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Dissertation in Integrated Master in Civil Engineering, in the area of Specialisation in Urbanism, Transportation and Transportation Infrastructures, guided by Doctor Professor Anabela Salgueiro Narciso Ribeiro and by Doctor Professor Rui Jorge Reis Gomes.

Coimbra, 31 July 2018

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Universidade de Coimbra

FCTUC DEPARTAMENTO DE ENGENHARIA CIVIL
FACULDADE DE CIÊNCIAS E TECNOLOGIA
UNIVERSIDADE DE COIMBRA

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ABSTRACT

Transport planning, in general, is based on data about pendular trips (work/school) and does not consider other types of travel such as leisure, social, tourism, etc. It also does not consider travel at all times of the day. This gap means that, in many cases, the supply does not correspond to the demand. With a lack of public transport or other infrastructures for transport sustainability, people are encouraged to use non-sustainable modes such as the car for out-of-routine travelling.

In recent years there has also been a brutal increase in the adoption and use of social media platforms and services. As an example, “Foursquare” platform has more than 50 million users worldwide, and more than 105 million mapped locations around the world. These provide information that allows not only the understanding of social activities but also the understanding of travel patterns, vicissitudes and trends of users. All this mobility data, together with modern geoprocessing techniques, Social Network Analysis (SNA) and data fusion, offer new possibilities for identifying destinations and activities, allowing the analysis of the connection between cybernetic and physical spaces.

In this work, we propose to study the mobility of users to extract mobility patterns in out-of-routine scenarios from multiple data sources. This study sought to combine mobility data collected from a mobile phone application and social networking data, specifically from "Facebook", "infoPorto" and "Foursquare".

Extensive analysis of the data was performed to identify patterns of mobility. The results should provide guidelines for decision support in sustainable mobility policies in the Greater Porto area. The programs used were ArcGIS and SPSS. Based on the results, two discrete choice models were developed. Through these models, we tried to identify which factors influence the choice of mode of transport for leisure travel, and also the choice of destination for the same purpose.

Keywords: Urban Mobility; Sustainable Mobility; Travel Behaviour; Destination Choice; Modelling; Modal Choice.

RESUMO

O planeamento de transportes é, geralmente, baseado em dados sobre viagens pendulares (casa-trabalho/casa-escola) e não considera outros tipos de viagem, como lazer, social, turismo, etc. Além disso, também não considera viagens em todos os momentos do dia. Essa lacuna leva a que, em muitos casos, a oferta não corresponda à procura. Com a falta de transporte público ou outras infraestruturas para a sustentabilidade do transporte, as pessoas são incentivadas a usar modos não sustentáveis, como o carro, para viagens fora da rotina.

Nos últimos anos, houve também um aumento brutal na adoção e uso de plataformas e serviços de redes sociais. Por exemplo, a plataforma "Foursquare" tem mais de 50 milhões de utilizadores em todo o mundo e mais de 105 milhões de locais mapeados em todo o mundo. Estes fornecem informações que permitem não só a compreensão das atividades sociais, mas também a compreensão dos padrões de viagens, vicissitudes e tendências dos utilizadores. Todos esses dados de mobilidade, aliados às modernas técnicas de geoprocessamento, Análise de Redes Sociais (SNA) e fusão de dados, oferecem novas possibilidades de identificação de destinos e atividades, permitindo a análise da conexão entre espaços cibernéticos e físicos.

Neste trabalho, propomo-nos a estudar a mobilidade dos utilizadores para extrair padrões de mobilidade em cenários fora de rotina de múltiplas fontes de dados. Este estudo procurou combinar dados de mobilidade recolhidos de uma aplicação de telemóvel e dados de redes sociais, especificamente do "Facebook", "infoPorto" e "Foursquare".

Uma extensa análise dos dados foi realizada para identificar padrões de mobilidade. Os resultados devem fornecer orientações para o apoio à decisão em políticas de mobilidade sustentável na área do Grande Porto. Os programas utilizados foram ArcGIS e SPSS. Com base nos resultados, dois modelos de escolha discreta foram desenvolvidos. Através desses modelos, procurámos identificar os fatores que influenciam a escolha do meio de transporte para viagens de lazer, e também a escolha do destino para o mesmo fim.

Palavras-chave: Mobilidade Urbana; Mobilidade Sustentável; Comportamento de Viagem; Escolha do Destino; Modelação; Escolha Modal.

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LIST OF ABBREVIATIONS

AMP	Área Metropolitana do Porto
ANTRAL	Associação Nacional dos Transportes Rodoviários em Automóveis Ligeiros
CO2	Carbon Dioxide
CP	Comboios de Portugal
EC	European Comission
EU	European Union
FCT	Fundação para a Ciência e a Tecnologia
FEDER	Fundo Europeu de Desenvolvimento Regional
FEUP	Faculty of Engineering of the University of Porto
GHG	Greenhouse Gas
GIS	Geographic Information System
GP	Greater Porto
GPS	Global Positioning Service
LBSN	Location-based social networks
OD	Origin-Destination
POCI	Programa Operacional Competitividade e Internacionalização
POI	Point of Interest
SNA	Social Network Analysis
SPSS	Statistical Package for the Social Sciences
STCP	Sociedade de Transportes Coletivos do Porto
URL	Uniform Resource Locators
WGS	World Geodetic System

1 INTRODUCTION

1.1 Motivation and Problem Overview

Urban areas currently face significant challenges related to the increase of private vehicles, distances travelled and energy consumption. Sustainable urban mobility requires a mind shift of the population in general. This fact has led transportation researchers over the past decades to study travel behaviour to curb the use of automobiles for commuting travel needs and replace those automobile trips with sustainable transport modes (e.g. walking, cycling, and public transit) (Moniruzzaman, M. and Farber, S., 2018). “Sustainable transport is any form of transport that does not use or rely on dwindling natural resources but rather on renewable or regenerated energy” (EarthTimes@, 2011). “Thesetransport modes are associated with numerous social benefits, such as the reduction of congestion, noise pollution and accident costs, and individual benefits, such as reducing the risk of chronic diseases and exercising” (URBY.Sense, 2015).

Society needs an apparently endless network of vehicles and transport systems to sustain societies and economies. Creating sustainable transport solutions is one of the most significant challenges today. It is necessary to look for solutions that guarantee the vital flow of people, goods and services while mitigating climate change and creating climate-safe cities (WWF@, 2017).

When studying the issue of sustainable mobility, it is essential to understand the way and the frequency with which individuals travel both on their usual pendular trips (work/school) and on occasional trips (leisure) (URBY.Sense, 2015).

According to Grigolon, Kemperman and Timmermans, demand for leisure activities has increased in recent decades because of such processes as increasing wealth, ageing populations, and changing lifestyles. Hence, in recent times, more importance has been given to the study of occasional trips, since they have made a significant contribution to "emission levels and congestion and, consequently, to a decrease in mobility and quality of life" (Grigolon, A. et al, 2013). Though, provision of public transport considering the characteristics of low-demand and unpredictable travel for leisure activities can become quite costly and therefore it is essential to understand personal travel patterns and shape of the demand (Grigolon, A. et al, 2013).

The study of urban movements can be accomplished using one of two main approaches, or a combination of both: a more traditional one, based on land use patterns and on mobility studies associated with it, or a more recent one, starting with the collection and subsequent analysis of data from mobile phones for "urban sensing" (Cuff, 2008). The first approach requires, for example, questionnaires and census, which can be expensive, time-consuming, requires active participation and provides a small historical stratum of mobility. The second approach has several advantages over traditional methods, as the steady growth of smart devices and transport system logs provide us with unprecedented "digital footprints", telling where and when people are (URBY.Sense, 2017).

The increased availability of location technology (for example, Global Positioning Service - GPS, and Wi-Fi) allows people to add a dimension to online social networks in various ways. These kinds of location-embedded and location-driven social structures are known as location-based social networks (LBSN), formally defined as follows:

> *"A location-based social network... consists of the new social structure made up of individuals connected by the interdependency derived from their locations in the physical world as well as their location-tagged media content, such as photos, video, and texts. Here, the physical location consists of the instant location of an individual at a given timestamp and the location history that an individual has accumulated in a certain period" (Zheng, Y., 2011).*

With the increase in the adoption and use of social media platforms and services, transport research began to use the concepts and methods of Social Network Analysis (SNA) to model and analyse transport demand, since they provide a vast and diverse source of data.

The SNA is the mapping and measuring of relationships and flows between people, groups, organisations, computers, Uniform Resource Locators (URLs), and other connected entities. The nodes in the network are the people and groups while the links show relationships or flows between the nodes. SNA provides both a visual and a mathematical analysis of human relationships (Orgnet@, 2018).

Thus, the virtual platforms of socialisation and consequent human interactions are fundamental not only for understanding social activities but also for understanding travel patterns, vicissitudes, and user trends (Carrasco, 2008).

This dissertation is part of the "URBY.Sense" project, a Foundation for Science and Technology (FCT) (Portuguese Science Foundation) project from the Faculty of Science and Technology of the University of Coimbra, which main objective is precisely to study individual's mobility for mining non-routine (leisure, social, etc.) mobility patterns from multiple data sources.

The "URBY.Sense" project suggests that all these new ways of collecting information add important highlights on mobility studies, especially in cases where traditional methods of gathering information are not available (for leisure activities and during the night). According to this project, the following mobility patterns are of great interest:

> "*Locations of significance (trip generators), modes of transport, trajectory patterns and location-based activities for destination choice modelling. Data collected via ubiquitous devices and smart metering combined with data from social media platforms provide a range of new close-to-real-time information for urban efficient mobility planning and management. When considered in isolation, each of these data sources has gaps/missing observations, so the matching of multiple data sources can facilitate transport analysis and enable operators to better tune public transportation within cities with the aim of travelling at lower costs, faster and producing a smaller carbon footprint"* (URBY.Sense, 2016).

In the scope of the Project "URBY.Sense", the data available have already been collected for the Faculty of Engineering of the University of Porto (FEUP) through a mobile application called "SenseMyFEUP" (SENSEMYFEUP@, 2018) from the "SenseMyCity" project (SENSEMYCITY@, 2018) and from social networking platforms, which in turn can be combined with other more traditional sources (mobility studies).

1.2 Objectives and Methodology

The analysis of mobility patterns is a useful tool for understanding the functioning of urban agglomerations and thus for municipal intervention based on a more detailed diagnosis of the territories in their different components (CMP, 2014). Focusing on out-of-routine travel in Greater Porto (GP) and throughout April 2016, this document is a contribution to strengthening this knowledge base.

The primary objective of this dissertation is to characterise individual mobility, for non-routine mobility patterns (leisure, social, or others) through the analysis of multiple data sources, based on the case study of the GP area, in Portugal. Several associated objectives can be stated as follows:

- Realize the influence that the attractiveness of the events/POIs has on the travel patterns;
- Identify factors that influence the choice of mode of transport for out-of-routine travel;
- Identify the factors that influence the choice of destination for leisure activities.

This study aims to evaluate the data collected in the scope of the "URBY.Sense" project by looking for relational patterns between them.

The methodology follows two main steps:

1. First by analysing the data in an exploratory way and characterising it;
2. Secondly, this study also estimates two discrete choice models:
   - One to obtain a more comprehensive understanding of what factors affect the mode choice;
   - Other to see what factors influence the choice of the destination.

In the first case, a cluster analysis based on two groups of mode choice responses was conducted to stratify the sample whereas a binomial logit regression approach was used to evaluate statistically the possible estimation of a mode choice model.

In the second case, based on four categories choice responses, the sample was stratified, and a multinomial logit regression approach was used to evaluate statistically the possible estimation of a destination choice model.

All the components of the dissertation unfold in an analysis at the inter-municipal scale relative to the 11 municipalities of GP (Espinho, Gondomar, Maia, Matosinhos, Porto, Póvoa de Varzim, Santo Tirso, Trofa, Valongo, Vila do Conde, and Vila Nova de Gaia) and in an intra-municipal approach centered in the parishes of the Municipality of Porto (Aldoar, Bonfim, Campanhã, Cedofeita, Foz do Douro, Lordelo do Ouro, Massarelos, Miragaia, Nevogilde, Paranhos, Ramalde, Santo Ildefonso, São Nicolau, Sé, and Vitória). In fact, some of these parishes are "unions" of parishes, resulting from the administrative reform implemented in 2013. This is the case of the following parishes unions: Aldoar, Foz do Douro, and Nevogilde; Cedofeita, Santo Ildefonso, Sé, Miragaia, São Nicolau, and Vitória; Lordelo do Ouro and Massarelos. However, these unions were not considered in order to make a more detailed study.

Information about the data used for the study is attached in the end of the document, with emphasis on the origin/destination matrices related to the out-of-routine movements referred to throughout the document. In this way, it is intended to provide a balance between the clarity of the presentation and the detail needed to treat a wide range of information collected.

1.3 Dissertation Structure

The present dissertation is organised into seven chapters. Below is a brief reference to the content of each of these chapters:

Chapter 1 is an introductory chapter containing relevant information to the understanding of the problematic to be addressed and the motivation for the elaboration of this Dissertation. This chapter also presents the objectives of the Dissertation. The methodology adopted to deal with the topic and how the document is organised.

Chapter 2 contains the bibliographic study of the following subjects: the different data sources available for the characterisation of mobility in general and studies done with a focus on out-of-routine travel.

Chapter 3 shows the scenario of the European Union, Portugal and the Porto Metropolitan Area concerning mobility patterns, based mainly on studies carried out by the European Union and the Porto City Council. The chapter ends with a description of the "URBY.Sense" project.

Chapter 4 presents the research hypotheses, the paradigm and methodology of the research, as well as the methodological options adopted in the various stages of the study. It describes the sampling frame, the sampling procedures and the methods for the analysis of the collected data.

Chapter 5 is dedicated to the case study analysed in this Dissertation. In a first phase, a general characterisation of mobility in the Greater Porto area is presented, encompassing geographic, demographic and mobility issues, as well as relations with events/POI as attractiveness factors. Next, a more detailed assessment of the mobility system is carried out in the Greater Porto area, and two discrete choice models are presented.

Chapter 6 presents the conclusions and the final considerations regarding the work developed in this Dissertation, as well as the proposals for future work.

Chapter 7 lists the bibliographic references used throughout the research work.

The Dissertation ends with a set of attachments that include supporting exploratory research documents, such as OD matrices and other information tables.

2 LITERATURE REVIEW

2.1 Introduction

This chapter aims to carry out the bibliographic review, introducing already existing studies that can help the present research, based on the field and focus of the study.

Initially, an approach to the new data sources is made for characterisation of mobility, followed by the presentation of some studies already done using various types of data sources. Posteriorly, we present studies that were done considering out-of-routine trips, that is with purposes other than work/school.

In this bibliographical research, we sought to collect recent studies and/or with some relevance to the world of investigation.

2.2 New Data Sources for Mobility Characterisation

Traditionally, transport planning depended on historical research methods and data, such as questionnaires and census. However, these methods are quite “expensive and time-consuming” (URBY.Sense, 2016) which has led to the search for new data sources. Several studies have already been done using data taken from mobile phones and social networks, confirming the various advantages of combining this type of sources with traditional methods.

Calabrese, Diao, Lorenzo, Ferreira and Ratti, presented several advantages related to the mobile phone as data provider: lower cost, larger sample size, higher frequency of updating, more spatial and temporal coverage and, also, provide unprecedented "digital footprints". However, they have also identified some gaps such as: the impossibility of accessing socio-economic and demographic characteristics due to privacy issues; the high probability that mobile phone users do not represent a random sample of the population tending to be biased; the difficulty of using the database due to its format because it is not prepared for modelling (Calabrese et al., 2013).

Anda, Fourie and Erath, did a literature review related to the various existing data sources, focusing on the new Big Data sources (mobile phone call data, smart card data and geo-coded social media records). The objective of the article was to provide an overview of how Big Data improves the understanding of mobility flows and has been applied to transport search models from a methodological point of view. They identified the advantages and disadvantages of the various methodologies and their applicability for use in transport predicting models. They drew several conclusions from this study, stating that to be able to extract quality behaviour of mobility and activity of human mobility sensors with quality, it is necessary to combine the information of the available datasets. They gave the following example: if the objective is to find the mode of transport from Call Detail Records, a viable option is to export public transport smart card data and available GPS tracking of taxi services in a probabilistic trajectory matching approach. They point out that there are some challenges in comparing different datasets, even if they are related. The main one is the different harvest periods and different spatial units. However, they also have the advantage of using different human mobility sensors and supplemental datasets, such as travel diary data, to complement the importance of the data fusion approach (Anda et al., 2016).

Thomas, Geurs, Koolwaaij and Bijlsma, examined the accuracy of travel detection and its characteristics through a mobile application called "MoveSmarter". The survey was carried out in the Netherlands for one month, registering departure and arrival times, origins and destinations, and travel reasons for a group of 615 volunteers. To compare automatically detected and reported trips, volunteers also had to participate in a requested web-based recall survey and answered additional questions. Most trips were identified without any apparent defects in the length or duration of the trip, and modes of transport were classified correctly in more than 80% of those trips. This study has led to the conclusion that smartphone-based travel detection helps reduce underreporting of trips, which is a common phenomenon in travel surveys (Thomas et al, 2018).

Studies have already been done that sought to develop models of analysis from mobile phones data. For example, Bachir, Gauthier, El Yacoubi and Khodabandelou, proposed a generic model for the estimation of daily population counts using mobile phone data, with the case study of the Greater Paris area. They considered this study as a powerful potential tool for urban analysis and transport planning, by allowing estimation of travel demand and anomaly detection. Research used mobile phone data to gain insight into seasonal variations in visitor rates, human mobility in transport planning, land use detection, socioeconomic characteristics of citizens, recreational event attendance, emergency and disaster detection, disease transmission and estimation of pollution rates (Bachir et al., 2017).

LBSNs such as “Foursquare”, “Gowalla”, “Google Latitude”, “Facebook Places” and “Twitter”, became an indispensable source of voluntary geographic information (Sun, 2016). As an example, “Foursquare” has more than 50 million users worldwide, and more than 105 million mapped locations around the world (Foursquare@, 2018). While providing data from biased age groups and site categories, geo-tagged social network data can complement regular household survey data to validate findings of mobility and urban structure and to reveal new insights about nature and human behaviour (Huang et al., 2017).

Some studies have already been done showing the importance of LBSNs data in mobility studies. For example, Salas-Olmedo and Quezada carried out an investigation that shows the usefulness of large open data to map mobility patterns. The study validates the use of Twitter data to map the impact of public spaces in different parts of the metropolitan area of Concepción, Chile, developing a methodology with the objective of complementing origin-destination surveys with spatial boundaries “à la carte” and updated data at minimal cost. The results show the main mobility patterns for social interaction spaces, such as malls, leisure areas, parks and so on (Salas-Olmedo, M. H., Quezada, C. R., 2017).

After the collection and comprehension of the mentioned studies, it was verified that the use of the Big Data presents many advantages for the characterisation of the mobility compared to traditional methods. For example: lower cost, larger sample size, higher frequency of updating, more spatial and temporal coverage, provide unprecedented "digital footprints" (Calabrese et al., 2013). Thus, several studies have found that for investigation related to mobility, it is best to combine information from the available data sets, from traditional sources to more recent ones (Anda et al., 2016; Huang et al., 2017; Thomas et al, 2018). This combination allows the use of different human mobility sensors and supplemental datasets (Anda et al., 2016).

Following are more specific mobility studies, focusing on out-of-routine trips.

2.3 Studies on Non-Routine Mobility Patterns

In recent decades, the demand for leisure activities has increased due to some reasons such as increasing wealth, ageing populations and changing lifestyles. This increase in demand has led to higher levels of emissions and congestion and, therefore, to greater concern on the part of researchers (Grigolon, A. et al., 2013).

Pendular travel (e.g., commute to work) have already been comprehensively researched. However, out-of-routine trips have only recently received more attention, despite their environmental impact. Some of the studies that have been done are presented below.

A study with some relevance was the one made by Steed and Bhat. They analysed the choice of recreational/social start time by estimating discrete choice models for home-based social/recreational and home-based shopping trips using the 1996 activity survey data collected in the Dallas-Fort Worth metropolitan area. The results indicated that this choice is mainly related to the sociodemographic characteristics of the individual and their employment. This fact led to the conclusion that the option of starting this type of activity is confined to certain times of the day due to restrictions imposed by other activities (Steed, J. L., Bhat, C. R., 2000).

