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Discovering Visiting Behaviors and City Perceptions by Mining Semantic Trajectory

GEO 511 Master's Thesis

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Abstract

Tourism is a crucial industry for many cities, necessitating the development of unique attractions to draw in more visitors. Understanding the visiting behaviors and perceptions of visitors helps to uncover the city's distinctive characteristics, thereby aiding in the further growth of its tourism industry. It's important to note that different population groups may exhibit varying visiting behaviors depending on the time of their visit, which in turn can shape their impressions of the city. This study explores the dynamic visiting behaviors and city perceptions of locals and tourists throughout different times of the day and week. The study area is London, one of the world's most famous tourist cities. To conduct this study, User-Generated Content (UGC) is utilized, specifically data from Foursquare check-ins and Flickr tags from April 3, 2012, to September 16, 2013.

The study first identifies the spatiotemporal distribution of hotspots for each population group based on their Foursquare check-ins. The relative concentration of locals and tourists is then examined through the difference ratio to understand their unique visiting preferences. Next, the spatiotemporal movements of locals and tourists and their city descriptions during their trips are analyzed by constructing semantic trajectories. The place is the fundamental element of a semantic trajectory, and places are constructed by clustering Foursquare check-ins. The property of the place is defined by three dimensions: location (represented by borough names), locale (represented by place categories), and sense of place (represented by topics generated in topic modeling based on Flickr tags). Semantic trajectories are then clustered based on their semantic dimensions, and typical trajectories are mined for each cluster. The distribution of trajectories and their semantic dimensions are compared between locals and tourists at different time spans to explore how London's impressions evolve over time.

The results suggest distinct visiting behaviors and city perceptions over time for locals and tourists. Both groups primarily concentrate in the city center, with small hotspots around the airport. However, locals tend to visit more suburban areas than tourists. Locals show higher preferences for business districts during the daytime and on weekdays, while tourists consistently show interest in shopping in the city center. In terms of city perceptions, the city center is associated with descriptions of cityscapes and transport during the daytime. At night, people tend to associate the same area with nightlife activities. Furthermore, locals are interested in leisure activities and fitness, while tourists tend to focus on tourist attractions and the Olympics.

Keywords: Visiting Behavior, City Perception, Semantic Trajectory, Hotspots, UGC, Topic Modeling

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Acronyms

AOI Areas of Interest. 4, 6

API Application Programming Interface. 8, 10

DBSCAN Density-Based Spatial Clustering of Applications with Noise. 4, 6, 11, 14, 27

GPS Global Positioning System. 11, 12

HDBSCAN Hierarchical Density-Based Spatial Clustering of Applications with Noise. 26, 27

KDE Kernel Density Estimation. 4, 24–26, 35–37, 75, 79

LBS Location-based services. 10

LDA Latent Dirichlet Allocation. 7, 8, 28

MSM Multidimensional Similarity Measure. 13, 30–32, 79

NLP Natural Language Processing. 6

POI Point of Interest. 1, 10–12, 17

PrefixSpan **Prefix**-projected **S**equential **pa**tter**n** mining. 14, 32, 33

UGC User-Generated Content. i, 1, 2, 4–6, 8, 10, 12, 15, 80, 81

1 Introduction

1.1 Motivation

What distinguishes one city from another? The unique characteristics of a city are often defined by its physical properties, such as landmarks, road networks, and city structures. For example, when one thinks of London, iconic structures like the London Eye, the Tower of London, and Big Ben readily come to mind. However, a city is not only defined by its physical properties, it is also a large human settlement (Goodall, 1987; Kuper, 2013). In his book "The Image of the City", Lynch (1960) introduced the concept of a city's imageability and explored the relationship between this mental image and the city's physical qualities. According to a city perception survey (Institute for Urban Strategies, 2022), the most frequently used words to describe London include Big Ben, England, Queen, Beautiful, London Bridge, and Rain. These descriptions suggest that people's perceptions of a city are shaped not only by its visible landmarks but also by their personal experiences associated with it. Understanding a city requires more than just knowledge of its physical properties. It involves recognizing how people interact with these properties and how their mental images, formed through these interactions, distinguish one city from another. In addition to studying these perceptions, it is also crucial to investigate the behaviors of those visiting the city. The way visitors navigate through the city, the landmarks they choose to visit, and their interactions with the local culture all contribute to their overall perceptions of the city. These visiting behaviors can provide valuable insights into how a city is perceived by outsiders and can further highlight its uniqueness. Investigating both the visiting behaviors and city perceptions helps to highlight the unique characteristics of the city and contribute to our understanding of its uniqueness.

Social media data has emerged as a valuable source for urban exploration, given its ability to provide spatially and temporally referenced information. Platforms such as Twitter [1], Flickr [2], and Foursquare [3] allow users to post contents that can offer insights into city dynamics. For instance, the high volume of user check-ins generated on Foursquare can be analyzed to study how people move around the city, providing valuable insights into visiting behaviors (A. P. G. Ferreira et al., 2015). Moreover, User-Generated Content (UGC) on these platforms, like images, reviews, and Point of Interest (POI), offers the potential to extract city perception from a bottom-up approach. This is because users share their experiences and observations about different cities, thereby contributing to a collective understanding of urban spaces. social media data serves as a rich and precise source of information for discovering and understanding cities, providing both quantitative data and qualitative insights.

Perceptions of a city are dynamic, varying both spatially and temporally, and can even differ among distinct population groups. To capture this dynamic, investigating the visiting behaviors of visitors can be a valuable approach. Social media data, with its spatial and temporal references, can enhance studies on visiting behaviors (Beiró et al., 2016). In particular, constructing trajectories that provide semantic information about people's visiting purposes and impressions of the city can offer valuable insights. The city perceptions extracted in this manner are more akin to a city image that reflects its distinctiveness, thereby enhancing its appeal to people and resources. In an urban context, such perceptions can supply public surveys to better understand citizens' needs and preferences. The abundance of social media data makes it possible to divide users into different population groups,

[1] `https://twitter.com/home`
[2] `https://www.flickr.com/`
[3] `https://foursquare.com/`

and their respective city perceptions can contribute to creating a more livable city for people of diverse ages and socio-economic backgrounds. In conclusion, social media data serves as a powerful tool for improving the quality of life by providing a nuanced understanding of city perceptions among various population groups.

1.2 Research Questions

City perception is traditionally collected through surveys involving a large number of participants, which can be labor-intensive and time-consuming. The advent of social media data has led many studies to leverage UGC to gain insight into how users perceive a city (Cranshaw et al., 2021; Huang et al., 2022). However, while most studies focus on specific regions of the city, there has been a noticeable lack of research exploring city perceptions from a perspective of visiting behaviors, such as trajectories. The identification of meaningful places is a crucial step in constructing trajectories. A place should not be merely a random point, but rather a space where people interact, which is characterized by attributes based on human consensus. For instance, an area with grass and trees may not necessarily be considered a place unless it attracts people and offers functionality for leisure purposes. Social media data allows for the identification of places. Foursquare check-ins, for instance, are often used to identify popular landmarks in a city (Santos et al., 2018; A. P. Ferreira et al., 2020). Foursquare venue names and categories enrich check-ins with meaningful attributes, laying the basis for constructing places. In addition to these objective attributes, subjective attributes are also worth exploring. Flickr allows users to add tags to their photos, which can serve as a valuable data source to enrich place attributes.

A trajectory represents the chronological sequence of places visited by people. While efforts have been made to extract movement patterns from trajectories to reveal underlying visiting behaviors (Vu et al., 2019), it is important to note that a trajectory should not be limited to geometric movements. The semantic information underlying trajectories is also valuable for exploration. When the semantic information of a trajectory is combined with spatial and temporal data, it forms what is referred to as a semantic trajectory (Yan, 2011). To understand visitor behaviors, most studies on semantic trajectories annotate the trajectories with attributes such as time, weekday, weather, etc. (Cai et al., 2018; Petry et al., 2019). However, existing studies have not adequately considered the enrichment of semantic information for trajectories based on place attributes. Semantic trajectories can vary across different groups of people. For instance, locals and tourists might organize their trips differently based on local knowledge and online travel reviews. Moreover, different time spans can also result in different semantic trajectories, as people tend to exhibit different visiting behaviors on weekdays and weekends. While existing studies have primarily focused on the visiting behaviors of locals and tourists (Straumann et al., 2014; Domènech et al., 2020), the city perceptions of these two groups of people at different time spans are still under investigation.

To bridge this research gap, this study proposes to construct the semantic trajectories of locals and tourists in London with Foursquare check-ins and Flickr tags to investigate both visiting behaviors and city perceptions. London, an English-speaking city that attracts a significant number of tourists each year, provides an ideal setting for this study. Moreover, the abundance of Foursquare and Flickr users sharing check-ins and photos in London lays a solid foundation for the construction of semantic trajectories. This study examines two research questions:

RQ1: Which areas are more popular among locals and tourists at different time spans?

Considering the diverse functionalities of different areas, they are likely to attract different populations with specific visitation objectives. To investigate the distribution of areas that cater to distinct population groups, it is crucial to first identify the hotspots of locals and tourists and assess the degree of mixture between locals and tourists in these areas (D. Li et al., 2018). In addition to the distribution of popular areas, the visiting objectives of locals and tourists can also be investigated based on local knowledge.

RQ2: How do locals and tourists perceive the city along their semantic trajectories at different time spans?

The visiting behaviors and perceptions of a city by people are subjective, and can vary not only between locals and tourists, but also evolve over time. To gain a more accurate understanding of these visiting behaviors and perceptions, it's beneficial to construct semantic trajectories that take into account both population groups and time spans. Specifically, semantic trajectories can be constructed for locals and tourists during different times of the day and week, including daytime and nighttime, as well as weekdays and weekends. By integrating the semantic attributes of places into these trajectories, The visiting behaviors and city perceptions of both locals and tourists across various time spans can be compared.

2 Related Work

2.1 Urban Studies

2.1.1 User-Generated Content (UGC)

UGC provides lots of information in urban studies, and it can be categorized into three main types: check-ins, texts, and photos. Each type of UGC conveys unique insights and has specific applications in urban studies. First, check-in data, such as those from Foursquare and Weibo, offer spatial and temporal information about users' movements. This data can be used to identify hotspots of activity and understand visiting behaviors among different groups of people, such as locals and tourists (Su et al., 2020; Wan et al., 2017; Vu et al., 2019). Second, text data, including Tweets, Flickr tags, and Google Maps reviews, provide rich semantic information about users' perceptions and experiences. These texts can be analyzed to evaluate aspects like crisis response (Yao & Wang, 2020) and urban outdoor area expressions (Santos et al., 2018). In terms of photo data, photos from platforms like Flickr and Panoramio can be used to visually represent city perceptions. Techniques such as clustering and classification can be applied to analyze these images and the associated tags, providing a comprehensive overview of people's perceptions of different areas (Dunkel, 2015; Zhou et al., 2015; Jailani et al., 2021).

The benefits of using UGC in urban studies are manifold. UGC provide diverse perspectives from a wide range of users, offering a more comprehensive understanding of visiting behaviors and city perceptions of different populations. The spatial and temporal information attached to many forms of UGC enable the study of visiting patterns over time and across locations. The rich semantic information in UGC helps to gain deeper insights into user perceptions and experiences. Lastly, the cost-effectiveness and large volume of UGC make it a robust and reliable source for data collection.

2.1.2 Visiting Behavior

The examination of the spatial distribution of locals and tourists provides valuable insights into the visiting behaviors among these two distinct groups. Hotspot detection can be an approach to discovering the distribution of locals and tourists. UGC has proven to be a valuable data source for hotspot detection. For example, images from Panoramio and Flickr, as well as Tweets shared by social media users, have been utilized to apply spatial autocorrelation indices such as Moran's I and Getis-Ord G statistics. These indices aid in the identification of hotspots and spatial clusters of tourism activities (García-Palomares et al., 2015; Kim et al., 2021). Check-in data has also proven to be a robust source for hotspot detection. Su et al. (2020) employed Kernel Density Estimation (KDE) on Weibo check-ins to identify and compare hotspots of tourists from Mainland China and residents of Hong Kong. Moreover, with this UGC, hotspot identification can be achieved by detecting Areas of Interest (AOI) using clustering techniques. These techniques include K-Means clustering (Hartigan & Wong, 1979), Density-Based Spatial Clustering of Applications with Noise (DBSCAN) (Ester et al., 1996), and self-developed algorithms (Y. Hu et al., 2015; Hasnat & Hasan, 2018).

The relative concentration of locals and tourists can be instrumental in detecting hotspots by population group, thereby capturing their distinct visiting preferences. Various indices have been employed in previous studies to measure the distribution patterns of different population groups. One such index is the *index of dissimilarity*, proposed by Sakoda (1981), which measures the distribution of two populations across geographic areas. D. Li et al. (2018) applied this index to represent the degree of mixture between locals and tourists, thereby studying their spatial interactions. The *index of dissimilarity* is calculated as the sum of the difference ratio of locals and tourists in each place, reflecting the overall distribution of locals and tourists over the study area. The difference ratio itself can also serve as an indicator to measure the popularity of individual places. McELROY et al. (1993) formulated the *density ratio* and the *penetration ratio* to reveal the degree of tourist influx into an area. The *Penetration ratio*, which shows the proportion of tourists in a specific place at a temporal scale, can also be used to measure the popularity of places among two groups of people. McElroy & de Albuquerque (1998) further developed the *tourism penetration index* to measure the degree of tourism penetration. This index involves three variables: per capita visitor spending, daily visitor densities per 1,000 population, and hotel rooms per square kilometer. The *tourism penetration index* is then calculated as the unweighted average of these three standardized indices. In the context of place popularity measurement, the second variable, which reveals the average tourist density, also indicates place popularity among locals and tourists. Standardizing this index helps to investigate the distribution of these two groups of people for each place. Furthermore, Faulkner & Tideswell (1997) proposed the *tourist ratio*, calculated as the ratio of the number of tourists to the number of residents in a specific area, an indication of the intensity of tourist influx.

Constructing trajectories serves as an alternative approach to discovering the distribution of locals and tourists through their movement patterns. Girardin et al. (2008) utilized people's mobile phone calls and Flickr images to investigate the visitor flows among major visitor attractions in Rome, Italy. They applied the Origin-Destination matrix to understand the visitor preferences. Some studies use the trajectory network to detect visitor movement patterns. A weighted network graph was constructed from clusters of Flickr and Twitter data, followed by network analysis like betweenness and eigenvector centrality to extract popular attractions and routes (Straumann et al., 2014; F. Hu et al., 2019). Other studies construct trajectories based on the street layout. For example, Mohíno et al. (2018) identified the main tourist routes of Flickr users along the street network, and Domènech et al. (2020) established the hierarchy of the street network based on the number of trajectories passing through. This helped to better understand the city structure and context. Yin et al. (2011) also ranked street-based trajectories with various ranking methods, contributing to location recommendation at the trajectory level.

2.1.3 City Perception

City perception has significant implications for the city's vitality and is a critical topic in the field of urban planning and design (Jacobs, 1961). It can be revealed through the investigation of how people experience and interact with the urban environment, involving individuals' subjective impressions, cognitive maps, and emotional responses towards urban spaces (Lynch, 1960). UGC plays an important role in studies of city perceptions. Some studies of city perceptions aim to improve specific subjects within the city, and landscape amenities have received widespread attention among these studies. For example, Huang et al. (2022) utilized Google Maps reviews to evaluate park performance and user experience, which showed the potential of using these reviews to enhance urban landscapes. There are also some studies investigating the soundscape of parks, as city perception can be reflected from an acoustic perspective. Such studies mainly focus on the evaluation of acoustic comfort and people's acceptability of the urban environment (Tse et al., 2012; J. Liu et al., 2014). Urban safety is another popular topic in city perception research. Some cities, despite being popular tourist destinations, suffer from natural disasters or negative publicity about crime, making perceived danger a worthy topic of investigation. Yao & Wang (2020) applied Tweets to build a real-time urban analytical and geo-visual system to provide early alerts for crises and emergencies. D. Yang et al. (2018) collected crime data and Tweets to predict and visualize crime hotspots.

Some studies investigate city perceptions to uncover people's impressions of the city. The extraction of semantic information from UGC is a common approach. For instance, Dunkel (2015) clustered Flickr images and subsequently mapped the tags associated with each cluster, with the size reflecting the frequency, which presented a comprehensive overview of people's perceptions of the study areas. Zhou et al. (2015) applied DBSCAN to detect Flickr images communities and then employed random forest to classify Flickr tags into three categories based on the spatial, temporal, and user features. This helped to describe detected communities with more precise word clouds. D. Li et al. (2018) identified hotspots of locals and tourists to find tourist attractions based on Flickr tags, and created location-based word-cloud maps to uncover how these attractions are described by Flickr users. Santos et al. (2018) collected reviews about places from Google Places and Foursquare tips, and generated perception maps to uncover how the urban outdoor areas were expressed in social media. Bahrehdar & Purves (2018) went one step further by applying topic modeling to mine abstract topics from Flickr tags and mapped users' perceptions of the space. Jailani et al. (2021) used Term Frequency-Inverse Document Frequency (TF-IDF) to assign weights to keywords of Flickr data, including tags, titles, and descriptions, and utilized DBSCAN to cluster weighted keywords, thus the discovered AOIs were integrated with intrinsic semantic information. Researchers have also attempted to extract semantic information from trajectories to interpret city perceptions. Unlike raw trajectories that only contain spatial and temporal information, semantic trajectories are also annotated with higher-level semantic information at each point. Wan et al. (2017) incorporated the venue categories of Sina check-ins when constructing users' semantic-graphic traces and detected their movement patterns using a density-based clustering algorithm. To gain deeper insights into visitors' characteristics and activity preferences, topic modeling was employed to analyze the venue categories of their check-ins (Vu et al., 2019; A. P. Ferreira et al., 2020). In addition to venue categories, other factors such as weather and time were also considered in the construction of semantic trajectories (Cai et al., 2018; C. Liu & Guo, 2020). This multi-faceted approach provides a more comprehensive understanding of city perceptions and visitor behavior.

2.1.4 Topic Modeling

Natural Language Processing (NLP) has emerged as a powerful tool for information retrieval. Within the realm of NLP, topic modeling has become increasingly popular, particularly in the context of text mining for UGC. Topic modeling, a subfield of generative probabilistic modeling, is employed to identify latent themes within a large corpus. In the process of topic modeling, a *word* or *term* signifies a single token, which serves as the fundamental unit of individual data. A *document* encompasses a piece of text composed of multiple words. A *corpus*, a collection of documents, forms the foundation for topic modeling. A *vocabulary* comprises all unique words in a corpus. A *topic* represents a latent theme discovered through topic modeling and is characterized as a probability distribution spanning a given vocabulary (Vayansky & Kumar, 2020). As depicted in Figure 2.1, topic modeling involves inputting a corpus to generate a set of topics. Each topic represents a cluster of words with the probability of belonging to that particular topic. The results of topic modeling include the distribution of topics within each document, indicating the degree of association between the topics and the document, as well as the frequency of words within each topic. The origin of the topic model can be traced back to Latent Semantic Indexing (LSI) proposed by Papadimitriou et al. (2000). However, LSI is not a probabilistic model. To address this limitation, Hofmann (2001) introduced Probabilistic Latent Semantic Indexing (PLSI), and subsequently, Blei et al. (2003) proposed Latent Dirichlet Allocation (LDA), which is a more complete generative probabilistic model (L. Liu et al., 2016). Compared with PLSI, LDA generates better disambiguation of words and more precise identification of topics in documents due to its consideration of a sparse Dirichlet prior in the topic distribution (Barde & Bainwad, 2017).

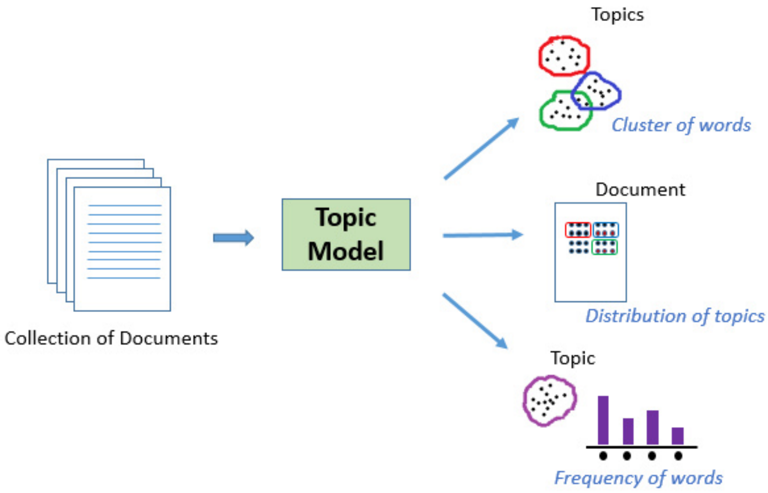


Figure 2.1: Framework of topic modeling (Usmani et al., 2021).

The LDA method has proven to be a valuable tool for understanding unstructured data. Several tools are available for implementing the LDA model in practice. The MAchine Learning for LanguagE Toolkit (MALLET) [4] is a Java-based package that provides efficient and sampling-based implementations of LDA related models. Gensim [5] is a Python library that implements popular topic modeling algorithms, including LDA and LSI. The Stanford Topic Modeling Toolbox (TMT) [6] is another tool that trains topic models to create summaries of the text. An evaluation of MALLET and Gensim was conducted to compare their performances (Ebeid & Arango, 2016). To facilitate the interpretation of LDA results, Sievert & Shirley (2014) developed LDAvis [7], a web-based interactive visualization of topics. LDAvis allows users to select a topic to reveal the most relevant terms for that topic. Users can also select a term to reveal its conditional distribution over topics (Figure 2.2). LDAvis leverages the R language, specifically the shiny package, to enable users to visualize topics. Additionally, a Python library, pyLDAvis [8] was developed to provide interactive topic model visualization in Python.

[4] https://mimno.github.io/Mallet/index
[5] https://radimrehurek.com/gensim/
[6] https://downloads.cs.stanford.edu/nlp/software/tmt/tmt-0.4/
[7] https://github.com/cpsievert/LDAvis
[8] https://github.com/bmabey/pyLDAvis

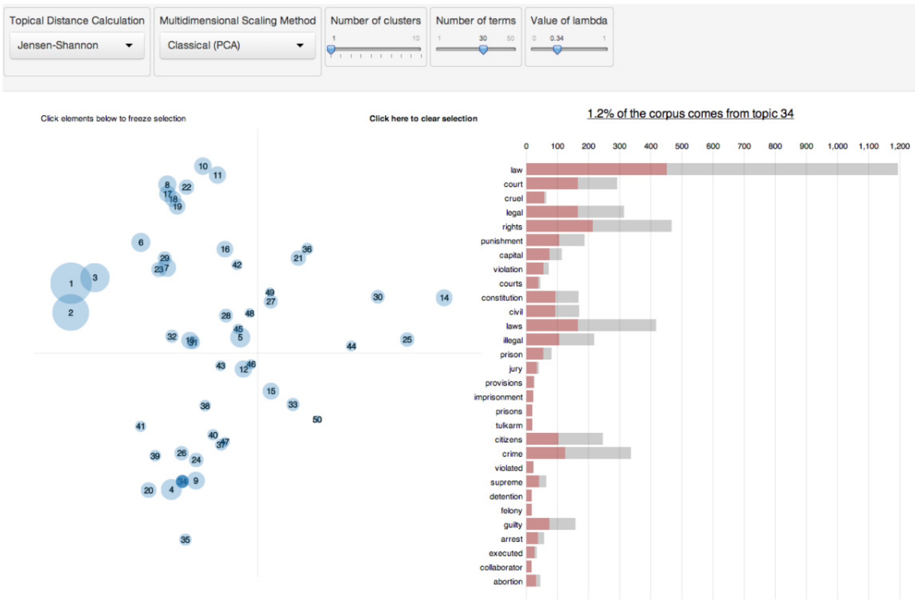


Figure 2.2: The layout of LDAvis (Sievert & Shirley, 2014).

Topic modeling using LDA has been widely adopted for extracting information from UGC. For instance, Flickr tags were utilized for investigating the properties of places and semantic similarity of streets (Bahrehdar & Purves, 2018; Bahrehdar et al., 2020). In addition, the venue categories of Foursquare check-ins were used to extract semantic information about places. LDA was applied to the venue categories of users' check-ins along their movements to depict different types of users with distinct character profiles (A. P. Ferreira et al., 2020) and discover implicit activity preferences of users (Vu et al., 2019). Furthermore, Google reviews were found to be a good data source for extracting leisure activity potentials in urban space (van Weerdenburg et al., 2019). These applications demonstrate the versatility and effectiveness of LDA in extracting valuable insights from UGC.

2.1.5 Identification of Locals and Tourists

Distinguishing between locals and tourists can yield valuable insights as these two groups might have different preferences when visiting a city. The time interval is a commonly used indicator for identifying locals and tourists. Typically, locals are assumed to stay in the city for longer periods than tourists. Researchers have used the time interval between a user's first and last posts within a city boundary on social media platforms to estimate the length of their stay, with time intervals ranging from 10 days to 30 days (Girardin et al., 2008; F. Hu et al., 2019; Höpken et al., 2020). For example, given a 30-day threshold, a Twitter user whose first and last Tweets were posted within a 20-day time interval would be classified as a tourist. However, it is important to note that some locals may share content only for short periods, and some tourists may stay longer and continue sharing content. User profiles on social media platforms like Foursquare, Flickr, and Twitter, which offer APIs to collect user profiles containing information on their city of residence and hometown, were also used to identify users' origins (A. P. G. Ferreira et al., 2015; D. Li et al., 2018). However, this approach has some limitations as many users may leave their profiles incomplete without providing the city of residence. To overcome these limitations, A. P. Ferreira et al. (2020) combined both the time interval and user profiles. If a user's time interval suggests that he is a local, but his profile indicates that he is from another city, he would be classified as a tourist. There are also other indicators for the identification of locals and tourists. In addition to the time interval, Hallot et al. (2015) also analyzed the categories of the place visited and the frequency of visits within the same place to extract tourists. L. Yang & Durarte (2021) assumed that locals and tourists might have different numbers of Foursquare check-ins, total travel distances, and time intervals, and applied K-means clustering to separate users into locals and tourists based on these indicators. Hasnat & Hasan (2018) used the number of Tweets within the geographical boundary as an indicator to identify tourists. For example, if a user posted fewer Tweets within the geographical boundary of Florida between 12 am and 6 am than outside the boundary, he would be assumed as a local. Overall, these approaches help researchers to effectively differentiate between locals and tourists, enabling them to investigate the visiting behaviors of different groups of people.

2.2 Semantic Trajectory

2.2.1 Place Conceptualization

The perception of a city is influenced by individuals' perceptions of various places. The first step in investigating place-based perception is to define the concept of place. According to Tuan (1975), a place is a human construct, designed for human purposes, encompassing not only geometrical and ideographic perspectives but also an experiential perspective. It is important to differentiate between space and place. Space is an abstract, continuous, and unrestricted area that can be freely used or occupied, while place is a segment of geographical space loaded with human meaning, facilitating human interaction (Tuan, 1975; Agnew, 2011; Cresswell, 2014). Relph (1976) introduced an *insideness* scale to depict the social relationships of a place, incorporating knowledge of the physical details of the place, a sense of community connection, and a personal connection with the place. Williams & Vaske (2003) employed the *place attachment* as the scale to identify and measure the meanings of places based on *place identity* and *place dependence*. As the definition of place evolves, researchers contribute to the conceptualization of place dimensions. Jorgensen & Stedman (2006) described the place with three dimensions: (1) place-specific beliefs (*place identity*), (2) emotions (*place attachment*), and (3) behavioral commitments (*place dependence*). Ye et al. (2011) proposed that a place could be semantically described by two features: (1) *explicit patterns*, derived from all check-ins within the place, and (2) *implicit relatedness*, inferred from the network of related places. Agnew (2011) conceptualized the place with three dimensions: (1) *location*, (2) *locale*, and (3) *sense of place*. The *Location* dimension refers to the physical position of a place, which can be represented by its name and coordinates; the *Locale* dimension encompasses the properties and affordance of a place; the *Sense of Place* dimension is associated with the sentiments and emotions of individuals who visit the place (Bahrehdar & Purves, 2018). It is noteworthy that according to affordance theory, *affordance* can shape behavior and guide actions of individuals (Gibson, 1977), thus the affordance of place can influence how people perceive it.

In terms of the representation of place dimensions, the *Location* dimension is typically represented by the toponym. For the *Locale* dimension, Wartmann et al. (2018) refined it with categories of landscape elements, indicating the potential for representing this dimension with place categories. Koirala (2015) categorized places based on tourism ontologies, which include leisure, restaurant, attraction, emergency service, transport, accommodation, and other buildings. C. Liu & Guo (2020) constructed a location category hierarchy tree based on daily purposes, including work/study, food, entertainment, traffic, and live. Location-based services (LBS) providers also categorize places to offer place-related APIs for users to search for POIs by category (Table 2.1). However, these place categories are typically divided based on specific services provided by LBS providers, and the categorization bias might lead to incomplete categories. For instance, Waze provides services for driving directions and live traffic conditions updates, which means that its place categories tend to be traffic-oriented. Tripadvisor is an online travel agency that provides guidelines for visitors, and it divides places mainly based on where to stay and what to do during a trip. To address this limitation, some studies modified the place categories provided in LBS platforms based on their research objectives. For example, in the case of Foursquare check-ins, the place category system is structured hierarchically and there are subcategories under categories. A. P. Ferreira et al. (2020) and L. Yang & Durarte (2021) improved the place categories by moving some subcategories into other categories or new categories to gain a better understanding of visitors' behaviors. The *Sense of Place* dimension is closely linked to people's emotional attachment to the place. Conducting surveys is a way to gather information on people's emotional relationships with places and to understand their positive or negative experiences (Manzo, 2005). However, collecting data through surveys can be time-consuming, and UGC can provide an alternative means of exploring people's relationships with places. Wang (2015) utilized Foursquare check-ins to evaluate the performance of four different clustering algorithms in identifying meaningful places. Adams & McKenzie (2013) applied topic modeling to georeferenced travel blogs to generate meaningful topics describing places. Hallot et al. (2015) combined Google Place reviews and Foursquare check-ins to retrieve place-based semantics, enabling the inference of additional information about users based on their movements.

Table 2.1: Overview of place categories in various LBS providers.

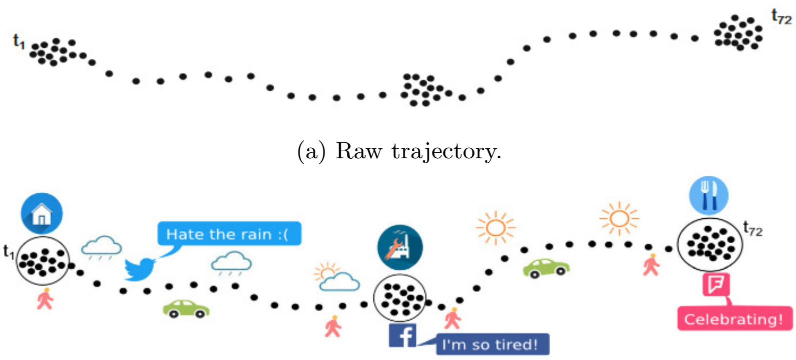
LBS Provider	Place Categories	Related API
Google Maps[a]	Airport, Amusement Park, Bank, Cafe, Embassy, Gym, Hospital, Library, Museum, Zoo, etc. (Google Maps divides places into 96 categories in total)	Places API
Esri ArcGIS[b]	Arts and Entertainment, Education, Food, Land Features, Nightlife Spot, Parks and Outdoors, Professional and Other Places, Residence, Shops and Service, Travel and Transport, Water Features	Geocoding REST API
Foursquare[c]	Arts and Entertainment, Business and Professional Services, Community and Government, Dining and Drinking, Event, Health and Medicine, Landmarks and Outdoors, Retail, Sports and Recreation, Travel and Transportation	Places API
Tripadvisor[d]	Hotel, Restaurant, Attraction	Location Search API
Waze[e]	Parking Lot, Car Services, Transportation, Professional and Public, Shopping and Services, Food and Drink, Culture and Entertainment, Other, Lodging, Outdoors, Natural Features	Waze API
HERE[f]	Eat and Drink, Going Out-Entertainment, Sights and Museums, Natural and Geographical, Transport, Accommodations, Leisure and Outdoor, Shopping, Business and Services, Facilities, Areas and Buildings	Geocoding & Search API
TomTom[g]	Agriculture, Beach, Castle, Factory, Garden, School, Railroad Stop, Temple, etc. (TomTom divides places into 778 categories in total)	Category Search API

Source: LBS provider websites as of May 2023.

[a] `https://www.google.com/maps`
[b] `https://www.arcgis.com/index.html`
[c] `https://foursquare.com/`
[d] `https://www.tripadvisor.com/`
[e] `https://www.waze.com/live-map/`
[f] `https://www.here.com/`
[g] `https://www.tomtom.com/`

2.2.2 Trajectory Construction

The detection of movement patterns from visitor trajectories helps in understanding their visiting behaviors. However, interpreting these patterns can be challenging due to the lack of contextual information. To address this, efforts have been made to incorporate semantic descriptions into raw trajectories to construct semantic trajectories. A trajectory can be assumed as a sequence of stops and moves (Spaccapietra et al., 2008). Stops represent specific points along the trajectory where the moving object stays for a certain duration, typically indicating locations of interest. For instance, in tourism studies, stops could include sightseeing spots, hotels, airports, etc. (Yuan et al., 2017). Moves represent the transitions between stops in a trajectory, indicating the segments from one stop to the next. Unlike raw trajectories that only capture spatial or spatiotemporal properties (Figure 2.3a), semantic trajectories enrich stops and moves with contextual data such as weather, transportation means, and place type (Figure 2.3b). The integration of semantic information enables the extraction of meaningful trajectory behaviors. For example, in the context of tourism, a tourist behavior of sightseeing can be identified if the trajectory begins and ends at an accommodation place, with several stops at museums or tourist attractions (Parent et al., 2013). The construction of a semantic trajectory involves identifying stops, which are the important places of trajectory. Subsequently, stops or moves are annotated with semantic information, and this process is also known as semantic enrichment.



(a) Raw trajectory.

(b) Semantic trajectory.

Figure 2.3: Example of trajectories (Ferrero et al., 2020).

Global Positioning System (GPS) data is widely used for constructing trajectories. There are various methods for identifying stops from GPS data. One approach detects stops by examining the absence of GPS signals or when the velocity remains zero during a specific time interval (Ashbrook & Starner, 2003). However, the presence of signal errors reduces the accuracy of identifying actual stops using this technique. Alternatively, other approaches consider both the GPS data and background geographic information to identify stops. Alvares et al. (2007) developed an algorithm named SMoT (Stops and Moves of Trajectories) for extracting stops and moves. In their study, a stop is defined as a location where an object remains for a minimal amount of time, and it is annotated with the corresponding place type and timestamp. Density-based clustering algorithms are also employed to identify stops. Palma et al. (2008) treated stops as POIs and utilized various DBSCAN algorithms to cluster points as places based on the speed between two points. To enrich trajectories with semantic information, different scales were employed to annotate trajectories, including semantic regions, semantic lines, and semantic points (Yan et al., 2013). Semantic regions refer to meaningful geographic areas, such as land use. Stops in trajectories can be annotated with semantic information by considering their topological correlation with these regions. Semantic lines typically represent transportation networks. The movements within trajectories can be linked to road segments through map-matching algorithms, helping to infer the transportation mode, such as walking, driving, and using public transportation. Semantic points correspond to POIs with meaningful place types, like restaurants, museums, and train stations. Stops in trajectories can be linked to the closest POI to annotate semantic information. Furthermore, stops and moves can be annotated with activities, like staying at home, having lunch at a restaurant, or working at a company, by considering the time the individual spends at different POIs and his routines (Parent et al., 2013).

