

Intersecting the location and the geodemographic context of museums at the national scale

Andrea Ballatore*¹, Stefano De Sabbata², Jamie Larkin³ and Fiona Candlin³

¹Department of Digital Humanities, King's College London, UK

²Department of Geography, University of Leicester, UK

³Center for Creative and Cultural Industries, Chapman University, CA, USA

⁴Department of History of Art, Birkbeck, University of London, UK

GISRUK 2023

Summary

The geography of the cultural sector concerns the location of producers, consumers, and venues of the Cultural and Creative Industries (CCIs) to answer questions about their development and dynamics. Considering the case of the UK museums, we use national data from the Mapping Museums project to study their geodemographic context at the Local Authority District level. Across the UK, we observe the distribution of different types of museums according to their governance type and subject matter in areas belonging to different geodemographic categories. Both in terms of simple counts and divergence from expected values, different types of museums show vastly different distributions and trends, reflecting the variety of the sector.

KEYWORDS: geodemographic classifications; museum context; museum studies; cultural geo-analytics; cultural and creative industries

1 Introduction

Geographic data science can play a crucial role in the study of the cultural sector, improving our understanding of the spatial distribution of cultural resources and activities as well as the complex relationships between cultural production, consumption, and place. The area of Cultural and Creative Industries (CCIs) focusses on the activities that produce and distribute cultural goods, services, and experiences. They include a diverse range of sectors, such as film and television production, music and performing arts, visual and graphic arts, publishing, broadcasting, and digital media, as well as museums, libraries, archives, and heritage sites (Hesmondhalgh, 2018).

Deploying spatial analytics to study CCIs can reveal novel patterns in cultural production and consumption, for example accounting for their clustering in specific areas, and proximity to suppliers,

*andrea.ballatore@kcl.ac.uk

audiences, and creative milieux. To date, most studies that investigate the relationship between CCIs and place stem from economic geography (Pratt, 2011), with theoretical reflections on what factors drives the success of these heterogeneous sectors (Tomczak and Stachowiak, 2015) and regional studies on particular clusters (Clifton et al., 2015). While valuable, these approaches overlook the geodemographic profile of places (Webber and Burrows, 2018), i.e., the characteristics of the resident population, which can provide an important contextual aspect that can explain the presence and absence of cultural activities.

In this exploratory study of cultural geo-analytics, we start with a basic spatial question about CCIs: Where are cultural organisations located in terms of the residential population? In other words, what are the geodemographic factors that support or inhibit the presence of cultural venues in a given area? More specifically, as a case study, we ask: *RQ: What types of museums tend to be located in areas of different geodemographic profiles?* Drawing on our recent work in the Mapping Museums project (Ballatore and Candlin, 2022), we focus on the distribution of museums in the UK, characterising areas with an open geodemographic classification based on Census data.

2 The geodemographic context of museums

Museum data. The museum data used in this analysis originates from Mapping Museums project, which surveyed the sector from 1960 to 2020 for historical and geographical research.¹ Each museum is described with a set of attributes, including *governance*, which refers to museum management, either government (Local Authorities are particularly important) or independent; *size*, based on the annual number of visitors (small, medium, large, huge); *subject matter* of the museum, using an up-to-date hierarchical categorisation produced for the project, including for example “arts,” “local history,” “buildings,” and “rural industry.”

The *location* of a museum was linked to the location of its buildings, estimated by converting the museum’s postcode to latitude and longitude coordinates using the ONS Postcode Lookup Dataset. Museums typically have one location, but some have multiple buildings and locations, such as Tate Group. In these cases, each museum is listed separately and the most recent address is used if the museum has moved (Candlin et al., 2020). The data used in this study captures the state of affairs as of December 2017, when 3228 museums were open in the country, ranging from extremely small to very large organisations across the four UK nations. While more recent data exist, this snapshot was used to generate results comparable with our published, detailed geography of the sector (Ballatore and Candlin, 2022).

