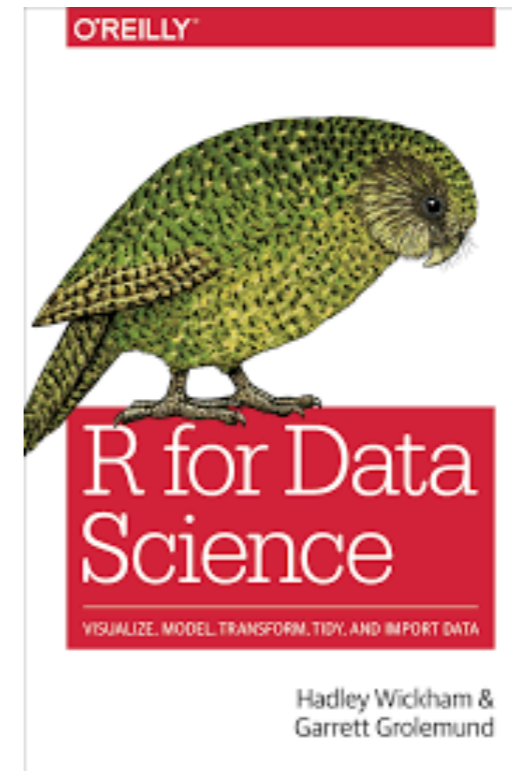




Targeted Marketing and Response Modelling

Roger Beecham
www.roger-beecham.com





Targeted Marketing and Response Modelling

Roger Beecham
www.roger-beecham.com

Targeted Marketing

Examples

- Recommender systems
- Loyalty cards
- Microtargeting
- Segmentation — RFM, geodemographics

Practice

- Select variables (demographic and behavioural)
- Select “outcomes”
- Generate target

Targeted Marketing *df.*

Use of data and analytics to

characterise customer populations, such that groups of customers likely to **respond best** to a message can be **targeted**

and marketing **messages** can be **personalised** according to customer group

Recommender systems

Recommender systems

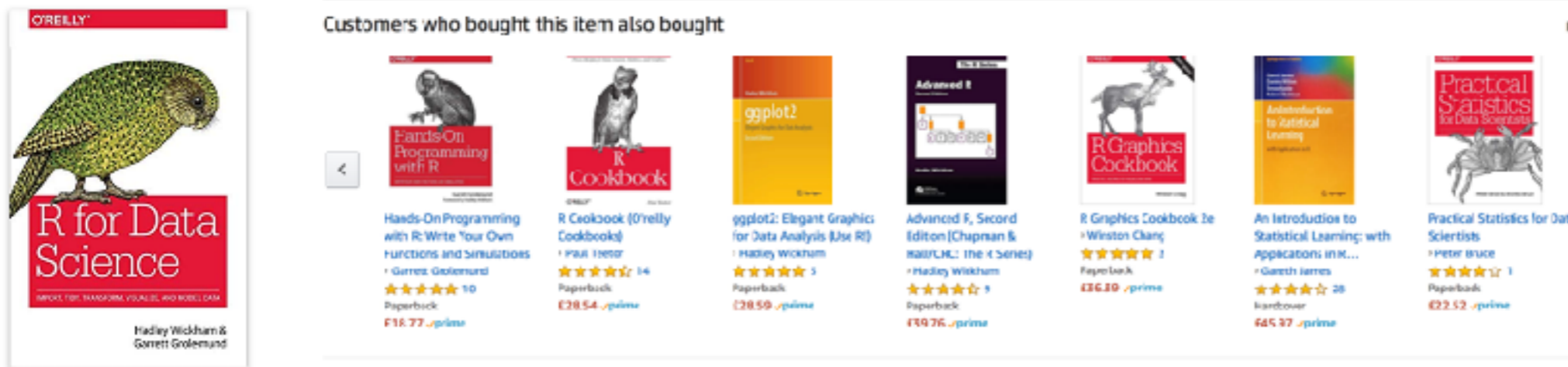


Customers who bought this item also bought

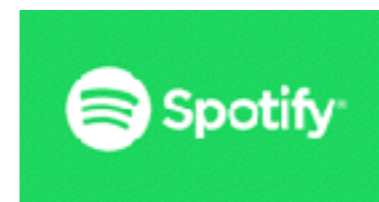
Book Title	Author	Rating	Format	Price
Hands-On Programming with R: Write Your Own Functions and Simulations	Garrett Grolemund	★★★★★ 10	Paperback	£18.77
R Cookbook (O'Reilly Cookbooks)	Paul Iker	★★★★★ 14	Paperback	£28.54
ggplot2: Elegant Graphics for Data Analysis (Use R!)	Hadley Wickham	★★★★★ 5	Paperback	£28.59
Advanced R, Second Edition (Chapman & Hall/RNL: The R Series)	Hadley Wickham	★★★★★ 5	Paperback	£29.76
R Graphics Cookbook 2e	Winston Chang	★★★★★ 1	Paperback	£26.10
An Introduction to Statistical Learning: with Applications in R	Garth James	★★★★★ 28	Hardcover	£45.97
Practical Statistics for Data Scientists	Peter Bruce	★★★★★ 1	Paperback	£22.52

Linden, G., Smith, B. and York, J. (2003) Amazon.com Recommendations: Item-to-Item Collaborative Filtering, IEEE Internet Computing, 7(1): 76-80

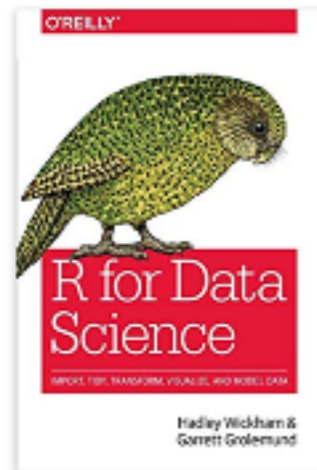
Recommender systems



Linden, G., Smith, B. and York, J. (2003) Amazon.com Recommendations: Item-to-Item Collaborative Filtering, IEEE Internet Computing, 7(1): 76-80



Recommender systems



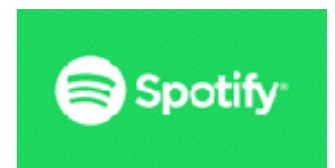
Customers who bought this item also bought



Linden, G., Smith, B. and York, J. (2003) Amazon.com Recommendations: Item-to-Item Collaborative Filtering, IEEE Internet Computing, 7(1): 76-80

content based

generate probabilities that a user will like a particular product based on past likes — e.g. spotify recommending tracks



demographic based

recommend based on similar users and past behaviour



A/B testing and personalisation

A/B testing and personalisation

EXPERIMENTATION

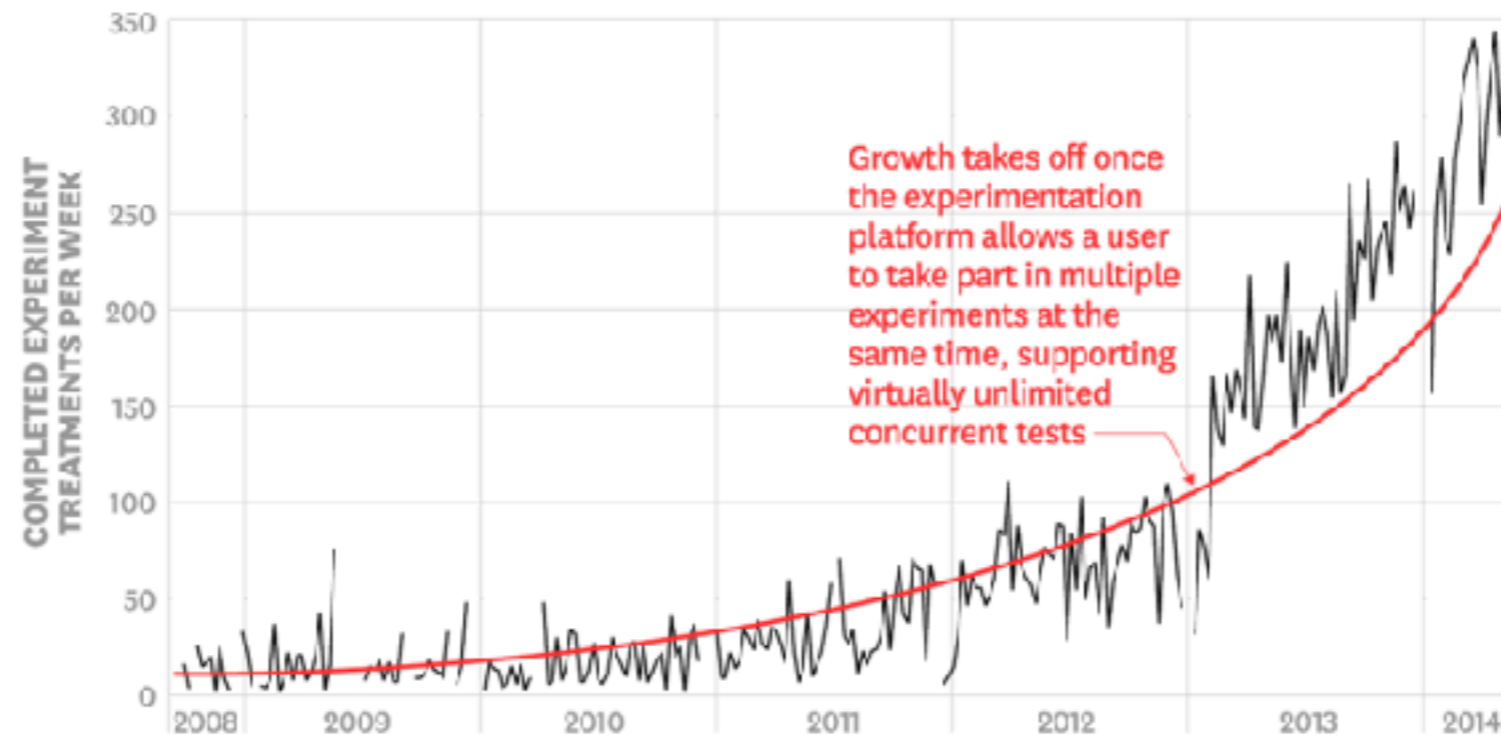
The Surprising Power of Online Experiments

Harvard
Business
Review

by Ron Kohavi and Stefan Thomke

From the September–October 2017 Issue

The Growth of Experimentation at Bing



FROM "THE SURPRISING POWER OF ONLINE EXPERIMENTS,"
SEPTEMBER–OCTOBER 2017, BY RON KOHAVI AND STEFAN THOMKE

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Micro-targeting and personalisation

Micro-targeting and personalisation

micro-targeting is a marketing strategy that capitalizes on the consumer's demographic, psychographic, geographic, and behavioral data to predict his buying behavior, interests, opinions, and influence that behavior with the help of a hyper-targeted advertising strategy

Pawha, 2018

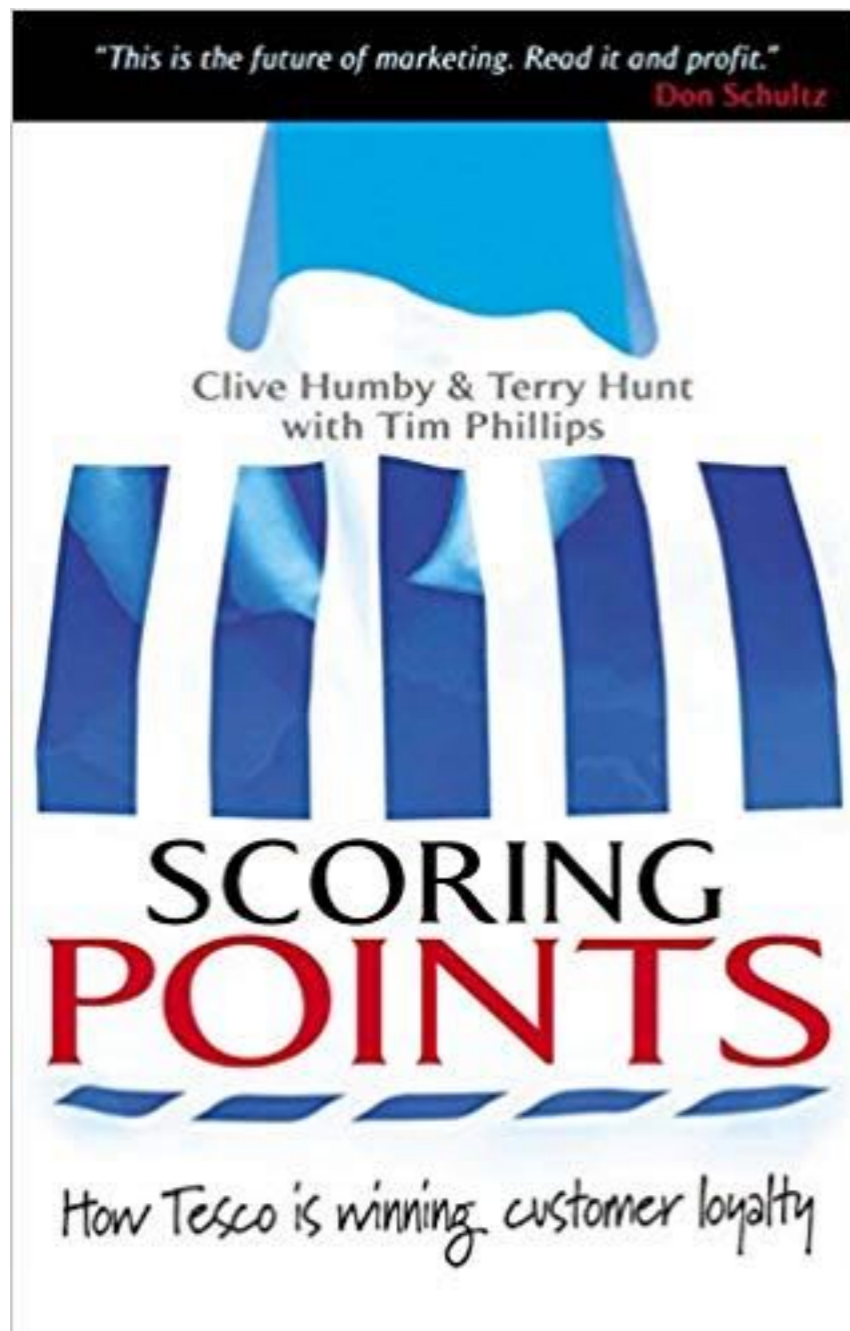
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Pawha, 2018



Targeting and personalisation in 1990s



data mining techniques on 12million transactions per week for:

tailored campaigns/promotions targeted to certain groups

pricing strategies for target groups

new products new ranges (e.g. *Finest*)

products bought by loyal customers prioritised

Segmentation

Segmentation

df.

