DECODING CITY SQUARES WITH BIG DATA: A METHOD FOR URBAN ANALYTICS

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

ASLIHAN ÖZEN

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF ARCHITECTURE
IN
ARCHITECTURE

MAY 2022

Approval of the thesis:

**DECODING CITY SQUARES WITH BIG DATA:
A METHOD FOR URBAN ANALYTICS**

submitted by **ASLIHAN ÖZEN** in partial fulfillment of the requirements for the degree of **Master of Architecture in Architecture Department, Middle East Technical University** by,

Prof. Dr. Halil Kalıpçılar
Dean, Graduate School of **Natural and Applied Sciences**

Prof. Dr. F. Cânâ Bilsel
Head of the Department, **Architecture**

Assoc. Prof. Dr. İpek Gürsel Dino
Supervisor, **Architecture, METU**

Examining Committee Members:

Assoc. Prof. Dr. Funda Baş Bütüner
Architecture, METU

Assoc. Prof. Dr. İpek Gürsel Dino
Architecture, METU

Prof. Dr. Matteo Robiglio
Architecture and Design, Politecnico di Torino

Date: 12.05.2022

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name Last name : Aslıhan Özen

Signature :

ABSTRACT

DECODING CITY SQUARES WITH BIG DATA: A METHOD FOR URBAN ANALYTICS

Özen, Aslıhan
Master of Architecture, Architecture
Supervisor : Assoc. Prof. Dr. İpek Gürsel Dino

May 2022, 125 pages

The responsive city nowadays is considered as an assemblage of a large number of complex characteristics. Similar to cities, people's social behavior is a complex system. Seeing cities with Big Data allows architects and urban designers to understand social networks of cities.

This study outlines a computational tool to uncover latent characteristics of cities by combining Machine Learning and Social Media Analytics so that it may be possible to render an “image” and visualize a dense web of a city. The thesis aims to reveal visual characteristics of city squares and create a model that can learn the unique features of squares to support urban design processes that integrate big data-informed predictions. In order to achieve these goals of the research, the following questions were formulated. 1) Can we analyze social media data as a knowledge discovery tool to uncover city squares’ visual characteristics? 2) How can we map social communities by using visual social media data visualization and deciding points of interest in city squares?

Keywords: Responsive City, Social Sensing, Social Media Analytics, Big-Data Informed Urban Characteristics, Machine Learning

ÖZ

BÜYÜK VERİ İLE KENT MEYDANLARINI ÇÖZMEK: KENT ANALİTİĞİ İÇİN BİR METOT

Özen, Aslıhan
Yüksek Lisans, Mimarlık
Tez Yöneticisi: Doç. Prof. Dr. İpek Gürsel Dino

Mayıs 2022, 125 sayfa

Günümüzde duyarlı şehir, çok sayıda karmaşık özelliğin bir araya gelmesi olarak kabul edilmektedir. Şehirlere benzer şekilde, insanların sosyal davranışları da karmaşık bir sistemdir. Şehirleri Büyük Veri ile görmek, mimarların ve kentsel tasarımcıların şehirlerin sosyal ağlarını anlamalarını sağlar.

Bu çalışma, bir "imge" oluşturmanın ve bir şehrin yoğun ağını görselleştirmenin mümkün olabilmesi için Makine Öğrenimi ve Sosyal Medya Analitiğini birleştirerek şehirlerin gizli özelliklerini ortaya çıkarmak için bir hesaplama aracının ana hatlarını vermektedir. Bu tez, kent meydanlarının görsel özelliklerini ortaya çıkarmayı ve büyük veriye dayalı tahminleri bütünleştiren kentsel tasarım süreçlerini desteklemek için meydanların benzersiz özelliklerini öğrenebilecek bir model oluşturmayı amaçlar. Araştırmanın amaçlarına ulaşmak için şu sorular formüle edilmiştir. 1) Kent meydanlarının görsel özelliklerini ortaya çıkarmak için bir bilgi keşif aracı olarak sosyal medya verilerini analiz edebilir miyiz? 2) Sosyal medya verisini görselleştirerek ve şehir meydanlarında ilgi çekici noktalara karar vererek sosyal toplulukları nasıl haritalayabiliriz?

Anahtar Kelimeler: Duyarlı Şehir, Sosyal Algılama, Sosyal Medya Analitiği, Büyük Veri Bilgili Kentsel Karakteristikler, Makine Öğrenmesi

To My Family,

ACKNOWLEDGMENTS

I would like to thank the following people: I could not have completed this dissertation without their presence.

First, I wish to express my gratitude to my supervisor Assoc. Prof. Dr. İpek Gürsel Dino for their criticism and insight throughout the research.

I would also like to thank my jury members for providing me support and criticism to successfully complete the thesis.

Many thanks to Prof. Dr. Matteo Robiglio for his suggestions, feedbacks, and guidance throughout my studies at Politecnico di Torino. It was an honor to be able to discuss my research with you and his critics always inspired me to develop my research.

I would like to thank to Dr. Laura Martini and rest of the Future Urban Legacy Lab team for their collaborative support.

My sincere gratitude to all my friends who contributed to my thesis with intellectual conversations.

In addition, I could not have completed this dissertation without the support of Berk Güngör who provided technical discussions and his love.

And finally, my deepest gratitude my parents Necla - Metin Özen who endured this long process with me, always offering support and love. I am always lucky to have you and you are always there for me...

TABLE OF CONTENTS

LIST OF TABLES

TABLES

LIST OF FIGURES

FIGURES

LIST OF ABBREVIATIONS

ABBREVIATIONS

AOI: Areas of Interest

CNN : Convolutional Neural Network

DCNN: Deep Convolutional Neural Network

DL: Deep Learning

GAN: Generative Adversarial Networks

GIS: Geographical Information System

GSV: Google Street Views

LBSN: Location-Based Social Networks

ML: Machine Learning

OSM: OpenStreetMap

POI: Points of Interest

SLIC: Simple Linear Iterative Clustering

SNA: Social Network Analysis

UGC: User-Generated Content

VGI: Volunteer Geographic Information

CHAPTER 1

INTRODUCTION

1.1 Motivation of the Research

Cities are multidimensional systems consisting of architectural, social, economic, cultural, political, and environmental factors. The rapid urbanization and huge cities with increasing populations bring many problems worldwide. Many different disciplines work in urban research to solve these problems. This multidisciplinary cooperation is essential to understand the city layer by layer and bring permanent solutions to urban problems to improve the city. Thanks to developing technologies and increasing data sources, many analysis methods are used today to solve the problems of cities and improve cities. The data collected by the city management, network, communication system suppliers, software suppliers, and urban researchers enable cities to be sustainable and livable by adapting to time.

There are studies based on the numerical methods of hard sciences to understand the morphological structure of the city (Batty, 1976; Batty and Longley, 1994). It is critical to focus on the complexity of the physical urban pattern to understand the city form (Alexander, 1965). At the same time, the space that forms the form of the city has syntactic features such as integration, connectivity, and intelligibility. There is also a close relationship between the social, economic, and environmental performance of the spaces and the spatial configurations (Hillier, 1984). In addition to these approaches, urban researchers need to develop new methods, which focus on human perceptions constantly, point out the flexibility of use of spaces, and the form of the city develops and changes over time to adapt to this.

The important point here is that cities are constantly evolving and developing. Due to ever-changing urban conditions, existing urban approaches, models, analysis, planning, and design methods may soon become invalid. In this context, analysis of different data types with interdisciplinary studies and holistic use of different analysis methods are required.

In this context, a deeper and holistic understanding of urbanism, and thus of the urban design process, is required while linking on an equal footing with the contributions of both hard and soft sciences to the field of urban research (Portugali, 2011). As a result, the urban models being designed to actualize sustainable urban development will not be sufficient alone; The need to use different analysis methods that complement each other emerges.

Whatever tools are used for (re)designing urban spaces, a proposed city layouts always needs to be supported with other analytical "social" data, since human-oriented design strategies are essential for sustainable urban design. And today we have computational tools to address complex urban problems with which we can measure micro-scale data.

City is a database which is an assemblage of multiple dimensions and complex interactions. Urban analysis tools that reveal the relationship of the human factor with their environment are the basis and have been used in recent years. With these tools, it is aimed to involve more users in the design decision processes by especially examining the human-environment relationship. Analysis of social media sharing platforms such as Instagram and Twitter are among the most used methods for understanding relationship between human and environment. These platforms provide an opportunity to reach more comprehensive data analysis than the traditional old data collection methods like surveys. Moreover, these data can be input into data mining processes with interdisciplinary studies.

Initial motivation about this research is to uncover latent characterictics of cities by means of combining state-of-the-art computational tools such as Machine Learning (ML), Big Data analysis (BDA) and Social Media Analytics (SMA) so that it may be possible to render an *"image"* and visualize a dense web of a city. The holistic analysis conducted throughout the research may be turned into a method to extract the *"characteristics"* of cities.

Another motivation was to observe people's behavior in urban spaces and explore semantics between cities' own citizens' perspectives. This is because the first rule of designing a sustainable space in architectural practice is to do it so that the user can act in it most efficiently. Complex relationship between people and the city as a context is as important as, perhaps even more so, every designed structure and its context. In this thesis, the characteristics of the cities have been revealed by implementing the proposed research method to the Castello square in Turin and Taksim square in Istanbul, which were selected as case studies.

Along with these motivations, the whole purpose of the courses that I took by establishing interdisciplinary connections with other academicians was to manage my research path and develop inclusive method and results.

1.2 Data as Ground for the Common

From various conceptual aspects, the notion of space has always been studied and always will be as long as people continue to express their opinions and communicate each other in physical or virtual environments. In this study, Bourriaud's microtopias are considered as an complex assemblage of relations in cities[1] It is possible to exemplify the relationship between people and their context below:

"[...] *Practices which take as their theoretical and practical point of departure the whole of human relations and their social context, rather than an independent and private space* [...]"

Besides, Derrida, who reinterprets Plato's concept of Timaeus, takes us to another notion of a space apart from the space that is sensible and intelligible. This notion is a *third space*, where is the source of the community, where creates a sense of identity

[1] The term "relational" refers to relationship between human and their social microtopia. See:
- (Bourriaud, 2002)

that brings together the past and the future, where everything to take place.[2] This third space is such a space that it includes human potential to change and revolutionize. The third space is a multilayered space that includes its own absence and presence and contains its contradictions, just like *Aporia.*[3]

Therefore, while public space refers to the concept of third space, it can also be defined as common space. In common space as a ground for intersubjectivity, individuals can find the expression of their internality creatively and objectively. In addition, common spaces are not also the places where people do, feel, sense, and express but also a part of the search for meaning in their daily lives. [4] Moreover, such common spaces are not only reside spaces, but also space of experience that people influence environment and interact with their environment. In other words, in today's society, social media does not just express ideas but constitutes a third space as a mediator in which the dialectic between power and the society is constructed.[5]

The most effective use of the squares, which were used for various purposes in different periods of history, was during the Ancient Greek and Roman Empires. During the Middle Ages, Industrial Revolution, capitalism, modernism, and globalization periods, there were changes in city squares' functions and physical structures. Throughout history, squares were used for the purposes such as official ceremonies, rallies, marches, exhibitions, concerts, fairs, etc. Therefore, the activities carried out in the spaces have determined the form of public spaces. In this context, public spaces have occurred in a temporary way, not as designed spaces, but as lived spaces, the activities carried out in them, and the spaces occupied by people. (Stavrides, 2016) Therefore, the form of public spaces reforms under the pressure of time (Kostof, 1992).

---

[2] Lee, H. D. P. and Plato. (1977). Timaeus and Critias. Harmondsworth, Eng: Penguin Books.
[3] Derrida, J. (1993). Khôra. Paris: Galilée.
[4] Lefebvre, H. (1991). Production of Space .New York: Wiley-Blackwell.
[5] Castells, M. 2000. The Rise of the Network Society (2nd Edition). Malden, MA: Blackwell.

According to Lefevbre's spatial triad, the experience of space consists of three essential elements. These elements are: perceived as spatial praxis, designed as a representation of space, and lived as representational spaces. The dialectical relationship of these three elements also allows us to understand the concept of urban space. Moreover, at the same time, these elements are in flux, with the lively and dialectical simplification mingling with each other (Lefebvre, 1991).

As a result, squares are the spaces where all kinds of social, cultural, and economic activities occur, and everyone can be involved without any time limit. Furthermore, city squares are not strictly defined public spaces. City squares are spaces that allow everyday activities and common productions that can be defined by landmarks, nodes, paths, and edges, although their boundaries are vague. (Kostof, 1992; Lynch, 1960). Thus, city squares seem to physcially stand still but the urbanism is a process that have been constantly evolving as the organization of time [6].

1.3 Revealing Visual Characteristics of Cities

Initial idea of the study came from the willingness to know how we can read through cities their cityscape features so that we, as architects and urban designers, can (re)build imageable cities. According to Derrida's[7] deconstruction of signification theory in semiology people are tend to think a "square" always with their signifiers like landmarks and other distinct characteristics. Based on this inference,it is possible to render an image of city squares together with the surrounding places to analyse city squares as a whole.

---

[6] Kostof's "urban truth is in the flow" statement refers to living cities' evolution in order to survive.
[7] The term refers to concept of "différance" in semiology. See:
- (Derrida, La "différance", 1968)

Lynch[8] defines cityscape with five urban elements. These are paths, nodes, landmarks, districts and edges. And the imageability of the elements ensure the legibility of city scenes. In this respect, identifiable image quantitiy measures with landmarks and paths that penetrate squares that has activity along the distinctive plain surfaces. Moreover, the notion of "path" also refers to proximity to attractive small urban pieces, that is "nodes".

Gehl[9] explains that attractive streets and public spaces in a city can measure their key features such as social interactions, various events, shopping places. And he addresses that mixed-use areas are more appealing and dynamic areas than single-use zones. Jacobs[10] continues that sustainable life in a city only maintains with vitality which means spatial diversity and interaction with different cultures in a street or public squares. Therefore, urban planners and architects should create districts where attract various kinds of people who are from different backgrounds by ensuring vitality in the city. Moreover, the spatial diversity shapes human behavior and makes city people more contacted with each other. In addition, Whyte[11] also emphisases that what attracts people most is other people. Thus, socio-spatial diversity provides attractiveness for urban spaces and today we have micro-scale data and quantitative state-of-the-art methods measure people's relationship with each other without traditional observation studies. Similarly, Sennet also considers the city as open city[12] with porous edges, incomplete and open-ended spaces as a collage of people activities. The notion of "opennes" means that possibilities for unexpected uses and unlimitless behaviors.

---

[8] K. Lynch. The Image of the City, Volume 11. MIT press, 1960.
[9] Gehl, J. 1987. Life between Buildings. New York: Van Nostrand Reinhold.
[10] J. Jacobs. The death and life of American cities. Random House, 1961.
[11] Whyte, W. H. (2003). Social Life of small urban space. In D. Watson, A. J. Plattus & R. G. Shibley (Eds.), Time-Saver Standards for Urban Design. New York: McGraw-Hill
[12] Sendra, P. y Sennett, R. (2020). Designing Disorder. Experiments and Disruptions in the City. Londres-Nueva York: Verso. 160 pp. ISBN: 978-1-78873-780-7

In this thesis, the exploratory analysis method allows for analysis of the activity patterns of the citizens in the common spaces, thus how they use the spaces and for which functions. This spatial diversity also enables the formation of social communities.

1.4 Aim and Scope of the Thesis

This study will present a visual analysis model that integrates machine learning tools into social media analytics by revealing visual characteristics and socio-spatial clusters in public spaces. In this framework, the hypothesis of the study is to create an analysis tool that based on location and spatio-temporal image data that receives from the users of public spaces. Furthermore, there is a relational language that points to the appearance of urban and a creative production formed by combining the characteristics of that city. This research aims to formulate a creative and flexible prototype where urban “image” and spatial relations coincide with. In studies on urban research, environmental, economic, and social factors are both independent and mutually supportive components that should be considered. Therefore, in this thesis research, first of all, people and the way people relate to places will be analyzed with visual data in order to understand, design, and find solutions to the problems of cities by contributing new knowledge discovery to the urban analysis literature.

This study defines social media data as a common space in today's responsive cities. Therefore, social media could be used as an analysis method in the (re)design of cities' public spaces so that we, architects, may learn the physical and perceptual characteristics of the city in which the people live by reading their own data. In order to achieve the above objectives, data were collected from the squares in Istanbul and Turin over a period of six months in this thesis.

1.5 Research Questions

Two research questions have been identified to achieve these goals:

1) Can we analyze social media data as a knowledge discovery tool to uncover city squares' visual characteristics?

This research outlines a framework to decode urban characteristics such as physcial proportions of urban scenes and imagebility for city form quality. This framework asserts that social media data analysis is a flexible implementation which has parameters since different squares have different urban characteristics. Two different city squares has been selected to implement this framework. Urban scenes of two squares have been analyzed according to their sky, building and road ratios by using semantic segmentation. Lynchian elements (nodes, landmarks and paths) has been detected throughout the social media data analysis (Lynch, 1960).

2) How can we map social communities by using visual social media data visualization and deciding points of interest in city squares?

This study refers visual social media data as a common space consist of social communities in it. Therefore, this explatory data analysis corresponds to map the relationships between visual environment and social communities. Among the target users of these research outputs, there are researchers and practitioners who are engaged in urban studies such as urban designers, architects, and sociologists who are interested in urban analytics, numerical and quantitative approaches.

A comprehensive exploratory method analysis was conducted to identify these research questions. As a result of these analyzes, these methods were applied to the selected case study areas. The research workflow may be seen in Figure 1.1.

1.6 Research Structure

Different city squares in Istanbul and Turin, considered case studies, will be studied with comparative analysis. The study is a quantitative research method. City squares, which are the most meaningful public spaces expressing user behaviors, will be monitored, objective measurements will be extracted with the users' visual social media. These data will be expressed and interpreted statistically in the context of imageability elements (Lynch, 1960). The sequence of method steps is as listed below:

1. Collection of user data from Instagram

2. Analyzing social media data based on location and time

3. Statistical visualization of the analyzed data with Gephi

4. By analyzing the various image dataset in selected squares with classification methods, to decide urban characteristics in urban spaces.

These data collection and analysis methods are holistic and convenient in reaching the aims of the study. The series of methods to be followed throughout the thesis research, although its applications have been seen in the international literature in recent years, have not been applied much at a national level in urban design and especially in public spaces. As a result of the research, it is aimed to integrate the holistic method formed in order to reveal visual urban characteristics.

The ever-increasing visual data (photographs describing an urban space with different activities) will enable to have deep learning models predicting cities' characteristics. It can also initiate new applications in the field of comparison and classification of urban and spatial qualities.

The possible outcomes of the thesis may be listed as:

Output (1) Image data collection may be used to create urban feature detection tool and compose visual archive for the cities.

Output (2) Classification method with Machine Learning will be adapted not only to urban space but also to the field of building design and interior design, and will enable new articles to be revealed by representing the effects of visual perception on urban design.

Chapter two introduces the concepts of smart city and responsive city with computational tools such as statistical analysis and geographic information sciences, and big data analysis based on machine learning. In this chapter, current methods in urban context and solutions to urban problems have been reviewed. Reviewed articles were mostly about social media data analysis and visual exploration studies within the scope of urban design.

Chapter three clarifies the methodology and the results of series of analysis. In the first part, Google Maps and Instagram data ranking results in two cities has been explained. Secondly, custom categorization of the places in Instagram has been defined according to Foursquare categorization. Third, the photos obtained from Instagram has been distributed according to their location in Instagram API. Thus, social communities have been mapped via distribution of Instagram photos. Lastly, CNN model has implemented to two city squares by training visual city models and classifying 'Istanbul' and 'Turin' labels. Thus, the model detects place informative objects in city squares according to each cities' visual data exploration manually by examining Instagram data.

In chapter four, current urban phonemena and analysis tools have been reviewed and limitations and obstacles have been disccussed for thesis research. Finally, further studies and developments regarding urban research field has been explained.

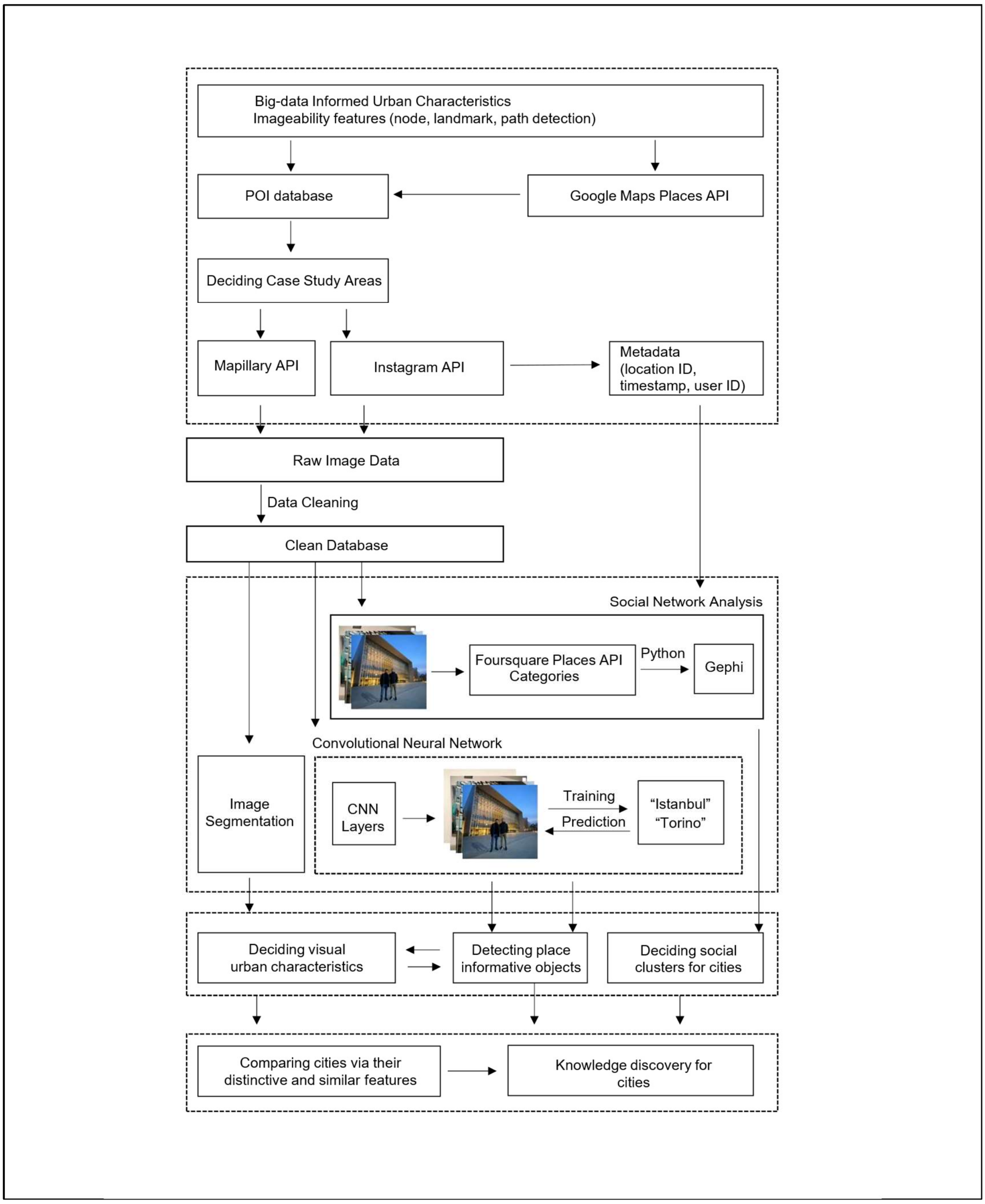


Figure 1.1. Research Workflow Chart

CHAPTER 2

URBAN ANALYTICS

During this chapter of the study comprises of three parts that are (1) urban big data analysis (2) social sensing and (3) big data analysis as a design tool.