In addition to GPS data, UGC data also shows its potential in semantic trajectory construction by providing more semantic information beyond the spatial location. Trajectories have been built using check-ins gathered from platforms like Foursquare, Gowalla, and Brightkite. In these cases, a stop is defined as a semantic POI with a minimum of 10 check-ins, and consecutive check-ins within a 10-min threshold are removed as duplicates (Petry et al., 2019; Ferrero et al., 2020). Another approach employed by Gabrielli et al. (2014) involved aggregating geotagged tweets to create trajectories, associating them with Foursquare categories to construct the Semantic Origin Destination Matrix of Foursquare categories. Geotagged photos from Flickr also serve as a valuable data source for building semantic trajectories. Cai et al. (2018) conducted semantic trajectory clustering using geotagged photos from Flickr to mine mobility patterns. Additionally, they identified semantic regions of interest where a high density of trajectories passed, providing more meaningful descriptions of the trajectories. Similarly, L. Yang et al. (2017) utilized geotagged Flickr photos to extract tourist trajectories, expanding the trajectory dimensions from topological and temporal spaces to semantic spaces. This allowed for a better understanding of travel motifs and the discovery of meaningful patterns of tourist behavior. In terms of semantic enrichment, various attributes were employed to enrich the semantic information of trajectories, including place type, price tier, rating, day of the week, time of day, and weather information were used to enrich semantic information for trajectories (Cai et al., 2018; Petry et al., 2019; Ferrero et al., 2020). Place type is a piece of contextual information associated with semantic trajectories, which can be collected from online geographical databases such as GeoNames or represented by venue categories derived from check-ins. Studies that utilized check-ins to construct trajectories also consider the price tier and rating associated with the check-ins. These attributes, together with place type, provide additional information about the visited places. Day of the week and time of day assist in interpreting mobility patterns with greater time granularity. For instance, it is possible to identify typical trajectories where an individual commutes from home to work at 8 am, and has lunch at a restaurant at 12 pm on weekdays.

2.2.3 Semantic Trajectory Pattern Mining

The movement patterns of individuals can be mined from semantic trajectories to understand their behaviors. Clustering and classification are the two primary techniques employed for the discovery of movement patterns. These techniques group trajectories that share similar information. The key distinction between clustering and classification is that clustering is an unsupervised learning technique, which does not rely on prior knowledge of target groups. On the other hand, classification is a supervised learning technique that requires prior knowledge to determine target groups before the learning progress. To cluster semantic trajectories, it is important to construct the similarity matrix with appropriate distance measures. Various distance functions are available to measure diverse attributes. In the context of semantic trajectories, spatial distance is typically evaluated using either the Euclidean Distance function or the Haversine Distance function. The Euclidean Distance function calculates the straight-line distance between two points and is suitable for coordinates in a projected coordinate system. The Haversine Distance function measures the great-circle distance between two points on the Earth's surface and it is suitable for latitude and longitude coordinates in a geographic coordinate system. Semantic trajectories may also encompass attributes with categorical values, such as place type and weather. For measuring the distance between such attributes, discrete distance functions like the Hamming Distance function and Jaccard Distance function are commonly employed. These functions are particularly useful for binary or categorical data, allowing for the quantification of the distance between different attribute values.

To extract typical trajectories, it is essential to measure trajectory similarity. Commonly used similarity measures for trajectories include Dynamic Time Warping (DTW) (Berndt & Clifford, 1994), Multidimensional Dynamic Time Warping (MD-DTW) (ten Holt et al., 2007), Longest Common SubSequence (LCSS) (Vlachos et al., 2002), and Edit Distance (EDR) (L. Chen et al., 2005). A comparative study of these trajectory similarity measures was conducted by Tao et al. (2021). DTW measures the distance between time series and is specifically suitable for numerical values. It determines the optimal alignment of two sequences to identify the contiguous path with the minimum total distance between the series. However, DTW only considers one dimension. To address this limitation, MT-DTW was developed to adapt DTW for multidimensional sequences. It assigns weights to different dimensions and constructs the distance matrix for each pair of elements in the sequences by normalizing the distance values across all dimensions. However, both DTW and MT-DTW are sensitive to noises, such as distant elements. LCSS, proposed as a similarity measure for raw trajectories, overcomes this limitation by introducing the distance and matching threshold to identify the longest common subsequence. If the distance between two points falls within the matching threshold, a similarity value of 1 is assigned, otherwise, 0 is assigned. LCSS can also be extended to measure trajectories with additional dimensions. EDR, derived from LCSS, also utilizes the matching threshold with binary values (0, 1) to represent the distance. It calculates the distance between trajectories by seeking the sequence with the minimum number of inserts, deletes, and replacements of points required to transform one trajectory into another. However, most trajectory similarity measures only consider a fixed number of dimensions and deal with fixed types of values. Furtado et al. (2016) proposed Multidimensional Similarity Measure (MSM) to compute the similarity of trajectories with multiple dimensions, including space, time, and semantics. MSM assumes that different dimensions may have varying levels of importance in different problems, thus assigning weights to dimensions and utilizing thresholds to calculate similarity scores. This approach increases the flexibility of similarity measures. However, MSM does not consider the sequence of the movement, and it defines two trajectories as similar even if they visit the same place types in different orders. Petry et al. (2019) developed the MUltiple-aspect TrAjectory Similarity (MUITAS) to measure the similarity of trajectories with heterogeneous semantic dimensions, which supports different relationships between features. A feature represents a unit of analysis within a trajectory, and multiple aspects constitute the feature. Different weights can be assigned to different features based on the importance of aspects within the feature. This approach helps to better capture the complexity of trajectory similarity.

Trajectories can be clustered using various methods, including density-based, hierarchical-based, spectral-based, and community-based trajectory clustering techniques (C. Liu & Guo, 2020). A density-based clustering method identifies clusters with high object density within a given area, enabling the detection of clusters with arbitrary shapes. One of the most renowned density-based clustering algorithms is DBSCAN, which relies on two parameters, namely, *Eps* (radius of the neighborhood) and *MinPts* (minimum number of neighbors within the radius). Ordering Points To Identify the Clustering Structure (OPTICS) proposed by Ankerst et al. (1999) is another density-based clustering method. OPTICS orders objects instead of clustering them as DBSCAN does, and the ordered objects can be grouped into clusters based on the reachability distance. For instance, Cai et al. (2018) applied OPTICS to cluster trajectories with multiple semantic dimensions constructed on geotagged Flickr photos, and identified semantically common trajectory patterns. In the hierarchical-based clustering approach, Zhang et al. (2018) proposed a hierarchical trajectory clustering method based on periodic pattern mining, incorporating semantic spatiotemporal information. This method extends Trajectory Clustering (Traclus) (Lee et al., 2007) and builds upon Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN) (Campello et al., 2013) to detect hierarchical clusters. Regarding community-based trajectory clustering, El Mahrsi & Rossi (2013) employed a modularity-based community detection algorithm to group frequently visited road segments from different trajectories. This approach enables the discovery of a hierarchy of nested clusters of road segments. S. Liu et al. (2013) proposed Trajectory cOmmunity Discovery using Multiple Information Sources (TODMIS) to mine communities from trajectories, which combines additional information, such as velocity and semantics, with raw trajectories and applied dense sub-graph detection to discover distinct communities.

Classification is a process that groups similar trajectories into predefined classes. In the context of semantic trajectories, Lee et al. (2007) initially clustered interesting line segments derived from trajectories. Subsequently, they assigned a class to each cluster and classified other trajectories by placing them into these predefined classes. To delve into the analysis of trajectory data, Giannotti et al. (2011) developed M-Atlas, a comprehensive system that facilitates the exploration of both raw and semantic clustering and classification, and discovered human mobility through querying and mining trajectory data. Within their study, trajectories were clustered, and new trajectories were classified by assigning them to the identified clusters. Ferrero et al. (2020) introduced a new parameter-free method known as MasterMovelets. This approach identifies the most relevant sub-trajectories while considering various combinations of dimensions. By leveraging this method, trajectory classification can be achieved more efficiently and effectively.

Clustering and classification techniques are employed to group semantic trajectories that share similar attributes. In addition to these methods, sequential pattern mining serves as a complementary approach to extract frequently occurring mobility patterns within trajectories. Sequential pattern mining allows for the occurrence of frequent points in a specific temporal order, which means that each point can occur multiple times as long as it is visited several times during the same period. One of the pioneering algorithms in sequential pattern mining is the Generalized Sequential Patterns (GSP) algorithm proposed by Srikant & Agrawal (1996). This algorithm accommodates the specification of (1) time constraints between adjacent elements of the sequential pattern, (2) sliding time windows of the transaction, and (3) user-defined taxonomies. In the study by Höpken et al. (2020), the GSP algorithm was applied to identify behavioral patterns of tourists using Flickr data. The authors compared the typical trajectories mined through association rule analysis and sequential pattern mining. Pei et al. (2004) introduced a **Prefix**-projected **S**equential **pa**tter**n** mining (PrefixSpan) algorithm to mine sequential patterns through a pattern-growth approach, which consumes less memory space than GSP. Furthermore, Yin et al. (2011) applied the PrefixSpan to discover the trajectory patterns of Flickr users. They also employed various ranking methods to find top-ranked patterns based on different criteria.

2.3 Research Gaps

The visiting behaviors and perceptions of visitors within a city have been extensively investigated in various studies. However, there are several research gaps that are worth further investigation.

- Dynamic city perceptions: City perceptions can vary based on different groups of people and over various time spans. However, these dynamic city perceptions have not been fully compared by population and time.
- City perceptions through semantic trajectories: Previous studies have demonstrated the feasibility of exploring city perceptions with UGC, such as geotagged social media data like Tweets and Flickr tags. However, there is a lack of research that integrates UGC as semantic information for trajectory construction and relates city perception studies with semantic trajectories.
- Semantic enrichment of trajectories: Most existing studies directly assign information extracted from UGC, such as place type, rating, and price tier, to trajectories as the semantic information. However, UGC also contains latent information that requires additional techniques for extraction.

This study aims to address these gaps by constructing semantic trajectories for locals and tourists over different time spans to investigate their dynamic visiting behaviors and city perceptions. Trajectories will be constructed based on Foursquare check-ins, and their semantic dimensions will be enriched based on the place dimensions: location, locale, and sense of place, with each dimension enriched by direct information assignment and topic modeling. In general, this study seeks to provide insights into city perception from a holistic and nuanced perspective.

3 Study Area and Data Preprocessing

3.1 Study Area

The study area is located in London (Figure 3.1). As an English-speaking city, London covers an area of 1,572 km^2 and has a population of 9.5 million inhabitants. According to tourism statistics of City of London, before the Covid-19 pandemic, London attracted approximately 21 million visitors annually from across the world. Among these visitors, 19.7 million were day trippers, while 1.3 million stayed overnight. The high volume of visitors makes London an ideal location for studying city perceptions of both locals and tourists. The boundary of London used in this study was obtained from LONDON DATASTORE website [9].

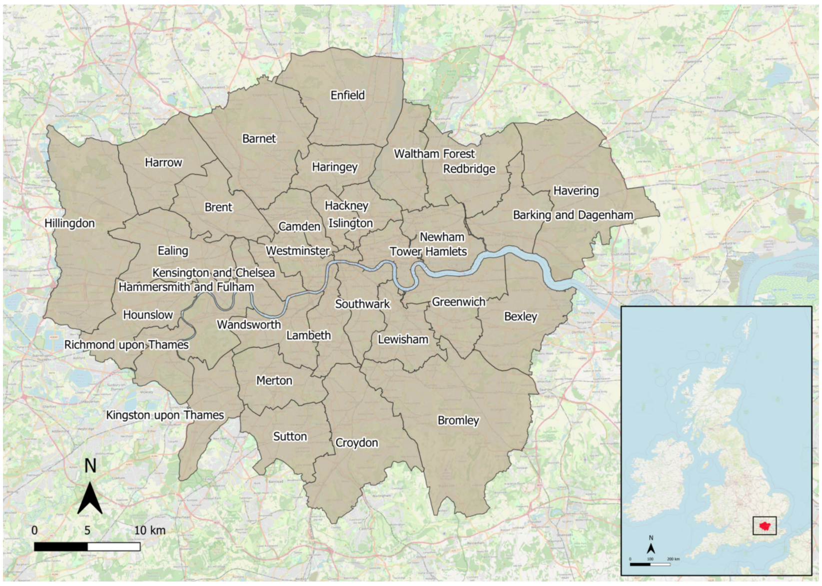


Figure 3.1: Study area (London boroughs map).

3.2 Data Preprocssing

Foursquare check-ins and Flickr tags in London from April 3, 2012, to September 16, 2013, were collected to investigate how people move around the city and how they perceive it.

This study examines the city perceptions of locals and tourists, during the daytime and nighttime, as well as on weekdays and weekends. Therefore, it is crucial to differentiate between these two population groups across different time spans. To distinguish between locals and tourists, a combination of user profiles and time intervals was utilized for identification. The user profile served as the primary criterion, with individuals whose hometown or city of residence is London in their profiles categorized as locals. In cases where the user profile was unavailable, the time interval between the user's initial and final Foursquare or Flickr posts in London was employed. Users with a time interval exceeding 30 days were classified as locals. Regarding time spans, daytime is defined as 6 am to 6 pm, while the remaining hours are considered nighttime. Weekdays encompass Monday to Friday, while the weekend comprises Saturday and Sunday.

[9] https://data.london.gov.uk/dataset/statistical-gis-boundary-files-london

3.2.1 Foursquare Data

Foursquare is a platform for users to check in at venues and share their experiences through reviews. As of 2022, Foursquare has more than 55 million monthly active users worldwide. The Foursquare data used in this study was obtained from the Global-scale Check-in Dataset D. Yang et al. (2015), containing two datasets: (1) Foursquare check-ins and (2) Foursquare POIs from April 3, 2012, to September 16, 2013, on a global scale.

For the dataset Foursquare check-ins, a total of 187,336 check-ins shared by 9,717 users in London were extracted. This dataset includes the following fields:

- User ID
- Venue ID
- UTC time
- Timezone offset

Another dataset Foursquare POIs stored Foursquare venues, and there were 27,608 POIs in London. This dataset contains the following fields:

- Venue ID
- Venue category name
- Coordinates
- Country code

Foursquare check-ins were merged with Foursquare POIs by the venue ID to get the coordinates of venues. The merged Foursquare data should be further cleaned and differentiated as either locals or tourists, and the preprocessing steps are as follows:

1. Merged check-ins with POIs to get the coordinates for each check-in.
2. Removed duplicated check-ins.
3. Updated venue categories of check-ins based on the Foursquare category [10]. The Foursquare category system uses a three-level hierarchy. For example, the Arts & Entertainment first-level category includes a second-level category called Movie Theater, which in turn contains three third-level categories: Drive-in Theater, Indie Movie Theater, and Multiplex. This study kept only the first-level categories to represent check-ins.
4. Removed check-ins that were labeled as Residence to protect the privacy of Foursquare users.
5. Removed users whose total travel distances were less than 1 km. This study aims to investigate city perception through the analysis of trajectories. As such, trajectories with short travel distances are considered unsuitable for discovering meaningful patterns of city perception. Therefore, users with short travel distances were removed.
6. Identified locals and tourists based on the number of days spent in London, total travel distances, and user profiles. Users who spent more than 30 days in London and had a total travel distance greater than 100 km were considered locals. For the remaining users, those who listed London as

[10] `http://foursquare-categories.herokuapp.com/`

their hometown in their profiles were also categorized as locals. The user profiles were retrieved using Get User Details [11] provided by Foursquare API.

After all these steps, a total of 177,207 check-ins by 7,183 users in London were left. Out of these users, 1,087 were identified as locals and they posted 109,558 check-ins, which was far more than the number of check-ins posted by tourists, who amounted to 6,096, but posted only 67,649 check-ins (Table 3.1). Figure 3.2 shows the distribution of Foursquare check-ins, and most check-ins were concentrated in the central area of London. Moreover, compared with tourists, locals tended to share more check-ins in peripheral areas.

Table 3.1: Summary of Foursquare data.

Time	Population group	No. of users	No. of check-ins
Overall	All Users	7,183	177,207
	Locals	1,087	109,558
	Tourists	6,096	67,649
Daytime	All Users	7,055	141,353
	Locals	1,082	87,803
	Tourists	5,973	53,550
Nighttime	All Users	4,932	33,256
	Locals	1,018	20,469
	Tourists	3,914	12,787
Weekday	All Users	6,692	128,797
	Locals	1,072	81,677
	Tourists	5,620	47,120
Weekend	All Users	5,174	45,812
	Locals	1,022	26,595
	Tourists	4,152	19,217

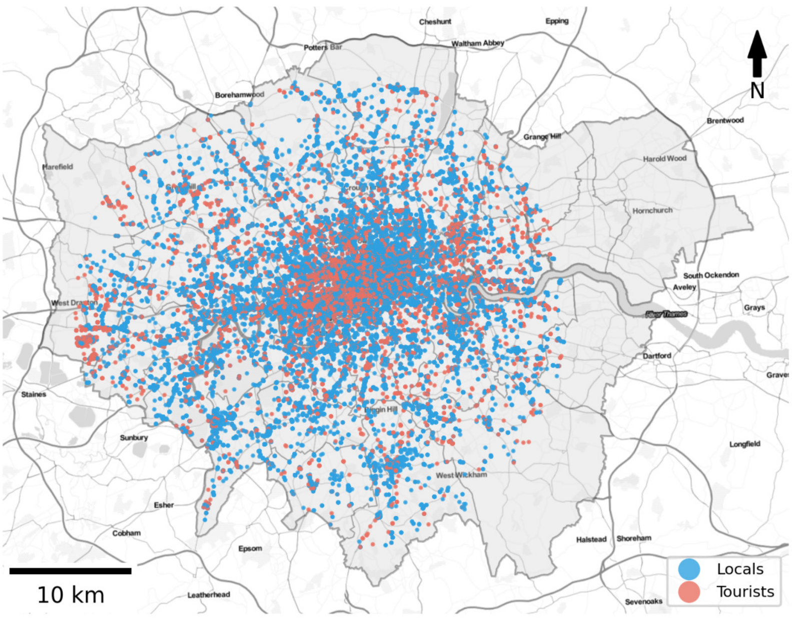


Figure 3.2: Distribution of Foursquare check-ins of locals and tourists.

[11] `https://location.foursquare.com/developer/reference/v2-users-user_id`

For venue categories, Foursquare categorizes the place types into ten categories, namely (1) Travel & Transport, (2) Food, (3) Professional & Other Places, (4) Outdoors & Recreation, (5) Shop & Service, (6) Nightlife Spot, (7) Arts & Entertainment, (8) College & University, (9) Event, and (10) Residence. Category (9) Event was not contained in the check-ins used in this study, and Category (10) Residence was removed to protect the privacy of users. The number of check-ins for each Foursquare venue category is shown in Table 3.2. There are several combined categories in the Foursquare category system, such as Professional & Other Places and Outdoors & Recreation, which makes it ambiguous to determine the visiting purposes of individual check-ins. To overcome this limitation, this study divided venues into 11 categories by separating the combined categories and defining new ones based on the third-level categories in the Foursquare category system. The number of check-ins for modified venue categories is presented in Table 3.3. In terms of the category distribution among locals and tourists, the categories Transportation and Restaurant were the most prevalent among both locals and tourists. However, certain categories showed a higher prevalence among a specific group, for instance, Shopping Place, Art Place, and Accommodation were more welcomed by tourists, whereas Sports Place received a greater number of check-ins from locals (Figure 3.3).

Table 3.2: Foursquare venue category.

No.	Foursquare venue category	No. of check-ins
1	Travel & transportation	43,051
2	Food	34,376
3	Professional & Other Places	22,184
4	Outdoors & Recreation	20,429
5	Shop & Service	19,772
6	Nightlife Spot & Service	18,418
7	Arts & Entertainment	14,285
8	College & University	4,692

Table 3.3: Modified Foursquare venue category.

No.	Modified venue category	No. of check-ins	Foursquare venue category	Example
1	transportation	36,994	Travel & transportation	Airport, Train Station, Bus Station, etc.
2	Restaurant	34,376	Food	Sandwich Place, Asian Restaurant, Italian Restaurant, etc.
3	Professional Place	29,118	Professional & Other Places, College & University	Office, Government Building, Police Station, etc.
4	Entertainment Place	22,434	Arts & Entertainment, Shop & Service, Nightlife Spot	Casino, Bowling Alley, Zoo, Bar, Nightclub, etc.
5	Shopping Place	18,127	Shop & Service	Outlet Mall, Clothing Store, Market, etc.
6	Art Place	11,132	Arts & Entertainment, Outdoors & Recreation	Museum, Movie Theater, Art Gallery, Music Venue, etc.
7	Green & Blue Space	8,220	Outdoors & Recreation	Park, Plaza, Garden, Lake, etc.
8	Accommodation Place	5,902	Travel & transportation	Hotel
9	Sports Place	5,852	Outdoors & Recreation	Athletics & Sports, Pool, Playground, etc.
10	Others	3,346	Outdoors & Recreation, Professional & Other Places, Travel & transportation	Building, Bridge, Well, etc.
11	Service Place	1,706	Travel & Transport, Shop & Service	Bank, Drugstore, Car Wash, Laundry Service, etc.

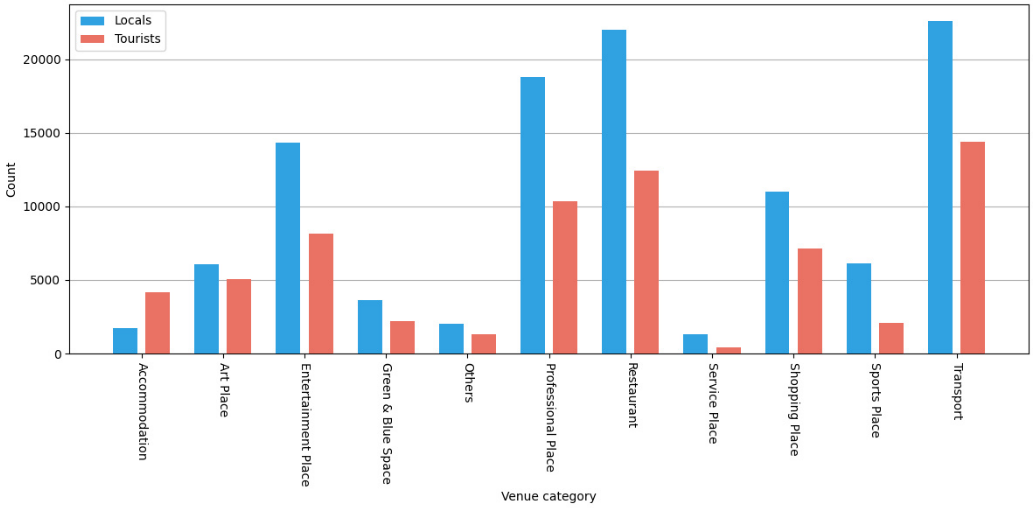


Figure 3.3: Number of venue categories visited by locals and tourists.

3.2.2 Flickr Data

Flickr is an online photo management and sharing application where users can upload photos. As of 2023, the Flickr community has shared tens of billions of photos. Flickr data was collected via Flickr API with the Python library flickrapi [12]. To collect Flickr photos, the method flickr.photos.search [13] was applied to get photos. A total of 954,260 photos with 250,254 unique tags uploaded by 28,633 users in London from April 3, 2012, to September 16, 2013, were collected. The main fields of Flickr data include:

- Photo ID
- User ID
- Date taken
- Accuracy
- Coordinates
- Tags
- Title
- Photo URL
- Number of views

The Flickr data required additional cleaning and identification of locals and tourists. The preprocessing steps are as follows:

1. Removed photos without tags because Flickr tags were one of the main semantic information in this study.
2. Removed photos with an accuracy level below 14. Flickr divides the accuracy level on a scale of 1 to 16, with 1 representing world-level accuracy, 2-3 representing country-level accuracy, 4-6

[12] `https://stuvel.eu/software/flickrapi/`
[13] `https://www.flickr.com/services/api/flickr.photos.search.html`

representing region-level accuracy, 7-11 representing city-level accuracy, and 12-16 representing street-level accuracy. Only photos with an accuracy greater than 14 were kept in this study.

3. Removed tags that were non-Ascii characters, special characters, numbers, stop-word (e.g., a, an, the), prepositions (e.g., from, to), general place names (e.g., britain, uk, england, london), and other irrelevant tags (e.g., nikon, samsung, instagram, flickr).

4. Removed duplicates. Duplicated tags in the same list were removed. Moreover, duplicated photos of the same user at the same location with the same tags were removed.

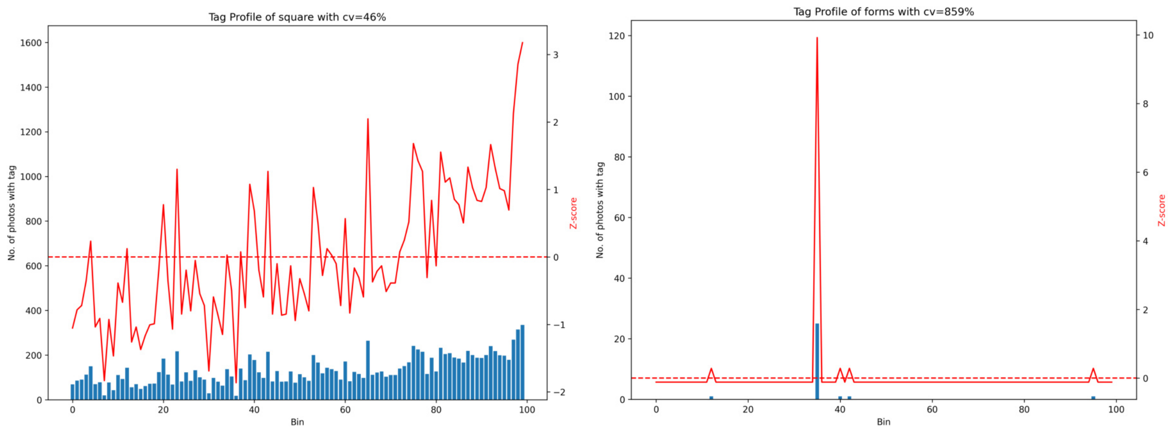
5. Removed prolific and unprolific users. Prolific users were defined as those who contributed more than 5% of all photos in the dataset, while unprolific users were defined as those who uploaded less than five photos in total per day.

6. Removed tags with a coefficient of variation (cov) greater than 300 to reduce the contribution bias. Some tags were dominantly used by prolific users, which might lead to distortions of tags. The cov measures whether a tag is evenly used among prolific and unprolific users (Hollenstein & Purves, 2010). To determine the cov, the Flickr photos were sorted based on user contribution, with the most prolific users' photos at the top. Subsequently, all photos were equally distributed into 100 bins. For each tag, a tag profile was constructed, which stored its frequency in each of the 100 bins. The cov was calculated as the ratio of the standard deviation to the mean of the tag frequencies in the 100 bins. The lower the cov, the more evenly the tag is distributed. For instance, based on the histogram that displays the number of photos with a certain tag in a user distribution order, the tag *square* with a cov less than 300 (Figure 3.4a) is more evenly distributed than the tag *forms* with a cov greater than 300 (Figure 3.4b).

7. Removed tags that were place names in London. GeoNames offers Free Gazetteer Data [14] that includes place names in Great Britain. Place names in London were filtered out from the downloaded data, and any tag that matched with these place names was removed.

8. Identified locals and tourists based on the number of days spent in London and user profiles. This study used flickr.profile.getProfile [15] provided by Flickr API to collect user profiles, which contained information about the users' hometowns and cities. Users who had stayed in London for more than 30 days were considered locals. For the remaining users, this study would also flag them as locals if their hometown or city in their profiles was listed as London.

[14] http://download.geonames.org/export/dump/
[15] https://www.flickr.com/services/api/flickr.profile.getProfile.html



(a) Tag profiles with a cov less than 300.

(b) Tag profiles with a cov greater than 300.

Figure 3.4: Tag profiles.

After all these steps, 177,568 photos were left with a total of 717,747 tags (3,365 unique tags). These tags were used by 4,687 users, with 851 locals and 3,836 tourists uploading 259,967 and 457,780 tags respectively (Table 3.4). The distribution of Flickr photos indicates that the majority of photos were taken in the center of London, while tourists tended to share more photos around Heathrow Airport (Figure 3.5). The word cloud in Figure 3.6 illustrates the most frequently used tags, including city, architecture, street, park, and art.

Table 3.4: Summary of Flickr data.

Time	Population group	No. of users	No. of photos	No. of tags
Overall	All Users	4,687	177,568	717,747
	Locals	851	65,403	259,967
	Tourists	3,836	112,165	457,780
Daytime	All Users	4,254	144,748	580,753
	Locals	768	52,908	206,737
	Tourists	3,486	91,840	374,016
Nighttime	All Users	2,372	32,820	136,994
	Locals	479	12,495	53,230
	Tourists	1,893	20,325	83,764
Weekday	All Users	3,307	94,167	378,574
	Locals	618	34,243	132,779
	Tourists	2,689	59,924	245,795
Weekend	All Users	2,755	83,401	339,173
	Locals	592	31,160	127,188
	Tourists	2,163	52,241	211,985

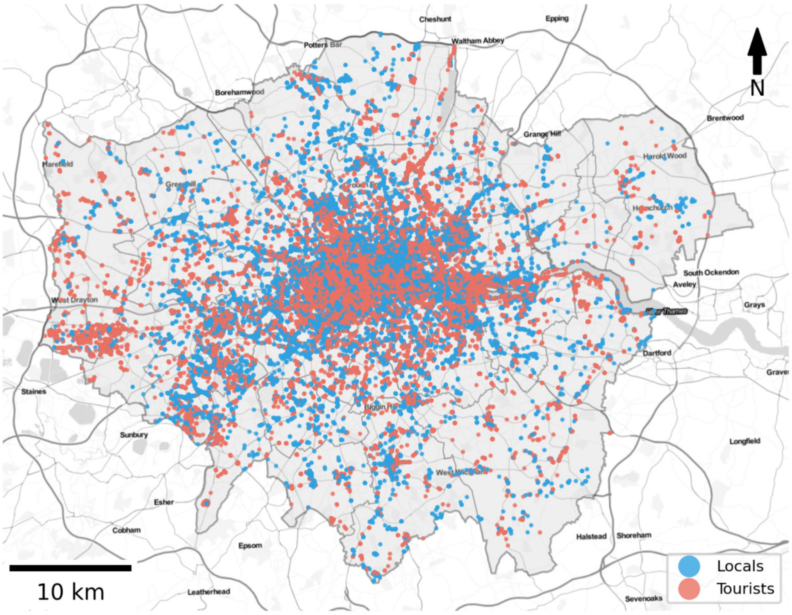


Figure 3.5: Distribution of Flickr photos of locals and tourists.

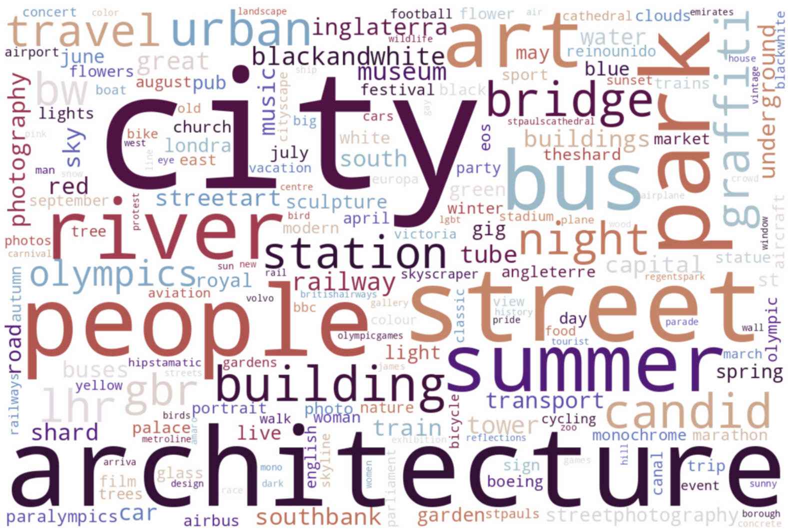


Figure 3.6: Flickr tag cloud.

4 Methodology

This chapter introduces the methodology applied in this study. The workflow of this study is illustrated in Figure 4.1. To explore the city perception, Foursquare check-ins and Flickr tags were utilized, and the process of data preprocessing is elaborated in Section 3.2. This workflow is designed to address two research questions. The first research question was answered by employing the methods discussed in Section 4.1, which involved identifying hotspots of locals and tourists by applying Kernel Density Estimation (KDE) to their Foursquare check-ins. To investigate the popularity of specific areas among locals or tourists, the difference ratio between these two groups of people was calculated and visualized in rasters. For the second research question, the construction of semantic trajectories was necessary. Prior to the trajectory construction, the Place was modeled and enriched with semantic information based on its dimensions (Section 4.2). Subsequently, semantic trajectories were clustered, and typical semantic trajectories of each cluster were extracted through sequential pattern mining (Section 4.3). These two research questions were investigated under eight scenes to compare the popular areas and city perception among locals and tourists across different time spans, as illustrated in Figure 4.2. This study was conducted with Python 3.10.12 [16].

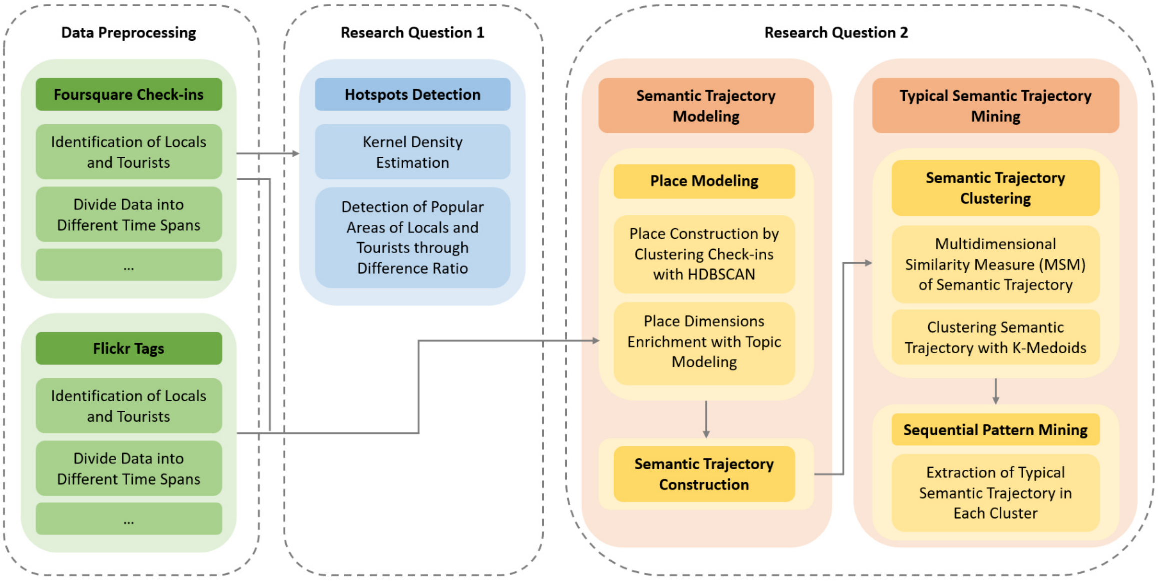


Figure 4.1: Workflow.

[16]https://www.python.org/downloads/release/python-31012/

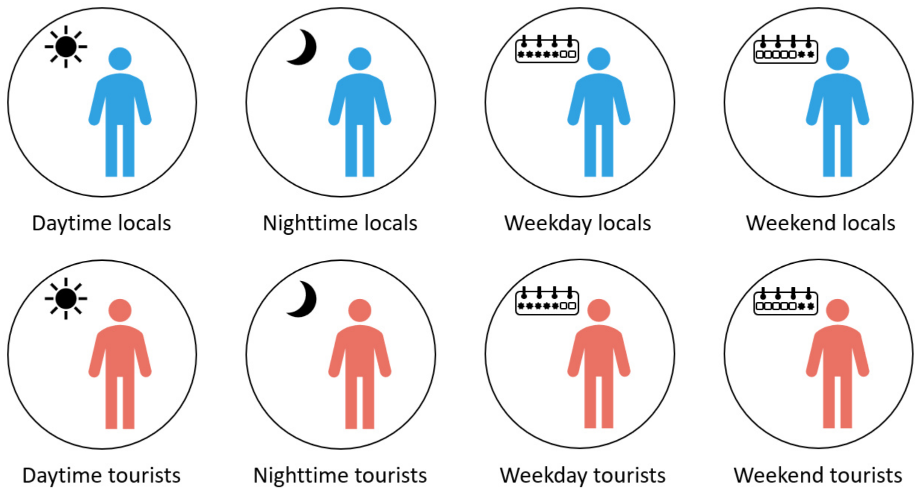


Figure 4.2: Study scenes.