Partition objects — places, businesses, **customers** — into groups according to shared characteristics

age
income
occupation
geographic location

often indirect measures clearly defined and generally static

purchase behaviour
brand awareness
ad response

direct measures
defined analytically
and can change

Segmentation : techniques

Recency-Frequency Monetary Value (RFM) —

quantile-based

4 min read : <https://bit.ly/2KrVUia>

Clustering —

k-means, density-based, hierarchical

11 min read : <https://bit.ly/355i01K>

Decision Trees —

chaid, cart, id3

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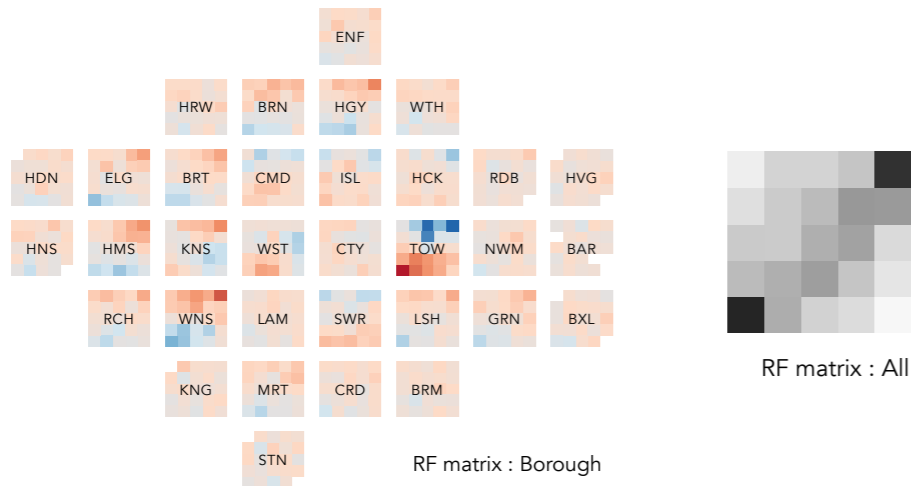
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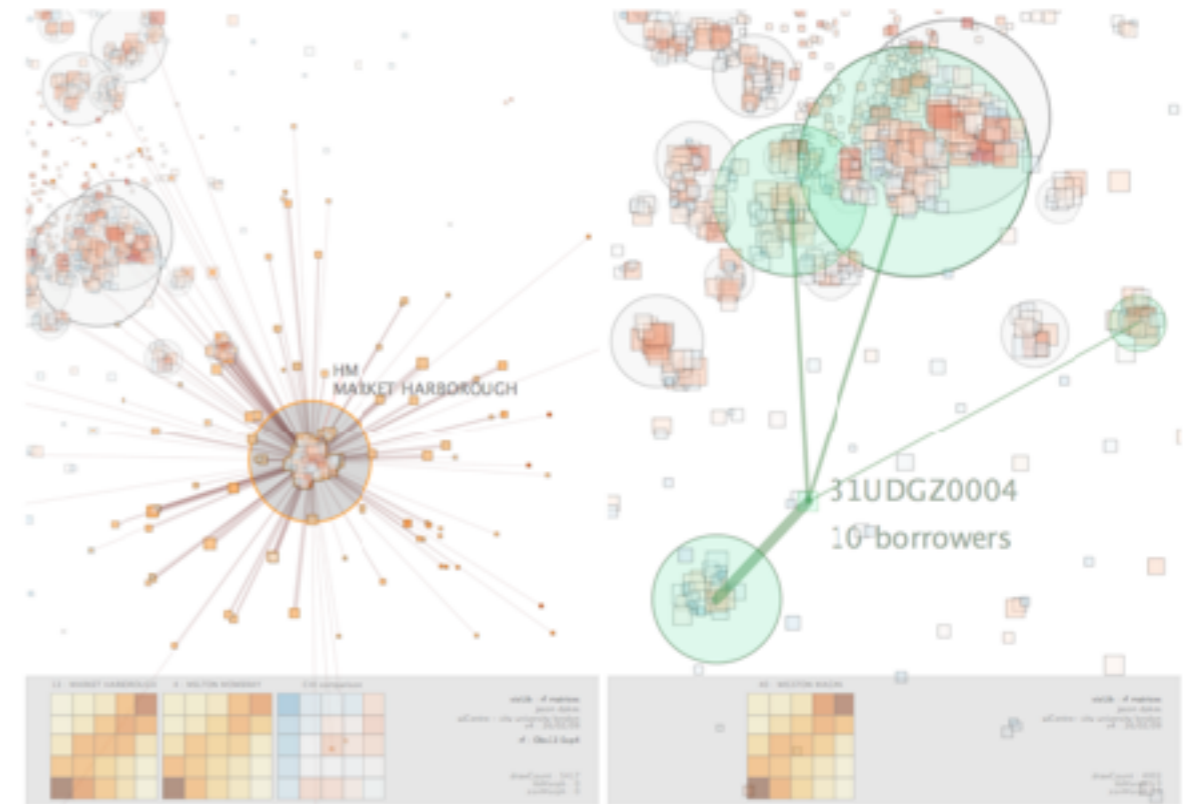
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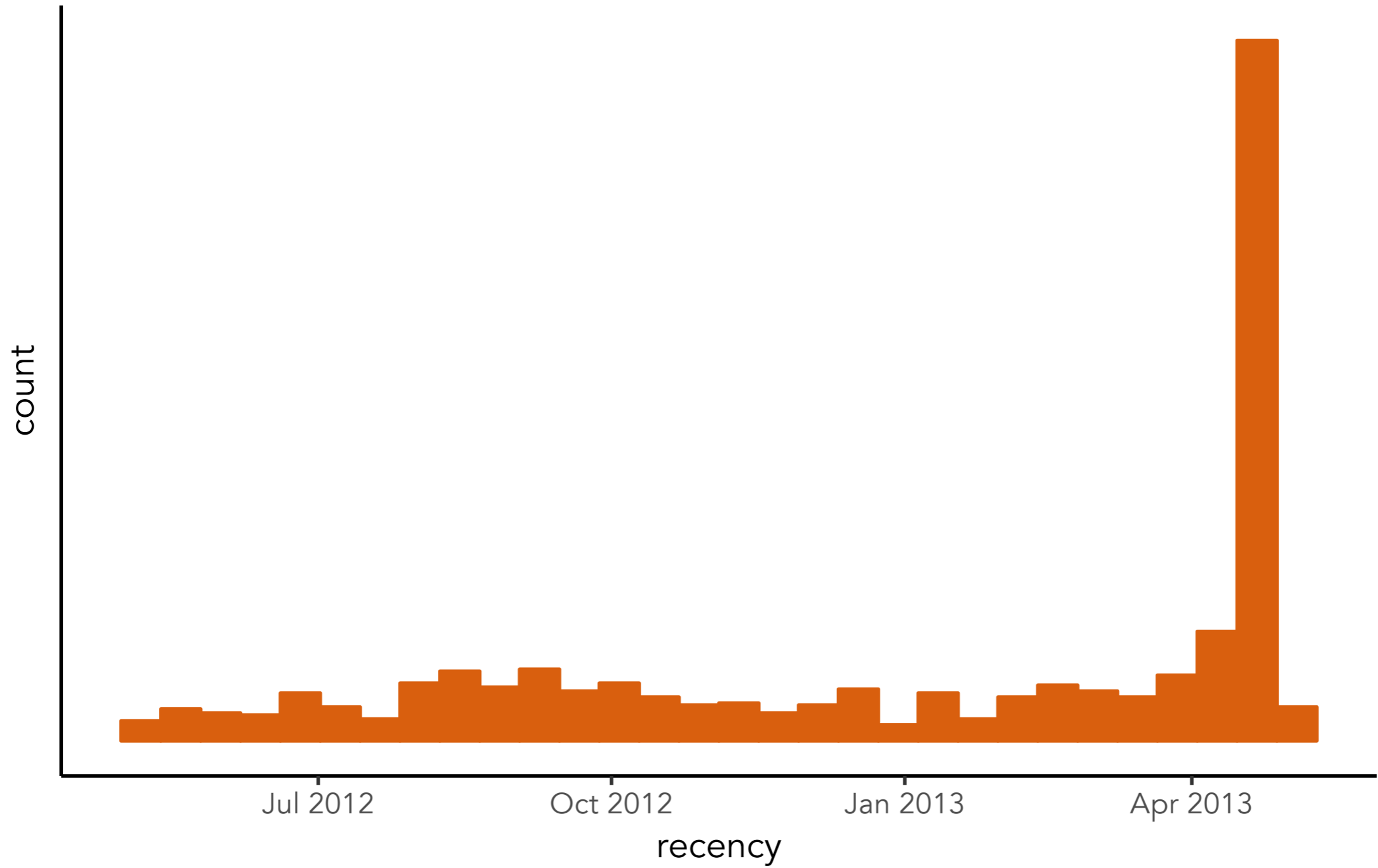
Beecham, R. & Wood, J.
 Exploring gendered cycling behaviours
Transport Planning & Technology
 doi: 10.1080/03081060.2013.844903



