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USER-GENERATED DATA IN CULTURAL MAPPING: ANALYZING GOOGLE POINT OF INTEREST REVIEWS IN DUBLIN

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ABSTRACT:

International migration is changing the social structure and cultural landscape of countries and big cities worldwide, especially in developed countries which are the target of job and asylum seekers. On the other hand, cultural diversity is becoming an important concept from different perspectives, such as boosting innovation and spatial segregation in urban planning and studies. Google point of interest (POI) data, as a commercial type of user-generated spatial data, is a secondary data source that can provide some information on the gender and nationality of reviewers, and this information can be used as a proxy indicator of cultural and background diversity. Yet, the potential application of the Google POI data has not been investigated in urban cultural and diversity measurement. In this study, we used artificial intelligence and text analytics methods through the NamSor API to identify the nationality and gender of Google POI reviewers in the Dublin Metropolitan Area. This study aims to highlight the potential application of spatial user-generated data in cultural mapping. The results are relatively consistent with official data in Ireland. Moreover, the results show that the number of male reviewers may be significantly higher than women reviewers, and this difference might be because of the gender digital divide. Finally, this paper discusses the potential challenges of using Google POI data and the implemented methodology and tools for cultural and diversity mapping and measurement. The proposed data and implemented methods in this study may have implications for other purposes in urban studies as well.

1 INTRODUCTION

International migration and population movement are changing the social structure and population landscape of countries and big cities worldwide, especially in developed countries, which are the target of tourists, students, jobs, and asylum seekers (Segal et al., 2009). This means that the population composition and cultural landscape of cities are changing every day, and cities are becoming increasingly more diverse in terms of the cultural background of their residents.

While the concept of diversity comes from ecology (Odum, 1953), it is used in wider disciplines from social science to information science to measure cultural and demographic diversity (Stirling, 2007). Cultural diversity, or multiculturalism, in terms of nationality, is an important concept in social research, and researchers are concerned about the segregation of immigrants with different backgrounds (Morén-Alegret and Wladyka, 2020), and some others believe that diversity has meaningful relationships with innovation, creativity, economic prosperity, and economic growth of countries and cities (Bove and Elia, 2017).

Cultural diversity is usually measured by official census surveys and data. Many attempts have been made to measure cultural diversity at different scales using different data sources (Fearon, 2003; Simon and Piché, 2012). In recent years, web-based crowdsourced or user-generated data and mapping have emerged as competitors of official data and their authoritative producers and institutions (Perkins et al., 2011).

This study was designed based on the concept of "*city and citizen as a text*" (Karimzadeh et al., 2013); it means if we consider the city as a text citizens are the authors who may translate their identity to this text and leave their footprints on the city and urban data. Therefore, we used the names of reviewers from the Google Place of Interest (POI) data as a type of crowdsourced or user-generated data about the cultural background and gender of reviewers. These digital footprints can be used to describe and understand a city.

In addition, to serve this purpose, Artificial Intelligence (AI) methods were used to identify the possible nationality and gender of reviewers as a proxy indicator of cultural diversity in the Dublin Metropolitan Area (hereafter Dublin). This study aims to explore the potential of Google POI as a type of user-generated data to map cultural diversity in a global city, Dublin, the capital city of Ireland. The results were compared to the official data to test the consistency of the findings.

This study also discusses the potential challenges in using (commercial) user-generated spatial data in cultural and urban studies, including 1. Socioeconomic, cultural, and behavioural,

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2. Geographical 3. Technological, and 4. Financial factors that limit this area of research.

2. DATA AND METHODS

2.1. Case Study

During the last decades, Dublin has been experiencing an unprecedented wave of job seekers (Mac Éinrí and White, 2008), especially in information and communication technology (ICT), along with other low and high-skilled workers in the service economy (Porto et al., 2021). Also, this city is one of the most attractive touristic destinations in Europe for international tourists. Furthermore, Dublin universities are absorbing many international students (Rabiei-Dastjerdi and McArdle, 2020). These conditions make Dublin a good case study for analyzing the nationality and gender of reviewers of Google POI data with different nationalities and backgrounds.