Tarigan and Kitamura made another important study. They used a travel diary survey from Germany to examine the effect of the frequency of leisure trips per week on the variability in the number of such trips over weeks. They found that factors such as gender, age, life-cycle stage, vehicle ownership, and location of residence have a significant influence on leisure travel patterns. The number of cars at home has a positive impact on the number of activities per week related to shopping and recreational activities, but not so much in social contact activities. On the other hand, the more bicycles there are at home, the more trips are per week related to sporting and nature activities. Another fact was that individuals living in the suburbs tended less to participate in nature-related activities than those living in the city (Tarigan, A., Kitamura, R., 2009).

Sener, Bhat and Pendyala analysed physical leisure activities. They explored nature, location, timing, social context and duration of activities based on data from the 2007 American Time Use Survey. After estimating a mixed multiple discrete-continuous extreme value model, the results showed that socioeconomic, demographic, domestic, employment-related and environmental variables affect the choice of physical recreation activity, relative to location, time of day, the day of the week and social context (Sener, I., Bhat, C., Pendyala, R., 2011).

More recently, Mao, Ettema and Dijst, investigated travel time attributed to non-work stops. In this analysis, they included socio-demographic variables, spatial characteristics and mode shift, based on a database provided by the "Daily Activity and Travel Survey of Beijing 2012". Several conclusions were drawn from this study, some of which are as follows:

- Nearly 20% of multipurpose travel trips included a mode shift for a more motorised transport mode than their direct counterparts;

- The extra travel time due to deviations is significantly related to the duration of the activities;
- Longer work duration reduces travel time, regardless of the type of activity;
- The terms of interaction between personal factors/travel/spatial factors and duration of activities show that the impacts differ between types of activities;
- The gender difference was found only for eating out, which suggests that male passengers travel longer for the same amount of activity time;
- A higher mix of facilities close to the workplace helps reduce the extra travel time invested in a unit of time for shopping and family/personal/other activities;
- Users that travel on foot or by bicycle have less travel time to eat out than users of public transport;
- Time, work duration and duration of travel as variables related to the time budget show negative impacts on extra travel time for food, shopping and family/personal/other activities (Mao et al., 2016).

Gkiotsalitis and Stathopoulos, did a study focused on the optimisation of joint leisure activities. They presented a perceived utility model that automatically captures users' mobility/activity patterns from data generated by historical users. Besides, it simultaneously models the perceived utility of users while participating in joint leisure activities. Based on the spatiotemporal nature of social media data generated by users, the utility maximisation model considered only the total distance of travel as the primary criterion for the accomplishment of joint leisure activity (Gkiotsalitis, K. and Stathopoulos, A., 2016).

Feng, studied the travel behaviour of the elderly, taking as a case study urban China. Based on quantitative and qualitative data, it was investigated how socio-cultural configurations, interacting with built environments, affect the travel behaviour of this specific group of travellers. It was found that access to public transport instead of transport accessibility, vegetable markets rather than supermarkets and convenience stores, open spaces and parks, chess and card rooms rather than gyms and sports centres are more decisive in affecting the behaviour of the elderly (Feng, J., 2016).

Gössling, Lohmann, Grimm and Scott, investigated holiday travel patterns in Germany based on data from annual travel surveys. Data on the number of trips, modes of transport and travel distances have been assessed, indicating that the Greenhouse Gas (GHG) emission related to holiday travel were significant in an average of 320 kg of CO2 per trip per person. The results also show that the distribution of holiday travel emissions was highly disparate among the population and depended heavily on the type of travel (Gössling et al., 2017).

Große, Olafsson, Carstensen and Fertner, studied the relationship between daily travel patterns and non-daily travel behaviour, such as holidays and long weekend trips. The study was based on a questionnaire survey conducted in an urban district in the centre of Copenhagen and a small city in the suburb of Greater Copenhagen, seeking to establish an understanding of the influence of urban structure on travel behaviour in different domains of travel. The results showed that the urban structure of a residential place influences the constitution of daily mobility styles and that there is a greater tendency to carry out weekend trips and holidays in the urban sample. Thus, it was concluded that there was an interdependence between the style of mode, residential location, ownership/use of car and use of airplanes expressed in specific travel behaviours (Große et al, 2018).

Czepkiewicz, Heinonen and Ottelin, made a bibliographical review of the relationship between high urban densities and high emissions caused by long-distance leisure travel, seeking to associate conclusions. There were many limitations among the various studies, such as:

- There is a wide dispersion in calculation methods, data sources, time intervals and scopes, making comparability and generalisation of results difficult;
- Studies are inconsistent in reporting and aggregating results for different modes of travel, travel purposes, and geographic extent;
- The accuracy and completeness of the measurement are compromised by survey designs, precisely by the short recall times, counting on distance estimates by the interviewees, and not collecting data on travel destinations;
- Most studies do not include emissions, include only direct emissions or calculations as if they were all emitted at the ground level;
- Sociopsychological variables are often not controlled.

The most common explanations of the associations between urban form and long-distance travel behaviour found in the review included: rebound effects, compensation or flight hypothesis, access to transport infrastructure, lifestyles and other socio-psychological characteristics and dispersion of networks social policies. Despite the limitations found, it was possible to draw some conclusions from the studies, such as:

- People living in densely built, pedestrian friendly and centrally located neighbourhoods travel farther to travel longer distances than those living in more suburban locations;

- When only domestic or regional trips were included, the association between urban density and the amount of long-distance travel seemed contrary. When international travel was included, the association between urban density and the amount of long-distance travel seemed positive;
- Increased long-distance travel slightly outweighs the gains from reduced car use, but the magnitude varies from study to study (Czepkiewicz et al, 2018).

Some studies have already been done considering trips out-of-routine (leisure, social, tourism, etc). However, as this type of studies has only recently been given more relevance, they still have some gaps, such as: dispersion in calculation methods, data sources, time intervals and scopes, the accuracy and completeness of the measurement are compromised by survey designs, sociopsychological variables are often not controlled, and more.

Our study proposes to develop a methodology that contributes to the improvement of this type of studies.

3 CASE-STUDY

3.1 Sustainable Mobility in Europe and Portugal

Most European citizens live in urban environments, with over 60% living in urban areas with more than 10,000 inhabitants. Mobility in these areas accounts for 40% of all Carbon Dioxide (CO_2) emissions related to road transport and up to 70% of other transport pollutants (EC@, 2018).

Increasingly, transport and traffic are causing problems in European cities. One challenge facing these cities is how to improve mobility, ensure accessibility, and create efficient, high-quality transport systems, while reducing congestion, pollution and accidents, since mobility in urban areas is an essential enabler for growth and employment and sustainable development in European Union (EU) areas (EU, 2017). The European Commission (EC) believes that cities themselves will better find the answers to these challenges, considering their specific circumstances (EC@, 2018).

Since the year 2001, the number of private vehicles has increased in the EU-27[1] countries and all the surrounding countries: from 437 per 1000 inhabitants in 2001 to 474 per 1000 inhabitants in 2010, an increase of 8.24% (EC, 2013). However, 2008 was a year characterised by the beginning of an economic crisis which led to a fall in growth of this rate, showing the relationship between economic growth and the transport sector (Inturri, G. and Ignaccolo, M., 2016).

The growth in the use of private cars has been accompanied by increased urban sprawl and displacement, while the expansion of public transport networks in many cases has not been developed at the same pace (EU, 2017). Increasing transport volumes lead to higher energy consumption and emissions of pollutants and greenhouse gas (GHG). Hence, lower transport

[1] EU-27- Countries of the European Union from 1 January 2007 to 30 June 2013 (Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Poland, Portugal, Romania, Slovak Republic, Slovenia, Spain, Sweden, the United Kingdom) (EC@, 2018).

volumes, a modal shift from vehicles to trains and public transport or lower material consumption help reduce energy consumption and therefore GHG emissions (EU, 2015).

The development of the current EU urban transport policy has been based on many policy documents that have been discussed and published over the years. Here are some of these documents (EU, 2017):

- Green Paper "Towards a new culture for urban mobility" (2007) - sought to stimulate the debate on urban mobility at a European level intending to seeking appropriate solutions;

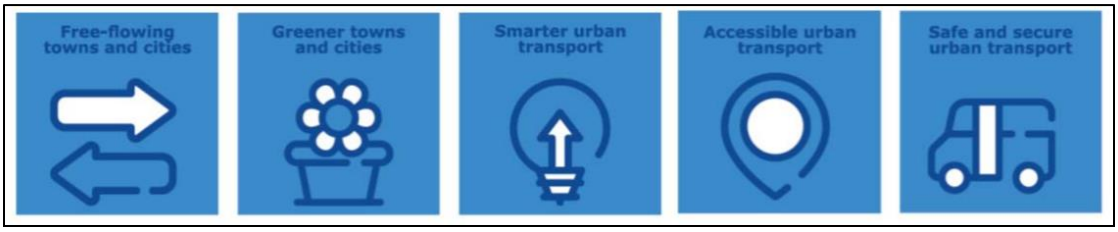


Figure 1- Main challenges that were defined in the "Green Paper" document (EU, 2017)

- White Paper "Roadmap to a Single European Transport Area" (2011)- Presented a vision for a competitive and sustainable transport system. The EC has adopted a roadmap of 40 initiatives for the next decade to develop a competitive transport system that will increase mobility. In this way, EU urban transport policies will contribute to the use of conventionally fueled cars in cities by 2030 and achieve CO_2-free logistics essentially in major urban centres by 2030;

- Urban Mobility Package (2013) - Defined relevant action proposals at local, Member State and EU level. Encourages relevant stakeholders at the local level to develop new integrated strategies for sustainable urban mobility as well as transport plans that can support their successful implementation. The Commission invites the Member States to assess the current and future performance of urban transport systems in their urban areas; developing a (national) approach in the field of urban mobility; review the set of current tools and instruments available to local actors and complement and modify this setting;

- Paris agreement (2015)- At the Paris Climate Conference (COP21) in December 2015, 195 countries adopted the first global, legally binding and universal climate agreement. The agreement recognises the role of non-parties involved in addressing climate change, including cities, other subnational authorities, civil society, the private sector and others. They are invited to broaden their efforts and support actions to reduce emissions, build resilience and reduce vulnerability to the adverse effects of climate change, and advocate for and promote regional and international cooperation.

The situation of Portugal in comparison with other countries is not very favourable. In 2012, Portugal was unable to meet the Europe 2020 targets (EC@, 2018). In fact, it was part of the eight EU-27 countries where there was an increase in national GHG emissions between 1990 and 2012 (Figure 2).

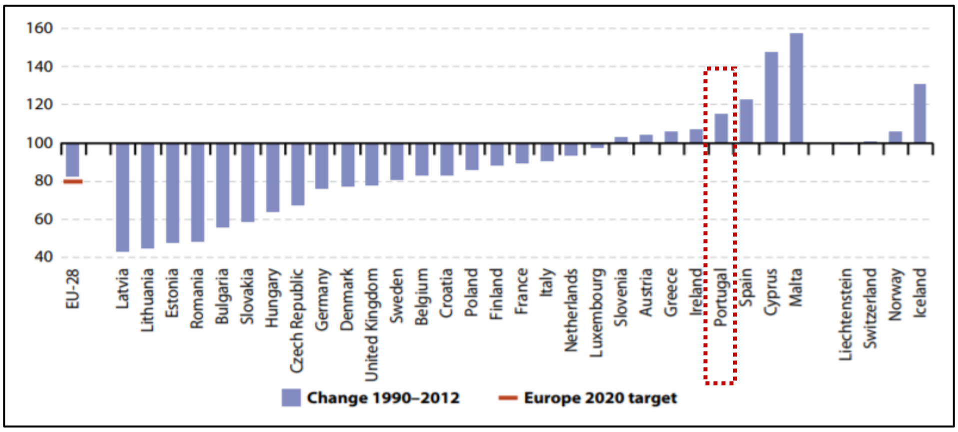


Figure 2- GHG emissions, by country, 2012 (index 1990 = 100) (adapted from EU, 2015)

As for the modal split of passenger transport, in 2013, road transport shares in most countries were around 80% of total inland passenger-kilometres. However, Portugal was in the group of countries with a higher percentage of total inland passenger-km of passenger cars, constituting almost 90% of the distribution (Figure 3).

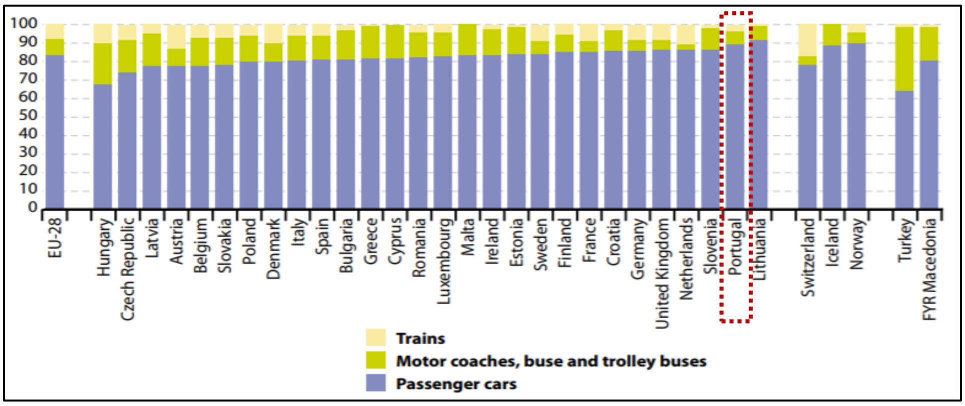


Figure 3-Modal split of passenger transport, by country, 2013 (% in total inland passenger-km) (adapted from EU, 2015)

3.2 Sustainable Mobility in Porto Metropolitan Area

Emissions are a problem and Portugal is not producing enough offer or controlling demand, regarding sustainable transport, that can overcome this problem.

Thus, it is important to study an urban space that has enough diversity and for which large number of points of interest (POIs) are available from collaborative platforms. Hence, for this study it was selected the city of Porto and its surroundings.

Therefore, it is fundamental to understand the main offer concerning transport in Porto, and the already studied mobility patterns, to understand the results in terms of the specific mobility patterns we want to explore.

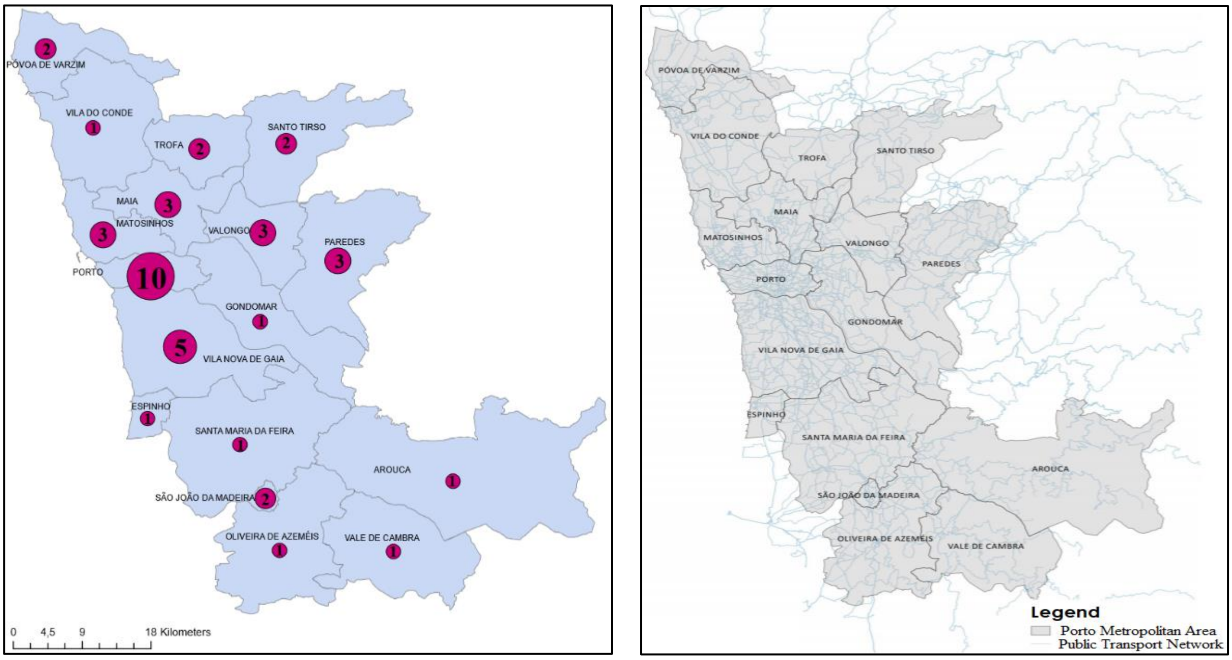
Porto Metropolitan Area (AMP) has a very extensive access network. Among the 17 municipalities that constitute this area, there are 29 road operators and a total of 725 authorised lines (AMP@, 2018).

The following table shows all operators functioning in the AMP, concerning the type of transport mode:

Table 1- AMP operators (AMP@, 2018).

Type	***Operators***
Air	Francisco Sá Carneiro Aeroport
Bicycle	Bikesharing- "biConde", "BiclaZ"
Rail	Porto Metro, CP - Portugal Trains, Electric
River	River Taxis- "Douro River Táxi", "Lancha Flor do Gás", "Taxi-Boat"
	Touristic Boats - "Cruzeiros Douro", "Douro Azul"
Maritime	Porto de Leixões Cruise Terminal
Road	Buses- 29 operators
	Touristic Buses- "Bluebus", "Yellow Bus Sightseeing Tours", "City Sightseeing Porto"
Taxi	ANTRAL – National Association of Road Carriers in Light Automobiles
Cable	Guindais Funicular, Gaia Cable Car

The interfaces in the AMP are more concentrated in the Municipality of Porto, and they are distributed as it can be seen in Figure 4.a). On the right, in Figure 4.b), is showed the public transport network in AMP.



a) b)

Figure 4- a) PMA interfaces (AMP@, 2018); b) PMA public transport network (adapted from AMP, 2016b)

The bus and metro networks can be viewed in more detail on their respective websites, STCP and Metro do Porto, respectively (STCP, 2012; STCP, 2013; Metro do Porto, 2018).

Until the summer of 2015, the Metropolitan Transportation Authority of Porto was responsible for the management of public transport of the AMP. With Law nº52 / 2015, approving the Legal Regime of the Public Transport Service of Passengers, in August of 2015, these functions were delegated to the municipalities and metropolitan areas. AMP became the competent Transport Authority for public intermunicipality passenger transport services, and the municipalities were responsible for the management of the municipal lines. As for public operators such as Metro do Porto, STCP and CP, they continued to be under the State management (AMP, 2016b).

The road network of AMP is very extensive and varied. In it cross many roads: main itineraries, such as IP 4 between Porto and Quintanilha, complementary itineraries, such as IC 2 between Lisbon and Porto, and IC 23, between Porto and Vila Nova de Gaia, regional roads such as R326-1 in Arouca , national roads such as N 12, Porto Circunvalation in Matosinhos, and N 14 between Porto and Braga, municipal roads such as M 548 in Vale de Cambra, and freeways such as A 1 between Lisbon and Porto called "North Freeway". The road network is organised as follows:

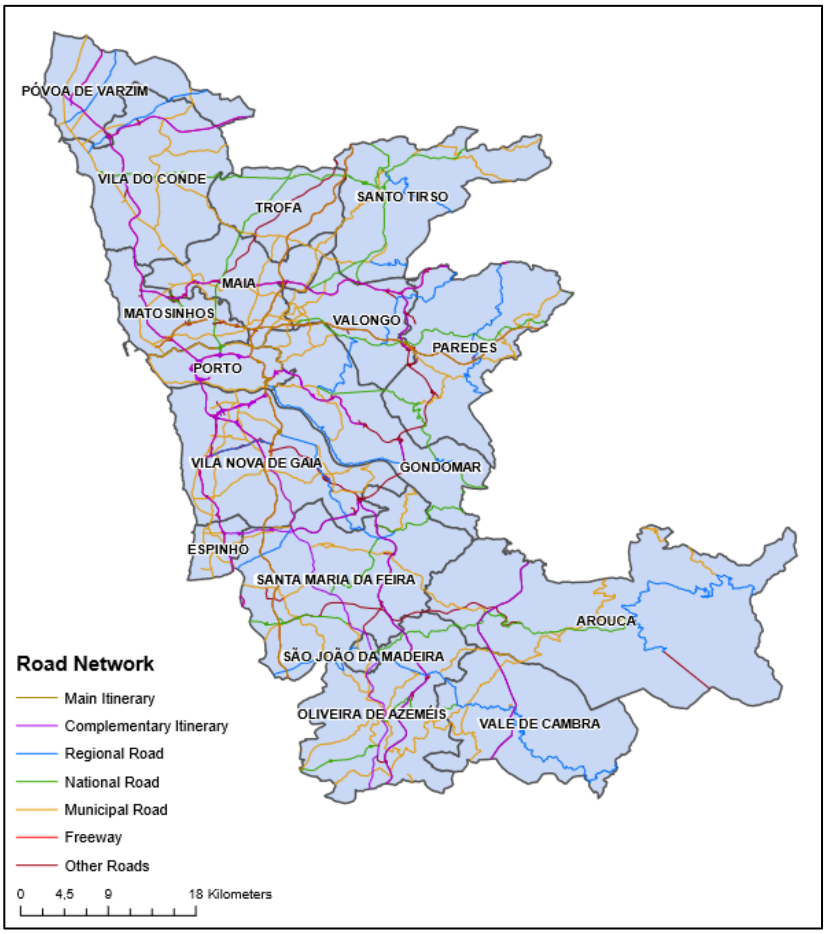


Figure 5- AMP road network

In 2014, a study was developed by the Council of Porto to analyse the evolution of home/work and home/school trips in GP over the last decade, exploring data from the population and housing Census of the years 2001 and 2011 (CMP, 2014). Many conclusions were drawn from this study. For example, between 2001 and 2011:

- Home/work and home/school commuting in GP decreased;
- Intra-municipal movements declined, despite remaining majority;
- Reduced the number of trips with origin or destination in the Municipality of Porto, a trend associated with the decentralisation of the resident population, employment and the offer of education;
- Increased number of movements between neighbouring municipalities of Porto;

- Improvement in the provision of road infrastructures, with the entry into service of Metro do Porto, the restructuring of the Transportable Society of Porto (STCP) network and the introduction of the "Andante" intermodal ticketing integration system;
- The number of movements made with the individual car increased, to the detriment of the sustainable modes (public transport, bicycle, walking);
- The metro attracted more passengers from the bus than from individual transport (CMP, 2014).