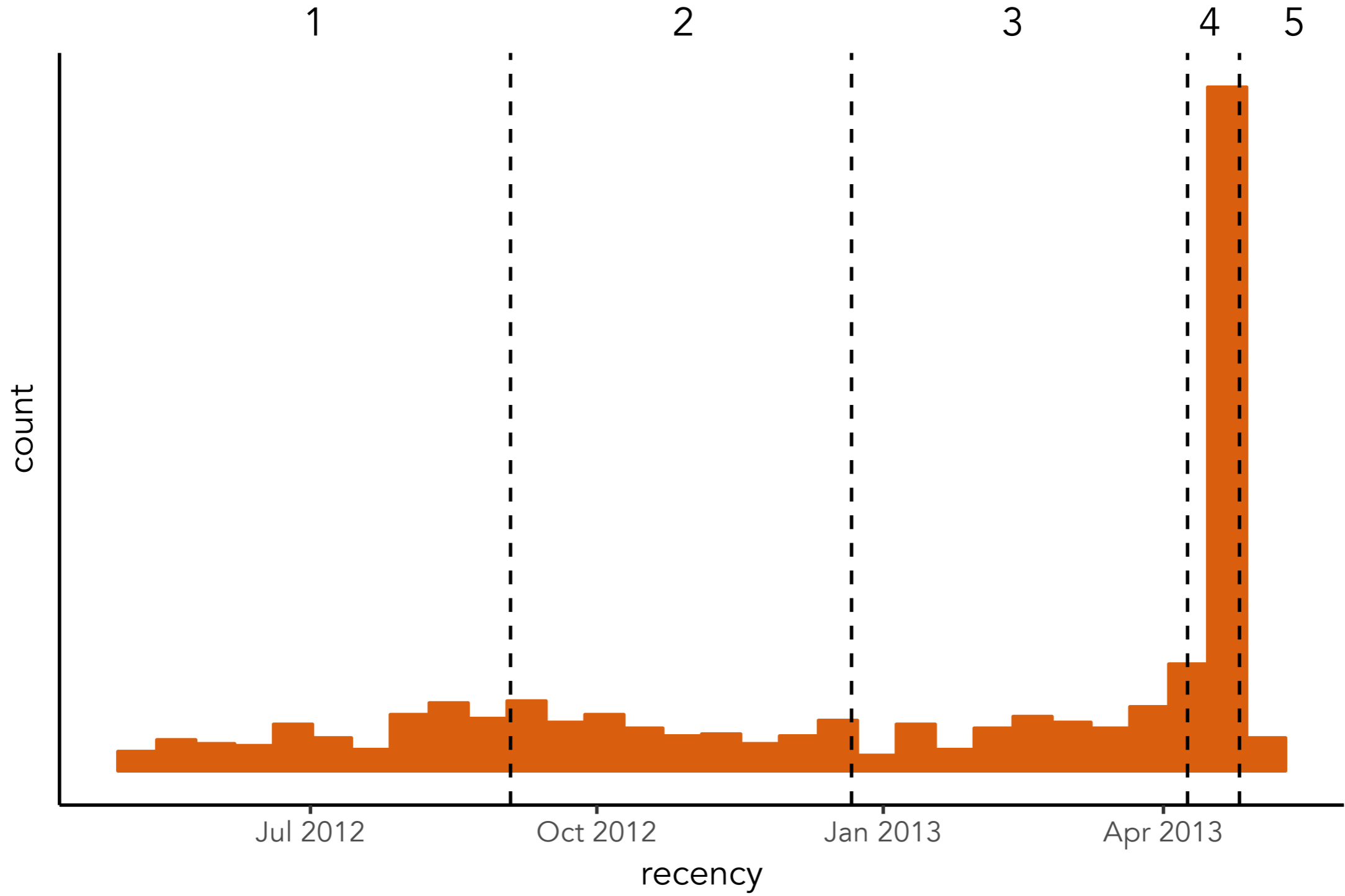
Radburn, R., Dykes, J. & Wood, J.
 vizLib: Using The Seven Stages of Visualization to Explore
 Population Trends and Processes in Local Authority Research