2.1 Urban Big Data Analysis

The quantitative revolution that emerged in the 1950s and 1960s gave urban researchers the role of social scientist and economist at the same time. Thus, geographical data is integrated with mathematical and statistical techniques into urban analysis. In the late 1960s, social, economic, cultural, behavioral, and cognitive aspects began to be discussed in urban studies. In the 1970s, statistical methods such as pattern and impact analysis, multidimensional analysis, spatial correlation, multidimensional optimization analysis, multicriteria models, and interactive decision models were added to these quantitative methods. In the late 1980s and 1990s, a synthesis of statistical analysis and cartography, GIS dominated urban analysis studies based on database technology. Since the late 1990s, computational methods and techniques have been used for urban data analysis, such as AI, ML, neural networks, pattern recognition, knowledge-based systems, high-performance computing, and data visualization (Sokmenoglu Sohtorik, 2016).

The "smart city" concept has arisen to address problems and produce solutions for social deprivations and environmental conditions (Batty, 2013), (Miguel-Rodriguez, Galan-Paez, Aranda-Corral, & Borrego-Diaz, 2016). "Responsive city," on the other hand, is a multidisciplinary city concept consisting of human behavior analysis, computer science, urban planning, and design disciplines. Such cities can respond to the city's changing dynamics and may be designed for future scenarios with the insights derived from the analyzed urban daily flow data. (Goldsmith & Crawford, 2014).

Using big data technologies with the conventional method is complicated to exploit due to big data characteristics (volume, variety, speed, etc.). Thus, various methods and technologies have been developed to benefit from data. One of the most important methods is data mining. Furthermore, Data mining includes the following steps: data cleaning, merging, selection, transformation, and uncovering patterns in data. (Kitchin, The Real-time City: Big Data and Smart Urbanism, 2014). In recent years analytical studies have been conducted on big data by using ML/DL techniques on the data to run analytical queries and gain insights and make predictions, especially in urban studies.

2.2 Social Sensing

Urban researchers may obtain the flows of people that can not be obtained from bird's eye architectural photographs from the human perspective by going down to the human eye level (Whyte, 1980). In this way, they may understand the different perspectives of individuals and reveal the tacit knowledge and deep needs of urban users through social computing since people are experts in their own experience. (Visser, Stappers, Lugt, & Sanders, 2005).

City squares tend to self-leveling. People also tend to behave complicated, clustered and crowded (Whyte, 1980). In open public spaces, this creates an uncontrollable situation. According to urban data analysis, the user capacities of the spaces can be transformed into a process that can be predicted and monitored remotely in real-time (Koenig, 2020). Therefore, with urban sensing, architects and urban designers might determine which routes people use, at what time intervals, and even for what purposes. That may be a very holistic data collection method in addition to the quantitative and observable data collection method (Barthelemy, 2017).

Urban sensing aims to develop a way of seeing everyday scenes. Sensing people in order to catch the clues and human traces in the city can be the most accurate, measurable and observable solution in responsive cities (Ratti & Offenhuber, 2014).

2.3 Big Data Analysis as a Design Tool

With the spatially referenced data technologies people have become to be able to imagine cities visually. That also gives new responsibilities to urban researchers and architects to integrate urban design layouts with georeferenced data by aiming have better knowledge in urban studies.

Each city has own characteristics with its own citizens and social relationships. Livehoods project presents a clustering model for collective behaviors of its residents and allows us to visualize social flows of people of a city and describes borders of neigborhoods by superposing designed borders and defined one by residents of a city with questionnairres. With analyzed twitter check-ins to develop an clustering algorithm, participants are asked to divide neighborhoods by identifying points and places where they realize a “shift in a feel”. In other words, they are asked to redefine social communities (Cranshaw, Schwartz, Hong, & Sadeh, 2021). This dynamic methodology, enables urban researchers to understand people’s movements and (re)design city borders according to own citizens (Figure 2.1). This pioneer research promotes a general framework could be a guideline to design urban spaces and neighborhoods collectively. However, it remains biased in most senses since it was carried out with a limited number of participants. If the data of many people were analyzed with the data mining method, the study could have become more comprehensive. With Instagram geotags, urban researchers understand how cities function and where specific social activities, events occur.

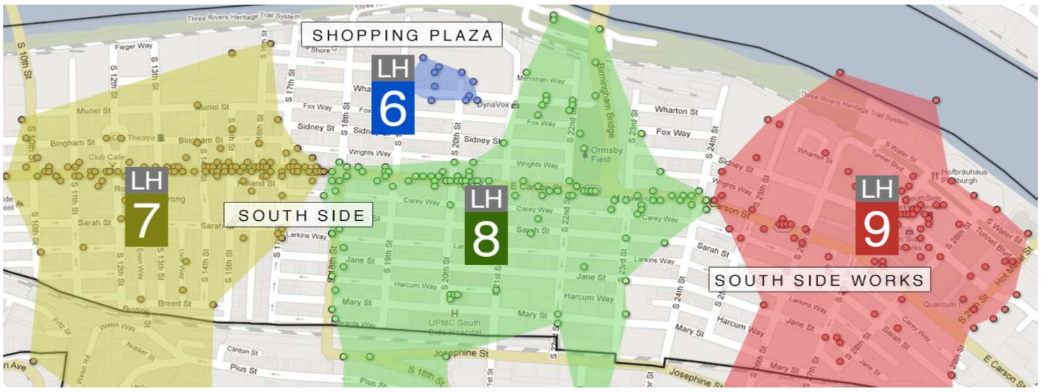


Figure 2.1. The municipal borders (in black) and Livehoods for South Side (Cranshaw, Schwartz, Hong, & Sadeh, 2021)

Zasina (2018) presents the results of investigating Instagram photos featuring outdoor city views taken in Lodz, Poland. First purpose of the study is to compare the cities' images "created" with "curated" in city branding strategies. Second purpose is that revealing city components and cityscape features in human perception by refering to Lynch's studies. The author analized user's preferences and appreciations in taking photographs by featuring cityscape's components such as, architectural buildings, public spaces and public arts (Table 2.1). Similar to this thesis research, the study shows that people do not perceive cityscapes as a whole but rather tend to perceive urban spaces with their components presenting places and objects as a result of analyzing Instagram data.

Table 2.1 Distribution of photographs assigned to pre-established categories (Zasina, 2018)

Category	**Sub category**	**Feature**	**No.s of photos (n)**	**Share of photos in subcategory (%)**	**Share of photos in the entire set (%)**
Architecture	Age	Historic	1045	77.70	55.97
		Modern/contemporary	286	21.26	15.32
		Unclassified	14	1.04	0.75

Table 2.1 (continued)

	Type	Residential	679	50.48	36.36
		Industrial	303	22.53	16.23
		Civic	176	13.09	9.43
		Commercial	109	8.10	5.84
		Unclassified	78	5.80	4.18
	Visual appearance	Well-kept	1012	75.24	54.2
		Neglected	255	18.96	13.66
		Unclassified	78	5.80	4.18
Public space	Type	Street	336	37.5	18.00
		Semi-public	285	31.81	15.27
		Park	182	20.31	9.75
		Square	42	4.69	2.25
		Unclassified	51	5.69	2.73
	Public art featured	Mural/graffiti	247	68.04	13.23
		Sculpture/monument	100	27.55	5.36
		Other	16	4.41	0.86
Recent	-	-	137	-	7.34

Other than cityscape physical features, Gatti & Procentese (2021) recognize that "Sense of Community" means social media community-related practices can have in modifying how citizens experience their cities as local places and relational entities. Exploring the experience re-openes of urban spaces and sociability. Furthermore, Instagram may be an instrument to strengthen users' relationships and social, environmental qualities of places as socially connoted representations of real places in a city (Figure 2.2). Therefore, Instagram data is selected as input in the thesis.

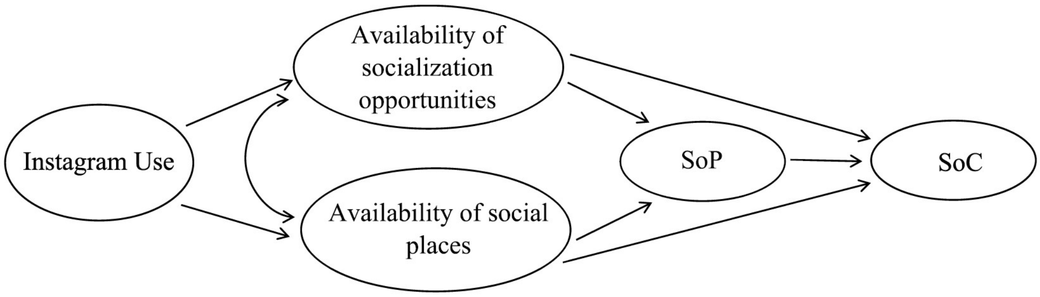


Figure 2.2. Hypothesized Model. (Instagram Use = Instagram Use to Look at Local Social Places and Gatherings; SoP = Sense of Place; SoC = Sense of Community) (Gatti & Procentese, 2021)

Instagram has not only a great potential shaping public image of a city but also provides city branding strategies to both city planners and urban researchers to extracting city elements, building a visitor destination’s image and attacting more tourists. (Oguztimur & Akturan, 2016), (Iglesias-Sánchez, Correia, Jambrino-Maldonado, & Heras-Pedrosa, 2020). Another related work on urban tourism is that an analysis of spatial distribution patterns of Instagram photographs to identify the spatial impact of tourist behaviour and locate central spaces in Barcelona. Projected images generated by Consortium of Tourism of Barcelona – CTB investigated and compared with perceived images in tourist posts in order to have an insight ot tourist movements and behaviors in a city (Augusti, 2021).

Arefieva, Egger, & Yu (2021) conducted a cross-disciplinary study that connects semiotics, marketing, and data analytics in urban tourism, the researchers used text analytics to extracting keywords to define tourist experiences in Austria by appliyng three machine learning models; (1) k-means clustering based on document-term matrix, (2) correlation explanation (CorEx) topic model based on document-term matrix, and (3) k-means clustering based on Doc2Vec vectors. They obtained relatively good results with k-means clustering. This study highlights an interdisciplinary framework to uncover tourists’ experiences through visual contents The results of this study can be shown in Figure 2.3. and 2.4.

Boy & Uitermak (2016) defines Instagram as useful and potential data source in urban studies and cross-disciplinary research. They collected Instagram photos geotagged in Amsterdam for 12 weeks to explore socio-spatial patterns and differences. The researchers demonstrate that the data collected may refer to places, sets of places, and social networks to understand the relationships between different spaces and people by determining which types of users use which spaces. Likewise, in this thesis aims to reveal the hidden relationships between places and people.

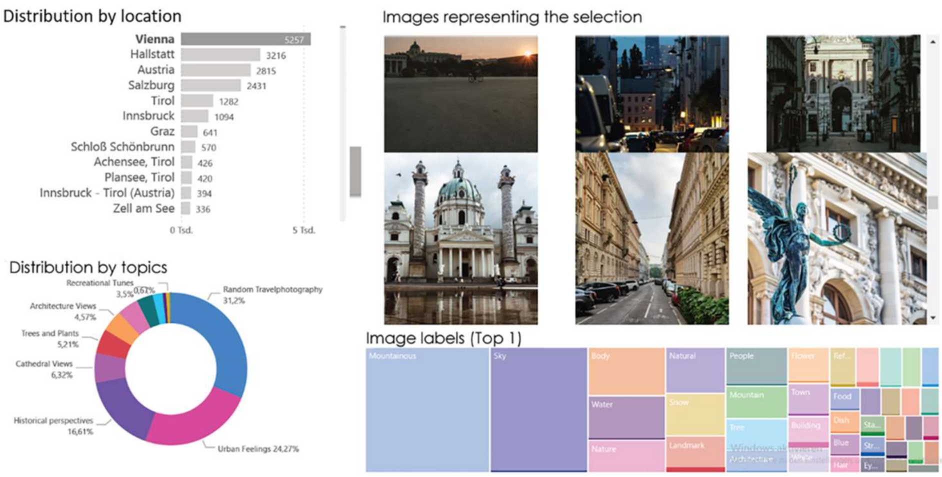


Figure 2.3. Power-BI dashboard (Arefieva, Egger, & Yu, 2021)

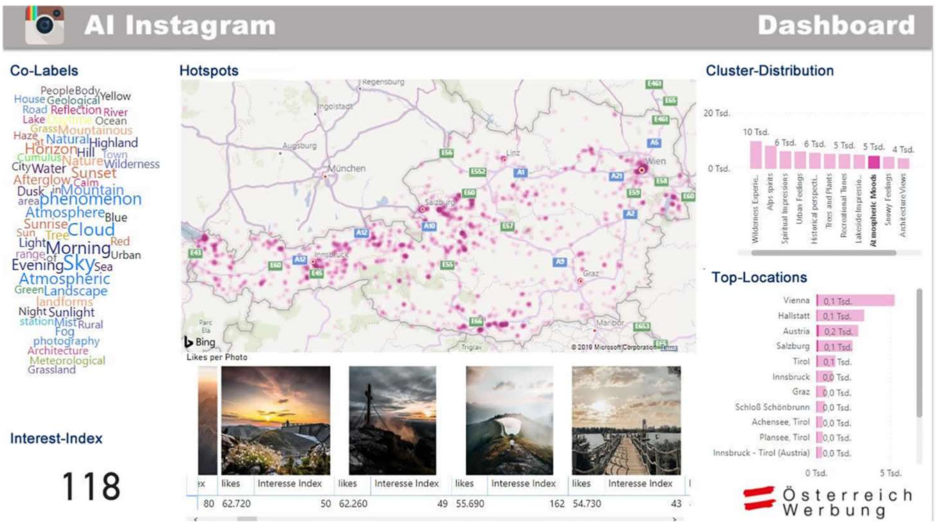


Figure 2.4. Results of photographs' distribution (Arefieva, Egger, & Yu, 2021)

Zhou, Liu, Oliva, & Torralba (2014) used 7 high-level attributes related to the form of the city (amount of vertical buildings, type of architecture, water coverage, and green space coverage) and related to the social function of the city (transportation, athletic activity, social activity). They created the City Perception Database by collecting 2 million geotagged images from Panoramio from 21 cities on three continents. They classified the attributes in the images using the SUN Attribute Database (Patterson & Hays, 2012) and Deep Learning. They conducted a city identification experiment that was an answer to the question, "Is it New York or Prague?". Unlike other studies, instead of identifying landmarks in images, this research aims to reveal the semantic features of the city form and city function that constitute city identity. Furthermore, they clustered the similar cities to their attributes in 7 high-level attributes (Figure 2.5.) (Zhou, Liu, Oliva, & Torralba, 2014).

First, using the Sun Attribute Database (Patterson & Hays, 2012), they classified scene attributes with pre-trained ImageNet as D-CNN. Secondly, the researchers trained a linear SVM classifier for each scene attribute by using Liblinear. The spatial analysis of these attributes according to the cities is shown in the Figure 2.6. This spatial distribution also shows the spatial popularity of places.

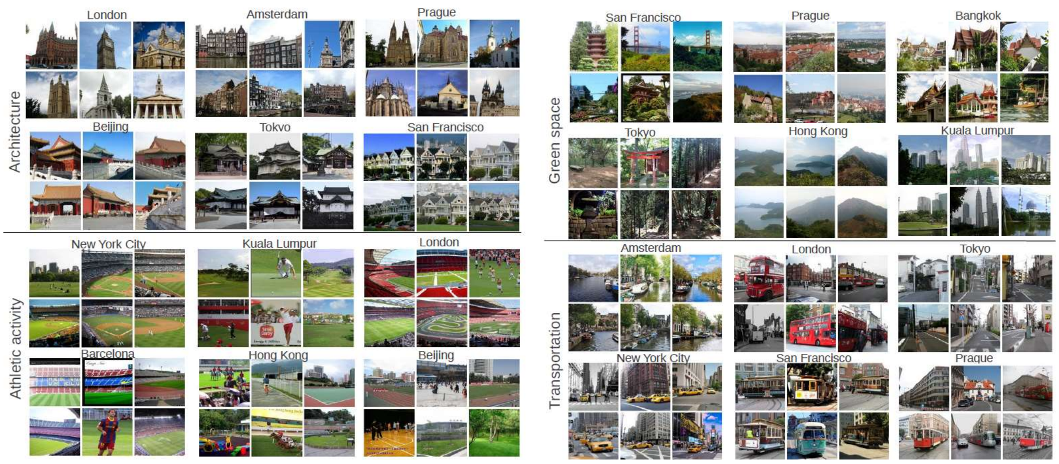


Figure 2.5. 4 city identity attributes (Zhou, Liu, Oliva, & Torralba, 2014)

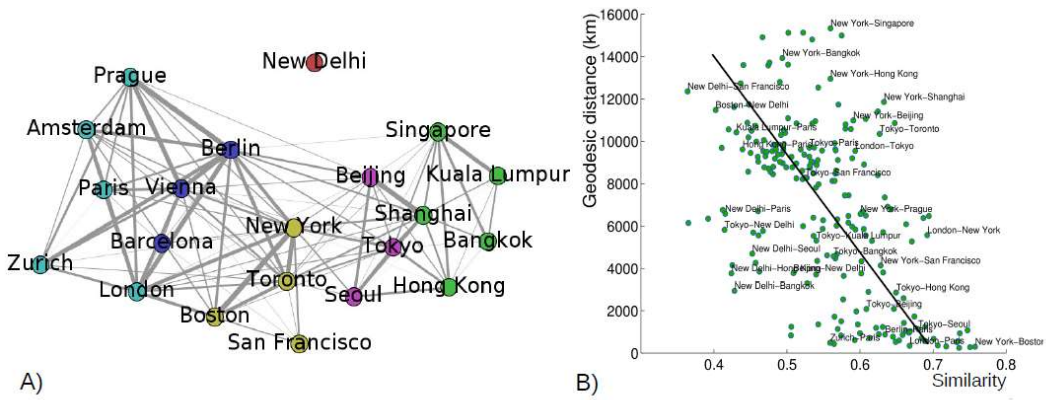


Figure 2.6. A) Similarity network plot of all the 21 cities B) The scatter of the data-driven similarity over geodesic distance of cities (Zhou, Liu, Oliva, & Torralba, 2014)

Another related work on city identity recognition belongs to MIT Senseable City Lab. The study aims to reveal the distinctive features of 18 cities, including landmarks and distinctive objects of the cities. In the first stage of the experiment, Panoramio was used for image data. In order to exclude non-place-relevant images in Panoramio data, the researchers trained a support vector machine (SVM) classifier with image samples from Caltech 101, Places2. In addition, they used pre-trained image object detection model with COCO dataset. A classification with DCNN was implemented to predict which city the images belong to which city. In the second step, a confusion matrix was created for each city category to compare cities' visual similarity and distinctiveness. Thus, the misclassification rate was determined. In the last step of the study, place-informative scenes and objects of the city are defined. This study provides a useful dataset and inspiring model to explore city characteristics in this thesis research. (Zhang, Zhou, Ratti, & Liu, 2019).

Selected urban characteristics examined within the scope of the thesis can be seen in Figure 2.6. The first of these characteristics is the physical features of the urban scenes. In this context, sky, building, and road ratios in urban scenes were defined by using semantic segmentation.

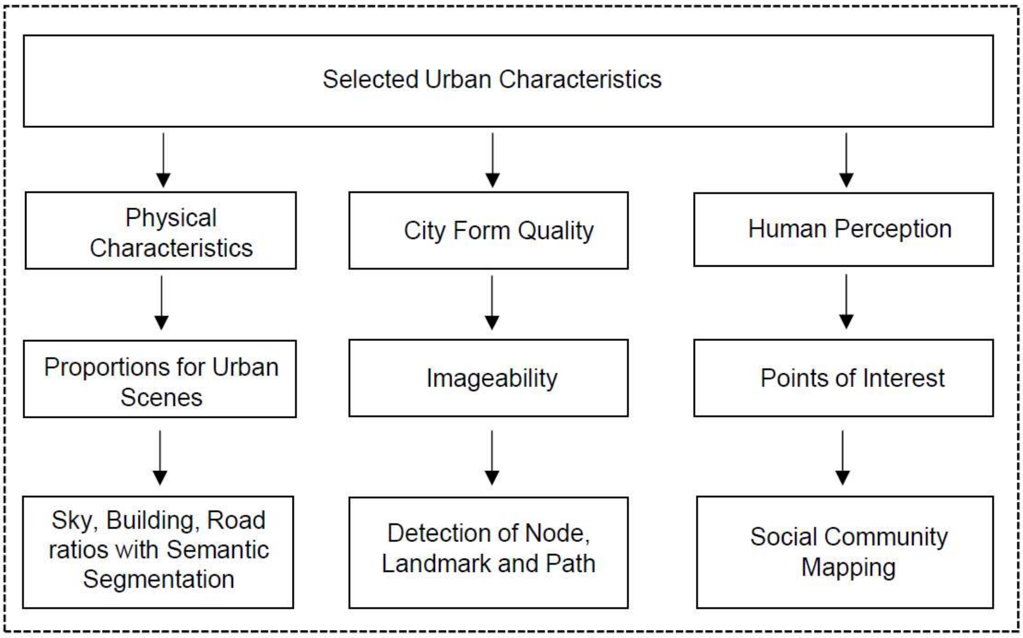


Figure 2.7. Selected Urban Characteristics (produced by the author)

(Li, 2021) examined relationship between the spatial distribution of Green View Index and the social variables with correlation analysis and regression models. This study aimed to extract streetscape future in GSV images to monitor temporal change of green canopy in New York city during the last 10 years in human-oriented way. The research presents that distribution of Green View Index differentiate across neighborhoods of different racial/ethnic groups in New York City according to analysis racial/ethnic statuses of residents, social variables from the census data. Segmenting streetscape features to obtain quantitative information about streetscape is a common issue since street-level images are captured in changing illuminations and conditions. Mostly, BlendMask, YOLACT, Mask RCNN, and Detectron2 is used for instance segmentation (Verma, Mumm, & Carlow, 2021). Li used a segmentation method called Pyramid Scene Parsing Network (PSPNet) trained on the ADE20K dataset PSPNet can segment the street-level images into 150 categories, such as trees, buildings, pavement, and sky (2021). The image segmentation process may be shown in Figure 2.8.

