Estimating Mobility Flows: Comparative Analysis of Deep Gravity Model and Spatial Interaction Model for non-work flows in London

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I, Felipe Santos Almeida, confirm that the work presented in this dissertation is my own. Where information has been derived from other sources, I confirm that this has been indicated in the work. It is 10,250 words in lenght, from the introduction to conclusion, excluding figures.

Abstract

The dynamics of human mobility have experienced a profound transformation in recent years due to a confluence of factors. The interplay between transportation systems has shaped this evolution due to the increased urban population, the integration of computational techniques, advanced data collection methods, and Artificial Intelligence (AI). This dissertation examines the evolving nature of human mobility in London, focusing on work-related and non-work-related flows.

This study aims to compare and evaluate the performance of two models, namely the Deep Gravity Model and the Production-constrained Model, concerning their ability to predict mobility patterns in London. A comprehensive understanding of their efficacy and applicability is established by comparing the outcomes of these models against observed flow patterns. The study specifically concentrates on the London region, containing its diverse cultural, economic, and infrastructural facets. This comprehensive approach is crucial for comprehending the complex commuting patterns across the city.

Three key datasets are utilised to conduct this analysis: Mobility flows, Points of Interest, and Census 2021. Mobility data offers essential aggregated origin-destination flow data within the hexagons grid system, a unique hierarchical classification to each cell, serving as this study's foundational index. The additional datasets are integrated into this index through area-weighted spatial joins, ensuring data coherence.

The findings of this study are on the predictive capabilities of the Deep Gravity Model, highlighting its effectiveness in capturing and foreseeing human mobility patterns. The comparison between the Deep Gravity Model and the Production-constrained Model provides valuable insights into mobility dynamics, contributing to advancing transportation research and policy-making.

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Chapter 1

Introduction

1.1 Context

The complex nature of human mobility has undergone a notable transformation in recent times due to various factors. Contemporary transportation has evolved, encompassing a dynamic interplay between private vehicles and public transport systems. This evolution has been further driven by the surging urban population, which has led to a paradigm shift in mobility patterns(Batty, 2018; Townsend, 2013). Notably, the convergence of computational techniques, advanced data collection methods, and the utilisation of Artificial Intelligence (AI) has paved the way for innovative approaches to address the challenges posed by the new dynamic of human mobility.

Within this context, the study of human mobility has gained significant attention, focusing on multifaceted aspects such as city migration, rural depopulation, urban mobility pattern modelling, city population estimation, disaster-induced migration, climate-driven shifts, and predicting traffic dynamics and crowd movements. These areas emphasise mobility's dynamic and complex nature, reproducing the increasing complexity of contemporary human movement((Batty, 2008; Luca et al., 2021). Simini et al. (2021) emphasise the expanding sphere of influence that human mobility acts on in many domains, from urban planning to epidemiology.

The importance of human mobility modelling resonates deeply within various research domains, shaping our understanding of diverse processes. The shift in the dynamic of mobility flows impacted the spatial distribution, city density, population distribution, and disease dissemination. Such transformative impacts illustrate the role of mobility in shaping urban dynamics and social phenomena, in addition to the emergence of new computational tools to deal with this new scenario(Simini et al., 2021; Luca et al., 2021).

Mobility flows are complex, and people have various reasons for their travels, such as going to their jobs or schools. These routines usually happen on weekdays, creating a clear pattern that we can represent with a linear relationship with people's origin and destination flows(Simini et al., 2021). This basic understanding of daily urban movement allows us to see how people's travels impact public infrastructure, transportation options, and where people live and work.

However, as seen in 1.1, not all travel fits this pattern. The citizens also commute for leisure, sports, healthcare, and other reasons that do not follow a predictable schedule. These kinds of trips have a complex point A to point B and a point C, mostly without a daily pattern. We need different tools to handle the irregularity to grasp these more complex movements. One promising tool is neural networking, which can better comprehend and predict these intricate movements with a non-linear relationship analysis(Camburu, 2021). As cities expand and people travel for various purposes, adopting these new methods can benefit designing transportation systems that capture diverse needs more effectively.

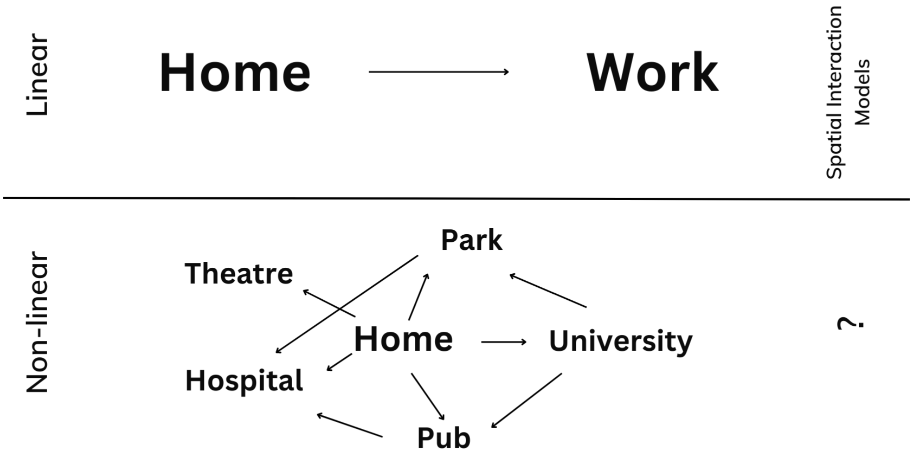

Figure 1.1: Work x non-work flows

Using a spatial interaction model to predict movement patterns has proven to be a valuable tool for urban planning and understanding how cities change(Wilson, 1971). However, the rise of big data in today's technology-driven age, with access to vast amounts of previously unseen information, has posed challenges for traditional models. Therefore, new models such as the Deep Gravity Model, in which the Gravity Model is combined with neural network architecture, show great promise in efficiently estimating mobility flows. As a result, innovative approaches that involve artificial intelligence and machine learning are being explored to update transportation modelling methods. These modern methods hold great potential for revolutionising the way we model and plan for transportation in cities.

In summary, urban mobility is a multifaceted challenge. Regular commuting forms a predictable pattern, but other types of travel involve diverse motivations and schedules. By embracing innovative techniques, we can unravel the complexities of various movements within cities. This adaptable approach to understanding mobility enhances our planning and accommodates the evolving dynamics of urban life and travel.

Hence, the main objective of this study is to assess the effectiveness of the deep gravity model in predicting mobility patterns for non-work-related flows. In this regard, evaluating the Deep Gravity model's performance against traditional Spatial Interaction Models assumes significant importance.

This comparison between work-related and non-work-related flows offers a comprehensive understanding of the model's capabilities in estimating complex mobility patterns. Such an analysis is crucial in investigating the potential value that deep learning methodologies bring to non-work-related flow prediction and estimation.

1.2 Research Question

How do Deep Gravity and Spatial Interaction Models differ in their predictive capabilities for estimating mobility flows, considering non-work-related and work-related trips?

1.3 Report Structure

- **Chapter 2:** Literature Review - This chapter overviews key methodologies and limitations in estimating mobility flows. It delves into the structure of the spatial interaction model while introducing the application of deep learning to mobility flow analysis. Additionally, the chapter introduces the deep gravity model as another method for flow estimation.

- **Chapter 3:** Methodology - This chapter explains the architectural foundations of both models. It also delves into the dataset employed in this study and how it was structured for utilisation in both models. The chapter concludes by outlining the evaluation metrics that will be used to assess the performance of these models.

- **Chapter 4:** Results and Discussion - First, the evaluation of the models takes centre stage. The chapter showcases visualisations of the generated flows and presents the principal findings alongside their associated limitations.

- **Chapter 5:** Conclusion - The concluding chapter summarises the significance of the analysis undertaken. It also underscores potential avenues for further investigation in the following studies.

Chapter 2

Literature Review

2.1 Estimate mobility Flows

Flow generation aims to synthesise real flow patterns between different geographical locations. It involves considering the specific attributes of these locations, such as population density, Points of Interest (POIs), land use characteristics, and the distances among them. This process is executed without direct access to real-world flow data, highlighting the dependence on generative models to represent mobility patterns accurately (Luca et al., 2021).

Moreover, Mobility data captured through electronic devices provide invaluable insights into the movements of individuals over specific time intervals(Luca et al., 2021). These movements are recorded as spatiotemporal trajectories or aggregated mobility flows. Spatiotemporal trajectories and spatial aggregations, such as spatial-temporal points and tessellation, are crucial in this analysis as foundational elements for analysing and modelling mobility patterns(Luca et al., 2021; Simini et al., 2021).

The implications of flow generation extend across various sectors, including urban planning, spatial economics, sustainable community design, and epidemiological modelling. The ability to generate accurate mobility flows is critical for addressing issues related to transportation planning, reducing socioeconomic inequalities, designing resilient communities, and understanding the spread of diseases within populations(Luca et al., 2021). Thus, the focus on flow generation and the generation of realistic mobility trajectories holds promise for enhancing various aspects of urban planning, spatial analysis, and public health.

2.2 Spatial Interaction models

A significant moment in the research of flow estimation was in 1946 when Zipf (1946) introduced a conceptual framework for estimating mobility flows(Simini et al., 2021; Wilkinson, 2023). This model illustrated a parallel with Newton's universally accepted law of gravitation. This model, known as the gravity model, assumes that the amount of travellers moving between two specific locations is directly proportional to the population size of these locations. In parallel, this flow decreases in inverse proportion to their spatial separation(Wilson, 1971).

While the gravity model has gained considerable attention due to its notable outcomes, some limitations exist. In particular, the gravity model needs help accurately capture some patterns inherent in real-world flows(Wilkinson, 2023). Furthermore, the generative process of flows, as predicted by the gravity model, does not consider the influence of other factors, such as Points of Interest (POIs), street networks, and other contextual variables(Luca et al., 2021).

Besides that, spatial interaction models have some limitations in handling extensive datasets, such as loyalty card information, where basic calibration techniques can face constraints due to computational capabilities. (Wilkinson, 2023)

In parallel, some alternatives, such as the production-constrained model, have emerged to improve and extend the gravity model's efficacy. The Production-Constrained Model, conceived by Wilson (1971), introduces a key adjustment to traditional modelling techniques. Instead of relying on a single constant of proportionality, denoted as K, this model substitutes it with a set of constants commonly referred to as 'balancing factors'. This innovative approach allows more integration of additional knowledge as constraints within the modelling framework.

The production-constrained or retail model considers critical input data, specifically the population distribution and corresponding purchasing power, to arrive at meaningful insights(Wilson, 1971). Related to transport, the production-attraction-constrained model serves as a valuable tool. It operates assuming that 'trip ends,' which denote the predetermined number of origins and destinations within each zone for a given type of trip, are available as input data. The primary aim of this model is to estimate the attractiveness factor based on this crucial information. To illustrate, constructing a model to analyse commuting patterns corresponds to the number of residents working in a region and the number of jobs(Wilson, 1971). This innovative approach provides a more comprehensive understanding of the dynamics involved in various scenarios and underscores the versatility of the production-constrained model in diverse analytical contexts(Pooler, 1994; Wilkinson, 2023; Wilson, 1971).