Recency - Frequency Segmentation

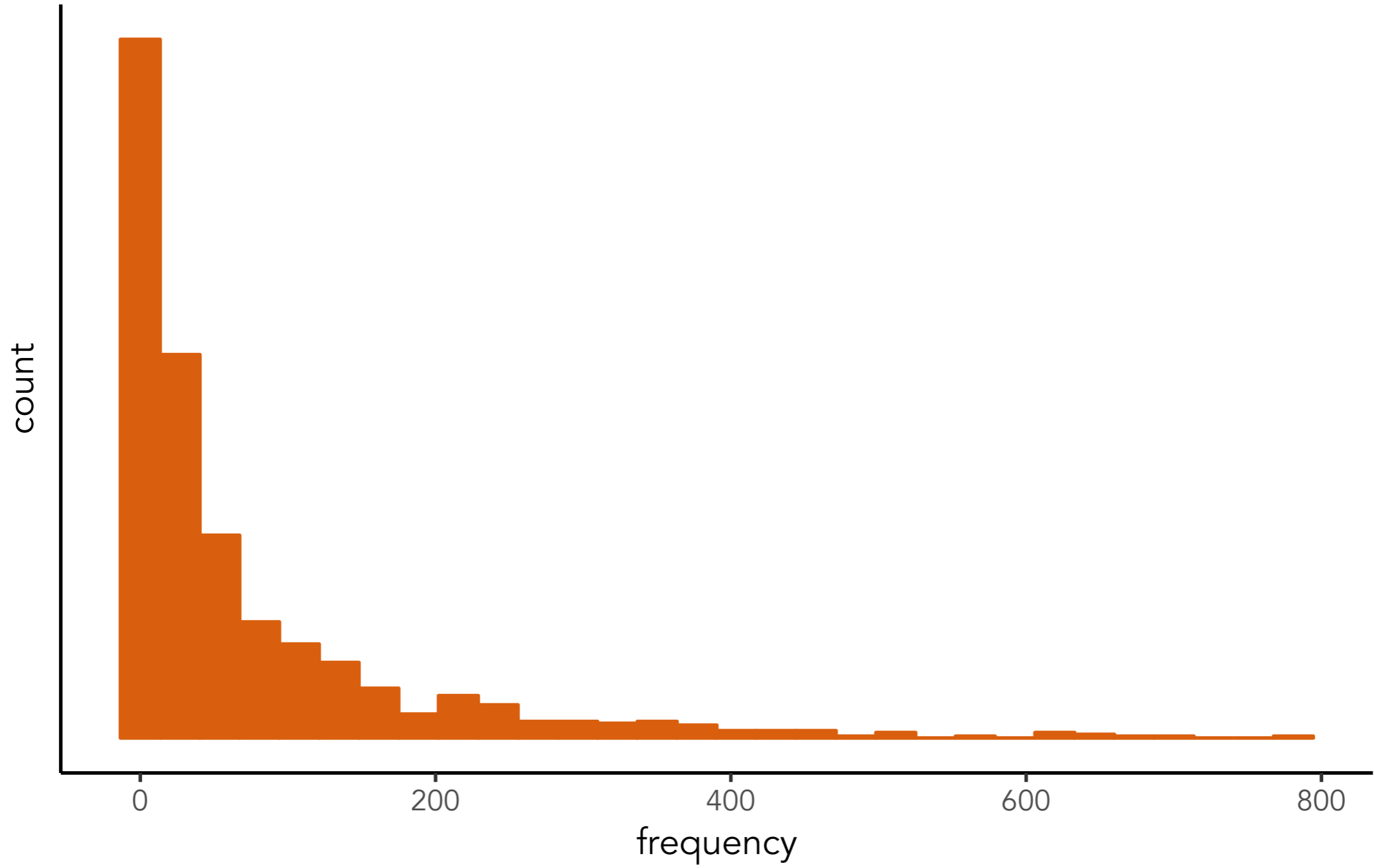
Recency



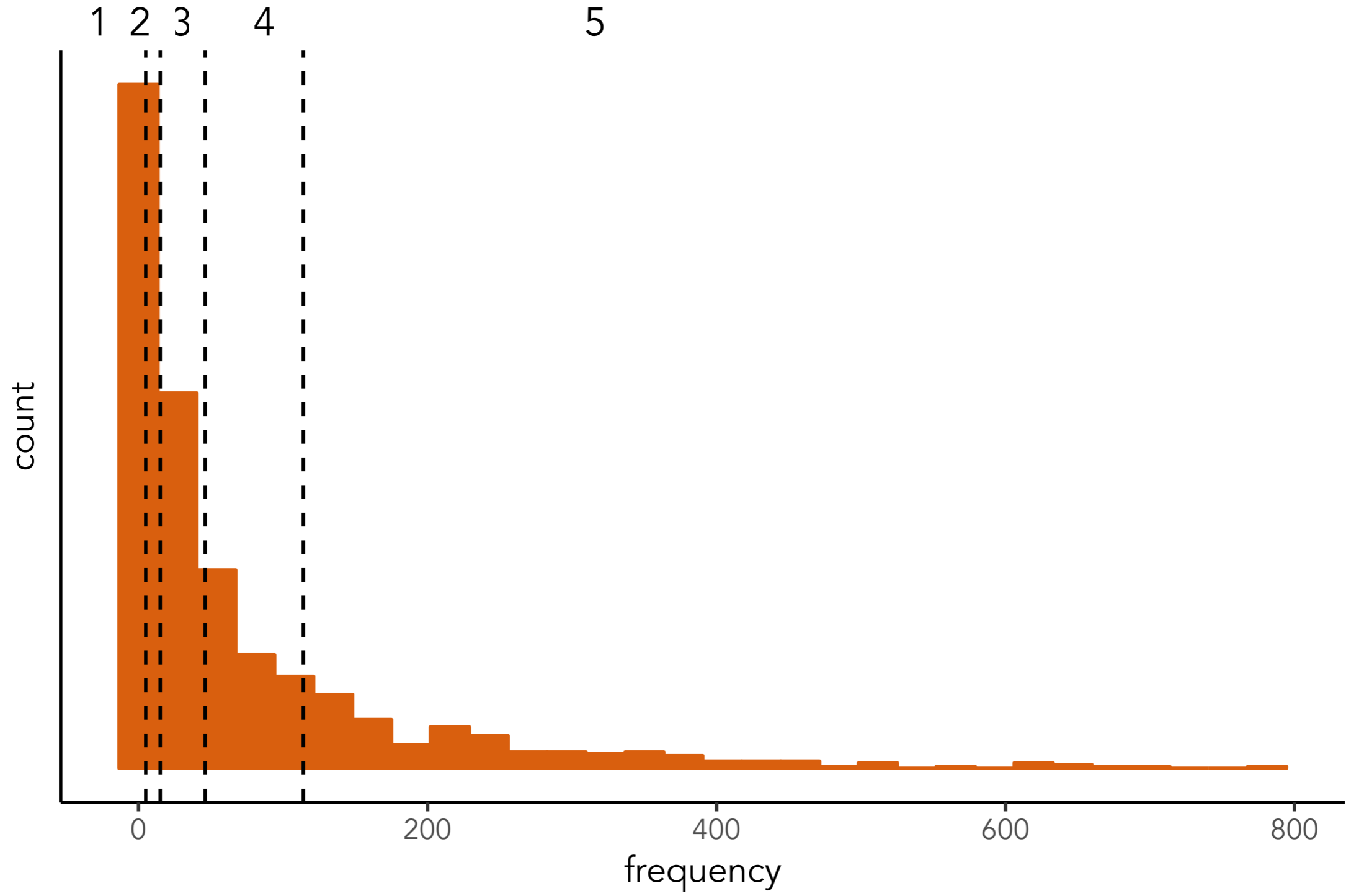
Recency

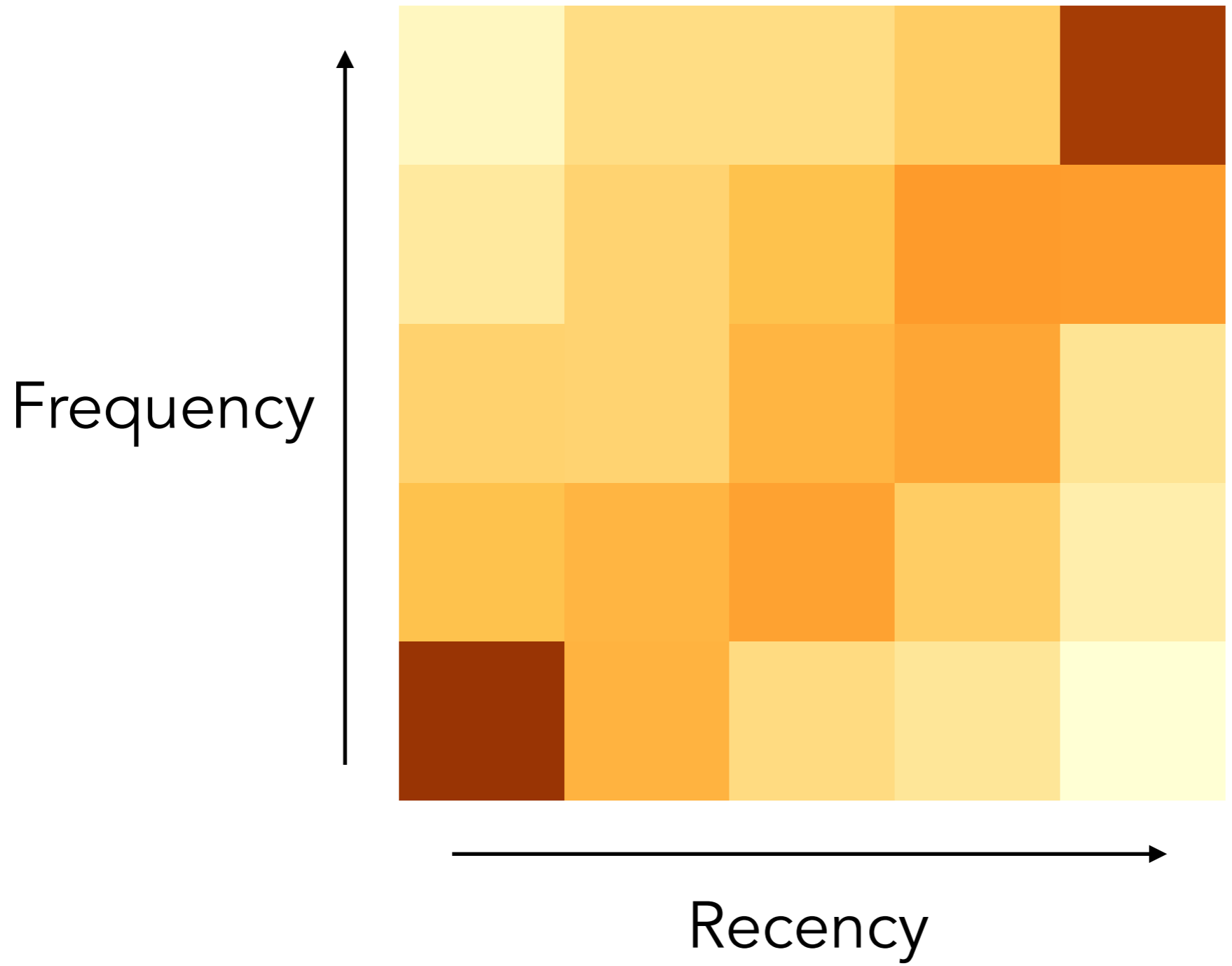


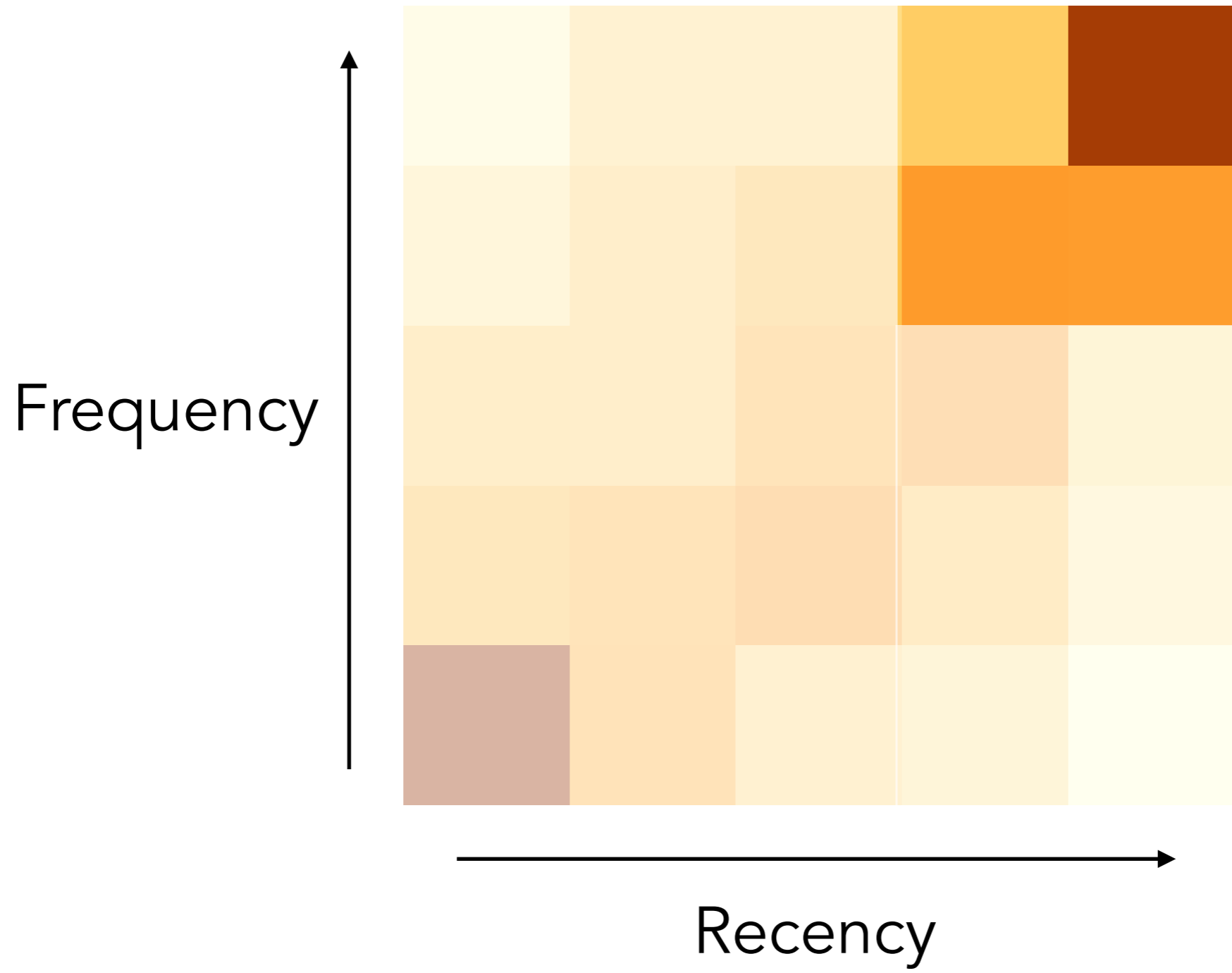
Frequency



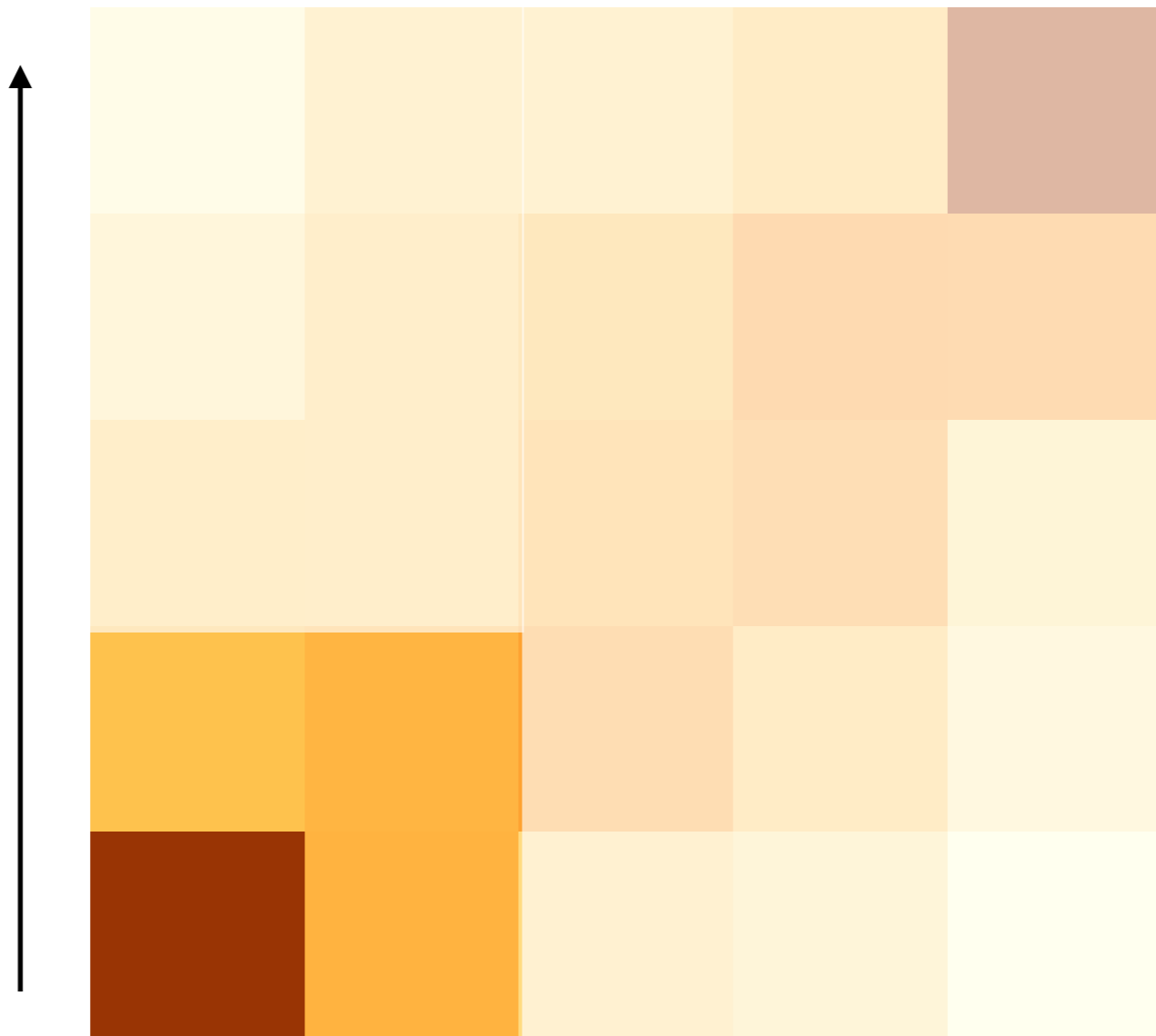
Frequency



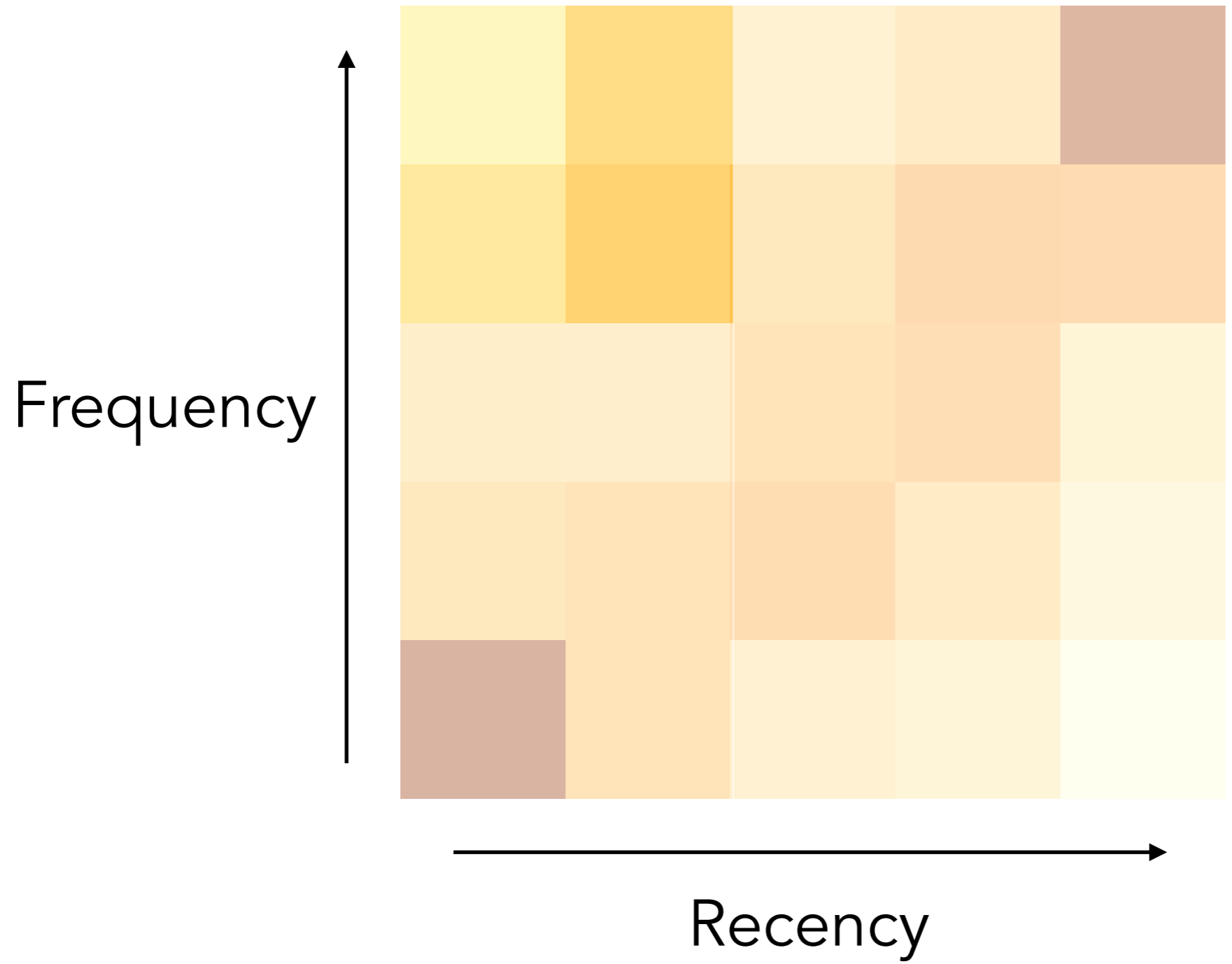


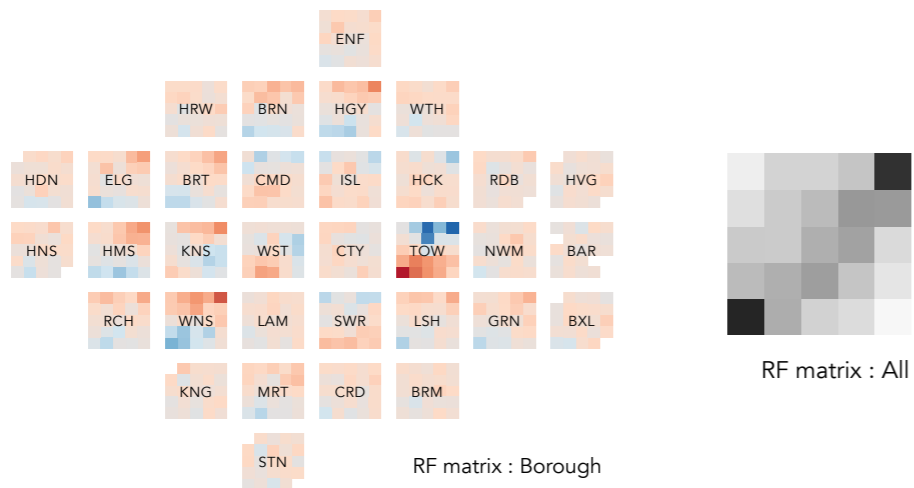
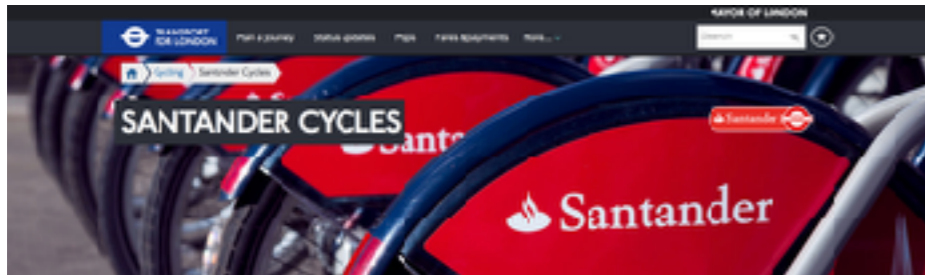


