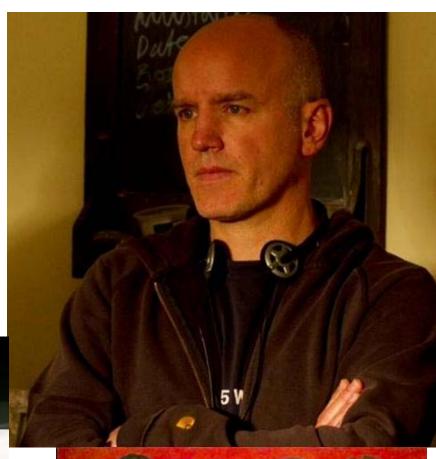
'using educational status in England 1170-2012 as an example, ... the true underlying [intergenerational] correlation of social status is in the range 0.75-0.85. Social status is more strongly inherited even than height.'

This 'stems from the nature of inheritance of characteristics within families. Strong forces of familial culture, social connections, and genetics must connect the generations. There really are quasi-physical "Laws of Inheritance."





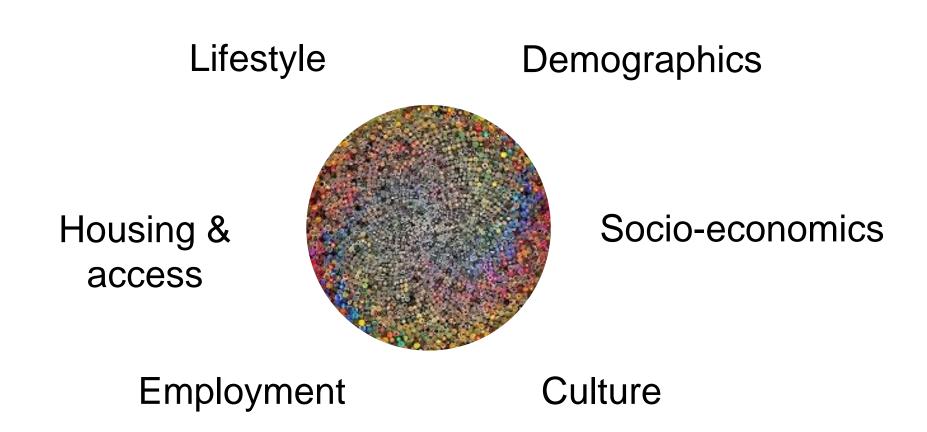






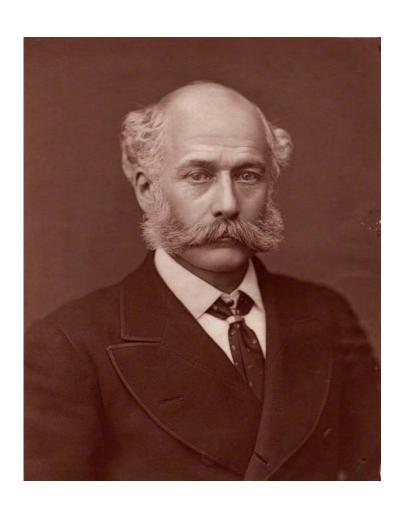


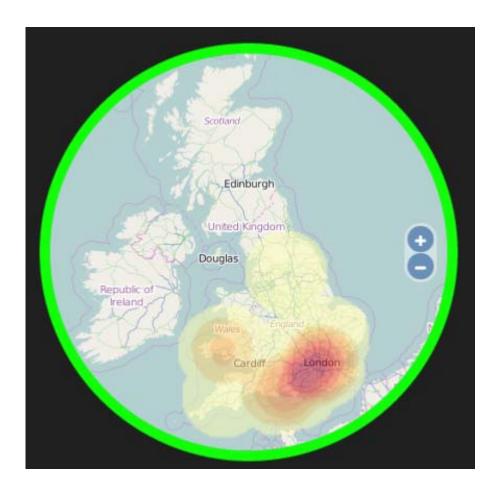
How are cities differentiated?