In addition, it was found that in 2011 there was an attractiveness related to the geographical proximity, residents of the Municipality of Porto used more collective transport than residents in other municipalities, the bus corresponded to the mode used as a last resort and the socio-economic indicators were related to the choice of mode of transport (CMP, 2014).

In March 2016, within the scope of the Sustainable Urban Mobility Action Plan of the Porto Metropolitan Area, a report was drawn up, motivated by the growing change in mobility patterns in previous years (AMP, 2016a).

In this report were presented some factors considered decisive for the present difficulty of adaptation and response to the new mobility patterns in the AMP. Concerning the pedestrian routes, it was stated that in almost all municipalities of the AMP "there were numerous discontinuous pedestrian routes associated with urban barriers, such as the absence of sidewalks or the existence of undersized pavements, irregular or degraded pavement, absence of kerb downgrade in crossings, tree boilers, and other barriers that do not contribute to increasing pedestrian use, especially for people with reduced mobility "(AMP, 2016a). Regarding the cycling network in urban areas, "these were very deficient regarding continuity, lacking a strategy of integration and connection to the main poles that generate travel and attracting poles in other municipalities" (AMP, 2016a).

In 2016, a study was carried out by the Mobility Planning and Management Division on AMP. (AMP, 2016b). The chart below was developed within the scope of this study showing the kilometres travelled by public passenger transport vehicles in each municipality of the AMP. It was possible to verify, through the differences between each municipality, that there were inequalities in the supply available in each one (AMP, 2016b).

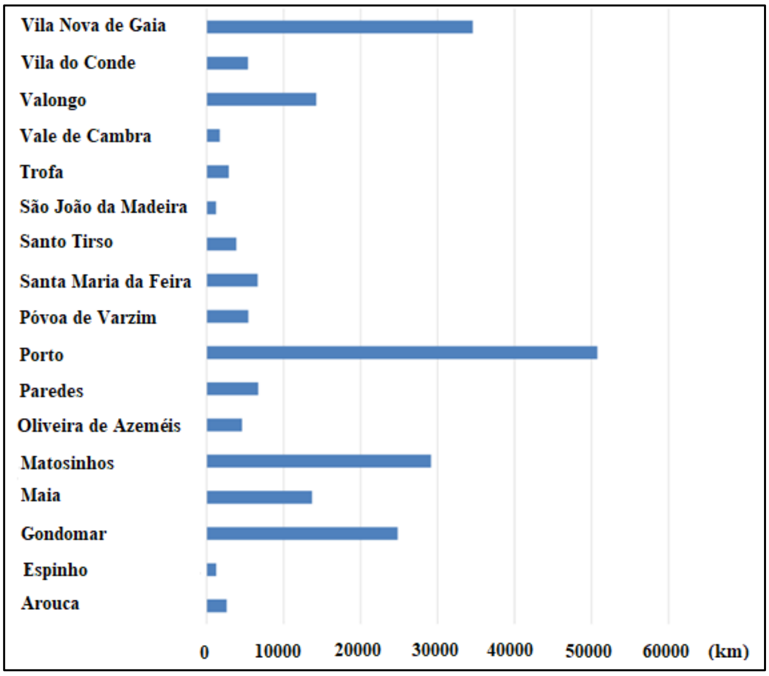


Figure 6- Kilometers travelled by public passenger transport vehicles in AMP, by municipality (adapted from AMP, 2016b)

For this reason, an analysis was also made combining the working day of km travelled by municipality and its ratio per 1000 inhabitants, allowing to articulate the population density with the size and scale of the territory of the 17 municipalities. The results were obtained by the following expression (AMP, 2016b):

$$\frac{Vehicles * km}{N.Inhabitants} * 1000Inhabitants$$

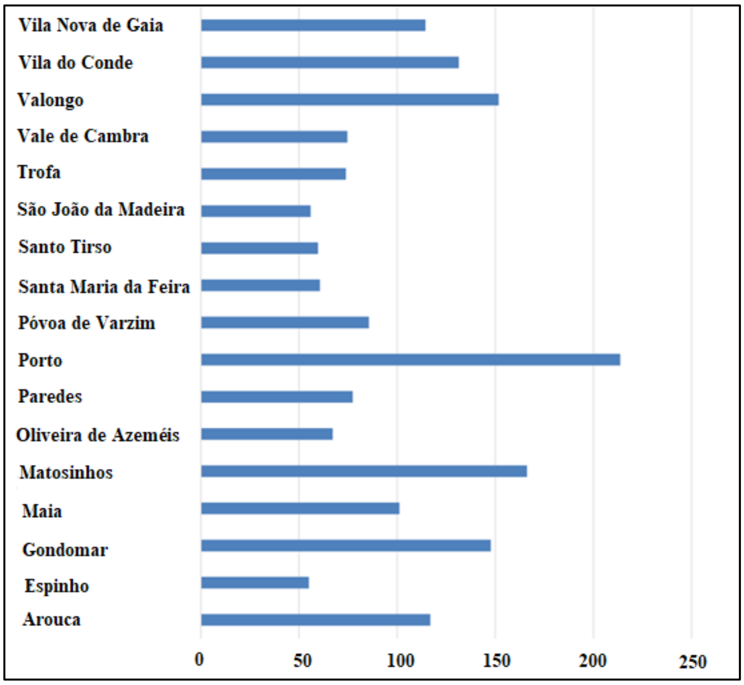


Figure 7- Kilometers travelled by public passenger transport vehicles in AMP per 1000 inhabitants, by municipality (adapted from AMP, 2016b)

From this analysis the study concluded that, for example, there were buses making, each working day, 51 thousand km in Porto, 34 thousand in Vila Nova de Gaia, 29 thousand in Matosinhos, 24 thousand in Gondomar, but also almost 7 thousand in Santa Maria da Feira, Paredes or Póvoa de Varzim and about 3 thousand in Arouca or Trofa. Also, it was found that 25% of the total kilometres of the AMP were traversed in the Municipality of Porto and that of all operators, the largest operator is the public operator, STCP, with 34% of the total kilometres in AMP (AMP, 2016b).

There is a problem of excess of emissions extensive to Portugal and a transport infrastructure in the case of Porto (where the case study is located) that does not answer properly to the need for a more sustainable mobility system.

One of the less studied segments of this system is the “Non-Routine Mobility Patterns”. The “URBY.Sense” project results provide some highlights on this.

3.3 The “URBY.Sense” Project

Thus, the “URBY.Sense” project was proposed with the aim of studying the mobility of users to extract mobility patterns, focusing on out-of-routine scenarios and resorted to multiple data sources. In this project, crowdsourced data were collected from a mobile phone application developed by a project called "SenseMyCity" and also from social networking platforms such as "Facebook", "Foursquare" and "infoPorto".

The “URBY.Sense” project defends that:

> *“Data collected via ubiquitous devices and smart metering combined with data from social media platforms provides a range of new close-to-real-time information that can be combined with the data from more traditional sources (surveys, transport system records and static data) for urban efficient mobility planning and management. When considered in isolation, each of these data sources has gaps/missing observations, so the matching of multiple data sources can facilitate transport analysis and enable operators to better tune public transport within cities with the aim of travelling at lower costs, faster and producing a smaller carbon footprint”* (URBY.Sense, 2016).

The study presented in this dissertation falls in Task 4 of the project "URBY.Sense". This task is aimed at “understanding locations of significance, modes of transport, trajectory patterns and location-based activities for destination choice modelling” (URBY.Sense, 2016). In spite dealing with unstable and noisy data from heterogeneous sources, it was possible to analyse mobility patterns and develop models of choice of mode and destination.

In the following chapters, it is presented the whole process carried out during this study, as well as the results obtained and several conclusions.

4 METHODOLOGY

4.1 Introduction

The accomplishment of this work consisted of three phases:

1. Data collecting, through more than one data source;

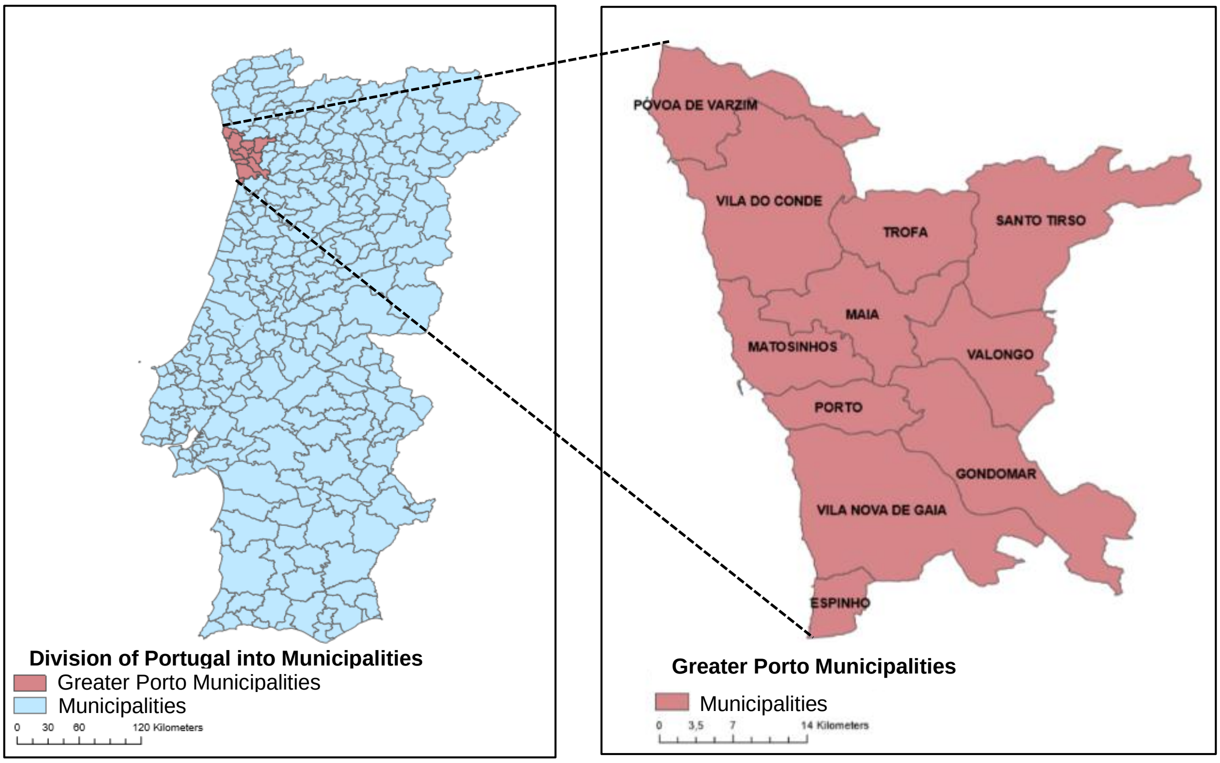
2. Data processing, to form a database with quality;

3. Data analysis, creating relational patterns in a first exploratory-descriptive approach, and then, in a modelling approach, identifying the most determining factors in the choice of a given location and mode of transport.

All the methodologies adopted in each of these phases are presented below.

4.2 Data Collecting

As already mentioned, the area defined for the study corresponds to the city of Porto and its surroundings, more specifically the GP area. What led us to this choice was the fact that there is large-scale data on social networks, both at points of interest and events. To detect and collect movements of people, the “SenseMyCity” project developed a mobile application. This application is an opportunistic mobile crowdsensing tool available for researchers to design and implement data collection campaigns for studying large-scale processes. The application was developed by the team responsible for the execution of the “Data Acquisition” task in “URBY.Sense” project and has been thoroughly described in the literature (Rodrigues et al., 2016). The data was collected during April 2016 for the following municipalities, which constitute the GP area: Espinho, Gondomar, Maia, Matosinhos, Porto, Póvoa de Varzim, Santo Tirso, Trofa, Valongo, Vila do Conde and Vila Nova de Gaia (Appendix 1 of Decree-Law no. 68/2008 of April 3rd). The GP is a Portuguese multi-municipal metropolis, integrated into the new statistical sub-region (NUTS III[2]) of the AMP, part of the Northern Region (NUTS II[3]). It consists of about 1023.2 km2 of total area and 1,364,454 inhabitants in 2016 (PORDATA@, 2016).



a) b)

Figure 8- a) Division of Portugal into municipalities; b) Division of "Greater Porto" area into municipalities (adapted from CAOP, 2011)

As already said, the samples from this study were taken from a population made up of students, teachers, researchers and employees of FEUP. This collection was previously carried out by the "SenseMyCity" project in campaign, using the "SenseMyFEUP" application.

This application provided data relative to both travel and user characteristics.

[2] NUTS III- Nomenclature of Territorial Units for Statistical Purposes Level III, consisting of 30 units, of which 28 are on the continent, and two corresponding to the Autonomous Regions of the Açores and Madeira (DR, 38/1989).

[3] NUTS II- Nomenclature of Territorial Units for Statistical Purposes Level II, consisting of seven units, five of which on the continent corresponding to the areas of activity of the regional coordination commissions, as well as the territories of the Autonomous Regions of the Açores and Madeira (DR, 38/1989).

Regarding sample demographics, the following characteristics were provided per user:

- Age;
- Gender;
- Function (between 1st, 2nd and 3rd cycle student, teacher, researcher and non-teaching personnel);
- Possession or not of own vehicle.

	age text	gender text	car text	role text
1	41	F	1	Professor
2	29	M	1	Funcionário não docente
3	24	M	1	Student 2nd cycle / Master's / 4th-5th year
4	31	M	1	Estudante 3° ciclo (Doutoramento)
5	22	F	0	Estudante 2° ciclo (Mestrado / 4°-5° ano)
6	22	M	1	Estudante 2° ciclo (Mestrado / 4°-5° ano)

Figure 9- “Demography” Data Base

However, due to data protection reasons, only the role of each user was associated with the trips made. Also for the sake of security, each user was given a “daily user id” that begins and ends at 4 a.m.. The “daily user id” is made up of one or more “session ids”, changing whenever the mobile phone has disconnected or been left without a network.

As for the movements made, these were provided in two ways: trips and segments. Each trip is associated with “daily user id” and consists of one or more segments. A new segment begins whenever the user has changed a mode of transport or has had a waiting period without travelling, either waiting for the bus, waiting for the traffic light to turn green or stopped in traffic.

The initial and final geographic coordinates of each trip and segment were given, as well as the start and end hours, distance travelled and the most used mode of transport.

The coordinates were provided in the World Geodetic System 1984 (WGS 84). This coordinate system is a norm, defined in 1984, applied in geocentric origin cartography used by the GPS navigation system and Google Earth (Gonçalves, J., 2015). The WGS represents an ellipsoid whose positioning, orientation and dimensions best fit the equipotential surface of the Earth that matches the geoid. (WEB.ARCHIVE@, 2010).

The travel hours were provided on Unix milliseconds. The Unix epoch is the number of milliseconds that have elapsed since 1 January 1970, without counting leap seconds (@EpochConverter, 2018).

Furthermore, information was provided on an estimate made by FEUP through the "SenseMyFEUP" application for the modes of transport most used in each trip and segments, based on speed and acceleration profiles. For each trip and segment, there was a probability of having travelled the most by car, bicycle, bus, metro, or by walk.

	trip_id [PK] integer	daily_user_id integer	session_ids integer[]	seconds_start integer	lat_start double precision	lon_start double precision	seconds_end integer	lat_end double precision	lon_end double precision	distance double precision	foot real	bike real	car real	bus real	metro real	travel_mode text	role text
1	303628	397	{647}	1459464770	41.1547911	-8.6178673	1459465213	41.1548151	-8.6178273	203.388648720926	995886	0	411398	0	0	foot	Student 3rd cycle / Doctora...
2	303633	390	{652}	1459467971	41.1523521	-8.6097233	1459468051	41.1524966	-8.6096833	42.7424443438547	1	0	0	0	0	foot	[null]
3	303637	392	{656,657}	1459465282	41.14454009	-8.56292593	1459467132	41.1631127	-8.5870161	5921.07030809987	038515	899003	827202	985056	0.0267869	car	Estudante 1° ciclo (Licencia...
4	303638	392	{658}	1459467825	41.15471869	-8.58187465	1459468622	41.1331649	-8.5588037	3539.58248843601	206046	070506	657833	115568	0.0198489	car	Estudante 1° ciclo (Licencia...
5	303642	383	{663}	1459466113	41.1474065	-8.6203623	1459466838	41.1775054	-8.594714	4959.94473246965	0	0.05	0.875	0.05	0.025	car	Student 1st cycle / Bachelo...
6	303656	399	{677,678}	1459461768	41.1491537	-8.6109186	1459467085	41.5407166	-8.4053333	56609.54845491	152317	448681	0.93315	505553	00614586	car	Docente
7	303657	400	{679}	1459483427	41.2379837	-8.6724295	1459483679	41.2379705	-8.6724721	71.3039161899396	1	0	0	0	0	foot	[null]
8	303662	406	{691}	1459491336	41.159521	-8.6257462	1459494838	41.179673	-8.5951729	6527.81198736429	993546	379415	550513	569122	0	foot	Estudante 3° ciclo (Doutor...

Figure 10- "Trips" Data Base

	session_id [PK] integer	segment_id [PK] integer	seconds_start integer	secmillis_start bigint	lat_start double precision	lon_start double precision	seconds_end integer	secmillis_end bigint	lat_end double precision	lon_end double precision	length real	movement boolean	speed_profile sensemycity.metrics	acceleration_profile sensemycity.metrics
1	647	0	1459464770	1459464770212	41.1547911	-8.6178673	1459464893	1459464893598	41.1547971	-8.6178964	2.52444	false	(0.0,0.005115274999999...	(0.0,0.0,0.0,0.0,0.0,0.0,0....
2	647	1	1459464898	1459464898555	41.1548103	-8.6176552	1459464898	1459464898555	41.1548103	-8.6176552	0	true	(4.0822799999999999,4....	(0.0316480999999999...
3	647	2	1459464903	1459464903543	41.1548057	-8.6176742	1459464903	1459464903543	41.1548057	-8.6176742	0	false	(0.33480500000000002,...	(0.376819999999999999...
4	647	3	1459464908	1459464908640	41.1548083	-8.6177666	1459464913	1459464913706	41.1548133	-8.6176327	11.2172	true	(1.51796,1.69205999999...	(0.0685232999999999...
5	647	4	1459464918	1459464918741	41.1548279	-8.6176372	1459464918	1459464918741	41.1548279	-8.6176372	0	false	(0.330816,0.330816,0.33...	(0.186471,0.186471,0.1...
6	647	5	1459464923	1459464923880	41.1548183	-8.6177324	1459464944	1459464944009	41.1548092	-8.617794	22.5539	true	(0.63903200000000004,...	(0.00419393000000000...
7	647	6	1459464948	1459464948998	41.1548091	-8.6177952	1459464948	1459464948998	41.1548091	-8.6177952	0	false	(0.02024940000000000...	(0.0662081999999999...
8	647	7	1459464953	1459464953997	41.154817	-8.6178766	1459464959	1459464959219	41.1547706	-8.6178834	5.1875	true	(0.99346400000000001,...	(0.03721,0.0617865000...