2.3 Deep Learning for mobility flows

The application of neural network methodology in spatial interaction modelling marked a significant advancement in data science methodologies. A new approach from traditional models could provide more accurate predictions. (Wilkinson, 2023)

Comparative studies between neural network models and established frameworks revealed promising insights. These investigations indicated that neural networks could surpass the predictive accuracy of the Wilsonian model (Fischer and Gopal, 1994; Black, 1995; Wilkinson, 2023). However, it is crucial to note that these neural network models were frequently contrasted against unconstrained Ordinary Least Squares (OLS) calibrated models, raising queries about the true advantages of neural networks in spatial interaction modelling(Mozolin et al., 2000; Wilkinson, 2023).

According to Wilkinson (2023), incorporating neural networks presents specific challenges. The key requirement is the development of loss functions that are unambiguous, relevant, and clear. These functions play a pivotal role in estimating the total income of retail stores. The complexities of this implementation are highlighted in the iterative calibration phase, where the reliance on metrics such as average trip distance is emphasised. The early applications of neural networks in spatial interaction modelling demonstrated their potential to enhance predictive accuracy in commodity flows, trade, and migration domains. However, a comprehensive understanding of their advantages over traditional models requires more nuanced comparative assessments. Deep Learning models offer the advantage of high performance in capturing complex mobility patterns, a valuable method for flow generation. However, it is important to note their effectiveness on the data they are trained on, raising questions about their applicability across different geographical contexts.

Luca et al. (2021) study aims to investigate the use of deep learning techniques in mobility-related tasks. The research focuses on estimating mobility flows, particularly on generating realistic trajectories that replicate actual movement patterns. The study aims to enhance our understanding of complex mobility networks and their applications in various domains by utilising deep learning.

Besides that, an inherent characteristic of Deep Learning models is their opacity, often called "black boxes". As stated by Luca et al. (2021), This opacity can make interpreting the underlying logic behind generating trajectories or predicting locations and flows challenging. Nevertheless, interpretability is essential to comprehend mobility patterns and uncover potential biases in the model's decision-making process.

According to Luca et al. (2021), while Deep Learning models offer promise, they also introduce privacy concerns during the training and prediction phases. For instance, a critical issue in trajectory generation lies in assessing the risk of re-identifying real individuals from synthetic trajectory data. This concern becomes even more pronounced when data availability for model training is limited.

The evaluation of flow generators typically relies on commuting data obtained from official statistical institutes' censuses. The assessment of flow generation commonly revolves around calculating the Common Part Of Commuters (CPC) between real and generated flows. Additionally, widely used metrics like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) are also employed for this purpose.

To summarise, integrating Deep Learning into generative tasks related to mobility patterns is a relatively recent development poised to gain prominence in the near future. While these models hold the potential to unravel complex mobility dynamics, their reliance on training data, lack of transparency, privacy considerations, and evaluation metrics emphasise the multifaceted nature of their application in this domain.

In the figure 2.1 below, where Luca et al. (2021) surveys deep learning models centred on flow generation, it becomes evident that the Deep Gravity Model stands out for its ability to incorporate spatial patterns and geographic characteristics. This model aligns perfectly with the objectives of this study.

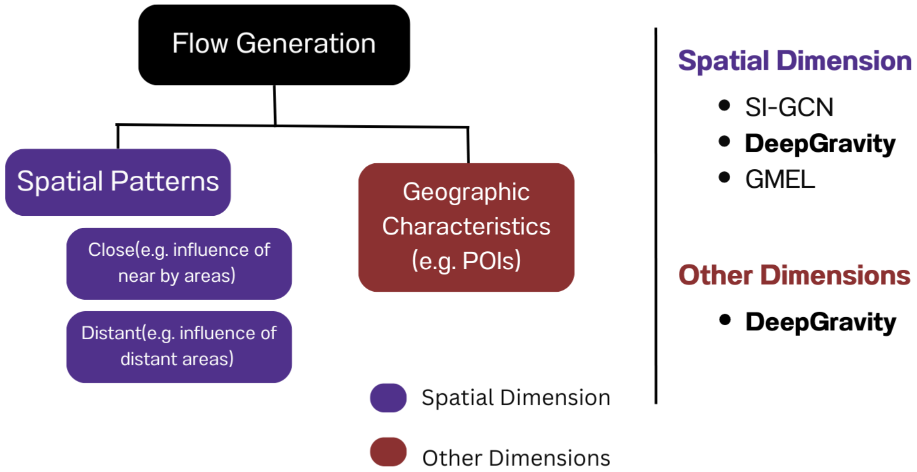

Figure 2.1: Deep Learning for Mobility Flows
Adapted from: Luca et al. (2021)

2.4 Deep Gravity Model

Deep learning methodologies have marked a significant landmark in mobility studies, particularly in analysing and predicting mobility flows. Some studies have presented the potential of deep learning techniques to encapsulate complex relationships embedded within mobility data while also drawing attention to the challenges inherent in the inherent opacity of these models, such as privacy concerns and the salient role of geographic features in enhancing the fidelity of flow predictions.

Luca et al.'s study underscores the unique capacity of deep learning models to navigate intricate and non-linear associations within the data. This feature enables the seamless assimilation of supplementary data about specific locations, such as population density and Points of Interest (POIs). This feat eludes conventional spatial interaction models. This novel approach drives the understanding of mobility patterns beyond the linear models, providing a more holistic comprehension(Luca et al., 2021).

Luca et al. (2021)'s work lies in the innovative concept of the Common Part of Commuters (CPC), an instrumental metric that assesses flow generator performance. This metric involves a comparative analysis of the model-generated flows against real-world data, thereby quantifying the accuracy of predictions. In addition to CPC, the study underscores the significance of employing a diverse array of evaluation metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), to offer a comprehensive understanding of model efficacy (Luca et al., 2021).

Beyond the technical aspects, the research presents the challenges tied to the inherent opacity of deep learning models, spotlighting the critical need to address privacy concerns, especially in scenarios involving trajectory generation where limited data availability poses a formidable obstacle (Luca et al., 2021).

Simini et al.'s work, adds a new dimension to the discourse by delving into flow prediction and generation. A key aspect of their approach is the strategic application of geographic features extracted from OpenStreetMap to improve the accuracy of mobility flow predictions. This strategic incorporation of geographical attributes forms the bedrock upon which the Deep Gravity model, a deep neural network, is trained.

The acknowledgement of the opacity challenge intrinsic to deep learning models is worth highlighting, which they address by supporting the input of explainable AI techniques to enhance the interpretability and transparency of the model's decision-making process (Simini et al., 2021).

Regarding model performance, Simini et al.'s research shed light on the superior efficacy of the Deep Gravity model vis-à-vis conventional shallow neural networks and established gravity models. This contrast in performance underscores the intrinsic potency of deep learning in uncovering nuanced relationships within geographical attributes, ultimately yielding more precise flow predictions (Simini et al., 2021). .

The study also highlights the pivotal role of the intricate interplay of diverse geographic features, particularly in densely populated regions. This intricate dance of geographic attributes significantly enhances the model's predictive capabilities, especially in scenarios where traditional models fall short (Simini et al., 2021).

In summary, the combined endeavours of Luca et al. (2021) and Simini et al. (2021) offer an insightful glimpse into the potential of deep learning models to decode and simulate the complex tapestry of mobility flows. These studies collectively illuminate the capacity of these models to untangle intricate relationships embedded within mobility data and underscore the significance of embedding geographic features to elevate the precision of flow predictions.

While these studies grapple with the challenges of model opacity and privacy concerns, they collectively herald the transformative potential of deep learning in enhancing our understanding of mobility patterns. By extrapolating from these findings, the Deep Gravity model emerges as a promising contender for replication across a diverse spectrum of contexts, effectively transcending the constraints of census data that formed the foundation of the original studies.

This extension holds the promise of extracting invaluable insights from high-accuracy datasets, as exemplified in the bustling urban milieu of London, potentially revolutionising the landscape of urban planning and decision-making.

2.5 Conclusion

In this literature review, we have explored the importance of estimating mobility flows and the relevance of spatial interaction models in this context, focusing on recent developments in deep learning models. Flow estimation, crucial for understanding urban mobility, involves synthesising patterns of movement between different geographical locations, considering factors such as population density, Points of Interest (POIs), land use, and distances. These flow patterns play a pivotal role in various domains, including urban planning, spatial economics, community design, and epidemiological modelling, addressing challenges related to transportation planning, socioeconomic disparities, community resilience, and disease spread.

Spatial interaction models offer valuable insights into flow estimation but have limitations in capturing complex real-world patterns and considering contextual factors like POIs and street networks. On the other hand, Deep learning models have brought significant advancements in mobility flow estimation, surpassing traditional models' predictive accuracy. These models excel in capturing complex relationships within mobility data, albeit with concerns about their opacity and privacy implications.

The Deep Gravity model, combining geographic features from OpenStreetMap with deep neural networks, demonstrates superior performance in flow prediction compared to conventional models, further emphasizing the potential of deep learning in unravelling nuanced relationships within geographical attributes. The studies collectively suggest that these models can improve our understanding of mobility patterns, especially when applied to high-accuracy datasets in urban planning and decision-making contexts.

Chapter 3

Methodology

This study analyses the performance exhibited by the Deep Gravity and Production-constrained models concerning work-related and non-work-related flows within London. As a result, this work establishes a comprehensive comparison between the outcomes generated by these models and the observed flow patterns present in the context of London. This comparative investigation provides a more robust understanding of the efficacy and applicability of the Deep Gravity and Production-constrained models.

3.1 Study Area

This study focuses on the entire region of London, its inner and outer areas. London has diverse cultures, nationalities, incomes, transportation options, public services, and amenities. To truly understand how people travel across the city, looking at the entire region is essential. This approach intends to understand the commuting patterns, considering all the factors contributing to how people move around in this diverse and dynamic urban environment.

3.2 Data

This study relies on three primary datasets: Locomizer, Point of Interest, and Census 2021. Locomizer serves as the central component of the analysis, with the aggregated origin and destination flow for London within hexagons as geographic area units. The hexagon ID serves as the primary index, and to ensure coherence, the remaining datasets are incorporated into this index via an area-weighted spatial join.

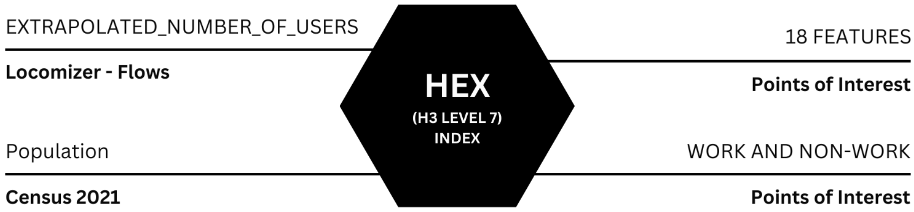

Figure 3.1: Methodology framework

3.2.1 Mobility data

The Locomizer is a human mobility dataset derived from mobile phone devices, ensuring that the participants have explicitly consented to utilise their data. This dataset contains a variety of key metrics. It captures observed and extrapolated counts of users who have spent time within a specified geographic area over a specific timeframe. Moreover, it includes the number of signals, effectively representing observations, at each location.