4.1 Hotspots Detection

4.1.1 Kernel Density Estimation

Locals and tourists show distinct visiting preferences, which can be revealed through their distribution patterns. In this study, KDE was employed to identify visiting hotspots of these two groups based on the distribution of their check-ins. KDE estimates the probability density of data points with the kernel function, which helps to visualize the continuous distribution of discrete data points. Specifically, the estimated distribution is based on the distribution of existing data points in the neighborhood, and the more neighboring data points, the greater the estimated density is. To formally define KDE, consider a set of independent distributed random points, denoted as $x_1, x_2, ..., x_n$, the unknown density f at any given point x can be expressed as:

$$\hat{f}_h(x) = \frac{1}{nh \sum_{i=1}^{n} k\left(\frac{x-x_i}{h}\right)} \tag{1}$$

where h is a bandwidth parameter that controls the degree of smoothing in KDE. Choosing an appropriate bandwidth is crucial as a large bandwidth may over-smooth the estimate, while a small bandwidth may under-smooth it, potentially hiding important features or introducing random noise. The kernel function k is a smooth function to calculate the weighted average of neighboring observed data points. This weighting process effectively smooths out the data, with closer points receiving higher weights (Y.-C. Chen, 2017).

In this study, the kdeplot provided by the Python library seaborn (Waskom, 2021) was used to apply KDE to the Foursquare check-ins of locals and tourists and visualize the estimated distribution of these check-ins. The coordinates of the check-ins were converted to the EPSG:27700 projected coordinate system for the United Kingdom. The bandwidth method Scott was applied to calculate the estimator bandwidth as the rule of Scott allows fast computation for bandwidth selection. Additionally, the Gaussian kernel was used as the kernel smoother.

Since the distribution of check-ins of locals and tourists was assumed to differ across various time spans, this study applied KDE to visualize the distribution of check-ins for these two groups during the daytime and nighttime, as well as on weekdays and weekends. Visiting hotspots were determined based on the estimated density value in the output plot. By comparing the hotspots across different scenes (e.g., locals during the daytime, tourists on weekdays), along with the difference ratio discussed in the next section, this study aimed to explore which areas were more popular among locals and which areas were more popular among tourists.

4.1.2 Calculation of Difference Ratio

Investigating the popularity of an area among locals and tourists can be achieved by examining the degree of their interaction within that area. In this study, the study area was rasterized, and the mixture degree of locals and tourists was investigated through raster analysis to identify popular areas among these two groups. The polygon of London was divided into equal-sized rasters. The raster size of 1 km by 1 km was used as it performed the best among 500 m by 500 m, 1 km by 1 km, and 1.5 km by 1.5 km. When assessing the mixture degree, both the number of visitors and the number of check-ins in each raster could be used, but the latter better reflected the activity density. To avoid bias caused by significant differences in the number of check-ins between locals and tourists within each raster, this study applied the difference ratio R, as previously utilized in a study by D. Li et al. (2018), to assess the mixture level between locals and tourists. The difference ratio is defined as:

$$R = \frac{t_i}{T} - \frac{l_i}{L} \tag{2}$$

where t_i represents the number of tourists' check-ins in the raster i, and T represents the total number of tourists' check-ins shared citywide. Similarly, l_i represents the number of locals' check-ins in the raster i, and L represents the total number of locals' check-ins across the entire city. This ratio provides insights into the relative activity density between locals and tourists within each raster. A larger positive value of R indicates a higher density of check-ins shared by tourists in that particular raster, while a larger negative value of R indicates a higher density of check-ins shared by locals in the raster.

Similar to the identification of hotspots using KDE, the mixture degree between locals and tourists was also calculated and visualized across various time spans. To better compare the relative concentration of locals and tourists, the difference ratios over time are displayed within the same range based on the extreme values of difference ratio across scenes. Specifically, the minimum and maximum values for the color mapping were set to -0.3 and 0.3, respectively. This ensured that all difference ratio values were colored within the same range. The hotspots identified through KDE were further analyzed using the difference ratio to determine their popularity among locals or tourists.

4.2 Place Modeling

4.2.1 Place Construction

In this study, the concept of place refers to a part of geographical space that holds meaningful attributes, while check-in is a specific instance that represents an individual's interaction with a place. Figure 4.3 shows the process of place construction. Foursquare check-ins were clustered to build places using the Hierarchical Density-Based Spatial Clustering of Applications with Noise

(HDBSCAN) (Campello et al., 2013) algorithm. HDBSCAN is a hierarchical extension of DBSCAN that automatically determines the optimal number of clusters and can handle clusters of varying densities, which helps to reduce user input bias. Prior to clustering, a distance matrix among check-ins was computed and the features used for distance calculation included the coordinates and categories of check-ins. The Gower distance (Gower, 1971) was used to construct the distance matrix as it could measure the dissimilarity between items with mixed numeric and categorical attributes. The coordinates of check-ins were standardized. And the check-in categories were converted into numerical values using label encoding and treated as categorical data in the distance measure. The importance of features was also considered, with coordinates weighted at 80% and categories weighted at 20%.

The hdbscan provided by the Python library HDBSCAN (McInnes et al., 2017) was used to cluster check-ins. A minimum of three check-ins within a cluster was set as the criterion for defining a place, ensuring that each place encompassed a certain number of check-ins. HDBSCAN labeled check-ins with their corresponding clusters, while check-ins labeled as -1 were considered outliers and removed. To represent the boundary of a place, the convex hulls were constructed for the clusters of check-ins, creating polygons that approximated the areas covered by places. And the coordinate of the place was represented by the centroid of its convex hull, as shown in Figure 4.3. It is important to note that check-ins of locals and tourists were differentiated across various time spans before constructing places, ensuring that each scene had its own distinct set of places.

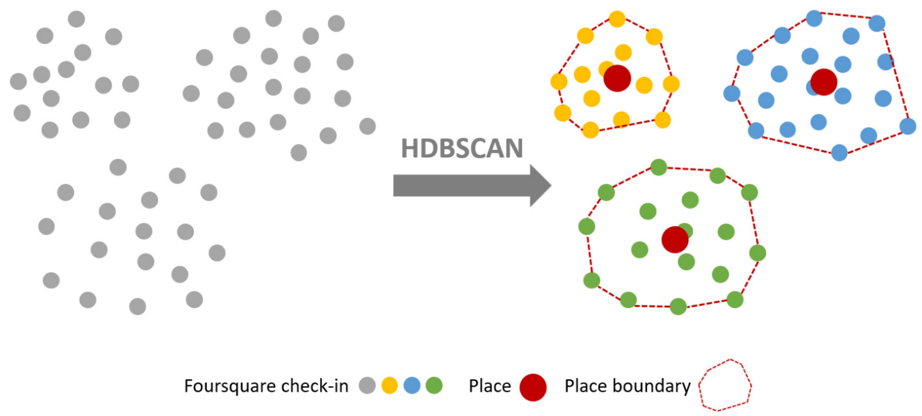


Figure 4.3: Place construction: Utilizing HDBSCAN for clustering Foursquare check-ins into meaningful places. These places are defined by the convex hulls encapsulating each cluster, while the place's central coordinate is established through the centroid of the convex hull (in practical applications, certain place boundaries might overlap).

To enrich the semantic information of places, three dimensions conceptualized by Agnew (2011), namely *Location*, *Locale*, and *Sense of Place*, were annotated. The *Location* dimension was represented by the borough name, specifically the borough where the majority of check-ins within a place cluster were located. The *Locale* dimension was determined by the most frequently occurring check-in category within the place cluster. The *Sense of Place* dimension utilized Flickr tags associated with the place cluster to capture people's perceptions. Topic modeling was applied to generate a set of topics based on these tags, providing a representation of the *Sense of Place*. The process of topic modeling is introduced in the next section. With these three dimensions annotated, places in different scenes were compared across different scenes based on their distributions and the frequency of the three dimensions.

4.2.2 Topic Modeling

This study applied Latent Dirichlet Allocation (LDA), a topic modeling technique, to generate topics describing places based on Flickr tags, and the process is illustrated in Figure 4.4. LDA discovers underlying topics from a large collection of words. In this study, after the preprocessing steps outlined in Section 3.2.2, the Flickr tags within each place were gathered as words to form a *document*, with each *document* comprising the Flickr tags for a specific place. The input to the LDA model is a *corpus* consisting of *documents*. The *corpus* is a matrix with the size of *word* $\times$ *document*. Each row of this matrix stores the frequency of words in each document, denoted as a vector $w = w_1, w_2, ..., w_v$. v is the number of words in the *vocabulary* (all distinct words in a corpus), and w_v denotes the frequency of word v in the document. It is important to note that Flickr tags were also separated based on two groups of people in different time spans, thus the corpus in every scene was unique.

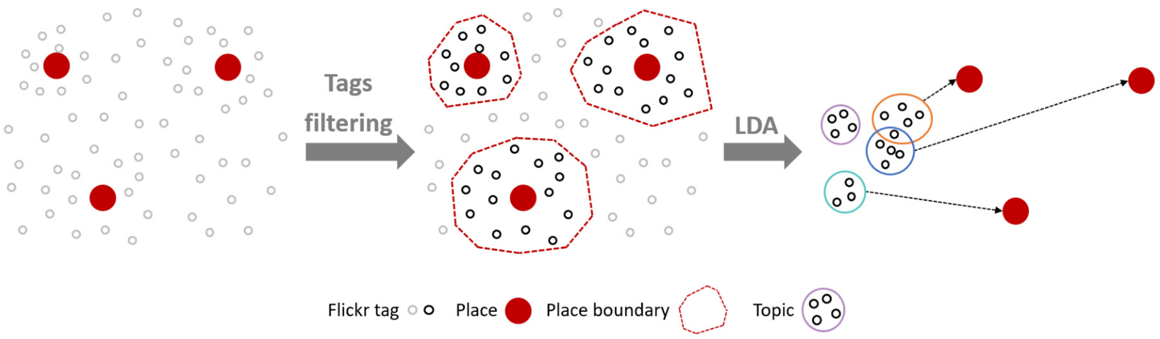


Figure 4.4: Topic modeling: Employing LDA model to generate topics for places based on Flickr tags within place boundaries.

The LDA model generated a set of topics as its primary output, along with topic distribution and topic terms, facilitating the determination and interpretation of topics for each place. The topic distribution for each place consisted of a list of topics and the corresponding probabilities of the place belonging to each topic. The topic terms for each topic comprised a list of tags, accompanied by their probabilities of association with that topic. In this study, each place was assigned the most probable topic, and the interpretation of topics relied on the corresponding tags and probabilities. This study implemented the LDA model using the LdaMallet provided by the Python library gensim (Řehůřek & Sojka, 2010).

The semantic quality of the generated topics is sensitive to the number of topics. If too many topics are generated, some topics might become similar to each other, making it difficult to interpret topics. The LDA model requires users to determine the number of topics as input, thus it is crucial to choose appropriate topic numbers. The *coherence value* was employed to measure the semantic quality of topics. This value was calculated based on the co-occurrence probability of words within a topic, specifically within the place clusters assigned to that topic. The *coherence value* can be defined as:

$$coherence = \sum_{i} \sum_{j<1} \log \frac{D(w_j, w_i) + \beta}{D(w_i)} \tag{3}$$

where β serves the purpose of preventing errors caused by taking the logarithm of zero. $D(w_j, w_i)$ denotes the frequency of two words co-occurring within a document, while $D(w_i)$ signifies the frequency of the more probable word. A higher coherence value indicates that the words within a topic are closely related to each other and the topic is more interpretable to humans (Bahrehdar & Purves, 2018).

In cases where certain places had no tags within their convex hulls, an imputation was employed to assign topics to those empty places. The basic idea of this imputation is similar to the nearest neighbors (NN) imputation, which fills missing values based on the values of n nearest neighbors, and n is a predefined number of nearest neighbors (Troyanskaya et al., 2001). NN imputation is an ideal algorithm to estimate the topics for empty places as it provides an unbiased estimator that preserves the data structure without distorting the distribution of the imputed variable (Beretta & Santaniello, 2016). This study did not define the number of nearest neighbors but considered the topic distribution of all other places that did contain Flickr tags in a weighted average approach. The imputed topic distribution was calculated for each empty place, which represented the probability distribution across topics. Based on this imputed topic distribution, each empty place was assigned the most probable topic. The calculation for imputed topic distribution of the target empty place can be expressed as:

$$P_{imputed} = \frac{1}{W} \sum_i n w_i P_i \tag{4}$$

where P_i represents the topic distribution for place i, and n is the number of all other non-empty places. The weight assigned to each place w_i is determined by the distance between place i and the target empty place, and it is defined as:

$$w_i = \exp\left(\frac{-d(i,j)^2}{2\sigma^2}\right) \tag{5}$$

where σ controls the smoothness of the weighting function. $d(i, j)$ is the distance between place i and place j. A larger value of σ gives more weight to places that are closer to the target empty place, while a smaller value of σ gives more weight to places that are farther away. This study set σ as 500 m for topic imputation in all scenes. W ensures that the sum of the weights to 1 so that the imputed topic distribution is a valid probability distribution, and it is defined as:

$$W = \sum_i^n w_i \tag{6}$$

4.3 Typical Semantic Trajectory Mining

4.3.1 Semantic Trajectory Construction

This study aimed to compare city perceptions under different scenes by analyzing semantic trajectories. Semantic trajectories were constructed based on the places defined in Section 4.2.1. The semantic trajectories can be defined as a sequence of places $T = \langle p_1, p_2, ..., p_n \rangle$, with $p_i = (x, y, D)$ being the place i at the position (x, y) annotated by the three dimensions of the place D, including *Location*, *Locale*, and *Sense of Place*.

By connecting places in a visiting order, it becomes possible to track individuals' movements. However, there might be multiple trajectories within one's movement. Hence, it is necessary to determine the beginning and end of each trajectory, as illustrated in Figure 4.5. In this study, a time gap of five hours served as a criterion to determine whether two consecutive places belonged to the same trajectory. Precisely, if the time gap between two consecutive places exceeded five hours, the former place was considered the last position of the current trajectory, while the latter place marked the beginning of the new trajectory. The selection of a five-hour time gap was based on the distribution of time gaps between two consecutive places within one's movement, with over 75% of time gaps falling below five hours in all scenes.

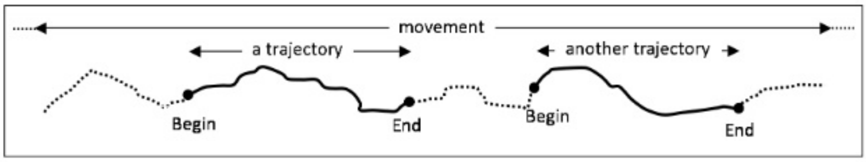


Figure 4.5: Trajectories extracted from a movement track (Parent et al., 2013).

Moreover, the analysis of city perception focused on long trajectories as they conveyed more information. To ensure sufficient information for analysis, the minimum number of places within the trajectory was set during trajectory construction. Three threshold values, namely 3, 5, and 10, were experimented with. Trajectories with a minimum of three places predominantly exhibited travel distances within 5 km, which were considered too short to effectively reflect city perceptions. On the other hand, trajectories with at least ten places were scarce, resulting in the loss of valuable information. Therefore, only trajectories comprising more than five places were included in this study.

4.3.2 Semantic Trajectory Similarity Measure

Before clustering semantic trajectories, it is essential to measure their similarity. Existing methods often focus on the spatial or spatiotemporal aspects of raw trajectories, neglecting the multiple dimensions present in semantic trajectories. To address this, the Multidimensional Similarity Measure (MSM) proposed by Furtado et al. (2016) was employed in this study to construct the similarity matrix for semantic trajectories.

MSM is a similarity measure for multidimensional sequences, considering the similarity across all dimensions. In two semantic trajectories denoted as T_1 and T_2, the general term for each dimension D_k ($k = 1, 2, 3, 4$) represents the following: D_1 represents the spatial position of the semantic trajectory, while D_2, D_3, and D_4 correspond to the three semantic dimensions: *Location*, *Locale*, and *Sense of Place*. The distance between two places, $p_1 \in T_1$ and $p_2 \in T_2$, is computed using the distance function $dist_k(p_1, p_2)$. Additionally, a maximum distance threshold $maxDist_k$ is set for each dimension to determine whether a pair of places (p_1, p_2) can be considered a match in D_k.

The similarity score was calculated by considering each dimension separately, and the scores in all four dimensions were summed up. Each dimension was assumed to have different importance, represented by the weight w_k assigned to the corresponding dimension D_k. In this study, multiple sets of weights were examined for the similarity measure of trajectories, and the following sets were considered: (1) $w_1 = 0.4$, $w_2 = 0.1$, $w_3 = 0.3$, $w_4 = 0.2$, (2) $w_1 = 0.7$, $w_2 = 0.1$, $w_3 = 0.1$, $w_4 = 0.1$, (3) $w_1 = 0.25$, $w_2 = 0.25$, $w_3 = 0.25$, $w_4 = 0.25$, (4) $w_1 = 0.2$, $w_2 = 0.1$, $w_3 = 0.5$, $w_4 = 0.2$. Among these sets, the one with weights $w_1 = 0.4$, $w_2 = 0.1$, $w_3 = 0.3$, $w_4 = 0.2$ performed the best. The reason for assigning these weights was as follows: D_1 (spatial distance) was assumed to be more important in the similarity measure for trajectories, thus weighted 0.4. D_2 (*Location*) weighted only 0.1 as it was represented by borough names in the space, which was correlated with D_1. D_3 (*Locale*) and D_4 (*Sense of Place*) weighted 0.5 in total so that the non-spatial dimensions could also be equally considered. The similarity score between the two places p_1 and p_2 is defined as the sum of the weighted match scores across all dimensions, as represented in the following equation:

$$score(p_1, p_2) = \sum_{k=1}^{4} (match_k(p_1, p_2) w_k) \tag{7}$$

where $match_k(p_1, p_2)$ determines whether the places are matched or not based on the max distance threshold $maxDist_k$, and it is defined in Equation 8. In this study, to handle the different data types of dimensions, each dimension was assigned a specific distance function and a threshold to determine whether p_1 and p_2 were matched. For the spatial position dimension D_1, the Euclidean distance was applied, as defined in Equation 9, where x and y represent the coordinates of places. A maximum distance threshold $maxDist_1$ of 1 km was set, meaning that if the distance between p_1 and p_2 exceeded 1 km, the match score of these two points was 0. For the semantic dimensions D_2, D_3, and D_4, which were categorical data, the discrete distance was applied, as shown in Equation 10. In this case, the distance can only take the value 0 or 1. The maximum distance threshold $maxDist_2$, $maxDist_3$, and $maxDist_4$ was set as 0.5. This means that if the distance between two points in D_2, D_3, or D_4 was 0, it was less than the threshold of 0.5, and thus a match score of 1 was assigned.

$$match_k(p_1, p_2) = \begin{cases} 1 & \text{if } dist_k(p_1, p_2) \leq maxDist_k \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

$$dist_{euclidean}(p_1, p_2) = \sqrt{(p_1.x - p_2.x)^2 + (p_1.y - p_2.y)^2} \tag{9}$$

$$dist_{discrete}(p_1, p_2) = \begin{cases} 0 & \text{if } p_1.type = p_2.type \\ 1 & \text{otherwise} \end{cases} \tag{10}$$

Since a place $p_1 \in T_1$ can be matched with multiple places in T_2, the objective of MSM is to find the best matching score for each place p_1 with T_2. The parity of T_1 with T_2, denoted as $parity(T_1, T_2)$, is defined as the sum of the highest score of all places $p_1 \in T_1$ with T_2, and the equation is:

$$parity(T_1, T_2) = \sum_{p_1 \in T_1} \max\{score(p_1, p_2) : p_2 \in T_2\} \tag{11}$$

Finally, the multidimensional similarity measure $MSM(T_1, T_2)$ is calculated by averaging the parity of T_1 with T_2 and the parity of T_2 with T_1, as defined as:

$$MSM(T_1, T_2) = \begin{cases} 0 & \text{if } |T_1| = 0 \text{ or } |T_2| = 0 \\ \frac{parity(T_1, T_2) + parity(T_2, T_1)}{|T_1| + |T_2|} & \text{otherwise} \end{cases} \tag{12}$$

In this study, the Python library trajminer developed by Petry & others (2019) was applied to construct the similarity matrix for semantic trajectories, with the distance functions, thresholds, and weights specified. Overall, by employing the MSM, this study considered the multiple dimensions of semantic trajectories and computed a similarity matrix that captured the matching scores and weights for each dimension, providing a comprehensive assessment of trajectory similarity.

4.3.3 Semantic Trajectory Clustering

The K-medoids algorithm was employed to cluster semantic trajectories. The term K-medoids was introduced by Kaufman (1990) with their Partitioning Around Medoids (PAM) algorithm. K-medoids is a classical clustering technique that divides the dataset of n objects into $k(k < n)$ clusters, with the number of clusters k predefined. Similar to K-means, K-medoids aims to minimize the distance between data points and the center point within a cluster. The reason for applying K-medoids to cluster trajectories is that it selects existing points as the centers of the clusters, making the cluster centers more interpretable.

In the K-medoids algorithm, the dissimilarity between trajectories needs to be measured. In this study, the dissimilarity was precomputed based on the trajectory similarity described in Section 4.3.2. The trajectory dissimilarity between each pair of trajectories is defined as:

$$dissimilarity(T_1, T_2) = 1 - MSM(T_1, T_2) \tag{13}$$

To perform the clustering for semantic trajectories, the trajminer.clustering.KMedoids function from the Python library trajminer was employed. With the precomputed dissimilarity matrix, the initial cluster medoids were determined using the approach introduced by Park & Jun (2009). This approach iteratively updates the medoids and assigns trajectories to each cluster until the sum of distances from all trajectories to their medoids reaches the minimum.

The K-medoids algorithm also requires users to define the number of clusters as input. Selecting the number of clusters is critical as too few clusters will include data with different patterns within the same cluster, leading to the loss of important information, while too many clusters will create meaningless clusters, making it hard to interpret. This study determined the optimal number of clusters based on the intra-cluster distance. The intra-cluster distance is the average distance between trajectories within a cluster and measures the compactness of the cluster. A larger intra-cluster distance indicates that the trajectories within the same cluster are less similar. The principle of cluster number selection is to minimize the intra-cluster distance (van der Merwe & Engelbrecht, 2003).

After clustering all semantic trajectories, exploratory data analysis was conducted to investigate the distribution of trajectories and the frequency of three semantic dimensions within each cluster. This analysis aimed to uncover the unique characteristics of these clusters, providing additional insights into the investigation of city perception through semantic trajectories.

4.3.4 Sequential Pattern Mining

While the trajectories selected as the cluster centers by the K-medoids algorithm can serve as representatives of their clusters, it is beneficial to identify typical semantic trajectories within each cluster to enhance the interpretation of clustering results. In this study, the **Prefix**-projected **S**equential

patter**n** mining (PrefixSpan) algorithm (Pei et al., 2004), a sequential pattern mining technique, was applied to detect frequently visited sequences under different scenes. The fundamental concept of PrefixSpan is to recursively project the sequence databases into smaller projected databases based on current sequential patterns. It utilizes a user-defined support threshold to mine sequential patterns by identifying frequent subsequences in a sequence database. The support represents the number of occurrences of the subsequence in the database, and subsequences with support above the specified threshold are extracted as the sequential patterns of interest.

For the sequential pattern mining, the Python library prefixspan [17] was utilized in this study. The semantic trajectories within each cluster were treated as the sequence database for the mining process. Considering the number of trajectories at different time spans, the minimum support was set from 2 to 5 to ensure that the typical trajectories could be mined. For instance, the trajectories during the nighttime were sparse, and there would be no sequences mined if the minimum support was greater than 2. The output for each trajectory cluster contained several sets of frequently visited places in sequential order, along with their corresponding support values. These sequences of places mined from each cluster would be treated as the typical trajectories of the corresponding cluster for further analysis.

The study of city perceptions in different scenes involved analyzing the semantic trajectories of each cluster. The distributions of these trajectories at different scenes were compared to explore the areas visited by locals and tourists across different time spans. In addition, the frequency of three semantic dimensions was analyzed by cluster to better understand the feature of each cluster. The first two semantic dimensions *Location* and *Locale* were utilized to examine the visiting purposes of these popular trajectories. And the third semantic dimension *Sense of Place* was applied to capture people's descriptions along these trajectories. Furthermore, the typical trajectories extracted from each cluster were visualized to reveal the popular regions in the city, which helped to investigate how these regions were considered by locals and tourists for different visiting purposes at different time spans.

[17] `https://pypi.org/project/prefixspan/`

5 Results

This chapter presents the results of this study. The spatiotemporal patterns of hotspots are displayed in Section 5.1 to investigate the popular areas among locals and tourists across various time spans, which answers RQ1. Section 5.2 shows the distribution of places as these places are the fundamental elements in the construction of semantic trajectories. The distribution of semantic trajectories and the city perceptions along these trajectories across various time spans are presented in Section 5.3 to answer RQ2.

5.1 Spatiotemporal Patterns of Hotspots

To investigate the popularity of different areas among locals and tourists at various times, Foursquare check-ins are utilized to detect spatiotemporal hotspots. Figure 5.1 reveals the number and temporal pattern of check-ins. Locals are more active than tourists, generating a greater number of check-ins throughout different periods. Notably, daytime check-ins outnumber nighttime check-ins. Figure 5.2 shows the temporal pattern of check-ins. Locals display three prominent spikes in the number of check-ins during the daytime, specifically at 8 am, 12 pm, and 6 pm. Conversely, their activities diminish during the nighttime, particularly at midnight. On the other hand, tourists are more active at 12 pm but show reduced activity levels after 6 pm. Furthermore, weekdays experience a higher number of check-ins compared to weekends. Locals exhibit a consistent sharing pattern from Mondays to Thursdays, with a notable spike on Fridays, and when it comes to weekends, locals share significantly fewer check-ins. Tourists display a similar pattern from Monday to Thursday but exhibit increased activities on Fridays and Saturdays, followed by fewer check-ins on Sundays.

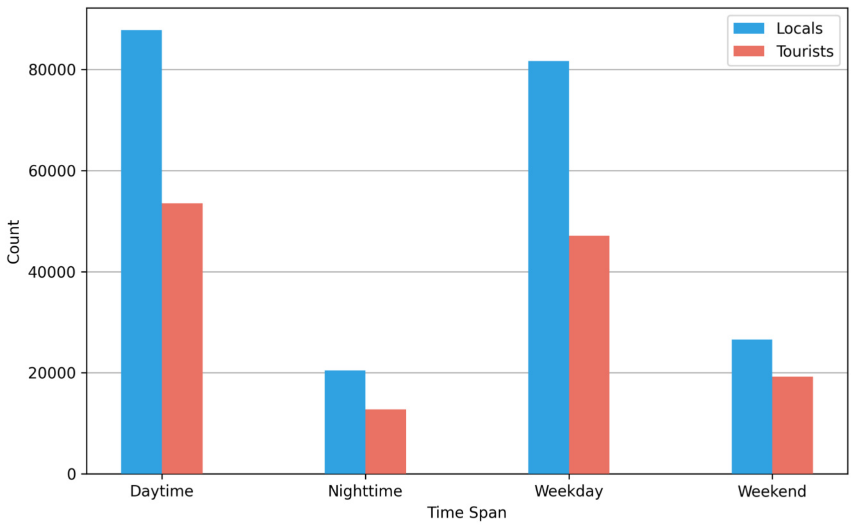
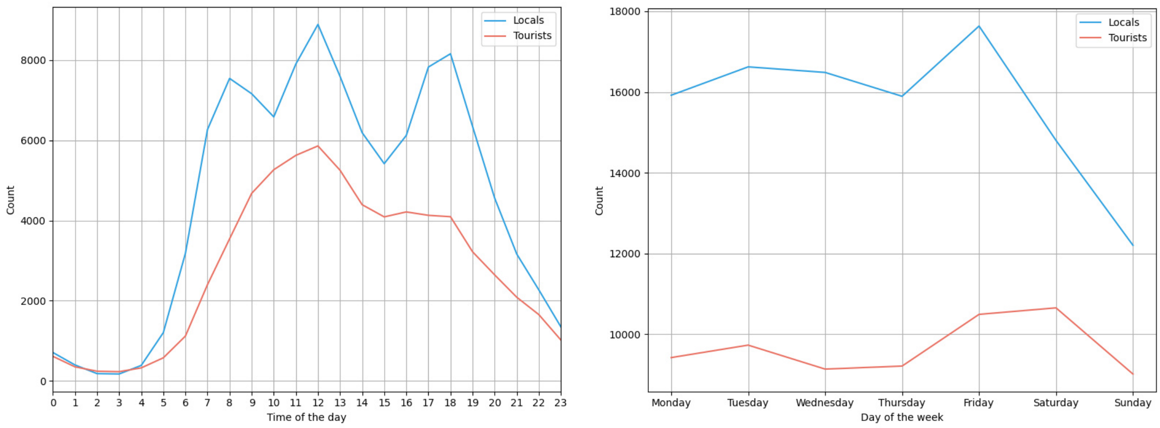


Figure 5.1: Number of Foursquare check-ins of locals and tourists across time spans.



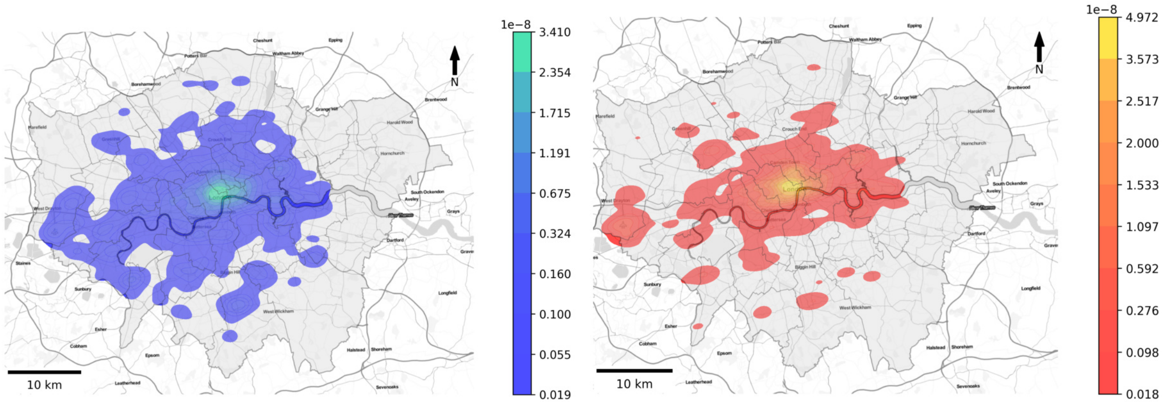
(a) Day pattern. (b) Week pattern.

Figure 5.2: Temporal pattern of Foursquare check-ins.

5.1.1 Hotspots Distribution

5.1.1.1 Daytime vs. Nighttime

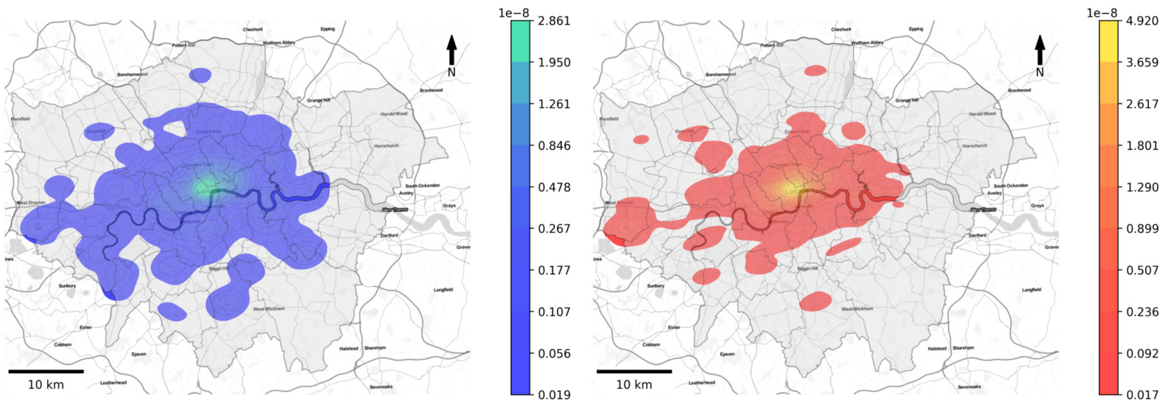
The estimated distribution of Foursquare check-ins during the daytime is displayed in Figure 5.3. The bandwidths for KDE of locals and tourists, determined by using the Scott method, are approximately 26 km and 28 km, respectively. Locals exhibit a similar hotspot distribution pattern with tourists but share fewer check-ins across London. The primary hotspots of locals and tourists are located in the city center, specifically Westminster, Camden, and the City of London. These boroughs contain an abundance of cultural and historical landmarks with high transportation connectivity, leading to a substantial influx of people. Another notable hotspot is situated around Stratford in Newham, where the Stratford Shopping Centre is located, appealing to individuals who enjoy shopping. Additionally, the southern region of Hillingdon, where Heathrow Airport is located, is another hotspot where people share a large number of check-ins. Furthermore, the boundary of Richmond upon Thames and Kingston upon Thames reveals an aggregation of check-ins, and these boroughs contain thriving communities with history and natural beauty. One notable difference between locals and tourists is the presence of work-related hotspots for locals. The City of London is found to be attractive to locals as this area serves as a major business hub, with numerous corporate headquarters providing employment opportunities. Similarly, Canary Wharf, located near the Isle of Dogs within Tower Hamlets, represents another hotspot for locals due to its status as part of London's central business district. Moreover, boroughs located on the outskirts of London, such as Croydon, Merton, Bromley, Brent, and Harrow, form smaller yet noteworthy hotspots. These areas are characterized by their residential settlement and exhibit a greater concentration of locals compared to tourists.



(a) Locals. (b) Tourists.

Figure 5.3: Kernel density estimation of Foursquare check-ins during the daytime.

During the nighttime, the KDE bandwidths for locals and tourists are approximately 33 km and 36 km, respectively. The city center remains the primary hotspot for both locals and tourists. However, locals become less active compared to the daytime, with a decreased concentration of check-ins, while tourists keep similar activity levels (Figure 5.4). In addition to its cultural and historical attractions, the city center is also a renowned area that offers abundant shopping and entertainment options. For instance, Oxford Street and Regent Street in central London provide vibrant nightlife scenes. For locals, the concentration of check-ins in the city center during the nighttime is lower compared to the daytime. Furthermore, the hotspot around Canary Wharf, a bustling business district, diminishes, which indicates a reduced number of locals visiting this area during the nighttime. However, the hotspots around Heathrow Airport and outskirts boroughs, such as Croydon, Bromley, and Harrow, remain prominent. This suggests that these areas are aggregated with a significant number of locals, possibly due to air transport activities ad residential settlements. In terms of tourists, although the primary hotspot remains in the city center, the concentration of check-ins in this area decreases during the nighttime. Moreover, there is a reduction or disappearance of hotspots in the outer part of London except for the area around Heathrow Airport, indicating a decrease in the number of tourists visiting these settlement regions during the nighttime.

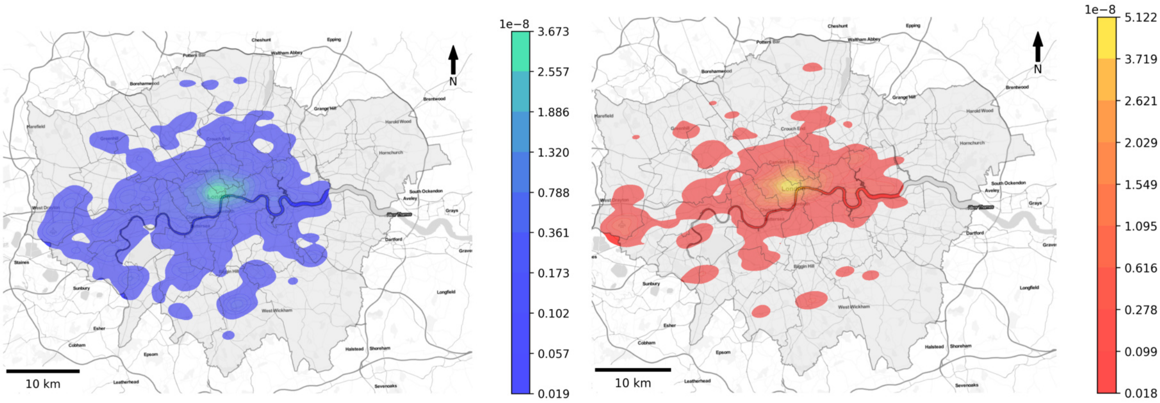


(a) Locals. (b) Tourists.