2.2. Data

The Google point of interest (POI), as the name shows, is a location that a person may find interesting such as touristic attraction, urban facilities service, etc. The spatial data collected from the Google Maps Website consisted of 54,856 POIs and 110,713 reviews. Reviewers contribute to the content of Google Maps by scoring or describing a POI with rates and short texts based on their personal experience, sharing photos and videos, updating POI information, or adding missing places on Google Maps. The data represented the period from 15 January to 27 February 2021.

Figure 1 shows the spatial distribution of Google POIs in Dublin. As can be seen, the focus of POIs is on the city centre and immediate neighbourhoods, the Docklands, and some sporadic locations in the northern and western parts of the city. Due to the limitation of the Google POI platform, we were only able to download five reviews for each POI. It means the actual number of reviews is higher than reviews used in this study. Still, we use them as a representative sample of residents and visitors to identify the possible nationality and gender of reviewers, which can be used as a proxy for cultural diversity.

2.3. Methodology

We used the NamSor API (1) to identify the reviewers' likely country of origin and gender. NamSor SAS is a European vendor of specialized big data mining software that can conduct various types of analysis on personal names. Onomastics is a branch of sociolinguistics that can be applied to mine big data and categorize personal names according to various taxonomies, e.g., gender, linguistic, and cultural origin (MacKenzie, 2018). Namsor trained its algorithm using data sets from across the world and claims accuracy of greater than 85% for national origin and greater than 95% for gender.

As a simplification, we describe how a machine learning model can be trained to classify personal names by an example. A name like ***Giorgi Beridze (****in Georgian* **გეორგი ბერიძე**, in Cyrillic ***Беридзе***) is more likely to be a Georgian name than ***John Smith***. This comes from morphology (-dze termination) but also relative name frequency by geography.

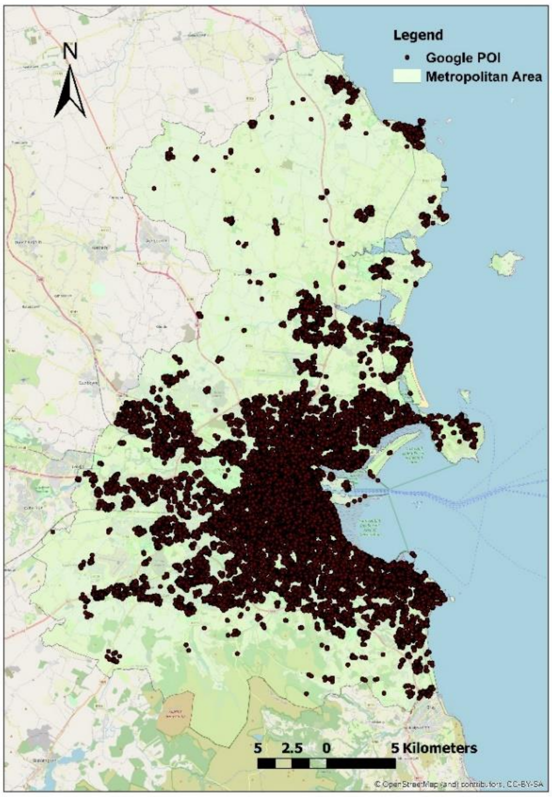

Figure 1: Geographical distribution of Google POI in Dublin

All personal names cited in this example are names that are very frequent and cannot be traced to a specific individual (e.g., ***John Smith***, etc.). We can start, for example, with a public list of dentists in the United Kingdom and a list of dentists in Georgia.

Dentists in the UK are more likely to have English names than dentists in Georgia; conversely, more dentists in Georgia are likely to have Georgian names than dentists in the UK.

NamSor's classifier first learns from name features (including name frequency, morphology and termination, etc.) and can then detect an English name in the list of dentists in Georgia, and conversely, a Georgian name in the list of dentists in the U.K. The same method can be applied to 150+ countries (Japan, Russia, Turkey, Iran, etc.).