These metrics are organised based on different movement categories, distinguishing between pedestrian and non-pedestrian activities. Additionally, the dataset categorises users based on visitation modalities, differentiating "workers" from the overall population. Identifying the "common daytime location (CDL)" or the workplace for these worker users is accomplished by analysing device-level data and areas with the highest dwell time during typical working hours. This specific analysis aids in understanding and inferring the work-related locations of these users. To decrease granularity, worker users are aggregated, and the resulting data is presented at the point level, utilising a 69-meter radius around each point of interest (POI).

The dataset applied in this study contains aggregated data at level 9(Figure 3.2, with each dataset file including more than 4 million rows. The careful cleaning of this dataset emerged as an essential requirement to ensure the integrity of subsequent analyses. Hexagons play a key role in understanding spatial relationships, particularly mobility flows. Despite the computational limitation of running the spatial interaction model to deal with a high amount of data, it required a transition from hexagonal level 9 to level 7. This transformation was facilitated through the H3 package(Uber, 2023) in Python. At level 9, a hexagon has a relatively small area, approximately 0.10 square kilometres. In contrast, at level 7, a hexagon covers a significantly larger area, approximately 5.16 square kilometres.

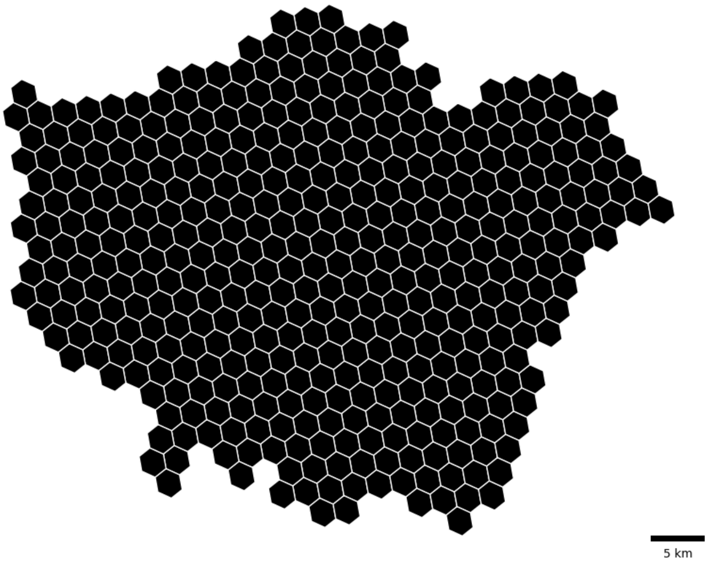

Figure 3.2: London in Hexagons at level 7

The dataset contains two fundamental segments: the origins, while the other relates to destinations. Both datasets are characterised by columns ORIGIN and DESTINATION. However, only the top 100 destinations were retained within the' Origin' segment. On the other hand, only the top 100 origins were incorporated in the' Destination' segment. This approach provides a more comprehensive overview of the system's dynamics. Flows lacking a defined origin or destination, denoted by '0' entries, were excluded. Moreover, it eliminated duplicated flow instances from the final dataset.

The 'extrapolated number of users' concept is introduced to estimate user presence within a specific geographic region over a designated time frame. Diverse movement modalities are available in the dataset, with the entirety ('all') and the workforce ('workers'). The 'transient' aspect, defined as the difference between the overall movement and the workforce, is established for non-work flows. The dataset explores variations in movement modes, such as walking/non-walking. However, this study considers the 'All' categorization to investigate the general mobility patterns.

It was chosen to focus only on data from a single day despite the availability of extensive datasets. Wednesday was chosen as the focus day to represent a regular workday without exceptional events, such as strikes. Additionally, Sunday was considered suitable for examining non-work-related movements, providing insights into mobility unaffected by work duties.

The Table 3.1 below summarizes the main aspects of the dataset. It provides insights into the utilized hexagonal grid, the identifiers for origin and destination points, the mode of movement, the temporal scope of analysis, and the specific days selected for work-related and non-work-related flows.

Features	**Description**
Grid	Uber H3 hexagons at Level 8
Origin_Code	Origin HEX ID
Destination_Code	Destination HEX ID
Visitation Modality	All
Movement Modality	All/ Workers/ Transients[1]
Daytime	25 (00.00-23.59)
Work Flow Date	08/03/2023 (Wednesday)
Non-work Flow Date	12/03/2023 (Sunday)

Table 3.1: Features classification - Locomizer Dataset

Hexagons at level 7 in London have 415 hexagons, resulting in 172,225 possible origin and destination flow combinations. Consequently, the dataset concerning work and workflows displays a distinct distribution, as shown in Figure 3.3. This distinction arises because workflows constitute only a fraction of the overall flow. As a result, this dataset showcases both a reduced maximum value and a lower mean value. This value difference leads to a more balanced workflow data distribution, as the accompanying graph shows. Furthermore, the distance from the mean (standard deviation) is notably smaller. Therefore, the values shown in the graphs are presented in logarithmic scale to accommodate the dataset's extensive size and prevent value distortion.

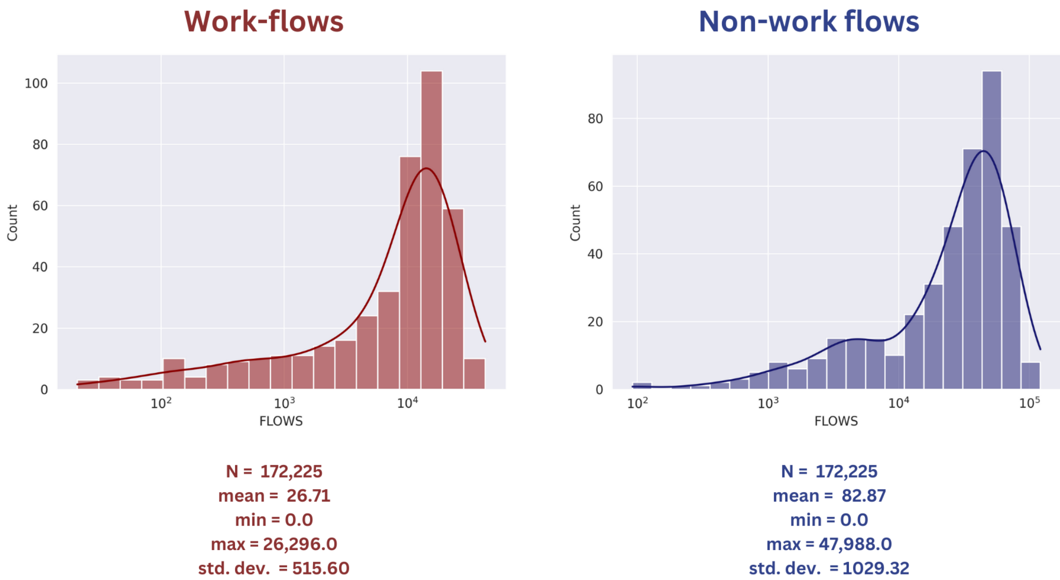

Figure 3.3: Data Values

3.2.2 Points of Interest(POI)

The Points of Interest is a dataset categorising various establishments and services across Great Britain, both public and private. The classification system is structured across three levels, each contributing to a comprehensive categorisation of various entities(OS, 2022*a*).

At the initial level, nine broad Groups serve as the foundation for classification, see Table 3.2 . These Groups contain diverse areas such as accommodation, eating and drinking establishments, commercial services, attractions, sports and entertainment facilities, education and health institutions, public infrastructure sites, manufacturing and production facilities, and retail and transport services.

COD	Categories	Examples
AED	Accommodation, Eating and Drinking	Hotels, Cafes, Pubs
CS	Commercial services	Construction, marketing services
AT	Attractions	Art Galleries, Zoos, museums
SE	Sport and Entertainment	Sports Complex, Cinemas
EH	Education and Health	Health centres, Primary Schools
PI	Public infrastructure	Police stations, Wi-Fi hotspots
MP	Manufacturing and production	Conservatories, Farming
RT	Retail	Bakeries, Department stores
TR	Transport	Bus stops, Tube stations

Table 3.2: POI categories

Moving to the next level, Level 2, this classification system becomes more refined, consisting of 52 distinct Categories. These Categories further study the entities, providing a more detailed perspective within each Group. Within these categories, specific subcategories define each entity's characteristics. Finally, Level 3 is the most specific classification level, featuring 600 individual Classes. This categorisation ensures a high level of granularity, allowing for precise differentiation and more understanding of the entities within the dataset.

A hierarchical structure of three distinct levels is evident within this framework(OS, 2022*b*), as shown in Figure 3.4. To provide a concrete example, let us examine the hierarchy within the context of transportation. At the highest level, we have the "Transport" category, a broad umbrella term. Moving down the hierarchy, we encounter the more specific "Category" known as "Bus Transport," which limits the focus to a subset of bus-related transportation. Finally, we reach the most granular level, "Class," exemplified by "Bus Stops". This hierarchical arrangement offers a versatile spectrum of possibilities and classification options, allowing for a comprehensive and structured approach to organising information within the given system.

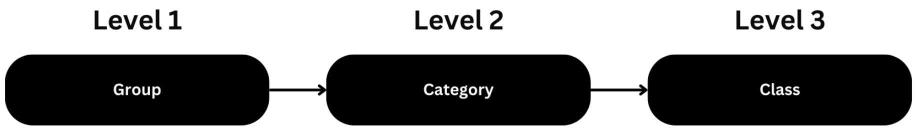

Figure 3.4: POI levels

Due to its increased complexity and adaptability to diverse geographic characteristics, the deep gravity model requires a comprehensive approach when applied to the POI dataset. This model requires a total set of 18 unique geographic features, each contributing specific information about each geographic unit, which, in this context, are represented by hexagons. We derived a classification based on the one in Simini et al. (2021) and the one given by the Ordnance Survey, see Table 3.3.

Therefore, the approach involves considering all available data points for extraction. The categories were restructured because the POI dataset initially included only nine distinct groups, while the Deep Gravity Model required 18 features as input. This restructuring aimed to optimise compatibility with the Deep Gravity Model and provide an equitable information distribution across the new features.

Item	Category
1	Bus Transport
2	Public Transport, Stations and Infrastructure
3	Water
4	Air
5	Education
6	Health
7	Accomodation
8	Restaurants
9	Fast Food
10	Pubs, Bars and Inns
11	Cafes, Snack Bars and Tea Rooms
12	Retail
13	Commercial Services
14	Sport and Entertainment
15	Attractions
16	Infrastructure and Facilities
17	Central and Local Government
18	Organisations

Table 3.3: Features classification based on POI dataset

The "Transport" category was disaggregated into four distinct features, each designed to encapsulate the richness of information originally associated with the broader transport aspect. These features effectively retained the essence of the original category names. Moreover, the "Education and Health" group has a similar transformation, grouping many correlated points of interest. Recognising that users often have varying motivations for visiting such locations, this group was split into two separate features: one dedicated to Education and the other to Health.