Figure 11- “Segments” Data Base

Another type of complementary information corresponding to georeferenced social networks was available. This sample was obtained from social network platforms by the "URBY.Sense" project for April 2016, in the AMP. This information was about the following social networks:

- “Facebook”

“Facebook's mission is to give people the power to share and make the world more open and connected. People use Facebook to stay connected with friends and family, to discover what's going on in the world, and to share and express what matters to them” (Facebook@, 2014).

- “infoPorto”

“The “infoPorto” social network is an information services platform, encompassing a portal to disseminate information about the Porto Region. It allows the consultation and research of events to take place in the Porto Region. This service is available free of charge to the public” (infoPorto@, 2017).

- “Foursquare”

“Foursquare is a technology company that uses smart location to create consumer experiences and significant business solutions. For developers and businesses, it offers hosted data and technology to create context-sensitive smart apps, aware of the location. “Foursquare's Places” technology provides location data for Apple, Uber, Twitter, Microsoft, Samsung and 100,000 other developers” (Foursquare@, 2018).

From the “Facebook” social network, were collected places of interest and events, separately. Each place record provided the following relevant information:

- Name;
- Place category;
- Geo-referenced location;
- Fan count;
- The number of total check-ins;
- Place’s identification (ID) (to allow the correspondence between places and events).

	id [PK] bigint	name character varying (300)	fan_count integer	hours character varying (700)	checkins integer	category character varying	category_list character varying (450)	city character	country character	latitude double precision	longitude double precision	street character varying	zip character	website character varying
1	43722199359	Rua Miguel Bombarda | ...	25433	[null]	4226	Street	[{"id": "151810238222...	Porto	Portugal	41.1494886165	-8.62138443481	Centro Comercia...	4050-381	[null]
2	62848313655	Serralves	229007	{"sun_1_close": "20:00...	51306	Art Museum	[{"id": "384382644921...	Porto	Portugal	41.1593170554	-8.6588681373	Rua D. João Cast...	4150-417	http://www.serralves.pt
3	67203494422	Teatro Nacional São João	44426	[null]	6559	Performance Art T...	[{"id": "173883042668...	Porto	Portugal	41.1448168075	-8.60722474286	Praça da Batalha	4000-102	www.tnsj.pt
4	71969543864	Casa da Música	406837	{"sun_1_close": "18:00...	116582	Cultural Center	[{"id": "619759428190...	Porto	Portugal	41.1587910023	-8.63086601004	Av. da Boavista, ...	4149-071	http://www.casadam...
5	121166749965	FEUP	35910	[null]	26914	College & University	[{"id": "2602", "name": ...	Porto	Portugal	41.1777467096	-8.59629518294	s/n Rua Doutor R...	4200-465	www.fe.up.pt
6	126860029718	PITCH	42829	{"sat_1_open": "23:45"...	26969	Dance & Night Club	[{"id": "191478144212...	Porto	Portugal	41.14722	-8.60814	Rua Passos Man...	4000-381	http://www.pitch-club....
7	130559106745	Plano B	86042	{"sat_1_close": "06:00"...	25405	Dance & Night Club	[{"id": "191478144212...	Porto	Portugal	41.14655	-8.61392	Rua Cândido dos...	4050-150	http://www.planobpor...
8	132830011041	Faculdade de Arquitectur...	16625	[null]	3223	College & University	[{"id": "2602", "name": ...	Porto	Portugal	41.150239369	-8.6349105835	Via Panorâmica ...	4150-755	www.arq.up.pt

Figure 12- "Facebook Places" Data Base

From the same social network, the following attributes about each event was provided:

- Name;
- Date (including start hours and, in just a few, end hours);
- Attending count;
- Place’s ID.

	id [PK] bigint	name character varying (300)	attending_count integer	category character	interested_count integer	is_canceled boolean	maybe_count integer	noreply_count integer	description character varying (20000)	date_start timestamp with time zone	date_end timestamp with time zone	fb_place_id bigint
1	)804193655639	Curtas de João Nicolau / 61ª...	79	[null]	220	false	220	990	Ciclo #02.2016 – "Da Te...	2016-04-06 22:00:00+01	[null]	5662463786514
2	5783199830732	JACK TUSSO - Live at RUA	18	[null]	52	false	52	134	O melhor do Rock volta ...	2016-04-29 23:50:00+01	[null]	4455458610673
3	5575902168306	NomadTalks: Crónicas da A...	119	[null]	309	false	309	575	NomadTalks + National ...	2016-04-01 21:00:00+01	2016-04-01 23:00:00+01	2470104456967
4	5997512364321	Filme-concerto "O Mundo P...	5	[null]	18	false	18	137	Este filme histórico (192...	2016-04-15 21:30:00+01	[null]	1651216533406
5	)990294365735	TERTÚLIAS GUERRA JUNQU...	2	[null]	7	false	7	1	A partir de 30 de Janeir...	2016-01-30 17:30:00+00	[null]	0769515211521
6	)692774324820	Ana Deus lê textos de Álvar...	15	[null]	48	false	48	653	No próximo sábado, 16 ...	2016-04-16 17:30:00+01	[null]	6460984203387
7	)513309008083	A solo a solo a dois	4	[null]	19	false	19	453	Este trabalho é sobre o ...	2016-04-16 16:00:00+01	[null]	9352407777683
8	'282831663466	Pintarola Wine Affair	39	[null]	70	false	70	341	A marca PINTAROLA, qu...	2016-04-07 18:30:00+01	2016-04-07 23:30:00+01	2119827851652

Figure 13- "Facebook Events" Data Base

From the "infoPorto" platform events were collected. The information obtained for each event consisted of the data below:

- Name;
- Event category;
- Date (including start and end hours);
- Geo-referenced location.

	id [PK] integer	name character varying (300)	date_start timestamp with time zone	date_end timestamp with time zone	location character varying (250)	location_latitude double precision	location_longitude double precision	website character varying	fb_event_id bigint	category character varying	description character varying (20000)
1	1507745343	Exposição – A Arte da ...	2016-03-26 08:00:00+00	2016-04-08 16:00:00+01	Casa-Museu Guerra J...	41.1425396	-8.6107064	https://www.facebook...	147263725910	Exposições	"Depois de beber, cada ...
2	1507745350	Exposição "Macau: U...	2016-03-31 17:30:00+01	2016-04-07 18:00:00+01	Forte De São João Da ...	41.1489989	-8.6743988	https://www.facebook...	604956439841	Exposições	Entre os dias 31 de mar...
3	1507745357	Hora do Empreended...	2016-04-01 10:00:00+01	2016-04-01 12:00:00+01	Cidade das Profissões...	41.144309	-8.6129073	https://www.facebook...	702420891738	Cursos e Workshops	Uma vez por mês a Incu...
4	1507745366	Franco Charais expõe ...	2016-04-01 17:30:00+01	[null]	Ateneu Comercial do ...	41.1471669	-8.6078721	https://www.facebook...	761565695064	Exposições	FRANCO CHARAIS expõ...
5	1507745373	Poesia no Castelo – "N...	2016-04-01 17:30:00+01	[null]	Forte Sao Joao Baptist...	41.1489989	-8.6743988	https://www.facebook...	600254831311	Literatura;Outros	Poesia no Castelo – "No ...
6	1507745378	15 Anos de Maus Hábi...	2016-04-01 19:00:00+01	2016-04-03 17:00:00+01	Maus Hábitos - Espaç...	41.1466188	-8.6057114	https://www.facebook...	881774733798	Clubbing;Exposições;...	:: 15 Anos de Maus Hábi...
7	1507745385	Catherine Christer He...	2016-04-01 19:00:00+01	[null]	Serralves, Rua D. João...	41.1597898	-8.6596661	http://www.serralves....	[null]	Exposições;Música e ...	Com a participação do l...
8	1507745391	A Viagem de Peer Gyn...	2016-04-01 20:00:00+01	[null]	Casa da Música, Av. d...	41.158881	-8.630696	https://www.facebook...	102445091128	Música e Concertos	Orquestra Sinfónica do ...

Figure 14- "infoPorto" Data Base

Finally, from "Foursquare" were collected POIs. The information provided about each POI is shown hereunder:

- Name;
- POI category;
- Geo-referenced location;
- The number of users;
- The number of total check-ins.

	id [PK] character varying	name character varying	rating real	stats_tipcount integer	stats_checkinscount integer	stats_ intege	stats_userscount integer	location_city character varying	location_lat double precision	location_lng double precision	categories character varying
1	4b3b6e5ef964a520b07325...	Casa da Música	[null]	93	9661	[null]	5760	Porto	41.158753734988	-8.63083362579346	[{"pluralName": "Concert Halls...
2	4b3b6ff9f964a520c97325e3	A Cozinha do Manel	8.7	7	237	569	329	Porto	41.1461957837337	-8.5928458541695	[{"pluralName": "Portuguese R...
3	4b525e6df964a520c67927...	Café Lusitano	[null]	20	956	[null]	475	Porto	41.1491700631581	-8.61438305671309	[{"pluralName": "Gay Bars", "p...
4	4b527d00f964a5208b7f27...	O Bem Arranjadinho	[null]	11	115	[null]	71	Leça da Palmeira	41.1869456629325	-8.70082145962082	[{"pluralName": "Portuguese R...
5	4b5288abf964a520588127...	Rota do Chá	[null]	83	1677	[null]	1087	Porto	41.1492585891617	-8.62240328855435	[{"pluralName": "Tea Rooms", ...
6	4b5337cef964a520ba9227...	Parque da Cidade	[null]	[null]	[null]	[null]	[null]	Póvoa de Varzim	41.3973179365846	-8.75682104403512	[{"pluralName": "Parks", "prim...
7	4b533b4ff964a520569327...	Shopping Cidade d...	[null]	[null]	[null]	[null]	[null]	Porto	41.1549013709334	-8.62987275525959	[{"pluralName": "Shopping Mal...
8	4b54a72ef964a52003c527...	NorteShopping	8.4	68	[null]	[null]	[null]	Matosinhos	41.1804196475854	-8.65502826315394	[{"pluralName": "Shopping Mal...

Figure 15- "Foursquare" Data Base

4.3 Data Processing

With the aim of characterising the individual mobility of the sample under study, it was necessary to adopt a methodology to extract the treated information from the data.

Since the geographical coordinates of user movements were provided, a Geographic Information System (GIS) map was developed. This type of maps "allows us to visualise, question, analyse and interpret data to understand relationships, patterns and trends" (Esri@, 2018).

The GIS map was created using the ArcGIS program. This software enabled us to perceive that the information provided included trips that had the origin and/or destination in various parts of the country. Hence, the movements that were within the area defined for the study, the GP area, were identified.

Then, it was necessary to define the period to be analysed. The collection was performed during every hour of April 2016. Since this is a study focused on out of routine movements, we studied every day of that month only from 7 p.m. to 7 a.m., except for the weekends for which the full day was analysed. For an easier understanding during the study, the conversion of Unix time to human readable date was made, using the "Epoch Converter" (EpochConverter@, 2018).

Thus, data with the following characteristics were eliminated:

- Trips whose origin and/or destination were not in the GP area;
- Trips that were performed between 7 a.m. and 7 p.m during the weekdays.

As mentioned previously, an estimation of the modes of transport per trip and segment was provided. It was assumed, therefore, that the transport mode with the highest probability was used.

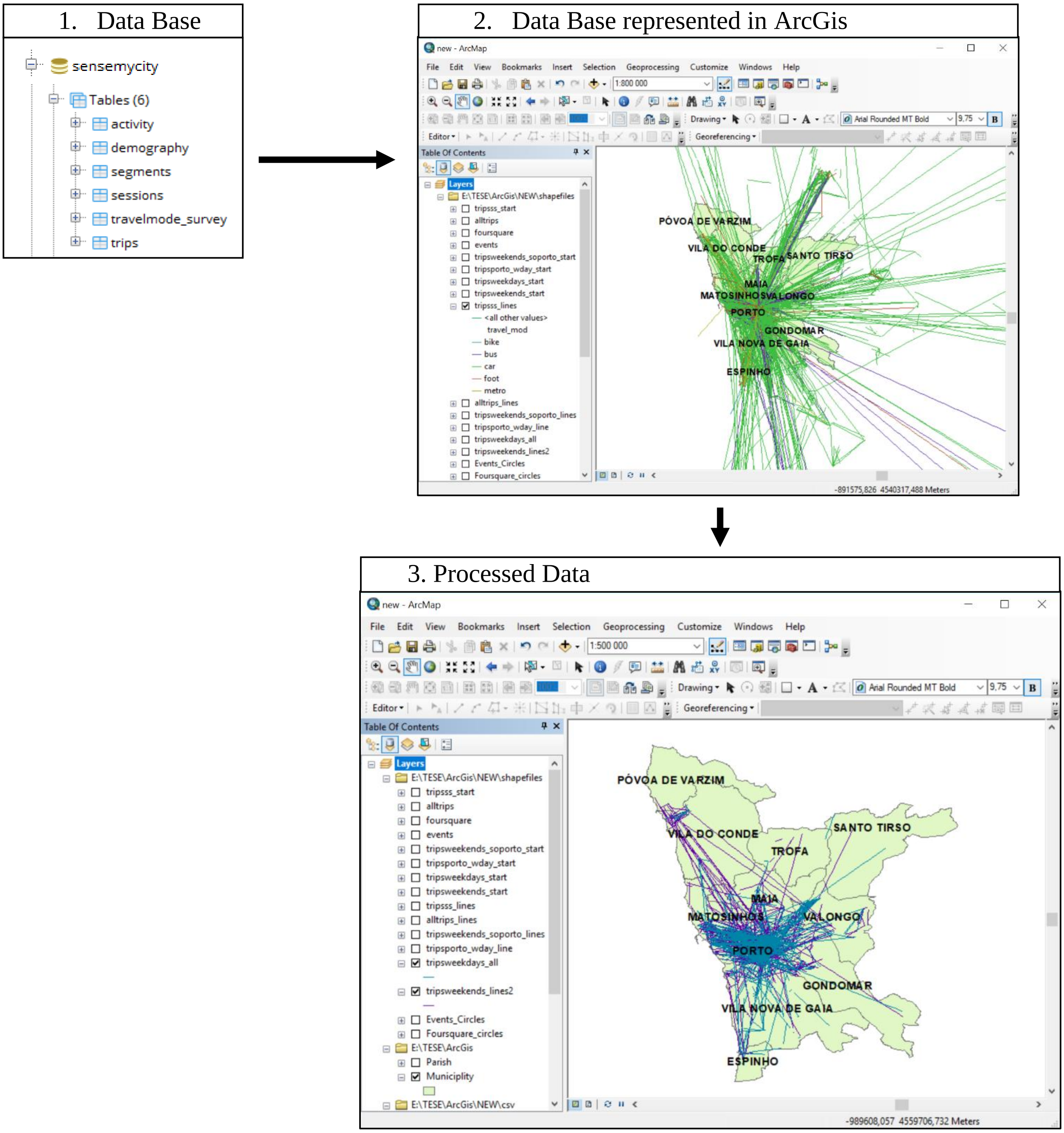


Figure 16- Data processing ("SenseMyCity")

Regarding the social network database, a methodology similar to the previous one was adopted, eliminating data with the following characteristics:

- Events and POIs whose origin and/or destination were not in the GP area;
- Events and POIs opened between 7 a.m. and 7 p.m during the weekdays;
- And, moreover, for events that were reported both in “Facebook” and “infoPorto”, just one was kept.

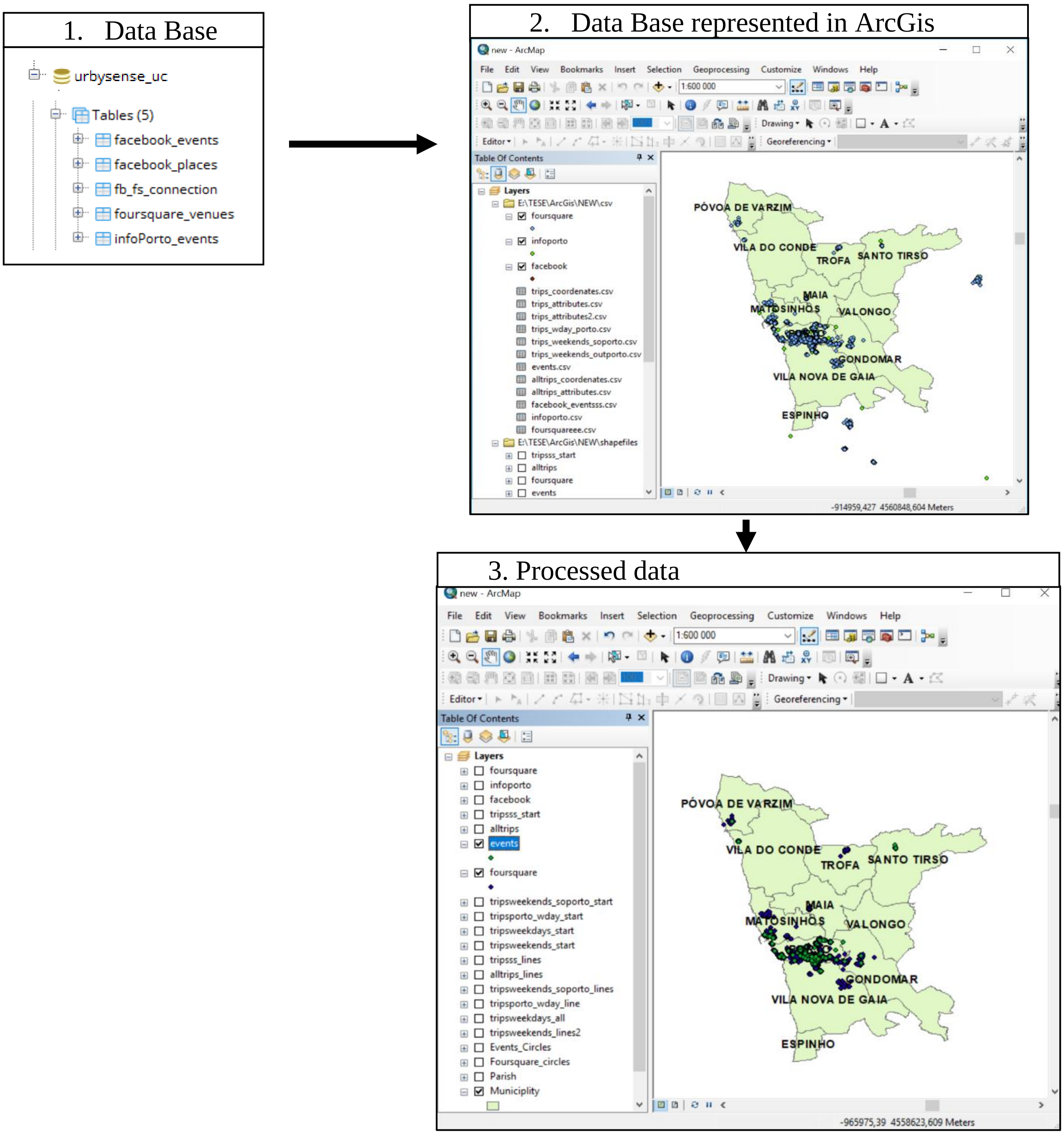


Figure 17- Data processing (“URBY.Sense”)

4.4 Data Analysis

The characterisation of individual mobility was done in two approaches: one more general, trying to understand how, globally, people move in hours out of routine; and a more specific one, choosing a weekday and a weekend day relating the trips to the events/POIs.

4.4.1 Exploratory-Descriptive Phase

In the first approach, we tried to evaluate the set of all trips made regarding the mode of transport used, distance travelled, and time spent. Since the study hours depend on the day in study, the sample was divided into two distinct groups: weekdays and weekend days.

To understand trends, at certain stages of the study movements were aggregated as follows:

- "Intra-municipal" movements, that is, with origin and destination in the same municipality;
- "Radial" movements, that is, with origin in the Municipality of Porto and destination in another municipality in the GP area (and vice versa);
- "Transversal" movements, that is, with origin and destination in other municipalities of GP than the Municipality of Porto.