Other independent databases are used to estimate the error rates, i.e., to determine the likeness of confusing a name from Georgia with a name from Japan, Russia, Turkey, Iran, etc. The name classification is returned with a probability estimate for correctness. The accuracy estimate is a minimum estimate, and the actual accuracy is generally higher (Munz et al., 2020).

The Namsor API has some limitations as well. For example, it cannot account for all changes of name patterns, mixed marriages, or outliers in naming conventions. For instance, disambiguating a name such as 'Elena Smith' in the context of a mixed marriage could require access to additional data, such as the name at birth (ex. 'Elena Rossini' vs 'Elena Sokolova'). Another limitation can be identifying gender in countries

[1]. https://www.namsor.com/

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where names are not necessarily traditionally gender specific (Santamaría and Mihaljević, 2018).

3. RESULTS AND DISCUSSION

The results show that in addition to Irish reviewers, there are likely reviewers from 171 other countries. Table 1. lists the top 30 countries and the percentage of reviewers from these countries. Not surprisingly, Irish reviewers are the leading reviewers of Google POIs in Dublin. This table reflects the flow and origins of international immigration and visits to the country very well. The number of American reviewers shows the historical and cultural close ties between Ireland the US, the similarity of Irish names and Americans, or the high number of Americans who live, work, and study in Ireland or visit the country. Moreover, immigrants with Irish ancestors can obtain Irish citizenship via Jus sanguinis that means people with Irish background can legally claim Irish citizenship (Kostakopoulou, 2008).

Table 1 shows that almost 46 percent of the reviewers are probably Irish, 14.7 percent are likely to be from the United States. Polish reviewers (2.29 percent of reviewers) are the third most represented in the data, and Indians (2 percent of reviewers) are in fourth place in this list. After them, the most popular Google POI contributors are from Great Britain (1.72 percent), Romania (1.5 percent), Italy (1.45 percent), Spain (1.45 percent), New Zealand (1.39 percent), France (1.36 percent), Pakistan (1.02 percent), Portugal (0.95 percent), Brazil (0.95 percent), and Germany (0.83 percent), respectively.

No	Country	%	No	Country	%
1	Ireland	46.09	16	Lithuanian	0.70
2	United States	14.70	17	Nigeria	0.68
3	Poland	2.29	18	Canada	0.66
4	India	2.00	19	Moldova	0.52
5	Great Britania	1.72	20	Russia	0.52
6	Romania	1.50	21	Croatia	0.51
7	Italy	1.45	22	Austria	0.50
8	Spain	1.45	23	Hungary	0.49
9	New Zealand	1.39	24	Hong Kong	0.48
10	France	1.36	25	Latvia	0.46
11	Pakistan	1.02	26	S Arabia	0.45
12	Portugal	0.95	27	Philippines	0.43
13	Brazil	0.95	28	Netherlands	0.43
14	Germany	0.83	29	Turkey	0.41
15	Austria	0.73	30	South Africa	0.41

Table 1: Top 30 Identified Nationality in Google POI Review

The Polish community is well established in Ireland, and Polish is the second spoken language in Ireland (O'Boyle et al., 2016; Machowska-Kosciak, 2020; Pszczółkowska and Lesińska, 2021), but other communities, especially from outside of the European Union, such as India, Pakistan, Brazilian, Nigeria, Moldova, and Russia, are not well studied, and should be studied by researchers in different fields such as sociology, demography, and public policy.