"Accommodation, Eating, and Drinking" showed many non-work-related opportunities, rendering it one of the most densely populated categories. As a result, this group was divided into four features, reflecting the underlying categories. On the other hand, "Retail," "Commercial Services," and "Attractions" were considered to retain their original classification without further splitting, maintaining a simplified representation. Moreover, the "Public Infrastructure" category garnered significant attention in the regression analysis(Tables 4.1 and 4.2), categorising it into three distinct features.

The detailed structure of the feature classification is available in the appendices A. It is important to highlight that this new classification strategy does not consider the "level class" despite the limitations in feature count and the analytical complexity.

Within the Spatial Interaction Model (SIM) framework, the Point of Interest (POI) dataset aggregates the cumulative counts of points relevant to work-related and non-work-related amenities. This categorisation was the foundation for a statistical analysis to unveil the relationships between specific POI groups and Mobility Data Flows. Two separate regression analyses were conducted—one tailored to work-related flows and another to non-work flows.

3.2.3 Census data

The census data plays a crucial role in both models. In the spatial interaction model, the population is one of the independent variables used to calculate predicted flows alongside factors like distance and attractiveness. Meanwhile, the Deep Gravity Model population data contributes to the location feature vector, which offers a spatial representation for each hexagon. This feature vector includes information from the Points of Interest (POI) dataset and the population size of hexagons obtained from the 2021 census.

Data consistency is vital, given that the mobility data collected is from 2023, while the Points of Interest data is from 2022. Therefore, including the 2021 census data on London's population becomes crucial for maintaining coherence in the final data analysis. Thus, to prepare the data for use in the models, it was necessary to aggregate it under a common index—specifically, the Mobility data index in Hexagons at level 7. This aggregation step ensures the data is structured consistently for both models' analyses.

Moreover, population data include an integral part of the 'Population and household estimates for England and Wales: Census 2021'. The Census employs a definition of a usual resident, encompassing individuals who were in the UK on Census Day (21 March 2021) and intended to stay for at least 12 months. Meanwhile, a household is defined as a single person living alone or a collective group.

3.3 Research scope

3.3.1 Deep gravity Model

According to Simini et al. (2021), To generate flows from a given origin location, denoted as l_i, the Deep Gravity Model employs a set of input features to calculate the probability $p_{i,j}$ that any of the n locations within the region of interest, represented as l_j, serves as the destination for a trip originating from l_i. This model produces an n-dimensional vector of probabilities $p_{i,j}$ for $j = 1,\dots,n$. The computation of these probabilities follows a three-step process.

Firstly, the input vectors $x(l_i,l_j) = \text{concat}[x_i,x_j,r_{i,j}]$ for $j = 1,\dots,n$ are derived by concatenating various input features. Here, x_i denotes the feature vector of the origin location l_i, x_j signifies the feature vector of the destination location l_j, and $r_{i,j}$ represents the distance between the origin and destination. For each origin location, l_i, n input vectors $x(l_i,l_j)$ are created, one for each potential destination location within the region of interest.

These input vectors $x(l_i,l_j)$ are concurrently fed into the same feed-forward neural network in the second step. This network comprises 15 hidden layers, with dimensions of 256 for the bottom six layers and 128 for the remaining layers. Specifically, the output of the initial layer, denoted as $h = 0$, is given by the vector $z(0)(l_i,l_j) = a(W(0)\cdot x(l_i,l_j))$, and for subsequent layers with $h > 0$, it is expressed as $z(h)(l_i,l_j) = a(W(h)\cdot z(h-1)(l_i,l_j))$, where W represents matrices with entries representing parameters learned during the training process.

The output of the final layer is a scalar $s(l_i,l_j) \in [-\infty,+\infty]$, referred to as the score. A higher score for a pair of locations (l_i,l_j) implies a greater likelihood of observing a trip from l_i to l_j according to the model. These scores are subsequently transformed into probabilities through a softmax function, given by $p_{i,j} = e^{s(l_i,l_j)} / \sum_k e^{s(l_i,l_k)}$. This function converts all scores into positive values that collectively sum up to one.

The generated flow between two locations is obtained by multiplying the probability (i.e., the model's output) by the total outflow from the origin.

Additionally, Deep Gravity considers the geographic distance, $r_{i,j}$, between two locations, l_i and l_j, measured along the earth's surface between the centroids of the two polygons representing the locations. Each flow in Deep Gravity is described by 39 features, comprising 18 geographic features of the origin and 18 of the destination, along with the distance between the origin and destination and their populations.

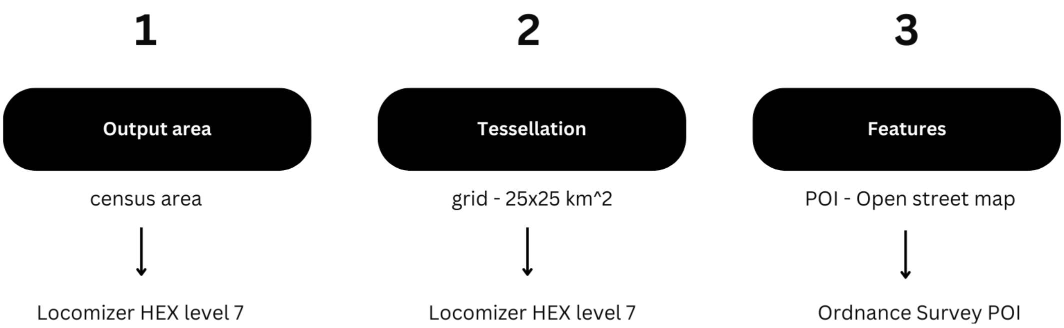

Figure 3.5: Deep Gravity Model inputs

Moreover, deep gravity(Simini et al., 2021) is a model developed using Pytorch. This Python library conducts real-time execution of dynamic tensor computations, incorporating automatic differentiation and GPU acceleration while maintaining performance levels on par with the fastest contemporary deep learning libraries(Paszke et al., 2019).

3.3.2 Spatial Interaction Model

The selected spatial interaction model for assessing commuting flows for work and non-work purposes is the production-constrained model, commonly called the retail model. This model offers the advantage of constraining origin information, employing categorical variables, the distance and incorporating data on destination attractiveness. It enables us to gain insights into the dynamics of commute flows from various origins to potential destinations. Our study determined destination attractiveness by considering the total counts of points of interest associated with each flow type, as outlined in the Dataset section.

The availability of the Mobility dataset plays a crucial role, enabling the collection of work and non-work flows between origin and destination hexagons. Consequently, the equation of this model can be expressed as follows:

$$T_{ij} = A_i O_i D_j^{\gamma} d_{ij}^{-\beta} \tag{1}$$

where

$$A_i = \frac{1}{\sum_j D_j^{\gamma} d_{ij}^{-\beta}} \tag{2}$$

- A_i stands for a vector of size n containing the Hexagon origin balancing factors, essential for maintaining the total out-flows in the predicted flows.

- O_i represents a vector of size n that indicates the total number of flows originating from the origin i (Hexagon Origin ID).

- $f(d_{ij}) = d_{ij}^{-\beta}$ is a function of cost or distance, referred to as the distance-decay function.

The model is calibrated using a Poisson Regression function

$$\lambda_{ij} = \exp(\alpha_i + \gamma \ln D_j - \beta \ln d_{ij}) \tag{4}$$

where α_i

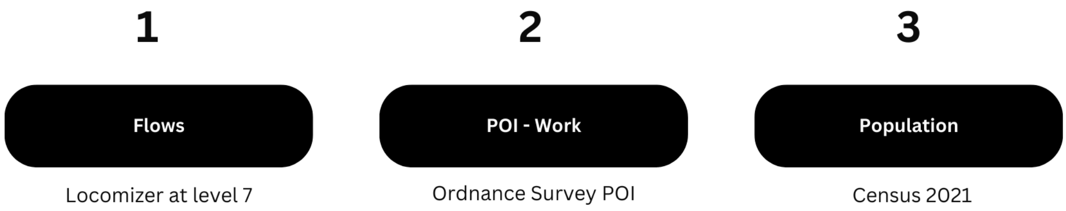

Figure 3.6: Spatial Interaction Model Inputs

3.3.3 Validation

The main objective of this study is to use the Root Mean Squared Error (RMSE) to validate models designed for both work and non-work flows. Alongside RMSE, other frequently employed metrics include the Mean Average Error (MAE) and the Mean Average Percentage Error (MAPE). Several error metrics, such as MAE, Mean Squared Error (MSE), RMSE, and MAPE, are frequently employed within this context. These metrics operate within the $[0, \infty]$ range, where in lower values indicate superior performance. Moreover, The evaluation of flow generation is also carried out by measuring the Common Part of Commuters (CPC) between real and generated flows(Luca et al., 2021).

As Luca et al. (2021) stated, MAE considers the absolute value of errors, neglecting the direction of overestimation or underestimation. On the other hand, MSE emphasizes larger errors more significantly than MAE and is also sensitive to outliers. RMSE, the focus of this study, places a greater emphasis on errors than MAE, penalizing models that produce substantial errors. This particular metric is expressed in the same units as the predicted values due to the squared nature of the calculation.

Therefore, this study's pursuit of employing RMSE to validate models dealing with work and non-work flows aligns with established evaluation practices.

3.3.4 Ethical Consideration

The Locomizer dataset encompasses mobile device-derived information aggregated at hexagons levels, with data updates occurring hourly. The provider of this dataset, LOCOMIZER Ltd, has affirmed its adherence to the General Data Protection Regulation (GDPR) of 2018. This data repository comprises mobility data sourced from mobile devices, procured exclusively with explicit user consent and meticulous observance of local privacy regulations, including but not limited to GDPR.

The dataset adopts a spatial aggregation approach utilizing hexagonal cells, specifically at H3, level 9, and encompasses the geographical expanse of London. Each hexagonal cell corresponds to an approximate area of 0.1 km^2. The data's temporal granularity follows an hourly structure, which is subsequently summarized daily within the scope of a designated month. Consequently, the intrinsic design of the dataset precludes the identification of individualized locations.

In this context, the Locomizer dataset was obtained by Foster and Partners, the project partner of this dissertation project. This collaborative initiative has established prior authorization for data usage as stipulated within the agreement between the two parties. As a result, the ethical implications surrounding this study were considered low risk, culminating in the project's approval by the Committee for the Centre for Advanced Spatial Analysis (CASA) at University College London (UCL).

Chapter 4

Results and Discussion

4.1 Parameters

4.1.1 Flows

As evident from the observed movement patterns from the Mobility Dataset in Figure 4.1 , work-related and non-work-related flows exhibit a concentration of commuting trajectories within central London. Moreover, substantial flows are concentrated in the northeastern and southwestern regions of the city. The most notable difference between these two categories of flows lies in the concentration level: Work-related flows demonstrate a heightened level of convergence, whereas non-work-related flows display a distribution that extends spatially across a broader area.