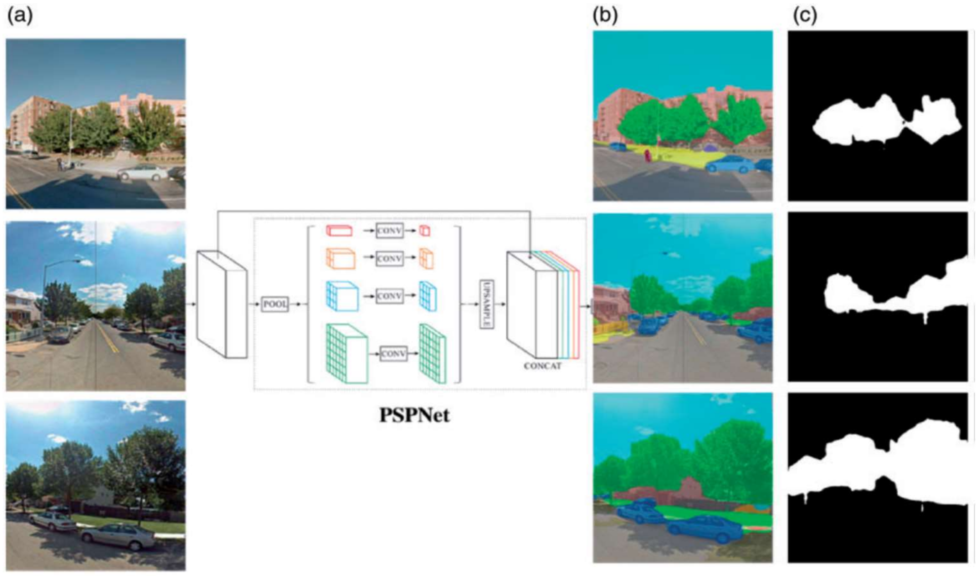


Figure 2.8. The image segmentation on street-level images using the PSPNet (Li, 2021)

Deep learning and computer vision algorithms are used to automatically extract quantitative information about streetscape features from street-level images, which is usually considered difficult (Li, 2021). Thus, this thesis used state-of-the-art method which is called Simple Linear Iterative Clustering (SLIC) superpixel algorithm with a Convolutional Neural Network (CNN) to extract information in urban scenes of Castello and Taksim Square (Correa Martins, et al., 2021).

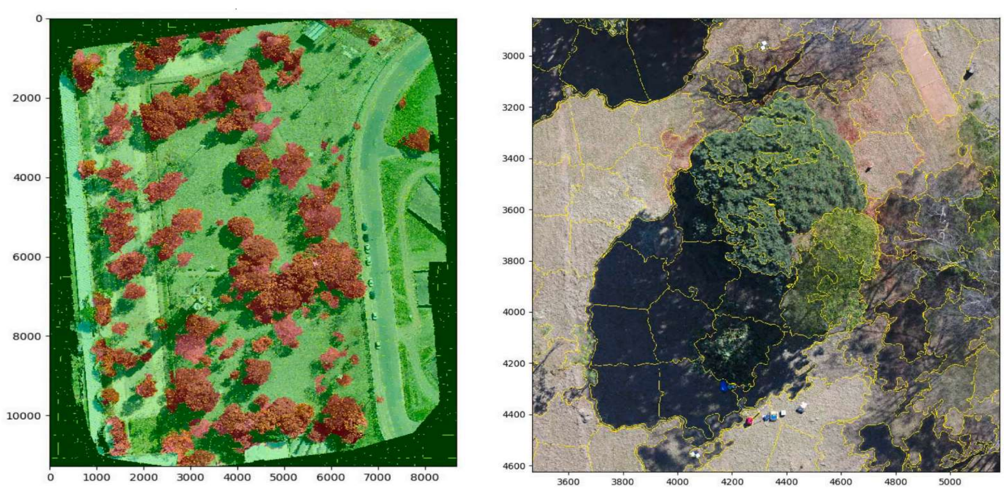


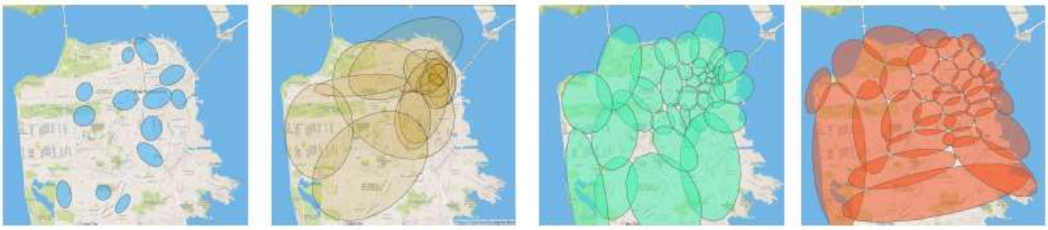
Figure 2.9. a) results of the SLIC superpixel segmentation b) the yellow lines represent the border of each SLIC superpixel (Correa Martins, et al., 2021)

The notion of imageability, which is a criterion determining the quality of the urban form, was chosen as the second urban characteristic. Path, node, and landmark analysis were mapped in two different city squares in this context. The third chosen urban characteristic is human perception. In this thesis, social sensing method was used while mapping the social community with Points of interest data.

Frias-Martinez, Soto, Hohwald, & Frias-Martinez (2012) evaluated the use of geolocated tweets as a complementary source of information for urban planning applications by detecting land use of urban areas with two methods: 1) A Self-Organizing Map (SOM) is an unsupervised neural network to be able to represent tweets distribution as a map 2) to identify urban points of interest as places with high activity of tweets with characterizing each land segment in the Voronoi tessellation by its average tweet activity.

Figure 2.10. Geographical representation of land use clusters in Twitter data mapping shows, respectively, a) business b) leisure c) nightlife d) residential (Frias-Martinez, Soto, Hohwald, & Frias-Martinez, 2012)

Similary, this thesis aims to understand human behavior but also on modeling the way people live and interact in their urban environments. (Çelikten, Le Falher, & Mathioudakis, 2016).



(a) Hoodsquare (b) Our method (c) Livehoods (d) SOM

Figure 2.11. All methods show that activity in New York city occurs mainly downtown but it also highlights differences between approaches (Çelikten, Le Falher, & Mathioudakis, 2016)

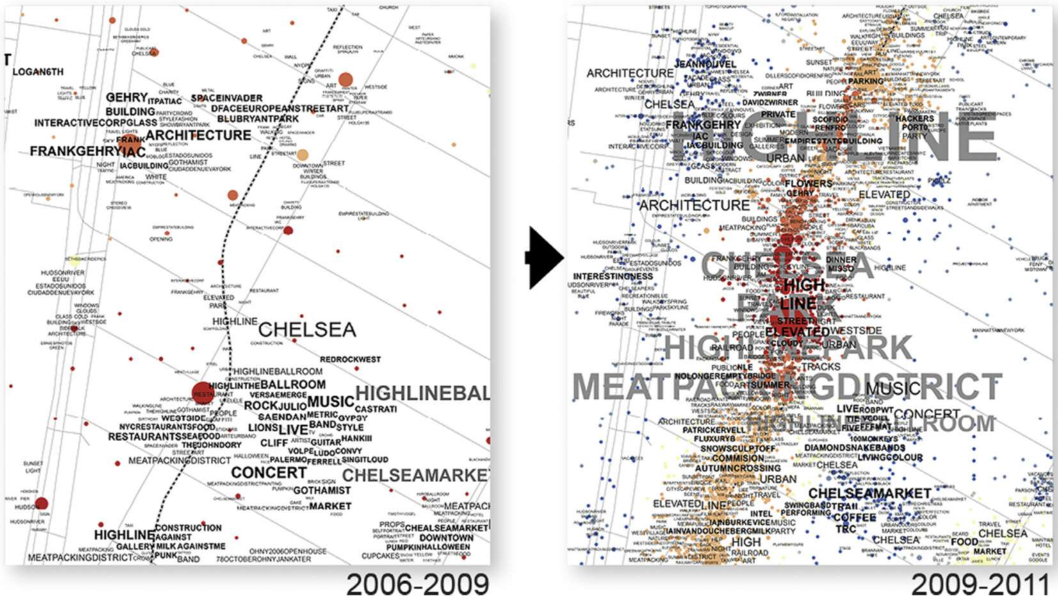


Figure 2.12. Map for the district of Chelsea (NY), with data from before the opening of the High Line (left) and afterwards (Dunkel, 2015)

The use of different urban spaces at different times and examining the points of activity density allow us to identify the different and temporary usage of the urban landscape (Dunkel, 2015). In this thesis, it is possible to see an urban life developing along the Istiklal Street, which is the extension of Taksim Square like Via Giuseppe

Luigi Lagrange, Via Garibaldi and Via Roma in Castello Square (Fassino, 2020) .The categorization of Instagram data according to the spatial distribution expressing densities provides evidence that existing urban planning processes develop around important focal points or focal promenades. Urban designers and architects need to provide information on the aesthetic and perceptual aspects and the perceived character of urban space while designing within the scope of human-environment relation (Global Public Space Programme, 2019) (Global Public Space Programme, 2020) Therefore, identifying urban characteristics with computational tools is a complementary way to design sustainable urban spaces.

Another relevant study using Social Media data is a social network analysis that was used to detect communities and examine relationships, especially among twitter user groups. The researchers utilized the degree and betweenness centrality methods with Gephi software. This method investigates the relations between hashtags and humans as actors in social networks (Bastian, Heymann, & Jacomy, 2009).

Social networks as visual maps represent the relationships between tweets to calculate the degree for each node, calculate the centrality for each node and detect the main communities in a social network. (Abascal-Mena, Lema, & Sèdes, Detecting Sociosemantic Communities by Applying Social Network Analysis in Tweets, 2015; Abascal-Mena, Lema, & Sèdes, From Tweet to Graph: Social Network Analysis for Semantic Information Extraction, 2014), (Newman M. E., 2006). This thesis was inspired by the studies applied with Twitter data and the social network analysis method to Instagram data in order to visualize social communities in Istanbul and Turin (Figure 2.14.).

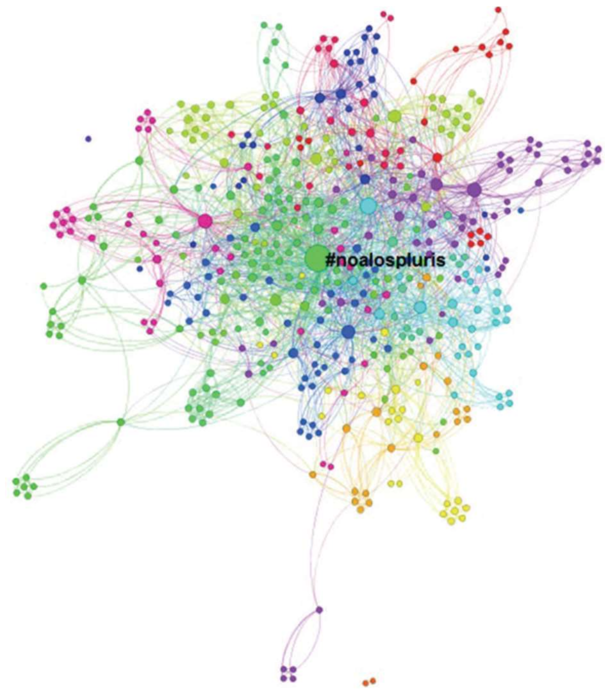


Figure 2.13. Network of hastags in a Social Network Analysis (SNA) (Abascal-Mena, Lema, & Sèdes, Detecting Sociosemantic Communities by Applying Social Network Analysis in Tweets, 2015)

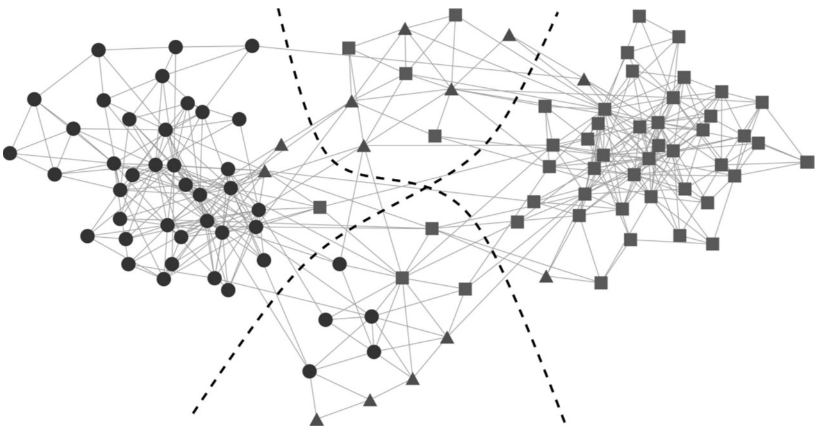


Figure 2.14. Representation of dividing networks into communities. (Network of books on American politics. Nodes represent books and edges join books frequently purchased by the same readers) (Newman M. E., 2006)

A total of 101 articles were examined for the literature review of this thesis. These articles can be found in Appendix A. 71 of them are about methods for urban big data analysis. These are detailed in Table 2.2, 2.3, 2.4 and 2.5. In 51 articles of them, social sensing methods were examined. Instagram in 10 of them, Flickr in 12, Twitter in 12, Foursquare in 8 of them, Open Street Map in 4 of them, and Google Street View data in 5 of them were used as input (Figure 2.15.).

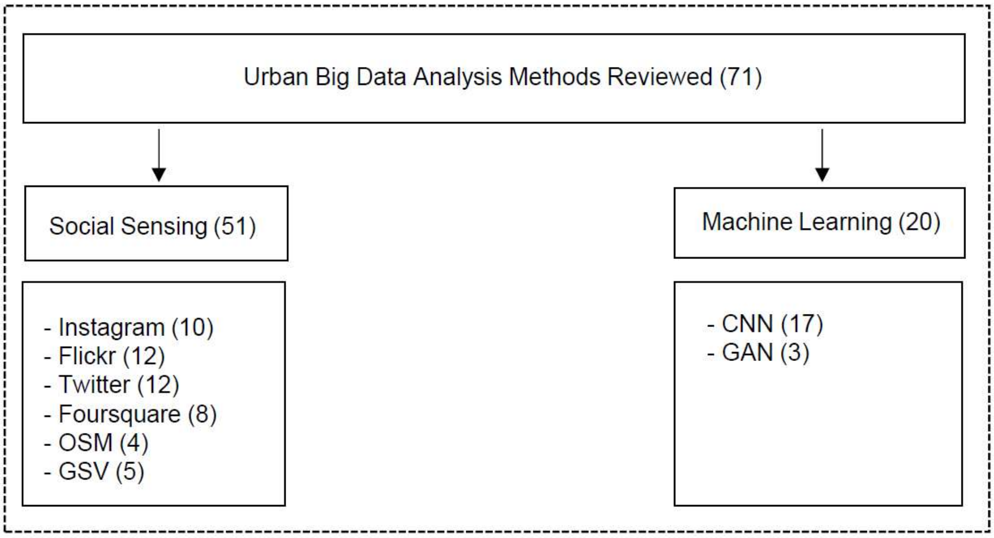


Figure 2.15. Numbers of Urban Big Data Analys is Methods Reviewed (produced by the author)

In the literature review, studies involving visual content and human activity and studies using Instagram as an input were examined in urban studies. (Tables 2.2 , 2.3). In most of the studies reviewed, social media photos were used as input to reveal the visual characteristics of cities. (Table 2.4) Creating a CNN Model by taking social media photos as input to identify specific elements in urban scenes and thus revealing the characteristics of cities has been inspiring for the methods used in this thesis (Zhang, Zhou, Ratti, & Liu, 2019).

While two of the four key “city similarity” studies examining urban spaces compare similar daily life flows in cities using Twitter data (Takerngsaksiri, Wakamiya, & Aramaki, 2019), (Zasina, 2018), another study uses photos on social media platforms such as GSV and Panoramio (Zhang, Zhou, Ratti, & Liu, 2019), (Zhou, Liu, Oliva, & Torralba, 2014) to analyze urban data.

Considering today's social media usage shows that Instagram should contribute more to urban studies as a data collection platform for visual and spatial purposes. For this reason, it is necessary to increase the number of studies using Instagram data in terms of urban space discovery in the literature.

Among reviewed computational methods, some novel methods were used in the examined urban studies. Although there are urban studies that collect visual social media data (Zhang, Zhou, Ratti, & Liu, 2019), (Zhou, Liu, Oliva, & Torralba, 2014), in particular, an urban analysis method that integrates machine learning technology into the data obtained from Instagram has not been found in the literature. Zasina (2018) has analyzed Instagram data and succeeded in analyzing urban perception in visual city exploration studies (Table 2.2). However, there is no research in the literature that uses this data to create a social network analysis or city prediction model at the same time. In order to adapt the city models and the changing environmental, social, and economic conditions of the city, it is important to reveal the characteristics of the city prediction models and cities.

Especially, in current urban studies, Gephi software, which visualizes data on social networks, is very rare. Sociological concepts and methods need to be more involved in urban research processes since the city is not only a designed layout but also a flexible and multi-layered whole reformed by people. Based on this, the social network visualization, which is one of the methods used in this thesis, will reveal the hidden relationships between the actors and spaces of urban and the quality of the city form based on human perception. Therefore, this thesis created a visual city prediciton model, first with the social network analysis method, and second, with machine learning algorithms that analyze Instagram data.

Table 2.2 Instagram as Input in City Studies

Article Name	**Authors**	**Year**	**Journal**
The Instagram Image of the City. Insights from Lodz, Poland	(Zasina, 2018)	2018	Bulletin of Geography. Socio-economic Series
Instagram as a Co-Creation Space for Tourist Destination Image-Building: Algarve and Costa del Sol Case Studies	(Iglesias-Sánchez, Correia, Jambrino-Maldonado, & Heras-Pedrosa, 2020)	2020	Sustainability
Experiencing urban spaces and social meanings through Social Media: Unravelling the relationships between Instagram city-related use, Sense of Place, and Sense of Community	(Gatti & Procentese, 2021)	2021	Journal of Environmental Psychology
The clustering of city images on Instagram: A comparison between projected and perceived images	(Augusti, 2021)	2021	Journal of Destination Marketing & Management
A machine learning approach to cluster destination image on Instagram	(Arefieva, Egger, & Yu, 2021)	2021	Tourism Management
Color and engagement in touristic Instagram pictures: A machine learning approach	(Yu & Egger, 2021)	2021	Annals of Tourism Research
How to Study the City on Instagram	(Boy & Uitermark, How to Study the City on Instagram, 2016)	2016	Public Library of Science

Table 2.3 Urban Studies According to Contents

Article Name	**Authors**	**Year**	**Journal Name**	**Content**
Discovering Place-Informative Scenes And Objects Using Social Media Photos	(Zhang, Zhou, Ratti, & Liu, 2019)	2019	Royal Society Open Science	Similarity

Table 2.3 (continued)

Exploring Venue-Based City-To-City Similarity Measures	(Preotiuc-Pietro, Cranshaw, & Yano, 2013)	2013	UrbComp '13	Similarity
City Link: Finding Similar Areas in Two Cities Using Twitter Data	(Takerngsaksiri, Wakamiya, & Aramaki, 2019)	2019	Web and Wireless Geographical Information Systems	Similarity
The Similarity of European Cities Based on Image Analysis	(Dobesova, 2019)	2019	Proceedings of 3rd Computational Methods in Systems and Software	Similarity
Understanding volume and correlations of automated walk count: Predictors for necessary, optional, and social activities in Dilworth Park	(Lee, 2021)	2021	Urban Analytics and City Science	Social Activities, Urban Space
Integrated environmental and human observations for smart cities	(Fang, Shaw, Yang, Santi, & Tu, 2021)	2021	Urban Analytics and City Science	Human Activities, Urban Space
The Death and Life of Great Italian Cities: A Mobile Phone Data Perspective	(Nadai, et al., 2016)	2016	Proceedings of the 25th International Conference on World Wide Web	Human Activities, Urban Space
Characterizing Urban Landscapes using Geolocated Tweets	(Frias-Martinez, Soto, Hohwald, & Frias-Martinez, 2012)	2012	International Conference on Social Computing	POI
Identifying subcenters with a nonparametric method and ubiquitous point-of-interest data: A case study of 284 Chinese cities	(Long, Song, & Chen, 2021)	2021	EPB: Urban Analytics and City Science	POI
Extracting and understanding urban areas of interest using geotagged photos	(Hu, et al., 2015)	2015	Computers, Environment and Urban Systems	AOI

Table 2.4 Visual Exploration Studies on Urban Scenes

Article Name	**Authors**	**Year**	**Journal Name**
URBAN-i: From urban scenes to mapping slums, transport modes, and pedestrians in cities using deep learning and computer vision	(Ibrahim, Haworth, & Cheng, 2021)	2021	EPB: Urban Analytics and City Science
Discovering place-informative scenes and objects using social media photos	(Zhang, Zhou, Ratti, & Liu, 2019)	2019	Royal Society Open Science
A Large-Scale Measurement and Quantitative Analysis Method of Façade Color in the Urban Street Using Deep Learning	(Zhang, Fukuda, & Yabuk, 2020)	2020	Proceedings of the 2020 DigitalFUTURES
Streetscore - Predicting the Perceived Safety of One Million Streetscapes	(Nikhil, Philipoom, Raskar, & Hidalgo, 2014)	2014	IEEE Conference on Computer Vision and Pattern Recognition Workshops
StreetVizor: Visual Exploration of Human-Scale Urban Forms Based on Street Views	(Shen, et al., 2018)	2018	IEEE Transactions On Visualization And Computer Graphics
Urban function recognition by integrating social media and street-level imagery	(Ye, Zhang, Mu, Gao, & and Liu, 2021)	2021	Urban Analytics and City Science
Using deep learning to examine the correlation between transportation planning and perceived safety of the built environment	(Hollander, Nikolaishvili, Adu-Bredu, Situ, & Bista, 2021)	2021	EPB: Urban Analytics and City Science
Identifying Streetscape Features Using VHR Imagery and Deep Learning Applications	(Verma, Mumm, & Carlow, 2021)	2021	Remote sensing
Recognizing City Identity via Attribute Analysis of Geo-tagged Images	(Zhou, Liu, Oliva, & Torralba, 2014)	2014	Computer Vision – ECCV

Table 2.5 Machine Learning Applications in City Studies

Article Name	**Authors**	**Year**	**Journal Name**
The Similarity of European Cities Based on Image Analysis	(Dobesova, 2019)	2019	Proceedings of 3rd Computational Methods in Systems and Software
Social media as passive geo-participation in transportation planning – how effective are topic modeling & sentiment analysis in comparison with citizen surveys?	(Lock & Pettit, 2020)	2020	Geo-spatial Information Science
Collective sensing of evolving urban structures: From activity-based to content-aware social monitoring	(Bokanyi & Kallus, 2021)	2021	Urban Analytics and City Science
Towards A New Image Archive for the Built Environment	(Date & Allweil, 2021)	2021	Urban Analytics and City Science
A Machine Learning Approach to Cluster Destination Image On Instagram	(Arefieva, Egger, & Yu, 2021)	2021	Tourism Management
Color and Engagement in Touristic Instagram Pictures: A Machine Learning Approach	(Yu & Egger, 2021)	2021	Annals of Tourism Research
Using social media to understand drivers of urban park visitation in the Twin Cities, MN	(Donahuea, et al., 2018)	2018	Landscape and Urban Planning
Using image recognition to automate assessment of cultural ecosystem services from social media photographs	(Richards & Tunçer, 2018)	2018	Ecosystem Services
SUN Attribute Database: Discovering, Annotating, and Recognizing Scene Attributes	(Patterson & Hays, 2012)	2012	IEEE Conference on Computer Vision and Pattern Recognition
Using deep learning to examine the correlation between transportation planning and perceived safety of the built environment	(Hollander, Nikolaishvili, Adu-Bredu, Situ, & Bista, 2021)	2021	EPB: Urban Analytics and City Science

CHAPTER 3

METHODOLOGY AND RESULTS: EXPLORATORY ANALYSIS OF TAKSIM AND CASTELLO SQUARES

This section covers the methods that examine first squares in Turin and Istanbul and then selecting pair of squares among these squares to uncover and determine their similarities and differences with the holistic analysis method. The first method is social media analysis, and the second method is deep learning neural networks, a machine learning method. In addition, the social groups, categorization of spaces, usage types of spaces, relations between spaces of Turin and Istanbul will be examined, and landmarks, paths and nodes as imaginary elements of city concept will be determined.