Frequency

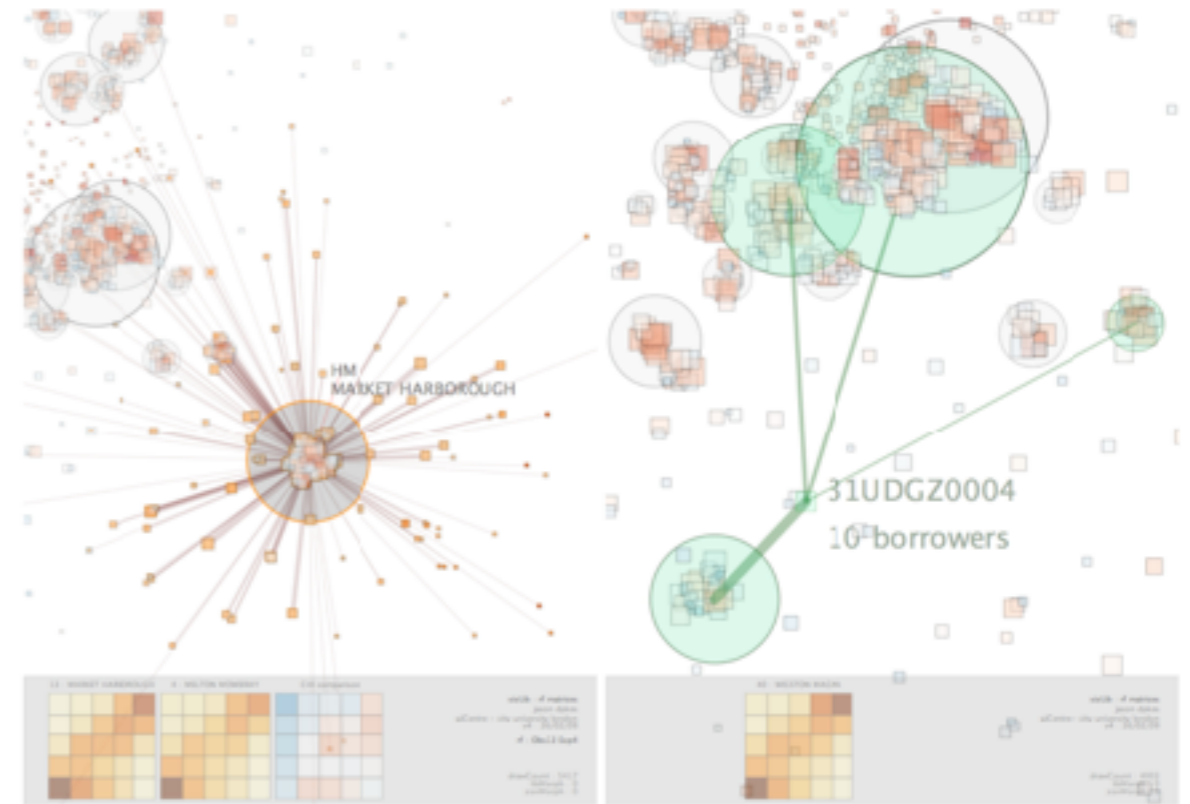


Recency





Beecham, R. & Wood, J.
 Exploring gendered cycling behaviours
Transport Planning & Technology
 doi: [10.1080/03081060.2013.844903](https://doi.org/10.1080/03081060.2013.844903)



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chaid, cart, id3

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Segmentation — clustering

df.

Partition objects — places, businesses, people — into groups
according to shared characteristics

such that

objects **within** groups are similar

AND

objects **between** groups are different





Width : Income

big income

£79,000



£39,000

UPPER



£18,000

MIDDLE



LOWER

Width : Income

small income



Height : novels read

big income |
read lots



£65,000
200 novels

MIDDLE → UPPER



UPPER

£35,000
160 novels



UPPER → MIDDLE

MIDDLE

£29,000
80 novels



LOWER

width : income | height : novels read

small income |
read little



Directors



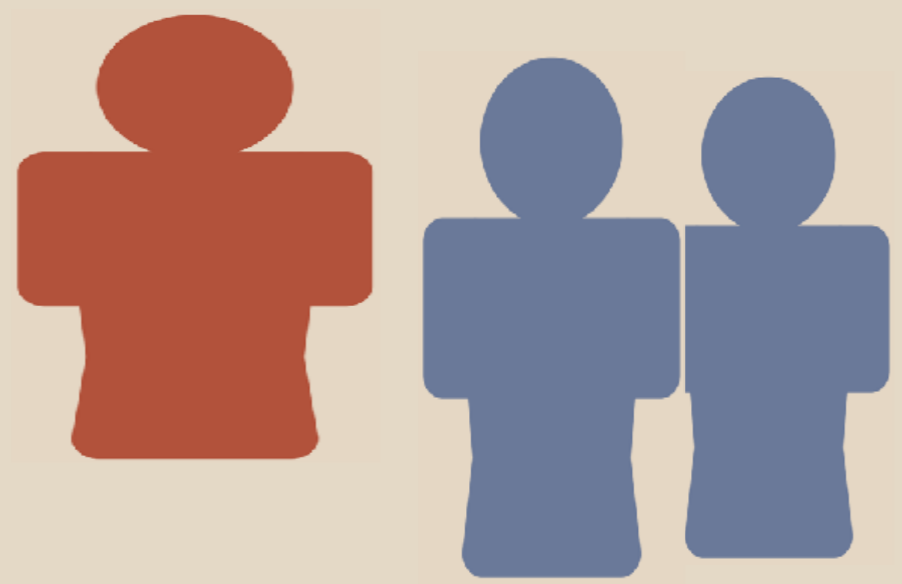
Professionals



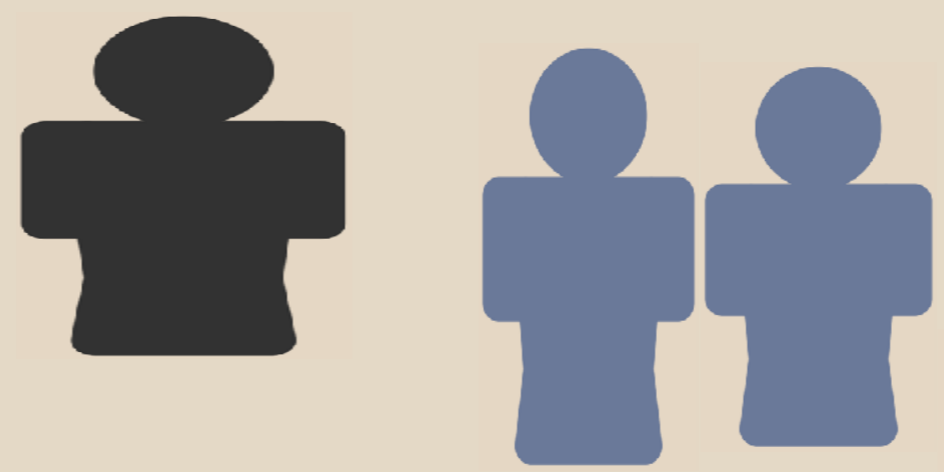
Trades

Colour : Father's
occupation

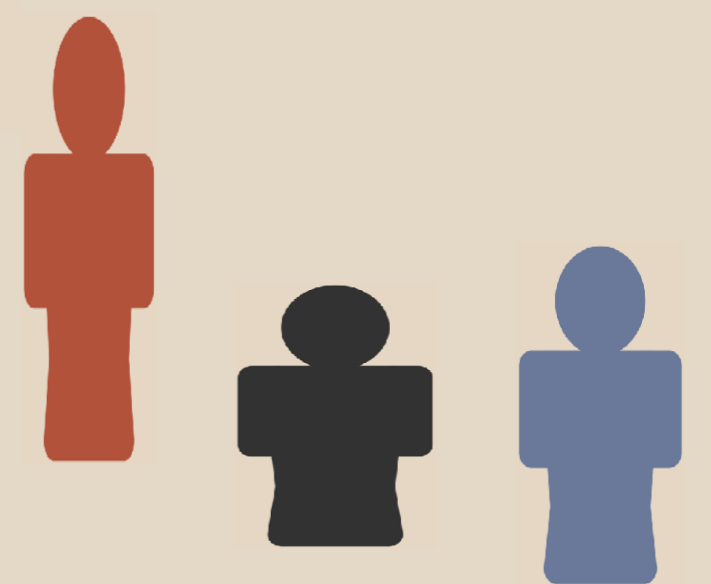
big income |
read lots |
director



UPPER

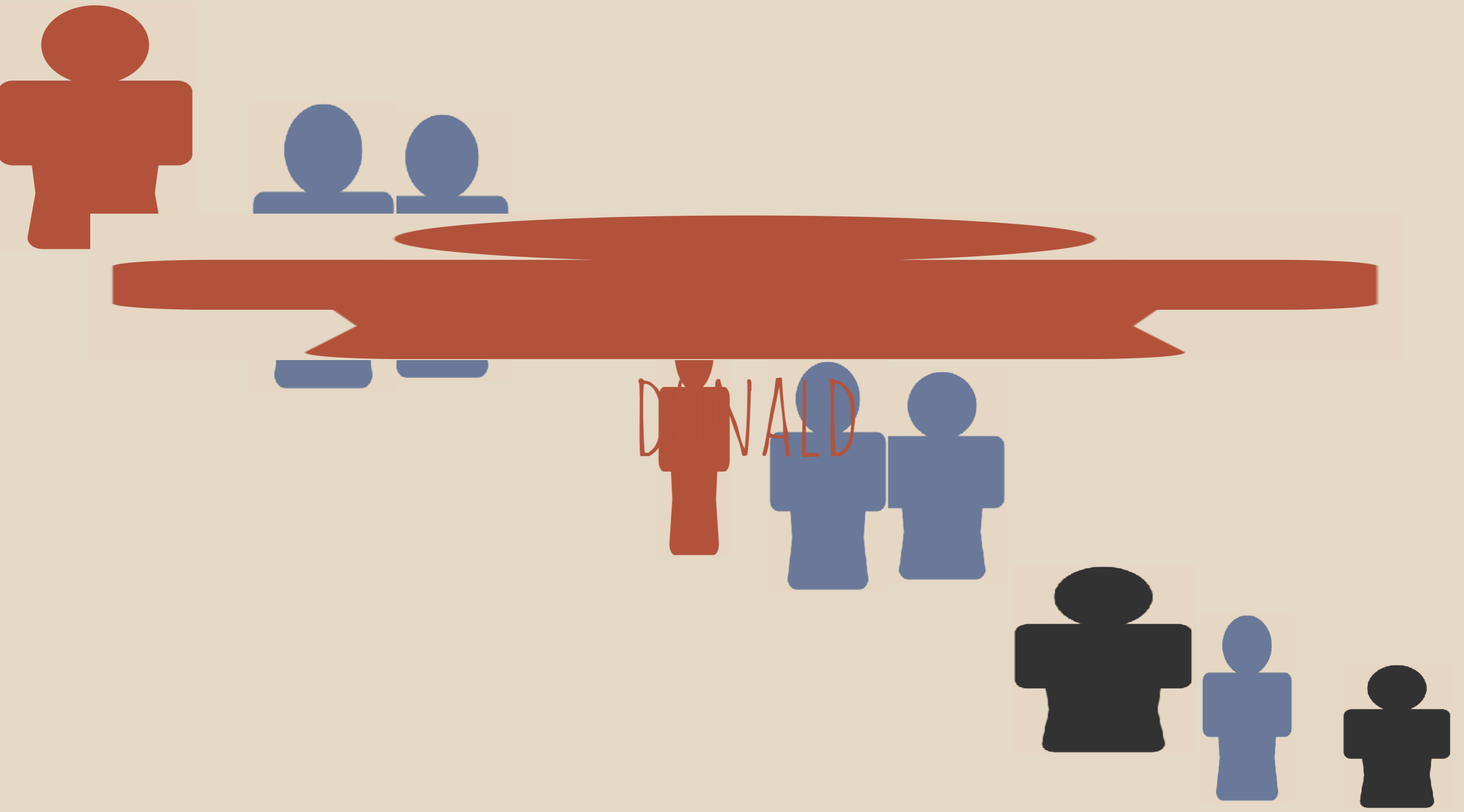


MIDDLE



LOWER

width : income | height : novels read | colour : father's occ. |
small income | read little | trades



width : income | height : novels read | colour : father's occ.