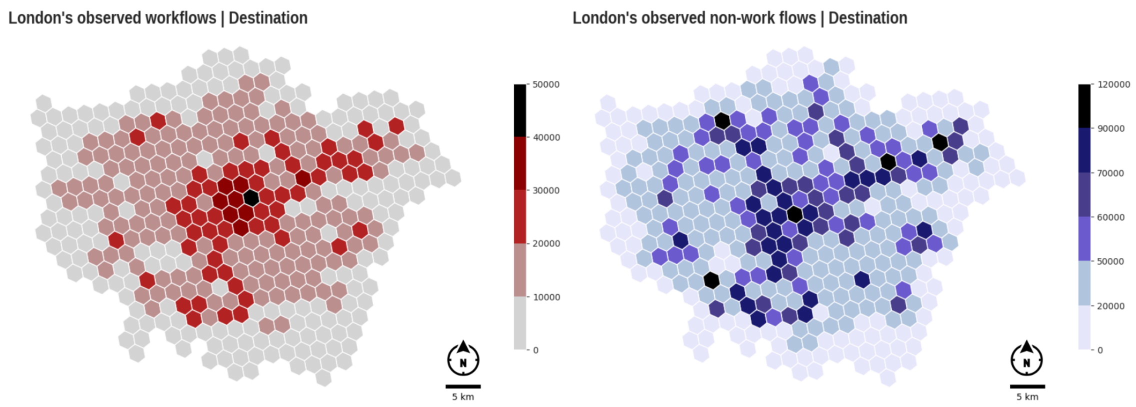

Figure 4.1: London's observed flows: work and non-work.

4.1.2 Features

4.1.3 Attractiveness Factor

In the workflow regression analysis(Table 4.1), it is evident that the variables "EH," "PI," and "TR" have statistical significance since their p-values are low (all below 0.001). This indicates that these variables noticeably affect the dependent variable we are studying. Additionally, the high R-squared and adjusted R-squared values (0.863 and 0.860) signify that the model effectively explains much of the variation in the dependent variable.

As part of the analytical refinement process, it was excluded the variables "CS" (commercial services) and "SE" (Sport and Entertainment). These variables were omitted due to their elevated p-values, above 0.4, signalling a lack of statistical significance. Additionally, both models exhibited a notably high condition number. However, a significant improvement was observed upon removing these two variables. The condition number, originally at 1.27e+03, was substantially reduced to a more manageable 647 in both regression models.

Variables	**coef**	**std err**	**P>|t|**
Intercept	932.6236	284.803	0.001
AED	-14.0624	3.827	0.000
AT	-42.8778	9.624	0.000
EH	**33.2344**	**6.902**	**0.000**
MP	-32.6702	6.067	0.000
PI	**80.2838**	**6.608**	**0.000**
RT	5.8310	2.613	0.026
TR	**18.1677**	**6.916**	**0.009**
R-squared	0.863		
Adj. R-squared	0.860		
Cond. No.	647.		

Table 4.1: OLS Regression Results

Thus, within the context of workflows, the collective counts of Points of Interest from these three categories, namely "EH," "PI," and "TR," represent the Work-related Points of Interest. As shown in Figure 4.2, these variables represent a linear relationship with the observed flows.

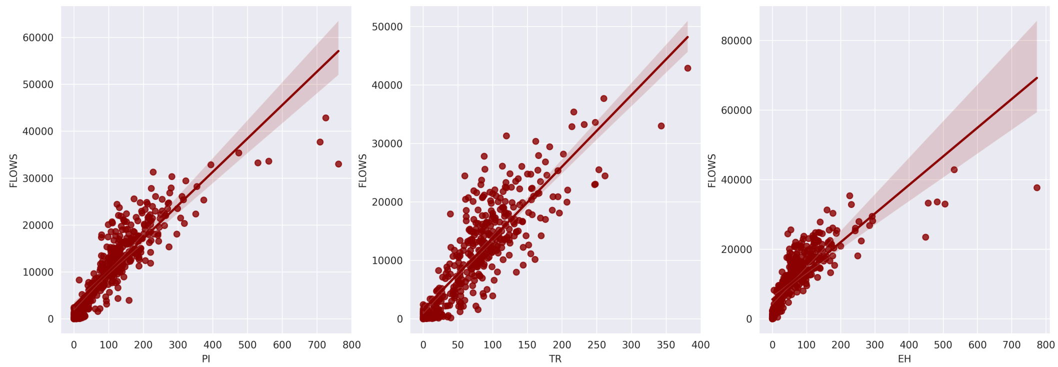

Figure 4.2: Work - Linear Regression: Flows vs POI

Regarding the non-work flows regression analysis in Table 4.2, we observe that the variables "EH," "PI," "RT," and "TR" also demonstrate statistical significance, as their p-values are very low (all below 0.001). This implies that these variables significantly impact the dependent variable. The R-squared and adjusted R-squared values (0.782 and 0.778) indicate that our model effectively clarifies a significant portion of the variation in the dependent variable.

Variables	**coef**	**std err**	**P>|t|**
Intercept	5655.2406	1030.797	0.000
AED	-75.1430	13.851	0.000
AT	-201.4072	34.834	0.000
EH	**113.3599**	**24.982**	**0.000**
MP	-131.6164	21.959	0.000
PI	**218.6156**	**23.916**	**0.000**
RT	**58.1842**	**9.456**	**0.000**
TR	**73.5557**	**25.033**	**0.003**
R-squared	0.782		
Adj. R-squared	0.778		
Cond. No.	647.		

Table 4.2: OLS Regression Results

In the non-work flows context, the combined counts of Points of Interest from these four categories, "EH," "PI," "RT," and "TR," symbolise the Non-Work-related Points of Interest. Thus, both regression models(Figure 4.3) appear well-suited for explaining the relationships between the independent and dependent variables.

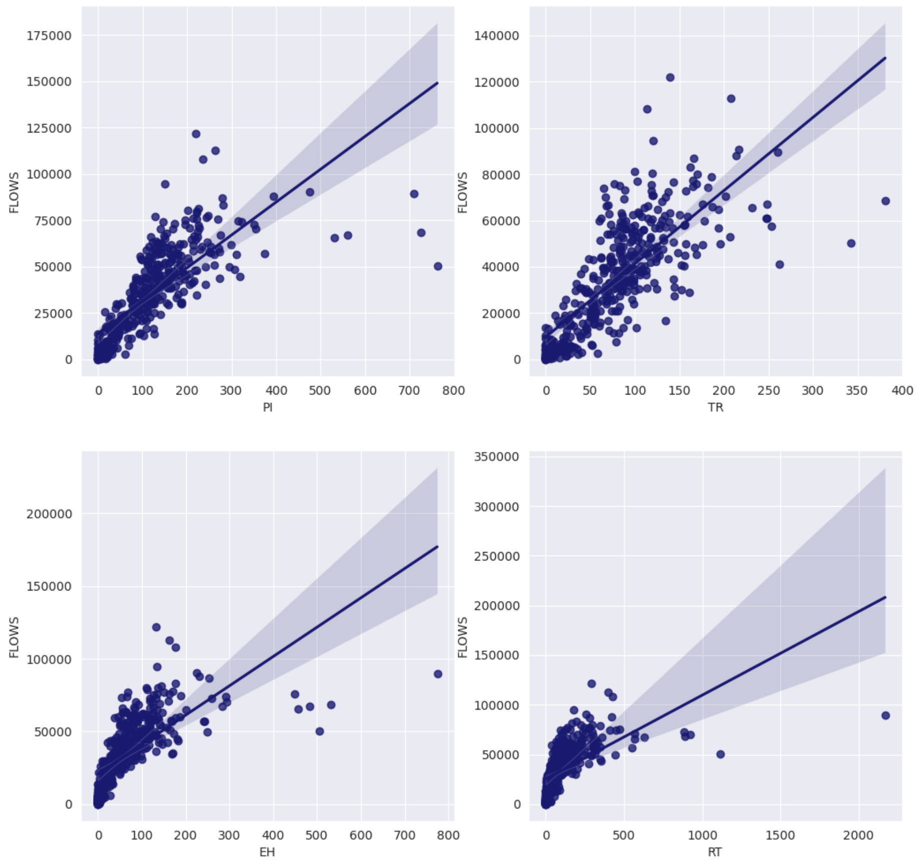

Figure 4.3: Non-Work - Linear Regression: Flows vs POI

In the context of residuals within both models(Figure 4.4), it is crucial to note that their distribution is normal, a fundamental assumption in regression analysis. This normal distribution holds significance because it indicates that errors in the model's predictions are distributed evenly around zero. Furthermore, the concentration of values is near zero when assessing the relationship between residuals and fitted values. This pattern confirms the suitability of the chosen linear regression models for the analysis.

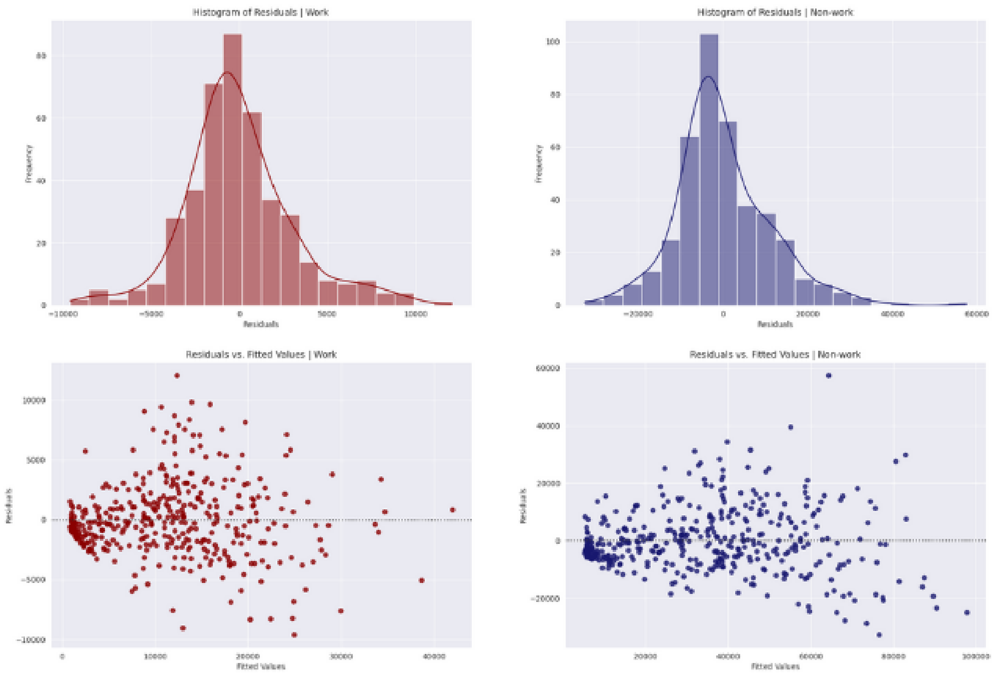

Figure 4.4: Residuals - Overview

The map below(Figure 4.5) illustrates the spatial distribution of Points of Interest (POI) in London, categorising them into work-related and non-work-related. It becomes evident that their distribution across the city exhibits a degree of similarity, predominantly concentrating in inner London instead of outer London. However, it is worth emphasising that the total number of points differs significantly due to the non-work category that contains four distinct POI groups. The POI values for non-work are also correlated with mobility flow values distribution, as the proportions remain consistent. Work-related flows represent only a fraction of the city's overall journeys, whereas non-work flows encompass a broader spectrum of activities.