With the most used mode of transport per trip, we sought to elaborate the modal split of the two study groups, originating five Origin-Destination (OD) matrices for the weekdays and other five for weekends. The modes of transport available were: car, bus, metro, bicycle, and on foot.

With this data, it was possible to elaborate GIS maps with graduated colours according to the attributes. This process made possible a better understanding of the data and its analysis.

4.4.2 Modelling Phase

The modelling phase consisted of two models with different purposes:

1. Application of a binomial logistic regression, to study the factors that influenced the choice of the transport mode;

2. Use of multinomial logistic regression, seeking to study what affected the choice of destination.

To support this analysis, it was used the Statistical Package for the Social Sciences (SPSS) software. “SPSS is a comprehensive system for analysing data. SPSS Statistics can take data from almost any type of file and use them to generate tabulated reports, charts and plots of distributions and trends, descriptive statistics, and complex statistical analyses” (SPSS Statistics Base 17.0).

To be able to elaborate these models, it was necessary to adopt a methodology for extracting the data to be used for the modelling.

A weekday and a weekend day were chosen. This process considered several variables and had as objective the elaboration of two OD matrices and to identify the respective modal split.

These OD matrices were obtained by crossing information from the trips and the events and POIs, the latter only considering those with more than 500 check-ins (the most popular ones). At this stage, the trips were treated at the scale of the segments. With an area of influence defined as a circle of radius equal to 500 meters and centre in the places of the events/POIs, it was tried to determine the destinations of the trips made. Thus, in the case of these matrices, the origins correspond to the beginning of the trip and the destination to the parish/municipality where the event or the POI took place, or vice versa.

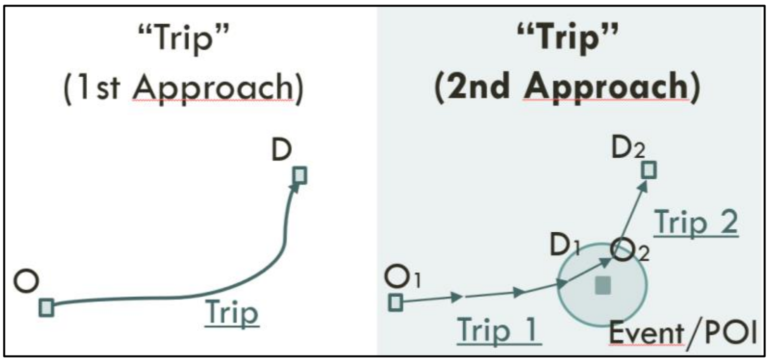


Figure 18- "Trip" Concept (O- Origin; D-Destination)

The chosen days were April 21 (starting from 7 p.m. and ending at 7 a.m. of day 22) and 23 (this one for all day hours), Thursday/Friday and Saturday, respectively. In the decision process, the number of events occurred in each day and the number of trips that intersected the areas of influence defined for the places of the event/POI were considered, to obtain the most significant possible sample.

This modal split was done concerning both the distance travelled and the time spent since it was considered self-evident that they would give different results and it was worth the reflection on the subject.

The results obtained by this methodology were later used for the elaboration of the two discrete choice models.

Discrete choice models can be classified according to the number of available alternatives, as it follows:

- Binomial choice models: two available alternatives;
- Multinomial choice models: three or more available alternatives.

In a first phase, the aim was to understand the probability of using sustainable modes of transport in relation to using the car mode concerning specific variables. Thus, the modes were divided into two groups: sustainable modes (bus, metro, bicycle, and walk), and car mode.

Binomial logistic regression was used. This regression allows us to predict the probability that an observation falls into one of two categories of a dichotomous dependent variable based on one or more independent variables that can be either continuous or categorical, going against what we intended (Laerd@, 2018a).

Part of the process involved checking to make sure that the data could be analysed using binomial logistic regression. To give a valid result, the data must consider the following assumptions (Laerd@, 2018a):

1. The dependent variable (in this case, sustainable modes and car groups) should be measured on a dichotomous scale;
2. To have one or more independent variables, which can be either continuous or categorical;
3. To have independence of observations and the dependent variable should have mutually exclusive and exhaustive categories;
4. There needs to be a linear relationship between any continuous independent variables and the logit transformation of the dependent variable.

The first three assumptions were checked before entering the data in SPSS and the fourth assumption was reviewed after, using the software.

After all these conditions were verified, the data provided by the SPSS were interpreted.

In the second phase, the purpose was to identify which destination choice model best adapted the patterns found.

Each category was mapped to four main categories, on which the search was performed:

- Art Exposition/Market;
- Coffe/Bar/Restaurant;
- Dance and Night Club;
- Theatre/Music Concert/Talkshow.

In this analysis, it was necessary to resort to a multinomial logistic regression since, instead of having only two categories for the dependent variable, there were four.

Multinomial logistic regression is used to predict a nominal dependent variable given one or more independent variables. As with other types of regression, multinomial logistic regression can have nominal and/or continuous independent variables and can have interactions between independent variables to predict the dependent variable (Laerd@, 2018b).

The process was similar to the logistic regression, and it was necessary to verify if the data could be used in this type of regression. However, some assumptions were different (Laerd@ (2018b):

1. The dependent variable shall be measured at the nominal level;
2. Independent variables should be treated as continuous or categorical, not as ordinal variables;
3. To have independence of observations and the dependent variable should have mutually exclusive and exhaustive categories;
4. There should be no multicollinearity between independent variables;
5. There must be a linear relationship between any independent variables and the logit transformation of the dependent variable;
6. There should be no outliers, high leverage values or highly influential points.

The first three assumptions were checked before entering the data in SPSS. The fourth, fifth and sixth assumptions were reviewed after, using the software.

As for the binomial regression, after all these conditions were verified, the data provided by the SPSS were interpreted.

5 ANALYSIS AND RESULTS

5.1 Introduction

The accomplishment of this work consisted in three essential phases:

1. Data selection based on the data base that was made available;
2. Data treatment in order to prepare the data base for this study;
3. Data analysis, exploring the selected data and using logit approaches in the search for patterns about the factors that might be influencing the choices for transport mode and type of events, to better understand this off the routine mobility.

An important step in the process was the filtering of the data towards the study objectives, which was done on the data treatment phase.

5.2 Data Processing

The data collection phase was performed in the previous steps of the “URBY.Sense” project. Brief descriptions of each group of data are given below (a more detailed explanation was already made in the “Methodology” chapter), while the extensive treatments that have been done are presented.

5.2.1 People Movements

The information about people movements was obtained by the mobile phone application “SenseMyFEUP” developed at FEUP. The data collection was carried out in April 2016, at the same establishment.

This information consisted of the following components.

5.2.1.1 Demography

The study included 300 volunteers, aged 17 to 58 years with an average of 24. Of these 300 people, 190 were males and 110 females. It is known that 135 have a private car, that is, less than half.

The following table shows the distribution of roles by the volunteers. It could be verified that the significant part were students, a total of 87%, and only 2% were teachers.

Table 2- Volunteers by role

ROLE	*No.*	*%*
Student 1st cycle / Bachelor's / 1st-3rd year	90	30
Student 2nd cycle / Master's / 4th-5th year	159	53
Student 3rd cycle / Doctorate (PhD)	12	4
Teacher	5	2
Non-teaching personnel	16	5
Researcher	18	6
Total	300	100

For the sake of data protection, only the role information was associated with session ids. The concept of "session id" was explained in the “Methodology” chapter.

5.2.1.2 Trips

Each “daily user id” corresponds to a “trip”. A total of 9173 trips were collected.

The total number of trips collected indicates an average daily trip per person equal to one trip. The results obtained from a study done in England in 2016, indicated an average daily trip per person of around 2.5 (Department for Transport, 2017). Thus, it was concluded that the sample presents limitations related to its size. This fact can be justified by failures in detecting travel from the mobile phone application, not always dividing them whenever a new one was started, but a union between several trips. Also, the sample presents problems related to bias, being mainly composed of students.

The initial and final geographic coordinates of each trip were given, as well as departure and arrival times and distance travelled. To each is associated the user role and an estimate of the modes of transport most used in each trip.

As it was said in Chapter 4, it was necessary to define the study area and the period to be analysed.

The trips that had origin or destination outside the GP area were eliminated, both in Portugal and in the rest of the world (possible errors).

Then, for April 2016, it was decided to study the trips from 7 p.m. to 7 a.m. when it was a weekday and the full day when it was a weekend day. Hence, the sample was divided into weekdays, a total of 21, and weekend days, a total of 9.

Consequently, a total of 2577 trips was retained.

The following tables present some of the characteristics of the trips evaluated using this data base. On further studies this data should be compared with data from other mobility studies in Porto.

Table 3- Trips characteristics by travel mode

Travel Mode	*Trips*		*Distance Travelled (average-km)*		*Time Spent (average-min)*	
	No.	%	Weekdays	Weekends	Weekdays	Weekends
Car	1260	48.9	5.729	6.188	19.98	29.37
Bus	68	2.6	3.832	5.183	17.29	34.30
Metro	38	1.5	5.591	4.331	22.05	29.95
Bicycle	20	0.8	3.277	5.459	17.45	61.99
Foot	1152	44.7	0.941	1.055	16.75	18.96
Unknown	39	1.5	-	-	-	-
Total	2577	100				

Table 4- Trips characteristics by user role

User	*Trips*		*Distance Travelled (average-km)*					*Time Spent (average-min)*				
	No.	%	Car	Bus	Metro	Bicycle	Foot	Car	Bus	Metro	Bicycle	Foot
Student 1st cycle	727	28.21	5.690	3.196	3.741	0.000	0.960	21.82	34.30	16.68	0.00	18.57
Student 2nd cycle	1234	47.89	5.665	3.853	7.420	4.586	0.925	25.60	17.55	33.06	44.18	16.76
Student 3rd cycle	244	9.47	5.752	5.483	1.628	0.000	1.456	21.12	22.19	9.57	0.00	23.05
Researcher	89	3.45	5.393	5.318	4.978	0.000	1.327	19.94	24.30	26.22	0.00	18.08
Teacher	35	1.36	15.227	14.835	0.000	0.000	0.668	49.89	84.50	0.00	0.00	11.63
Non-teaching personnel	102	3.96	8.421	4.069	0.000	0.000	0.952	31.00	50.52	0.00	0.00	18.92
Unknown	146	5.67	-	-	-	-	-	-	-	-	-	-
Total	2577	100										

Regarding the car, as can be seen in Table 3, it was the most used mode of transport. Comparing, on the weekend days were travelled greater distances than in the days of the week. However, there is a much more significant difference in time spent between the different phases of the week. Table 4 shows that those who travel more distances and spend more time using the car are the teachers, in contrast to the researchers.

As for public transport, bus and metro, there was not much recourse to these modes. Were travelled more distances on weekdays by metro and on weekend days by bus. In both modes, the time spent was higher on weekends. The teachers were the ones who used the bus more but never used the metro. The students of the second cycle were those who used the metro the most, both in distances travelled and in time spent.

Bicycle use is very low compared to other modes. It is to be verified that greater distances were travelled in the weekends and, also, much more time was spent. The students of the second cycle were the only ones who resorted to cycling, having spent more time in this mode than in all others.

About walking, it was almost found in the same proportion as the use of the car. The difference is not too high, but more distances have been travelled and more time was spent on the weekend days. The students of the third cycle were those who walked the most, both in the distance travelled and in time spent. In contrast are the teachers who were the ones that walked fewer distances and spent less time.

5.2.1.3 Segments

Each trip is composed of one or more segments, and each segment is associated with a session id. A total of 193696 segments was collected.

There is also a probability that a mode of transport has been used for each segment, between car, bicycle, bus, metro, and on foot.

As for the trips, segments that had the origin and/or destination outside the GP area were eliminated and those that were made outside the period defined for the study (from 7 p.m. to 7 a.m. when it was a weekday and all day when it was a weekend day).

5.2.2 Social Networks

The project gathered information for the AMP, also for April 2016, from the following social networks: "Facebook", "infoPorto", and "Foursquare". The detailed information provided for each one is presented underneath.

5.2.2.1 "Facebook" and "infoPorto" Events

Names of 272 events from "Facebook" and their geographical coordinates were collected, as well as the day and time of start and end. It is also provided information about the number of people who joined the event on the platform and about the category of the spot where the event took place.

From "infoPorto" platform, names of 409 events and their geographical coordinates were given, also the day and time of start and end, and event category.

Events that occurred outside the GP area were eliminated, as well as events that occurred outside the period defined for the study and for those that were duplicated, only one was maintained.

Consequently, 224 events were selected.

The days with most events were 9th and 29th, Saturday and Friday, respectively. On both days, most of the events were concentrated between 9 p.m. and 11:59 p.m..

The following table presents the number of events occurred in each municipality, by category. Additionally, it distributes events between weekdays and weekend days.

Table 5- Events in GP, by category

	Total	*Weekdays*	*Weekends*	*Arts and Entertainment*	*Dance and Night Club*	*Market*	*Music Concert*	*Sports*
Espinho	0	0	0	0	0	0	0	0
Gondomar	4	0	4	3	0	0	1	0
Maia	0	0	0	0	0	0	0	0
Matosinhos	5	4	1	2	0	0	3	0
Porto	206	130	76	89	46	9	60	2
Póvoa de Varzim	1	1	0	1	0	0	0	0
Santo Tirso	2	0	2	2	0	0	0	0
Trofa	0	0	0	0	0	0	0	0
Valongo	0	0	0	0	0	0	0	0
Vila do Conde	1	0	1	0	0	0	1	0
Vila Nova de Gaia	5	3	2	3	0	2	0	0
Greater Porto	224	138	86	100	46	11	65	2

Events were grouped into categories. Since we have not been given the category of each one, these categories have been defined considering the category available in the initial database regarding the place where the event took place and also some personal criterion trying to assign the category that best suited the event in question. Therefore:

- “Arts and Entertainment” category included, for example, “Ciclo de Teatro – Bonfim ao Palco”, “Poesia no Castelo - No Castelo A luz", and “Ciclo de Cinema Filosófico: Waking Life (2001)”;
- “Dance and Night Club” category included, for example, “Funk Productions 8 Years”, “FESTA - Blues no Espiga”, and “LIL LOUIS - The Founding Father of House Music”;
- “Market” category included, for example, “Pink Market”, “PORTO-Stock Off de Mobiliário Vintage”, and “Urban Market BY Portugal Lovers - Cardosas Fashion Weekend”;
- “Music Concert” category included, for example, “Dead Combo e As Cordas da Má Fama”, “Ludovico Einaudi ao vivo - Coliseu Porto”, and “Fado à Vez - Paraíso da Foz”;
- Finally, “Sports” category included “Corrida do Mar 2016”, and “UPFit Active Day”.

It should be noted the high concentration of events in the Municipality of Porto. There were more events on weekdays than on weekends, and the category with the most significant number of events was “Arts and Entertainment”.

5.2.2.2 “Foursquare” Points of Interest

The names of 9018 POIs were collected in the project along with their geographical coordinates, categories and the number of check-ins made on each page.

As for the events, POIs that were located outside the GP area were eliminated.

Therefore, 2790 POIs were gathered.

The POIs were grouped considering the category indicated in the original database. However, these were grouped into more global categories to eliminate categories such as "Portuguese Restaurant", "Tea Room" or "Coffee Shop". The "Others" column included categories that were considered not to motivate leisure travel, such as "University", "Tech Startup" and "Office". This allocation was made to limit the number of categories to be used in the study, making the process easier.

The following table presents the number of POIs in each municipality, by category.

Table 6- Points of Interest in GP, by category

	Total	*Coffee Shop*	*Restaurant*	*Athletics / Sports*	*Supermarket / Market*	*Park*	*Theater / Live Shows*	*Night Club*	*Others*
Espinho	0	0	0	0	0	0	0	0	0
Gondomar	84	14	13	5	3	1	0	0	48
Maia	28	1	4	0	2	1	1	1	18
Matosinhos	204	18	47	6	5	4	1	7	116
Porto	2116	173	434	28	38	23	34	149	1237
Póvoa de Varzim	27	3	0	2	0	1	1	0	20
Santo Tirso	28	5	5	1	0	0	0	3	14
Trofa	26	3	3	0	1	1	0	2	16
Valongo	0	0	0	0	0	0	0	0	0
Vila do Conde	29	4	4	0	0	0	2	0	19
Vila Nova de Gaia	248	25	54	5	1	5	5	10	143
Greater Porto	2790	246	564	47	50	36	44	172	1631

Once again, the Municipality of Porto is highlighted, with a higher concentration of POIs concerning all other municipalities, followed by Vila Nova de Gaia. The category with the highest number of POIs was “Restaurant”.

5.3 Individual Mobility Analysis

The characterisation of individual mobility was done in two approaches: one more general, trying to understand how, globally, people move in hours out of routine; and a more specific one, choosing a weekday and a weekend, searching for the development of two discrete choice models. As previously mentioned, the analysis was done at the municipal level for the whole of GP and the scale of the parishes of the Municipality of Porto. This division was more detailed due to the high concentration of trips in this area, as well as places of events (“Facebook” and “InfoPorto”) and POIs (“Foursquare”).

Figure 19- Division of Municipality of Porto into parishes

5.3.1 Exploratory-Descriptive Phase

In a more general approach, since the analysis period depends on the day being studied, the weekdays and the weekend days were examined separately. Nine weekend days were analysed (a total of 216 hours), and twenty-one days of the week (252 hours).

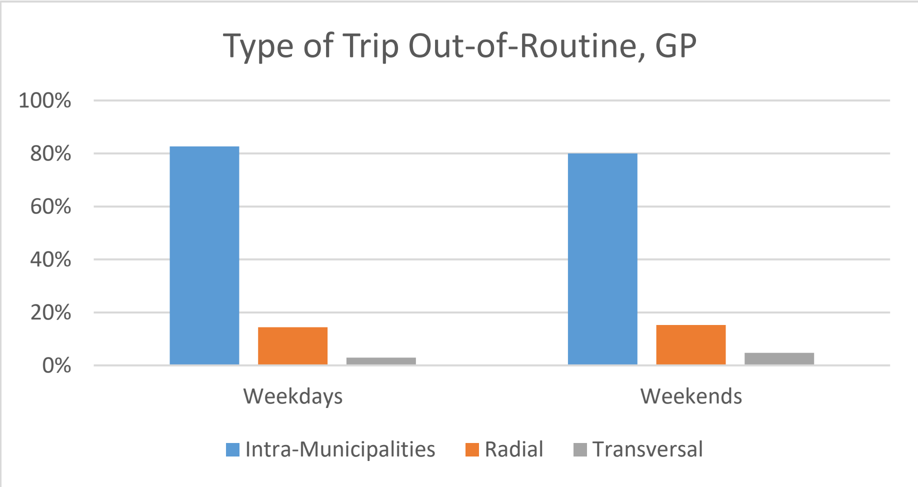
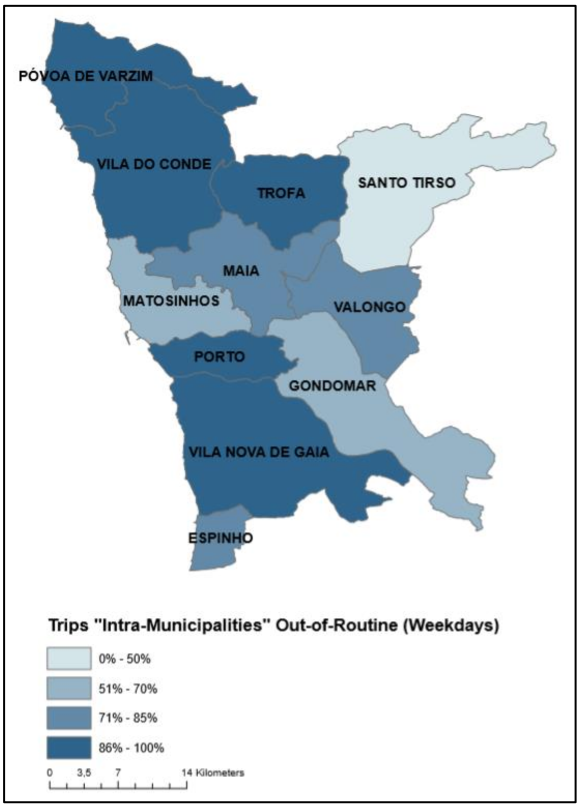
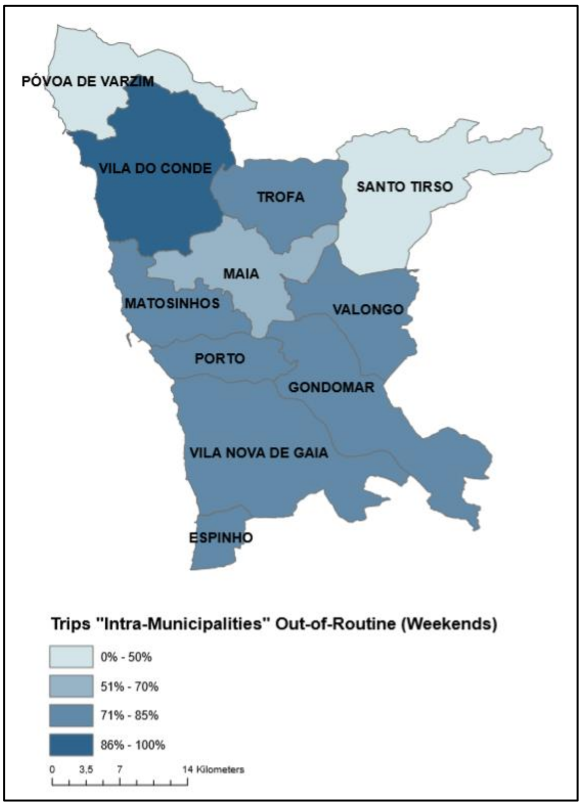


Figure 20- Trips out-of-routine by type

As can be seen in Figure 20, most trips were made within the own municipalities, and only a small percentage corresponds to trips made between municipalities other than Porto. It also appears that on weekends people were more likely to move to other municipalities, that is, to travel longer distances, than on weekdays.