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Think critically

About characteristics on which we choose to group.

They should be semantically unique and context appropriate.

About how coherent and stable groupings are.

Within-group similarity and between-group difference.

Remember that groupings are relative.

Groupings will change as new data arrive.

They are persuasive: they hide uncertainty.

YouGov profiles.

Geodemographics

Output Area Classification

DataShine 2011 OAC Geodemographics derived from the UK's 2011 Census

Rural Residents

Cosmopolitans

Ethnicity Central

Multicultural Metropolitan

Urbanites

Suburbanites

Constrained City Dwellers

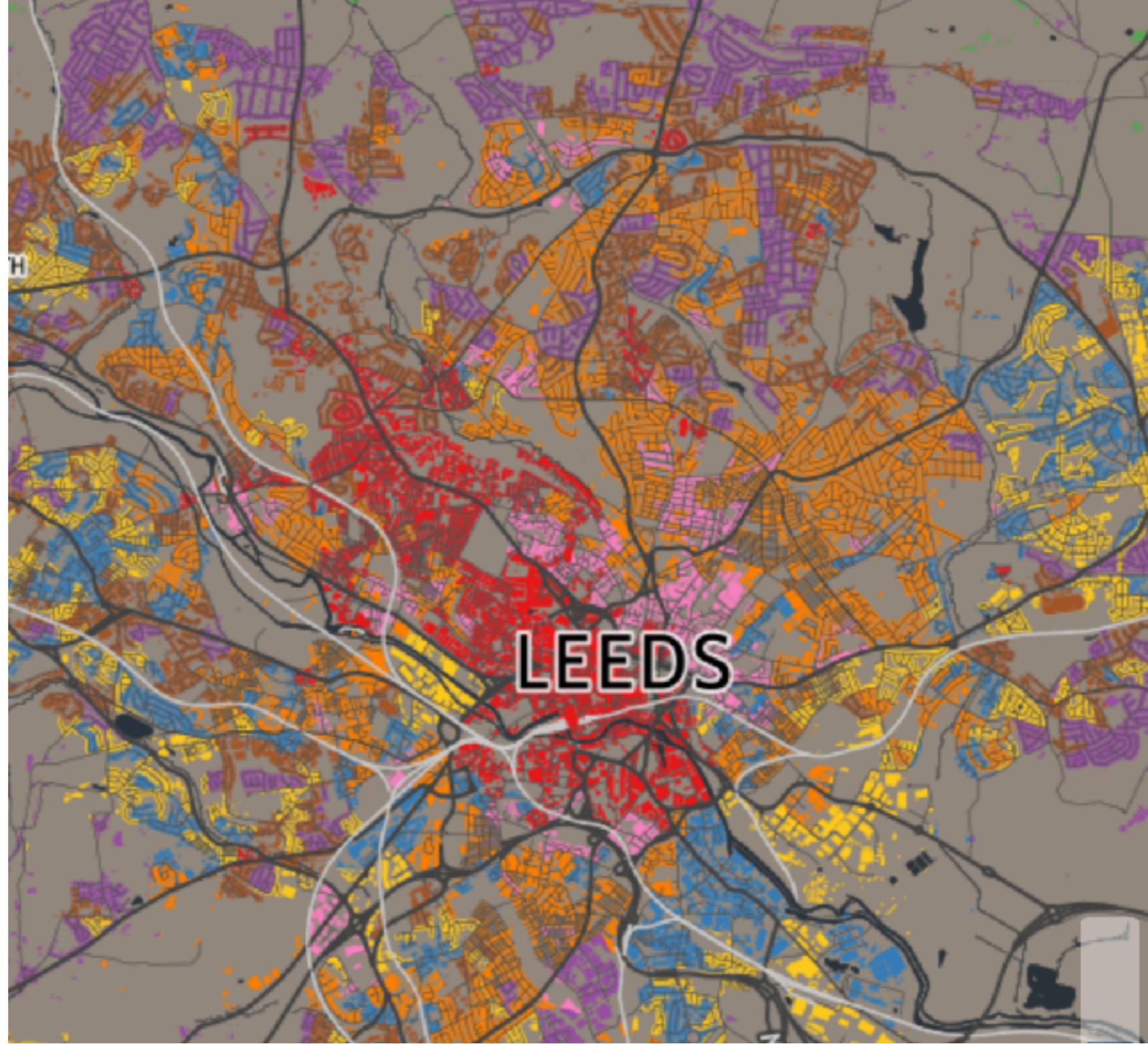
Hard-Pressed Living

Land

Labels

Postcode: L52

Go

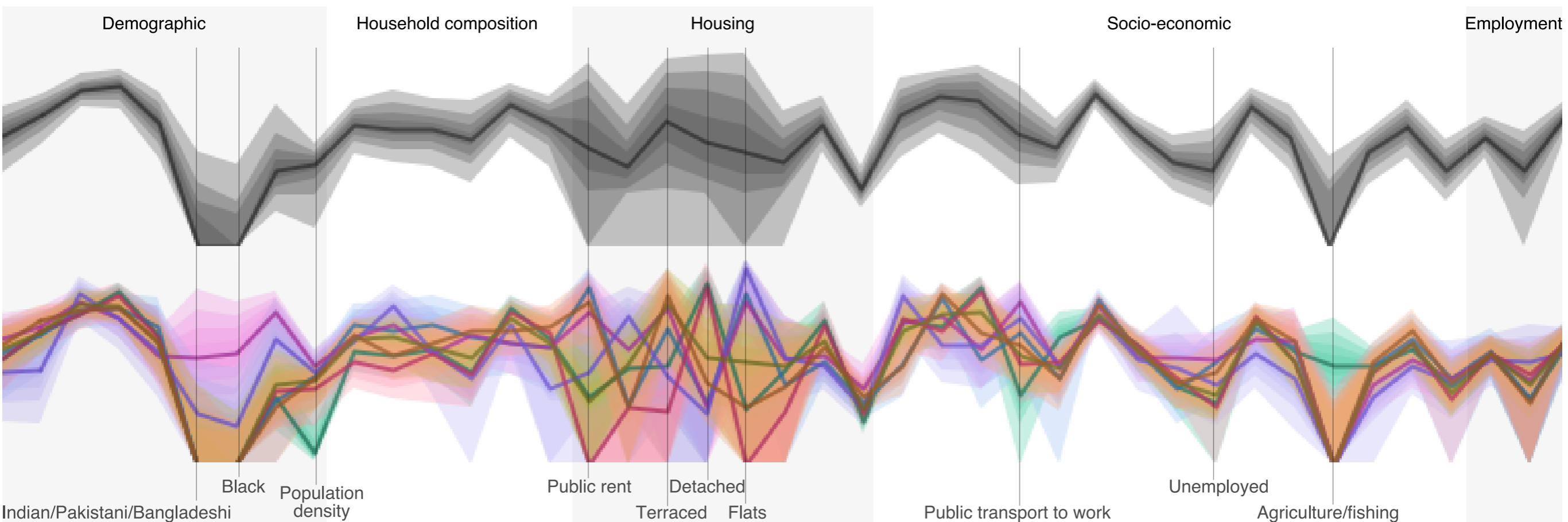


Geodemographics

Output Area Classification

Exploring Uncertainty in Geodemographics with Interactive Graphics

Aidan Slingsby, *Member, IEEE*, Jason Dykes, and Jo Wood, *Member, IEEE*





GEOG5927M: PREDICTIVE ANALYTICS

[SYLLABUS](#) [SCHEDULE](#) [R](#)

PRACTICAL 2 : TARGETED MARKETING

The aim of this practical is to perform a data analysis on the synthetic dataset you generated last week in order to identify a group (or groups) of customers at whom a marketing strategy could be targeted. You will generate summary statistics and data graphics that will characterise what makes your customer groups distinctive from the Leeds population as a whole.



break





GEOG5927M: PREDICTIVE ANALYTICS

[SYLLABUS](#) [SCHEDULE](#) [R](#)

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Assignment #1

You will take on the role of a customer segmentation expert for a travel company. Your task is to identify a **specific segment** of customers who could be targeted with a marketing strategy. You will use the 'synthetic' population produced through microsimulation during practical sessions 1 and 2 to identify the target customers. The **type of holiday destination** and **choice of customer sub-group(s)** to target is up to you. Note that your job is to identify the sub-population(s) to be targeted, explain your methods and clearly present your results. There is **no need** to discuss how you would reach the customers you identify. You are expected to incorporate at least some appropriate academic literature into your report.

An indicative structure for your report is below.

1. **Introduction:** Identify and justify the scope of your study -- the destinations, holiday type and customer groups of focus and why they are of interest.
2. **Data and methods:** Describe the data on which your study is based, the variables you have selected and any derived variables you have created. Be sure to justify these decisions with reference to your study's scope.
3. **Results and analysis:** A combination of charts, maps and tables – judiciously designed to address the area of focus outlined in the introduction.
4. **Conclusions:** Synthesise over the findings to identify the customers to which a marketing campaign could be targeted. Be sure to do so with reference to the evidence presented in your data analysis (section 3).

Assignment #1

GEOG5927M

<student-id>

Please use this document to complete assignment 1.
DELETE all of the blue boxes that contain instructions – they are just for guidance.
Use 'Styles' in Word to remove this formatting – revert paragraphs to 'Normal' style to remove boxes!

TITLE

INTRODUCTION

Use this section to identify and justify the scope of your study – the destinations, holiday type and customer groups of focus and why they are of interest.

Approx length: 200 words

DATA AND METHODS

Describe the data on which your study is based, the variables you have selected and any derived variables you have created. Be sure to justify these decisions with reference to your study's scope.

Approx length: 300 words

RESULTS

Profile your target market using a combination of charts, maps and tables – judiciously designed to address the area of focus outlined in the introduction.

Approx length: 300 words

CONCLUSIONS

Synthesise over the findings to identify the customers to which a marketing campaign could be targeted. Be sure to do so with reference to the evidence presented in your data analysis.