Figure 5.4: Kernel density estimation of Foursquare check-ins during the nighttime.

5.1.1.2 Weekday vs. Weekend

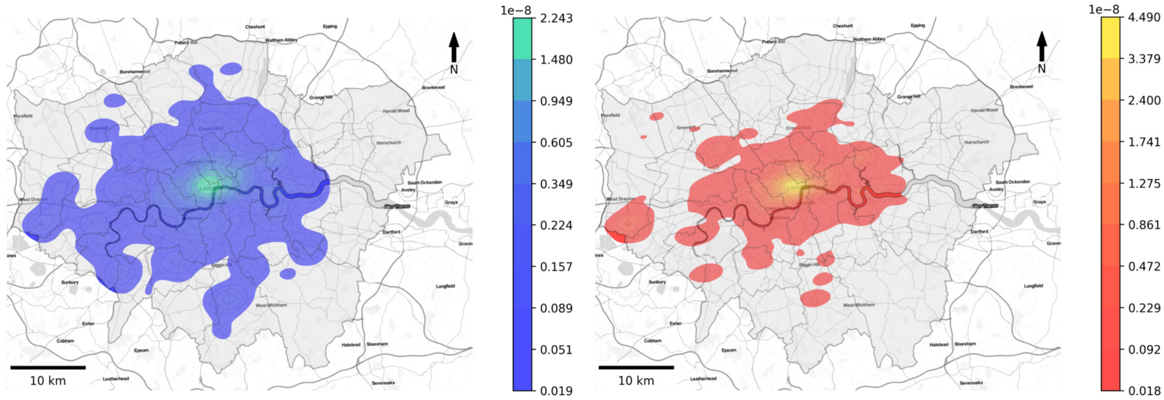
Figure 5.5 displays the estimated distribution of check-ins shared by locals and tourists on weekdays. The KDE bandwidths for locals and tourists are approximately 26 km and 29 km, respectively. Locals exhibit a relatively lower concentration of check-ins across London compared to tourists. Though both locals and tourists have their primary hotspots in the city center, the distributions of their hotspots are different. The primary hotspot of locals is close to the City of London and Canary Wharf, as these regions serve as important business districts for weekday work engagements. Consistent with the hotspot distribution observed during the daytime, locals also visit the outskirts of London, such as Heathrow Airport in Hillingdon, as well as settlement regions in Croydon, Merton, Harrow, etc. In contrast, the primary hotspot of tourists in the city center gravitates towards the vicinity of Westminster and Camden on weekdays. These areas contain numerous tourist attractions and shopping destinations, appealing to lots of tourists. The outer part of London is less popular among tourists, but it is noteworthy that Hillingdon, where Heathrow Airport is located, gains more popularity among tourists compared to other areas.



(a) Locals. (b) Tourists.

Figure 5.5: Kernel density estimation of Foursquare check-ins on weekdays.

On weekends, the KDE bandwidths for locals and tourists are 32 km and 34 km, respectively. Locals and tourists share fewer check-ins across London compared to weekdays (Figure 5.6). Locals keep visiting both central London and various outskirts boroughs as they do on weekdays. Conversely, the visiting areas of tourists shrink to the inner part of London, sharing fewer check-ins in the outer boroughs. In general, both locals and tourists exhibit a decrease in check-in density on weekends. The outskirts boroughs keep attracting locals throughout the week, while tourists focus their activities on the city center.



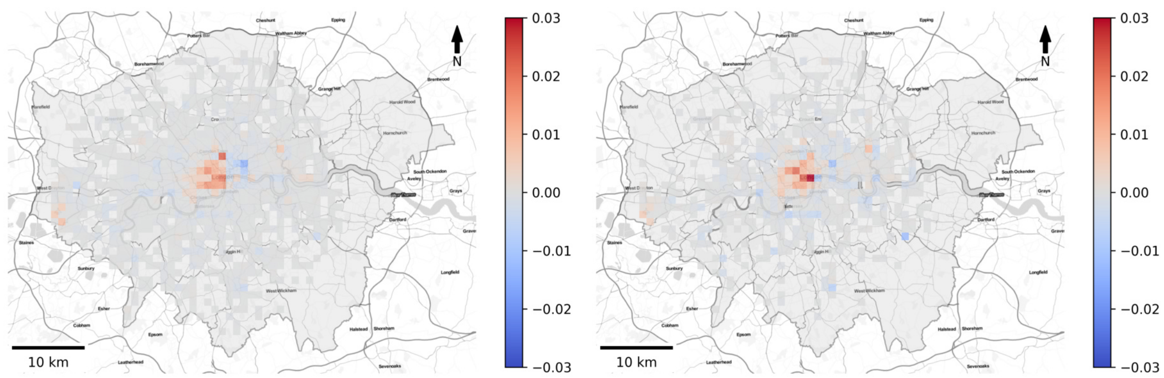
(a) Locals. (b) Tourists.

Figure 5.6: Kernel density estimation of Foursquare check-ins on weekends.

5.1.2 Mixture of Locals and Tourists in Hotspots

5.1.2.1 Daytime vs. Nighttime

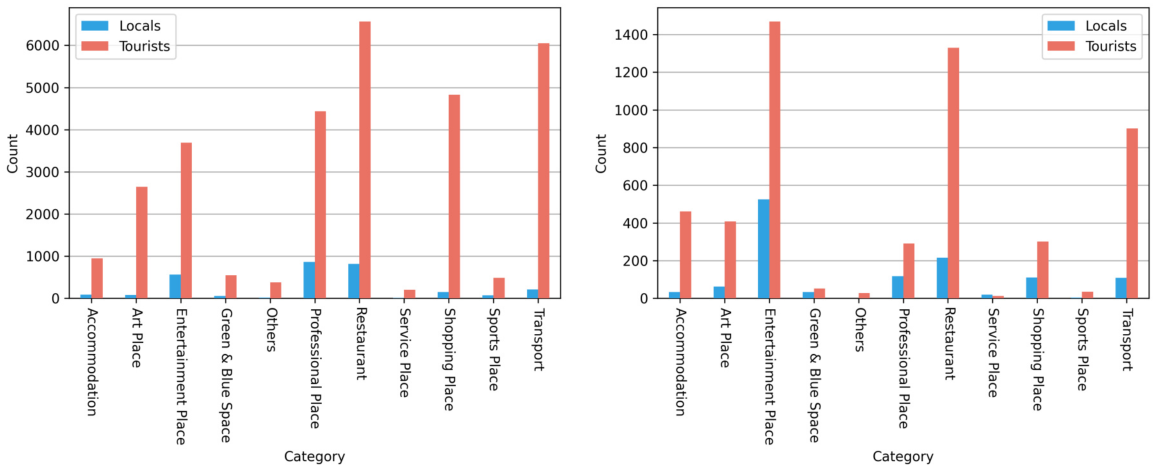
Figure 5.7 shows the difference ratio between locals and tourists within each raster throughout the day. The difference ratio reveals the mixture degree of check-ins shared by locals and tourists. A positively higher difference ratio indicates a larger activity density of tourists, while a negatively lower difference ratio suggests a higher concentration of locals' activities. During the daytime, most areas across London, except for the city center, receive similar popularity from both groups. Though both locals and tourists share a large number of check-ins in the city center, they have distinct areas of interest. Tourists tend to cluster in Westminster and Camden, while locals are more concentrated in the eastern region, particularly in the City of London, and the Canary Wharf in Tower Hamlets. These findings align with the observations in Section 5.1.1. In addition, the hotspot around Heathrow Airport displays a positive value of difference ratio, indicating a higher activity density of tourists (Figure 5.7a). Moving to the nighttime, the city center, especially Westminster, becomes increasingly popular among tourists, while the area around the City of London shows a balanced presence of locals and tourists, indicating reduced activities of locals during the nighttime. Furthermore, the difference ratio of some outskirts rasters becomes negative when it comes to the nighttime, indicating an outflux of locals from the city center (Figure 5.7b).



(a) Daytime. (b) Nighttime.

Figure 5.7: Difference ratio of rasters during the daytime and nighttime.

The category distribution of check-ins within rasters with significant difference ratios (greater than 0.01 or less than -0.01) is represented in Figure 5.8. During the daytime, tourists demonstrate a preference for restaurants, transportation places, and shopping places, while locals show a higher inclination towards professional places, restaurants, and entertainment places (Figure 5.8a). In terms of the nighttime, tourists exhibit a great interest in entertainment places while maintaining their preference for restaurants and transportation places. Locals, on the other hand, shift their focus from professional places to entertainment places while still showing interest in restaurants (Figure 5.8b). Table A.1 - Table A.4 in Appendix A list the top 10 popular venues within rasters with significant difference ratios. Popular daytime venues for tourists include transportation hubs like London King's Cross Railway Station, luxury department stores like Harrods, and prominent public squares like Trafalgar Square. On the other hand, locals during the daytime tend to visit more professional venues like Google Campus - London and other companies, as well as restaurants around Shoreditch. Regarding the nighttime, popular venues for both locals and tourists include nightclubs and pubs, alongside transportation hubs.

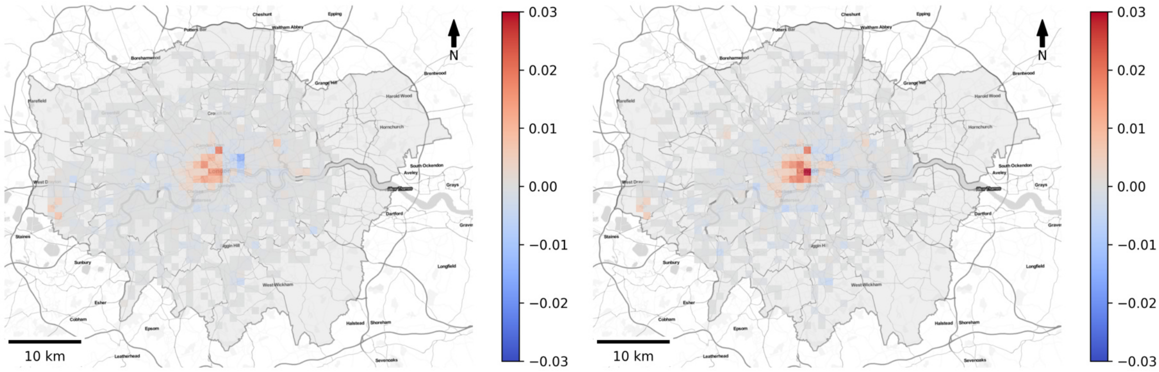


(a) Daytime. (b) Nighttime.

Figure 5.8: Number of check-in categories in popular areas during the daytime and nighttime.

5.1.2.2 Weekday vs. Weekend

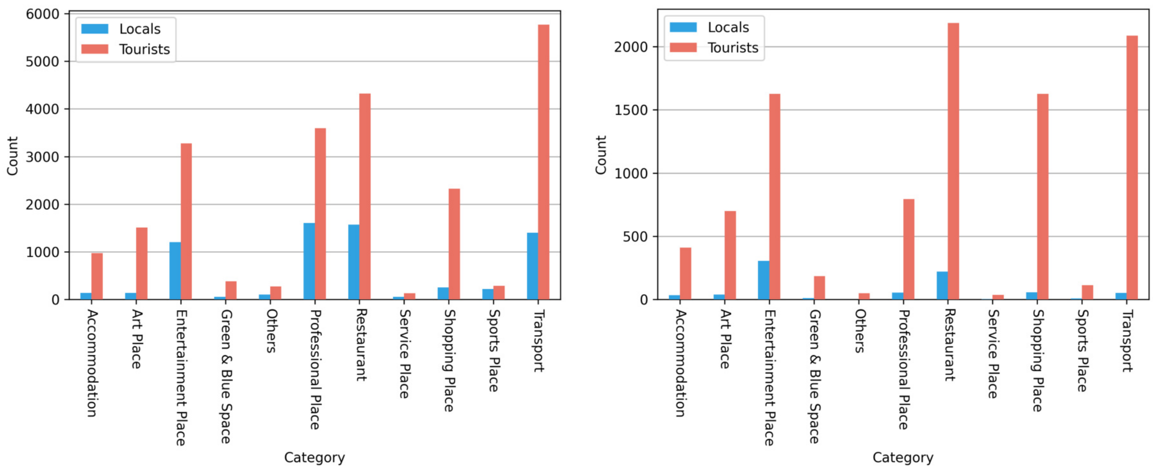
Figure 5.9 displays the mixture degree of locals and tourists throughout the week. On weekdays, locals and tourists tend to visit distinct areas in the city center, as shown in the significant positive and negative values of difference ratio around this area. As discussed in previous sections, tourists concentrate their activities in Westminster and Camden, while locals exhibit a higher activity density towards the east, particularly around the City of London, which is a prominent business district (Figure 5.9a). Moving on to weekends, the hotspot of tourists in the city center becomes more popular among tourists, with higher difference ratios in relevant rasters. Conversely, the increased difference ratios in the locals' hotspot in the city center indicate a reduced relative concentration of locals, suggesting a decrease in local visits to this area on weekends. In addition, some outskirts rasters experience a decrease in difference ratios, meaning that locals on weekends are more scattered across London compared to weekdays (Figure 5.9b)



(a) Weekday. (b) Weekend.

Figure 5.9: Difference ratio of rasters on weekdays and weekends.

The category distribution of check-ins in rasters with significant difference ratios (greater than 0.01 or less than -0.01) is depicted in Figure 5.10. On weekdays, both tourists and locals display a preference for entertainment places, professional places, restaurants, and transportation places (Figure 5.10a). But when it comes to the weekends, tourists switch interests from professional places to shopping places, with consistent interests in three other categories. Locals, on the other hand, reduce their visits to professional places and transportation places (Figure 5.10b). In terms of the popular venues in rasters with significant difference ratios, tourists exhibit a consistent preference for transportation hubs and public squares throughout the week. While locals shift their visits towards more leisure venues like coffee shops and bars on weekends, rather than company establishments on weekdays. For more detailed information, please refer to Table A.5 - Table A.8 in Appendix A.



(a) Weekday. (b) Weekend.

Figure 5.10: Number of check-in categories in popular areas on weekdays and weekends.

5.2 Spatiotemporal Patterns of Places

5.2.1 Place Distribution

In this study, places are clusters of check-ins. Table 5.1 shows the number of places locals and tourists visit at different times. During the daytime, locals and tourists visit 1,525 and 1,046 places respectively. At night, these numbers reduce to 598 for locals and 441 for tourists. On weekends, the number of places visited decreases to 855 for locals and 580 for tourists from 1,469 and 1,055 on weekdays. Despite more tourists, they visit fewer places than locals.

Table 5.1: Summary of places.

Time	Population group	No. of users	No. of places
	All Users	6,919	2,571
Daytime	Locals	1,077	1,525
	Tourists	5,842	1,046
	All Users	4,425	1,039
Nighttime	Locals	996	598
	Tourists	3,429	441
	All Users	6,497	2,524
Weekday	Locals	1,069	1,469
	Tourists	5,428	1,055
	All Users	4,886	1,435
Weekend	Locals	1,011	855
	Tourists	3,875	580

5.2.1.1 Daytime vs. Nighttime

Figure 5.11 displays the distribution of places during the daytime. The majority of places visited by locals are concentrated in the city center, and there are also a certain number of places located in outskirts boroughs, such as Hillingdon, Croydon, and Barnet. On the other hand, the places visited by tourists exhibit a more concentrated distribution in the inner part of London, with a sparser distribution in the outer areas. The nighttime distribution of places is depicted in Figure 5.12. The distribution follows a similar pattern to that of the daytime but with a lower density, indicating a reduced activity level during nighttime hours.

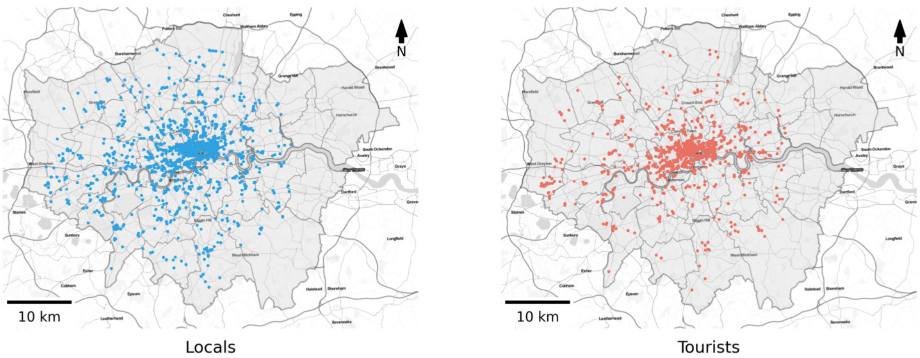


Figure 5.11: Distribution of places during the daytime.

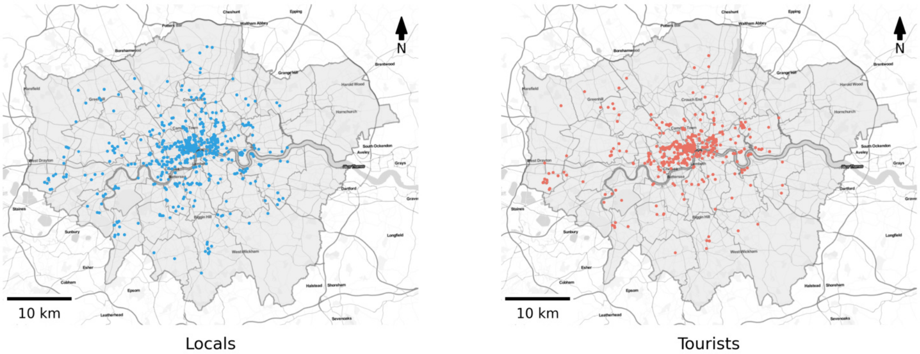


Figure 5.12: Distribution of places during the nighttime.

5.2.1.2 Weekday vs. Weekend

Figure 5.13 shows the distribution of places on weekdays. Both locals and tourists visit a significant number of places in the city center, but locals tend to visit more places in suburban areas compared to tourists. On weekends, the distribution of places for locals and tourists becomes sparser compared to weekdays, but the concentration in the city center remains evident. Similar to weekdays, locals continue to visit more places on the outskirts of London than tourists (Figure 5.14). Overall, both locals and tourists tend to concentrate in the city center but also exhibit distinct distribution patterns of places across time spans.

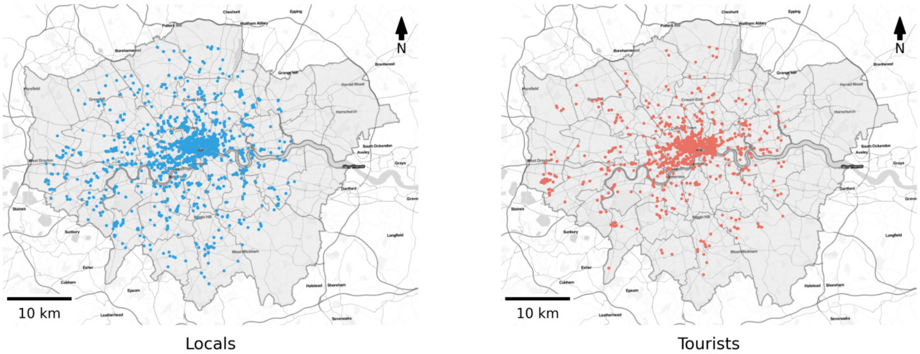


Figure 5.13: Distribution of places on weekdays.

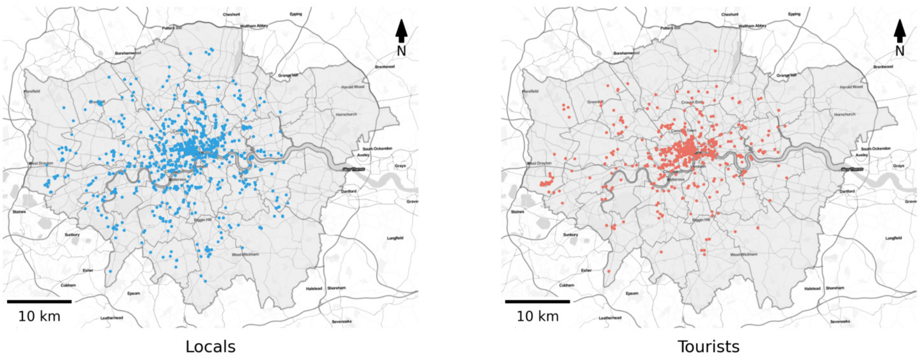


Figure 5.14: Distribution of places on weekends.

5.2.2 Place Dimensions

5.2.2.1 Daytime vs. Nighttime

Location

Figure 5.15 and Figure 5.16 provide insight into the distribution of places in the *Location* dimension during the daytime and nighttime. The central boroughs of Westminster and Camden contain the highest number of places visited by both locals and tourists throughout the day, which also validates the findings in the previous section. During the daytime, most outskirts boroughs have more places visited by locals rather than tourists. This trend is obvious in boroughs such as Barnet, Islington, Harrow, and Merton, as these outer areas serve as residential settlements. It is worth mentioning that Hillingdon, also an outer borough, exhibits a higher number of places visited by tourists, which can be attributed to the presence of Heathrow Airport in its southern region. Boroughs with a relatively equal number of places visited by locals and tourists are predominantly located in the inner part of London. These boroughs include Westminster, Camden, the City of London, Kensington and Chelsea, and Tower Hamlets, all of which boast a higher concentration of tourist attractions with high accessibility (Figure 5.15). In terms of the nighttime, while the overall number of places visited decreases in all boroughs during nighttime hours, the distribution remains similar to that of the daytime (Figure 5.16).

Locale

Figure 5.17 and Figure 5.18 show the distribution of places in the *Locale* dimension during the daytime and nighttime. During daytime hours, restaurants are the most frequently visited categories for locals and tourists, and categories like professional places, shopping places, entertainment places, and transportation places are also popular among these two groups of people. Locals visit more places across most categories, but tourists show a higher preference for accommodation and green & blue space categories than locals (Figure 5.17). At nighttime, fewer places are visited in each category and the popularity of these categories also undergoes a transformation. Restaurants remain highly popular among both locals and tourists, and entertainment places emerge as the second most popular category, while there is a noticeable decrease in the frequency of professional places and shopping places compared to daytime hours. Accommodation and green & blue spaces continue to attract more tourists than locals during nighttime hours. Notably, the accommodation category experiences an increased difference between the number of places visited by locals and tourists, indicating a higher demand for accommodation among tourists than locals during the nighttime (Figure 5.18).

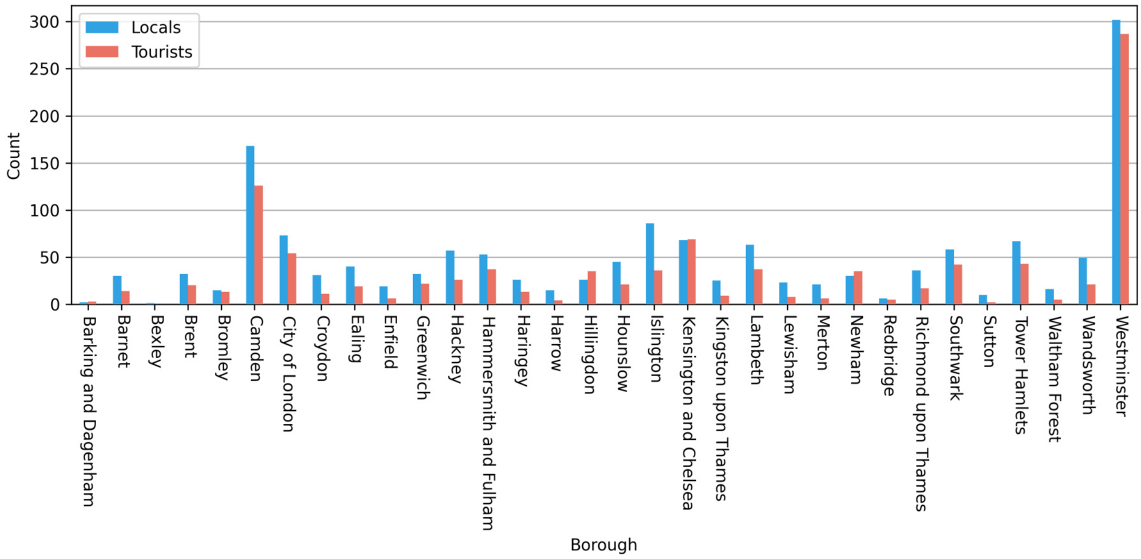


Figure 5.15: Location dimension of places during the daytime.

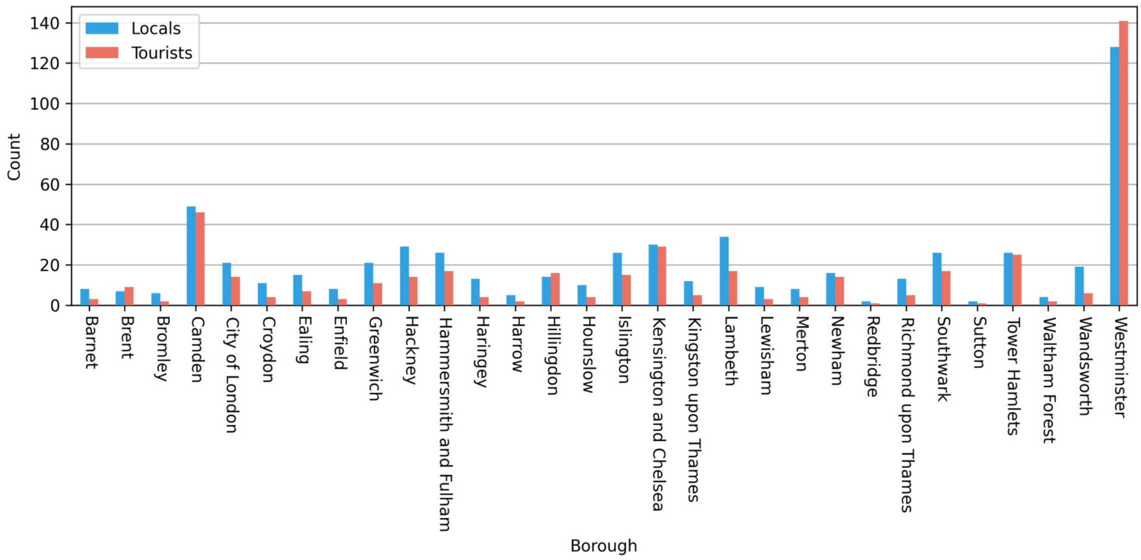


Figure 5.16: Location dimension of places during the nighttime.

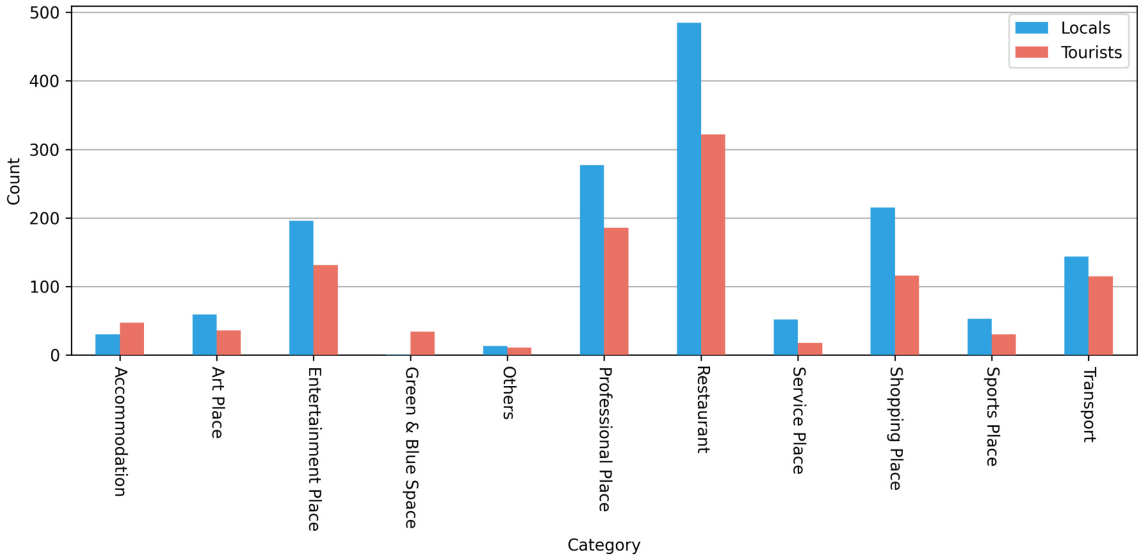


Figure 5.17: Locale dimension of places during the daytime.

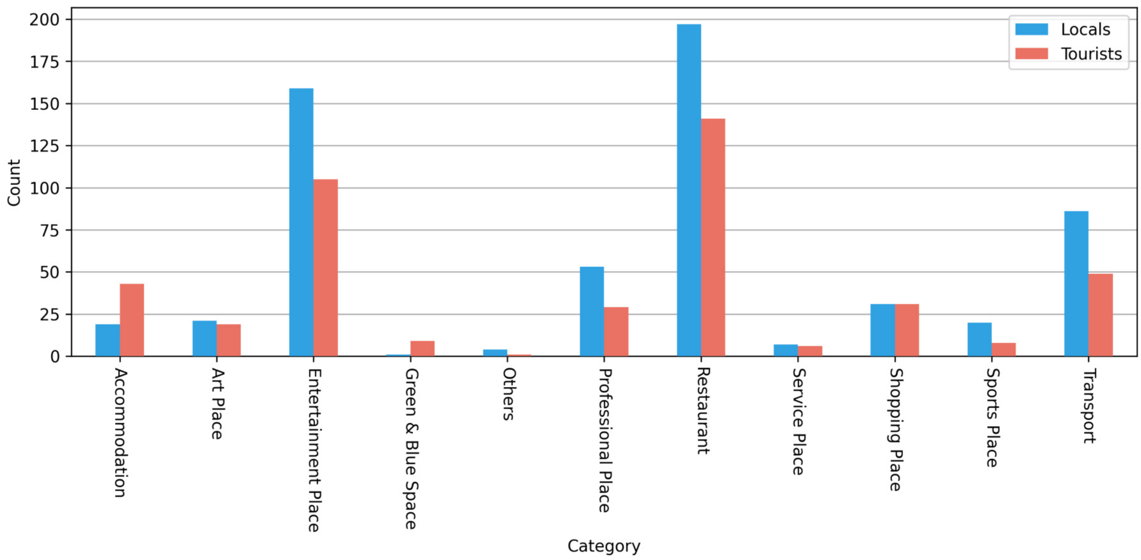


Figure 5.18: Locale dimension of places during the nighttime.

Sense of Place

The *Sense of Place* dimension is represented by the topics generated through topic modeling, which is based on the Flickr tags within places. However, there are instances where some places do not contain any Flickr tags. For these empty places, topics are assigned based on the topics of their neighboring places through the topic imputation method introduced in Section 4.2.2. Table 5.2 shows the quantile distribution of tag counts within places and also enumerates the number of empty places. It is observed that, except for the daytime locals scene, about 25% of the places in other scenes do not contain Flickr tags. The empty places require topic imputation to assign them relevant topics. The number of topics is determined by a sensitivity test evaluating coherence values, with the topic number ranging from 5 to 15. The optimal number of topics, along with their corresponding coherence values, are displayed in Table 5.3.

Table 5.2: Tag count quantiles and the number of empty places during the daytime and nighttime.

Time	Population group	Q.25	Q.50	Q.75	No. of empty places
Daytime	Locals	0	14	84	392
	Tourists	6	48	271	155
Nighttime	Locals	0	5	61	239
	Tourists	0	19	153	112

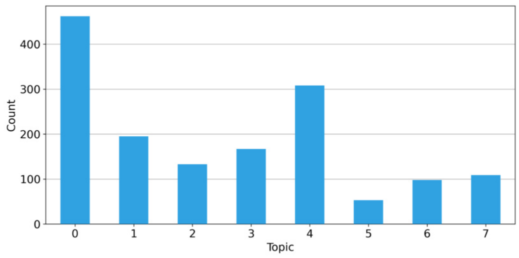
Table 5.3: Topic number and coherence value during the daytime and nighttime.

Time	Population group	No. of topics	Coherence value
Daytime	Locals	8	0.54
	Tourists	6	0.55
Nighttime	Locals	6	0.45
	Tourists	6	0.46

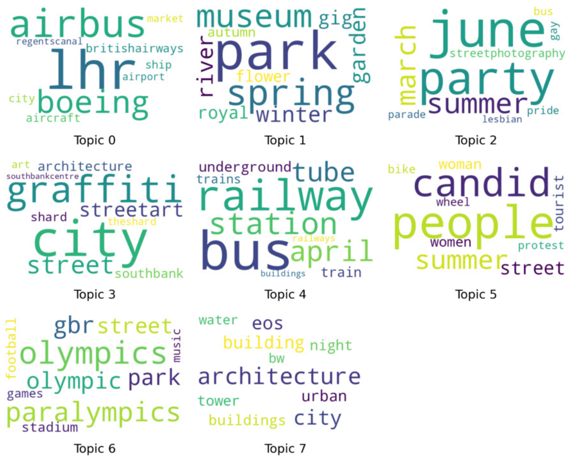
The distribution of locals' places in the *Sense of Place* dimension during the daytime is shown in Figure 5.19. Locals' descriptions of places are summarized by eight topics. Over 700 places are characterized by air and rail transportation (e.g., lhr[18], airbus, bus, railway), as illustrated in the high frequency of Topic 0 and Topic 4 (Figure 5.19a, Figure 5.19b). The distribution of topics in Figure 5.19c aligns with the topic content. For instance, the city center is characterized by places associated with Topic 1 (e.g., park, museum, spring) and Topic 2 (e.g., june, party, summer). Commonly, this area is recognized as a hub for leisure activities, given its abundance of renowned parks and museums. In addition, since the transport network covers most areas of the city, Topic 4 (e.g., railway, bus, station) has its places distributed across London. And the vicinity of London Stadium (built for the 2012 Olympics) in Stratford, Newham also exhibits a concentration of places associated with Topic 6 (e.g., olympics, paralympics).

In terms of tourists' daytime places in the *Sense of Place* dimension, six topics are generated (Figure 5.20). Compared to locals, tourists during the daytime demonstrate a preference for urban-related places (Topic 4) and the Olympics (Topic 0), with the number of associated places exceeding 350 and 250 respectively. Places related to air transport are less popular among tourists, as shown in the low frequency of Topic 1 (e.g., lhr, aircraft, airbus) (Figure 5.20a, Figure 5.20b). Figure 5.20c displays the spatial distribution of topics. The inner part of London is representative of urban life with numerous art venues, thus this area exhibits a concentration of Topic 4 (e.g., street, bus, city) and Topic 5 (e.g., museum, art, architecture). Places in Topic 1 are predominantly near Heathrow Airport, which is highly related to the topic content. Topic 2 describes places along the bustling part of the River Thames with tags like tower, city, bridge, and river. Additionally, topics related to the Olympics also show distinct distribution patterns. Topic 0 (e.g., olympics, paralympics) covers areas not only around London Stadium but also the city center. Moreover, similar to the route of the London 2012 Olympic Marathon, places in Topic 3 (e.g., marathon, city, urban) are mainly distributed along the River Thames.