3.1 Google Based Ranking

The top sight attractions were identified using the Google Maps Places API for both Turin and Istanbul, and lists with details of these attractions can be found in Appendix B and C.

Table 3.1 Top squares table according to Google Maps Data in Istanbul (data scrapped by the author)

Square name	Number of photos	Category Label-Foursquare	Likes Score-Google	No.s of Reviews	Categories-Google
Sultanahmet Square	101500	plaza	4.7	21782	Tourist attraction
Ortakoy Square	124000	plaza	4.6	3893	Tourist attraction
Beyazid Square	31400	plaza	4.5	18.155	Historical Place
Besiktas Square	5000	plaza	4.5	67	Tourist attraction

Table 3.1 (continued)

Taksim Square	30700	plaza	4.4	13.56	Tourist attraction
Kadikoy Square	11300	plaza	4.4	848	Tourist attraction
Eminonu Square	16200	plaza	4.3	122	Tourist attraction

Table 3.2 Top squares in Turin table according to Google Maps Data (data scrapped by the author)

Square name	**No.s photos**	**Category**	**Likes Score**	**No.s of Reviews**	**Categories**
Piazza Castello	176000	plaza	4.8	1925	Tourist attraction
Piazza Vittorio Veneto	97600	plaza	4.7	412	Tourist attraction
Piazza San Carlo	58500	plaza	4.7	19045	Tourist attraction
Porta Palazzo	11500	plaza	3.9	16	Tourist attraction
Piazza Cavour	1000	plaza	4.5	293	Tourist attraction
Piazza Statuto	1000	plaza	4.4	9193	Historical place
Piazza Cln	5000	plaza	4.5	750	Tourist attraction

In addition to top sights, top squares data also retrived from Google Maps Places API according to Table 3.1 and 3.2. Castello Square, as shown in Table 3.2, is the square with the most tourist attraction in Turin. As shown in to Table 3.1. and Sultanahmet Square, as shown in 3.2, is the square with the most tourist attraction in Istanbul.

3.2 Social Media Based Ranking

Social media data allows tracing the relationship of people with other people and their environment by analyzing spatio-temporal and location-based shared images, videos, and textual content. It also allows identifying POIs and AOIs (Hu, et al., 2015; Long, Song, & Chen, 2021; Frias-Martinez, Soto, Hohwald, & Frias-Martinez, 2012). The approximate number of users according to the 2020 data of social media platforms with various visual content is given in the table below.

Table 3.3 Most popular social media platforms nowadays - January 2022 analysis (Source: We Are Social Agency & Hootsuite, Digital Report, 2022)

SM Platform	*Approximate user numbers*
Facebook	2.910 billion
YouTube	2.562 billion
Instagram	1.478 billion
TikTok	1 billion
Snapchat	557 million
Pinterest	444 million
Twitter	436 million
Foursquare	50 million
Flickr	100 million

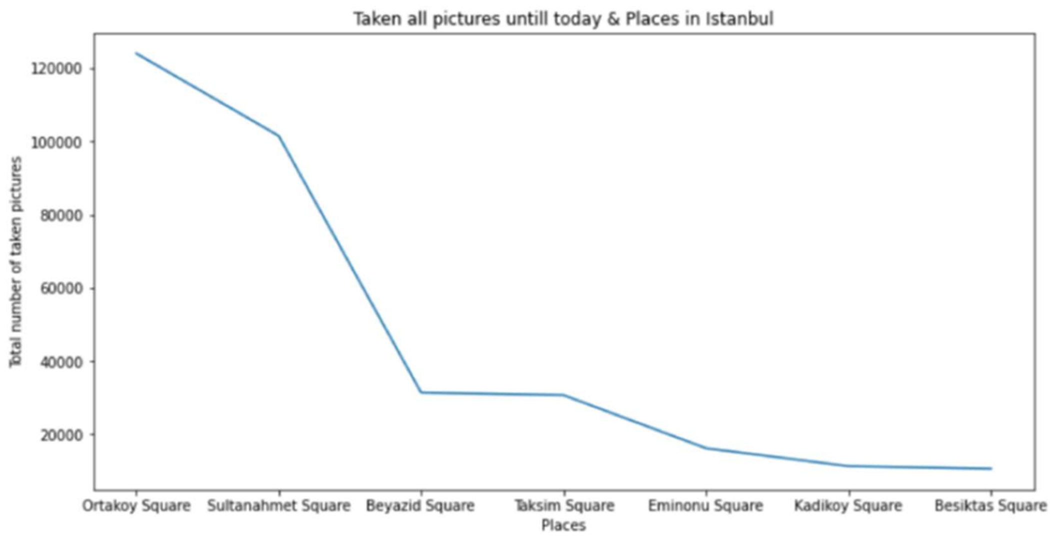


Figure 3.1. The chart shows number of total posts for each square in Istanbul until today (produced by the author)

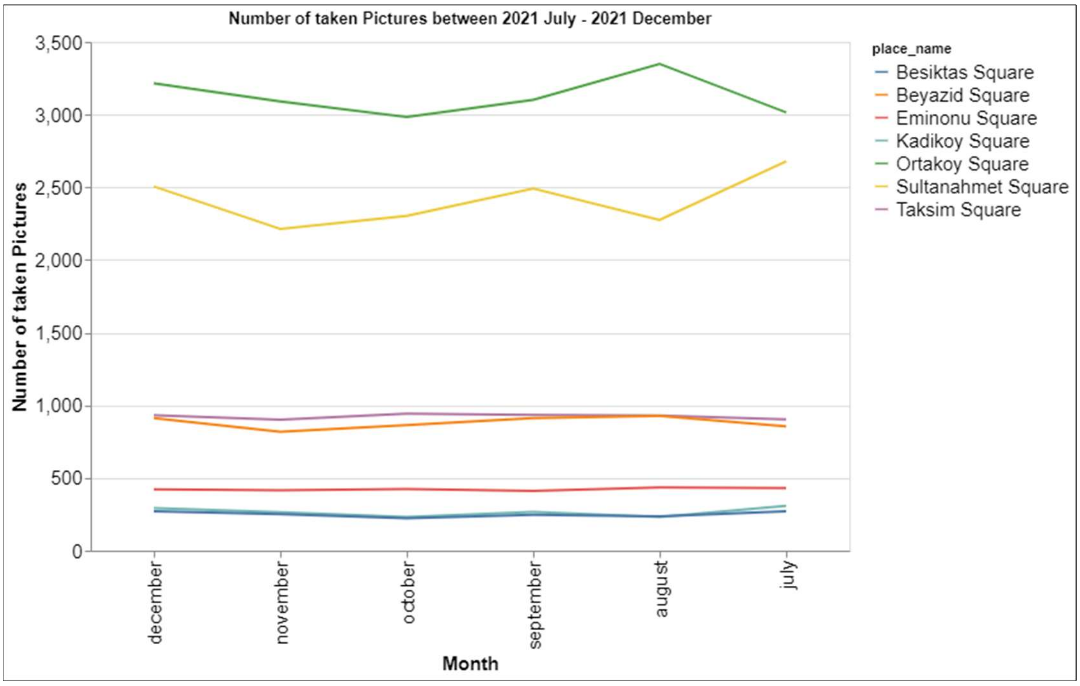


Figure 3.2. The chart shows number of total posts for each square in Istanbul for six months period (produced by the author)

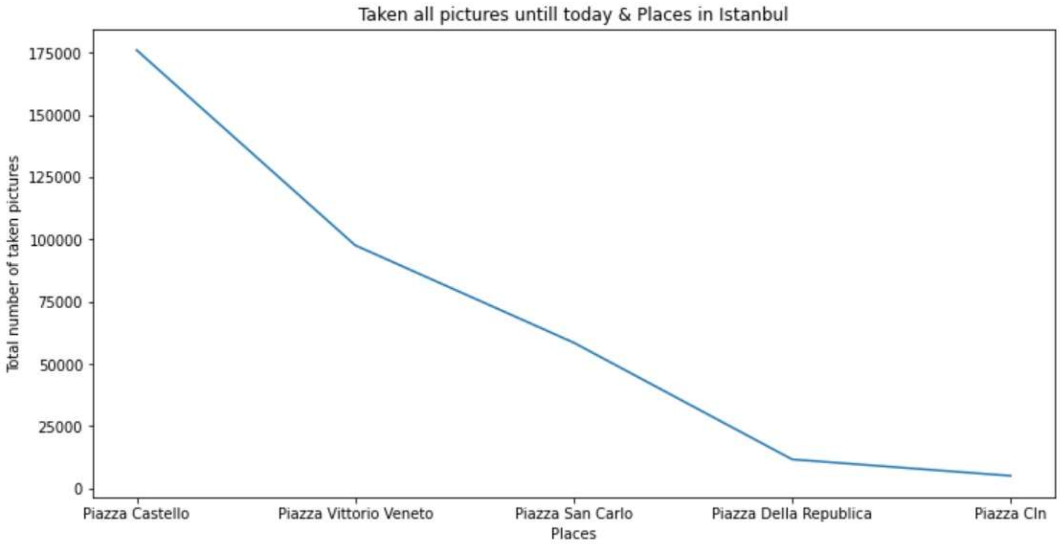


Figure 3.3. The chart shows number of total posts for each square in Turin until today (produced by the author)

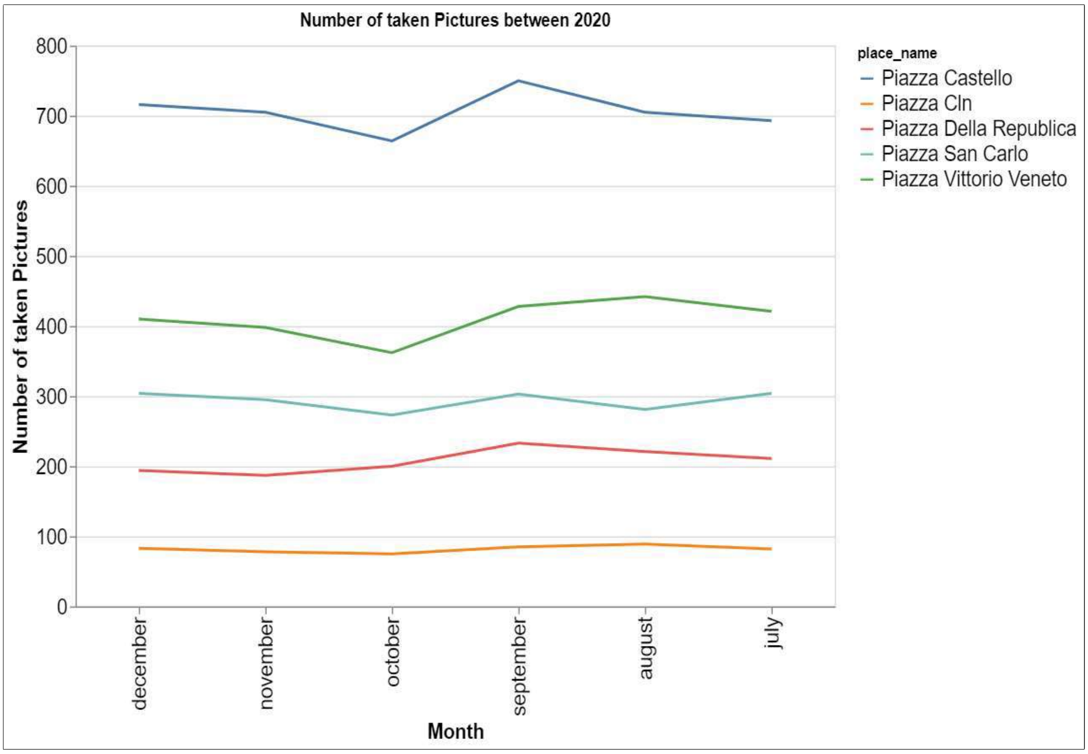


Figure 3.4. The figure shows number of total posts for each square in Turin for six months period (produced by the author)

3.3 Deciding Pair of Squares - Taksim Square- Castello Square

One of the most common areas used by residents in urban life is city squares. Castello and Taksim squares are the nodes with the most attractive ones of their cities where they are located. These are the two most meaningful squares to examine the relationships established by the nodes with the surrounding places, examine social diversity based on evidence, and observe the relations of different types of user groups with each other.

Taksim Square has been a hub of social events, common practices, and gatherings throughout its history. Moreover, it is the deepest social network point in Istanbul in terms of the relations established by social groups with both one another and the power. One of the most significant characteristics of a square is being at the center of social networks with its capacity to ensure different social clusters. Similarly, Castello square, just like Taksim square, is not only the most focal attraction point with the tourist attractions around Turin, but also the central point of its social networks.[13] In this context, two squares will be selected to examine in terms of imageability with surroundings and to discover urban knowledge with social sensing.[14] As shown in Figure 3.5 and Figure 3.6, although the landmarks in the squares are buildings designed as a result of historical discourses, they can become a part of the representation spaces in history. For this reason, events in squares are subjective spaces of lived occasions and are directly spatio-temporal. For these

[13] Fassino, G. (2020). Architecture And Urbanism As a Tourist Factor Documenting City change The city and Its Image 1928-1936. In T. M. Sala, & M. Bruzzo, I-Media-Cities: Inovative e-Environment for Research on Cities and the Media (pp. 53-61). Barcelona: Universitat de Barcelona Edicions.

[14] Pettenati G., Dansero E., Calafiore A. (2019), in Voghera A. e La Riccia L. (a cura di), Spatial Planning in the Big Data Revolution, Hershey, IGI Global, pp. 221-247.

reasons, Taksim and Castello squares were chosen for the exploratory analysis of the “designed-perceived-lived”, spatial triad of Lefebvre.

Figure 3.5. Taksim Square as Common Space

(source: https://www.publicspace.org/)

Figure 3.6. Castello Square as Common Space (source: Edoardo Melchiori’s portfolio)

This case studies are an exploratory analysis that considers the human factor of the squares rather than comparing the two squares by revealing the similarities in their social structure. These two pairs of squares, which have different urban morphology but similar social attraction points, were chosen to analyze the social networks in their close surroundings, which have an inseparable relationship with the squares.

Social media analytics provides us with time-spatial, behavioral, and predictive data. In this thesis, the social relations series of Taksim Square and Castello Square, which cannot be observed with traditional methods, will be visually understandable by reading through the spaces. In other words, social life, social diversity by overlapping each other. In other words, social life, social diversity, spatial diversity, typical users of spaces and relations will be revealed by overlaping. Furthermore, visual data is the most robust data source used to measure the legibility and perceptibility in urban spaces. As shown in the table, the popularity of Instagram in recent years and the parks, squares, and the relations in the city allow researchers to analyze visual environment. For this reason, POI data obtained by web-scraping with the Google Maps Places API. Furthermore,the places around Taksim and Castello have been analyzed in terms of the relationship between the visual perceptibility and the attractiveness variable.

3.3.1 Data Collection

Table 3.4 Chart shows Instagram Data Scraping Method for two squares (produced by the author)

Castello Square	[{"name": "Piazza Castello", "external_id": 130506907001819, "external_id_source": "facebook_places", "lat": 45.070902488051, "lng": 7.6849819832269, …
Taksim Square	[{"name": "Taksim Meydani", "external_id": 508134849371, "external_id_source": "facebook_places", "lat": 41.036986057027, "lng": 28.985396970945, …

Table 3.5 Chart shows Instagram Location ID scraping for two squares (produced by the author)

Castello	https://www.instagram.com/explore/locations/130506907001819
Taksim	https://www.instagram.com/explore/locations/508134849371236

3.3.2 Dataset

Photos of Taksim and Castello squares were scrapped from Instagram for a period of 6 months. And below, a clean dataset containing 3071 photos has been analyzed.

3.3.3 Categorization of Places - Social Cluster Detection

Categorization of the POI data obtained from Foursquare can be seen in Table 3.4. These categories were adjusted according to the variety of places in Castello and

Taksim and Castello was classified by the labels such as food, cultural, performance, shop, public, religion, nightlife, education, and travel, and formatted for Python data analysis as in Table 3.6.

Table 3.6 Foursqure venue classification (source: Foursquare)

Group	*Category Venues*
Arts & Entertainment	Art Gallery, Historic Site, Museum, Movie Theater, Concert Hall, Music Venue, Performing Arts Venue, Stadium
College	Academic Building, University
Nightlife Spot	Bar, Brewery, Lounge, Night Club, Cocktail Bar
Professional & Other Services	City Hall, Library, School, Post Office, Medical Center
Outdoors & Recreation	Plaza, Gym, Sports Club
Residence	Residential Building, Home

Table 3.6 (continued)

Food	Coffee Shop, Restaurant, Dessert Shop
Shops & Service	Arts & Crafts Store, Antique Shop, Bookstore, Clothing Store, Cosmetics Shop, Grocery, Shopping Mall, Travel Agency
Travel & Transport	Airport, Bus Station, Hotel, Metro Station, Train Station
Event	Christmas Market, Festival, Street Fair, Conference, Sport Event

Table 3.7 Custom categories of data chart (produced by the author)

Group	*Category Venues*
Food	Coffee Shop, Restaurant, Dessert Shop
Cultural	Museum, Historic Site, Art Gallery, Cinema
Nightlife	Bar, Brewery, Lounge, Night Club, Cocktail Bar
Education	Library, School, Academic Building, University
Travel	Airport, Bus Station, Hotel, Metro Station, Train Station
Public	Plaza, Monument, Park
Religion	Church, Mosque, Monastery, Synagogue, Temple
Performance	Theater, Concert Hall, Music Venue, Performing Arts Venue

Table 3.7 (continued)

Sport	Stadium, Gym, Sports Club
Shop	Arts & Crafts Store, Antique Shop, Bookstore, Clothing Store, Cosmetics Shop, Grocery, Shopping Mall, Travel Agency

Table 3.8 Social Cluster detection table (produced by the author)

Clustering	*Attribute*
Community 1	food
Community 2	cultural
Community 3	travel
Community 4	nightlife
Community 5	public
Community 6	performance
Community 7	education
Community 8	religion
Community 9	shop
Community 10	sport

The number of posts posted from the three most popular POI venues in Taksim and Castello Squares has been analyzed and shown in the figures below (Figure 3.7 and Figure 3.8). Moreover, according to the labels, it was distributed on the map obtained from OSM by using GeoPandas (Figure 3.9, 3.10, 3.11, 3.12).