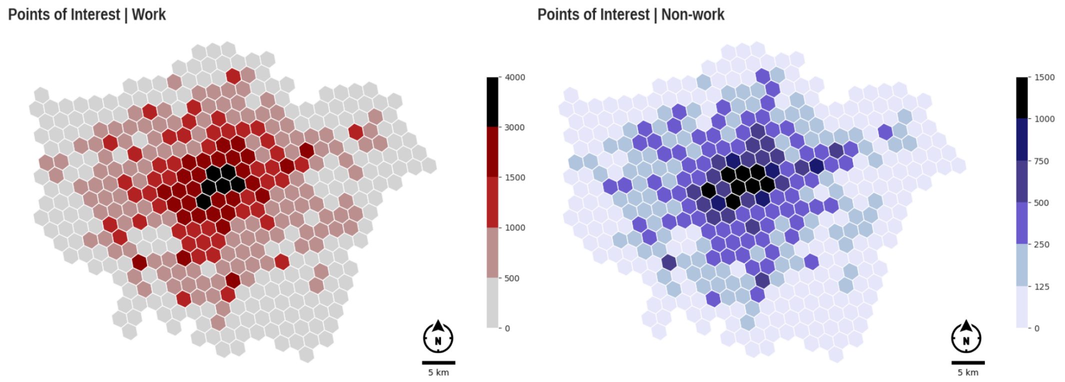

Figure 4.5: Points of Interest spatial distribution: Work and Non-work

Additionally, the analysis reveals varying concentration patterns between the two categories of amenities. Work-related amenities exhibit a higher concentration in the city centre, whereas non-work amenities exhibit a more gradual and dispersed distribution throughout the city. This nuanced spatial distinction highlights these amenities' differential nature and accessibility for London's residents and visitors.

4.1.4 Population

To standardise the data, the 2021 census population data was aggregated, aligning it with the level 7 hexagons, as visually represented in the map below(Figure 4.6). This aggregation illustrate a significant concentration of residents within inner London, especially within the northeastern quadrant. While some other areas display a more dispersed spatial distribution, central London's concentration closely reflects the distribution patterns evident in the Points of Interest dataset and the mobility flows data.

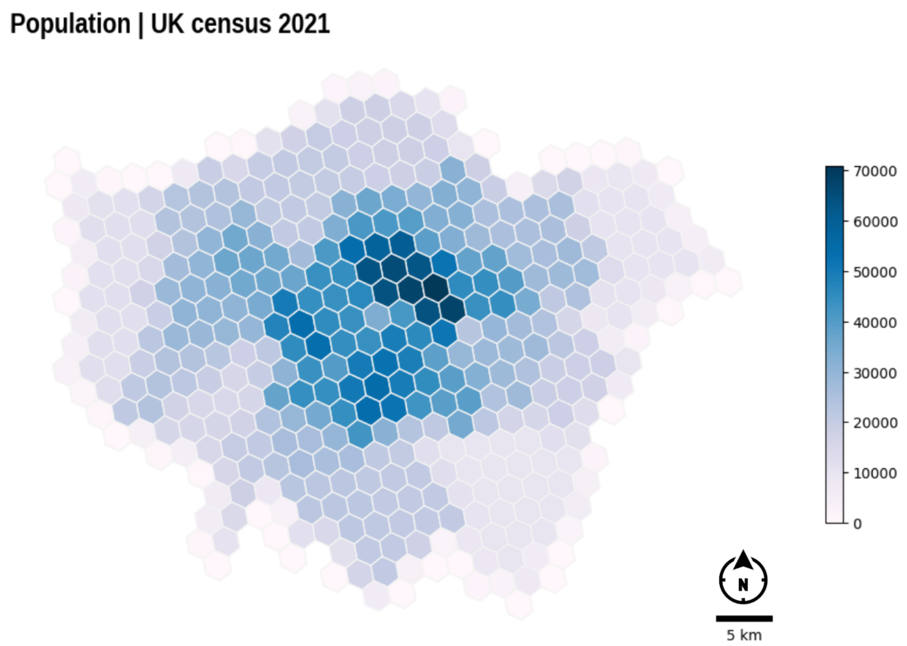

Figure 4.6: Population - UK Census 2021

4.2 Analyzing the models comparatively

The application of the spatial interaction model revealed limitations when processing the large dataset from the Mobility dataset. However, in contrast, the Deep Gravity Model demonstrated exceptional predictive capabilities, even in the face of substantial data volumes. The deep gravity model showcased its effectiveness when analyzing hexagons up to level 9, encompassing a vast geographical expanse of 17,636 hexagons and offering over 300 million potential origin-destination flows. On the other hand, the spatial interaction model was limited. It was restricted to operating exclusively within hexagons at level 7, where it relied upon the computational of a GPU equipped with high-performance RAM.

The architecture of the Deep Gravity Model entails a division of geographic region units into distinct training and test groups, a feature that has contributed to its challenges in effectively managing Big Datasets. Consequently, the model generates results exclusively for the training sample. Therefore, to maintain the integrity and consistency in our comparative analysis across various models and flow types, we opted to employ the same sample for the Production-Constrained Model, aligning it with the dataset utilised for the Deep Gravity Model. This approach ensured a comprehensive and meaningful evaluation of model performance and the complex flow dynamics patterns aimed to uncover and understand.

Some key findings in the regression plot(4.7) illustrate the relationship between the observed flows and those generated by the Deep Gravity Model (DG) and the Spatial Interaction Model (SIM). Therefore, the plot reveals a linear relationship on relationship between these variables. Furthermore, the graph unveils distinctive characteristics in the distribution of data values for each flow type. Specifically, when we examine the non-work flows, they exhibit a higher concentration, with values clustering closer to zero on the graph. In contrast, the non-work flows display a more dispersed pattern, with values distributed across a wider range of values. This divergence in the distribution patterns of the two flow types is a significant finding drawn from the regression plot. It emphasises the need for a differentiated analytical approach for each flow type.

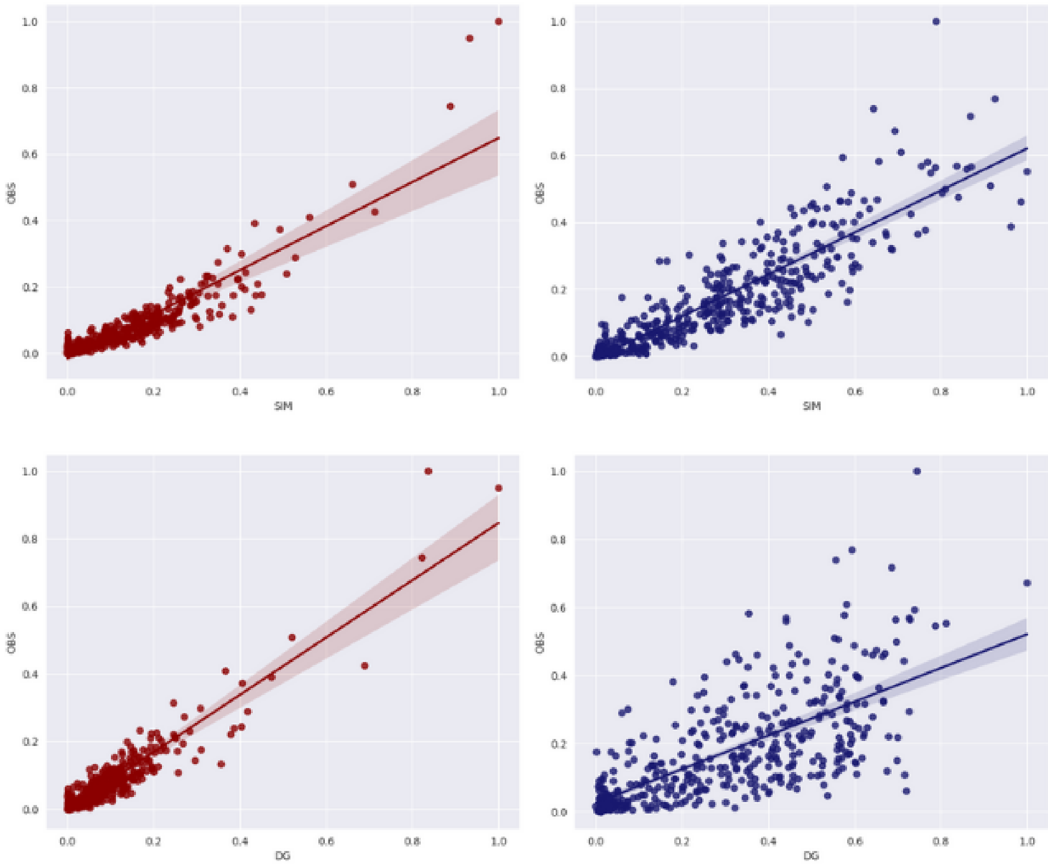

Figure 4.7: Flows - Regression plot
Red: Workflows. **Blue:** Non-work flows.

In assessing the performance of the models in predicting flows, it is evident that the R-squared values for Non-work flows outperform those for workflows, with a notable high value of 0.7 observed in the production-constrained model for non-work flows and 0.9 in the Deep Gravity Model. In the context of workflows, the DG model achieved a better performance of 0.9, while the SIM model had 0.6.

R-squared serves as a valuable metric for comprehending the influence of variables on flow prediction. Consequently, it becomes crucial to measure the efficacy of each model in estimating flows and the capability of selected independent variables in predicting the outcome. Among these variables, including distance, population, and the attractiveness factor derived from Points of Interest (POI), it is evident that they demonstrate superior performance in estimating flows, particularly within the Deep gravity model, outperforming the SIM model. Because of that, evaluating the Root Mean Square Error (RMSE) arises as an essential measure for comparing and evaluating the models against each other.

The performance of the models displayed significant variations depending on the specific type of flow under consideration. It is important to highlight that the Production-Constrained Model, when put to the test, yielded the lowest RMSE value, achieving a relevant score of 14.69 for work-related flows. On the other hand, the Deep Gravity Model showcased a significantly lower RMSE value as well, standing at 41.47 for workflows. The model performance across these different flow types is concisely summarised in Table 4.3, providing a comprehensive overview of how each model excelled in distinct aspects of mobility prediction.

Flows type	**Deep Gravity**	**Production-Constrained**
Work	41.47	14.69
Non-work	336.71	141.19

Table 4.3: RMSE

The contrast in model performance reveals a pattern: Models rooted in deep learning structures outperform the production-constrained model when predicting workflows. This result is evidenced by the high r-squared values and low RMSE (Root Mean Square Error) associated with these models. On the other hand, the prediction of non-work flows reveals a more complex context characterised by non-linear trajectories within the urban environment. Thus, both models achieve high r-squared values, with the deep gravity model slightly edging ahead. However, the SIM model records a lower RMSE value than the deep gravity model in this context.