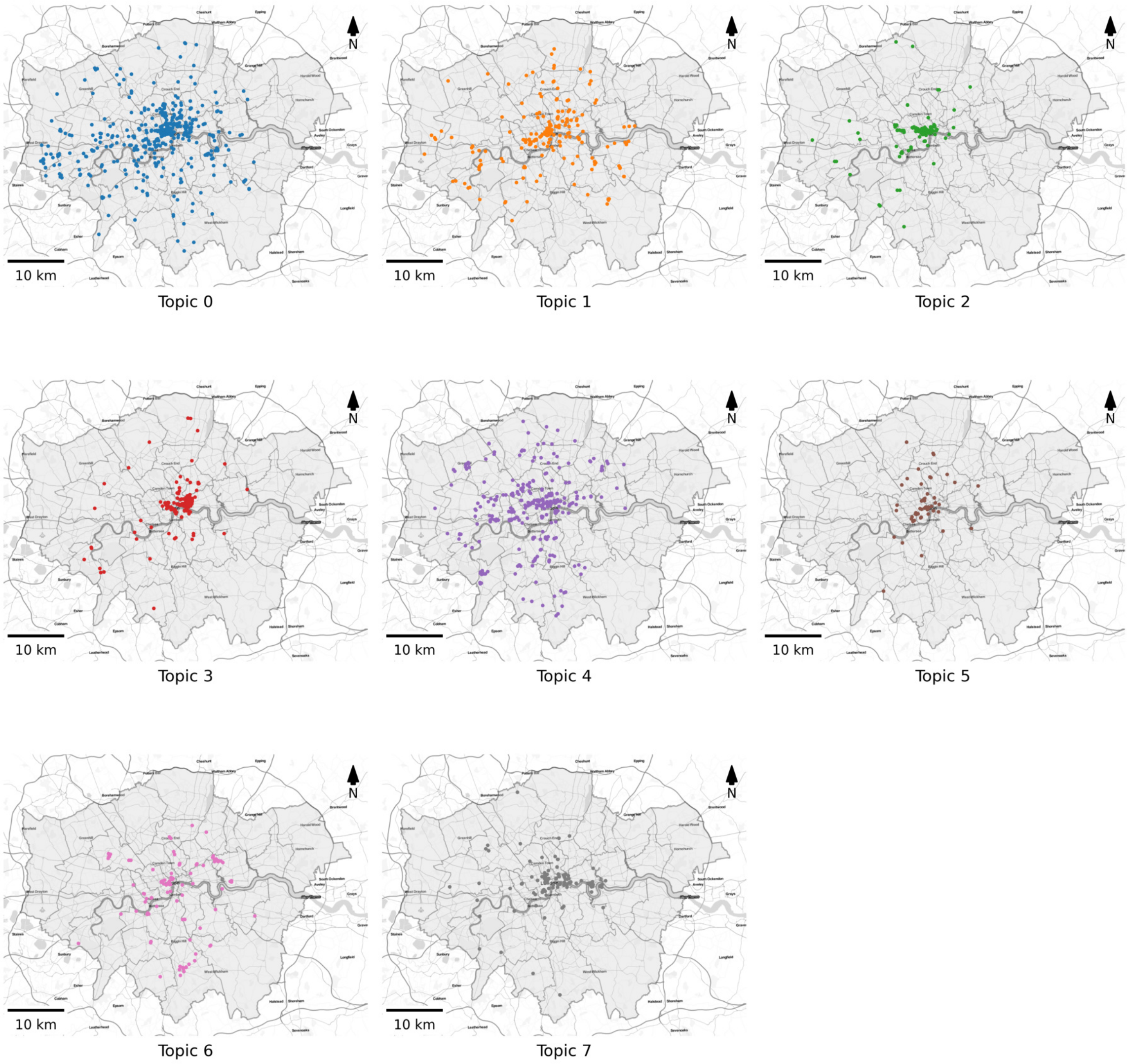
[18]The airport London Heathrow.



(a) Frequency of topics.

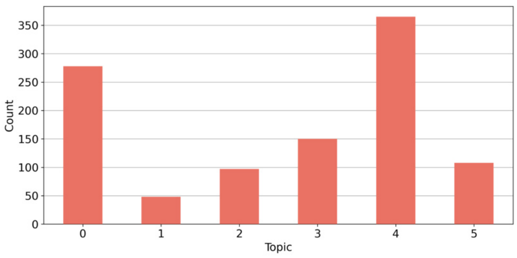


(b) Word clouds for topics.

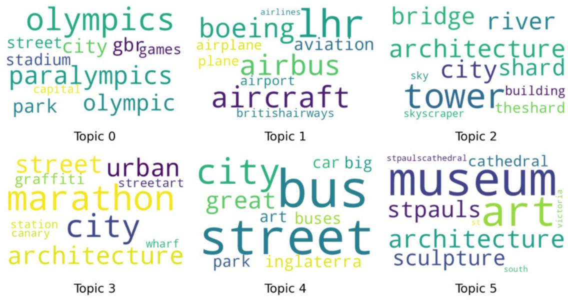


(c) Distribution of topics.

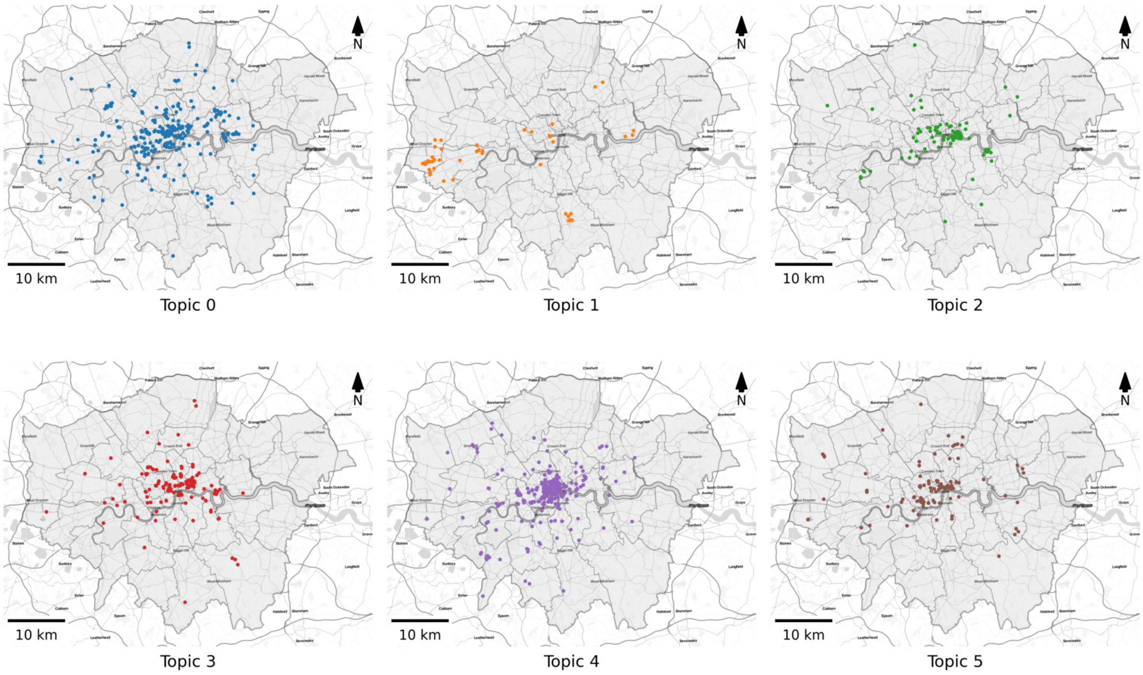
Figure 5.19: Sense of place dimension of locals' places during the daytime.



(a) Frequency of topics.



(b) Word clouds for topics.

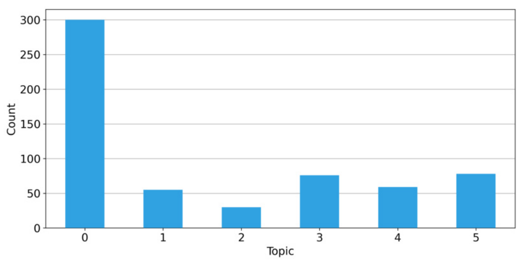


(c) Distribution of topics.

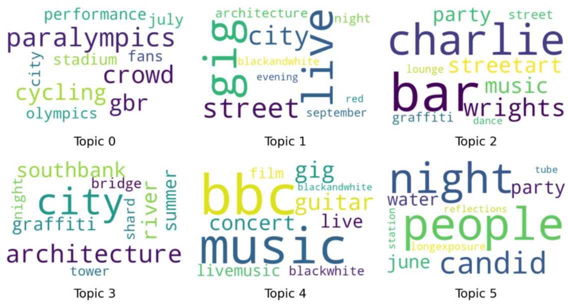
Figure 5.20: Sense of place dimension of tourists' places during the daytime.

As night falls, locals' descriptions of London are summarized by six topics (Figure 5.21). Topics during this period start to include words related to nighttime venues and events. Locals discuss live, music, gig, and concert, indicating a shift towards more leisurely activities. In terms of the frequency of topics, Topic 0 (e.g., paralympics, crowd, cycling, performance) emerges as the most popular topic, with approximately 300 associated places. The remaining five topics are less frequently mentioned, each comprising fewer than 100 places (Figure 5.21a, Figure 5.21b). Figure 5.21c displays the distribution of topics. Topic 1 (e.g., gig, live, street), Topic 2 (e.g., Charlie, bar, wrights, party), Topic 4 (e.g., bbc, music, gig), and Topic 5 (e.g., people, night, candid, party) are more related to nighttime activities. Topic 1 predominantly features places in Westminster, known for its vibrant gig and live music venues in the evening. Topic 2 concentrates its places in the vicinity of Shoreditch, where a multitude of bars and clubs are located. Topic 4 and Topic 5 display a more dispersed distribution of places, reaching the outskirts boroughs.

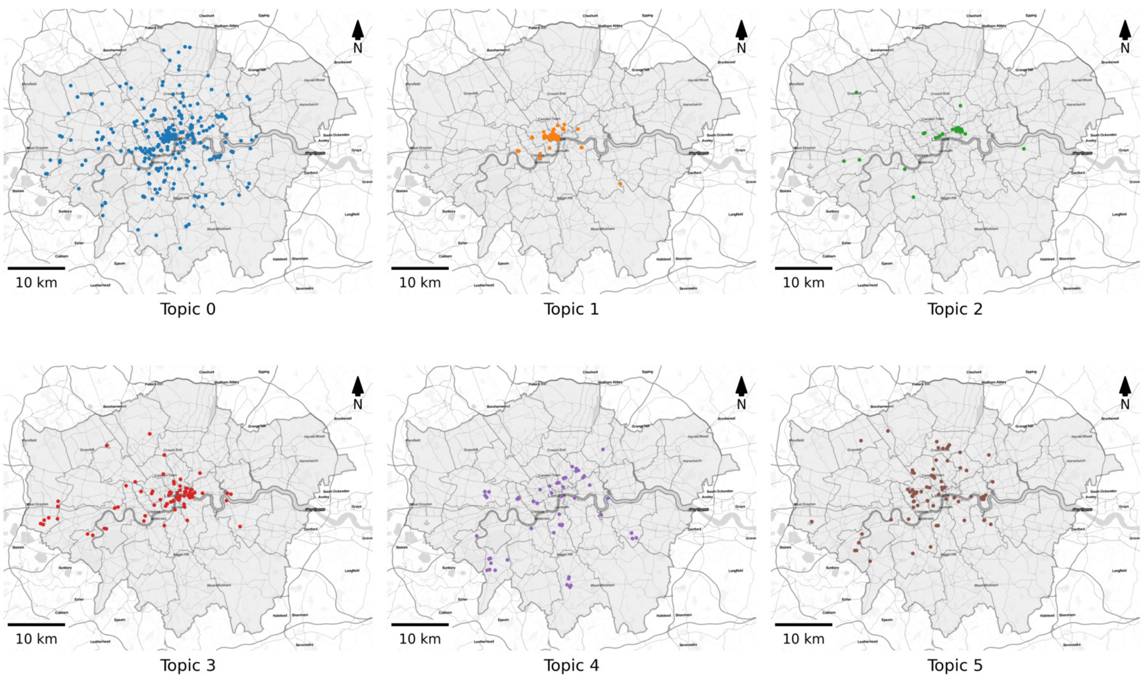
Five topics are generated for tourists in the *Sense of Place* dimension during nighttime hours (Figure 5.22). Similar to locals, tourists at this time also use words related to nighttime activities to describe London, reflected by the emergence of Topic 1 (e.g., concert, live, gig, music) and Topic 4 (e.g., nighttime, city). Compared to the daytime, although the number of places visited by tourists decreases, there is relatively increased interest in places related to museums and transportation, as evidenced by the prominence of Topic 0 (e.g., museum, lhr, station, railway) (Figure 5.22a, Figure 5.22b). The distribution of topics is displayed in Figure 5.22c. While both locals and tourists visit places related to gigs and live music, tourists prefer places around Shoreditch rather than Westminster, as indicated by the distribution Topic 1. Similar to locals, tourists also enjoy visiting places near bridges along the River Thames, which is evidenced by Topic 2 (e.g., architecture, bridge, night, city).



(a) Frequency of topics.

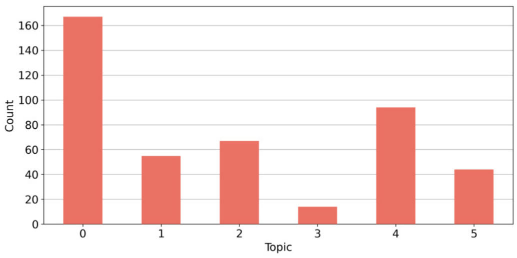


(b) Word clouds for topics.

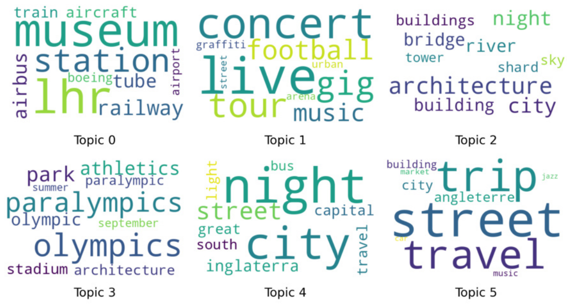


(c) Distribution of topics.

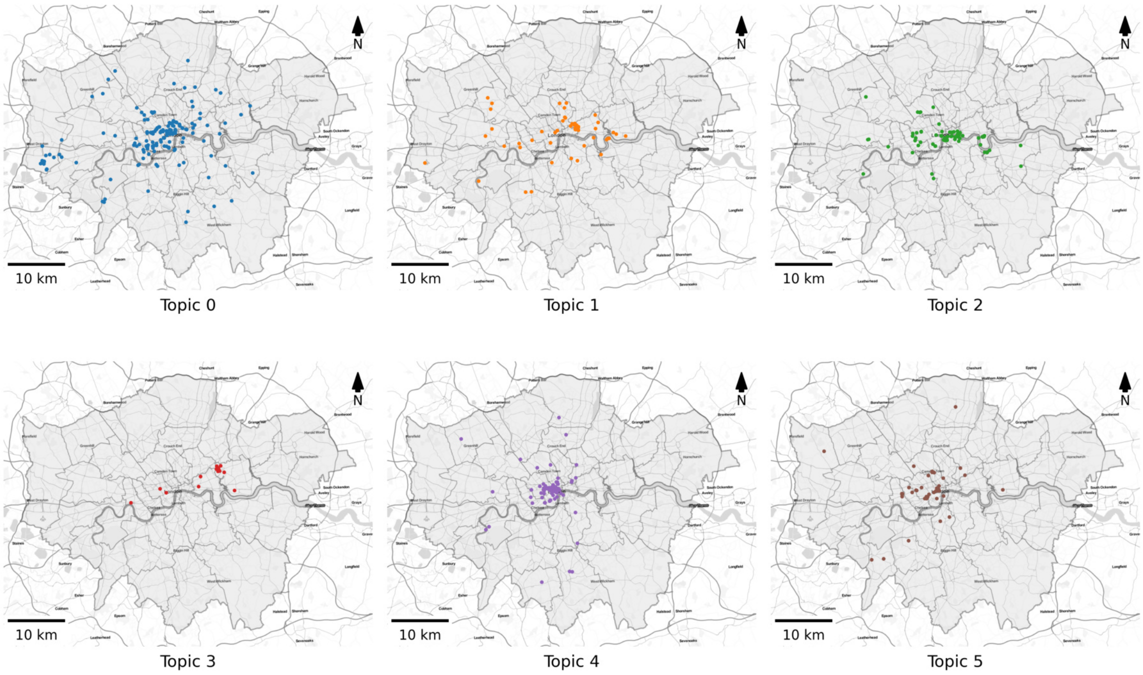
Figure 5.21: Sense of place dimension of locals' places during the nighttime.



(a) Frequency of topics.



(b) Word clouds for topics.



(c) Distribution of topics.

Figure 5.22: Sense of place dimension of tourists' places during the nighttime.

5.2.2.2 Weekday vs. Weekend

Location

The distributions of places in the *Location* dimension on weekdays and weekends are presented in Figure 5.23 and Figure 5.24. Generally, boroughs on weekends experience a decrease in the number of places, while the relative relationships of boroughs remain consistent, with Westminster and Camden being the most popular boroughs throughout the entire week. It is noteworthy that most boroughs are more frequently visited by locals, but Westminster and Hillingdon attract more tourists. Westminster, located in central London, boasts numerous tourist attractions and iconic architecture, making it appealing to tourists. Hillingdon, though situated on the outskirts of London, is home to Heathrow Airport, which draws a large number of tourists to visit.

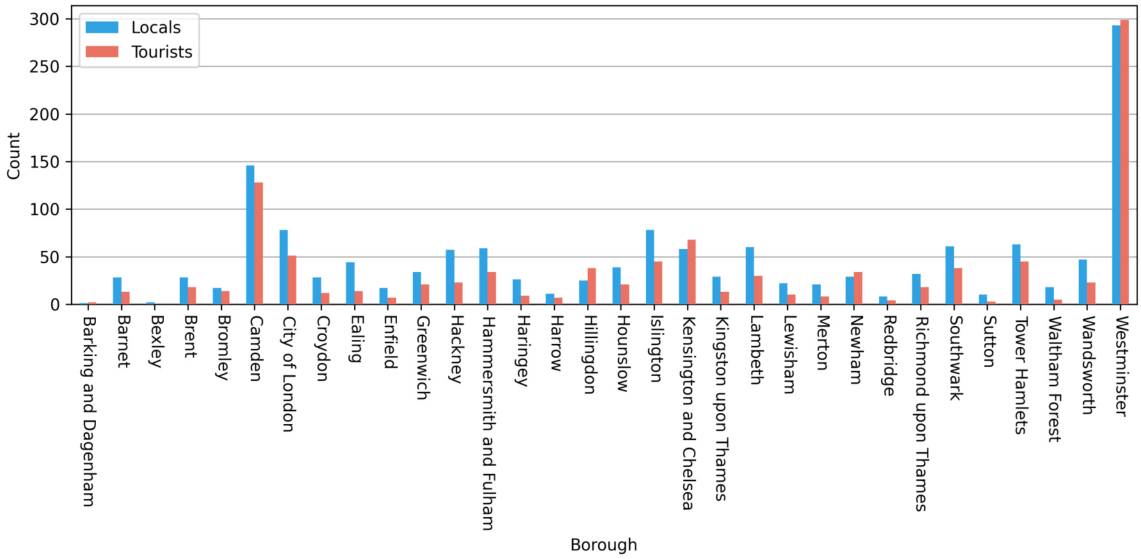


Figure 5.23: Location dimension of places during weekdays.

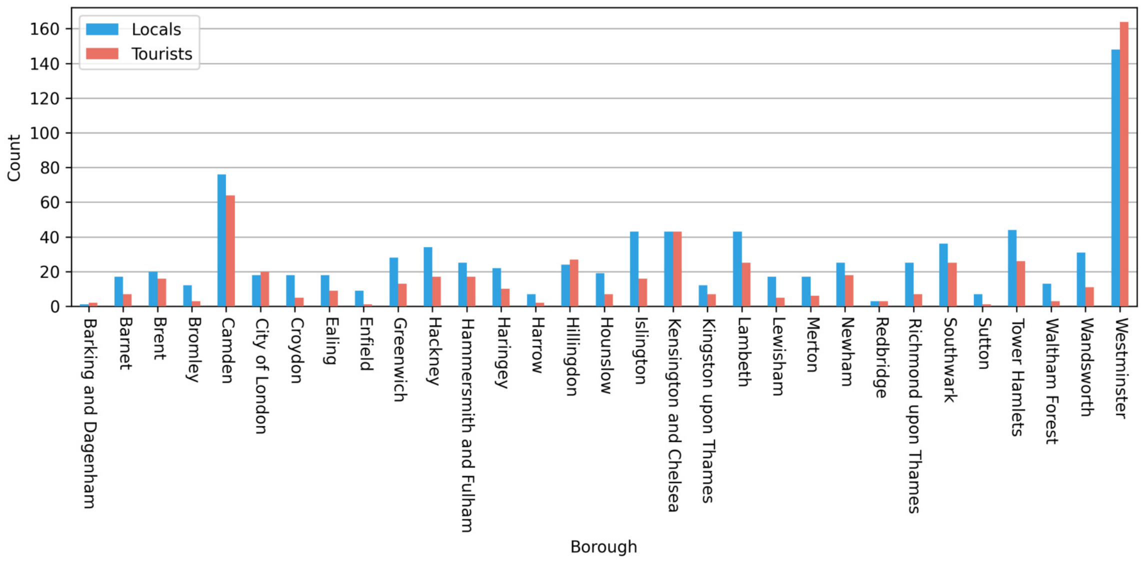


Figure 5.24: Location dimension of places on weekends.

Locale

The distributions of the *Locale* dimension on weekdays and weekends are displayed in Figure 5.25 and Figure 5.26. On weekdays, restaurants are more popular than other categories, followed by professional places, entertainment places, shopping places, and transportation places. Most categories have more places visited by locals, except for the accommodation category as tourists need to find hotels to stay overnight. The popular categories on weekends remain consistent with those on weekdays, with restaurants, entertainment places, shopping places, and transportation places retaining their popularity. However, professional places experience a decrease in visitation. Similar to weekdays, tourists on weekends tend to visit more places in the accommodation category than locals.

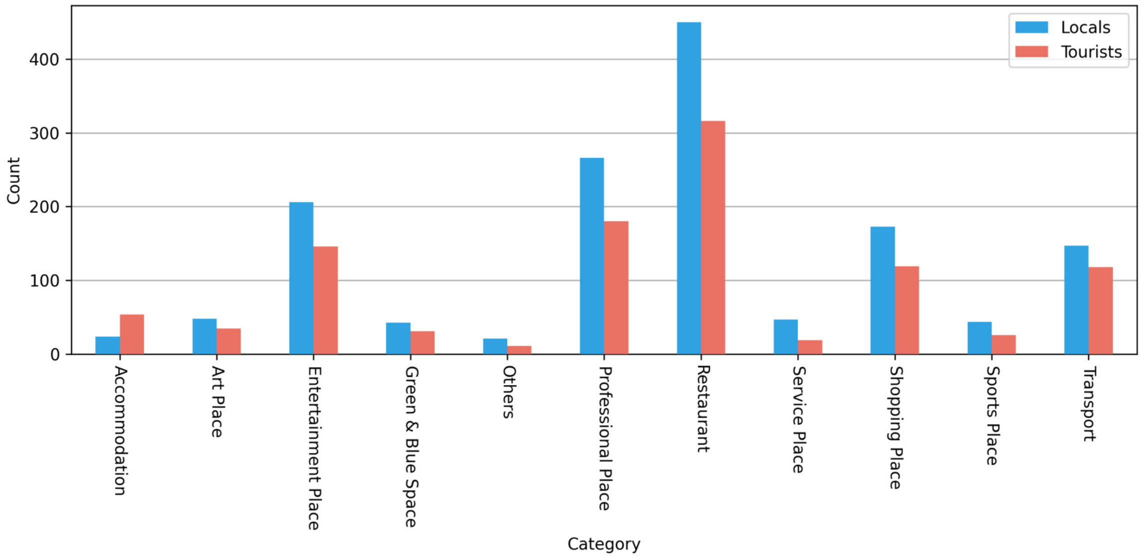


Figure 5.25: Locale dimension of places on weekdays.

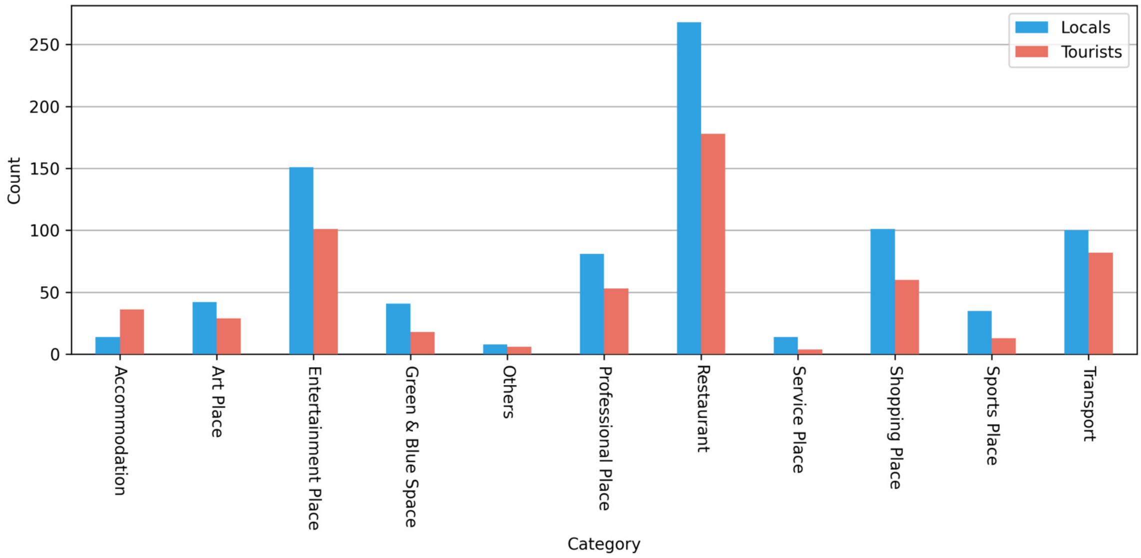


Figure 5.26: Locale dimension of places on weekends.

Sense of Place

The quantile distribution of tag counts within places as well as the number of empty places throughout the week are displayed in Table 5.4. Places with no Flickr tags within them are assigned topics through the topic imputation. Table 5.5 shows the optimal number of topics and their corresponding coherence values.

Table 5.4: Tag count quantiles and the number of empty places on weekdays and weekends.

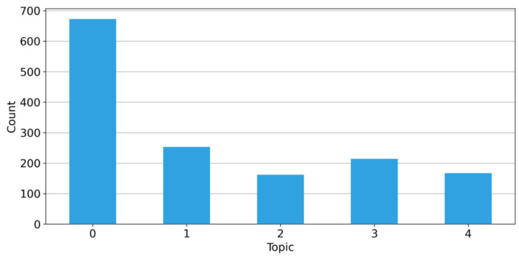
Time	Population group	Q.25	Q.50	Q.75	No. of empty places
Weekday	Locals	0	10	68	464
	Tourists	2	27	152	220
Weekend	Locals	0	15	114	224
	Tourists	5	49	323	93

Table 5.5: Topic number and coherence value on weekdays and weekends.

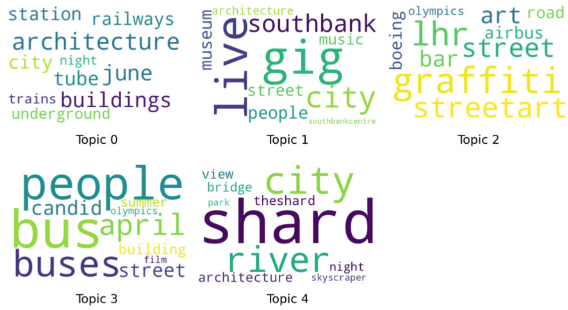
Time	Population group	No. of topics	Coherence value
Weekday	Locals	5	0.42
	Tourists	6	0.51
Weekend	Locals	6	0.60
	Tourists	6	0.53

The distribution of *Sense of Place* dimension of locals on weekdays is illustrated in Figure 5.27. The places visited by locals can be categorized into five topics with three purposes: urban life (Topic 0), entertainment (Topic 1), and cityscapes (Topic 2, Topic 3, Topic 4). Topic 0 stands out with nearly 700 associated places, while the other four topics contain around 200 places each (Figure 5.27a, Figure 5.27b). The distribution of topics on weekends in Figure 5.27c reveals that words like architecture and buildings (Topic 0) are frequently used to describe various areas in London, which also aligns with patterns observed in other time spans. In addition, central boroughs, such as Lambeth, Kensington and Chelsea, Westminster, Camden, and the City of London, can be described by words like live and gig, as illustrated in Topic 1. In terms of topics related to the cityscape, the inner part of London can be characterized by graffiti, street art, river, and city (Topic 2, Topic 4).

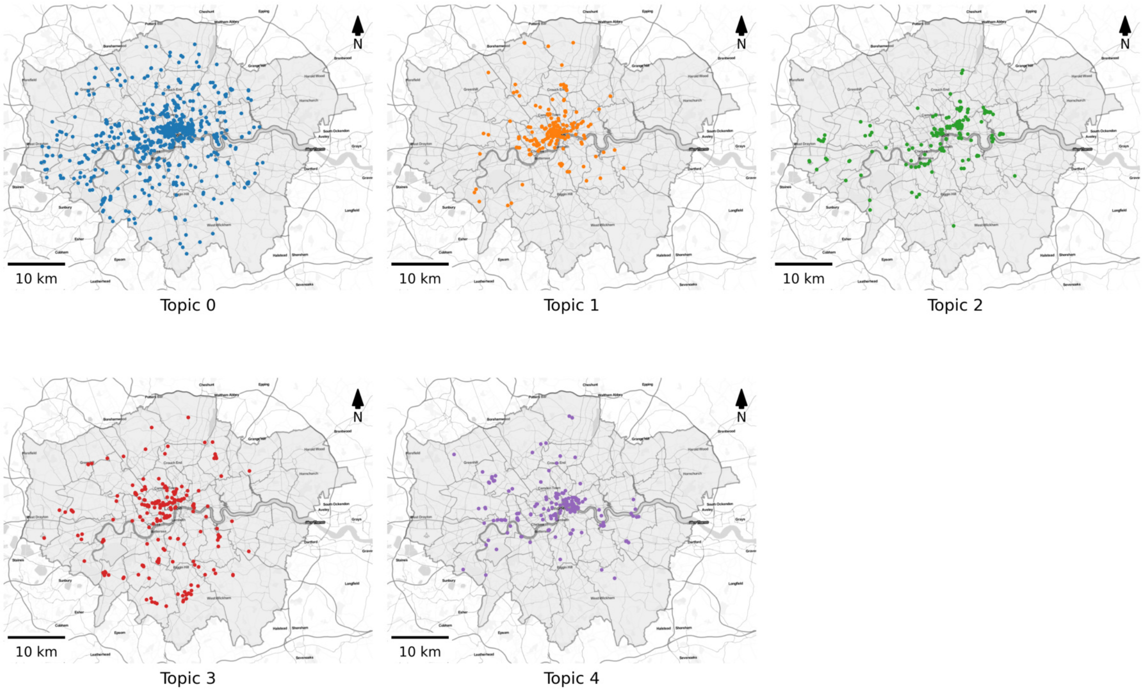
The weekday distribution of tourists' places in the *Sense of Place* dimension is displayed in Figure 5.28. Tourists tend to visit places associated with the Olympics (Topic 0) and cityscapes (Topic 5), with each topic comprising approximately 250 places. Tourists also like to visit places related to transport, art, and tourist attractions, as evidenced by the high occurrence of Topic 1 (e.g., museum, victoria, station, art) and Topic 3 (e.g., architecture, bridge, shard), both featuring over 150 associated places (Figure 5.28a, Figure 5.28b). The distribution of topics on weekdays in Figure 5.27c suggests that the inner part of London attracts the most descriptions from tourists, including topics related to the Olympics, cityscape, transportation, and art. Furthermore, the area surrounding Heathrow Airport leaves a strong impression on tourists, as indicated by a concentration of places in Topic 4 (e.g., lhr, airbus, boeing) in that region.



(a) Frequency of topics.

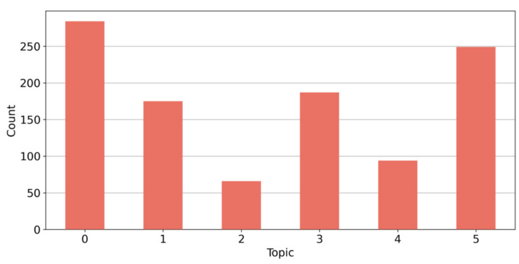


(b) Word clouds for topics.



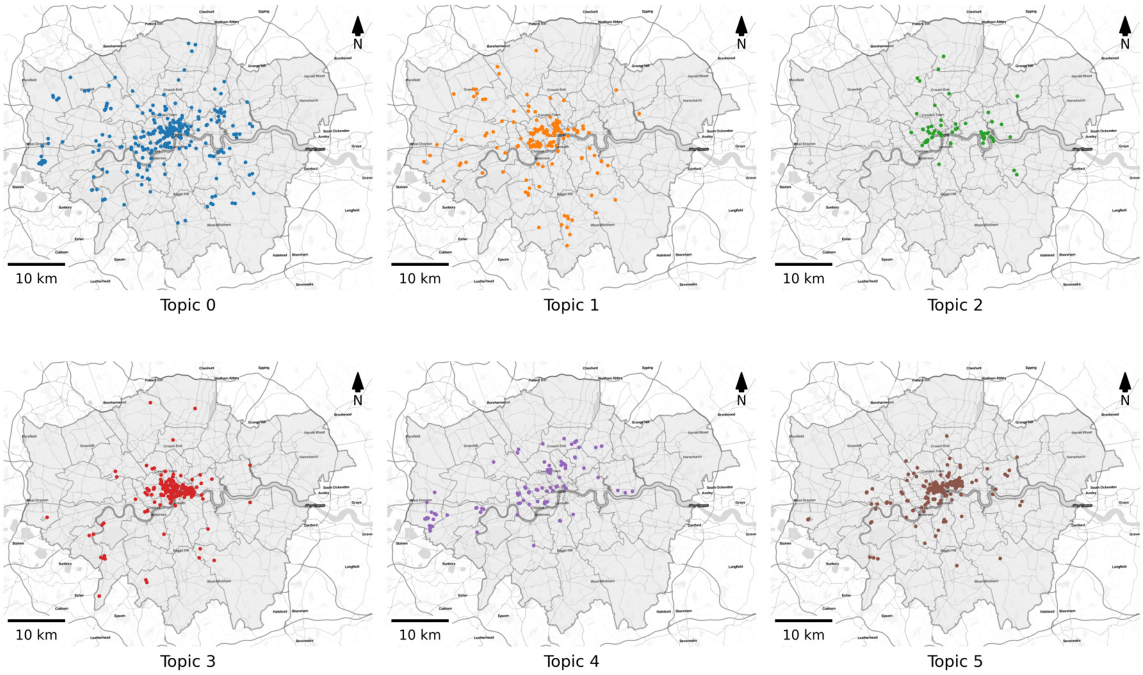
(c) Distribution of topics.

Figure 5.27: Sense of place dimension of locals' places on weekdays.



(a) Frequency of topics.

(b) Word clouds for topics.

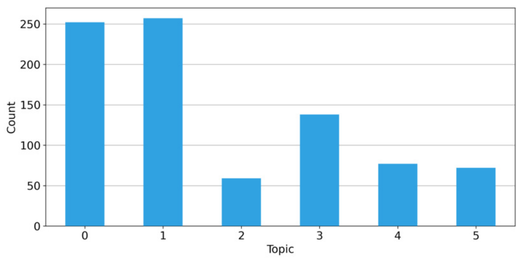


(c) Distribution of topics.

Figure 5.28: Sense of place dimension of tourists' places on weekdays.