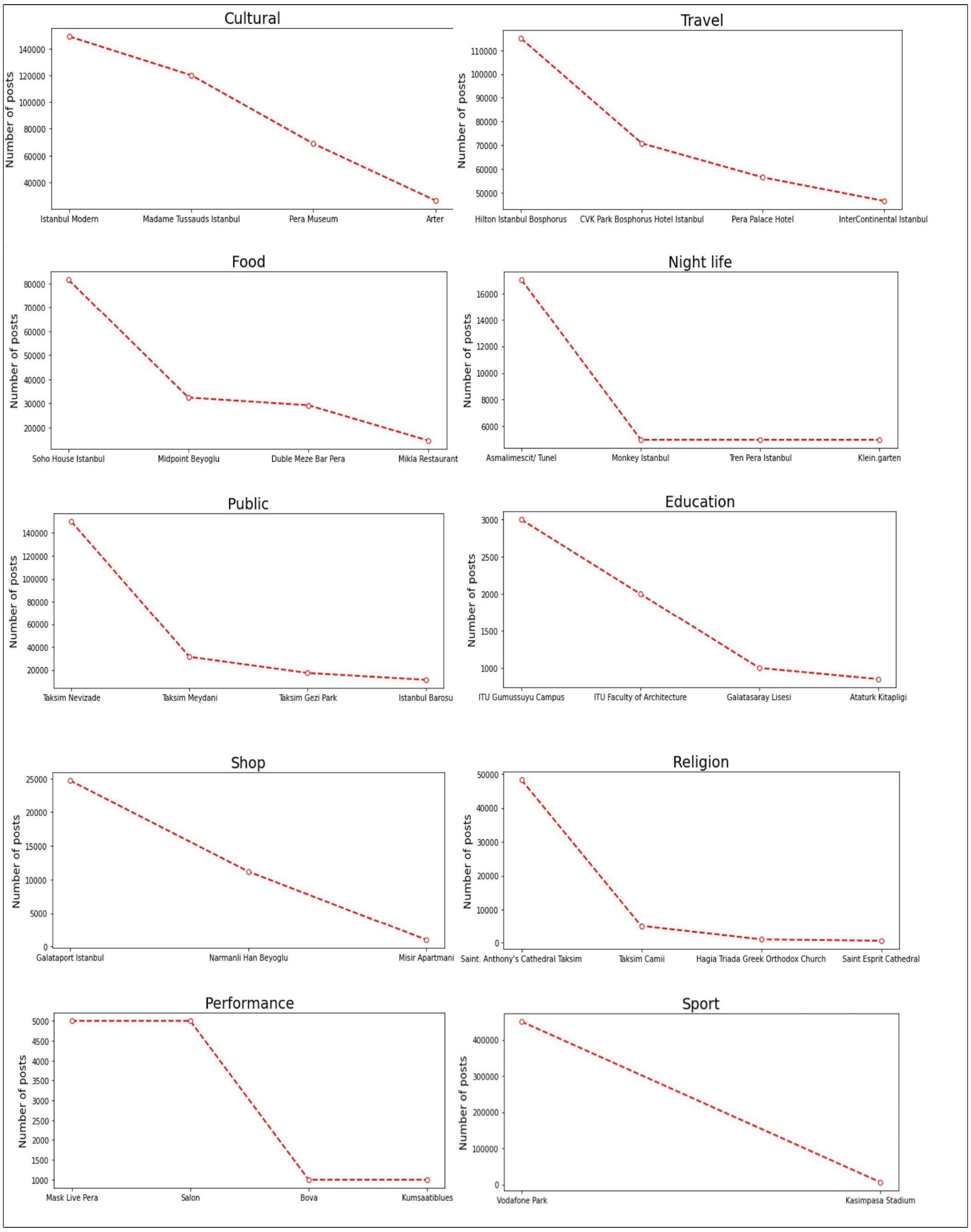


Figure 3.7. Most popular five places for each category in Taksim Square (produced by the author)

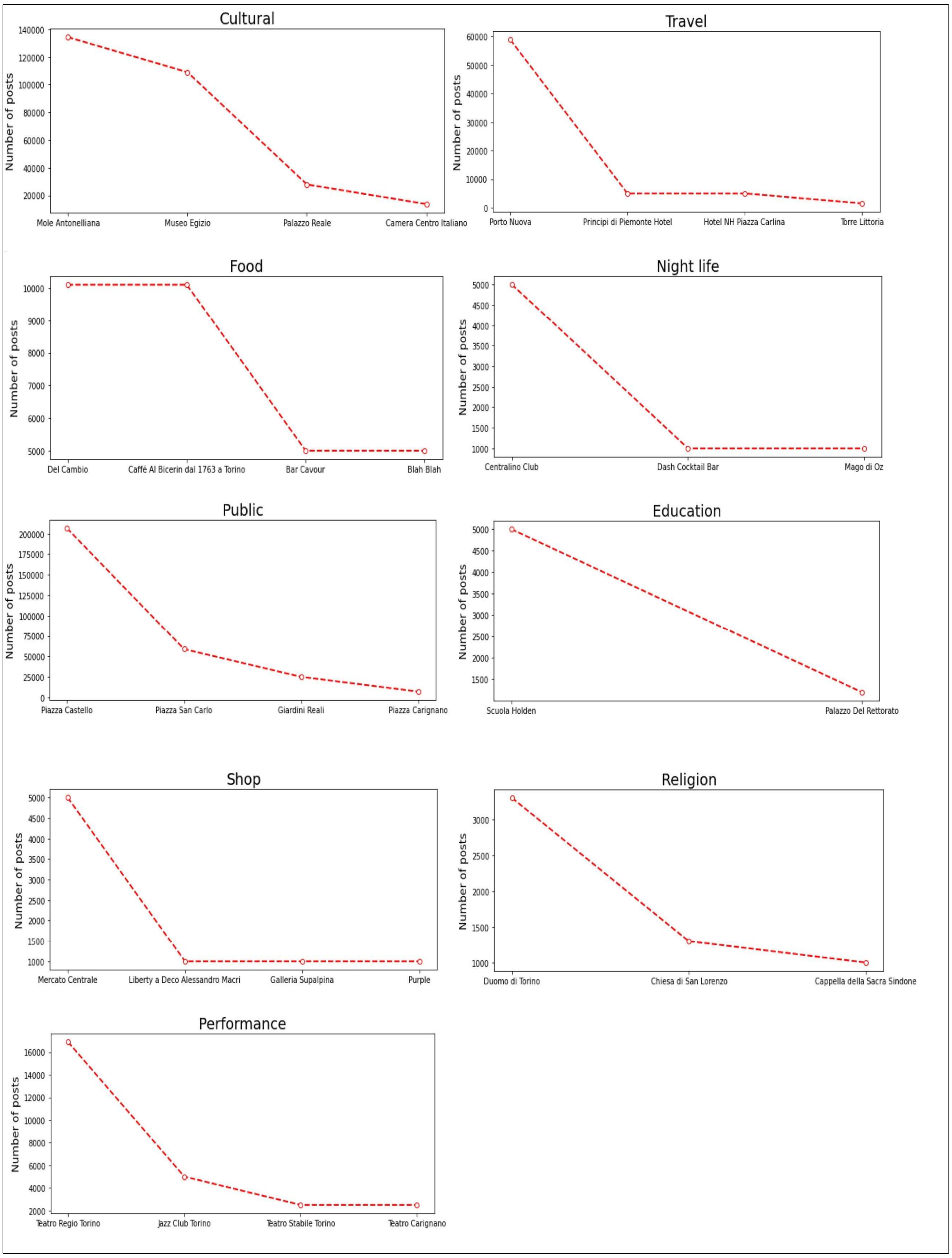


Figure 3.8. Most popular five places for each category in Castello Square (produced by the author)

The scatterplots below make it possible to see the POIs distributed by category (Figure 3.9) and the distribution of POI venues in the Taksim district (Figure 3.10).

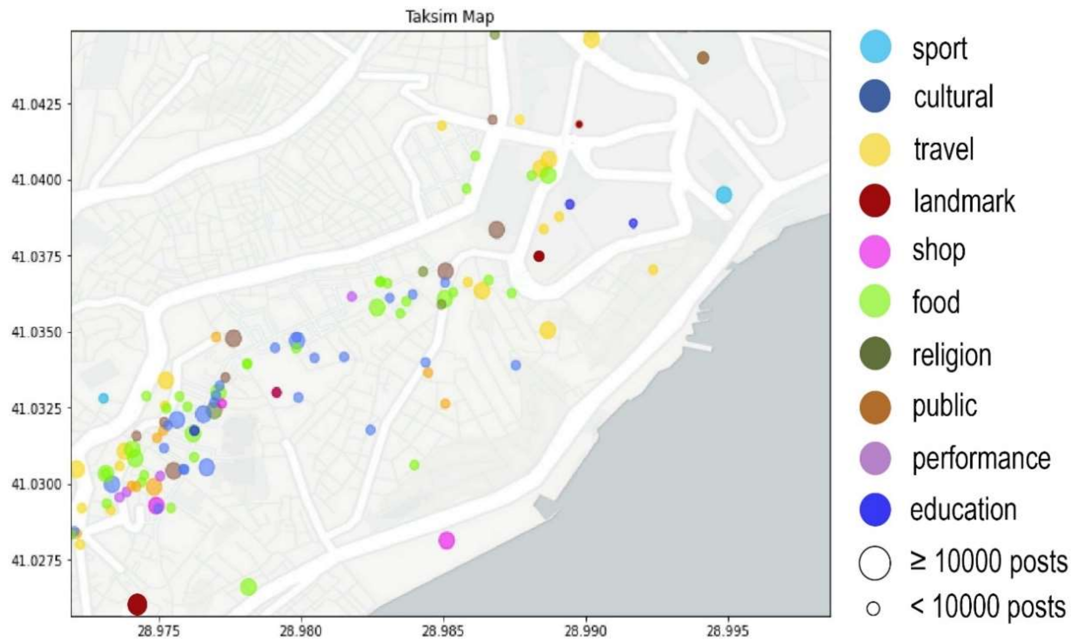


Figure 3.9. Scatterplot of Taksim Square (colors show POI categories, produced by the author)

Figure.3.10. Scatterplot of Taksim Square (dots show POIs, produced by the author)

The scatterplots below make it possible to see the POIs distributed by category (Figure 3.11) and the distribution of POI venues in the Castello district. (Figure 3.12).

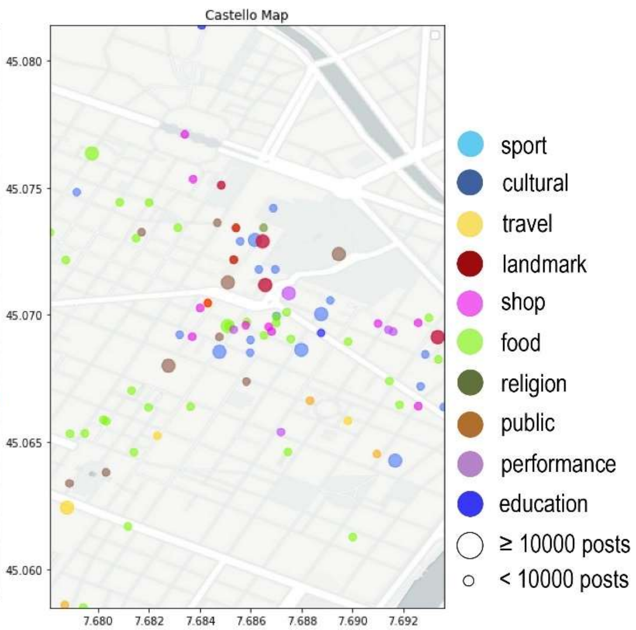


Figure 3.11. Scatterplot of Castello Square (dots show POIs, produced by the author)

Figure 3.12. Scatterplot of Castello Square (colors show POI categories, produced by the author)

As shown in Figure 3.14, with reviewing the social-media photographs, the users of the cultural places in Castello are mostly determined as tourists, city explorers, and large group travelers. It is possible to classify these user groups as belonging to a "cultural community" class. According to Lynch, landmarks are iconic structures that give people a place and direction in the city, wayfinding, stand out with their distinctive features compared to other buildings in the city, and can also be the city's symbol. In this context, Mole does not only appear as an external and singular object but also shows an attractive structure in terms of the number of photographs taken. Likewise, Palazzo Reale is a building perceived externally. Furthermore, it is also possible to define Palazzo Reale as an area of interest (AOI) since it provides scenic perspectives to Mole, an important landmark of the city (Hu, et al., 2015).

Similar to Palazzo Reale, Giardini Reale is also an area of interest because of its perspectives to the Mole. Continuing Figures 3.13, 3.14, 3.15 and 3.16, 3.17 ,3.18, 3.19, 3.20 show the photographs taken from the three most attractive and popular social clusters labeled as food, travel, and performance in Castello. In Figure 3.13, the photographs taken from popular dining venues show the social cluster of food where local people come together. Hence, it can be said that the users of popular places tagged travel, who are associated with the travel in Figure 3.17, are also local and tourists. Mercato Centrale, one of the places in the shopping cluster, hosts different events of different community groups, including mixed social groups. (Figure 3.15). Duomo and Chiesa on the "religion" label, Torre Littoria, Palazzo Reale, and Palazzo Madama on the Shop label are among the city's other landmarks in terms of its external relationship with the environmental image.

Figure 3.13. “Food” places in relation of Castello Square (sorted by popularity)

Figure 3.14. “Cultural” places in relation of Castello Square (sorted by popularity)

Figure 3.15. “Shop” places in relation of Castello Square (sorted by popularity)

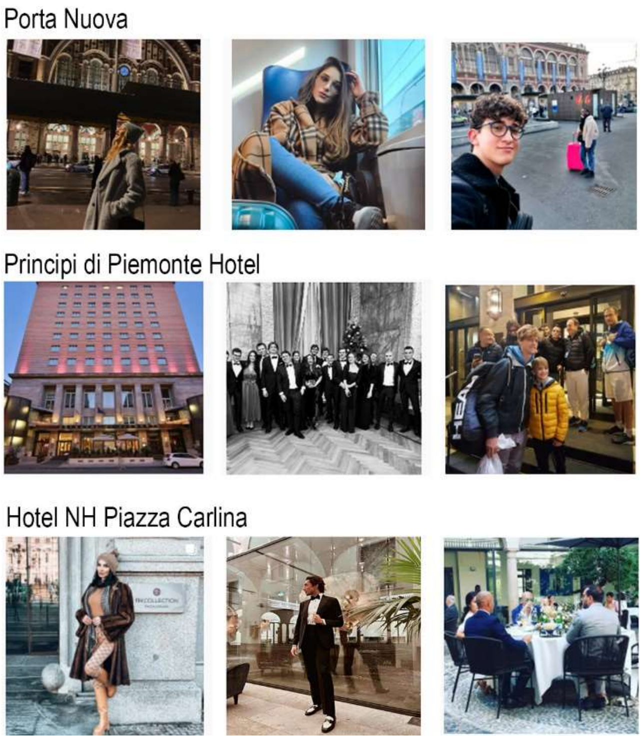


Figure 3.16. “Travel” places in relation of Castello Square (sorted by popularity)

Figure 3.17. “Performance” places in relation of Castello Square (sorted by popularity)

Figure 3.18. “Religion” places in relation of Castello Square (sorted by popularity)

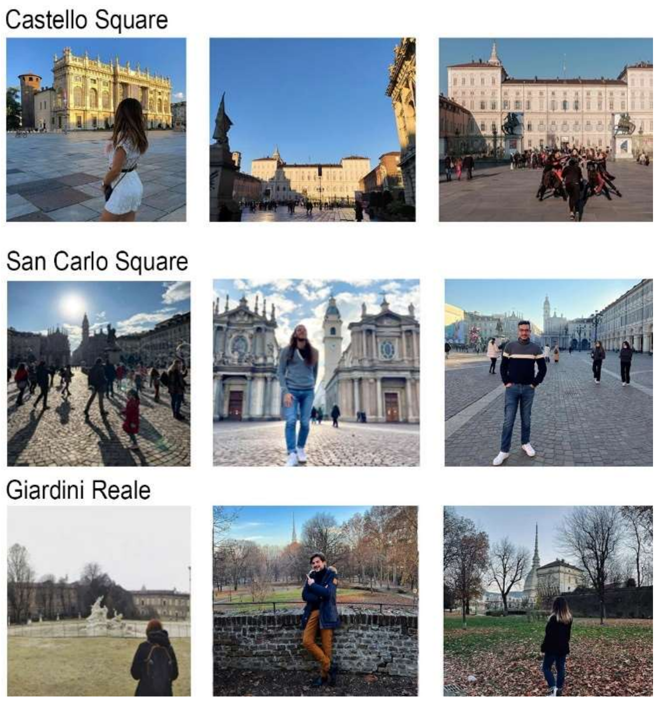


Figure 3.19. “Public” places in relation of Castello Square (sorted by popularity)

Figure 3.20. “Education” places in relation of Castello Square (sorted by popularity)

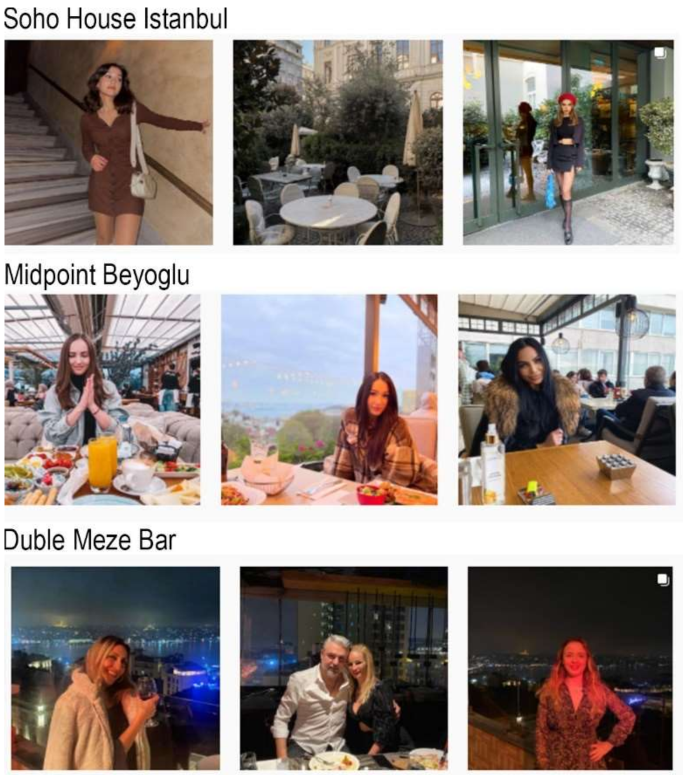


Figure 3.21. “Food” places in relation of Taksim Square (sorted by popularity)

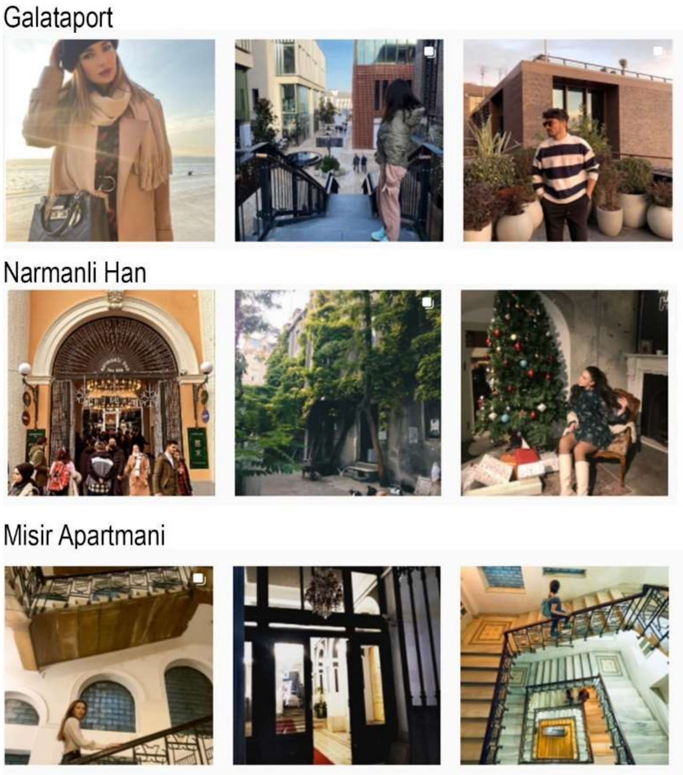


Figure 3.22. “Shop” places in relation of Taksim Square (sorted by popularity)

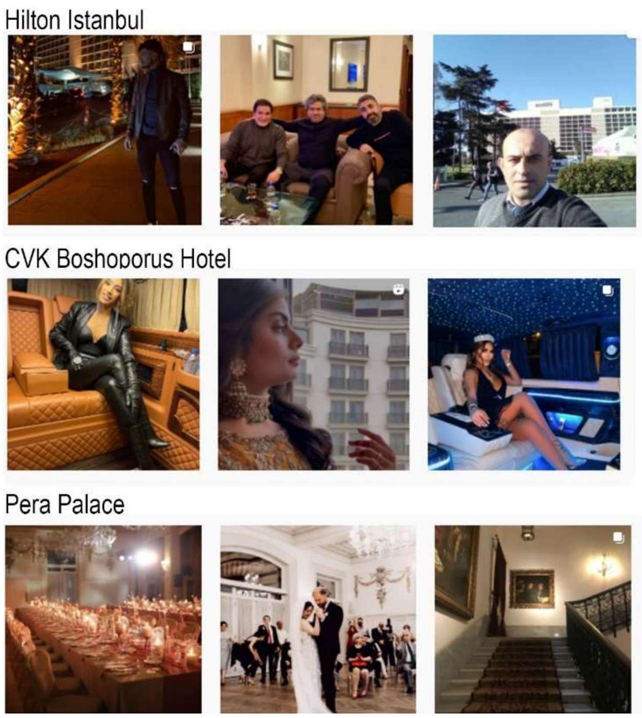


Figure 3.23. “Travel” places in relation of Taksim Square (sorted by popularity)

Figure 3.24. “Performance” places in relation of Taksim Square (sorted by popularity)

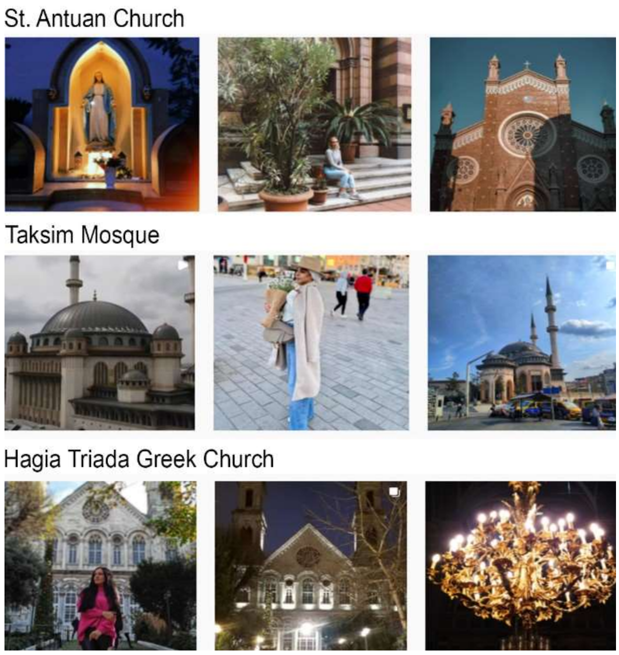


Figure 3.25. “Religion” places in relation of Taksim Square (sorted by popularity)