Geodemographic data. To characterise geographic areas in the UK in terms of their resident populations, we rely on geodemographic classifications. The 2011 Area Classification for Local Authorities provides a national open dataset that associates each Local Authority District (LAD) with a category, described through a pen portrait (Office for National Statistics, 2017). For example, in supergroup Affluent England (r1), residents “are much more likely to live in detached housing and to own their own property. The supergroup has an above average ethnic mix and below average

¹<https://museweb.dcs.bbk.ac.uk>, accessed in January 2023.

| Area classification groups (Local Auth.) | Museum Governance | | | | | | | | | | | | |
|--|-------------------|-----------------|----------|-------------|------------------|----------------------------|----------------|-----------------------------|----------------|---------|-------|------------|---------|
| | Govt. | | | Independent | | | | Other | | | | | |
| | Cadw | Local Authority | National | Other | English Heritage | Historic Environ. Scotland | National Trust | National Trust for Scotland | Not for profit | Private | Other | University | Unknown |
| 1ar Rural Urban Fringe | 11 | | | 2 | | 5 | | 49 | 4 | 3 | | | 2 |
| 1br Thriving Rural | 36 | 3 | | 3 | | 22 | | 125 | 42 | 4 | | 3 | 4 |
| 2ar Larger Towns and Cities | 108 | 23 | | 2 | 1 | 9 | 3 | 122 | 18 | 6 | | 31 | 1 |
| 2br University Towns and Cities | 19 | 1 | | | | | | 27 | 3 | 1 | | | 26 |
| 3ar English and Welsh Countryside ¹ | 88 | 4 | 1 | 15 | | 54 | | 258 | 120 | 24 | | 4 | 14 |
| 3br Remoter Coastal Living | 39 | 2 | | 11 | | 28 | | 173 | 61 | 16 | | 1 | 4 |
| 3cr Scottish Countryside | 48 | | | | 14 | 1 | 12 | 114 | 37 | 9 | | 2 | 3 |
| 4ar Ethnically Diverse Metropolitan Living | 30 | 4 | | 3 | | 2 | | 35 | 3 | 6 | | | 3 |
| 5ar London Cosmopolitan | 10 | 16 | | 2 | | 4 | | 83 | 19 | 2 | | 8 | 1 |
| 6ar Services Manfact. and Mining Legacy ² | 72 | 7 | | 5 | | 7 | | 78 | 13 | 7 | | 5 | 2 |
| 6br Scottish Industrial Heritage | 40 | 1 | | | 2 | | 6 | 46 | 12 | 2 | | 2 | 1 |
| 7ar Country Living | 43 | 1 | 1 | 2 | 1 | 31 | 4 | 192 | 60 | 26 | | 2 | 7 |
| 7br Northern Ireland Countryside | 25 | 1 | | | | 6 | | 15 | 9 | | | | 5 |
| 7cr Town Living | 33 | 1 | | 4 | | 6 | | 47 | 13 | 2 | | 2 | 5 |
| 8ar Manufacturing Traits | 75 | 2 | | | | 6 | | 65 | 15 | 5 | | 2 | 2 |
| 8br Suburban Traits | 30 | 1 | | 1 | | 2 | | 43 | 10 | 5 | | | 2 |

Figure 1: Counts of museums: OAC in Local Authority Districts (LAD) vs museum governance. Museums N=3228. For example, 258 museums of governance “not for profit” are located in LADs classified as “English and Welsh Countryside” (3ar).

number of UK and Irish born residents. Residents are far more likely to be represented in the 5 to 14 years age group than nationally.”² The categories are defined in a three-level hierarchy containing 8 supergroups, 16 groups, and 24 subgroups, produced by clustering a large number of 2011 UK Census variables.

Analysis. The socio-demographic environment of a museum can be defined in many different ways, varying the spatial units and attributes being considered. For this study, we considered LADs as suitable spatial units. LADs partition the UK into 382 population units of variable population size, with a median of 140,000 residents. This classification is also available at the output area level (OA), which is much more granular (about 120 households per unit). For this initial analysis, we

²<https://www.ons.gov.uk/methodology/geography/geographicalproducts/areaclassifications/2011areaclassifications/penportraitsandradialplots>, accessed in Jan 2023.