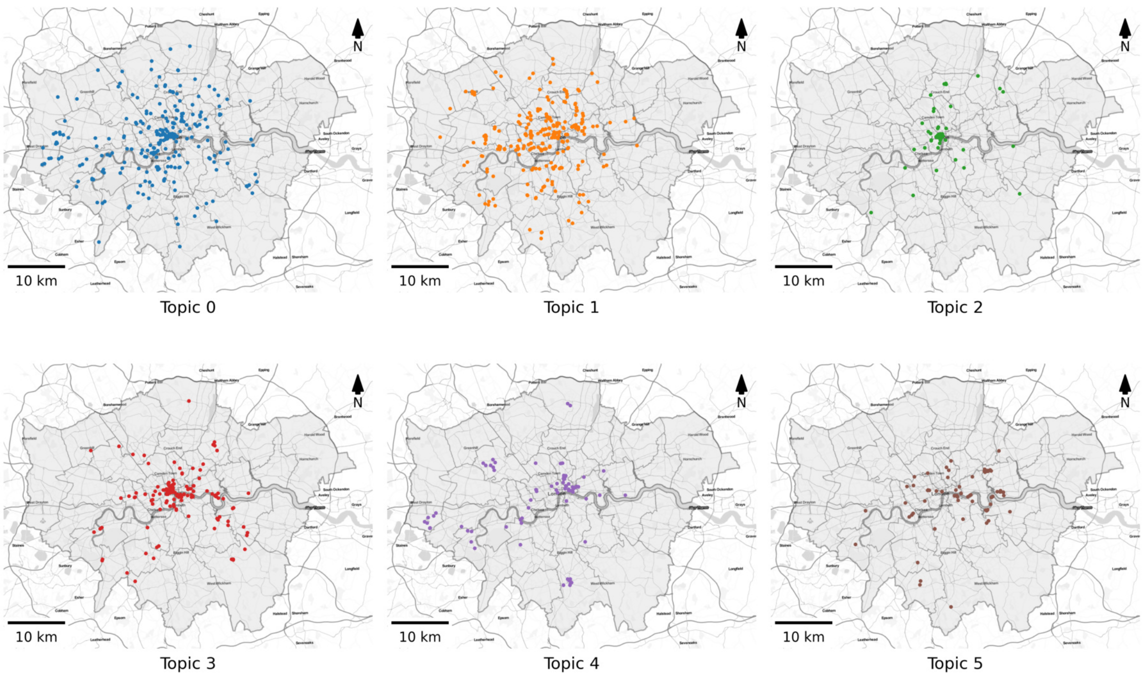
On weekends, locals' descriptions are summarized by six topics (Figure 5.29). In addition to the places known for graffiti and street art in Topic 1, which are consistently popular throughout different time spans, locals demonstrate a preference for more nature-related locations compared to weekdays. This preference is evident in the popularity of Topic 0, which includes words like park and garden, and encompasses approximately 250 associated places. Additionally, locals on weekends tend to explore sports-related places represented by Topic 4 (e.g., city, gbr, football, race) and Topic 5 (e.g., paralympics, olympics) (Figure 5.29a, Figure 5.29b). The places in Topic 0 and Topic 1 are scattered across London, as parks and graffiti can be found throughout the city. Regarding the areas that are described by locals with sports-related topics, the vicinity of sports venues like Emirates Stadium (a football stadium) and London Stadium are concentrated with places in Topic 4 and Topic 5 (Figure 5.29c).

Tourists' descriptions of the city on weekends are generalized with six topics (Figure 5.30). Tourists continue to visit places characterized by architecture, street art, and transport at this time span, which is similar to their choices on weekdays. Over 250 places visited by tourists are described with Topic 0 (e.g., marathon, city, architecture). And similar to locals' descriptions on weekdays, tourists also tend to visit places featured with graffiti and street art, as indicated by the popularity of Topic 1 (Figure 5.30a, Figure 5.30b). Concerning the distribution of places across various topics, except for places linked to Topic 0 which are distributed throughout London with a concentration in the city center, Topic 1, Topic 3 (e.g., olympics, gbr, park), and Topic 5 (e.g., city, architecture, bridge) are predominantly located in the inner part of London (Figure 5.30).



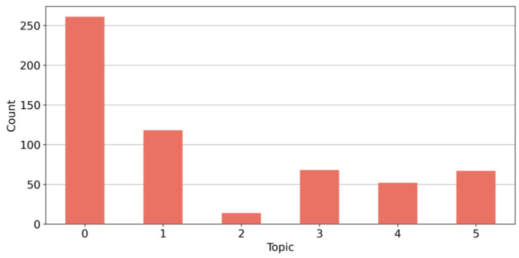
(a) Frequency of topics.

(b) Word clouds for topics.

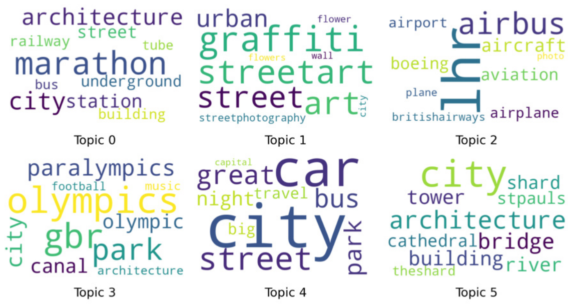


(c) Distribution of topics.

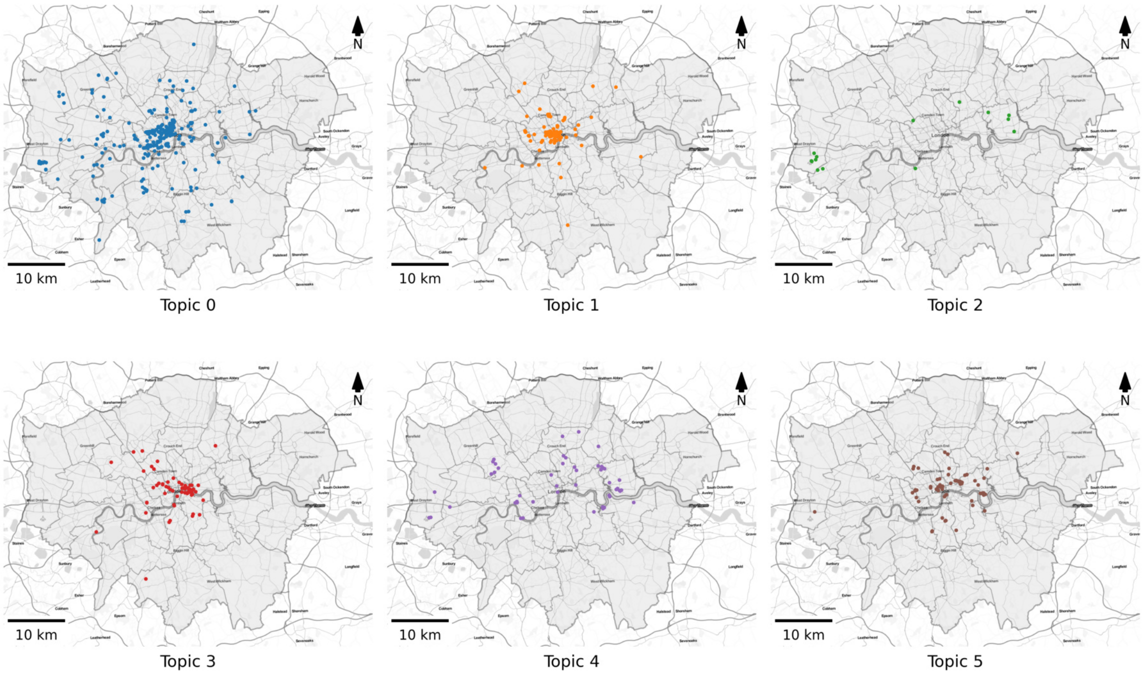
Figure 5.29: Sense of place dimension of locals' places on weekends.



(a) Frequency of topics.



(b) Word clouds for topics.



(c) Distribution of topics.

Figure 5.30: Sense of place dimension of tourists' places on weekends.

5.3 Spatiotemporal Patterns of Semantic Trajectory

To gain insights into the temporally dynamic city perceptions among locals and tourists along their trajectories, semantic trajectories were constructed for these two groups of people at different time spans, and the number of trajectories is summarized in Table 5.6. While the number of locals is smaller than that of tourists, both groups generate a similar number of trajectories. A total of 1,460 trajectories are generated by locals and tourists during the daytime, significantly more than the 121 trajectories during the nighttime. Similarly, the number of trajectories on weekdays (1,240) surpasses those on weekends (490). In order to delve into a more precise understanding of city perception through semantic trajectories, Section 5.3.1 shows the distribution of clustered trajectories as well as corresponding typical trajectories, and compare the visiting patterns of locals and tourists at different time spans. Furthermore, Section 5.3.2 combines the distribution of trajectories to analyze the frequency of semantic dimensions across different time spans, enabling the exploration of the dynamic nature of city perceptions.

Table 5.6: Summary of trajectories.

Time	Population group	No. of users	No. of trajectories
Daytime	All Users	6,919	1,460
	Locals	1,077	784
	Tourists	5,842	676
Nighttime	All Users	4,425	121
	Locals	996	63
	Tourists	3,429	58
Weekday	All Users	6,497	1,240
	Locals	1,069	659
	Tourists	5,428	581
Weekend	All Users	4,886	490
	Locals	1,011	213
	Tourists	3,875	277

5.3.1 Trajectory Distribution

The semantic trajectories are clustered based on their coordinates and three semantic dimensions using the K-medoids algorithm. The number of clusters is determined by the averaged intra-cluster distance, which is displayed in Table 5.7.

Table 5.7: Averaged intra-cluster distance.

Time	Population group	No. of clusters	Avg. intra-cluster distance
Daytime	Locals	5	0.57
	Tourists	4	0.61
Nighttime	Locals	3	0.46
	Tourists	2	0.62
Weekday	Locals	5	0.59
	Tourists	4	0.63
Weekend	Locals	5	0.53
	Tourists	3	0.60

5.3.1.1 Daytime

Figure 5.31 shows the five trajectory clusters of locals during the daytime, with their typical trajectories highlighted in dark red. The majority of locals tend to move within the city center, especially in Westminster, Camden, and the City of London. Some locals also visit the south of Greenwich from the city center, particularly around the Coldharbour Leisure Center, which offers a range of fitness facilities. Another noteworthy trajectory pattern is observed between central London and the outskirts boroughs, like Hillingdon, Merton, and Croydon. Looking into the typical trajectories, locals have a certain number of air transport-oriented trajectories in Cluster 1 and Cluster 2, as these trajectories mainly connect central London and the vicinity of Heathrow Airport, particularly in Islington and Hounslow. Moreover, these trajectories are primarily characterized by Topic 0 (e.g., lhr, airbus). Typical trajectories in Cluster 3 are primarily focused on locals' work purposes, as they frequently visit professional places and restaurants. Furthermore, these trajectories in this cluster predominantly link the city center with Merton and Wandsworth, which are residential districts. For more detailed distributions of typical trajectories, please refer to Figure A.1 in Appendix A.

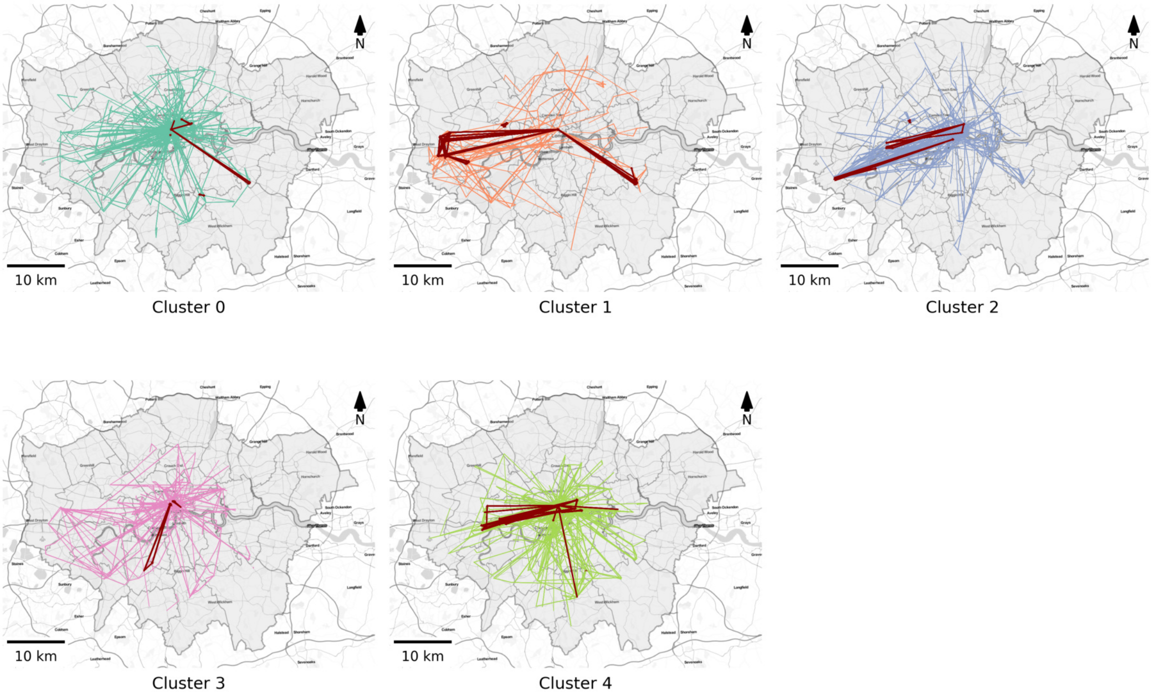


Figure 5.31: Distribution of locals' trajectories during the daytime (typical trajectories are represented by the dark red color).

Trajectories of tourists during the daytime are clustered into four groups. Compared with locals, tourists also exhibit a similar movement pattern within the city center, but with fewer trajectories connecting the outer and inner parts of London, as illustrated in Figure 5.32. The typical trajectories are represented in dark red. Cluster 0 and Cluster 1 are transportation-related as their typical trajectories primarily link the transportation hubs in central London, such as Stratford Station, King's Cross, and Waterloo Station. Cluster 1 also has typical trajectories connecting the city center and outer boroughs like Croydon and Merton. Cluster 2 is associated with shopping as its typical trajectories extend along Oxford Street, a renowned shopping street in London. Trajectories in Cluster 3 feature a substantial number of art places and entertainment places, and the typical trajectories passing through various tourist attractions and museums in Westminster, such as Trafalgar Square, Big Ben, and Victoria and Albert Museum (Figure A.2 in Appendix A). Thus, this cluster represents the sightseeing routes for tourists.

Figure 5.32: Distribution of tourists' trajectories during the daytime (typical trajectories are represented by the dark red color).

5.3.1.2 Nighttime

When it comes to nighttime, locals are less active compared to daytime, generating fewer trajectories. These trajectories are clustered into three groups (Figure 5.33). Locals have lower activity density in the city center during this period but display stronger connections with outskirts boroughs where large residential districts are located, such as Merton, and Croydon. Similar to the daytime, locals also have their trajectories mainly connecting transportation hubs at night. This is evidenced by the typical trajectories in cluster 0 that link between Ealing Broadway Station in Ealing and King's Cross in Islington. It is important to highlight that the typical trajectories of all three clusters pass through the southern part of Greenwich during the nighttime. This area is home to the Coldharbour Leisure Center and Mottingham Sports Ground/Foxes Fields, which offer numerous fitness facilities (Figure A.3). It can be concluded that locals during the nighttime are not concentrated in the city center, instead, they tend to commute back to the outskirts boroughs for rest or visit Greenwich for fitness exercises.

The trajectories of tourists are divided into two distinct clusters (Figure 5.34). There are significantly more tourists than locals during the nighttime. However, both groups generate a comparable number of trajectories. This is because many tourists' trajectories are disregarded as they fall short of the minimum length threshold of five. Contrary to locals, tourists during the nighttime tend to concentrate their movement within the city center, with fewer trajectories visiting outskirts boroughs. The typical trajectories of tourists at night exhibit distinct patterns compared to those of locals. These trajectories primarily connect shopping and entertainment places in the inner part of London. Specifically, they encompass places such as the Stratford Shopping Center in Newham, Shoreditch in Hackney, and renowned squares and streets in Westminster, including Piccadilly Circus, Leicester Square, and Oxford Street (Figure A.4). In summary, tourists display lower nighttime activity levels with fewer trajectories but maintain a consistent interest in vibrant areas for shopping and entertainment throughout the day.

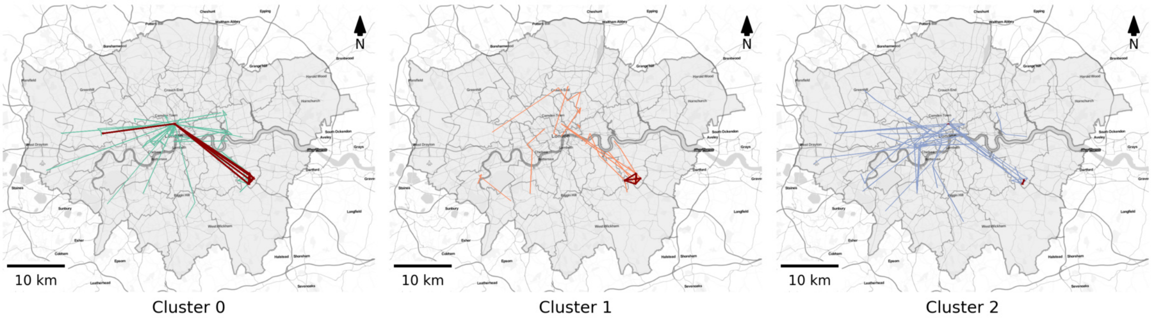


Figure 5.33: Distribution of locals' trajectories during the nighttime (typical trajectories are represented by the dark red color).

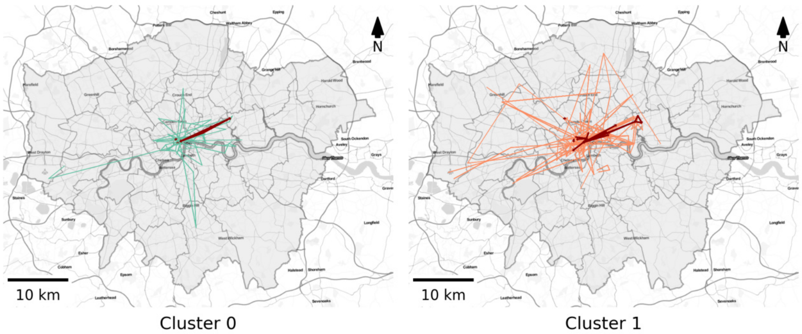


Figure 5.34: Distribution of tourists' trajectories during the nighttime (typical trajectories are represented by the dark red color).

5.3.1.3 Weekday

Trajectories of locals on weekdays are divided into five clusters and these clusters cover both the inner and outer parts of London (Figure 5.35). Some clusters have trajectories connecting the city center with various boroughs in the outskirts, while others show trajectories gravitating towards specific boroughs. For instance, Cluster 0, Cluster 3, and Cluster 4 have connections between the city center and many different boroughs like Enfield, Barnet, Croydon, and Merton. While Cluster 1 tends to primarily move between Hillingdon, Kingston upon Thames, and the inner London. And Cluster 2 shows an obvious visiting tendency to Greenwich and Merton. In terms of the typical trajectories, Cluster 0 and Cluster 4 might have their typical trajectories generated by local commuters as they connect outer boroughs with the main transportation hubs in the city center, which are similar to some movement patterns observed among locals during the daytime. Cluster 1 exhibits typical trajectories concentrated around Heathrow Airport and the nearby borough of Hounslow, reflecting a perception of airport-related areas. Cluster 2 displays typical trajectories covering the southern region of Greenwich, indicating its suitability for sports activities due to the presence of numerous fitness facilities (Figure A.5).

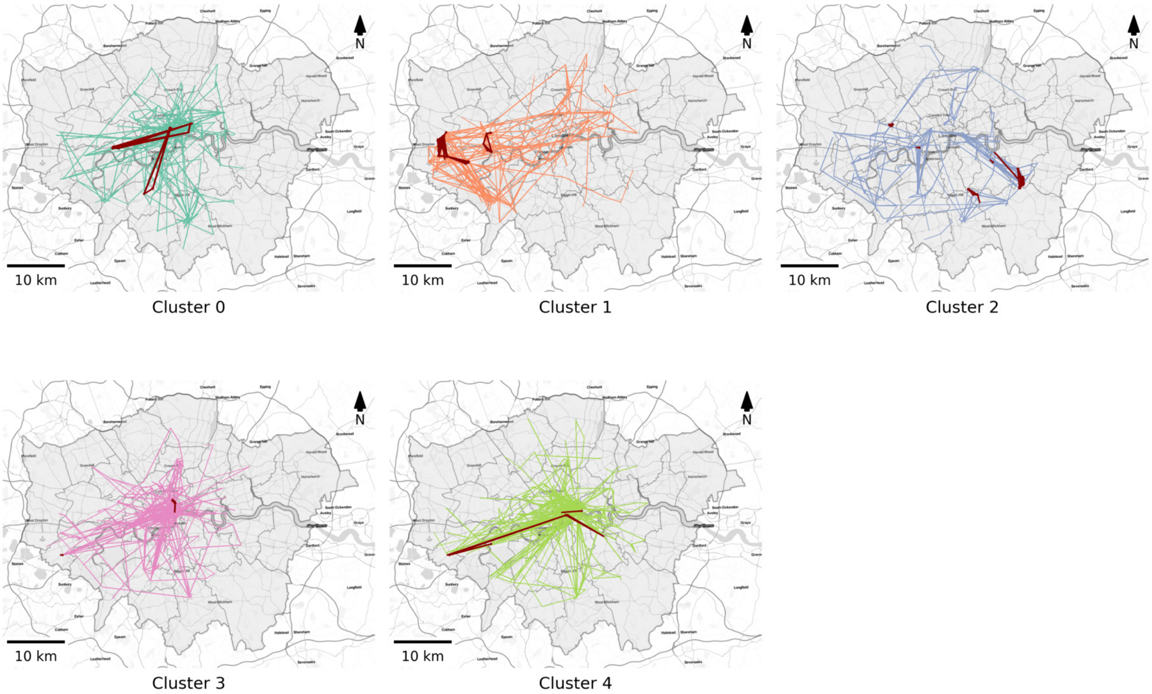


Figure 5.35: Distribution of locals' trajectories on weekdays (typical trajectories are represented by the dark red color).

On weekdays, tourists' trajectories are divided into four clusters. Tourists also explore the outer part of London. However, unlike locals, who often visit various outskirts boroughs, tourists mainly concentrate their movements in central London, showing particular interest in outer boroughs such as Hillingdon, Croydon, Enfield, Barnet, and Harrow (Figure 5.36). Typical trajectories of tourists on weekdays have many similarities to those observed during other time periods. Sightseeing and shopping continue to be the main activities within the city center throughout the day, and this pattern remains consistent on weekdays. Tourists tend to visit similar attractions, museums, and shopping streets to locals, such as Stratford Shopping Center, Shoreditch, and Leicester Square. Connections to outer boroughs are also observed, but they are not as strong as those observed among locals. Only Cluster 3 has its typical trajectories visiting Croydon while passing through Wandsworth (Figure A.6).

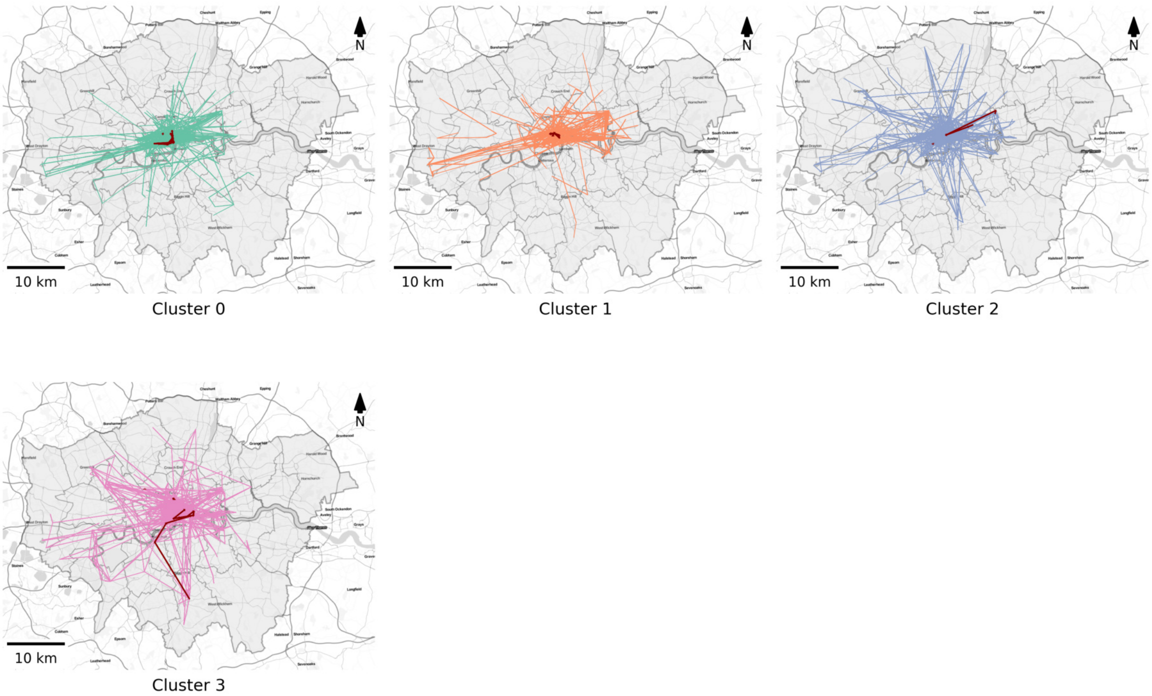


Figure 5.36: Distribution of tourists' trajectories on weekdays (typical trajectories are represented by the dark red color).

5.3.1.4 Weekend

On weekends, the activity level among locals decreases, which is reflected by a reduction in the number of trajectories they generate compared to weekdays. Locals' trajectories during this time period are divided into five clusters. Although locals still have connections with both the inner and outer parts of London, their trajectories become sparser (Figure 5.37). In terms of typical trajectories, locals on weekends do not exhibit obvious movement patterns as they do on weekdays. However, it is still noticeable that they engage in more leisure activities on weekends around Shoreditch and also go to church in Islington's Holy Trinity, as revealed by the typical trajectories in Cluster 0. Furthermore, locals maintain their interest in the boundary of Greenwich and Bromley, where various fitness facilities are located. This is demonstrated by the typical trajectories in Cluster 1 (Figure A.7).

Figure 5.38 shows the distribution of trajectories of tourists on weekends, which are divided into three clusters. Similar to locals, tourists also decrease their activity level on weekends, with fewer trajectories generated during this period. Outer boroughs, with the exception of Hillingdon, are less frequently visited by tourists. Tourists have a stronger connection to Hillingdon compared to locals. This could be attributed to the presence of Heathrow Airport in this borough, which serves the air transport needs of tourists on weekends. However, the visiting pattern to the airport is not evident in tourists' typical trajectories, as they tend to concentrate their activities in the city center. The typical trajectories of tourists on weekends can be characterized as sightseeing-related, as they primarily visit tourist attractions, leisure facilities, and transportation hubs in central London, including Buckingham Palace Garden, Hyde Park, and King's Cross (Figure A.8).

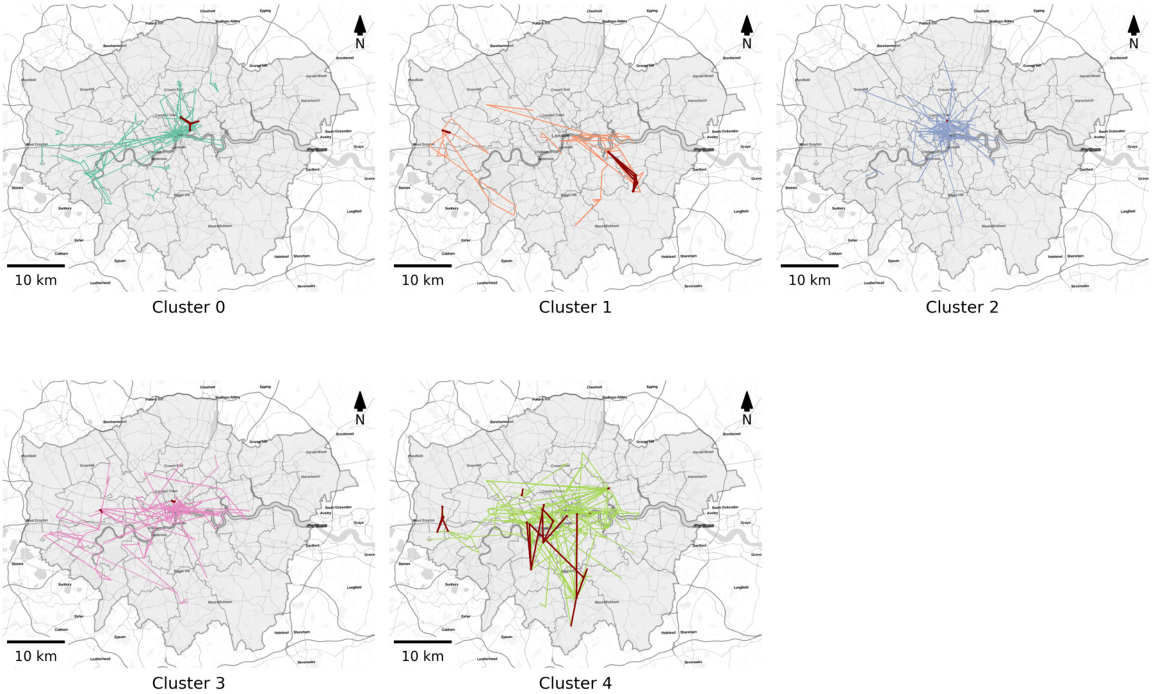


Figure 5.37: Distribution of locals' trajectories on weekends (typical trajectories are represented by the dark red color).

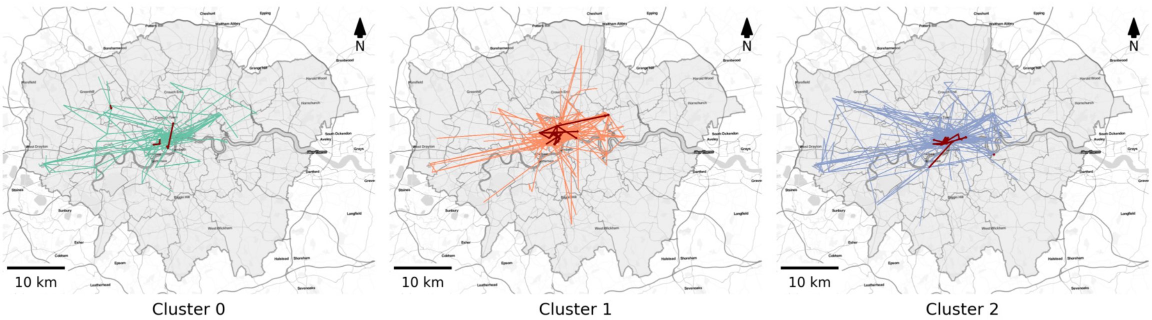
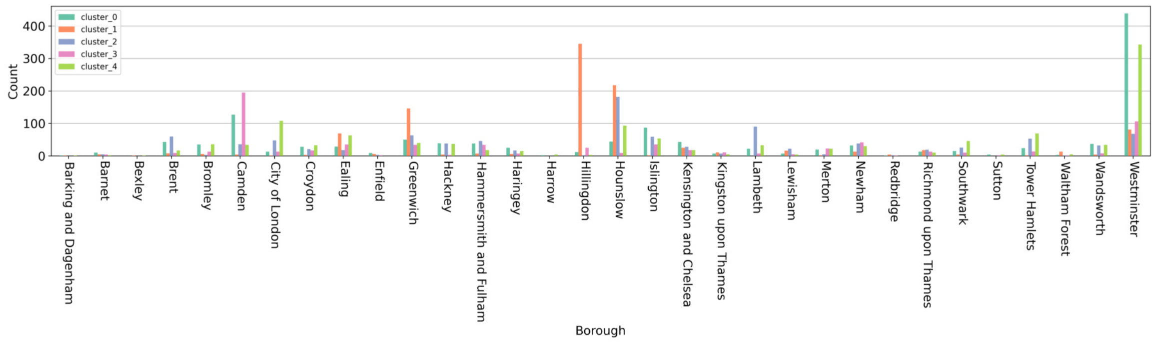


Figure 5.38: Distribution of tourists' trajectories on weekends (typical trajectories are represented by the dark red color).

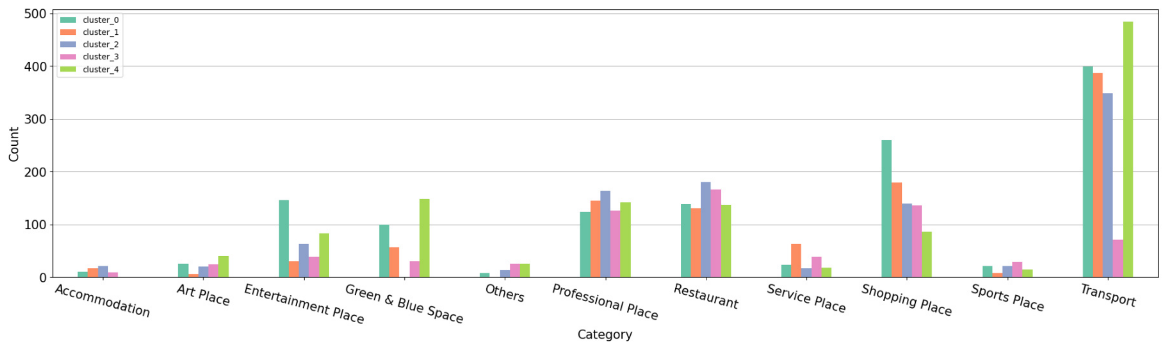
5.3.2 Trajectory Dimensions

5.3.2.1 Daytime

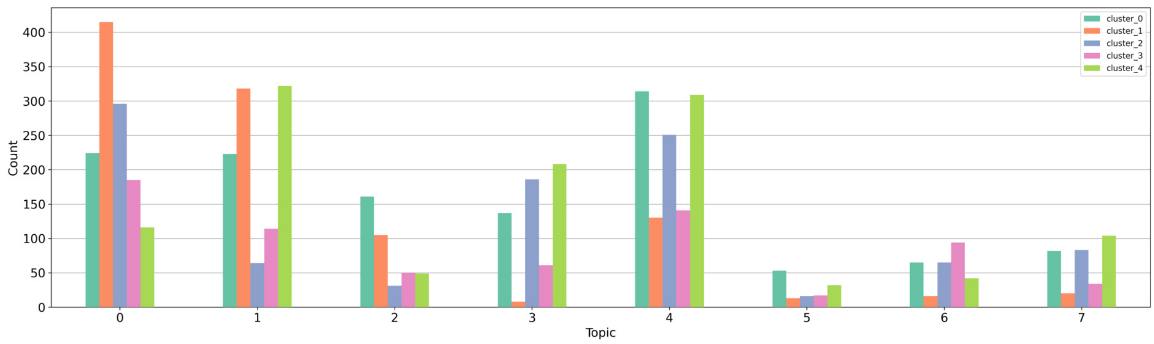
Figure 5.39 shows the frequency of locals' trajectories in three dimensions during the daytime. The popular boroughs in *Location* dimension align with the visiting patterns of typical trajectories shown in Figure 5.31. Inner boroughs like Westminster, Camden, the City of London, and Lambeth are significantly more popular among locals than other boroughs. But some outer boroughs like Hillingdon, Hounslow, and Greenwich are also frequently visited by locals (Figure 5.39a). In terms of the *Locale* dimension, trajectories in most clusters predominantly pass through places related to transportation, shopping, restaurants, and professional activities. Notably, entertainment places and green & blue spaces are also frequently visited by trajectories in Cluster 0 and Cluster 4 (Figure 5.39b). The *Sense of Place* dimension in Figure 5.39c provides insights into how locals describe the city along their trajectories during the daytime. The word clouds of topics are displayed in Figure 5.19b. Cluster 1 is characterized by air transport and nature, as indicated by the high frequency of Topic 0 (e.g., lhr, airbus, boeing) and Topic 1 (park, museum, spring, garden). This also validates the frequent visits of typical trajectories in Cluster 0 around Heathrow Airport and the green space in Hillingdon. Cluster 4 has a large number of trajectories for outdoor leisures, with more visits to green & blue spaces than other clusters in the *Locale* dimension. These trajectories are described by words associated with nature, cityscape, and transport, evidenced by the high frequency in Topic 1, Topic 3 (e.g., city, graffiti, street), and Topic 4 (e.g., bus, railway, station).



(a) Location.



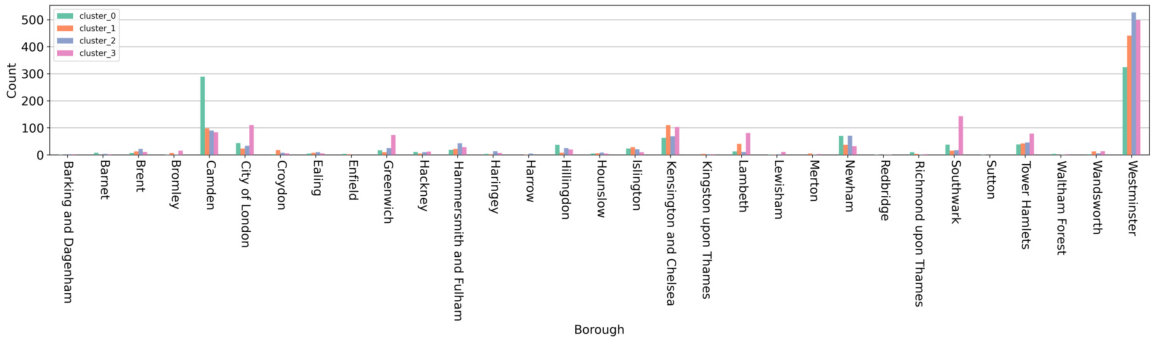
(b) Locale.