Approx length: 200 words

microdata.csv

15,189 records

Person_ID	OA_GRP	Sex	Ageband	NumberCh	CombinedI	OverSeasAi	UKAirport	OverallHoli	AgeSex	Supergroup
11603	8c	F	a35to49	2	26-30K	LEI	MAN	Excellent	F35to49	Hard-Press
11285	8c	F	a25to34	0	0-10K	IBZ	MAN	Fair	F25to34	Hard-Press
13938	8c	M	a50to64	1	16-20K	LCA	BHX	Fair	M50to64	Hard-Press
10255	8c	F	a25to34	1	26-30K	ALC	LBA	Poor	F25to34	Hard-Press
831	8c	M	a50to64	0	26-30K	AGA	MAN	Good	M50to64	Hard-Press
1754	8c	M	a65over	0	Not Answer	DLM	MAN	Good	M65over	Hard-Press
2330	8c	F	a65over	0	Not Answer	DLM	MAN	Excellent	F65over	Hard-Press
10818	8c	M	a25to34	0	36-40K	KGS	MAN	Fair	M25to34	Hard-Press
8237	8c	M	a65over	2	16-20K	FUE	MAN	Good	M65over	Hard-Press
11508	8c	F	a35to49	2	71-80K	ZTH	LBA	Poor	F35to49	Hard-Press

ageBand	demographics
incomeBand	demographics
oac	geodemographics
originAirport	preference
destinationAirport	preference/attitude
satisfactionScore	preference/attitude

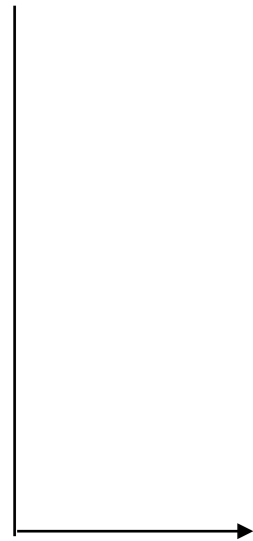




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Dataset

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11508	8c	F	a35to49	2	71-80K	ZTH	LBA	Poor	F35to49	Hard-Pressé

microdata.csv
15,189 records

ZoneID	Person_ID	OA_GRP	Sex	Ageband	NumberCh	CombinedI	OverSeasAi	UKAirport	OverallHoli	AgeSex	Supergroup
E00056750	11603	8c	F	a35to49	2	26-30K	LEI	MAN	Excellent	F35to49	Hard-Pressed Living
E00056750	11285	8c	F	a25to34	0	0-10K	IBZ	MAN	Fair	F25to34	Hard-Pressed Living
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E00056750	11508	8c	F	a35to49	2	71-80K	ZTH	LBA	Poor	F35to49	Hard-Pressed Living

simulated_population.csv
320,596 records

Targeting

Identify and profile a target market using:

Demographics –

income, age, household structure

Geography –

where and what types of areas they tend to live in

Psychographics –

their motivations and preferences

Targeting

microdata.csv

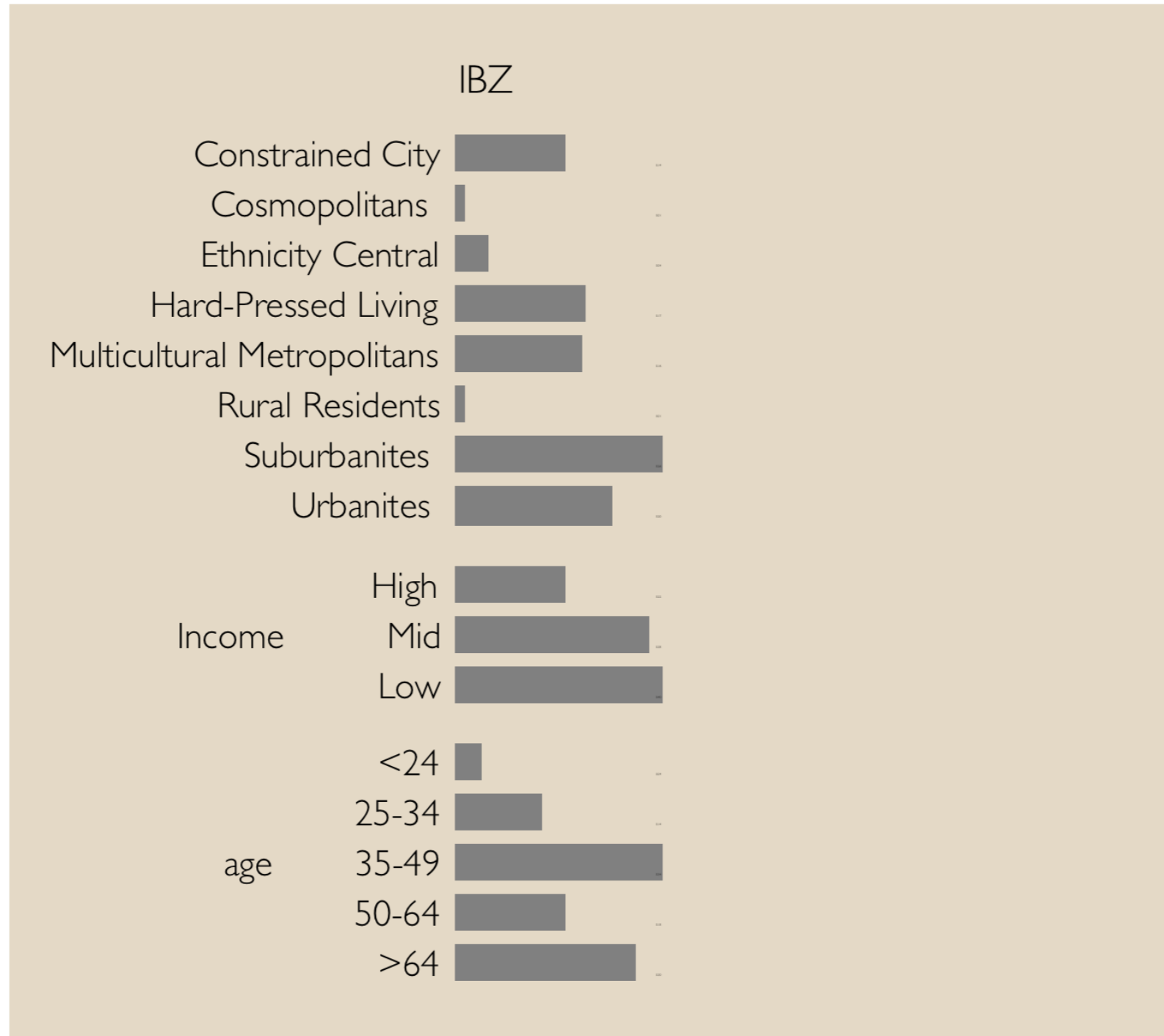
ageBand	demographics
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originAirport	preference
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Targeting

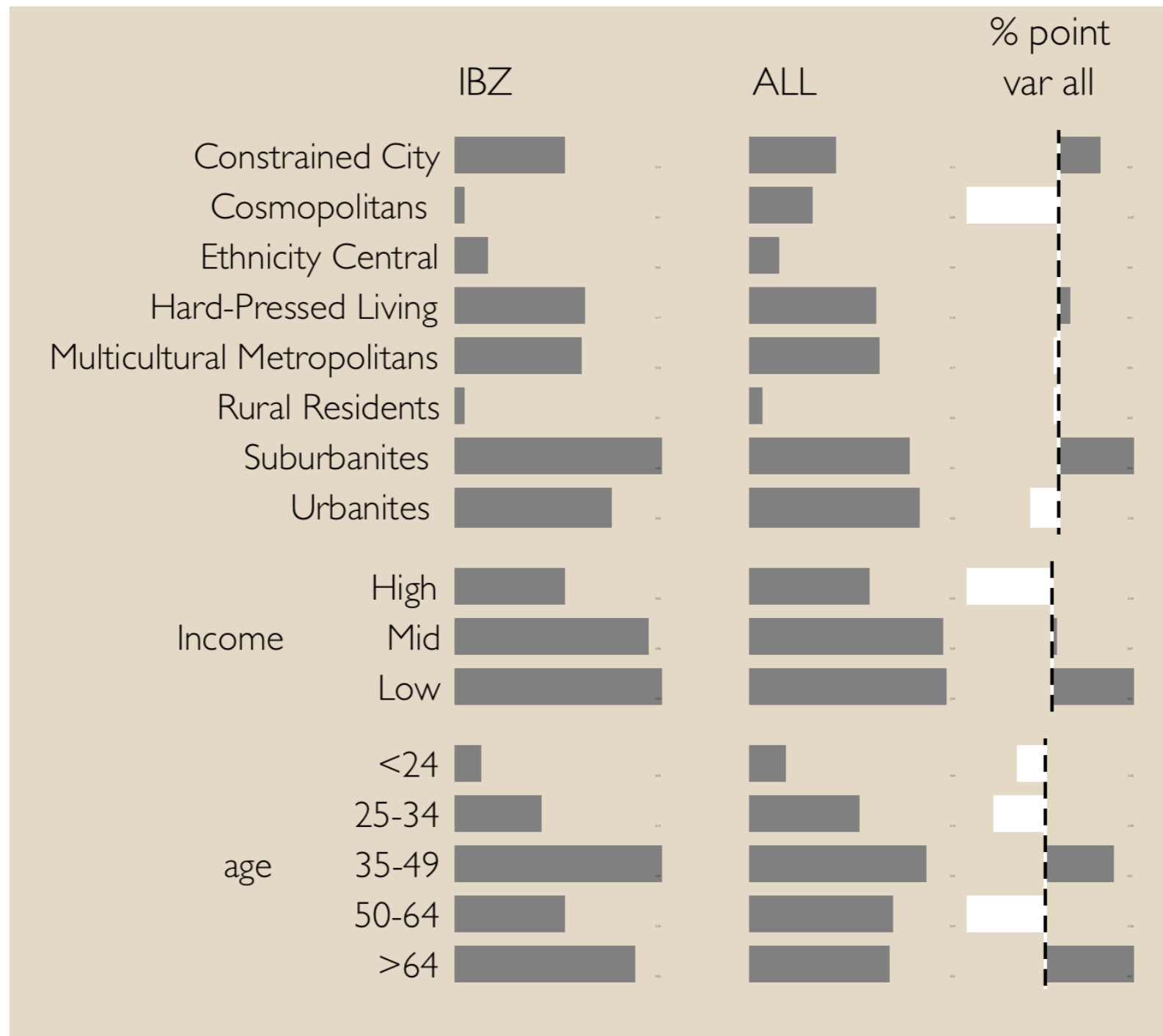
What makes your target market distinct when compared to the population as a whole?

ageBand	demographics
incomeBand	demographics
numChildren	demographics
oac	geodemographics
originAirport	preference
destinationAirport	preference/attitude
satisfactionScore	preference/attitude