| Area classification groups (Local Auth.) | 1ar Rural Urban Fringe | 1br Thriving Rural | 2ar Larger Towns and Cities | 2br University Towns and Cities | 3ar English and Welsh Countryside | 3br Remoter Coastal Living | 3cr Scottish Countryside | 4ar Ethnically Diverse Metropolitan Living | 5ar London Cosmopolitan | 6ar Services Manufact. and Mining Legacy | 6br Scottish Industrial Heritage | 7ar Country Living | 7br Northern Ireland Countryside | 7cr Town Living | 8ar Manufacturing Traits | 8br Suburban Traits | | |
|--|------------------------|--------------------|-----------------------------|---------------------------------|-----------------------------------|----------------------------|--------------------------|--|-------------------------|--|----------------------------------|--------------------|----------------------------------|-----------------|--------------------------|---------------------|------|------|
| | 4.6 | -0.2 | -2.5 | -3.4 | -1.9 | | | -0.8 | -1.5 | -4 | -2.8 | | | | | -1.3 | -1.9 | -2.3 |
| | 8.4 | -1.8 | -5.4 | -6.1 | 1 | -4.9 | -0.9 | 0.5 | -0.7 | -3 | 4.3 | -7.4 | -3.1 | -0.9 | 1.8 | | | |
| | 7.2 | 2.8 | 15.1 | 10.3 | -0.1 | 1.3 | 6.6 | -3 | 12.2 | 1.3 | -3.5 | 6.5 | 6.9 | -1.4 | 8 | | | |
| | 1.8 | 2.7 | 2.9 | 1.7 | -0.5 | | 4.5 | -1 | 4.7 | 0.6 | 0.9 | -0.7 | 6.1 | -0.5 | -1.5 | | | |
| | 12.3 | 9.9 | 1.4 | 2.8 | 11.5 | 5.3 | 7.7 | 4.6 | -3.2 | 8.8 | 10.4 | 7.7 | -0.3 | 6.8 | 5.7 | | | |
| | 6.1 | -0.6 | 0.7 | -1.5 | 2.2 | 0.2 | 1.4 | 6.7 | -0.3 | 1.7 | 7.5 | 23.3 | 3.8 | 6.7 | 5.4 | | | |
| | 2.8 | 12.7 | 1 | 13.5 | 4.3 | -1.4 | 0.9 | 8.4 | 1.7 | 11 | 1.7 | 5.6 | 2.1 | -1 | 2.7 | | | |
| | 4.9 | -3.7 | -2.3 | | -1.6 | -0.6 | 2.6 | -2.8 | -2.3 | -1.8 | -3 | -2.8 | -1.1 | -2.2 | -2.9 | | | |
| | 3.1 | -0.8 | 9.3 | 7.4 | -0.5 | 0.5 | 6.9 | -2.1 | -1.1 | 5.4 | | -2 | 12.6 | -1.7 | 0.8 | | | |
| | 11.2 | -2.4 | -3.6 | -4.3 | -8.3 | 8.5 | -8.8 | -5.5 | -2.9 | -7.6 | -9.4 | -4.9 | -6.3 | -2.4 | -5.5 | | | |
| | 3.3 | -2.2 | -2.9 | -1 | -0.6 | 0.2 | 0.4 | 2.7 | -0.1 | 0.3 | 2.1 | -0.2 | -0.8 | 0.2 | -1.4 | | | |
| | 10.5 | -2.7 | -5.8 | -2.4 | 4.6 | 3.6 | -8 | 5.7 | -5.3 | -3.3 | 5.9 | -6.3 | -5.1 | 6.8 | -2.1 | | | |
| | 2 | -0.9 | -1.2 | -0.9 | 0.3 | -1.3 | | -0.3 | -0.1 | 3.4 | 0.7 | | -0.8 | 1.1 | -0.4 | | | |
| | 7.7 | -3.2 | -5.1 | -5.3 | -3.9 | -4.1 | -6.4 | -4.3 | -3.2 | -5.3 | -2.2 | -6.6 | -5.6 | -3.7 | -2.2 | | | |
| | 8.2 | -4.8 | 3.8 | -2.4 | -3.6 | 4.5 | -3.2 | -5.1 | 5.4 | -5.2 | -5.5 | -1.9 | -4 | -3.3 | -5 | | | |
| | 5.9 | -4.8 | -5.5 | -3.6 | -3 | -5.2 | -0.9 | -2.9 | -0.7 | -3.5 | -2.2 | -3.8 | -3 | -2.8 | -1.1 | | | |

Museum subject matter

Areas %

archaeology

arts

belief and identity

buildings

industry & manufact.

leisure and sport

local histories

mixed

personality

rural industry

sea and seafaring

<others>

transport

war and conflict

Figure 2: Divergence from expected counts: OAC in Local Authority Districts (LAD) vs museum subject matter. Museums $N=3228$. For example, there are 29 art museums in London Cosmopolitan areas (12.4% of all art museums) and London Cosmopolitan LADs are just 3.1% of all areas. Therefore, the divergence d is $12.4 - 3.1 = 9.3$, indicating that this type of area is largely over-represented for this category of museums.

consider the LAD scale more appropriate, while OAs would be too small to meaningfully capture the context in which a museum is located.