Bazalgette





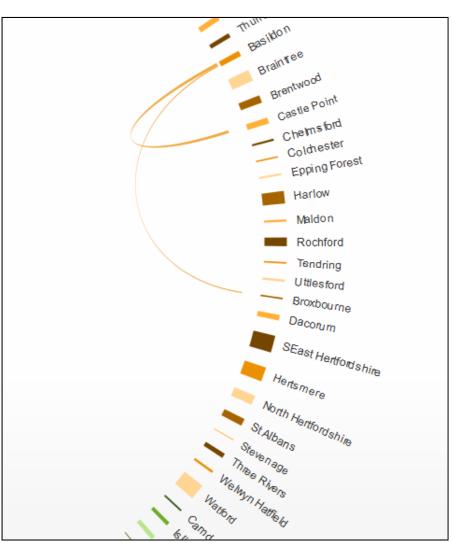
OSM, National Portrait Gallery



Initial Results

Movement out of Basildon:

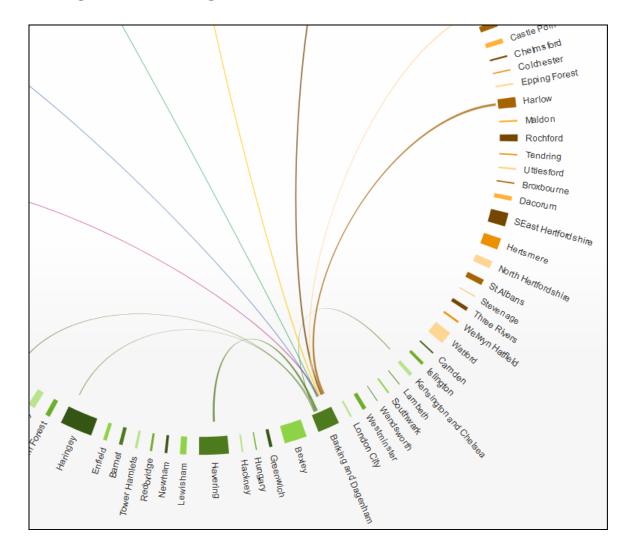






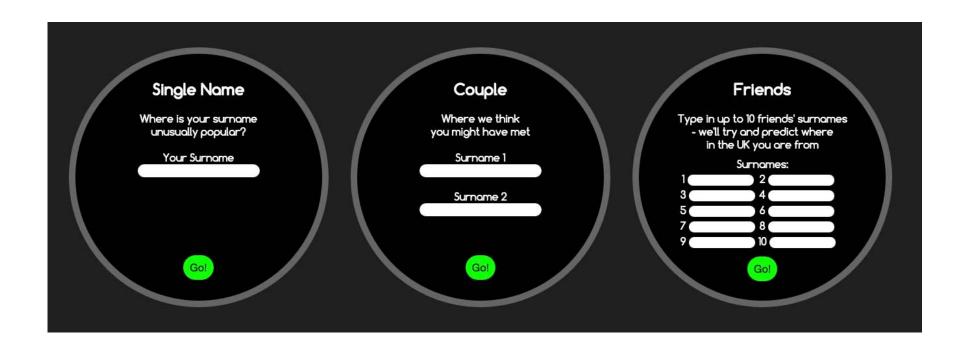
Initial Results

Movements into Barking and Dagenham:





named



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Conclusions

- Challenges of understanding geo-temporal data
 - Google flu trends; not the 'End of Theory'
 - "N = all" ??; Google Translate in a stable unchanging world but Twitter?
 - the "data exhaust" (Tim Harford); systematic bias
 - response rates and research methods: 2015 UK General Election
- Tesco 'data mining' (& Target false positives)
- Public acceptability of linkage based on anonymisation, not consent

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