Nevertheless, despite the spatial interaction model's computational limitations, the deep gravity model performs better when handling larger datasets. This is exemplified in Table 4.4, where the model demonstrates an r-squared of 0.7, lower than what was achieved at level 7. However, it is worth noting that the deep gravity model yields a lower RMSE, specifically

28.01, higher than the corresponding figure for the SIM model. Therefore, when the model aggregates data, the DG model experiences a decrease in performance in terms of RMSE, indicating the specificities of model behaviour under varying data conditions.

Flows type	**Level 8**	**Level 7**
Work	433.65	41.47
Non-work	28.01	336.71

Table 4.4: RMSE- Deep Gravity Model at Hexagons level 7 and 8

In this context, the non-work flows contain various activities and behaviours within a city, such as leisure, tourism, and social interactions. These activities tend to follow less predictable patterns, making them challenging to model accurately. However, with its inherent capacity to capture intricate relationships and dependencies within the data, the Deep Gravity Model excelled in this aspect. It showcased its ability to predict the diverse and sometimes complex mobility patterns associated with non-work-related activities, producing lower error rates.

The traditional Spatial Interaction Model demonstrated its comparative advantage in estimating flows characterised by a more linear and structured relationship, primarily those about work-related activities. Workflows often follow established commuting routes and daily routines, resulting in more predictable mobility patterns. In these scenarios, the traditional model indicated greater accuracy in the workflow predictions. However, it obtained an RMSE rate for non-workflows.

In addition to the previously mentioned metrics, a spatial analysis of how the two models reflect estimated flows is crucial. By using the Observed Flows (OBS) as a reference, we can better comprehend how these metrics evaluate the performance of both the Deep Gravity Model (DG) and the Spatial Interaction Model (SIM). Moreover, values were normalised to compare the models.

Examining the workflows illustrated on the left in red(see Figure 4.8), it becomes apparent that both models exhibit a similar pattern of flow concentration in central London. However, there is a significant distinction: the SIM model tends to overestimate some of the flows, with disparities varying from 0.15 to 0.30 compared to the Observed Flows. In contrast, the DG model's flow estimations closely align with the distribution of the Observed Flows, reinforcing the significance of its low RMSE value.

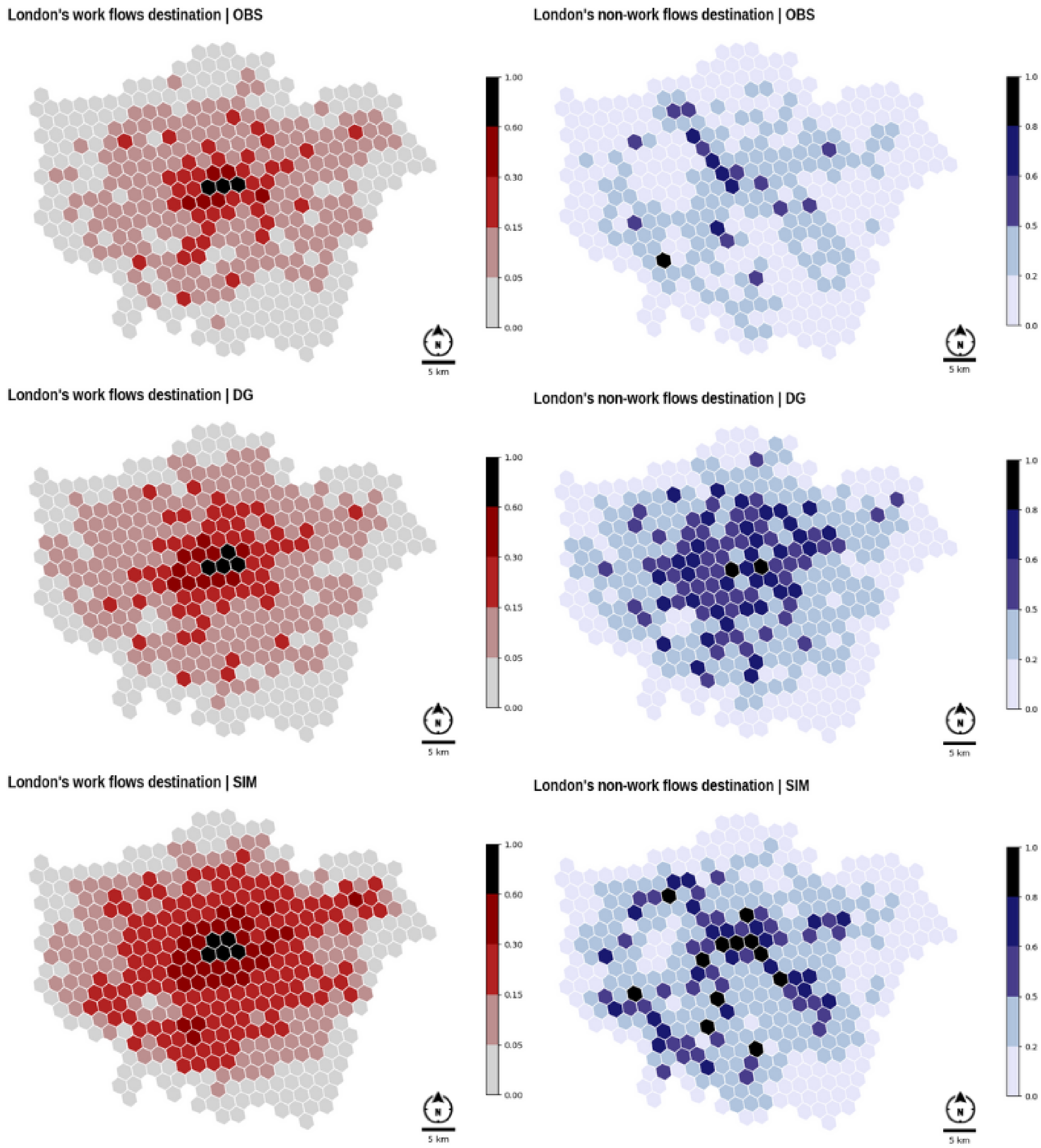

Figure 4.8: Observed and predicted flows for work and non-work flows
OBS: Observed, DG: Deep Gravity, SIM: Spatial Interaction model, Red: workflows, Blue: non-workflows

Shifting our focus to the non-work flows shown on the right in blue, we observe a different outcome. At this level 7 of Uber hexagons, the Spatial Interaction Model displays greater accuracy in estimating non-work flow data, consistent with its previously noted low RMSE value. In contrast, the Deep Gravity Model tends to overestimate the flows, with disparities ranging between 0.5 and 0.6 compared to the Observed Flows. These spatial insights further illustrate both models' nuanced performance characteristics regarding their strengths and limitations in different flow scenarios.

4.3 Discussion

The attractiveness factor utilised in the Spatial Interaction Model for Work and Non-work flows was constructed based on the categories within the POI dataset; see Figure 4.9. In the context of Workflows, the analysis revealed that Public Infrastructure (PI), Transport (TR), and Education and Health (EH) emerged as the most significant variables in the data collected from Mobility Data. In contrast, for the Non-work attractiveness factor, the primary variables align with those of the Workflows, except for Retail (RT).

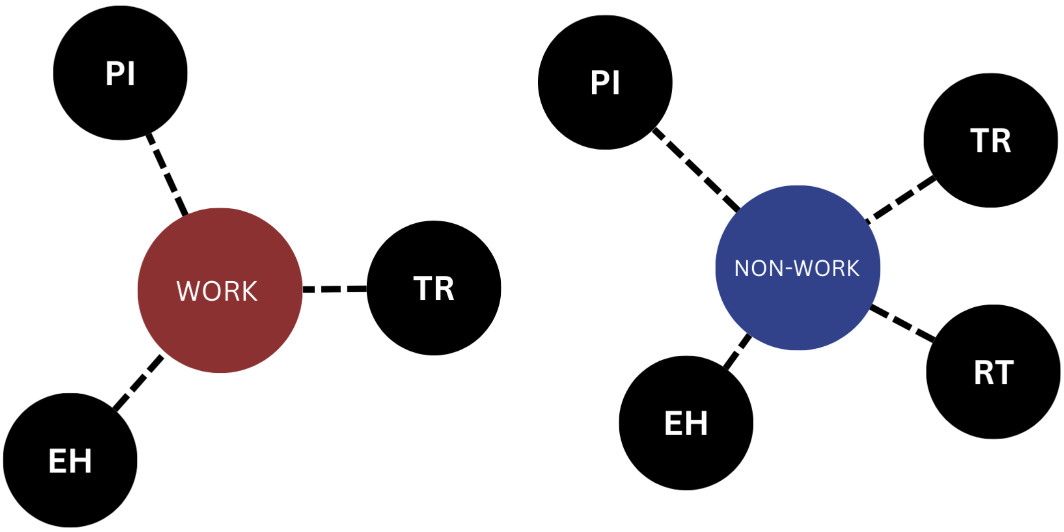

Figure 4.9: Attractiveness factor

Mobility data sourced from Locomizer has emerged as a valuable and contemporary resource for analysing commuting dynamics. The data used in this study, collected in March, contrasts with the 2021 Census data on Origin and Destination. While both datasets primarily target the retail market, they offer profound insights into urban planning, which is increasingly influenced by dynamic factors. These factors encompass climate crises, ranging from intense rainfall to scorching heat waves and socioeconomic variables, exemplified by recent strikes in various sectors across England.

Locomizer's dataset extends many possibilities for spatial analysis, many of which still need to be explored within the scope of this research. It offers the potential to unravel travel patterns by transportation mode and delve into user trajectories at different times of the day. Thus, it can provide hypotheses about how mobility impacts the city's dynamics across various temporal dimensions.

Regarding the features considered, this analysis primarily focused on geographic data related to the Points of Interest dataset. However, given that the Deep Gravity Model can accommodate up to 18 features in its vector, integrating additional databases, such as OpenStreetMap, holds the promise of introducing greater complexity. This complexity would help characterise the geographic region under study, the mobility flows, and the factors influencing urban movement.

Including the population census dataset played a pivotal role in running the four models. Nevertheless, it would be essential if Locomizer's Mobility data provided information on the Visitation Modality for worker users and residents. Despite indications in the dataset's documentation that such information is available, the version used for this research needed to have this important component. Including resident data could enhance data integrity and deepen our understanding of user mobility patterns within the Locomizer system.

The impressive performance of the Deep Gravity Model when handling large datasets underscores the potential of new models that leverage machine learning techniques, including deep learning. The model's capability extends to analysing hexagons up to level 9, encompassing 17,636 hexagons and 300 million origin and destination possibilities. These models enable the effective management of complex, contemporary databases that demand enhanced computational capabilities. However, documentation is crucial for reproducible analysis, especially for the Deep Gravity model, which boasts a sophisticated and innovative structure for flow estimation.

The lack of comprehensive documentation regarding input data structure and the complex code structure, employing PyTorch posed challenges when applying the large mobility dataset to the model.