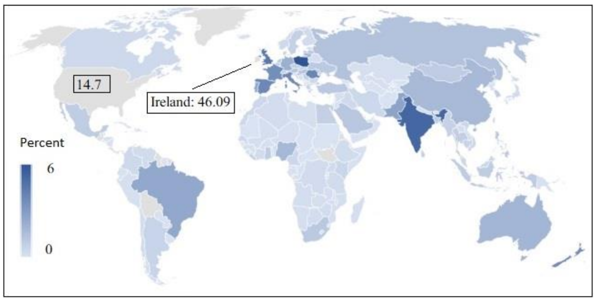

Figure 2: Nationality of Google POI Reviewers

Figure 2 is a map of reviewers' backgrounds, excluding Irish and American. Because of the high number of reviewers from Ireland and the US, we excluded them from our spatial analysis to better visualize the potential origin countries of other reviewers. This map shows that most reviewers have a European background in a spatial cluster, and reviewers from India, Pakistan, Australia, New Zealand, and Brazil are very active on the Google Map platform.

Usually, immigration data is based on the censuses of the population. Therefore, we downloaded population data from the Central Statistics Office (2) (CSO) of Ireland to compare our results with official statistics. Table 2 is the list of immigrant backgrounds in Ireland based on the CSO data. As we can see, while more than 85 percent of the population of the country is Irish (Table 2), their share in Google Map reviews is less than 50 percent (Table 1). A comparison of Table 1 and Table 2 shows that except for those identified with an Irish name have less contribution in Google Map in comparison of the demographic profile of the country, the contribution of other reviewers with different backgrounds are to some extent similar to the official data, including Polish, the UK, the US, Italians, and Spanish; therefore, the results presented in the paper accurately reflect the value of Google POI data. Therefore, the data can be used in cultural and urban studies, including cultural and diversity mapping and measurement and social behaviour in global cities like Dublin.

In addition, the results show that 61 and 30 percent of reviewers are potentially male and female, respectively, and the number of male reviewers is significantly higher than female reviewers. This difference may contribute to questions related to the *digital divide* (van Dijk, 2006) and gender inequality in terms of access to digital devices (Mariscal et al., 2019), which is rooted in different factors, such as access or ownership of digital devices. The real reason behind the gender differences should be investigated by comparing the number of male and female reviewers from different countries.

[2] . https://www.cso.ie/

No	Nationality	%	No	Nationality	%
1	Irish	87.03	16	American (US)	0.23
2	Polish	2.68	17	Slovak	0.21
3	UK	2.26	18	Chinese	0.21
4	Not stated	1.55	19	Hungarian	0.20
5	Lithuanian	0.80	20	Irish-Polish	0.20
6	Romanian	0.64	21	Pakistani	0.16
7	Latvian	0.44	22	Irish-Nigerian	0.15
8	Irish American	0.38	23	Irish-Other EU	0.14
9	Irish-UK	0.34	24	Nigerian	0.13
10	Brazilian	0.30	25	Irish-Australian	0.12
11	Spanish	0.26	26	Multi nationality	0.12
12	Italian	0.26	27	Croatian	0.12
13	French	0.26	28	Czech	0.11
14	German	0.25	29	Portuguese	0.11
15	Indian	0.25	30	Dutch	0.10

Table 2: Immigrant Background Based on CSO Data

4. POTENTIAL CHALLENGES

One of the main arguments in cultural diversity measurement is that single-item measures cannot capture cultural diversity, but multiple measures need more data, time, and resources (Williams and Husk, 2013). In this research, we used spatial data from Google POI and AI as partial solutions to this problem. The findings showed that using user-generated data in general and Google POI data in particular, the proposed methodology and tools in this research for measuring and mapping cultural diversity has some challenges because of different factors, which can be listed as follows.

4.1. Socioeconomic, cultural, and behavioural factors

Previous research has pinpointed that the geography of each platform of user-generated data and its richness depends on the socioeconomic context (e.g., population density, ethnicity, education, and income) (Ballatore and Sabbata, 2020). For example, the digital divide excludes people with less digital skill or access to digital devices from user-generated data production (Schradie, 2011). Some people do not provide reviews because of their cultural values, age, and lifestyle while they are using user-generated data and platforms (Wilson et al., 2012; Edelmann, 2013). Moreover, the name can show the potential nationality background of reviewers, but it is not valid for all cases. Some people might be Irish-born, or their names are similar to other nationalities. Some reviewers might use nicknames that are different from their real names or, in other words, there is an ecological fallacy (Duneier, 2006). Language barriers are also an impeding factor in excluding non-English speakers (Neimann Rasmussen and Montgomery, 2018).