The figure below (Figure 21), which refers to the proportion of intra-municipal movements concerning the total number of trips with origin in each municipality, indicates that Vila do Conde presented a significant percentage of intra-municipal trips both on weekdays and weekend days. The only municipalities that do not confirm the general tendency to move within their municipalities are Santo Tirso and Póvoa de Varzim (the latter, only on weekends).





a) b)

Figure 21- a) "Intra-Municipalities" out-of-routine trips made during the weekdays; b) "Intra-Municipalities" out-of-routine trips made during the weekends

As for the trips with origin in the Municipality of Porto, a greater tendency to move to other municipalities on weekend days than on weekdays was confirmed. However, it is a rather small difference: 15% and 14%, respectively.

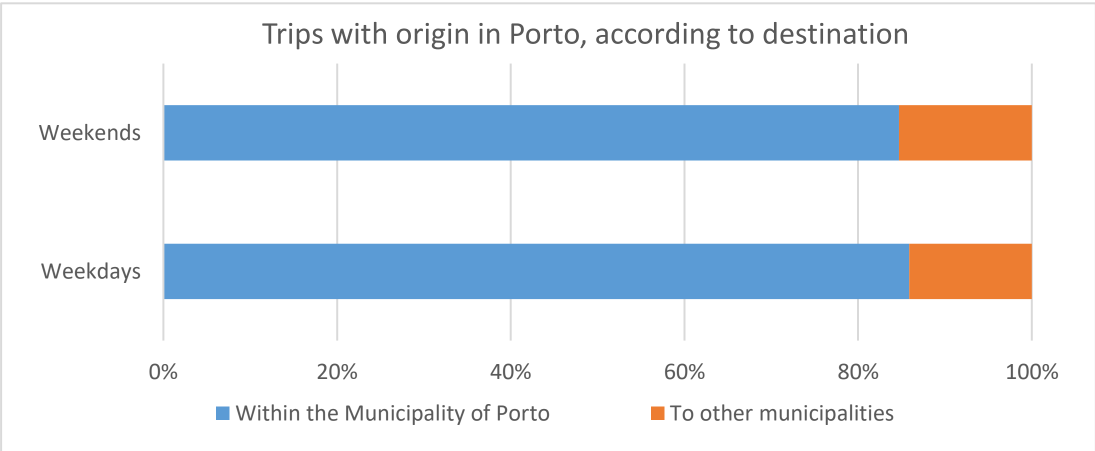


Figure 22- Trips with origin in the Municipality of Porto, according to the destination

The next figure (Figure 23) combines the total of trips made between each pair of municipalities, the number of events that occurred in each one and, furthermore, the number of POIs existent.

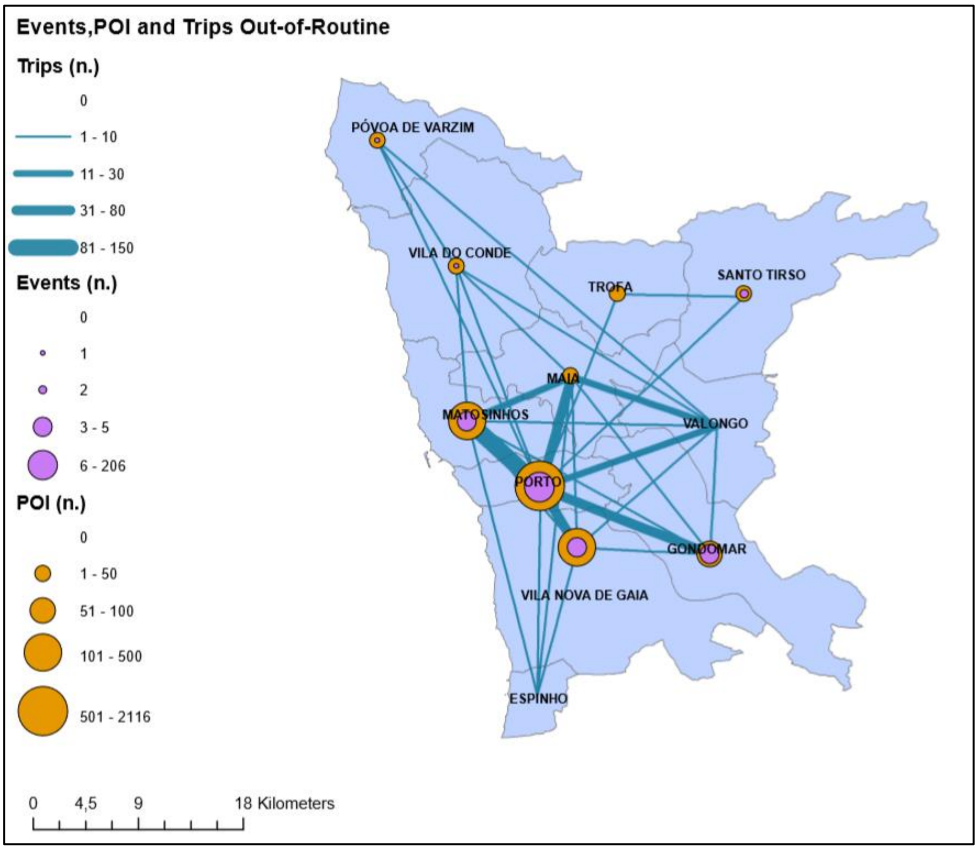


Figure 23- Events, POIs and trips out-of-routine made

The presence of concentrations of events and POIs of considerable size in several municipalities of GP generated a great diversity of inter-municipal displacements in April 2016. However, the radial movements stood out (that is, Porto and destination in another municipality of GP, and vice versa) This fact can be explained once it was situated in the Municipality of Porto about 76% of the total POIs and 92% of events occurred in that month.

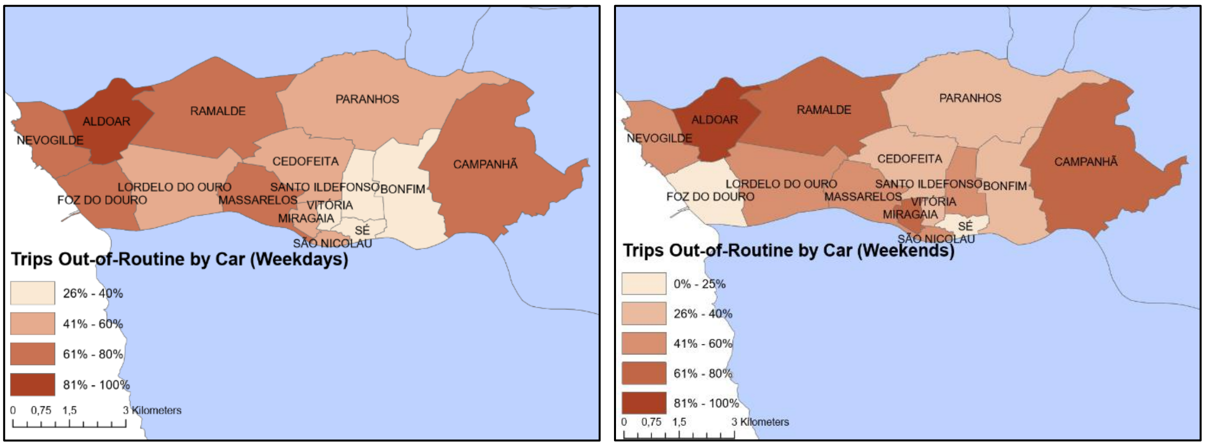
To validate these statements, we decided to perfom correlation tests between all these variables. From the obtained results, the strong relationship between the number of trips and the number of events and points of interest was confirmed since the correlation factors were very significant (close to 1) (Table 7).

Table 7- Correlation test

	Trips (n.)	*Events (n.)*	*Foursquare (n.)*
Trips (n.)	1		
Events (n.)	0.871132359	1	
Foursquare (n.)	0.895507393	0.994510441	1

Within the Municipality of Porto, there were many movements with origin and destination in the parishes where there was a higher offer. These parishes were: Campanhã, Cedofeita, Paranhos, Santo Ildefonso, and Vitória.

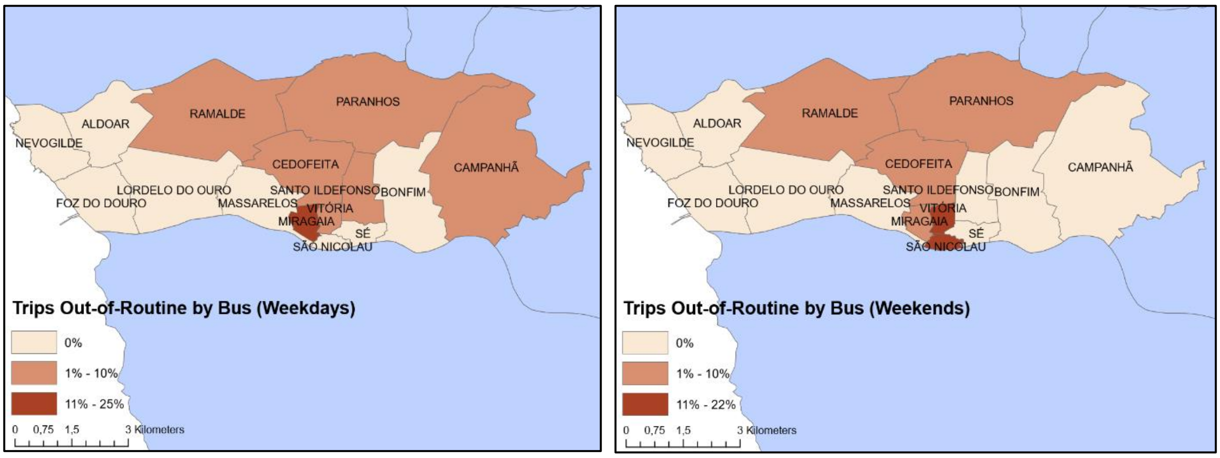
The figures below refer to the proportion of movements whose origin was in each parish of the Municipality of Porto concerning the travel mode used, concerning the total number of trips with origin in each parish.



a) b)

Figure 24- a) Trips Out-of-Routine by Car during the weekdays; b) Trips Out-of-Routine by Car during the weekends

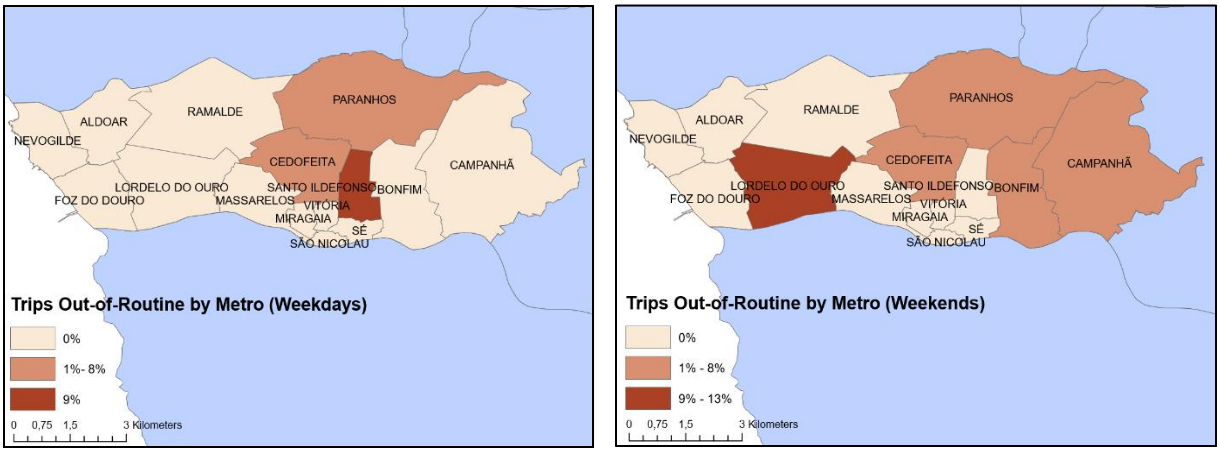
In the parish of Aldoar was where the car was resorted more, both on weekdays and weekends. In this parish there is a low offer of public transport, the metro does not even go there. There was little use of the car concerning other modes of transport on weekdays in a relatively central area of the municipality, where the public transport offer is more significant.



a) b)

Figure 25- a) Trips Out-of-Routine by Bus during the weekdays; b) Trips Out-of-Routine by Bus during the weekends

The bus was mainly used in the center city and little used mainly in the western parishes, Foz do Douro and Nevogilde, but in others also like Aldoar, Lordelo do Ouro, Massarelos, Sé and Bonfim. There is also a slight difference between this proportion on weekdays and weekends, with a more significant resource during the week.



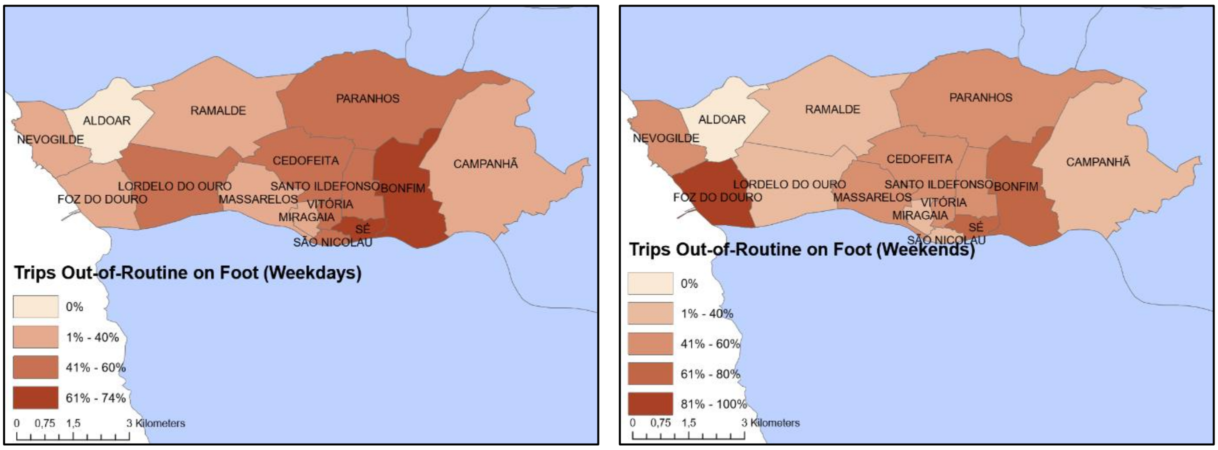
a) b)

Figure 26- a) Trips Out-of-Routine by Metro during the weekdays; b) Trips Out-of-Routine by Metro during the weekends

In out-of-routine trips, metro is less used than the bus. This fact can be justified by the working hours of each one: while the metro starts at 6 a.m. and ends at 1 a.m., buses (STCP) work 24 hours a day.

It should be noted that there is still a minimal amount of use of the mode of collective transport in general, particularly in the western parishes. This reality can be explained by the fact that, although there are some modes of transport operating during the study period, they work at a much lower frequency.

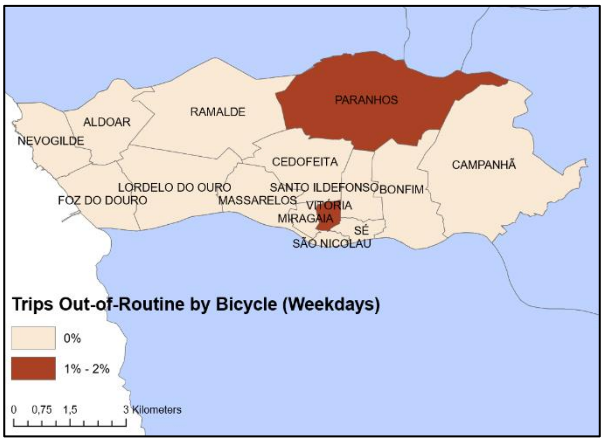
On foot was the second most used mode, following the car. Foot trips were more frequent among people in the central parishes than in the others, with the addition of Foz do Douro on the weekends (Figure 27 a) and b)).



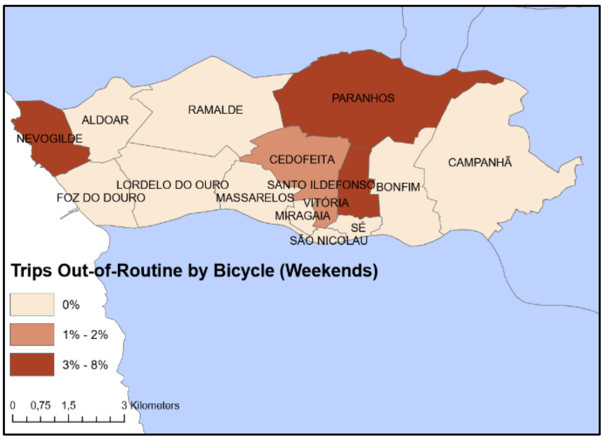
a) b)

Figure 27- a) Trips Out-of-Routine on Foot during the weekdays; b) Trips Out-of-Routine on Foot during the weekends

The bicycle was the least used mode of transport. However, there is a more significant proportion in the parish of Paranhos, and there is also an increase in the use of this mode on weekends (Figure 28 a) and b)).



a)



b)

Figure 28- a) Trips Out-of-Routine by Bicycle during the weekdays; b) Trips Out-of-Routine by Bicycle during the weekends

The Appendix I shows the number of trips with origin in each parish of Porto, depending on the travel time. It can be verified that the majority had a duration of fewer than 15 minutes. There was greater availability to spend more time on weekend days. On weekdays, more than half of the trips, about 57%, took less than 15 minutes and only 1% took more than 90 minutes. On weekend days 48% of trips took less than 15 minutes and about 5% more than 90 minutes.

As for the geographical proximity, analysing OD matrices, there was a greater tendency to move to neighbouring municipalities. The few municipalities where this is not verified are those that are further away from the centre of the GP area, Póvoa de Varzim and Espinho.

5.3.2 Modelling Phase

For modelling purposes, a weekday and a weekend day were chosen. The aim of this process was the elaboration of two Origin-Destination (OD) matrices and to identify the respective modal split to develop two discrete models. As it was mentioned in the Chapter 4.4.2, in the case of these matrices, the origins correspond to the beginning of the trip and the destination to the parish/municipality where the event or the point of interest took place, or vice versa.

The chosen days were April 21st and 23rd, Thursday and Saturday, respectively. In the case of day 21, the trips analysed corresponded to the period from 7 p.m. of that day to 7 a.m. of the following day (day 22). This interval was chosen so that trips that had begun one day and ended the next were not "interrupted".

From the OD matrix of day 21st/22nd, it was verified that there were many trips with origin and destination in Paranhos, 12 trips. In this parish is where FEUP is located. There were also many movements from and to Santo Ildefonso, 14 trips, and Vitória, 20 trips, where many events were concentrated.

According to the OD matrix of the 23rd, there were also many movements from and to Vitória, 13 trips, where there were too many events concentrated. Although, in this day, people had others preferred destinations. They moved a lot from and to the Municipality of Matosinhos and Vila Nova de Gaia, 16 and 17 trips, respectively. In this municipalities, there is a high concentration of POIs.