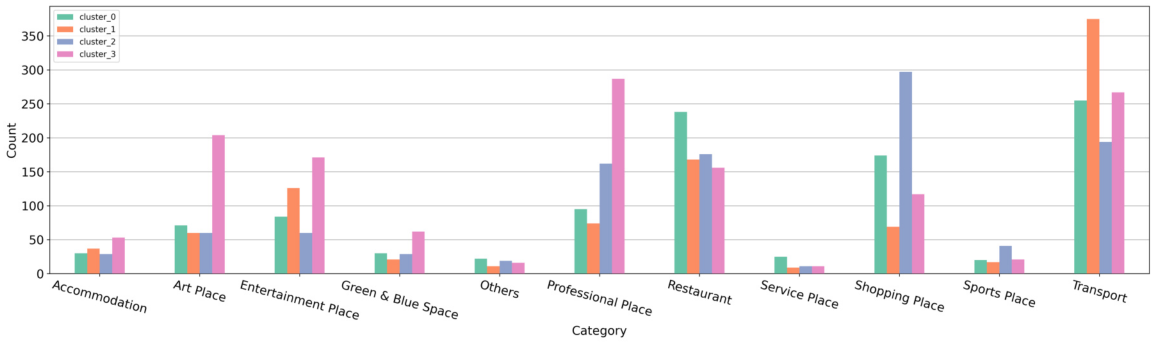
(c) Sense of Place.

Figure 5.39: Trajectory dimensions of locals during the daytime.

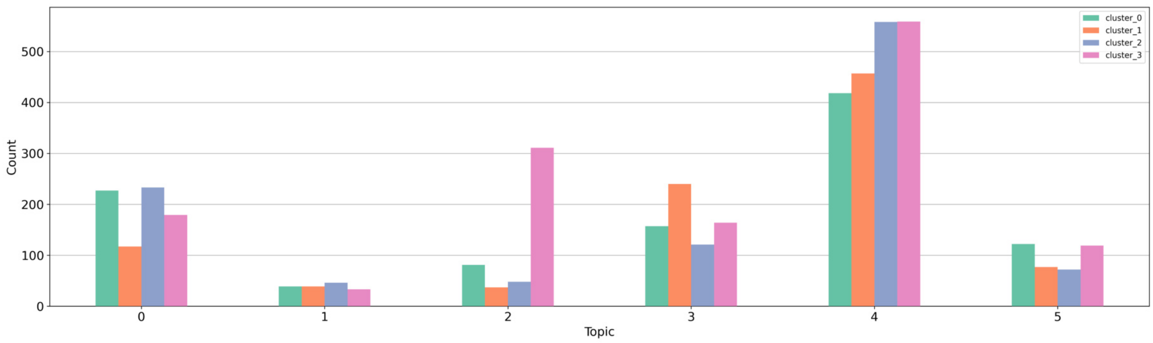
Figure 5.40 shows the frequency of dimensions in the semantic trajectories of tourists during the daytime. In the *Location* dimension, inner boroughs are popular among tourists, such as Westminster and Camden, and Kensington and Chelsea (Figure 5.40a). In the *Locale* dimension, tourists show interest in art places and entertainment places, in addition to transportation, professional places, restaurants, and shopping places that attract both locals and tourists. This is particularly true for typical trajectories in Cluster 3 that move between museums and tourist attractions in Westminster (Figure 5.40b). It is noteworthy that Cluster 2 has a large number of trajectories visiting shopping places, which also validates the shopping purpose of typical trajectories around Oxford Street (Figure 5.32). The *Sense of Place* dimension in Figure 5.40c and the word clouds of topics in Figure 5.20b demonstrate how tourists tend to describe the city during daytime hours. Compared with locals, tourists use similar words to describe the places they visit, with a focus on transportation and cityscapes, which is indicated by the high frequency of Topic 4 (e.g., street, bus, city) and Topic 3 (e.g., marathon, city, architecture). The Olympics is another popular topic discussed by tourists along their trajectories during the daytime, which is evidenced by a relatively high frequency of Topic 0 (e.g., olympics, Paralympics, stadium).



(a) Location.



(b) Locale.



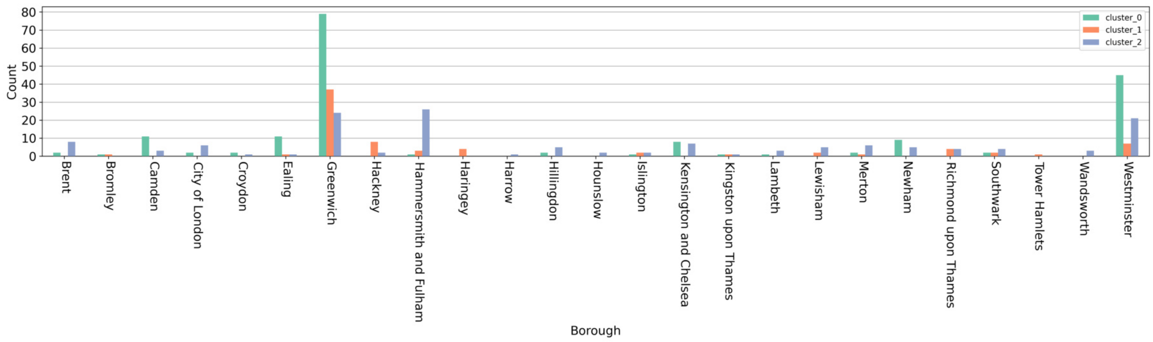
(c) Sense of Place.

Figure 5.40: Trajectory dimensions of tourists during the daytime.

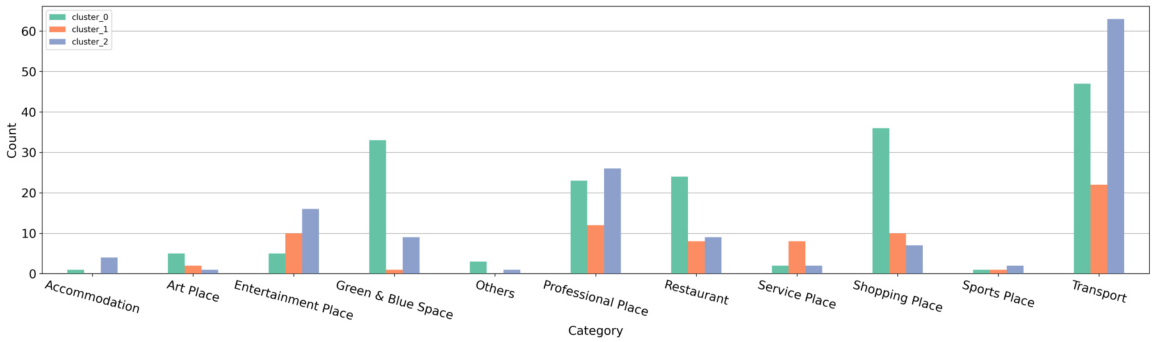
5.3.2.2 Nighttime

When it comes to the nighttime, locals have a different distribution of semantic dimensions in their trajectories compared to the daytime (Figure 5.41). In the *Location* dimension, Westminster remains the most popular borough. Notably, Greenwich emerges to be a frequently visited borough for tourists, with a high frequency in trajectories from all three clusters (Figure 5.41a). This finding aligns with the popular region among typical trajectories around Greenwich in Figure 5.33. In terms of the *Locale* dimension, transportation places, shopping places, restaurants, and professional places continue to be the most frequently visited places throughout the day. An increased interest in green & blue spaces among locals at night is observed, which is evidenced by a noticeably large visit to this category, particularly in Cluster 0 (Figure 5.41b). In the *Sense of Place* dimension, the descriptions of locals regarding the city shift from nature and transportation-related aspects to leisure and sports activities during the nighttime. This shift is reflected in the popularity of Topic 0 (e.g., paralympics, cycling, crowd), Topic 3 (e.g., city, architecture, southbank), and Topic 4 (e.g., music, bbc, concert, gig) (Figure 5.41c, Figure 5.21b). The nightlife activities drive locals to visit different regions and place categories, which in turn change their perceptions of the city.

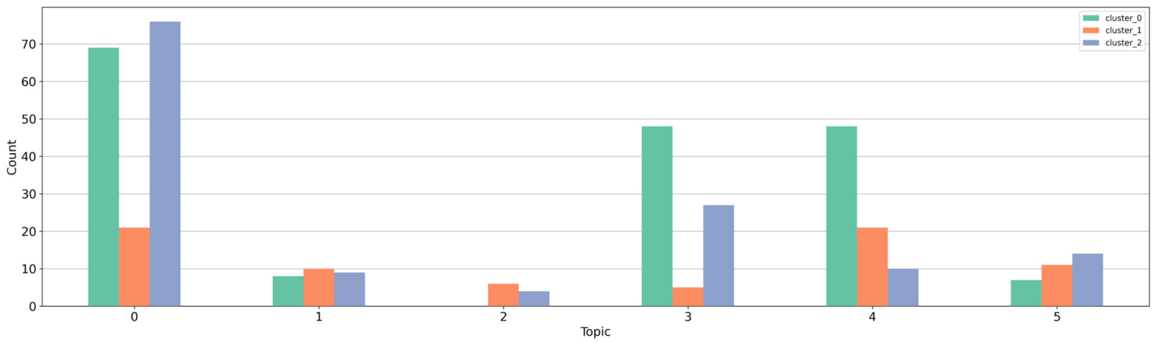
In terms of the distribution of tourists' semantic dimensions during the nighttime, it is illustrated in Figure 5.42. In the *Location* dimension, in addition to Westminster and Camden, tourists also exhibit interest in other inner boroughs like Tower Hamlets and Hackney (Figure 5.42a). In the *Locale* dimension, while both locals and tourists frequently visit transportation places, shopping places, restaurants, and professional places during the nighttime, tourists display a higher inclination towards art places and entertainment places rather than green & blue spaces like locals do (Figure 5.42b). Regarding the *Sense of Place* dimension, tourists tend to use more general words to describe London during the nighttime, such as city, street, and night. Additionally, words associated with art and transportation, such as museum, station, and railway, are also frequently mentioned. This is reflected in the high frequency of Topic 0 and Topic 4. Nightlife activities such as concerts, live performances, gigs, and football games (Topic 1) are also mentioned by tourists, but these activities tend to attract less attention from tourists compared to locals (Figure 5.42c, Figure 5.22b).



(a) Location.

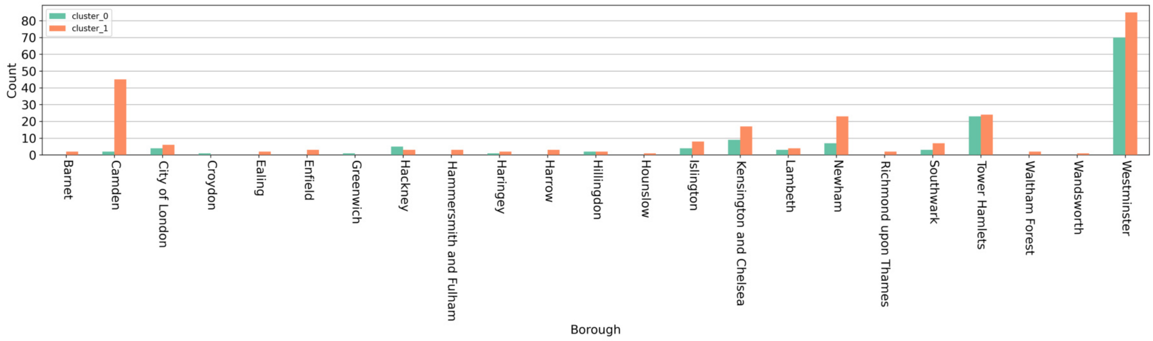


(b) Locale.

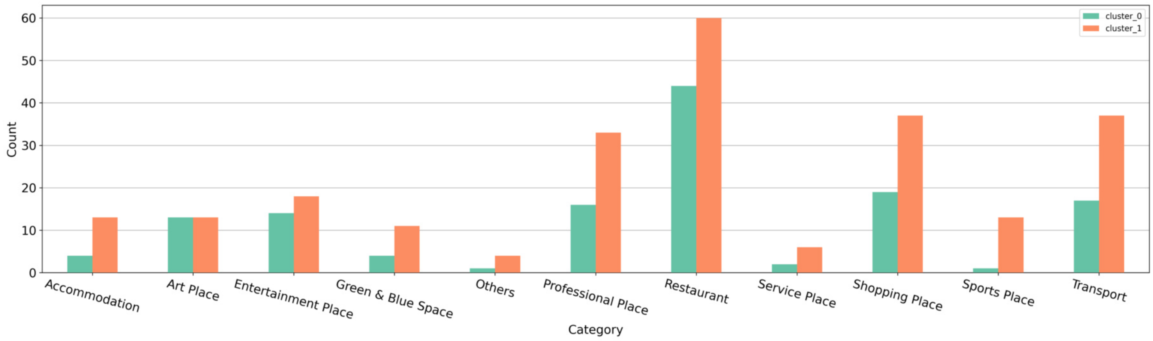


(c) Sense of Place.

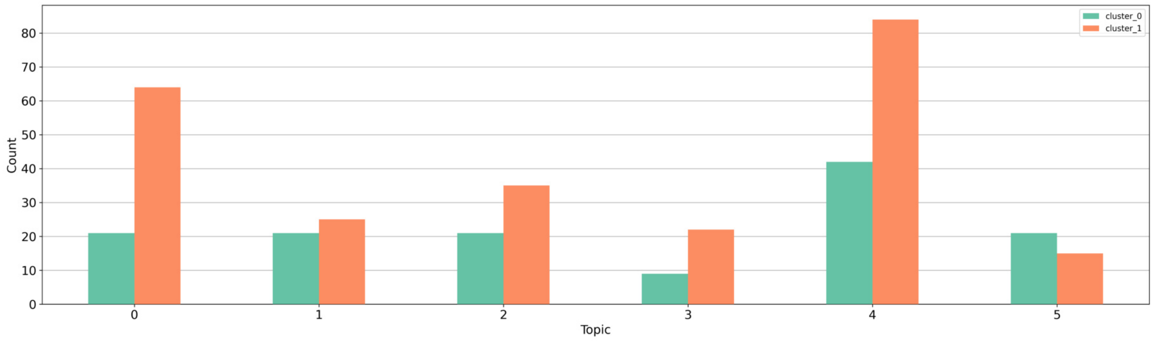
Figure 5.41: Trajectory dimensions of locals during the nighttime.



(a) Location.



(b) Locale.

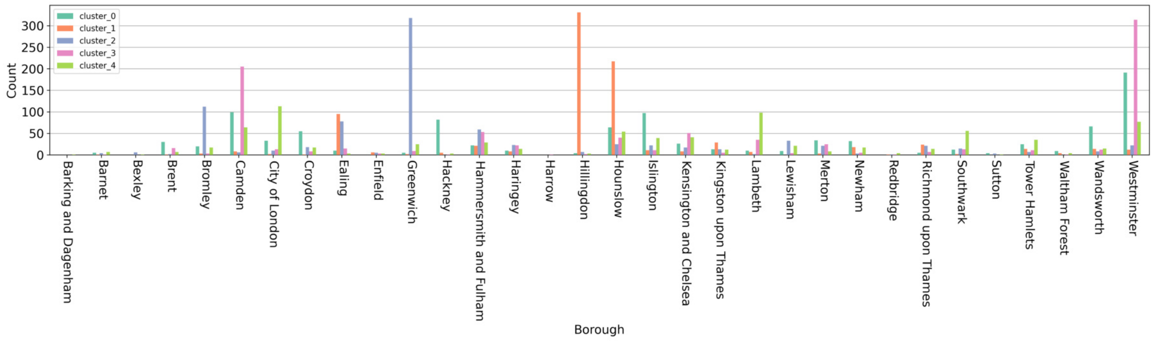


(c) Sense of Place.

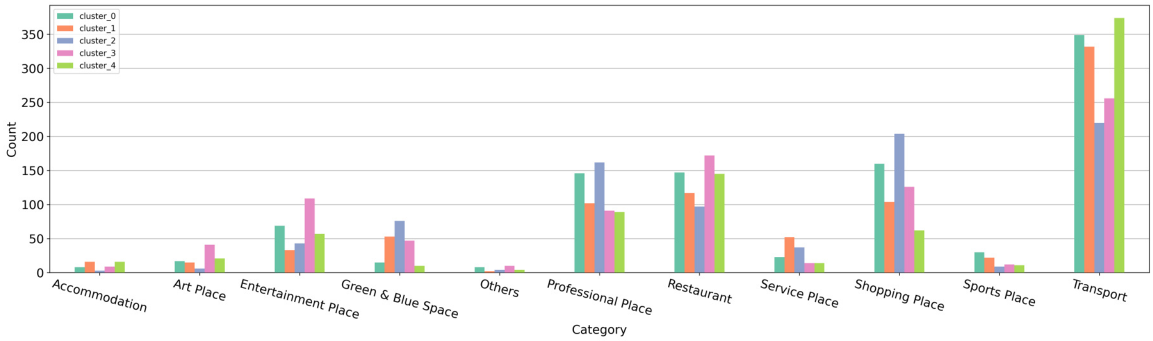
Figure 5.42: Trajectory dimensions of tourists during the nighttime.

5.3.2.3 Weekday

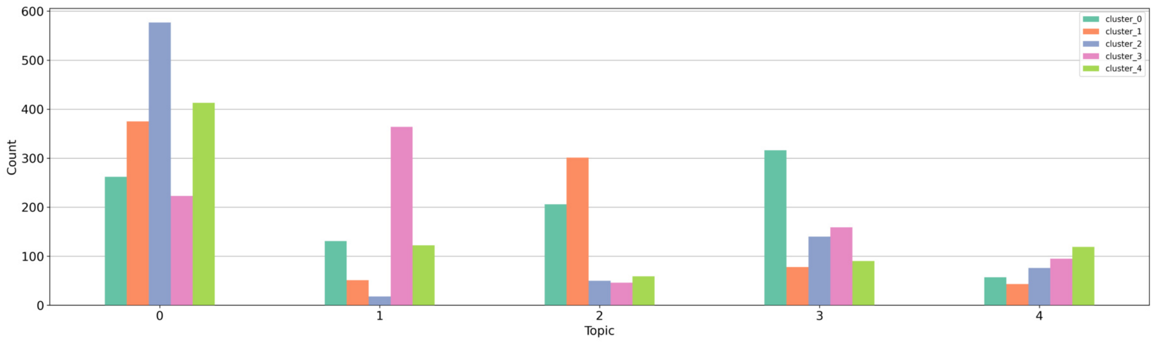
The semantic dimensions of locals on weekdays in Figure 5.43 help to reveal locals' visiting behaviors and perceptions of the city at this time span. In the *Location* dimension, Cluster 0, Cluster 3, and Cluster 4 have trajectories more concentrated in the city center, encompassing boroughs such as Westminster, Camden, and the City of London. Cluster 1 gravitates towards Southwest London, particularly Hillingdon and Hounslow. Cluster 2 is concentrated in Southeast London, with Greenwich being frequently visited (Figure 5.43a). Regarding the *Locale* dimension, transportation places remain the most frequently visited by locals on weekdays, accompanied by shopping places, restaurants, and professional places across all clusters (Figure 5.43b). In terms of the *Sense of Place* dimension, locals tend to use general words to describe the city. Topic 1 is assigned to a large number of trajectories in all five clusters, and it is about the cityscapes like architecture, buildings, and railways. Notably, Cluster 1 contains trajectories with a higher occurrence of Topic 2 (e.g., lhr, airbus), which aligns with its distribution around Heathrow Airport. Furthermore, Cluster 3 has a high frequency in Topic 1 (e.g., live, gig, southbank) and visits more entertainment places compared to other clusters, suggesting a more leisure-oriented focus (Figure 5.43c, Figure 5.27b).



(a) Location.



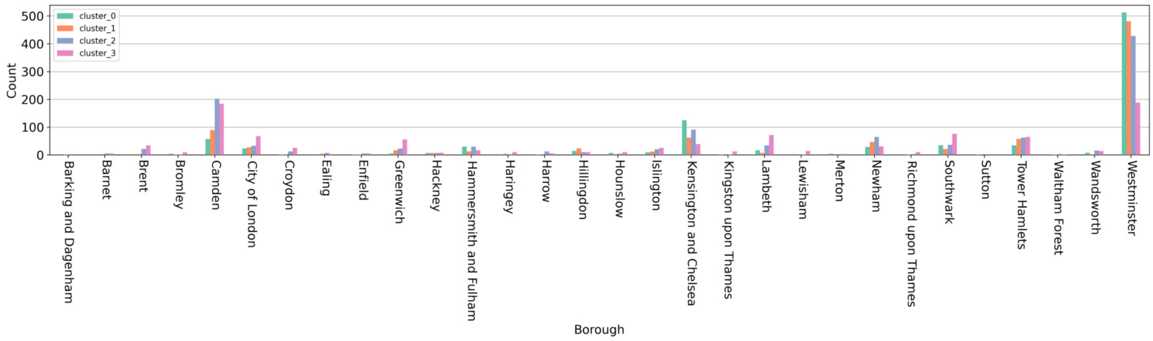
(b) Locale.



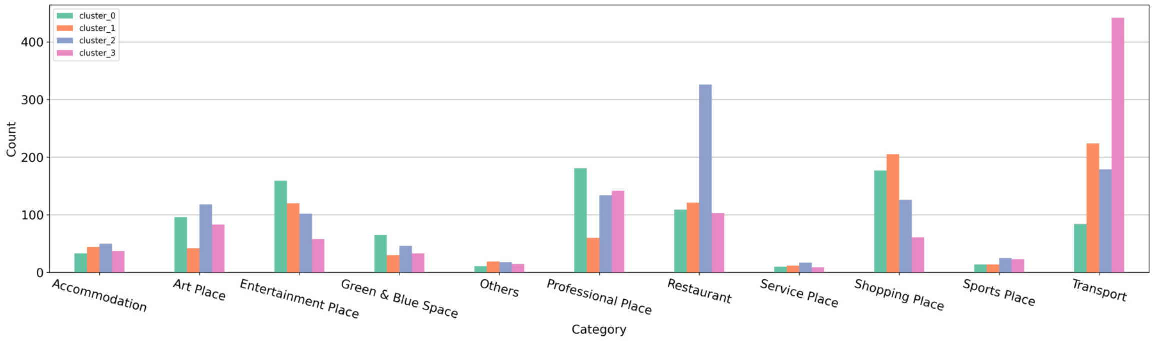
(c) Sense of Place.

Figure 5.43: Trajectory dimensions of locals on weekdays.

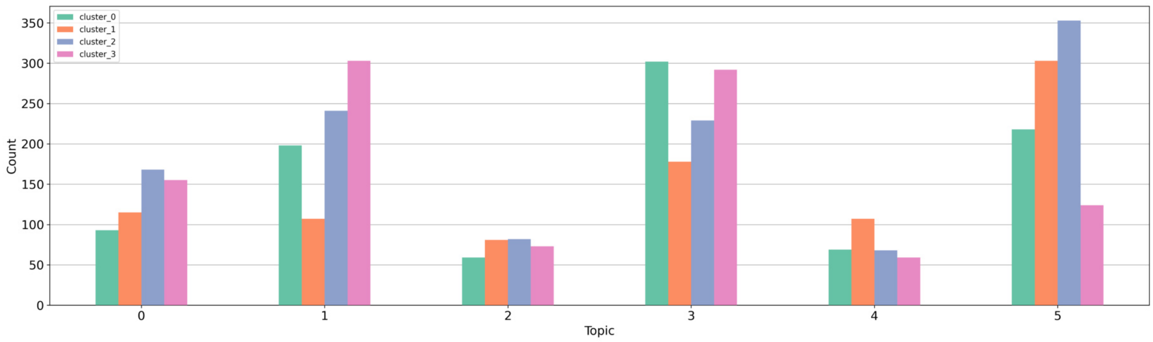
The semantic dimensions of tourists' trajectories on weekdays are displayed in Figure 5.44. The distribution of the *Location* dimension confirms the finding that tourists mainly move within central London in Figure 5.36. Westminster is the most frequently visited borough, followed by Camden and Kensington and Chelsea, all of which are in the city center. In contrast to locals who often visit outskirts boroughs, tourists rarely visit these boroughs (Figure 5.44a). Tourists also exhibit different preferences in place categories, as revealed by the *Locale* dimension in Figure 5.44b. While transportation remains popular in general, trajectories in some clusters are characterized by other categories like professional places, shopping places, and restaurants, particularly in Cluster 0 and Cluster 2. In terms of the *Sense of Place* dimension, tourists also tend to use general words to describe the city like locals do, such as street, architecture, and city. However, tourists display a greater interest in art and the Olympics, as indicated by the frequent mention of words like museum, art, and olympics in Topic 1, Topic 5, and Topic 0 (Figure 5.44c, Figure 5.28b).



(a) Location.



(b) Locale.

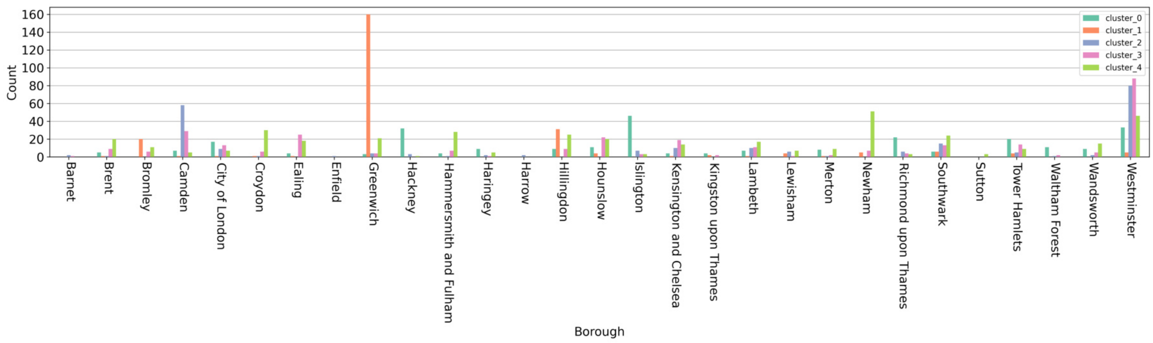


(c) Sense of Place.

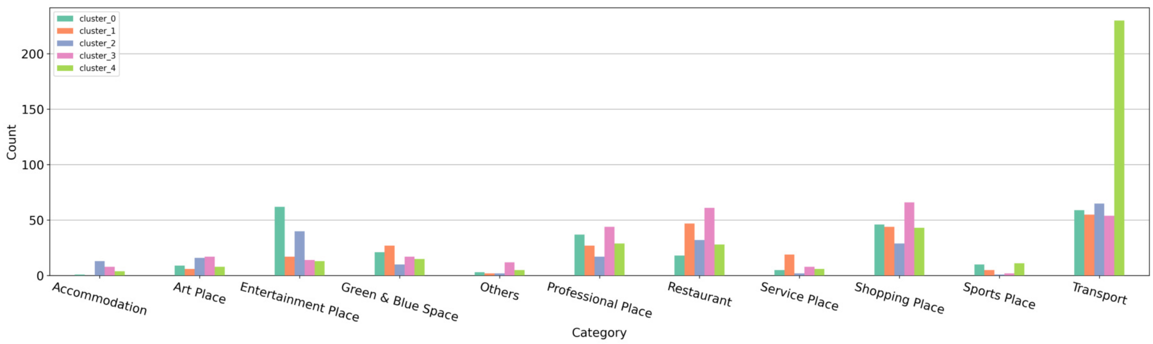
Figure 5.44: Trajectory dimensions of tourists on weekdays.

5.3.2.4 Weekend

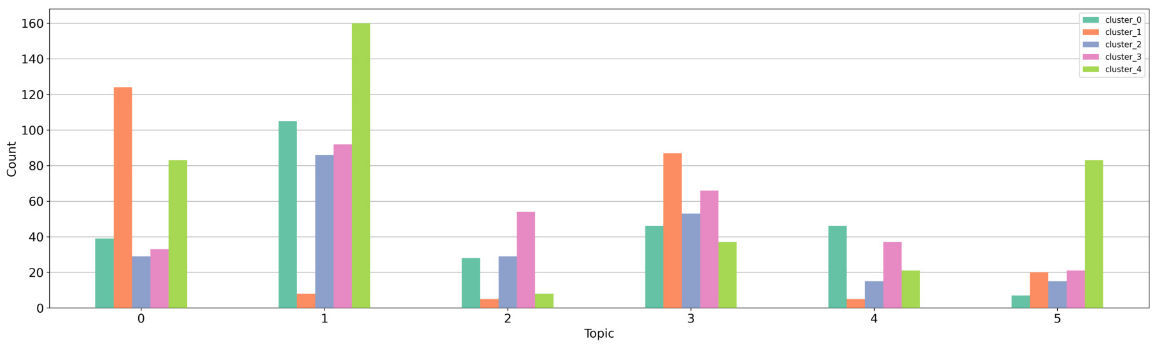
Figure 5.45 gives insight into how locals visit and perceive the city on weekends based on the semantic dimensions of their trajectories. The *Location* dimension in Figure 5.45a reveals a balanced visiting frequency across both inner and outer boroughs. Notably, Westminster, Camden, and Greenwich demonstrate a relatively higher frequency. This observation suggests that on weekends, locals are not sorely concentrated in the city center but rather spread across different parts of London. It is noteworthy that Greenwich attracts a significant number of locals to visit on weekends, particularly those who generate trajectories in Cluster 1. In the *Locale* dimension, locals on weekends have similar preferences for place categories to other time periods, like transportation places, shopping places, and restaurants, but show a decreased interest in professional places and an increased interest in entertainment places. Notably, Cluster 4 has its trajectories connecting various outer boroughs to the city center, and it has a high frequency of transport in this dimension (Figure 5.45b). In terms of the *Sense of Place* dimension, locals also use cityscapes-related words like architecture, city, street, and graffiti to describe the places along their trajectories, but nature-related words like park, garden, green, and flower (Topic 0) also emerge in their descriptions towards the city on weekends (Figure 5.45c, Figure 5.29b).



(a) Location.



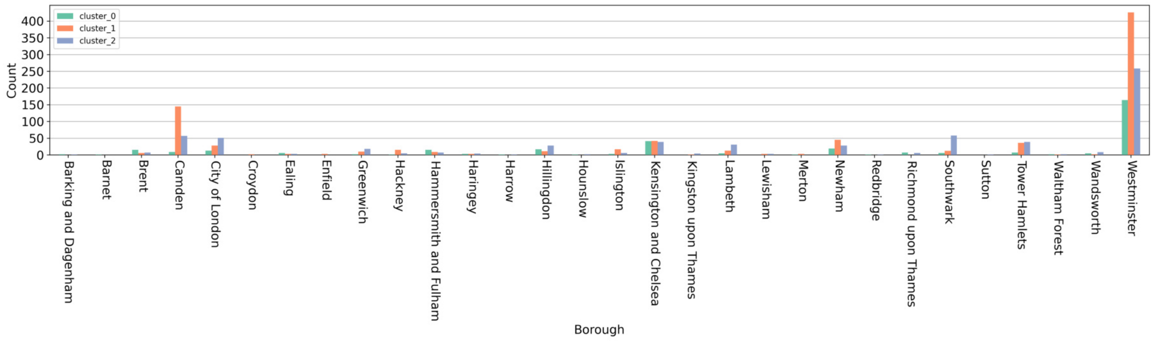
(b) Locale.



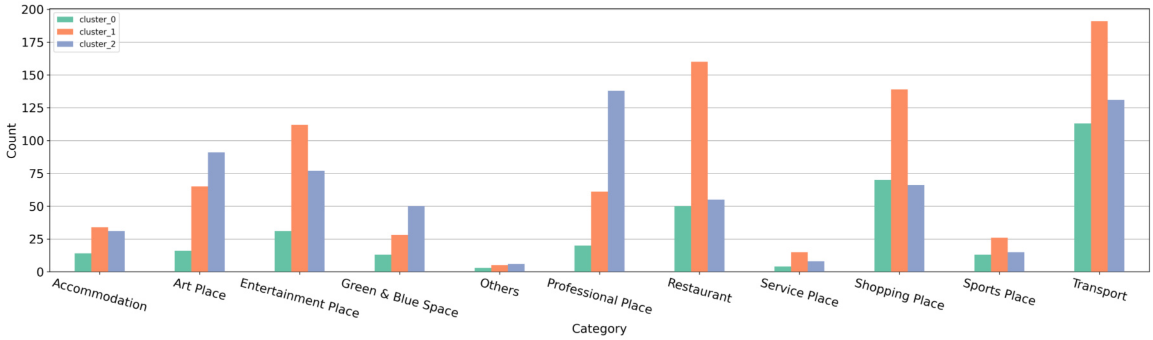
(c) Sense of Place.

Figure 5.45: Trajectory dimensions of locals on weekends.

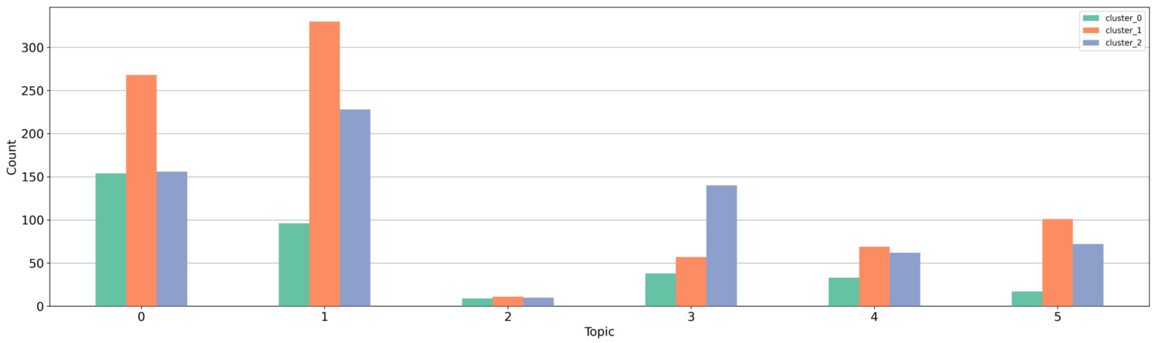
The semantic dimensions of tourists' trajectories on weekends are displayed in Figure 5.46. The *Location* dimension shows that tourists prefer the city center over suburban areas, with a notably lower frequency of visits to outer boroughs. Central boroughs like Westminster and Camden are the most popular areas, drawing a larger number of tourists to explore various places within these districts (Figure 5.46a). In the *Locale* dimension, tourists demonstrate a greater interest in entertainment places, art places, green & blue spaces, and accommodation, in addition to the four popular categories shared with locals: transport, shopping places, restaurants, and professional places (Figure 5.46b). The *Sense of Place* dimension shows that tourists on weekends tend to use cityscape-related words, such as graffiti, street art, and urban (Topic 1), to describe the places they visit, which is similar to other scenes. Additionally, transport-related words like bus, tube, and railway (Topic 0) are frequently used by tourists to describe the city on weekends (Figure 5.46c, Figure 5.30b).



(a) Location.



(b) Locale.



(c) Sense of Place.

Figure 5.46: Trajectory dimensions of tourists on weekends.

6 Discussion

This section discusses the findings of the research questions introduced in Section 1.2. Section 6.1 and Section 6.2 interpret how the findings answer RQ1 and RQ2, and each section relates these findings with correlating studies and mentions how they address knowledge gaps in the field. Moreover, the implications and limitations of this study are discussed in Section 6.3 and Section 6.4.

6.1 Visiting Preferences of Locals and Tourists through Hotspots

RQ1: Which areas are more popular among locals and tourists at different time spans?

In the context of tourism, it is important to identify specific areas that attract visitors. However, the popularity of these areas might vary spatially and temporally due to their dynamic functionalities for different population groups. The first research question of this study aims to analyze and compare the dynamic popular areas among locals and tourists over time. The results indicate that the city center is generally more attractive than other areas and that activity levels are higher during the daytime and weekdays compared to nighttime and weekends. These findings are consistent with common expectations.