4.2. Geographical factor

Another important point is that the focus of this study was on the core city, Dublin, while a large number of people and places are located in the city-region beyond the official border of Dublin (Rabiei-Dastjerdi et al., 2022) where the housing market pushes citizens, especially immigrants to peripheral areas and satellite towns of the core city. Although the results of this study are to some extent consistent with the official data of immigration available on the CSO website, the difference can be interpreted as the outcome of the growing number of international students and tourists who travel to visit Dublin (Rabiei-Dastjerdi and McArdle, 2020), which opens new questions of visitor behaviour on this platform and their contribution in reviewing Google POIs.

4.3. Technological factors

Technological infrastructure, including the quality of broadband networks and their spatial coverage, is another factor that plays a key role in user-generated data production and richness. The spatial coverage of internet networks may affect the richness of user-generated data and their geographical coverage. Consequently, the number and quality of reviews of user-generated data to specific urban areas with better access to broadband networks, such as the city centre or locations close to smart city projects and initiatives, are higher than other urban areas (Morozov and Bria, 2018).

4.4. Financial factors

The Google POI data used in this study is not publicly available and is commercial data, and this significantly affects the number of requested Google POI data and reviews. Considering recent suburbanization trends and development in Dublin (Rabiei-Dastjerdi and McArdle, 2021), Google POI data beyond the city border contains valuable information to extract, but due to the financial limitation of this research, we just downloaded the data within the metropolitan area . In addition, in this study, we used NamSor API, and all researchers and users may not have free access to it.

5. CONCLUSION

In this research, we used Google POI data to identify the background of the reviewers of the Google Map website using text analytics and machine learning. The results show that user-generated data and reviews in general and Google POI data, in particular, have valuable information to measure and map cultural diversity in global cities. While the findings are interesting and valuable. The research particularly highlights the potential of user-generated data to help understand cities' spatial and cultural aspects.

Researchers and policy designers can use the proposed data and methodology for urban cultural studies. Figure 1 shows that the geographical distribution of places of interest for the Google map users is uneven in the metropolitan areas, which shows high spatial inequality in access to urban facilities and services such as healthcare centres. Therefore, Google POI can be used in spatial inequality (Rabiei-Dastjerdi and Matthews, 2021), spatial accessibility measurement (Rabiei-Dastjerdi et al., 2018), urban consumption patterns (Rabiei-Dastjerdi et al., 2020) selection, identifying spatial segregation of communities by mapping and extracting invisible clusters based on the nationality or gender of reviewers (Farash et al., 2021), and extracting hidden sociospatial patterns of the underlying socioeconomic processes (Rabiei Dastjerdi, 2019) or characteristics of neighbourhoods in the city (Rabiei-Dastjerdi et al., 2021).

Moreover, other platforms with open access data, such as Foursquare (3) , can also provide cultural and socioeconomic insights. In addition, sentiment analysis methods, including natural language processing, text analysis, and computational linguistics (Liu, 2020), are practical tools to extract (locational) insights to be used in urban studies for various purposes. Also, AI and clustering methods are powerful tools to study the clustering and co-clustering of urban facilities and services to understand the role of location in urban businesses. Finally, from an applied sociocultural research perspective, user-generated data are a valuable source of information for immigration studies. For example, there are several studies about the Polish community in Ireland, but other immigrant communities, which were listed in this research, need more attention in terms of social cohesion, spatial segregation, and their assimilation into the society as they might have different social values, languages, religions (Gilmartin, 2013; Berumen, 2019). For example, the study presented here focused on Dublin as a whole; however, given more reviews, we can examine neighbourhoods to understand the cultural diversities in smaller city areas.

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[3] . https://foursquare.com/

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