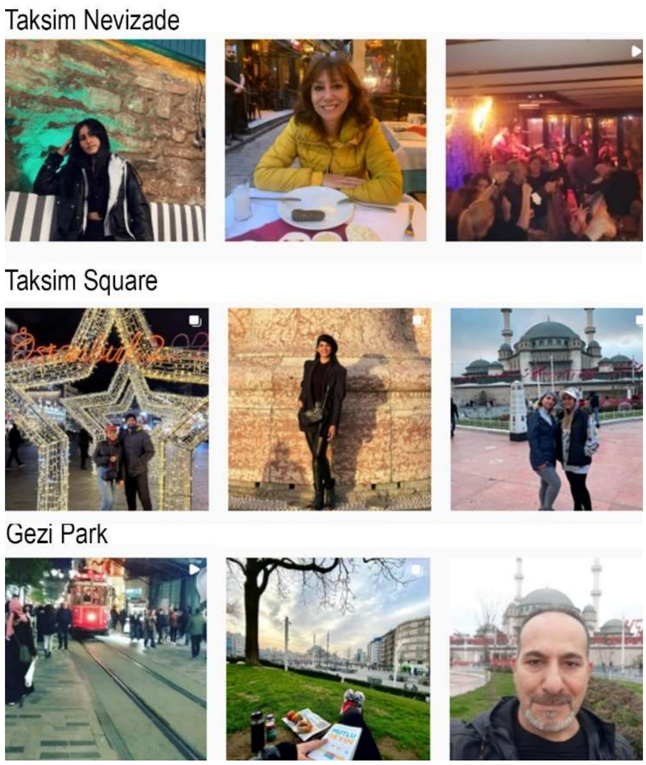


Figure 3.26. “Public” places in relation of Taksim Square (sorted by popularity)

Figure 3.27. “Education” places in relation of Taksim Square (sorted by popularity)

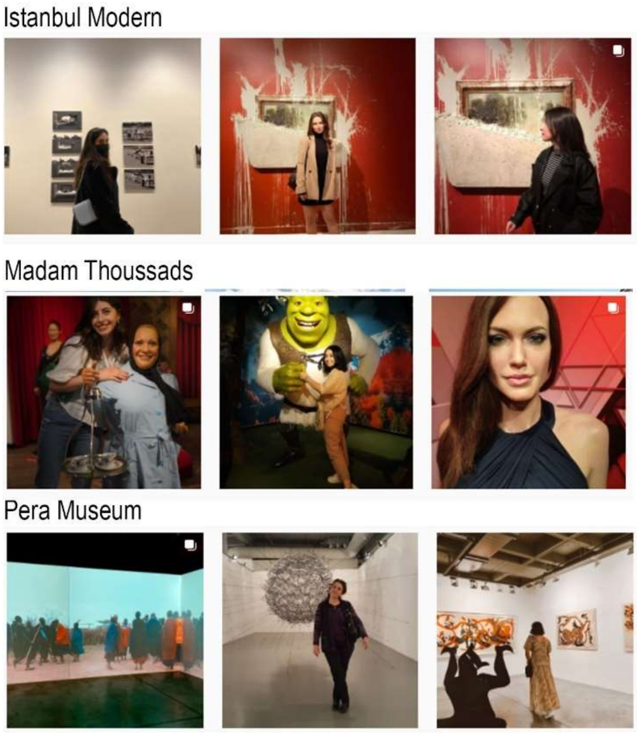


Figure 3.28. “Cultural” places in relation of Taksim Square (sorted by popularity)

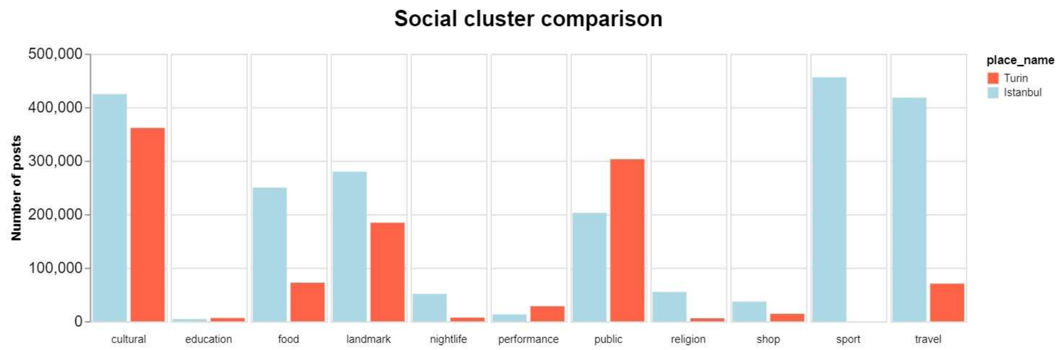


Figure 3.29. Social Clusters in Castello and Taksim Square (produced by the author)

As shown in the Table, the all cluster is more dense in Istanbul except for Inter the number of photos taken in Turin in the public category, public label of the social cluster is higher than in Istanbul. (Figure, 3.29).

It can be seen on the map in Figure 4 that the most important paths in Taksim Square are Cumhuriyet Avenue and Istiklal Avenue. In Castello Square, these paths are Via Roma, which is the High street, and Via Giuseppe Luigi Lagrange, where social activities, food venues, and social interaction are practied more intense that other streets.. In additon, Via Garibaldi, which has a continuous series of places along the street, which is a touristic street (Figure 3.30). The paths around Castello and Taksim Square, which turn into nodes and channels into the squares, can be seen in the figures below (Figure 3.30, 3.32).

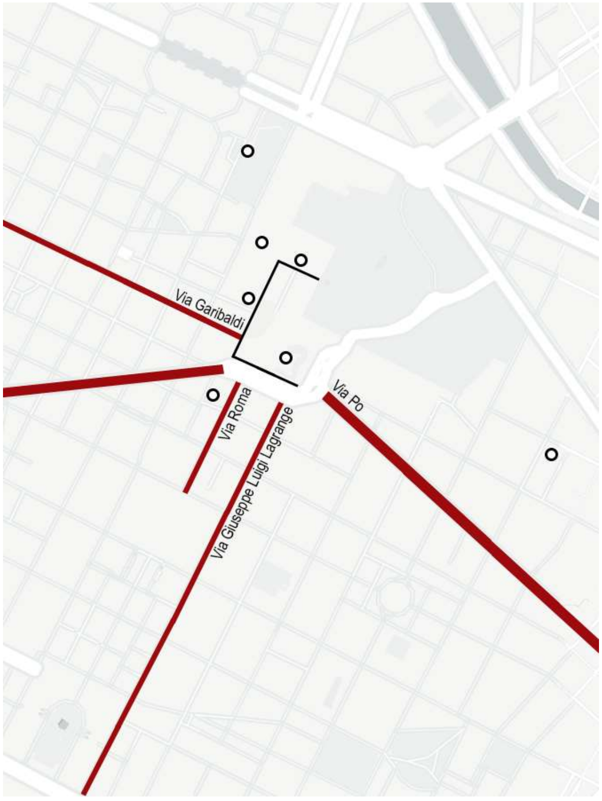


Figure 3.30. Paths-Landmarks-Node in Castello Square (produced by the author)

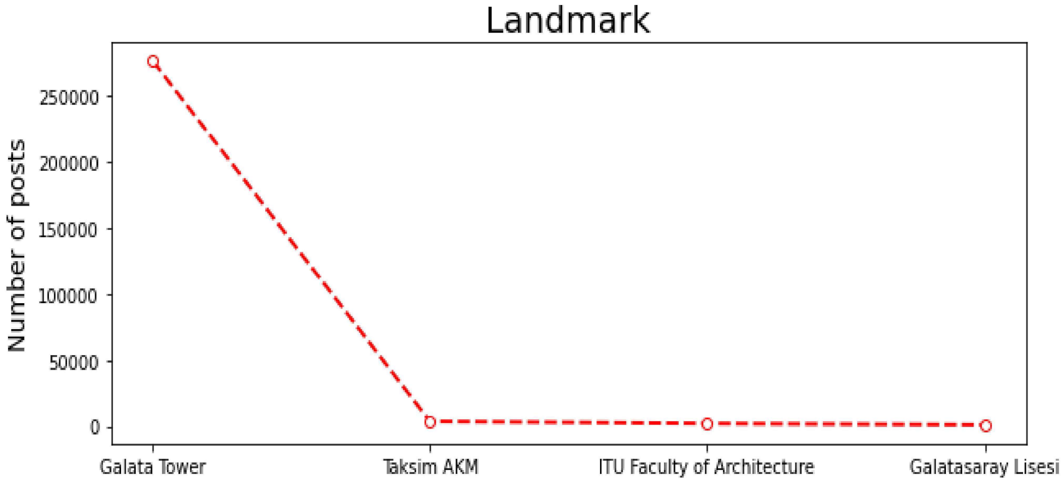


Figure 3.31. Landmark surrounding Taksim Square (produced by the author)

Figure 3.32. Paths-Landmarks-Node in Taksim Square (produced by the author)

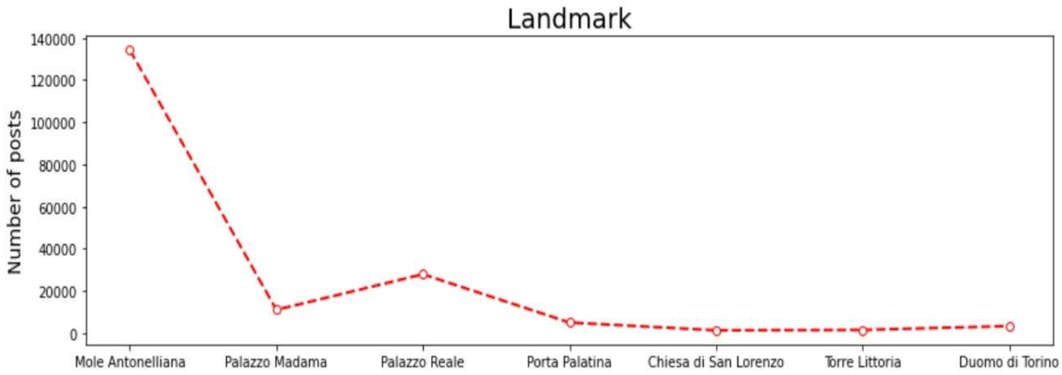


Figure 3.33. Landmark surrounding Castello Square (produced by the author)

3.3.4 Social Network Analysis

Latour[15] addresses that topological analysis[16] allows us to reveal hidden relations actor and their network so that one can understand between spatial relations and human. Social network consists of two components: actors that constitute the network and relationships and interactions between these actors. In social network analysis, actors refer to "nodes", and relations refer to "edges." Nodes can hold the metadata on the graph. The size of the nodes depends on the number of connexions, which is called the value of degree centrality. Centrality is an important measurement for determining the position of an actor in the network .It is about how close a node is relative to the network as a whole. There are some variations to visualize the

[15] Bruno Latour's term "actor" refers to relationship between human and their social network. See:
- Latour, B., 2005. Reassembling the Social: An Introduction to Actor-Network-Theory. ACLS Humanities E-Book. Oxford: Oxford University Press.

[16] Foucault provides a term called topology as a 'analysis tool to examine systems of correlations and transformation'. See:
- Foucault, M., .1997. "What is Critique?" in The Politics of Truth. Ed. Lotringer, Sylvère. Trans. Hochroth, L. and Porter, C. Semiotext(e), Los Angeles.
- Foucault, M., .2008. The Birth of Biopolitics: Lectures at the Collège de France, 1978–1979. New York: Palgrave Macmillan.

networks according to a type of centrality: such as degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality.
To detect groups in a network, clustering is applied. In addition, clustering coefficient is a measurement that compares the number of connections to other nodes compared to the potential number of connections to the other nodes in a group.

While exploring pair of connections between source and target node, weightness of edges has been defined from 1 to 3 as strongness of the connection which is a measurement of similarity of places and has a potential to make a connection. The edges among nodes has been defined for both Turin and Istanbul, and lists with details of these edges can be found in Appendix D, E, F, and G.

The social network analysis with Gephi software, allows us to see social clusters and interpret the data in different way. Thus, the "city image" can manifest as an important narrative within this classification and community detection. And this social clusters are composed of people with shared interests and places as "community" and connects with each other with sense of belonging-in-place in a neighbourly city (Roe & McCay, 2021).

Hence, considering the historicity of the common spaces mentioned in Chapter 1, social media subjects play a role as transformative actors in the spaces designed in city squares. Therefore, the types of people using the space are also the actors of this social network.

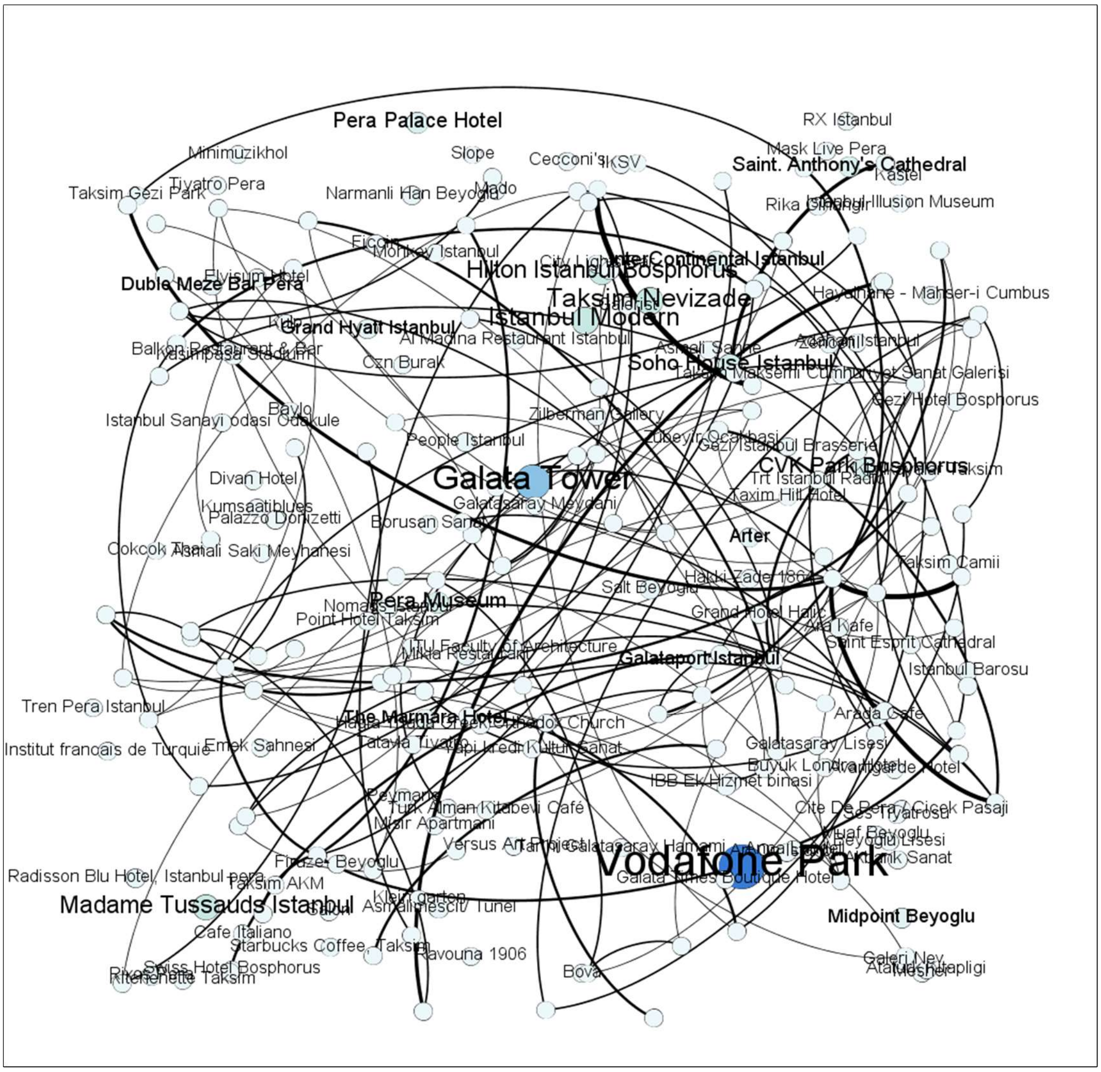


Figure 3.34. Taksim Square spatial relations (produced by the author on Gephi, Random Layout)

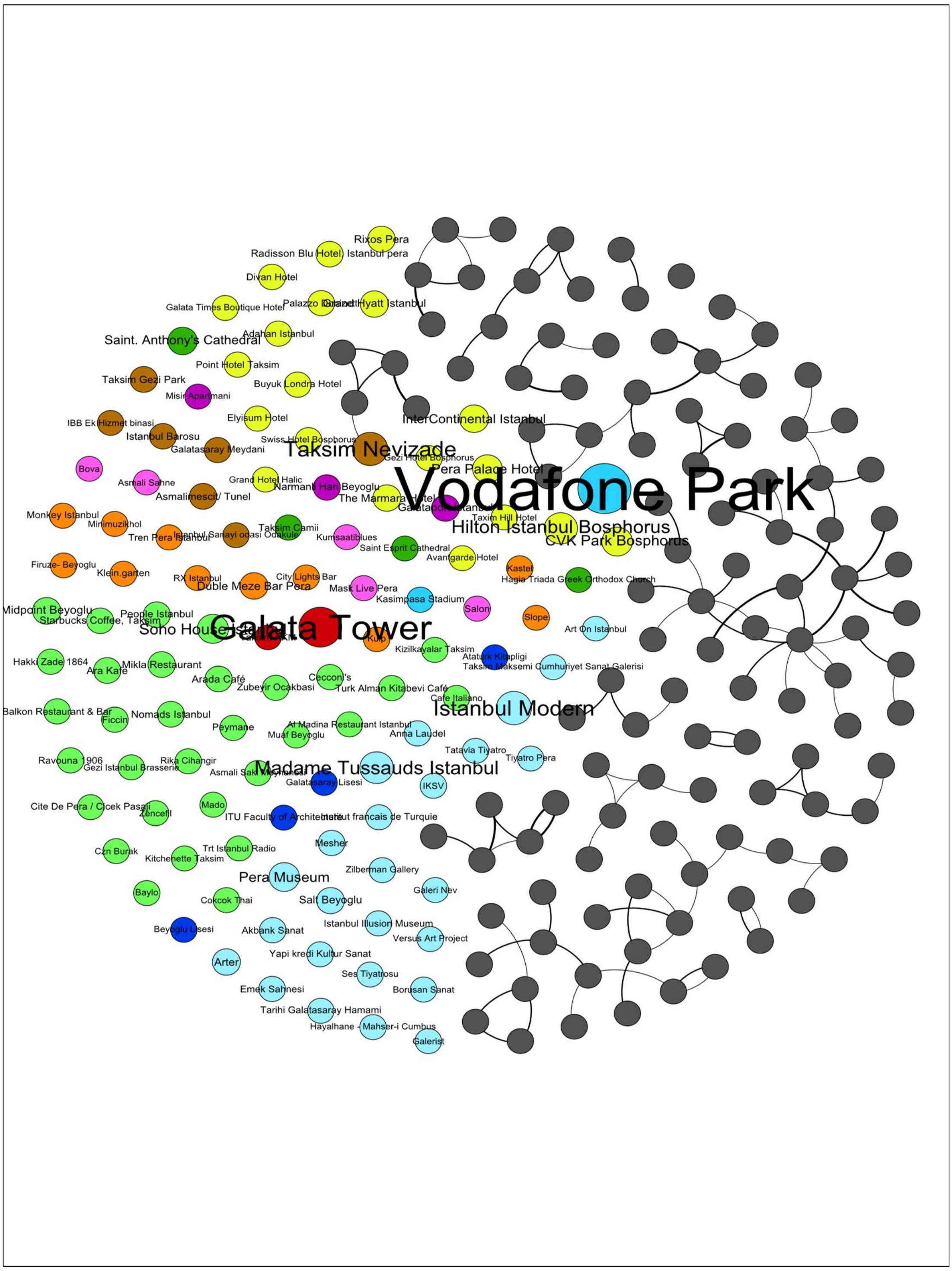


Figure 3.35. Taksim Square spatial relations (produced by the author on Gephi, Circular Layout)

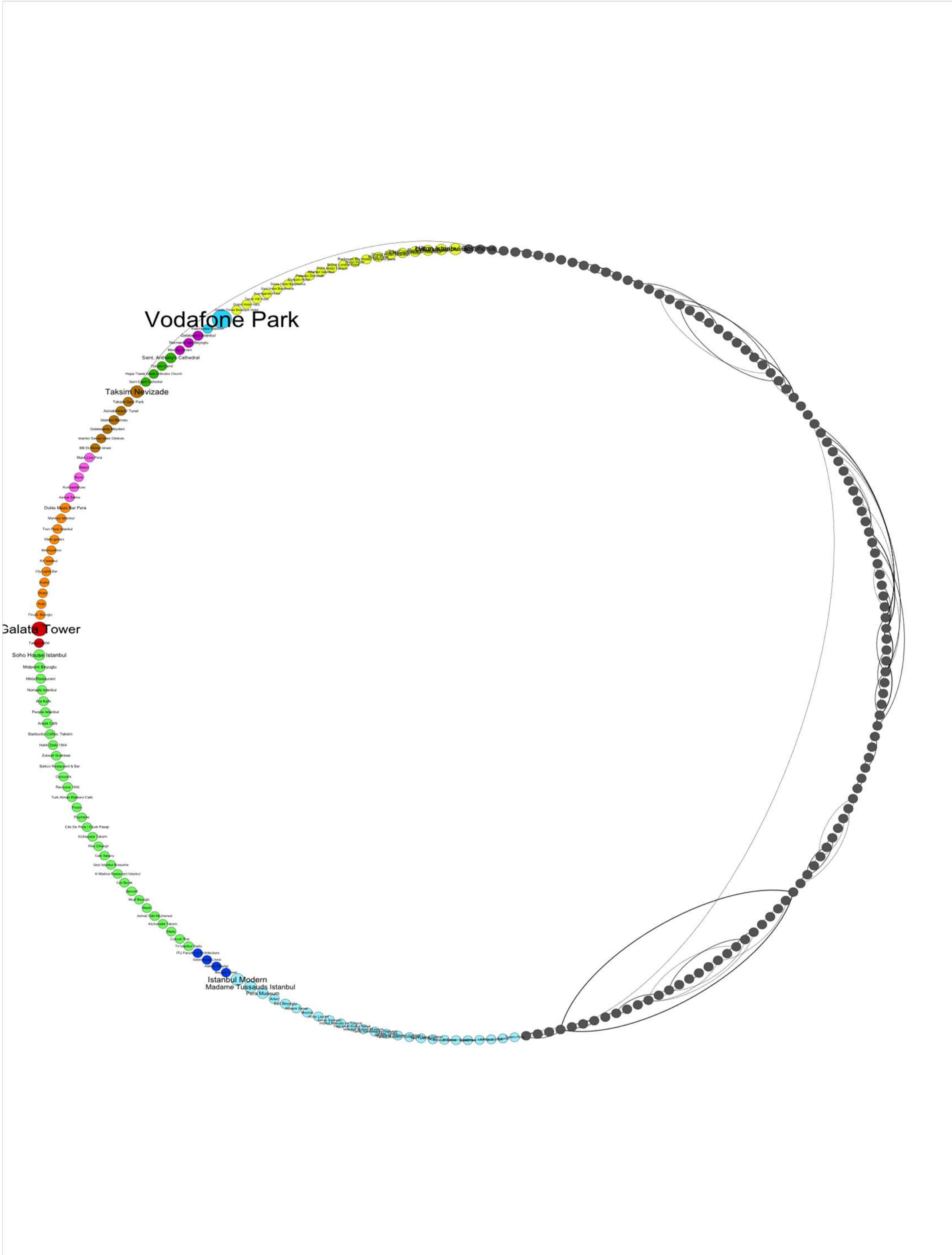


Figure 3.36. Taksim Square Circular Network (produced by the author on Gephi, Clockwise Layout)