Figure 1 summarises the counts of museums in different areas, grouped by the governance type. “Government” refers to museums funded and managed by the public sector, while “independent” is a broad group of non-governmental museums, each with sub-categories. The table shows several relevant aspects of the geography of museums. Considering the largest groups, Local Authority museums are predominant in urban areas (*2ar*), English and Welsh countryside (*3ar*), and mining areas (*6ar*, *8ar*). Not-for-profit museums are proportionally more present in rural areas than in urban ones. Some categories of museums tend to appear in specific geodemographic categories, e.g., National Museums in large cities, while English Heritage and National Trust museums are more rural. A chi-square analysis seems to indicate a significant association between museum governance

type and area classification $\chi^2(180) = 1194.7$, $p < .001$, although the results are not robust³.

Those counts show how no geodemographic category is entirely deprived of museums. However, the relative prevalence of museums is very uneven, and some areas might attract a lot of museums simply because they are relatively common across the UK (e.g., English and Welsh Countryside include 12.3% of all LADs). Hence, this geography can be more interestingly assessed in terms of over- and under-representation to a theoretical uniform distribution. We calculate the divergence from expected counts as an indicator of over- and under-representation of museums of a category in a given type of geographical context (LAD type). The divergence is calculated as $d = \left(\frac{|m_{ct}|}{|m_c|} - \frac{|a_t|}{|a|} \right) 100$, where m_{ct} is the number of museums of category c in area of type t , and a_t the number of areas of type t . Positive values indicate over-representation, and negative values under-representation.

In Figure 2, d is used to summarise the divergence between all types of areas and categories of museum subject matter. The first column shows the percentage of areas in the UK that are classified in a given geodemographic category. This approach makes some clear trends emerge. Some categories attract more museums than expected. Business, education and heritage centres have educated, diverse, and dense populations, and include Larger Towns and Cities (*2ar*), and University Towns and Cities (*2br*). London is also dominant, but only for a subset of categories. Another dominant group is Countryside Living (*3ar*, *3cr*), which tends to have an older, less dense population. By contrast, other categories are markedly under-represented across the board: Rural-urban fringe (*1ar*), ethnically diverse metropolitan areas (*4ar*), manufacturing and former mining areas (*6ar*), Town Living (*7cr*), and suburban areas (*8br*). These categories have in common relatively high levels of economic deprivation and a higher presence of ethnically diverse residents, but they also vary significantly in other respects. A chi-square analysis on the raw counts seems to indicate a significant association between museum subject matter and area classification $\chi^2(195) = 841.28$, $p < 0.001$, although the results might not be fully robust.⁴

The subject matter of museums is clearly linked to specific geodemographic contexts. Arts museums are an urban phenomenon; buildings (e.g., listed buildings) are greatly skewed towards English and Welsh Countryside; rural industry museums are located in Thriving Rural areas (*1br*); leisure and sport museums are the only category slightly over-represented in ethnically diverse areas; as one might expect, industry and manufacturing museums are skewed towards former mining and manufacturing areas, and the same occurs for seafaring museums and remote coastal communities; more interestingly, personality museums are over-represented in Scotland and Northern Ireland.

3 Towards cultural geodemographies

This analysis has investigated the geographical context of the museums in the UK at the national level, exploring governance and subject matter as important attributes that interplay with the residential geodemography of the cultural sector. Cultural geo-analytics can be used to study

³Only 76.44% of cells have expected value 1 or greater and 42.78% have expected value 5 or greater. A simulated p -value was calculated based on 2000 replicates.

⁴All cells have expected value 1 or greater, but only 71.42% have expected value 5 or greater. A simulated p -value was calculated based on 2000 replicates.

demographic and other aspects of CCIs, including museums (Ballatore and Candlin, 2022) and the film industry (Kaufmann and Ballatore, 2019; Ballatore et al., 2022), accounting for their heterogeneous geographies beyond the lens of economics that dominate this disciplinary focus.