Both models demonstrated strong performance in estimating flows, yet the analysis context proved critical in determining the most suitable methodology. The SIM model excelled with aggregate data, while the Deep Gravity model performed better with granular data, even operating at the hexagon level 9 to estimate origin-destination flows. However, the results highlighted the ongoing complexity and challenges of estimating non-work-related flows. Even the Deep Gravity model, with its new structure and advanced computational methods, faced limitations in predicting these flows accurately.

This outcome offers valuable insights into the relationship between these two flow types concerning user destinations. However, it is important to clarify that these Points of Interest do not necessarily imply exclusive representation of workplaces or leisure destinations. Instead, it signifies the coexistence of amenity categories within specific geographic regions (hexagons), where opportunities for work or leisure naturally converge.

To illustrate further, in the context of workflows, the coexistence of Points of Interest related to Public Infrastructure, Transport, Education, and Health suggests a probable concentration of work-related activities within that region. Conversely, non-work flows, which include Retail as a significant variable, present intriguing complexities. These flows encompass activities unrelated to work, such as visits to parks, schools, and cafes. Consequently, the aggregation of these four amenity types closely reflects the destinations of individuals in London who are primarily there for non-work-related purposes, thereby enriching our understanding of the diverse dynamics of urban mobility.

In this study, a series of critical questions deserve careful consideration:

Firstly, evaluating the relative performance of the Deep Gravity Model in estimating carbon emissions within the London area is essential. This assessment provides valuable insights into the model's effectiveness in capturing the complex dynamics of carbon emissions, which is crucial for understanding urban environmental impact. Secondly, the combined analysis of the Deep Gravity Model with accessibility measures presents a crucial path for investigation. This integration can enhance the model's predictive capacity by leveraging accessibility data, providing a more comprehensive understanding of the factors influencing carbon emissions.

Besides that, it is crucial to consider the limitations inherent in this analysis. Thus, consider additional performance metrics that can comprehensively assess the Deep Gravity Model's effectiveness relative to alternative methodologies to ensure a robust comparison.This broader perspective facilitates a comprehensive understanding of the strengths and weaknesses of each model, leading to more informed conclusions regarding their respective capabilities in mobility flow estimation.

The primary concern is that the two primary metrics commonly utilised in this context, namely R2 and RMSE/SRMSE, have previously been indicated as inadequate representations of the actual inherent model performance due to the unique characteristics of spatial interaction flow. Consequently, this can result in erroneous deductions regarding relative performance (Knudsen & Fotheringham, 1986) Wilkinson (2023). Despite the complexity of the datasets involved, particularly the Mobility Data, and the inclusion of multiple models (totalling four models), the principal focus of this study remains centred on utilising RMSE as the primary parameter and supplementing it with R-squared for individual model performance. However, it is crucial to acknowledge the limitation Wilkinson (2023) outlined for a more comprehensive analysis. As emphasized by Wilkinson, when assessing the efficacy of spatial interaction models, it becomes crucial to account for the outcomes generated by these models, ensuring their alignment with the dataset. He warns against only using a single metric for evaluation, as such an approach might generate inaccurate conclusions regarding modelling performance.

Thus, it resonates with the view that an evaluation is necessary to avoid misguided interpretations.

Furthermore, Wilkinson (2023); Luca et al. (2021) highlights a key consideration - the overall usage of two key metrics, R-squared and RMSE/SRMSE, may not necessarily capture the genuine underlying performance of a model. It is attributed to the inherent characteristics of spatial interaction flow, leading to potential inaccuracies in determining relative performance. Knudsen and Fotheringham (1986) suggest that these metrics might only partially reflect the true model performance due to the complex dynamics inherent in spatial interaction. Combining these perspectives, it is evident that while RMSE and R-squared offer valuable insights, their limitations must be acknowledged. Particularly, the exclusion of additional evaluation criteria and the potential inadequacy of certain metrics in capturing complex spatial dynamics need to be recognised. Additionally, as Wilkinson (2023) recommends, understanding how different features and datasets contribute to model performance is vital, especially in scenarios involving the integration of new datasets

Lastly, the scope of this analysis is limited to a specific day of the year. A broader temporal evaluation, encompassing an extended period, would greatly contribute to understanding the model's performance over time, enabling insights into its stability and consistency across varying time frames.

Chapter 5

Conclusions

In conclusion, this study has unveiled the intricate dynamics of urban mobility, offering insights into the evolving landscape of transportation modelling in contemporary cities. The primary focus of this research was to explore how Deep Gravity and Spatial Interaction Models perform in predicting mobility flows, with a specific emphasis on distinguishing between non-work-related and work-related trips.

Therefore, to address the research question, it was observed that the Deep Gravity Model excels in estimating mobility flows when dealing with a substantial volume of data. Conversely, the Spatial Interaction Model demonstrates strength when working with more aggregated data. Furthermore, the Deep Gravity Model consistently delivers impressive results when assessing the two models in the context of work and non-work flows, particularly compared to the Production-Constrained Model. However, the model reveals certain limitations for non-work flows, which may arise from either a simplified feature structure or the selected period, limited to a single day in this study.

A noteworthy aspect of this research is the innovative use of a private database containing the origin and destination data of individuals in London sourced from smartphone location information. This approach allows for an origin and destination analysis using exceptionally current data. In contrast, relying on Census data, last updated in 2011, would have provided a snapshot of a society undergoing rapid structural and social transformations over the past 12 years.

Today, the cities have evolved significantly with the widespread use of smartphones, advancements in deep learning techniques, and improved access to high-performance computing resources. Such advances enable individuals to conduct complex data analyses, even on powerful supercomputers, from the comfort of their own homes. This study was conducted on Google Colab, showcasing the accessibility of cutting-edge computational tools.

These developments converge to facilitate real-time analysis of city dynamics, a feat made possible through collaboration with private companies holding extensive data collections. This exploratory study represents an initial step in exploring these urban technologies, intending to develop increasingly sophisticated and effective models. Notably, the Deep Gravity model, a key focus of this research, was published in 2021. This study has focused on the predictive capabilities of Deep Gravity and Spatial Interaction Models, providing valuable insights into mobility flows and their differentiation between non-work and work-related trips.

Appendix A

Features Classification

Feature	Group	Categories/Group
Bus stops	TR	Bus Transport
Public Transport	TR	Public Transport, Stations and Infrastructure
Water	TR	Water
Air	TR	Air
Education	EH	Recreational and Vocational Education; Primary, Secondary and Tertiary Education; Education Support Services
Health	EH	Health Support Services; Animal Welfare; Health Practitioners and Establishments
Accomodation	AED	Banqueting and Function Rooms; Camping, Caravanning, Mobile Homes, Holiday Parks and Centres; Timeshare; Bed and Breakfast and Backpacker Accommodation; Self Catering Youth Accommodation; Hotels, Motels, Country Housesand Inns;
Restaurants	AED	Restaurants
Fast Food	AED	Fast Food and Takeaway Outlets; Fish and Chip Shops; Fast Food Delivery Services
Pubs, Bars and Inns	AED	Pubs, Bars and Inns
Cafes	AED	Cafes, Snack Bars and Tea Rooms; Internet Cafes
Retail	RT	Group
Commercial services	CS	Group
Sport and Entertainment	SE	Group
Attractions	AT	Group
Infrastructure	PI	Infrastructure and Facilities
Government	PI	Central and Local Government
Organisations	PI	Organisations

Table A.1: Table Caption

Appendix B

Code availability

The Python code and the Latex code of this dissertation are available at https://github.com/brfelipealmeida/LondonMobilityFlows

Appendix C

Meetings with supervisors

Nº	Date	Topic	Supervisor	Type
01	12/04/2023	Introduction	Elsa	Online
02	14/04/2023	Introduction with Project Partner	Elsa, Mateo	Online
03	16/05/2023	Literature Review and Methodology	Elsa	CASA
04	09/06/2023	Group Presentation	Elsa, Mateo	CASA
05	13/06/2023	Methodologies and Datasets	Mateo Neira	Online
06	23/06/2023	Methodology	Elsa	Online
07	06/07/2023	Locomizer dataset Meeting	Mateo Neira	Online
08	11/07/2023	Skeleton	Elsa	CASA
09	18/07/2023	Locomizer dataset	Elsa, Mateo	Online
10	20/07/2023	Results	Elsa	CASA
11	28/07/2023	Results	Elsa	CASA

Table C.1: Table Caption

References

Batty, M. (2008), 'The Size, Scale, and Shape of Cities', *Science* **319**(5864), 769–771.

Batty, M. (2018), *Inventing Future Cities / Michael Batty.*, MIT Press, Cambridge.

Black, W. R. (1995), 'Spatial interaction modeling using artificial neural networks', *Journal of Transport Geography* **3**(3), 159–166.

Camburu, O.-M. (2021), 'Explaining Deep Neural Networks'.

Fischer, M. M. and Gopal, S. (1994), 'Artificial Neural Networks: A New Approach to Modeling Interregional telecommunication Flows*', *Journal of Regional Science* **34**(4), 503–527.

Luca, M., Barlacchi, G., Lepri, B. and Pappalardo, L. (2021), 'A Survey on Deep Learning for Human Mobility'.

Mozolin, M., Thill, J. C. and Lynn Usery, E. (2000), 'Trip distribution forecasting with multilayer perceptron neural networks: A critical evaluation', *Transportation Research Part B: Methodological* **34**(1), 53–73.

OS (2022*a*), 'Points of Interest – Classification Scheme', https://www.ordnancesurvey.co.uk/documents/product-support/user-guide/points-of-interest-classification-schemes-v3.4.pdf.

OS (2022*b*), 'Points of Interest – Product Information', https://www.ordnancesurvey.co.uk/documents/product-support/user-guide/points-of-interest-product-information-v4.3.pdf.

Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., Killeen, T., Lin, Z., Gimelshein, N., Antiga, L., Desmaison, A., Kopf, A., Yang, E., DeVito, Z., Raison, M., Tejani, A., Chilamkurthy, S., Steiner, B., Fang, L., Bai, J. and Chintala, S. (2019), PyTorch: An Imperative Style, High-Performance Deep Learning Library, *in* 'Advances in Neural Information Processing Systems', Vol. 32, Curran Associates, Inc.

Pooler, J. (1994), 'An extended family of spatial interaction models', *Progress in Human Geography* **18**(1), 17–39.

Simini, F., Barlacchi, G., Luca, M. and Pappalardo, L. (2021), 'A Deep Gravity model for mobility flows generation', *Nature Communications* **12**(1), 6576.

Townsend, A. M. (2013), *Smart Cities: Big Data, Civic Hackers, and the Quest for a New Utopia*, W. W. Norton & Company.

Uber (2023), 'Tables of Cell Statistics Across Resolutions | H3', https://h3geo.org/docs/core-library/restable/.

Wilkinson, P. D. J. (2023), Spatial Interaction Models in a Big Data Grocery Retailing Environment, PhD thesis, University College London, The Bartlett Centre for Advanced Spatial Analysis.

Wilson, A. G. (1971), 'A Family of Spatial Interaction Models, and Associated Developments', *Environment and Planning A: Economy and Space* **3**(1), 1–32.

Zipf, G. K. (1946), 'The P1 P2/D Hypothesis: On the Intercity Movement of Persons', *American Sociological Review* **11**(6), 677–686.