Given that there was an estimation of the mode of transport per segment, and that for each trip there were several segments which add up to total time, the percentages of use of each mode of transport in the complete trip were estimated. The same happened for the distance travelled.

For the elaboration of modal matrices, we have chosen the modes obtained through travel time. This decision was taken because it was considered to be more unfavourable both to costs, to the environment, traffic and quality of life if a trip takes a long time and not if the distance travelled is considerable. Besides, almost all the modes most used in each trip obtained through travel time, corresponded doing the same process through the distance travelled.

After the elaboration and analysis of these two matrices and respective modal split, it was verified that there was no movement with origin or destination in the following municipalities: Espinho, Póvoa de Varzim, Santo Tirso, Trofa and Vila do Conde. For the sake of simplicity, these municipalities were removed from both the OD and modal split arrays.

5.3.2.1 Mode Choice Model (Binomial Logistic Regression)

Model Structure

This model is intended to answer the following question:

- The user's role, the location where the event happened, or the POI took place, the event/POI category, weekday vs weekend day, travel time and distance travelled may influence the choice of transport mode?

The transport mode choice was split into two groups:

- Sustainable modes (bus, metro, bicycle, on foot);
- Car.

Variable Specification

Several types of variables were considered in the mode choice model. These included both trip-related characteristics, individual socio-demographics and event/POI attributes.

Trip-related characteristics explored in our specifications included nominal variables:

- the mode used for the trip;
- whether the trip was on a weekday or on a weekend day.

And scale variables:

- the trip travel time;
- the distance travelled.

Event/POI attributes included two nominal variables: the parish/municipality where the event happened/the POI took place and category.

Individual socio-demographic characteristics included the only variable available that is the role of the user, a nominal variable.

The dependent variable considered was travel mode (two nominal categories, sustainable modes and car), and all the others were included as independent variables.

The Appendix L presents a summary of the variables used in the model and their characteristics.

Interpretation of the Results

Table 7 shows a summary of the cases processed in the analysis. The reference category used to calibrate the model refers to the “ sustainable modes” category.

Table 8- Summary of processed cases (Binomial Logistic Regression)

		No.	*Percentage*
Selected cases	Included in the analysis	97	89.0
	Missing cases	12	11.0
	Total	109	100.0
Non selected cases		0	.0
	Total	109	100.0

The "Model Summary" table indicates how the model can explain much variation in the dependent variable (Laerd@, 2018a).

Table 9 - Model Summary (Binomial Logistic Regression)

Step	*-2log likelihood*	*Cox & Snell R Square*	*Nagelkerke R Square*
1	85.456	.394	.526

The explained variation in the dependent variable based on this model ranges from 39.4% to 52.6%, depending on whether the reference is the Cox & Snell R^2 or Nagelkerke R^2 methods. Nagelkerke R^2 is a modification of Cox & Snell R^2, the latter of which cannot achieve a value of 1. For this reason, it is preferable to report the Nagelkerke R^2 value (Laerd@, 2018a).

If the estimated probability of the event occurring is higher than or equal to 0.5, SPSS Statistics classifies the event as occurring (using sustainable modes). If the probability is less than 0.5, SPSS Statistics classifies the event as not occurring (using the car) (Laerd@, 2018a). The "Classification Table" shows the results obtained.

Table 10 - Classification Table (Binomial Logistic Regression)

Observed			*Mode*		*Percentage Correct*
			Sustainable Modes	Car	
Step 1	Mode	Sustainable Modes	37	8	82.2
		Car	12	40	76.9
	Overall Percentage				79.4

Thus, we have that in the prediction for the choice:

- From the " Sustainable Modes" category, 45 cases were observed, 37 were correct, and 8 were errors, reaching a correct percentage of 82.2%;
- For the choice of the "Car" category, there were 52 observed values, 40 correct and 12 errors, that is, 76.9% of the cases were correctly classified.

The "Variables in the equation" table shows the contribution of each independent variable to the model and its statistical significance. The Wald test ("Wald" column) is used to determine statistical significance for each of the independent variables (Laerd@, 2018a). Analysing the statistical significance of the test, "Sig." column, the only variable that added significantly to the model (p<.05) was the "distance" variable. This table is shown below:

Table 11- Variables in the equation (Binomial Logistic Regression)

		B	*S.E.*	*Wald*	*df*	*Sig*	*Exp(B)*	*95% C.I. for EXP(B)*	
								Under	Over
Step 1	⋮								
	Distance	.547	.224	5.957	1	.015	1.727	1.114	2.680
	⋮								

From this table, we can state that:

- More distance travelled is more associated with choose to use "Car" as travel mode than to choose using " Sustainable Modes".

Conclusions

Analysing the obtained results, it is verified that the model performed reasonably well. About 52.6% (Nagelkerke R^2) is being explained by the model. The "Classification Table" shows that this model compared to the Null model gives better accuracies for both " sustainable modes" and "car" groups.

The only variable that added significantly to the model (p<.05) was the "distance" variable, concluding that more distance travelled is more associated with choose to use "Car" as travel mode than to choose using "Sustainable Modes".

A more detailed analysis will be made in the chapter "Conclusions" below.

5.3.2.2 Destination Choice Model (Multinomial Logistic Regression)

Model Structure

This model is intended to answer the following question:

- The user's role, the mode of transport used, weekday vs weekend day, travel time, distance travelled and the number of check-ins in the event/POI may influence the destination type choice?

The calibrated model considered the following categories of events/POI:

- Art Exposition/Market;
- Coffee/Bar/Restaurant;
- Dance and Night Club;
- Theater/Music Concert/Talkshow.

Variable Specification

As for the mode choice model, the destination choice model considered several types of variables. These included both trip-related characteristics, individual socio-demographics and event/POI attributes.

Trip-related characteristics explored in our specifications included nominal variables:

- the mode used for the trip;
- whether the trip was on a weekday or on a weekend day.

And scale variables:

- the trip travel time;
- the distance travelled.

Event/POI attributes included two variables: number of check-ins in the event/POI and category, scale and nominal variables, respectively.

Individual socio-demographic characteristics included the only variable available that is the role of the user, a nominal variable.

The dependent variable considered was event/local of interest category, and all the others were included as independent variables.

The Appendix M presents a summary of the variables used in the model and their characteristics.

Interpretation of the Results

Table 11 shows a summary of the cases processed in the analysis. The reference category used to calibrate the model refers to the "Art Exposition/Market" category.

Table 12- Case processing summary (Multinomial Logistic Regression)

		No.	*Marginal Percentage*
Category	Art Exposition/Market	13	13.4%
	Coffee/Bar/Restaurant	54	55.7%
	Dance & Night Club	12	12.4%
	Theater/Music Concert/Talkshow	18	18.6%
Role	Researcher	2	2.1%
	Student 1st cycle	44	45.4%
	Student 2nd cycle	39	40.2%
	Student 3rd cycle	10	10.3%
	Teacher	2	2.1%
Mode	Sustainable Modes	45	46.4%
	Car	52	53.6%
Weekday versus Weekend	Weekday	42	43.3%
	Weekend	55	56.7%
Valid		97	100.0%
Omission		12	
Total		109	
Subpopulations		97	

The reason there were subpopulations is that the model includes continuous covariates ("distance", "time" and "check-ins") which results in many subpopulations, 291 + 97 = 388 of them of which 291 are empty and 97 with data (Chan, Y. H., 2005).

Table 12 shows the chi-square test. According to Hosmer and Lemeshows (2000), if the test statistic is more significant than the level of significance adopted, it is rejected the hypothesis that there is no difference between the observed and predicted values implying, therefore, that the model describes the data well at the level adopted (Hosmer, D. W. e Lemeshow, S., 2000).

Table 13 - Goodness-of-Fit (Multinomial Logistic Regression)

	Chi-square	*df*	*Sig.*
Pearson	190.867	261	1.000
Deviance	107.358	261	1.000

However, because of many cells with zero frequencies, this goodness-of-fit is not relevant (Chan, Y. H., 2005).

The “Model Fitting Information” table provides an overall measure of the model that can be used to assess how well the model fits the data (Laerd@, 2018a).

Table 14 - Model Fitting Information (Multinomial Logistic Regression)

Model	*Model Fitting Criteria*	*Likelihood Ratio Tests*		
	-2log likelihood	Chi-square	df	Sig.
Intercept Only	226.304			
Final	107.358	118.946	27	.000

In Table 13 it is observed that the statistic of probability - 2log decreases what indicates a good fit of the final model. Furthermore, the final model is significant at a significance level of α = 0.050%, p=.000, which means that the full model statistically significantly predicts the dependent variable better than the intercept-only model (Chan, Y. H., 2005).

Table 14 shows three R^2 statistics. The R^2 statistic of Cox and Snell is based on the likelihood function, and its value is generally less than one, with value one indicating a perfect fit of the model. The Nagelkerke R^2 statistic is a variation of the one proposed by Cox and Snell seeking to ensure a variation between zero and one (Hosmer and Lemeshow, 2000). For the R^2 statistic of McFadden values around 0.4 already indicate a good fit of the model (Silva, T. et al, 2010).

Table 15 - Pseudo R-square (Multinomial Logistic Regression)

Cox and Snell	.707
Nagelkerke	.783
McFadden	.526

The "Pseudo R-square" table indicates the proportion of variation being explained by the model (Chan, Y. H., 2005). This model is explaining about 78% (maximum 100%). Considering the values of these tests, it can be said that the model has a good fit.
The Likelihood ratio test shows the contribution of each variable to the model (Chan, Y. H., 2005).

Table 16 - Likelihood Ratio Test (Multinomial Logistic Regression)

Effect	*-2 log likelihood of reduced model*	*Chi-square*	*df*	*Sig.*
Intercept	107.358	.000	0	
Distance	116.715	9.357	3	.025
Time	113.641	6.282	3	.099
Check-ins	181.054	73.696	3	.000
Role	111.819	4.461	12	.974
Mode	116.363	9.005	3	.029
Weekday vs Weekend	142.363	35.005	3	.000

After the interactions, four of the six variables presented significance to compose the final model. The variables "distance", "check-ins", "mode" and "weekday vs weekend" had a significant contribution ($p<0.05$), but not "time" and "role".

The "Classification" table shows if the model compared to the Null model gives better accuracies for each category group (Silva, T. et al, 2010).

Table 17 – Classification (Multinomial Logistic Regression)

Observed	*Predicted*				
	Art Exposition / Market	Coffee / Bar / Restaurant	Dance & Night Club	Theater / Music Concert / Talkshow	Percentage correct
Art Exposition / Market	6	3	1	3	46.2%
Coffee / Bar / Restaurant	1	53	0	0	98.1%
Dance and Night Club	2	0	7	3	58.3%
Theater / Music Concert / Talkshow	1	4	1	12	66.7%
Overall percentage	10.3%	61.9%	9.3%	18.6%	80.4%

Thus, we have that in the prediction for the choice:

- From the "Art Exposition/Market" category, 13 cases were observed, 6 were correct and 7 were errors, reaching a correct percentage of 46.2%;
- For the choice of “Coffee/Bar/Restaurant”, there were 54 observed values, 53 correct and 1 errors, that is, 98.1% of the cases were correctly classified, considered as a very good percentage;
- For the category "Dance and Night Club", 12 observed values, 7 correctly classified and 5 cases classified incorrectly, with 58.3% of cases correctly classified;
- Finally, for the choice of "Theater/Music Concert/Talkshow", 18 corresponds to the observed values, 12 values were correctly classified and 6 incorrect classifications, making a total of 66.7% correctly classified cases.

The model presented, therefore, a correct general percentage of 80.4%, which can be considered a good rate. The value of 80.4% is obtained by summing the total of correct percentages (6+53+7+12=78) and dividing by the total of observations (97) (Silva, T. et al, 2010).

Analysing the statistical significance of the test, “Sig.” column, the variables that added significantly to the model ($p<.05$) were “Check-ins”, “Weekday versus Weekend” and “Mode” variables. This table is shown below:

Table 18- Variables in the equation (Multinomial Logistic Regression)

		B	*S.E.*	*Wald*	*df*	*Sig*	*Exp(B)*	*95% C.I. for EXP(B)*	
								Under	Over
	⋮								
Coffee / Bar / Restaurant	Check-ins	-.004	.002	7.967	1	.005	.996	.993	.999
	Weekday versus Weekend	-4.778	2.047	5.449	1	.020	.008	.000	.465
Dance & Night Club	Weekday versus Weekend	3.022	1.504	4.040	1	.044	20.539	1.078	391.338
Theater / Music Concert / Talkshow	Mode	-2.504	1.267	3.908	1	.048	.082	.007	.979
	⋮								

For example, the table 22 shows that the odds of choosing to go to a “Dance & Night Club” is 20.539 times greater if you go on a weekday than on a weekend day.

From this table, we can also state that:

1. It is more likely that the user choses to go to a “Coffee/Bar/Restaurant” than to an “Art Exposition/Market” if the user goes on a weekend day rather than on a weekday;
2. It is more likely that the user choses to go to a “Dance and Night Club” than to an “Art Exposition/Market” if the user goes on a weekday rather than on a weekend day;
3. A higher number of check-ins is more associated with chose to go to an “Art Exposition/Market” than going to a “Coffee/Bar/Restaurant”;
4. It is more likely that the user choses to go to a “Theater/Music Concert/Talkshow” than to an “Art Exposition/Market” if the user uses “car” rather than “sustainable modes”.

Conclusions

The “Model Fitting Information” indicates a good fit of the final model. Also, the final model is significant at a significance level of $\alpha = 0.050\%$ which means that the full model statistically significantly predicts the dependent variable better than the intercept-only model.

Four of the six variables presented significance to compose the final model. The variables “distance”, “check-ins”, “mode” and “weekday vs weekend” had a significant contribution ($p<0.05$), but not “time” and “role”.

A more detailed analysis will be made in the chapter "Conclusions" below.

6 CONCLUSIONS AND FURTHER DEVELOPMENTS

6.1 Conclusions

With this dissertation, we sought to identify patterns and factors that influence mobility during out-of-routine hours in the Greater Porto area.

In the first phase, an overall analysis of mobility was made from the data provided. After an exhaustive treatment of the data, charts and GIS maps were elaborated to enable a better understanding and identification of mobility patterns.

From this approach, it was possible to verify that the type of trip, being on a weekday or a weekend day, time spent, distance travelled, number of events and existing POIs and user function influenced the choice of the mode of transport used in trips out-of-routine.

It was possible to see that most of the trips that were made had origin and destination in the same municipality, with a greater tendency on weekdays. At weekends, the tendency to move to other municipalities increases, concluding that the availability to travel more distances is higher on weekends compared to weekdays. There was some diversity of inter-municipal movements during the month studied. This fact can be justified by the distribution of concentrations of events and POIs by several municipalities, standing out the Municipality of Porto as a destination preference. In the Municipality of Porto, there was a greater number of movements in parishes with a higher offer of events/POIs, showing the attractiveness created by them. Geographic proximity also showed an influence, demonstrated both by the low travel times and by the proportion of trips to neighbouring municipalities concerning remote municipalities.

Regarding the modes of transport used during out-of-routine hours, the car was the most used, confirming the great tendency to use this mode already presented in other previous studies based on regular trips in AMP, followed by foot. Within the Municipality of Porto, there was little use of the car concerning different modes of transport during the weekdays in a relatively central area of the municipality. This is probably due to the greater offer of public transport and the proximity of facilities in this area. Teachers were those who travelled more distances and spent more time using the car, in contrast to the researchers. The sample consisted mainly of students, an average of ages of 24, which may explain the vast availability of walking. The modal split is very similar between weekdays and weekends. However, there is a greater tendency for spending more time and travel greater distances by walking and cycling on the weekends. Foot trips were more frequent among people in the central parishes than in the others and bicycle trips were made mostly by people in the parish of Paranhos. Comparing the two collective modes of transport introduced in the study, bus and metro, we can verify that there was a greater use of the bus. This reality can be explained based on the working hours of each one. While the bus (STCP) is in operation 24h, the metro only operates from 6 a.m. to 1 a.m.. Though, the proportions of use of public transport compared to car and foot use are quite low, revealing a low supply during out-of-routine hours. The teachers were the ones who used the bus more but never used the metro. The students of the second cycle were those who used the metro the most.

In a second approach, we tried to identify the importance that certain variables had in choosing the mode of transport for leisure travel and in choosing the destination.

For the first model, we resort to a binomial regression. We have therefore sought to determine the importance of the user's function, the location where the event happened, or the POI took place, the event/POI category, weekday vs weekend day, travel time and distance travelled in the choice of transport mode. Based on the analysis of the parameters, it could be said that the final model presented a good fit. It was verified that the only variable that added significantly to the model was the distance travelled, concluding that more distance travelled is more associated with choose to use the car as travel mode than to choose using sustainable modes. This conclusion is not in agreement with the first approach. However, it should be noted that the analysed samples differ in size and travel destinations.

In the second model, a multinomial logit regression was used. We aimed to identify the influence of the user's function, the mode of transport used, weekday vs weekend day, travel time, distance travelled and the number of check-ins in the event/POI in the choice of the destination type. After the analysis of the parameters, it could be concluded that the final model presented a good fit. Only the variables of distance travelled, the number of check-ins, travel mode and whether the trip was made on a weekday or a weekend had a significant contribution, but not time spent and user role. The results showed that there was a greater tendency to go to a “Coffee/Bar/Restaurant” than to an “Art Exposition/Market” if they go on a weekend day rather than on a weekday. Also, it was more likely that they go to a “Dance and Night Club” than to an “Art Exposition/Market” if they go on a weekday rather than on a weekend day. A higher number of check-ins is more associated with chose to go to an “Art Exposition/Market” than going to a “Coffee/Bar/Restaurant”. Another conclusion was that the use of car is more related to travel to a “Theater/Music Concert/Talkshow” than to an “Art Exposition/Market”.

After analysing the results obtained from the logistic models, it was verified that the distance was determinant in the choice of both the transport mode and the destination type, and the time did not. It follows, therefore, that it would have been more accurate to have done the modal split based on distance rather than time.

6.2 Further Developments

It should be noted that the presented results have significant limitations.

Many of these limitations stem from the database provided. The small sample size and the confidentiality and protection of the information provided also made the process very difficult, reducing the quality of the data. Another major problem with this harvest was that the intermediate travel destinations were not registered, we only had information from the first origin and the last destination. In the last approach of the data analysis, we tried to determine these destinations through the crossing of the trips with the events/POI. However, it is very probable that many of them do not correspond to the reality. In order to obtain more reliable results in the future, it would be necessary to collect a new sample with a greater dimension and less biased and still collect more variables related to the typology of people and habits, keeping people as unknowns.

In this first approach, due to the time factor, we opted to choose only two days for the development of discrete choice models. We were able to draw some conclusions, however, leading us to believe that it would be worth a more extensive analysis, such as analysing other two days allowing a comparison, a whole week or even the month.

The trips were divided mainly between car and foot, which manipulated a little the results obtained from the models. One hypothesis to improve the results will be, therefore, to divide the modes of transport into three groups: car, walking and other modes (public transport and bicycle).

We are aware that we have presented spurious correlations, that is, correlations that are "too evident" and that, in the future, we should avoid repeating.

This study was a first test taken. The initial objectives were met. The database has startup failures, and we decided to take only part of the analysis. To improve these conclusions, the methodology is already defined and proposed, allowing the development of new analyses.