Interpretation of Results

In a comparison of popular areas among locals and tourists in London, both groups primarily concentrate their activities in central London, particularly in popular boroughs such as Westminster, Camden, and the City of London. The high attractiveness of the city center can be attributed to the variety of facilities offered in these areas, such as restaurants, shopping malls, office buildings, and nightclubs (Lau & McKercher, 2006). Some outskirts boroughs with specific facilities, like airports and shopping centers, also attract people and form visiting hotspots, including Hillingdon and Newham. Despite both groups being aggregated in the city center, locals and tourists have their visiting hotspots gravitated towards different regions. Locals are more concentrated in the City of London and Canary Wharf, while Westminster and Camden demonstrate a higher relative proportion of tourists. This difference could be due to the varying visiting purposes of these two groups of people. Locals might visit the eastern part of the city center for work purposes, as the City of London and Canary Wharf in this area serve as the primary business districts of London. In contrast, tourists are more interested in visiting tourist attractions and shopping streets, which are more prevalent in the western part of the city center, including Westminster and Camden.

In terms of the popular areas over time, both locals and tourists exhibit lower activity levels during the nighttime and weekends. Specifically, the hotspots of locals around the business districts diminish during these periods, with locals tending to move outwards to suburban areas. This change in popular areas can be due to the commute of locals. They live in the outer part of London and travel to the city center for work. After work, they return to their residential areas. Compared to locals, tourists have a more consistent interest in the city center over time, with fewer visits to the outer part of London. Additionally, although less active during the nighttime and weekends, tourists during these periods show a higher proportion of concentration in the city center than locals. This suggests that tourist attractions and shopping streets within the city center are more attractive to tourists than to locals during the nighttime and weekends.

Correlation with Current Studies

The findings of this study align with other studies that have identified tourism hotspots. This study applies KDE to detect hotspots in London using Foursquare check-ins and finds that the city center has a higher concentration of visitors. Other studies have also identified hotspots in London through different methods and data sources. For example, García-Palomares et al. (2015) calculated the number of Panoramio photos within hexagons to represent the degree of concentration and applied spatial autocorrelation to identify spatial clusters. The hexagons with the highest number of photos corresponded to tourist attractions in central London, such as the British Museum, Camden Market, and Tower Bridge. Another study identified hotspots by clustering trajectories built on Tweets and also detected greater hotspots in central London that contained a large number of tourist attractions, such as Trafalgar Square and Soho (Ma et al., 2020). In addition to the hotspots in the city center, this study finds that the airport also attracts both locals and tourists and forms a hotspot, as it is an important transportation hub. The hotspot around the airport is also found in the study by Su et al. (2020). The convergence in findings between this study and existing research can be attributed to the common characteristics inherent in social media data. Despite the varying sources of data in these studies, it is evident that users across social media platforms exhibit analogous posting behaviors.

In addition to analyzing the distribution patterns of hotspots, this study also examines the visiting preferences of locals and tourists through the mixture degree of these two groups of people. It is found that locals tend to visit more suburban areas than tourists, as many residential districts are located in these areas. This greater visiting preference of locals for suburban areas compared to tourists has also been observed in a study by Su et al. (2020). In their study, in addition to the city center and airport which attract both locals and tourists, locals are also concentrated in areas that mainly serve residential purposes. In terms of the distribution intensity of these two groups of people, tourists share fewer check-ins than locals but represent a higher concentration, particularly in the city center. This visiting preference is consistent with the findings in studies by García-Palomares et al. (2015) and Su et al. (2020). The smaller number of check-ins but higher concentration of tourists indicates that they tend to visit similar destinations in the city center, while locals are relatively more scattered throughout the whole city. Both this study and prior research find distinct distribution patterns between locals and tourists, which affirms the existence of disparate visiting preferences within these two distinct groups.

Contributions to Addressing Knowledge Gaps

The detection of hotspots can be precise for different groups of populations or for different time spans. Existing studies have identified and compared the hotspots of locals and tourists, finding that both groups are primarily attracted to the city center (García-Palomares et al., 2015; Su et al., 2020). This study not only identifies hotspots using KDE but also investigates different visiting preferences of locals and tourists by calculating the difference ratio by raster to explore the relative concentration of these two groups of people. The difference ratio measures the mixture degree of locals and tourists, considering the imbalanced number of two groups. The results show that although both locals and tourists are mainly concentrated in the city center, the hotspots of locals gravitate towards business districts, while those of tourists are around tourist attractions. Some studies focus on the temporal distributions of visitors, counting the number of visitors by hour, week, month, season, and year to represent their temporal variation in activity levels (C. Li et al., 2011; Su et al., 2020). While this statistical analysis reflects the temporal distributions of visitors' activities, it does not reveal their spatial distributions. This study goes one step further by considering both spatial and temporal distributions of visitors and dividing data by time spans, namely by daytime and nighttime, and by weekdays and weekends. The hotspots of locals and tourists across time spans are detected separately, allowing for a comparison of the dynamic distribution patterns of hotspots across different scenes.

6.2 Visiting Behaviors and City Perceptions through Semantic Trajectory

RQ2: How do locals and tourists perceive the city along their semantic trajectories at different time spans?

The trajectories of people encompass not only spatial information but also a range of semantic information, including place categories, ratings, and personal impressions. Integrating this semantic information into trajectories helps to explore how the city is perceived. The second research question delves into distinct visiting behaviors and city perceptions held by locals and tourists across different time spans, achieved through the construction of semantic trajectories. The fundamental component of a trajectory is the concept of place, which this study annotates with three dimensions, namely *Location*, *Locale*, and *Sense of Place* (Agnew, 2011). The dimensions *Location* and *Locale* encapsulate the objective property of a place, represented respectively by borough names and place categories, and the *Sense of Place* dimension reflects people's subjective impressions of the place, represented by topics generated from topic modeling. The trajectories are then clustered based on the three semantic dimensions, and typical trajectories are mined for each cluster. It is assumed that the trajectories of locals and tourists exhibit different distribution patterns. Furthermore, their perceptions of London are different from each other and also evolve dynamically over time.

Interpretation of Results

Locals and tourists exhibit different distribution patterns of trajectories and perceptions of the city. Similar to the findings about hotspots in RQ1 (Section 6.1), the trajectories suggest that locals and tourists primarily move within central London, with locals exhibiting stronger connections to the outskirts of the city. An examination of the spatial distribution of clustered trajectories reveals that, while many clusters do not provide meaningful information, some can be generalized to serve particular purposes. For locals, air transport is one visiting purpose, as evidenced by several clusters of trajectories that frequently visit Heathrow Airport from the city center at different time spans. Additionally, commuting and fitness purposes are also discovered. The former can be inferred from the large number of trajectories connecting the city center and outskirts boroughs which contain many residential districts, while the latter can be deduced from frequent visits to fitness centers and gyms around Greenwich. For tourists, transportation and shopping purposes are detected from their clusters of trajectories. Their trajectories primarily pass through transportation hubs in the inner part of London, and shopping centers and shopping streets are also frequently visited by these trajectories.

The perceptions of the city are revealed through the semantic dimensions of trajectories. The distribution of *Location* dimension validates the concentration of trajectories of both locals and tourists in the city center, with central boroughs like Westminster, Camden, and the City of London having the highest visiting frequency. The *Locale* dimension suggests that in addition to popular categories such as transportation, shopping places, restaurants, and professional places, locals and tourists have their own preferences. Green & blue spaces, such as parks, are more attractive to locals, while art places, such as museums, and accommodations, such as hotels, are more frequently visited by tourists. In the *Sense of Place* dimension, locals and tourists have some similar descriptions of London. Both groups tend to use cityscapes and transport-related words to describe the city, such as city, street, and rail station. However, different perceptions of London also exist between locals and tourists. For instance, locals prefer to use words related to nature and fitness along their trajectories, while tourists are more focused on places related to art and the Olympics. This aligns with the findings in *Locale* dimension.

The distribution patterns of trajectories and perceptions of the city also vary over time. A comparison of daytime and nighttime reveals that during the daytime, the trajectories primarily move within central London. However, during the nighttime, the trajectories become sparser and exhibit different distribution patterns among locals and tourists. Locals shift their activities from the city center to the outer parts of London, with more trajectories visiting outskirts boroughs such as Merton, where many residential districts are located. It is noteworthy that tourists' visiting frequency to accommodations increases during the nighttime, while this pattern is not observed among locals. Moreover, locals' visiting purposes switch from work and enjoyment of nature to nightlife and fitness, which is evidenced by increased visits to nightclubs in Shoreditch and fitness centers in Greenwich. In contrast to locals who prefer to visit more outskirts boroughs, tourists have their trajectories more concentrated in the city center, aligning with the finding of high difference ratios around Westminster. Additionally, tourists show consistent interest in shopping throughout the day, with their trajectories frequently visiting Oxford Street. Regarding the temporal differences in city perceptions, during the daytime, locals are impressed with the transport, cityscapes, and nature of the city, with keywords like architecture, park, and railway, but when the nighttime falls, their focus turns to leisure, nightlife, and sports activities, with keywords like music, bar, party, and cycling. In terms of tourists, they consistently use general words to describe London, such as architecture, bridge, and people. London also leaves an impression on them about art and nightlife, but words related to these activities are less frequently mentioned than by locals.

When comparing weekdays and weekends, the distribution patterns of trajectories evolve throughout the week. On weekdays, locals move across different boroughs within London, while tourists move between the city center and other outskirts boroughs, with particular interest in Hillingdon, Hounslow, and Croydon, where Heathrow Airport and Whitgift Centre are located. On weekends, the number of trajectories decreases significantly. Locals have sparser trajectories across London, while tourists maintain their movements in the inner part of London and some particular boroughs. The commuting routes of locals between Merton and central London are discovered by their typical trajectories mined from trajectory clusters on weekdays. In addition, locals' frequent visits to areas around the airport and fitness facilities are also detected. The typical trajectories on weekends suggest that locals prefer leisure activities, such as going shopping around Stratford Shopping Center. In contrast to locals, tourists' typical trajectories remain in the city center. The differences in city perceptions between weekdays and weekends are not obvious. Locals decrease their visits to professional places and show an increased interest in entertainment places. But the shift in *Locale* dimension is not reflected in *Sense of Place* dimension. Both locals and tourists continue to use general words about cityscapes to describe London throughout the week, with some nature-related descriptions from locals emerging on weekends.

Correlation with Current Studies

The distribution patterns of trajectories found in this study are consistent with other studies. It has been found that the most frequently visited places are primarily the tourist attractions in central London, such as the London Eye, the British Museum, and Big Ben. The routes from the London Eye to Trafalgar Square and from Big Ben to Downing Street are particularly popular among visitors (Yin et al., 2011; Zheng et al., 2012). This study also discovers a high visiting frequency in Westminster, where these attractions are located. However, the typical trajectories mined from trajectory clusters in this study are not precise to particular attractions, as the places of trajectories are conceptualized from check-ins clusters. Moreover, unlike the spatially concentrated trajectory clusters in the study by Straumann et al. (2014), the trajectory clusters in this study are mixed in space because both the spatial and semantic information are considered in the process of trajectory clustering. This enriches trajectory clusters with more information but also makes the interpretation of each cluster difficult, as not every cluster is meaningful. When analyzing the popular place categories in trajectories, A. P. Ferreira et al. (2020) discovered a high interest in nightlife-related places such as pubs among both locals and tourists. This preference is also found in this study. Regarding descriptions of London, this study has similar findings to previous research about the place properties in London. For instance, both studies find that Oxford Street leaves visitors with an impression of shopping, Shoreditch with an impression of music and drinks, and Southbank with an impression of art (Bahrehdar & Purves, 2018). The concurrence of findings between this study and prior research validates the prevalence of popular routes and destinations in London, as well as the shared impressions that the city imparts to individuals.

Unexpected Findings

This study has some unexpected findings. The first one is the meaningless topics generated by topic modeling. For example, some topics contain words like people and candid, which is difficult to relate them to specific place properties or deduce perceptions of the city from them. The difficulty in interpreting topics has also been encountered by other studies (Bahrehdar & Purves, 2018; Adams & McKenzie, 2013), and it is normal for not every topic generated by topic modeling to be interpretable. In addition, there are inconsistencies between the content of topics and their spatial distribution. For instance, some topics are mainly related to air transport, and places with these topics should be located around Heathrow Airport. However, other areas like the city center are also covered by these topics. This can be due to differences between data sources. Topics are generated based on Flickr tags, while places are constructed based on Foursquare check-ins. The two data sources lack context for each other and some important information might be ignored, resulting in inconsistencies. Another unexpected finding is the inconsistencies between semantic dimensions. For instance, some clusters have a low frequency in green & blue spaces in the *Locale* dimension, but the *Sense of Place* dimension suggests that there are many places described by the topic related to parks and gardens. This can be due to the inaccurate construction of places and miscategorization of places. There are also inconsistencies between typical trajectories and their corresponding clusters. Some clusters exhibit an obvious connection between Heathrow Airport and central London, while the typical trajectories mined from these clusters do not cover areas around the airport but only central London. Two reasons could lead to these inconsistencies. The first is that there are indeed more sequences located in the city center, and the second is that there are many places around the airport, so the visiting frequency of these places might not be high. Although the gravitation to the airport is evident, typical trajectories cannot be mined.

Contributions to Addressing Knowledge Gaps

Numerous studies have investigated the movement patterns of visitors through their trajectories. Some went one step further by enriching trajectories with semantic information to explore their non-spatial properties (Parent et al., 2013; Yan et al., 2013). Similar to the study by Cai et al. (2018), this study also aims to find typical trajectories after clustering trajectories with semantic-level features. However, Cai et al. (2018) mainly focused on the general semantic trajectories, this study considers the different visiting behaviors of locals and tourists over time, differentiating scenes for two population groups at various time spans and constructing semantic trajectories for each scene separately. The separation of scenes in this study contributes to a more accurate exploration of the temporal movement patterns and travel purposes of different populations within the city. With respect to the selection of semantic dimensions of trajectories, existing studies have enriched trajectories with information such as weather, transportation means, and place category (Ferrero et al., 2020). This study novelly combines the place dimensions proposed by Agnew (2011), namely location, locale, and sense of place, with the semantic enrichment of trajectories. Trajectories annotated with these dimensions convey not only objective properties of places but also subjective descriptions of people. Thus, in addition to the spatial distribution, this study also delves into the frequency of the semantic dimensions of trajectories to explore their characteristics. Pertaining to the similarity measure of semantic trajectories in the process of clustering, this study examines the feasibility of Multidimensional Similarity Measure (MSM) proposed by Furtado et al. (2016). The semantic dimensions used in this study involve different types of data and each dimension should be weighted based on its importance. This study verifies that MSM is able to handle these requirements and measure the similarity of trajectories effectively.

6.3 Implications

This study identifies the visiting preferences of locals and tourists through their hotspots and investigates how they perceive the city through their semantic trajectories across different time spans. The findings of this study offer valuable insights for urban planners. Understanding the concentration of different populations and how they move through the city facilitates land use decisions and urban facility management. The findings could also be applied to promote tourism. This study uncovers characteristics of the city that can be used to improve the attractiveness of the city. Additionally, the dynamic distribution of hotspots over time can provide supplementary information for tourism destination recommendation systems, allowing them to recommend destinations based on time and improve visitors' experiences. Furthermore, this study also helps companies to discover potential business opportunities. Specifically, the dynamic distribution of trajectories and perceptions over time helps to target customers and provide better products and services that meet the needs of different populations.

6.4 Limitations

This study also has some limitations. For the first research question, one limitation is the parameter selection for KDE. The selection of bandwidth and kernel smoother is crucial when visualizing check-in distribution using KDE, and these parameters should be determined through a set of tests. This study only uses the default setting for parameters without trying different combinations, which could lead to incorrect conclusions. For example, if the bandwidth is too large, no hotspots might be detected in popular areas with many check-ins, while if the bandwidth is too small, hotspots might be detected in non-popular areas with only a few check-ins. Another limitation is the selection of the difference ratio value that determines whether the raster is popular or not. The threshold for popular rasters could be better determined by analyzing the value distribution of the difference ratio across rasters and finding the proper quantile values.

Regarding the second research question, one limitation is the data bias. This study utilizes UGC from Foursquare check-ins and Flickr tags to investigate people's perceptions of London. However, the users of these social media platforms are mainly young people, which may result in a bias in the age range and neglect of older people's city perceptions. Another limitation is the accuracy of places constructed by clustering check-ins. The boundaries of these places are determined by the convex hulls of check-in clusters, resulting in a significant variation in their sizes. While some are of a reasonable size, encompassing areas such as a shopping center or a transportation hub, others might be too small or excessively large to hold any meaningful interpretation. Moreover, the places are represented by three dimensions, but some characteristics of places are hidden behind these dimensions. Places might be miscategorized because the categories are only determined by the frequency of check-ins categories within places, leading to inconsistencies between each dimension. The parameter selection for sequential pattern mining is also a limitation. The minimum support should be determined by the number of trajectories, but tourists during nighttime and weekends have sparse trajectories. A minimum support of 2 is used to guarantee that there are typical trajectories extracted for each cluster, but trajectories with only 2 supports are not frequently visited and are not typical. There are also limitations in the analysis. The directions of trajectories are not considered. The flow direction helps to determine whether the movement is inward or outward, which serves as important information in the analysis of trajectory distribution patterns, but it is not covered in this study. Moreover, the analysis of city perception through semantic trajectories is not enough. Among the three semantic dimensions of trajectories, only the *Sense of Place* dimension involves people's descriptions of the city, while the other two dimensions focus on the trajectory distribution in space and place categories within trajectories, which is not relevant to city perceptions.

7 Conclusion

This study aims to investigate the dynamic visiting behaviors and city perceptions of locals and tourists over time. With the large volume of UGC available online, this study utilizes Foursquare check-ins and Flickr tags to detect hotspots and construct semantic trajectories to delve into how the city is described under various scenes (Figure 4.2). Specifically, the relative concentration of locals and tourists in hotspots is analyzed to explore their visiting preferences. The spatiotemporal differences in the movement patterns and impressions of the city between locals and tourists are investigated by constructing semantic trajectories for each population group across different time spans.

Main Findings

Locals and tourists have distinct visiting behaviors, and their perceptions of the city also vary over time. The findings of this study can be concluded as follows:

- Both locals and tourists are concentrated around the city center and the airport, but locals tend to visit more suburban areas than tourists.
- Locals prefer business districts in the city center during the daytime and weekdays, while tourists consistently visit attractions around Westminster.
- Locals tend to shift traveling purposes from work in the daytime to nightlife activities and fitness at night, while tourists maintain their movements in the city center over time, with a particular interest in shopping.
- Transportation, shopping places, restaurants, and professional places are consistently popular among both locals and tourists. However, tourists tend to visit art places and accommodations more frequently than locals.
- City perceptions vary by location and time, with the city center associated with descriptions of transport and cityscapes during the day, and nightlife at night, while the airport area is linked to air transport.
- The city leaves distinct impressions on locals and tourists. Locals are interested in nature and leisure activities in the city, while tourists tend to focus on the Olympics and tourist attractions.

Many studies have investigated the identification of hotspots and movement patterns, focusing on their general distributions. However, the distribution of hotspots and movement patterns can vary among different population groups across time spans. This study addresses this research gap by analyzing distributions under different scenes, distinguishing between locals and tourists during the daytime and nighttime, as well as on weekdays and weekends. The results show distinct patterns of hotspot and trajectory distributions across scenes. Additionally, while some studies have examined the use of semantic trajectories to understand visitor behaviors, this study integrates the conceptualization of place with location, locale, and sense of place dimensions, enriching trajectories semantically. The results demonstrate that the spatiotemporal differences in city perceptions could be extracted from trajectories with the three semantic dimensions. Furthermore, UGC proves to be a valuable data source for modeling user movements and discovering city perceptions due to its availability and accessibility.

Future Work

The study of dynamic visiting behaviors and city perceptions through semantic trajectories shows many potential areas for future research. First, different data sources can be used to investigate city perceptions. This study uses Foursquare check-ins and Flickr tags to construct semantic trajectories, other data sources such as Tweets and Google Street View images can also be used to build trajectories and extract additional information from them. Moreover, a comparison study of city perceptions discovered from different data sources can be conducted.

Second, future research could benefit from considering different population groups and time spans. By differentiating populations by age, gender, nationality, and other factors, or by analyzing time spans by month and season, researchers might be able to uncover new and nuanced city perceptions.

Third, other semantic dimensions can be incorporated into the semantic trajectory construction. For example, the social and cultural context of the city, such as events and festivals, plays an important role in influencing how people describe the city, and this information can also be annotated to trajectories.

Fourth, investigating the relationship between city perceptions and other factors can be interesting. City perceptions can be influenced by a variety of factors, including socioeconomic status, age, and cultural background, and studying the relationship between them contributes to improving the quality of life of residents.

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A Appendix

Table A.1: Top 10 popular venues within rasters with a difference ratio exceeding 0.01 (indicating a higher number of tourists) during the daytime.

No.	Venue Name	No. of Check-ins	Description
1	London King's Cross Railway Station (KGX)	1030	Transportation hub
2	London Victoria Railway Station (VIC)	806	Transportation hub
3	Harrods	716	Luxury department store
4	London St Pancras International Railway Station (STP)	682	Transportation hub
5	London St Pancras International Eurostar Terminal	511	Transportation hub
6	Piccadilly Circus	473	Public space with iconic illuminated billboards
7	Trafalgar Square	465	Public square with historical and cultural landmarks
8	Selfridges	464	Luxury department store
9	Buckingham Palace	459	Iconic official residence of the British monarch
10	Big Ben (Elizabeth Tower)	352	Iconic tower clock

Table A.2: Top 10 popular venues within rasters with a difference ratio lower than -0.01 (indicating a higher number of locals) during the daytime.

No.	Venue Name	No. of Check-ins	Description
1	Google Campus - London	160	Vibrant hub for tech startups and entrepreneurs
2	Shoreditch Grind	94	Trendy coffee shop and cocktail bar
3	Ozone Coffee Roasters	84	Renowned specialty coffee roastery
4	Old Street London Underground Station	84	Transportation hub
5	SapientRazorfish	77	Global digital consultancy
6	Shoreditch House	61	Private members' club
7	CCA International	59	Global customer experience management company
8	BOXPARK Shoreditch	56	Innovative retail and dining destination
9	Dishoom	50	Restaurant
10	Shoreditch Triangle	46	Cultural and creative hub

Table A.3: Top 10 popular venues within rasters with a difference ratio exceeding 0.01 (indicating a higher number of tourists) during the nighttime.

No.	Venue Name	No. of Check-ins	Description
1	London Euston Railway Station	199	Transportation hub
2	Piccadilly Circus	179	Public space with iconic illuminated billboards
3	London Paddington Railway Station (PAD)	165	Transportation hub
4	London Victoria Railway Station (VIC)	146	Transportation hub
5	Trafalgar Square	115	Public square with historical and cultural landmarks
6	Charing Cross Railway Station (CHX)	111	Transportation hub
7	Heaven	95	Nightclub
8	Leicester Square	91	Bustling entertainment hub
9	Harrods	57	Luxury department store
10	The Harp, Covent Garden	52	Pub

Table A.4: Top 10 popular venues within rasters with a difference ratio lower than -0.01 (indicating a higher number of locals) during the nighttime.

No.	Venue Name	No. of Check-ins	Description
1	Shoreditch House	45	Private members' club
2	Tesco Express	31	Convenience store
3	Old Street London Underground Station	21	Transportation hub
4	Xoyo	21	Nightclub
5	TfL Bus 314	21	Bus service
6	Strongroom 314	20	Recording studio
7	Zigfrid von Underbelly	19	Bar
8	Concrete	19	Nightclub
9	The Park	19	Green space
10	The Old Blue Last	19	Pub

Table A.5: Top 10 popular venues within rasters with a difference ratio exceeding 0.01 (indicating a higher number of tourists) on weekdays.

No.	Venue Name	No. of Check-ins	Description
1	London Euston Railway Station	1100	Transportation hub
2	London King's Cross Railway Station (KGX)	937	Transportation hub
3	London Victoria Railway Station (VIC)	695	Transportation hub
4	London St Pancras International Railway Station (STP)	562	Transportation hub
5	Harrods	544	Luxury department store
6	London St Pancras International Eurostar Terminal	454	Transportation hub
7	Piccadilly Circus	446	Public space with iconic illuminated billboards
8	Trafalgar Square	341	Public square with historical and cultural landmarks
9	Selfridges	329	Luxury department store
10	Buckingham Palace	319	Iconic official residence of the British monarch

Table A.6: Top 10 popular venues within rasters with a difference ratio lower than -0.01 (indicating a higher number of locals) on weekdays.

No.	Venue Name	No. of Check-ins	Description
1	London Liverpool Street Railway Station (LST)	604	Transportation hub
2	Google Campus - London	155	Vibrant hub for tech startups and entrepreneurs
3	Shoreditch Grind	84	Trendy coffee shop and cocktail bar
4	Shoreditch House	84	Private members' club
5	Old Street London Underground Station	83	Transportation hub
6	SapientRazorfish	77	Global digital consultancy
7	UBS Wealth Management	77	Global financial service firm
8	Ozone Coffee Roasters	75	Renowned specialty coffee roastery
9	Bank London Underground and DLR Station	73	Transportation hub
10	Liverpool Street London Underground Station	72	Transportation hub

Table A.7: Top 10 popular venues within rasters with a difference ratio exceeding 0.01 (indicating a higher number of tourists) on weekends.

No.	Venue Name	No. of Check-ins	Description
1	London Paddington Railway Station (PAD)	278	Transportation hub
2	London King's Cross Railway Station (KGX)	266	Transportation hub
3	London Victoria Railway Station (VIC)	257	Transportation hub
4	Trafalgar Square	239	Public square with historical and cultural landmarks
5	London St Pancras International Railway Station (STP)	229	Transportation hub
6	Harrods	229	Luxury department store
7	Piccadilly Circus	206	Public space with iconic illuminated billboards
8	Buckingham Palace	183	Iconic official residence of the British monarch
9	Selfridges	177	Luxury department store
10	Big Ben (Elizabeth Tower)	163	Iconic tower clock

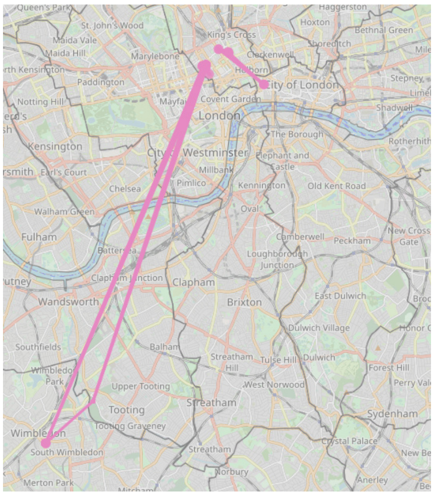
Table A.8: Top 10 popular venues within rasters with a difference ratio lower than -0.007 (indicating a higher number of locals) on weekends.

No.	Venue Name	No. of Check-ins	Description
1	BOXPARK Shoreditch	27	Innovative retail and dining destination
2	Shoreditch Grind	23	Trendy coffee shop and cocktail bar
3	Shoreditch House	22	Private members' club
4	Old Street London Underground Station	22	Transportation hub
5	Hoxton Grill	15	Restaurant
6	Shoreditch Triangle	15	Cultural and creative hub
7	The Hoxton, Shoreditch	15	Hotel
8	The Water Poet	13	Pub
9	Zigfrid von Underbelly	12	Bar
10	Ozone Coffee Roasters	12	Renowned specialty coffee roastery

(a) Cluster 0.

(b) Cluster 1.

(c) Cluster 2.

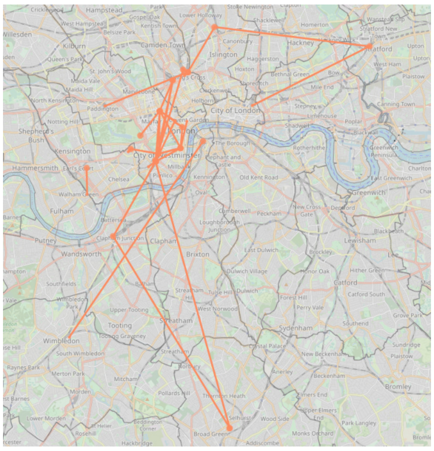


(d) Cluster 3.

(e) Cluster 4.

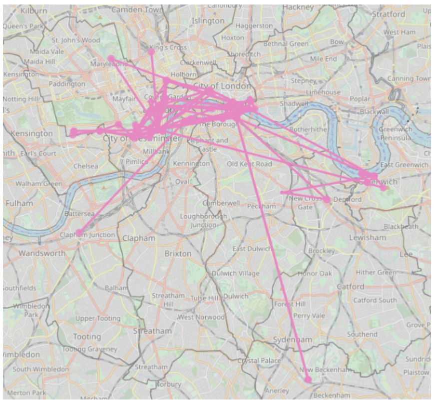
Figure A.1: Typical trajectories of locals during the daytime (The larger point represents the starting point of the trajectory).

(a) Cluster 0.



(b) Cluster 1.

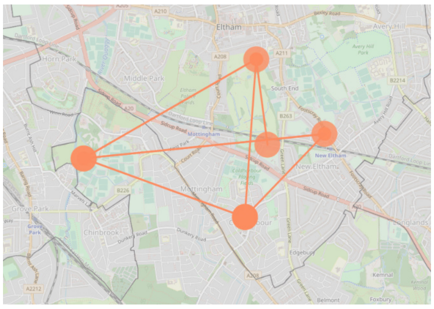
(c) Cluster 2.



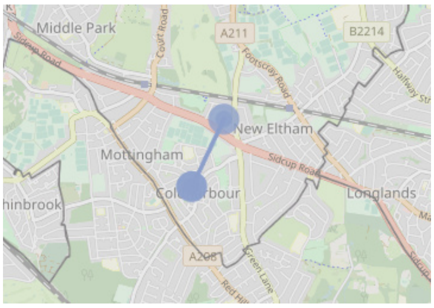
(d) Cluster 3.

Figure A.2: Typical trajectories of tourists during the daytime (The larger point represents the starting point of the trajectory).

(a) Cluster 0.



(b) Cluster 1.



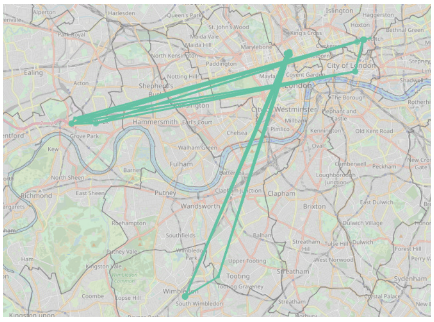
(c) Cluster 2.

Figure A.3: Typical trajectories of locals during the nighttime (The larger point represents the starting point of the trajectory).

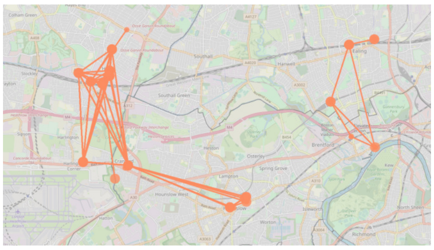
(a) Cluster 0.

(b) Cluster 1.

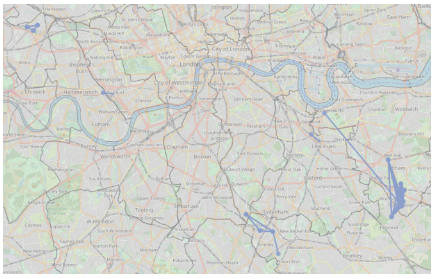
Figure A.4: Typical trajectories of tourists during the nighttime (The larger point represents the starting point of the trajectory).



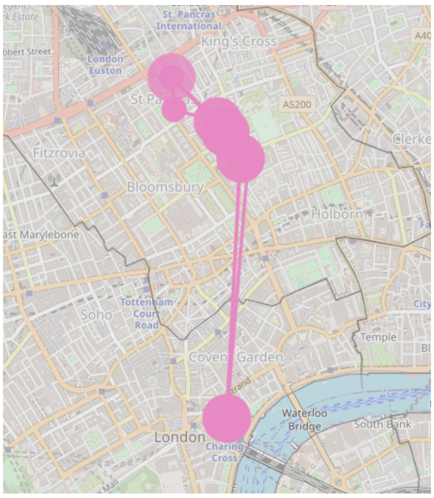
(a) Cluster 0.



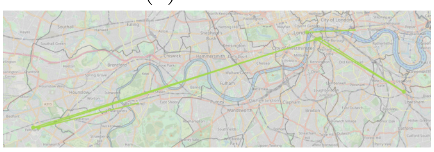
(b) Cluster 1.



(c) Cluster 2.

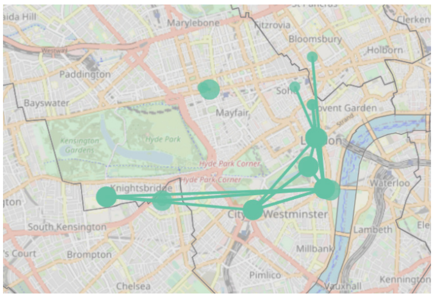


(d) Cluster 3.

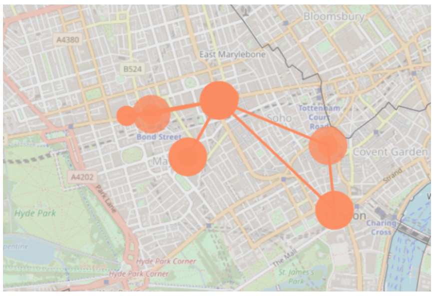


(e) Cluster 4.

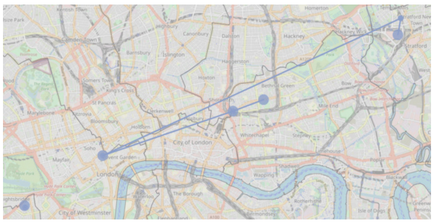
Figure A.5: Typical trajectories of locals on weekdays (The larger point represents the starting point of the trajectory).



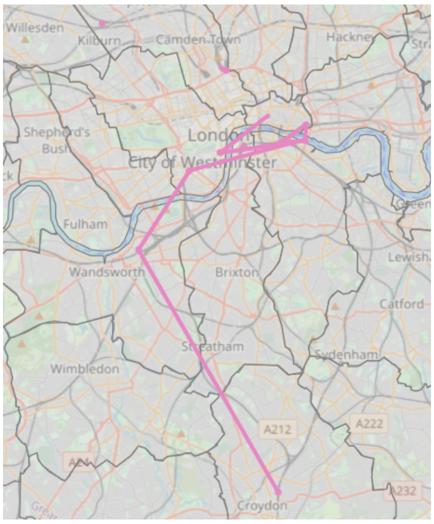
(a) Cluster 0.



(b) Cluster 1.

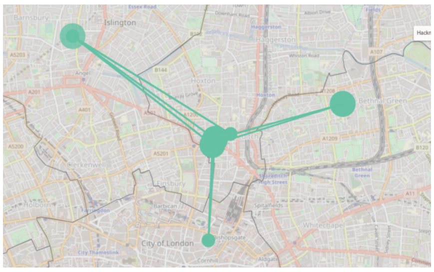


(c) Cluster 2.



(d) Cluster 3.

Figure A.6: Typical trajectories of tourists on weekdays (The larger point represents the starting point of the trajectory).



(a) Cluster 0.

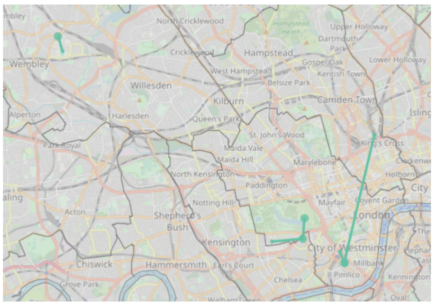
(b) Cluster 1.

(c) Cluster 2.

(d) Cluster 3.

(e) Cluster 4.

Figure A.7: Typical trajectories of locals on weekends (The larger point represents the starting point of the trajectory).



(a) Cluster 0.

(b) Cluster 1.

(c) Cluster 2.

Figure A.8: Typical trajectories of tourists on weekends (The larger point represents the starting point of the trajectory).

Personal Declaration

I hereby declare that the submitted thesis is the result of my own, independent work. All external sources are explicitly acknowledged in the thesis.

Leyi Xu

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Zurich, 25.08.2023