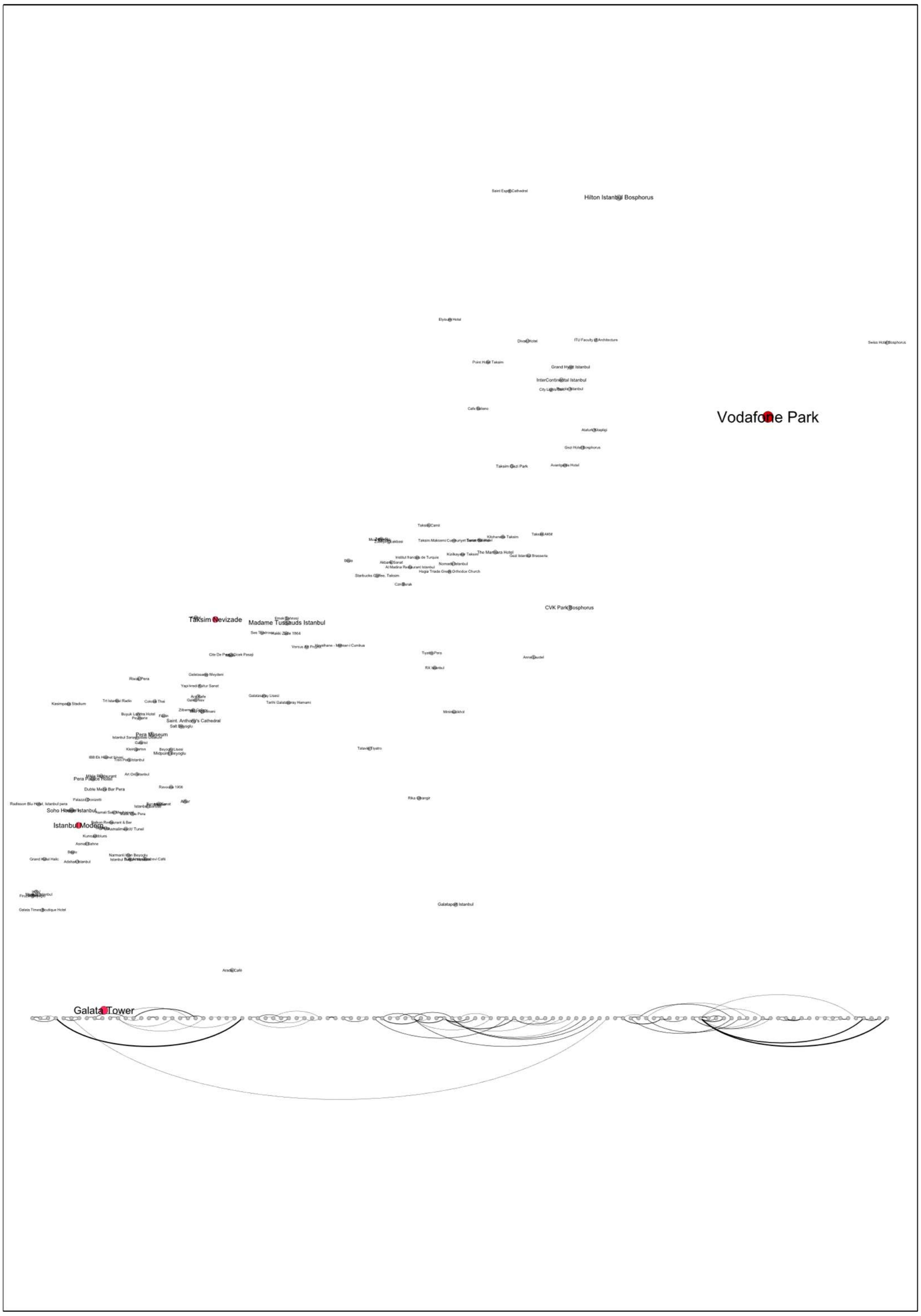


Figure 3.37. Taksim Square distances between places according to coordinates (produced by the author on Gephi, Geo Layout)

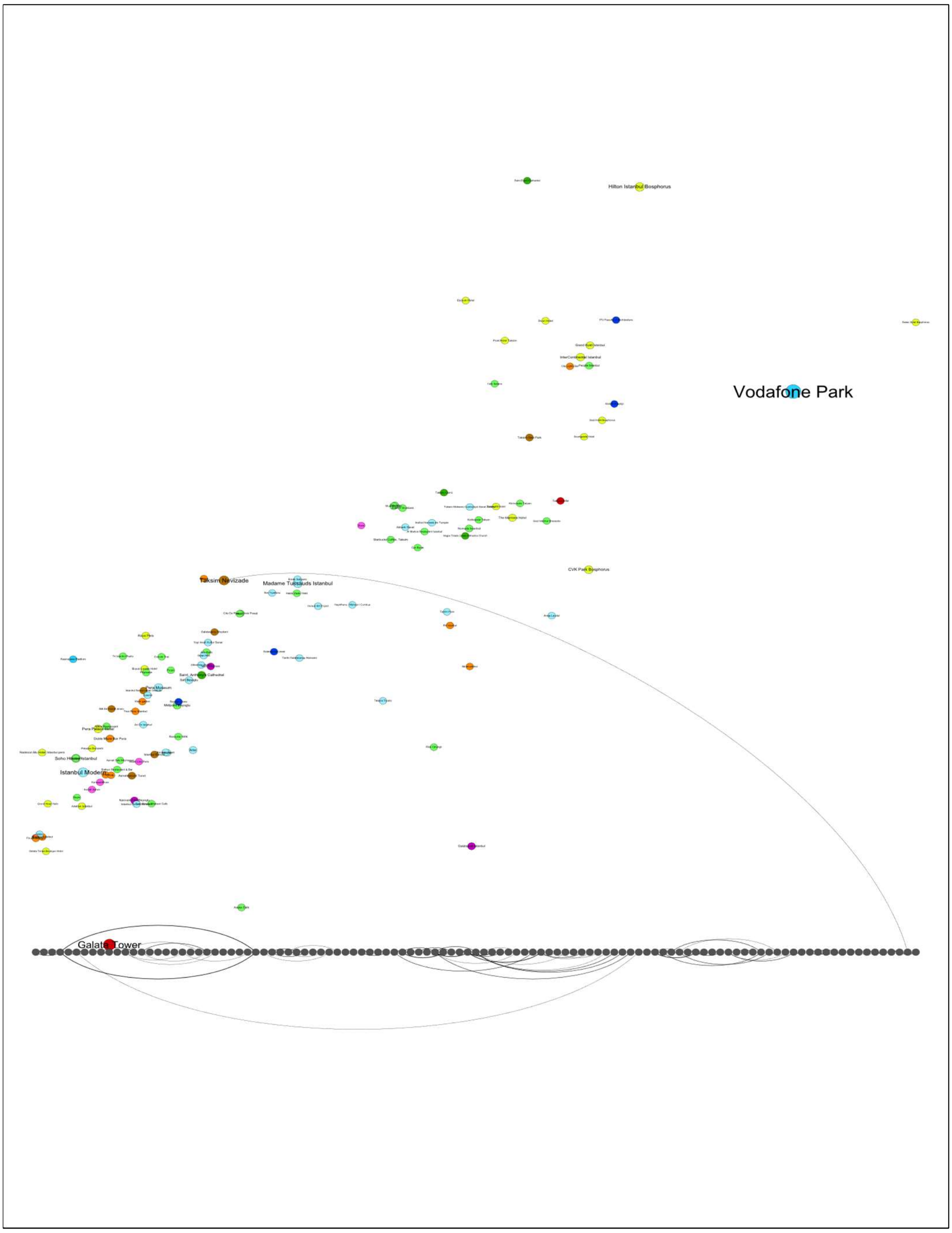


Figure 3.38. Taksim Square most popular places shown with red dots (produced by the author on Gephi, Geo Layout)

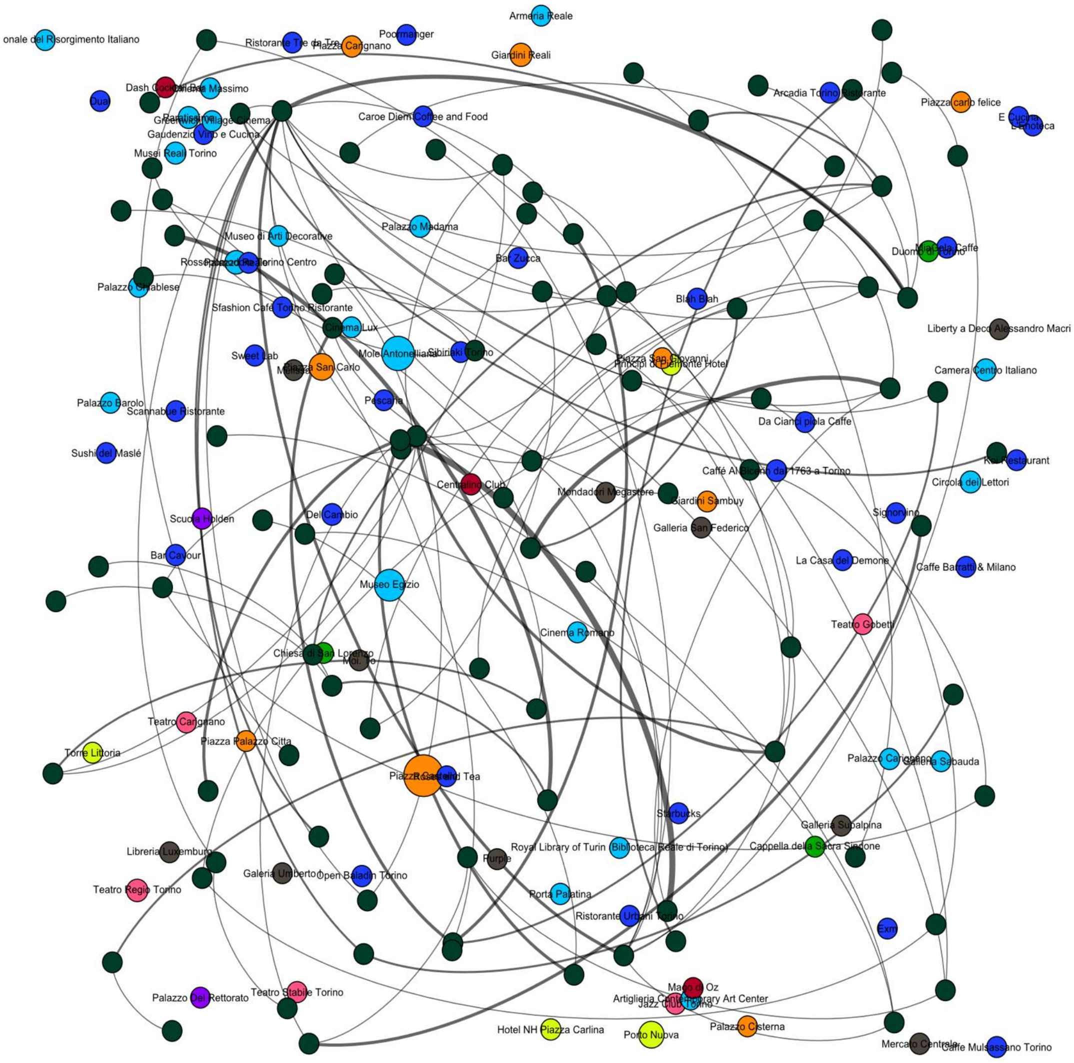


Figure 3.39. Castello Square spatial relations (node sizes show popularity rates of places, produced by the author on Gephi)

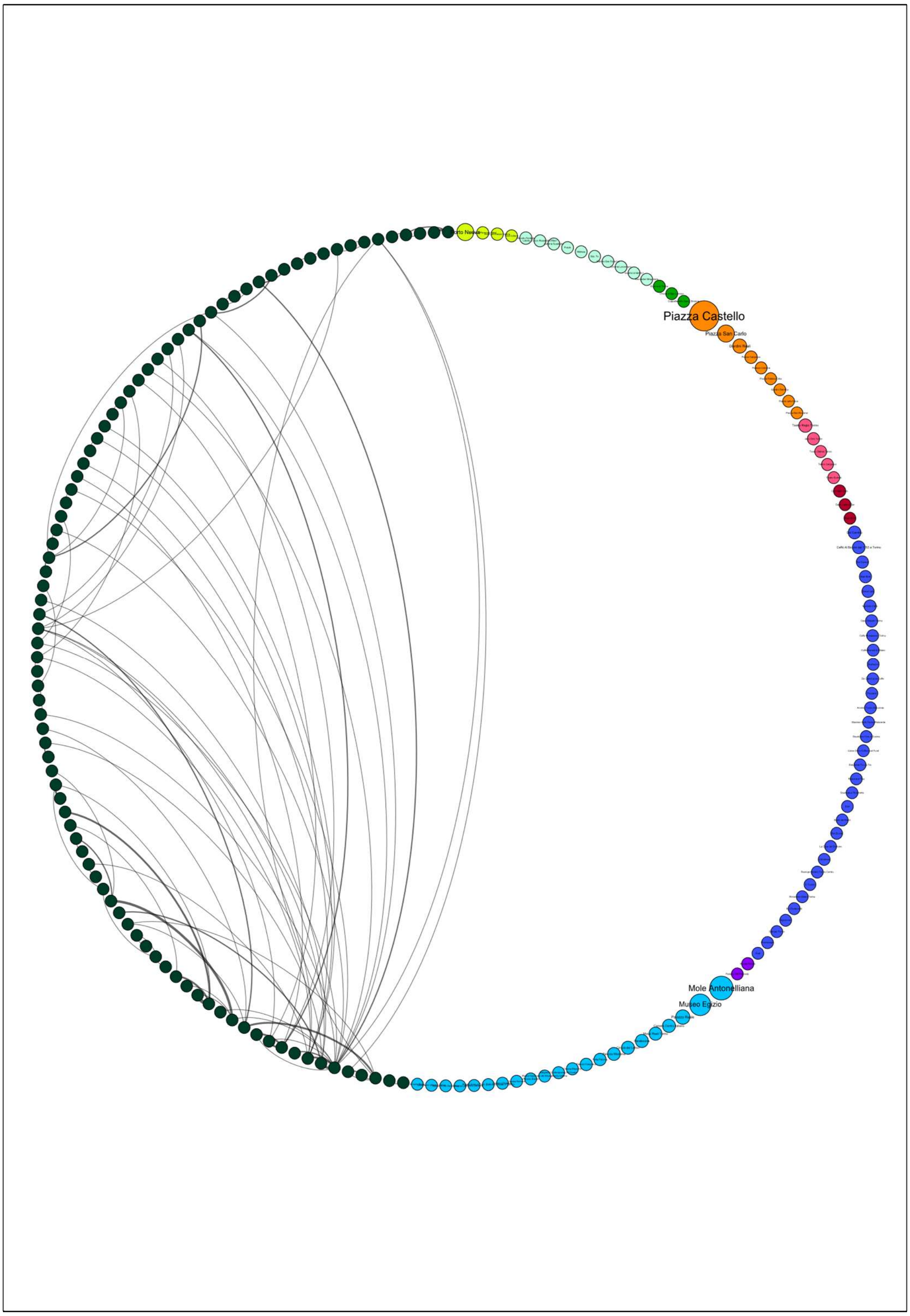


Figure 3.40. Castello Square spatial relations sorted by attractiveness sizes and functions (produced by the author on Gephi, Circular Layout)

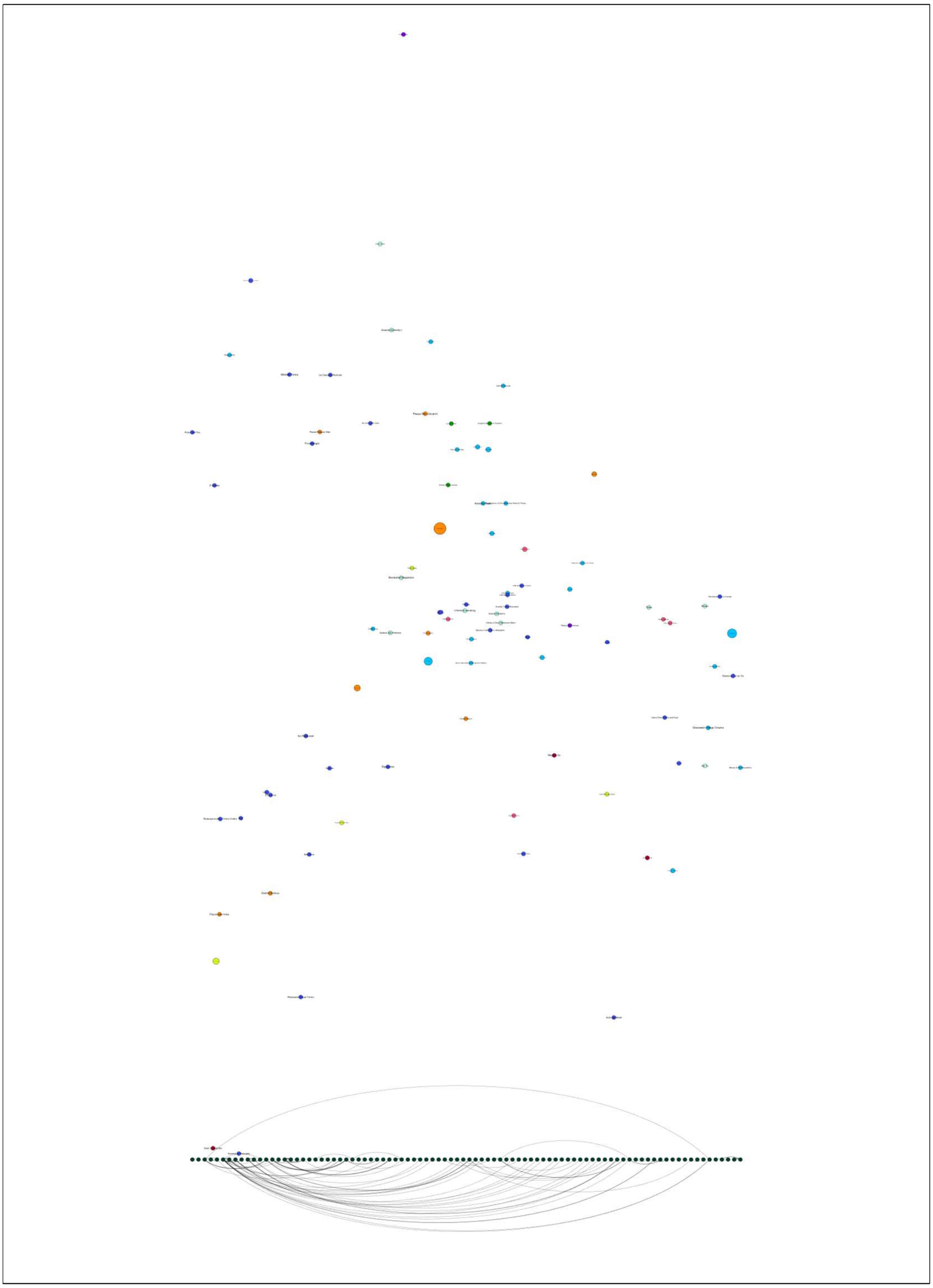


Figure 3.41. Castello Square according to coordinates (produced by the author on Gephi, Geo Layout)

3.4 Visual Model of Squares

Architectural style models are also attractive to build an environment archive by identifying semantic features of buildings (Date & Allweil, 2021). Likewise, this research may be a potential to create an visual model of squares with uncovering city's imageable features.

3.4.1 Data Collection

In recent years, most cityscape images in urban perception studies was collected by the GSV (Salesses, Schechtner, & Hidalgo, 2013; Yao, et al., 2021; Nikhil, Philipoom, Raskar, & Hidalgo, 2014; Dubey, Naik, Parikh, Raskar, & Hidalgo, 2016; Hollander, Nikolaishvili, Adu-Bredu, Situ, & Bista, 2021), in addition to measure spatial distributions (Li, 2021) with implementation of deep learning.

Regarding spatial analysis , Flickr photos has been used to mesure urban environments (Donahuea, et al., 2018; Richards & Tunçer, 2018; Zhang, Chen, & Li, 2019). There are other possible ways and social media platforms like Pinterest to collect visual data from with similar methods and analyze user profiles together with textual data. (You, Bhatia, & Luo, 2016).

For this visual model, primary dataset for this visual model is the Instagram dataset. Secondly, a dataset of 423 photos was obtained from Mapillary. The Mapillary API Python documentation allows visual datasets for academic studies. Like the GSV, Mapillary includes street-level imagery and photos from panoramic viewpoints. And the platforms allows to OSM users can contribute to Mapillary maps. After using Mapillary Python documentation, more comprehensive dataset was created by adding these photos to the data taken from Instagram.

3.4.2 Dataset

The custom dataset was collected manually under two classes in the folders Istanbul and Torino. The photos used in the training process and the photos used in the testing process created a custom dataset. (Fig, 3.42, 3.43).

```
data/
    train/
        torino/
            torino1.jpg
            torino2.jpg
            .
            .
            .
        istanbul/
            istanbul1.jpg
            istanbul2.jpg
              .
              .
              .
              .
    test/
            torino1.jpg
            torino2.jpg
            .
            .
            .
            istanbul1.jpg
            istanbul2.jpg
              .
              .
```

Figure 3.42. Custom dataset structure (produced by the author)

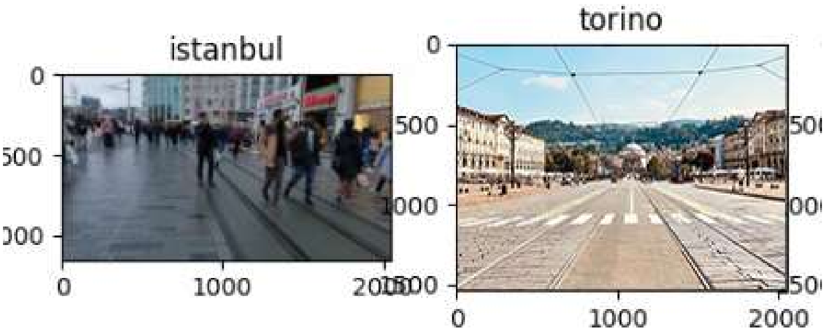


Figure 3.43. Training preview (produced by the author)

3.4.3 Extracting Proportions via Image Segmentations

Images are segmented to obtain a simpler representation that is easier and faster to analyze the image. As basic definition, segmentation methods subdivides the image into segments, many algorithms partition the image. The key elements in segmentation methods are proximity and similarity. In this task SLIC method for segmentation was prefered to implement with scikit-image module and have chosen segment numbers and compactness as two and four respectively due to extract sky an land features with contrast colors. SLIC superpixels are based on a local version of K-means and SLIC is very fast to compute and memory-efficient (Gonzalez & Woods, 2018).