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Table A.1- OD Matrix (Weekdays)

O/D	Porto	Espinho	Gondomar	Maia	Matosinhos	Póvoa de Varzim	Santo Tirso	Trofa	Valongo	Vila do Conde	Vila Nova de Gaia
Porto	858	3	30	19	53	0	0	1	16	0	19
Espinho	1	15	0	1	0	0	0	0	0	0	1
Gondomar	17	0	47	2	2	0	0	0	2	0	0
Maia	12	0	0	66	2	0	0	0	11	0	0
Matosinhos	25	0	1	4	66	0	0	0	1	1	3
Póvoa de Varzim	0	0	0	0	0	1	0	0	0	0	0
Santo Tirso	1	0	0	0	0	0	0	1	0	0	0
Trofa	0	0	0	0	0	0	0	8	0	0	0
Valongo	5	0	0	6	1	0	0	0	42	0	0
Vila do Conde	1	0	0	0	1	0	0	0	0	19	0
Vila Nova de Gaia	8	2	0	0	1	0	0	0	0	0	90

Table A.2- OD Matrix, Car Trips (Weekdays)

O/D	Porto	Espinho	Gondomar	Maia	Matosinhos	Póvoa de Varzim	Santo Tirso	Trofa	Valongo	Vila do Conde	Vila Nova de Gaia
Porto	333	2	25	13	34	0	0	1	14	0	16
Espinho	1	8	0	1	0	0	0	0	0	0	1
Gondomar	14	0	24	1	2	0	0	0	2	0	0
Maia	9	0	0	28	2	0	0	0	10	0	0
Matosinhos	20	0	1	3	28	0	0	0	1	1	3
Póvoa de Varzim	0	0	0	0	0	1	0	0	0	0	0
Santo Tirso	1	0	0	0	0	0	0	1	0	0	0
Trofa	0	0	0	0	0	0	0	4	0	0	0
Valongo	5	0	0	5	1	0	0	0	28	0	0
Vila do Conde	1	0	0	0	1	0	0	0	0	7	0
Vila Nova de Gaia	4	2	0	0	1	0	0	0	0	0	48

Table B.1- OD Matrix, Bus Trips (Weekdays)

O/D	Porto	Espinho	Gondomar	Maia	Matosinhos	Póvoa de Varzim	Santo Tirso	Trofa	Valongo	Vila do Conde	Vila Nova de Gaia
Porto	23	0	0	1	2	0	0	0	1	0	1
Espinho	0	0	0	0	0	0	0	0	0	0	0
Gondomar	0	0	0	1	0	0	0	0	0	0	0
Maia	0	0	0	1	0	0	0	0	1	0	0
Matosinhos	0	0	0	0	1	0	0	0	0	0	0
Póvoa de Varzim	0	0	0	0	0	0	0	0	0	0	0
Santo Tirso	0	0	0	0	0	0	0	0	0	0	0
Trofa	0	0	0	0	0	0	0	0	0	0	0
Valongo	0	0	0	0	0	0	0	0	1	0	0
Vila do Conde	0	0	0	0	0	0	0	0	0	0	0
Vila Nova de Gaia	0	0	0	0	0	0	0	0	0	0	9

Table B.2- OD Matrix, Metro Trips (Weekdays)

O/D	Porto	Espinho	Gondomar	Maia	Matosinhos	Póvoa de Varzim	Santo Tirso	Trofa	Valongo	Vila do Conde	Vila Nova de Gaia
Porto	16	1	0	0	1	0	0	0	0	0	1
Espinho	0	0	0	0	0	0	0	0	0	0	0
Gondomar	0	0	0	0	0	0	0	0	0	0	0
Maia	0	0	0	2	0	0	0	0	0	0	0
Matosinhos	0	0	0	0	2	0	0	0	0	0	0
Póvoa de Varzim	0	0	0	0	0	0	0	0	0	0	0
Santo Tirso	0	0	0	0	0	0	0	0	0	0	0
Trofa	0	0	0	0	0	0	0	0	0	0	0
Valongo	0	0	0	1	0	0	0	0	0	0	0
Vila do Conde	0	0	0	0	0	0	0	0	0	0	0
Vila Nova de Gaia	0	0	0	0	0	0	0	0	0	0	2

Table C.1- OD Matrix, Bicycle Trips (Weekdays)

O/D	Porto	Espinho	Gondomar	Maia	Matosinhos	Póvoa de Varzim	Santo Tirso	Trofa	Valongo	Vila do Conde	Vila Nova de Gaia
Porto	6	0	0	0	2	0	0	0	0	0	0
Espinho	0	0	0	0	0	0	0	0	0	0	0
Gondomar	0	0	0	0	0	0	0	0	0	0	0
Maia	0	0	0	0	0	0	0	0	0	0	0
Matosinhos	0	0	0	0	0	0	0	0	0	0	0
Póvoa de Varzim	0	0	0	0	0	0	0	0	0	0	0
Santo Tirso	0	0	0	0	0	0	0	0	0	0	0
Trofa	0	0	0	0	0	0	0	0	0	0	0
Valongo	0	0	0	0	0	0	0	0	0	0	0
Vila do Conde	0	0	0	0	0	0	0	0	0	0	0
Vila Nova de Gaia	1	0	0	0	0	0	0	0	0	0	0

Table C.2- OD Matrix, On Foot Trips (Weekdays)

O/D	Porto	Espinho	Gondomar	Maia	Matosinhos	Póvoa de Varzim	Santo Tirso	Trofa	Valongo	Vila do Conde	Vila Nova de Gaia
Porto	476	0	5	5	14	0	0	0	1	0	1
Espinho	0	7	0	0	0	0	0	0	0	0	0
Gondomar	3	0	23	0	0	0	0	0	0	0	0
Maia	3	0	0	35	0	0	0	0	0	0	0
Matosinhos	5	0	0	1	35	0	0	0	0	0	0
Póvoa de Varzim	0	0	0	0	0	0	0	0	0	0	0
Santo Tirso	0	0	0	0	0	0	0	0	0	0	0
Trofa	0	0	0	0	0	0	0	4	0	0	0
Valongo	0	0	0	0	0	0	0	0	10	0	0
Vila do Conde	0	0	0	0	0	0	0	0	0	9	0
Vila Nova de Gaia	3	0	0	0	0	0	0	0	0	0	31

Table D.1- OD Matrix (Weekends)

O/D	Porto	Espinho	Gondomar	Maia	Matosinhos	Póvoa de Varzim	Santo Tirso	Trofa	Valongo	Vila do Conde	Vila Nova de Gaia
Porto	521	0	17	18	39	2	0	0	4	0	14
Espinho	1	16	0	0	1	0	0	0	0	0	1
Gondomar	12	0	82	1	1	0	0	0	3	0	0
Maia	22	0	1	85	6	0	0	0	5	1	5
Matosinhos	37	0	0	4	112	0	0	0	0	1	3
Póvoa de Varzim	5	0	0	0	0	5	0	0	1	2	0
Santo Tirso	0	0	0	0	0	0	0	0	0	0	0
Trofa	1	0	0	1	0	0	0	9	0	0	0
Valongo	4	0	1	4	2	0	1	0	54	1	1
Vila do Conde	1	0	0	1	2	0	0	0	0	42	0
Vila Nova de Gaia	11	1	2	3	1	0	0	0	2	0	59

Table D.2- OD Matrix, Car Trips (Weekends)

O/D	Porto	Espinho	Gondomar	Maia	Matosinhos	Póvoa de Varzim	Santo Tirso	Trofa	Valongo	Vila do Conde	Vila Nova de Gaia
Porto	193	0	12	9	25	1	0	0	2	0	8
Espinho	1	6	0	0	1	0	0	0	0	0	1
Gondomar	9	0	42	1	1	0	0	0	2	0	0
Maia	12	0	1	44	6	0	0	0	3	1	3
Matosinhos	25	0	0	3	64	0	0	0	0	1	2
Póvoa de Varzim	2	0	0	0	0	2	0	0	0	1	0
Santo Tirso	0	0	0	0	0	0	0	0	0	0	0
Trofa	1	0	0		0	0	0	6	0	0	0
Valongo	4	0	1	4	1	0	1	0	30	1	1
Vila do Conde	1	0	0	1	1	0	0	0	0	21	0
Vila Nova de Gaia	8	1	2	2	1	0	0	0	1	0	34

Table E.1- OD Matrix, Bus Trips (Weekends)

O/D	Porto	Espinho	Gondomar	Maia	Matosinhos	Póvoa de Varzim	Santo Tirso	Trofa	Valongo	Vila do Conde	Vila Nova de Gaia
Porto	16	0	0	0	2	0	0	0	1	0	0
Espinho	0	0	0	0	0	0	0	0	0	0	0
Gondomar	0	0	0	0	0	0	0	0	0	0	0
Maia	1	0	0	1	0	0	0	0	0	0	0
Matosinhos	3	0	0	0	2	0	0	0	0	0	0
Póvoa de Varzim	0	0	0	0	0	0	0	0	0	0	0
Santo Tirso	0	0	0	0	0	0	0	0	0	0	0
Trofa	0	0	0	0	0	0	0	0	0	0	0
Valongo	0	0	0	0	1	0	0	0	1	0	0
Vila do Conde	0	0	0	0	1	0	0	0	0	0	0
Vila Nova de Gaia	0	0	0	0	0	0	0	0	0	0	2

Table E.2- OD Matrix, Metro Trips (Weekends)

O/D	Porto	Espinho	Gondomar	Maia	Matosinhos	Póvoa de Varzim	Santo Tirso	Trofa	Valongo	Vila do Conde	Vila Nova de Gaia
Porto	9	0	0	0	1	0	0	0	0	0	0
Espinho	0	0	0	0	0	0	0	0	0	0	0
Gondomar	0	0	0	0	0	0	0	0	0	0	0
Maia	0	0	0	1	0	0	0	0	0	0	1
Matosinhos	0	0	0	0	0	0	0	0	0	0	1
Póvoa de Varzim	0	0	0	0	0	0	0	0	0	0	0
Santo Tirso	0	0	0	0	0	0	0	0	0	0	0
Trofa	0	0	0	0	0	0	0	0	0	0	0
Valongo	0	0	0	0	0	0	0	0	1	0	0
Vila do Conde	0	0	0	0	0	0	0	0	0	0	0
Vila Nova de Gaia	0	0	0	0	0	0	0	0	0	0	0

Table F.1- OD Matrix, Bicycle Trips (Weekends)

O/D	Porto	Espinho	Gondomar	Maia	Matosinhos	Póvoa de Varzim	Santo Tirso	Trofa	Valongo	Vila do Conde	Vila Nova de Gaia
Porto	9	0	0	0	0	0	0	0	0	0	1
Espinho	0	0	0	0	0	0	0	0	0	0	0
Gondomar	0	0	0	0	0	0	0	0	0	0	0
Maia	0	0	0	0	0	0	0	0	0	0	0
Matosinhos	1	0	0	1	2	0	0	0	0	0	0
Póvoa de Varzim	0	0	0	0	0	0	0	0	0	0	0
Santo Tirso	0	0	0	0	0	0	0	0	0	0	0
Trofa	0	0	0	0	0	0	0	0	0	0	0
Valongo	0	0	0	0	0	0	0	0	0	0	0
Vila do Conde	0	0	0	0	0	0	0	0	0	0	0
Vila Nova de Gaia	0	0	0	0	0	0	0	0	0	0	0

Table F.2- OD Matrix, On Foot Trips (Weekends)

O/D	Porto	Espinho	Gondomar	Maia	Matosinhos	Póvoa de Varzim	Santo Tirso	Trofa	Valongo	Vila do Conde	Vila Nova de Gaia
Porto	292	0	5	9	11	1	0	0	1	0	5
Espinho	0	10	0	0	0	0	0	0	0	0	0
Gondomar	3	0	39	0	0	0	0	0	1	0	0
Maia	9	0	0	39	0	0	0	0	2	0	1
Matosinhos	8	0	0	0	43	0	0	0	0	0	0
Póvoa de Varzim	3	0	0	0	0	3	0	0	1	1	0
Santo Tirso	0	0	0	0	0	0	0	0	0	0	0
Trofa	0	0	0	1	0	0	0	3	0	0	0
Valongo	0	0	0	0	0	0	0	0	22	0	0
Vila do Conde	0	0	0	0	0	0	0	0	0	21	0
Vila Nova de Gaia	3	0	0	1	0	0	0	0	1	0	23

Table G- Trips distribution with origin in parishes of Porto (Weekdays)

O/D	Total	Own Parish	Other Porto Parishes	Espinho	Gondomar	Maia	Matosinhos	Póvoa de Varzim	Santo Tirso	Trofa	Valongo	Vila do Conde	Vila Nova de Gaia
Aldoar	2	0	2	0	0	0	0	0	0	0	0	0	0
Bonfim	27	16	6	0	1	0	3	0	0	0	0	0	1
Campanhã	33	12	7	1	9	2	1	0	0	0	0	0	1
Cedofeita	91	54	33	0	1	1	1	0	0	0	1	0	0
Foz do Douro	6	6	0	0	0	0	0	0	0	0	0	0	0
Lordelo do Ouro	20	12	5	1	1	0	1	0	0	0	0	0	0
Massarelos	22	8	9	0	2	2	0	0	0	0	1	0	0
Miragaia	4	0	3	0	0	0	0	0	0	0	0	0	1
Nevogilde	10	4	3	0	0	1	2	0	0	0	0	0	0
Paranhos	606	468	56	1	10	13	38	0	0	0	11	0	9
Ramalde	49	25	13	0	2	0	4	0	0	1	2	0	2
Santo Ildefonso	58	21	32	0	1	0	1	0	0	0	1	0	2
São Nicolau	4	1	3	0	0	0	0	0	0	0	0	0	0
Sé	9	5	2	0	0	0	0	0	0	0	0	0	2
Vitória	58	27	25	0	3	0	2	0	0	0	0	0	1
Porto	999	659	199	3	30	19	53	0	0	1	16	0	19

Table H- Trips distribution with origin in parishes of Porto (Weekends)

O/D	Total	Own Parish	Other Porto Parishes	Espinho	Gondomar	Maia	Matosinhos	Póvoa de Varzim	Santo Tirso	Trofa	Valongo	Vila do Conde	Vila Nova de Gaia
Aldoar	4	3	1	0	0	0	0	0	0	0	0	0	0
Bonfim	33	15	18	0	0	0	0	0	0	0	0	0	0
Campanhã	50	28	16	0	3	1	2	0	0	0	0	0	0
Cedofeita	66	36	24	0	0	1	3	1	0	0	0	0	1
Foz do Douro	1	1	0	0	0	0	0	0	0	0	0	0	0
Lordelo do Ouro	16	9	6	0	0	0	0	0	0	0	1	0	0
Massarelos	21	12	5	0	3	0	1	0	0	0	0	0	0
Miragaia	8	5	2	0	0	0	0	0	0	0	0	0	1
Nevogilde	12	5	6	0	0	0	1	0	0	0	0	0	0
Paranhos	271	188	35	0	4	12	25	1	0	1	1	0	4
Ramalde	33	19	8	0	2	1	1	1	0	0	0	0	1
Santo Ildefonso	38	10	17	0	2	1	1	0	0	0	2	0	5
São Nicolau	9	1	5	0	1	0	1	0	0	0	0	0	1
Sé	10	4	5	0	0	0	1	0	0	0	0	0	0
Vitória	43	20	17	0	0	1	4	0	0	0	0	0	1
Porto	615	356	165	0	15	17	40	3	0	1	4	0	14

Table I- Trips with origin in Porto, by parish, concerning travel time

O/D	*Total (no.)*		*Until 15 min (no.)*		*From 16 to 30 min (no.)*		*From 31 to 60 min (no.)*		*From 61 to 90 min (no.)*		*More than 90 min (no.)*	
	Weekdays	Weekends	Weekdays	Weekends	Weekdays	Weekends	Weekdays	Weekends	Weekdays	Weekends	Weekdays	Weekends
Aldoar	2	4	1	4	0	0	1	0	0	0	0	0
Bonfim	27	33	19	19	4	5	2	7	2	2	0	0
Campanhã	33	50	20	18	8	17	4	10	1	3	0	2
Cedofeita	91	66	58	33	18	11	10	16	4	1	1	5
Foz do Douro	6	1	3	1	1	0	1	0	0	0	1	0
Lordelo do Ouro	20	16	11	9	6	4	3	2	0	0	0	1
Massarelos	22	21	9	5	6	7	4	4	3	2	0	3
Miragaia	4	8	0	3	2	3	2	1	0	1	0	0
Nevogilde	10	12	6	6	3	2	1	2	0	2	0	0
Paranhos	606	271	351	152	154	54	83	47	12	10	6	8
Ramalde	49	33	29	9	9	7	8	8	1	2	2	7
Santo Ildefonso	58	38	25	12	15	12	14	9	3	5	1	0
São Nicolau	4	9	2	3	1	1	1	3	0	1	0	1
Sé	9	10	8	4	0	2	1	1	0	1	0	2
Vitória	58	43	25	18	17	9	12	11	3	5	1	0
Porto	999	615	567	296	244	134	147	121	29	35	12	29

Table J- OD Matrix, 21st/22nd April

O/D	Campanhã	Aldoar	Ramalde	Paranhos	Massarelos	Foz do Douro	Santo Ildefonso	Lordelo do Ouro	Bonfim	Cedofeita	São Nicolau	Sé	Miragaia	Vitória	Nevogilde	Gondomar	Maia	Matosinhos	Valongo	Vila Nova de Gaia
Campanhã	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	2	0	0	0	1
Aldoar	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ramalde	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Paranhos	0	0	0	4	0	0	1	0	0	0	0	0	0	1	0	0	0	2	1	0
Massarelos	0	0	0	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0
Foz do Douro	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
Santo Ildefonso	1	0	0	0	0	0	4	0	0	0	0	0	0	5	0	0	0	0	0	0
Lordelo do Ouro	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
Bonfim	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cedofeita	0	0	0	1	0	0	1	0	0	0	0	0	1	5	0	0	0	0	0	0
São Nicolau	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sé	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Miragaia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Vitória	0	0	0	0	1	0	1	0	0	3	0	0	0	3	0	0	0	0	0	0
Nevogilde	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0
Gondomar	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
Maia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Matosinhos	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Valongo	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0
Vila Nova de Gaia	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2

Table K- OD Matrix, 23rd April

O/D	Campanhã	Aldoar	Ramalde	Paranhos	Massarelos	Foz do Douro	Santo Ildefonso	Lordelo do Ouro	Bonfim	Cedofeita	São Nicolau	Sé	Miragaia	Vitória	Nevogilde	Gondomar	Maia	Matosinhos	Valongo	Vila Nova de Gaia
Campanhã	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
Aldoar	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ramalde	0	0	1	0	0	0	0	1	0	1	0	0	0	1	0	0	0	0	0	0
Paranhos	1	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0
Massarelos	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0
Foz do Douro	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Santo Ildefonso	0	0	0	1	0	0	0	0	0	0	1	0	0	2	0	1	0	0	0	0
Lordelo do Ouro	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Bonfim	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cedofeita	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0
São Nicolau	0	0	0	0	0	0	0	0	0	0	0	2	0	1	0	0	0	0	0	2
Sé	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0
Miragaia	0	0	0	0	0	0	1	0	0	0	0	0	4	0	0	0	0	0	0	0
Vitória	0	0	0	1	0	0	1	0	0	0	0	0	0	1	0	0	0	2	0	0
Nevogilde	0	1	0	0	0	0	0	1	0	0	0	0	0	0	2	0	0	1	0	0
Gondomar	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
Maia	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0
Matosinhos	0	0	0	0	0	0	0	0	0	1	0	0	0	0	2	0	0	7	0	1
Valongo	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1	0
Vila Nova de Gaia	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	13

Table L- Summary of analysis variables in mode choice model

	Description	Type	Sub-Categories
Dependent Variable			
Mode	The travel mode used for the trip	Nominal	Sustainable Modes
			Car
Independent Variables			
Role	User role	Nominal	Researcher
			Student 1^{st} cycle
			Student 2^{nd} cycle
			Student 3^{rd} cycle
			Teacher
Event Location	The location where the event happened, or the POI took place	Nominal	Aldoar
			Campanhã
			Cedofeita
			Foz do Douro
			Lordelo do Ouro
			Massarelos
			Matosinhos
			Miragaia
			Nevogilde
			Paranhos
			Santo Ildefonso
			São Nicolau
			Sé
			Valongo
			Vila Nova de Gaia
			Vitória
Category	Event/POI category	Nominal	Art Exposition/Market
			Coffee/Bar/Restaurant
			Dance and Night Club
			Theater/Music Concert/Talkshow
Weekday vs Weekend	Whether the trip was made on a weekday / weekend day	Nominal	Weekday
			Weekend
Distance	Distance travelled	Scale	-
Time	Trip travel time	Scale	-

Table M- Summary of analysis variables in destination choice model

	Description	**Type**	**Sub-Categories**
Dependent Variable			
Category	Event/POI category	Nominal	Art Exposition/Market
			Coffee/Bar/Restaurant
			Dance and Night Club
			Theater/Music Concert/Talkshow
Independent Variables			
Role	User role	Nominal	Researcher
			Student 1st cycle
			Student 2nd cycle
			Student 3rd cycle
			Teacher
Mode	The travel mode used for the trip	Nominal	Sustainable Modes
			Car
Weekday vs Weekend	Whether the trip was made on a weekday / weekend day	Nominal	Weekday
			Weekend
Distance	Distance travelled	Scale	-
Time	Trip travel time	Scale	-
Check-ins	Number of check-ins in the event/POI	Scale	-