It is important to acknowledge that this initial study does not capture the full complexity of the matter. This geography concerns the resident population only, regardless of their engagement with local museums, and the mere existence of presence, not their size and activities. A complementary geography of visitors would further unpack the relationship between museums and their spatial context. Moreover, the analysis is descriptive, and not inferential, and the spatial units are rather coarse and variable in size, limiting the inferences that can be drawn from the data.

In conclusion, demographic factors interact in non-trivial ways in the creation of and interaction with museums, and more research is needed to advance our understanding of the sector, particularly in relation to causal explanations. Having taken one small step forwards towards charting new geographies of the cultural sector, we plan to extend this approach to other CCIs. The large-scale geodemographic mapping of the location not only of firms, as done traditionally by economists, but also of music venues, theatres, and cinemas, would provide a powerful framework to understand the rich cultural life of cities and rural areas alike.

Data availability statement

All data and code are available online at <https://github.com/Birkbeck/mapping-museums> (folder: plots/geodemo_analysis/oac) under a Creative Commons license.

Acknowledgements

The museum data used in this work was collected with the help of the Arts and Humanities Research Council (Grant number: AH/N007042/1).

Biographies

All contributing authors should include a biography of no more than 50 words each outlining their career stage and research interests.

Andrea Ballatore (he/him) is a lecturer in Social and Cultural Informatics at the Department of Digital Humanities, King's College London. He is an alumnus of the Center for Spatial Studies, University of California, Santa Barbara. His research interests include geographic data science, cultural analytics, Internet geography, and geographic information retrieval.

Stefano De Sabbata (they/them) is an Associate Professor of Geographical Information Science at the School of Geography, Geology and the Environment and Research Theme Lead for Cultural Informatics at the Institute for Digital Culture of the University of Leicester. Their research focuses on geographic data science and the application of artificial intelligence to human geography and internet studies.

Jamie Larkin is Assistant Professor of Creative and Cultural Industries at the Center for Creative

and Cultural Industries, Chapman University, USA. His research interests include museum histories, museum commerce, and environmental sustainability.

Fiona Candlin is Professor of Museology in the History of Art Department at Birkbeck, University of London. She has written extensively on the history and theory of museums, and her books include *Art, Museums and Touch* (Manchester, 2010), *Micromuseology* (Bloomsbury, 2016), and *Stories from Small Museums* (Manchester University Press 2022).

References

- Ballatore, A. & Candlin, F. (2022). A geography of UK museums. *Transactions of the Institute of British Geographers*, <https://doi.org/10.1111/tran.12578>.
- Ballatore, A., De Sabbata, S., & Chavez Heras, D. (2022). Plotting film toponyms: A study in cultural geo-analytics. *Spatial Humanities 2022*, <https://doi.org/10.5281/zenodo.6702513>.
- Candlin, F., Larkin, J., Ballatore, A., & Poulouvassilis, A. (2020). Mapping Museums 1960-2020: a report on the data <https://eprints.bbk.ac.uk/id/eprint/31702/>.
- Clifton, N., Comunian, R., & Chapain, C. (2015). Creative regions in Europe: challenges and opportunities for policy. *European Planning Studies*, 23(12), 2331–2335, <https://doi.org/10.1080/09654313.2015.1104815>.
- Hesmondhalgh, D. (2018). *The Cultural Industries*. London: SAGE, 4 edition.
- Kaufmann, E. & Ballatore, A. (2019). New York Yankees and Hollywood Anglos: The persistence of Anglo-conformity in the American motion picture industry. *Nations and Nationalism*, 25(4), 1153–1189.
- Office for National Statistics (2017). 2011 Area Classification for Local Authorities. <https://www.ons.gov.uk/methodology/geography/geographicalproducts/areaclassifications/2011areaclassifications/>.
- Pratt, A. C. (2011). An economic geography of the cultural industries. In A. Leyshon, R. Lee, L. McDowell, & P. Sunley (Eds.), *The SAGE Handbook of Economic Geography* (pp. 322–337). SAGE.
- Tomczak, P. & Stachowiak, K. (2015). Location patterns and location factors in Cultural and Creative Industries. *Quaestiones Geographicae*, 34, 7–27.
- Webber, R. & Burrows, R. (2018). *The Predictive Postcode: The Geodemographic Classification of British Society*. London: SAGE.