Targeting

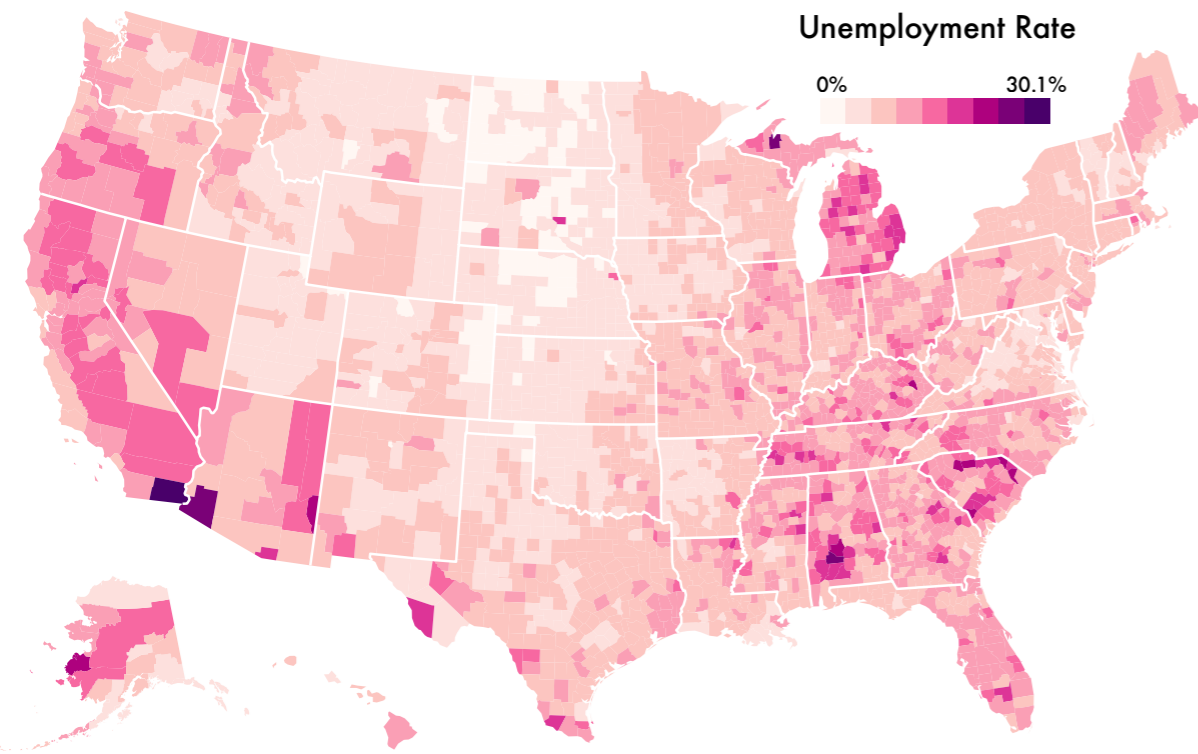


Targeting

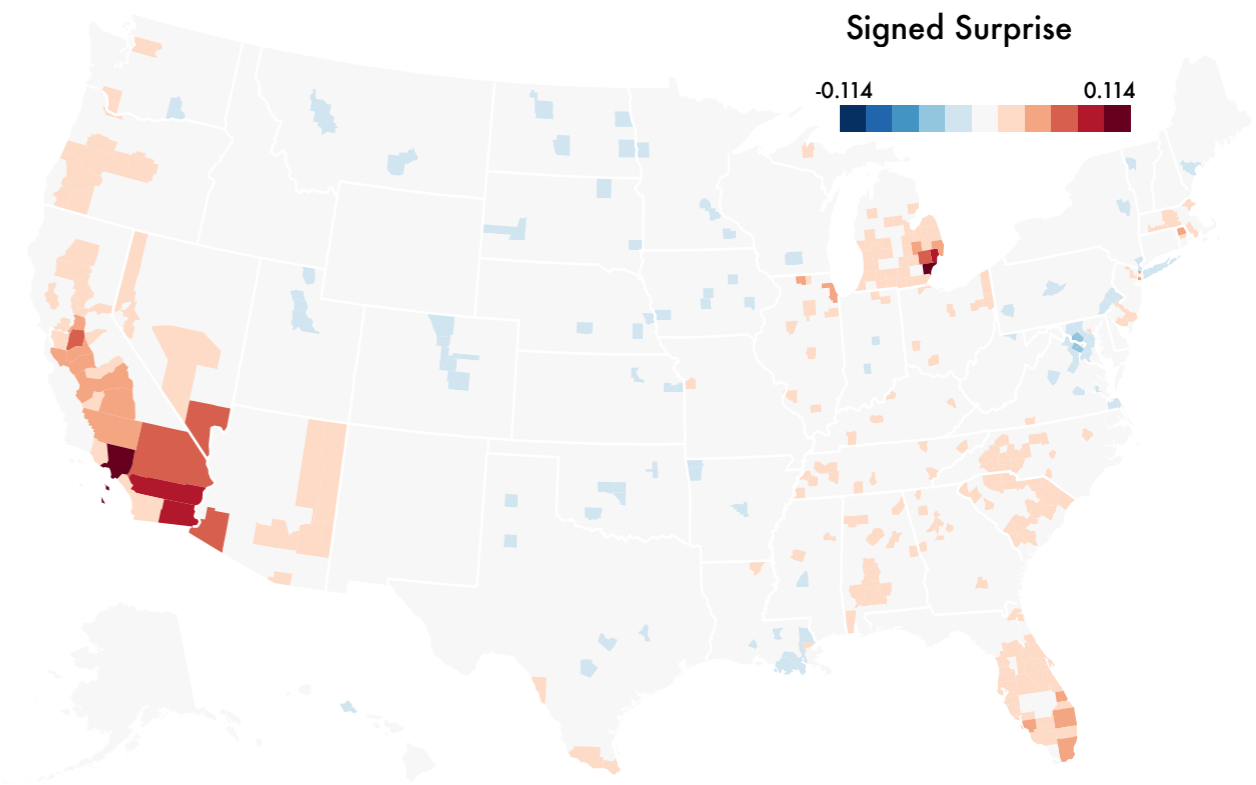


Deviation from Expectation

evidence model

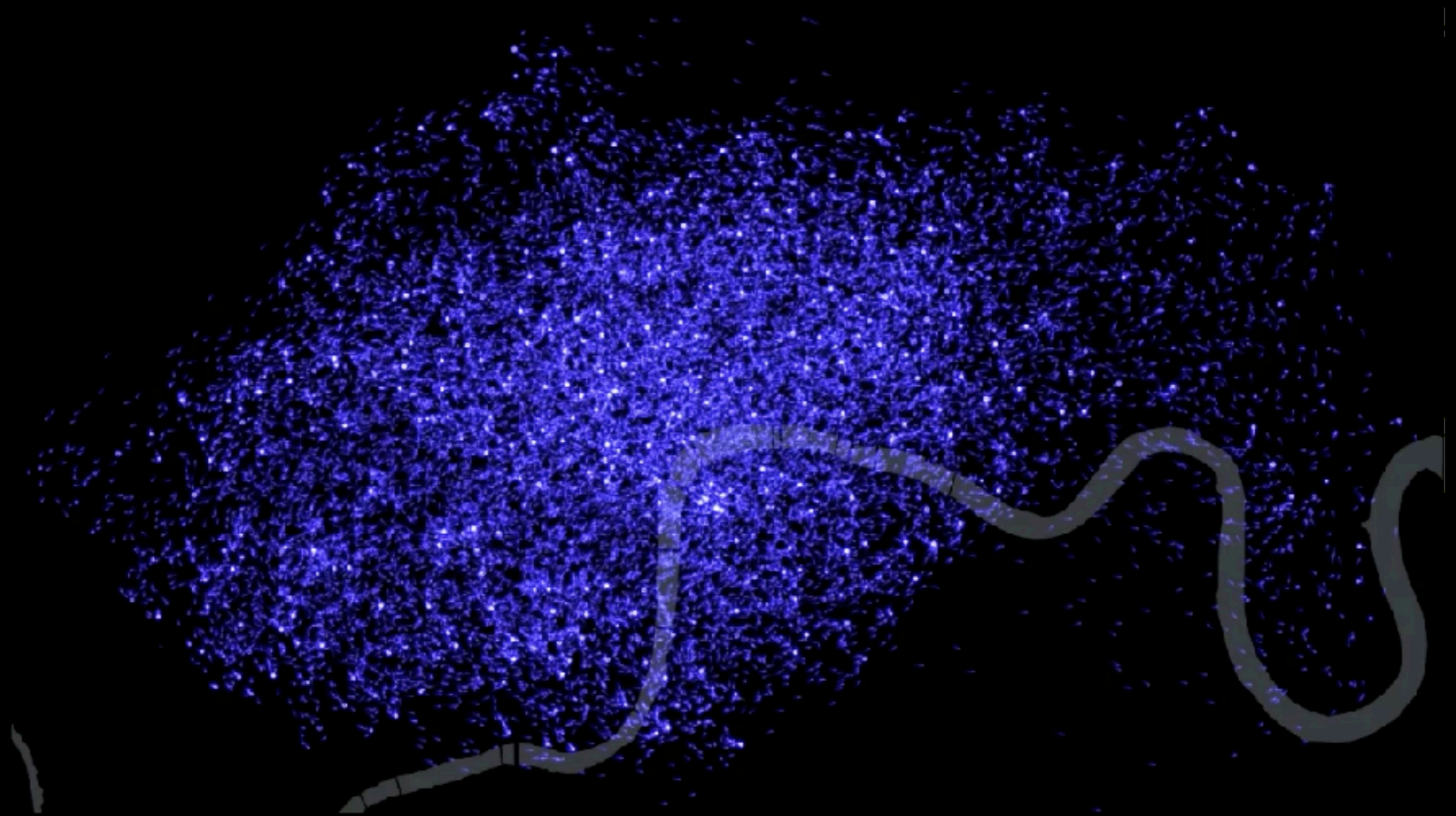


(a) Per capita event rate map.



(b) Signed Surprise Map.

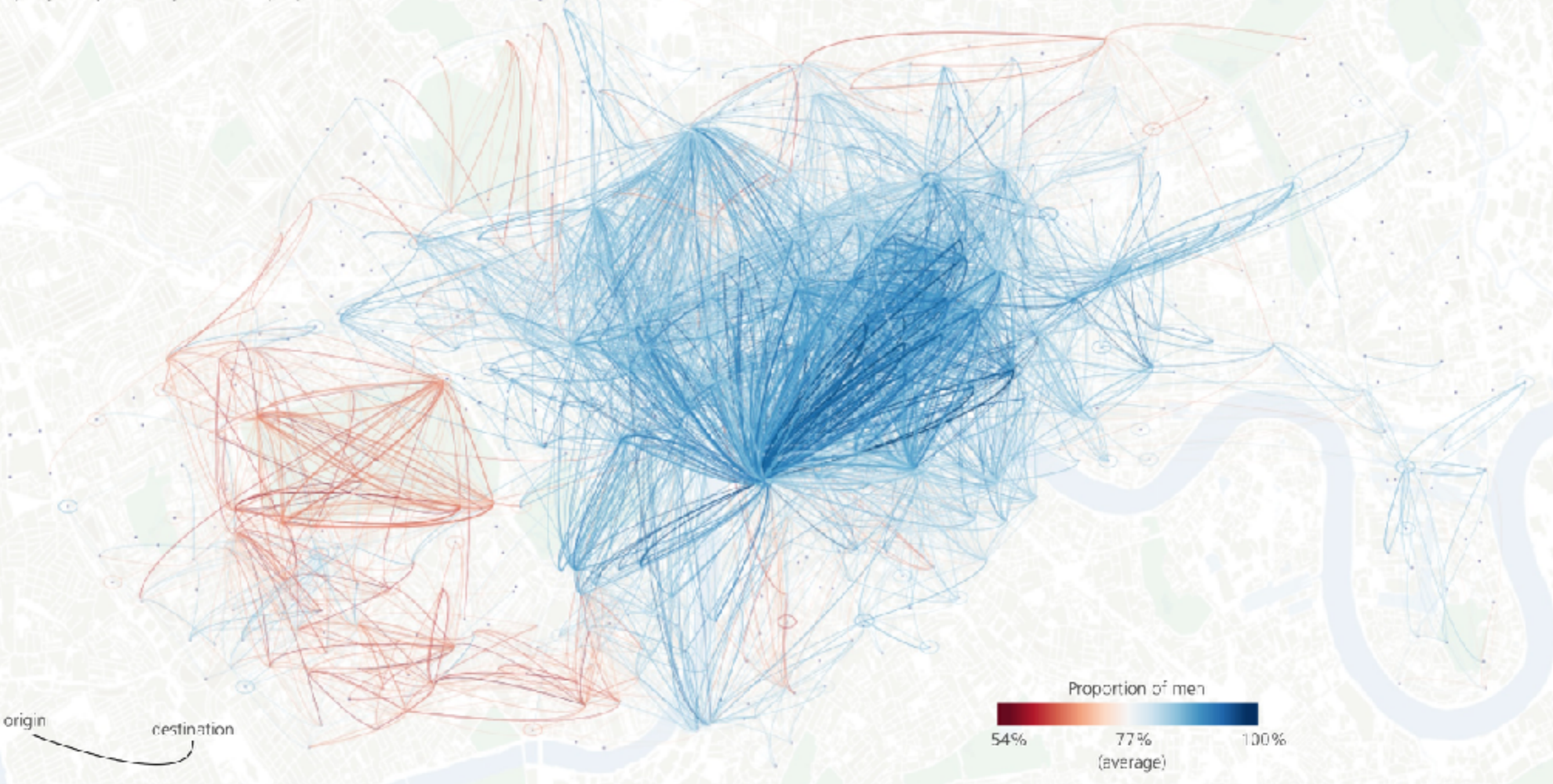
Correll & Heer (2017) Surprise! Bayesian Weighting for De-Biasing Thematic Maps, IEEE TVCG



Jo Wood

London Cycle Hire: Men's and women's journeys

Cycle journeys made by at least 50 people, Jan 2012-Feb 2013



Beecham and Wood, 2014

YouGov Profiles

YOU ARE CURRENTLY USING THE REDUCED FREE VERSION OF PROFILES - [UPGRADE TO THE PROFESSIONAL TOOL TO EXPLORE ANY GROUP!](#)



Now showing: Shows what is particularly true of UK Independence Party supporters compared to other groups of the same type. | Sample size: 13728 | Oct 12, 2016 | © YouGov | What is this data?

- ▶
- DEMOGRAPHICS**
- LIFESTYLE
- PERSONALITY
- BRANDS
- ENTERTAINMENT
- ONLINE
- MEDIA
- HELP!**
- UPGRADE TO PROFESSIONAL VERSION

DEMOGRAPHICS

- GENDER: MALE +
- AGE: 65+ +
- SOCIAL GRADE: C2DE +

TOP REGIONS

- SOUTH COAST +
- EAST ANGLIA
- MIDLANDS



PROFESSIONS

- MILITARY AND DEFENCE
- MANUFACTURING
- POLICE AND EMERGENCY SERVL

MONTHLY SPARE £

- LESS THAN £125





YOU ARE CURRENTLY USING THE REDUCED FREE VERSION OF PROFILES - [UPGRADE TO THE PROFESSIONAL TOOL TO EXPLORE ANY GROUP!](#)



Now showing: Shows what is particularly true of people who own an iPhone 6 compared to other groups of the same type. | Sample size: 348 | Oct 12, 2016 | © YouGov | What is this data?

-
- DEMOGRAPHICS
- LIFESTYLE
- PERSONALITY
- BRANDS
- ENTERTAINMENT
- ONLINE
- MEDIA
- HELP!**
- UPGRADE TO PROFESSIONAL VERSION

- DEMOGRAPHICS**
- GENDER: MALE -
- AGE: 25-39 -
- SOCIAL GRADE: ABC1 -

- TOP REGIONS** +
- LONDON
- SOUTH COAST
- NOR. HERN SCOTLAND



- PROFESSIONS**
- REAL ESTATE AND PROPERTY
- BUSINESS
- TRANSPORT AND LOGISTICS

- MONTHLY SPARE £**
- £1000 OR MORE





GEOG5927M: PREDICTIVE ANALYTICS

[SYLLABUS](#) [SCHEDULE](#) [R](#)

PRACTICAL 2 : TARGETED MARKETING

The aim of this practical is to perform a data analysis on the synthetic dataset you generated last week in order to identify a group (or groups) of customers at whom a marketing strategy could be targeted. You will generate summary statistics and data graphics that will characterise what makes your customer groups distinctive from the Leeds population as a whole.