Algorithm of SLIC superpixel segmentation was explained in the following pseudocode (Achanta, et al., 2012).

/ Initialization */*
Initialize cluster centers $C_k = [l_k, a_k, b_k, x_k, y_k]^T$ by sampling pixels at regular grid steps S.
Move cluster centers to the lowest gradient position in a 3×3 neighborhood.
Set label $l(i) = -1$ for each pixel i.
Set distance $d(i) = \infty$ for each pixel i.

repeat
  / Assignment */*
  for each cluster center C_k **do**
    for each pixel i in a $2S \times 2S$ region around C_k **do**
      Compute the distance D between C_k and i.
      if $D < d(i)$ **then**
        set $d(i) = D$
        set $l(i) = k$
      end if
    end for
  end for
  / Update */*
  Compute new cluster centers.
  Compute residual error E.
until $E \le$ threshold

Figure 3.44. Algorithm of SLIC superpixel segmentation (Achanta, et al., 2012)

Image segmentation can be a tool to measure proportions in the urban scene and extract an knowledge of landmarks on urban image. In this thesis, SLIC superpixel segmentation has been implemented to city model to segment images as sky, building and road proportions. Each color corresponds a different scene attribute.The percentage of scene attributes can be shown in Fig. 3.45, 3.46, 3.47.

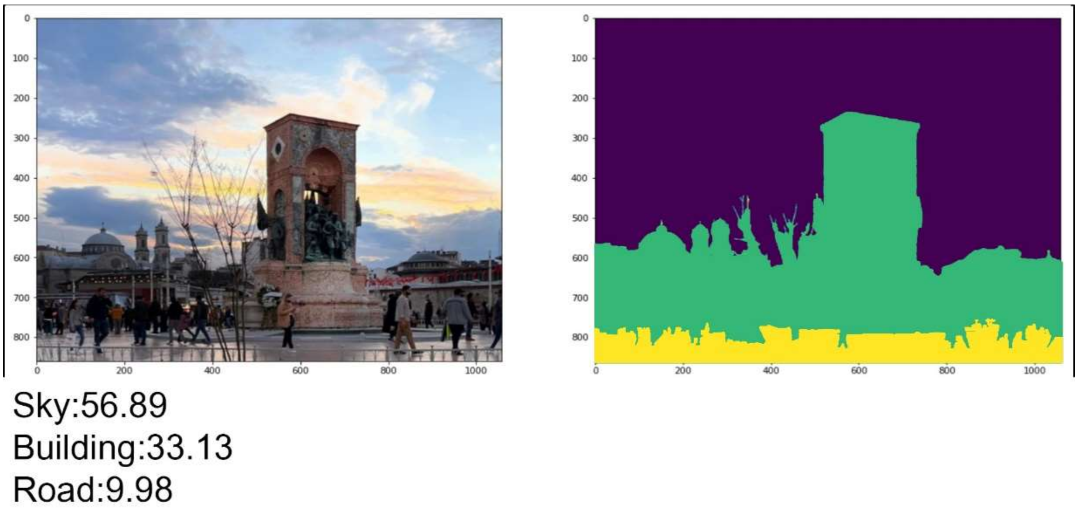


Figure 3.45. Republic Monument (produced by the author)

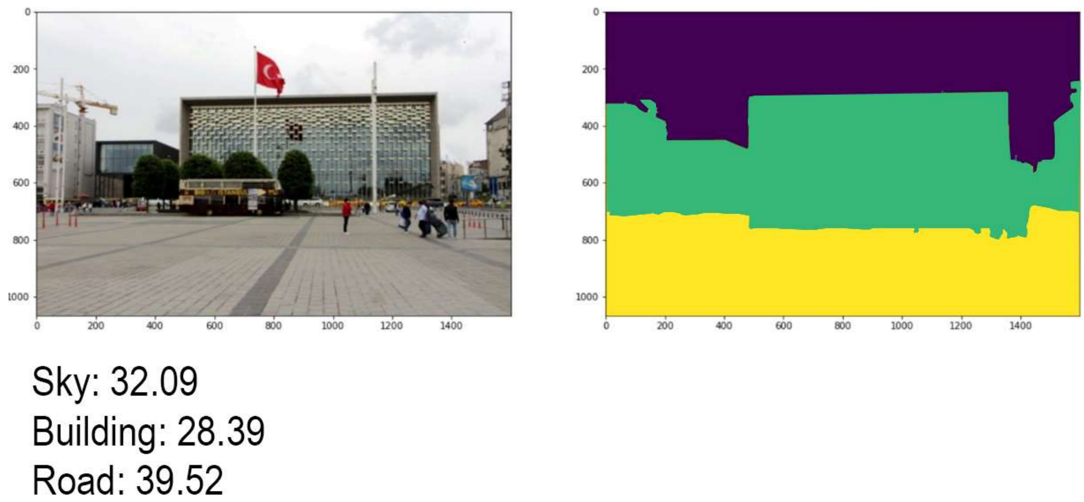


Figure 3.46. Ataturk Cultural Center (AKM) Semantic Segmentation (produced by the author)

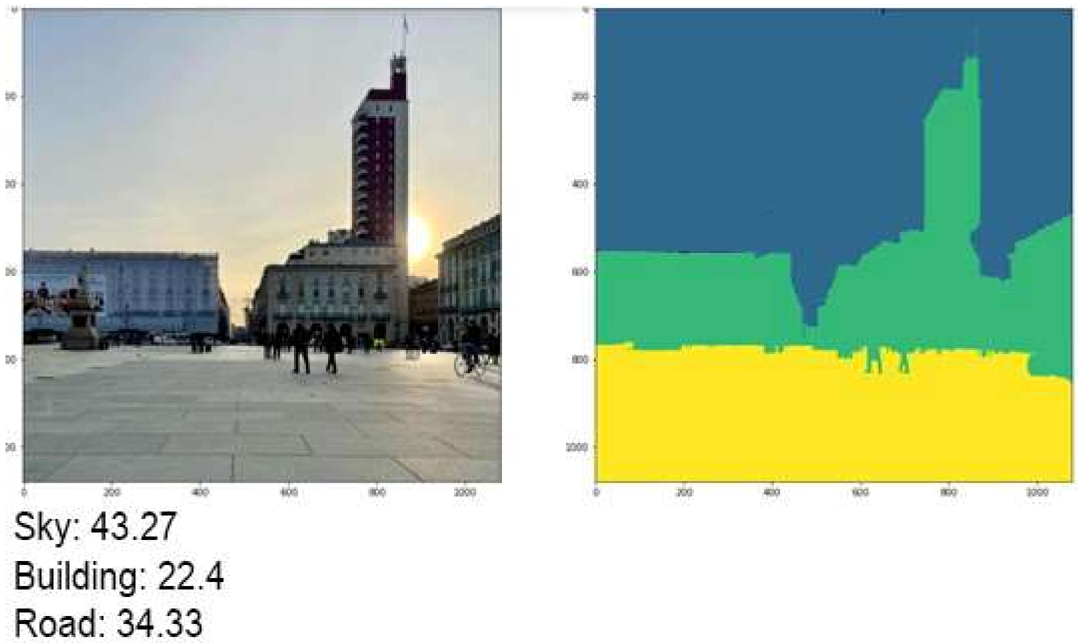


Figure 3.47. Torre Littoria Semantic Segmantion (produced by the author)

3.4.4 Implementation of Convolutional Neural Networks

This research method implemented with Convolutional Neural Networks as supervised learning to create a visual model. There are two frameworks where this method is used: in (1) detecting place-informative objects and (2) to predict city scenes.

3.4.4.1 Place-Informative Objects

As shown in the figures, some clues enable the perception of a place from part to the whole. Nostalgic tram lines, traditional dishes and drinks, signs, and information boards, which are separate and independent and have different meanings, stimulate a heterogeneous whole when they are brought together in perception, thus enabling us to visualize the image of a place (Derrida, La "différance", 1968).

Similarly, when the datasets are examined, objects that express the difference and distinctive features of the separate space are revealed for the spaces that connect with the place and create a sense of community (Zhang, Zhou, Ratti, & Liu, 2019; Zhou, Liu, Oliva, & Torralba, 2014).

Figure 3.48. Informative objects to define Castello Square (produced by the author)

Figure 3.49. Informative objects to define Taksim Square (produced by the author)

As shown in the figures, while the objects of Taksim that relate to the ground are tea, Turkish coffee, sweets, bagels, and chestnuts that refer to the food class, in Castello, the objects belonging to this food class are “Pasta”, “Spritz”, “Wine”, “Espresso” and similarly “Chestnuts”. All'Alfiere dell'Esercito Sardo monument in Castello and the Republic monument in Taksim may also be related pairs. Other place-informative objects that complete the square are the nostalgic tram in Taksim and the similar tram in Castello (Figure 3.48, 3.49).

3.4.4.2 Prediction of City Scenes

For several years, Convolutional Neural Networks (CNNs) have constituted the state-of-the-art in image classification and recognition. Also CNN is known as a DL algorithm which can take in an input image, make it learnable with weights and biases to different kinds of objects in the image and be able to classify the properties of each other (Verma, Mumm, & Carlow, 2021). CNN is commonly used on various applications like image recognition, image classification, forecasting time-series, topic classification etc. by using significant processes, such as Gradient Descent and Backpropagation. (Goodfellow, Bengio, & Courville, 2016), (Andrianaivo, D'Autilia, & Palma, 2019), (Bi, Li, & Fanb, 2021), (Ibrahim, Haworth, & Cheng, 2021).

CNN, often called ConvNet, has deep feed-forward architecture and has astonishing ability to generalize in a better way as compared to networks with fully connected layers. Typical CNNs are generated by hidden layers, feature maps and neurons. Representation of CNN layers used in this this research was shown in Figure 3.50.

All the models have been trained with the following frameworks: Pytorch / Tensorflow and Keras. In this model, Tensorflow with Keras and the Adam optimizer has been used with a learning rate of 10−4.

CNN models on a custom dataset which contains 3071 images with 2 classes as “Istanbul” and “Torino” where each image has different size of pixels in width and height. 80% of the total images are used to train and the rest are used for validation purposes. Implementation of CNN contains three types of layers which are the convolutional layers, pooling layers, and fully-connected layers and in this project Conv2D, Max pooling2D and Dense layers with relu activation function implemented our model with custom dataset and observed in 10 epochs. The CNN started with 0.98 accuracy ratio at the first epoch and has caught the 1.00 value at the second epoch as Table 3.9 below.

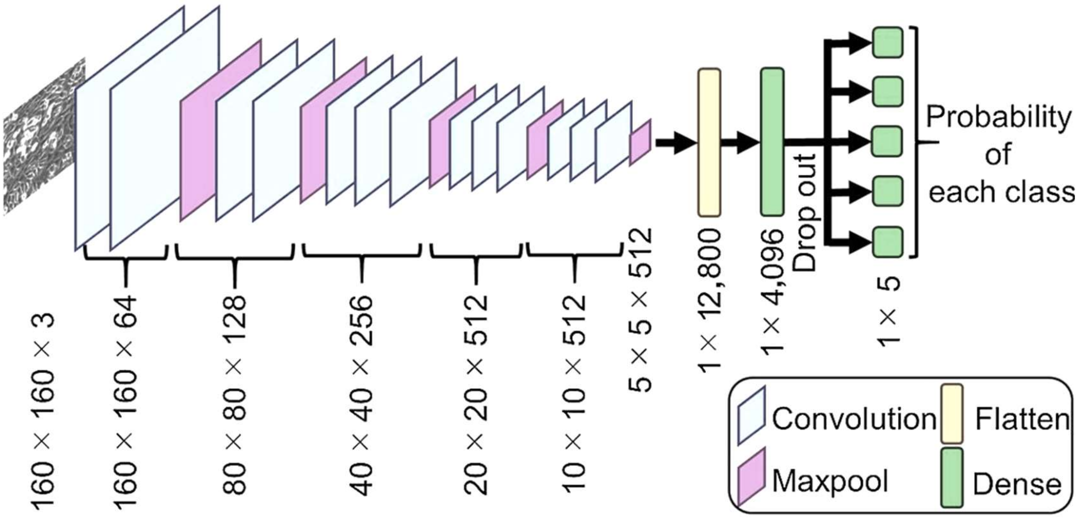


Figure 3.50. Architecture of CNN model used in City Prediction Model

Table 3.9 Training model results (produced by the author)

Epoch	*Loss*	*Accuracy*	*Validation Loss*	*Validation Accuracy*
1	0.6565	0.6289	0.6399	0.7196
2	0.5739	0.7025	0.5759	0.7243
3	0.4447	0.7830	0.6939	0.6729
4	0.3270	0.8576	0.8330	0.6869
5	0.2191	0.9183	0.9471	0.6636
6	0.1253	0.9533	1.2098	0.6916
7	0.0700	0.9802	1.5128	0.6075
8	0.0721	0.9778	1.6760	0.6449
9	0.0376	0.9883	1.3416	0.6916
10	0.0067	1.0000	1.8341	0.7103

After acquiring the CNN model, it was tried to be turned into a prediction model and chose a random Istanbul image out of the dataset to observe the prediction and obtained the 99% confidence that the sample is a “Istanbul”. As shown in Figure 3.51. and Table 3.8, second sample from Taksim Square has labeled “Torino” with %64 confidence, third sample from Taksim Square has labeled “Istanbul” with %99 confidence. The same process was applied for Castello Square. First sample has %94 confidence with “Torino” label and second sample has %99 confidence.

In summary, the prediction model could not distinguish the nostalgic tram of Taksim from the Turin’s. The result indicates that the complex background of images of place informative objects makes classifying the object difficult. Additional image datasets are required to learn these objects. Lastly, the implementation process validates that the model better learns that building has lines with a clear background.

Figure 3.51. Prediction images sorted respectively according to confidence rate chart (produced by the author)

Table 3.10 Confidence rate of city labels (produced by the author)

Scene	*Percentage*	*Label*
Taksim 1	99.76	“Istanbul”
Taksim 2	64.52	“Torino”
Taksim 3	99.92	“Istanbul”
Castello 1	94.31	“Torino”
Castello 2	99.97	“Torino”

3.5 Conclusive Remarks on Proposed Methodology

Social media analytics, as a method, allows to analyze visual data for human-oriented design in urban design processes. In addition, Instagram is a platform where social perception can be detected most effectively with its increasing usage in recent years and the location-based data and metadata analysis it provides. Therefore, in the first part of this chapter three, Google Maps and Instagram Data ranking results in two cities has been explained.

Secondly, custom categorization of the places in Instagram has been defined according to Foursquare’s categorization. As shown in the related figures, in which the three most photographed places of social communities are located, the activities performed in the places and the external relations with the landmarks of the city are photographed more than the forms of the places, and therefore they are more attractive. Thus, city form mostly perceived externally by people. In addition, the city squares have an extension along lines such as Istiklal Caddesi in Istanbul, Via Garibaldi and Via Roma in Turin. Therefore, city squares have great potential for unexpected events and gatherings. Squares function as common areas where social media users reflect their views and needs through their posts. For this reason, architects and urban designers should follow user opinions and include them in urban design process.

Third, the photos obtained from Instagram has been distributed according to their location in Instagram API. Thus, social communities have been mapped via distribution of Instagram photos. Furthermore, main communities detected for each cities' social network analysis on Gephi. Obviously, Gephi outputs also explaines people have tied with their social media posts to the specific place. In this respect, the photographs of popular places in commuities show how people like and use the place, and how place functions and close each other within the city layout.

In the last part of the proposed method, CNN model has implemented to two city squares by training visual city models and classifying 'Istanbul' and 'Turin' labels. Thus, the model detects place-informative objects in city squares according to each cities' visual data exploration manually by examining Instagram data.

Social media subjects objectify spaces through Instagram images. In the conceptual background explained in the introduction part of Chapter 1, the events that meet the spatial practices in people's daily lives clearly show that Taksim and Castello Squares are the intersections and focal points and flows in through paths. They are common urban spaces where different types of people come together and exchange feelings and thoughts. Events and activities are the unifying elements of cities, and squares are the intersection points of these that allow change and transformation to take place.

In a sense, architectural practice is produced on social media and consumed simultaneously. In this context, squares as perceived pieces of urban space provide a different perspective to urban researchers in reading the experience of space. It also provides significant findings to understand the social media users in terms of the number of visual content it produces, the place, and the elements it represents. These elements also contribute to the formation of an urban virtual memory as visual archive. Hence, these elements enable us to observe the events that take place in a square and how these events take place in the designed space, and how the citizens use the spaces designed by architects and urban designers. Furthermore, it enables the analysis of city squares as common spaces and a new perspective in urban research that intersects urban analytics methods and urban theory.

Lastly, it is necessary to design the space in such a way as to allow people to perform various activities and change their functions. This means a line between the designed and living spaces should be blurred. As mentioned in the section on selected squares in Chapter 2, what provides this blurred line and flexibility is the potential for users to perform their actions and events in that square and (re)organization of the squares' designed lines. Castello and Taksim squares are historically two squares where discourses and the analysis of "designed-perceived-lived" space can be applied. Even if the "designed" element of squares is produced on maps, plan scales, and aerial levels, the "perceived" element, human perception, can be measured through social media data analysis. Thus, digital traces of the use of boundaries of urban space and its designed functions can be observed in the events that are the "lived" elements of the squares. Consequently, social sensing will add another dimension to designing city squares.

CHAPTER 4

CONCLUSION

In this research, Taksim and Castello squares were chosen as case study areas, and an exploratory analysis was carried out using Machine Learning, Big Data, and Social Network Analysis. Therefore, the research results are not complete or entirely accurate results. These results and inferences consist of a series of methods to highlight data interpretation in urban analysis. Thus, this thesis outlines a holistic method for urban analytics.

This chapter indicates the results of the exploratory analysis and final remarks about the social media analysis for two squares. In the last part of the research, limitations and obstacles of the study will be evaluated and future research will be presented as an exploratory data analysis throughout this chapter. Throughout the chapters, it was introduced a bottom up, a method in urban analytics to design and reform cities. Urban design is the organization of space, time, and the relationships among elements and the underlying rules than with the elements themselves.

Social media are alternative public spaces that people from all walks of life use extensively and share a large part of their daily life with others. In this respect, knowledge discovery can be achieved in urban design processes by analyzing social media data.

Within the scope of this thesis, social media analysis methods have been developed with the help of artificial intelligence-based software, which is a part of today's technology era, and a method presents a contribution to designing city squares and other urban spaces. Thanks to the urban analysis method developed in this thesis, social media data and state-of-the-art machine learning techniques were evaluated within the scope of Lynchian elements (nodes, paths, landmarks, edges, and districts). Hence, the research reveals that social media data can be used as an analysis for urban researchers in urban design. Moreover, the thesis aims to use social media data as a data source that reveals hidden relationships between the urban spaces and people and thus has the potential to shape social communities and the urban design process.

Today, promoting places, products, or services in city and tourism research is mainstream on Instagram. Social media data also reveals that the boundaries of place and time are blurred, and physical activities can define places. In this respect, the social network analysis method used in the thesis research draws the framework of how social media data has significant potential in urban research and the relationship people establish with people and their physical environment. Thus, it creates a model that shows that this framework can be used as a method in urban research.

This research is a human-oriented exploratory urban space analysis study where the boundaries of sociology and architecture are vague and intertwined. The reflections of complex relations in city form and the users in public spaces have been examined. Furthermore, city squares should always be areas where different segments of society can share events in daily life. While making new urban layouts, new design approaches and the community's needs should be taken into account, and the opportunities obtained with the utilization of the technological advancements.

4.1 Main Contribution of the Methodology to the Field

The research results show that there may be intersections or differentiation between the designed cities and the boundaries perceived by the users. Exploring this segmentation and differentiation through Instagram or other "social" media channels will contribute significantly to urban design and planning processes.

The outcomes of the proposed methodology will be summarized through the research questions. The first research question was that analyze social media data as a knowledge discovery tool to uncover city squares' visual characteristics. In order to conduct the visual analysis, the framework has been introduced. The photographs of the urban scenes taken from two city squares and obtained from the social media were analyzed proportionally in the context of the quality of the city form. Although this method is used for urban scenes in squares including landmarks, it is a state-of-the-art and quantitive method that can also be implemented to other urban attraction points. In summary, urban researchers decide on the perceptual characteristics of the cities by analyzing visual urban characteristics of attraction points in the cities.

The second research question was related to mapping social communities by using visual social media data visualization and deciding points of interest in city squares. The research outlines an urban analytics method that uses social media to map social communities with Gephi software. This method has explored the distribution of places in urban spaces and their relationship with city squares by grouping users according to the activities occurring in the places. The contributions of this knowledge to design practice are likely to improve the quality of city form and its response to complexity.

Throughout the thesis research, the research questions that have been tried to be solved were used to create a city prediction model, one of the computational methods, using micro-scale data. These model reveals the need for interdisciplinary research for researchers interested in urban studies in today's responsive cities. Nevertheless, some difficulties and limitations have been encountered while creating the model.

4.2 Limitations and Obstacles of the Research

While using the comprehensive analysis method used during this thesis research, some obstacles were encountered in the data collection process. Due to Instagram's API privacy, limiting the number of photos that can be scrapped at one time has extended the collection process of the visual dataset. Therefore, extending the data collection process over time was important for creating a visual model and CNN prediction model that has more accurate.The photos taken from all location IDs do not belong to that location 100%. Among the photos taken in Location ID, too many photos are not spatially related to the square. And it took time to create a clean dataset by filtering these photos. Location names for Taksim, written in English and Turkish, were searched in hashtags and included in the training dataset to create a better visual model. Likewise, the same process has been applied for Castello Square.

A more comprehensive analysis may be implemented by examining the evaluations of local people and tourists about the city separately. Thus, land use and attractiveness issues may be investigated in the context of publicness degree. And the problematic or less attractive spots in the city were redesigned.It can also be used as an Instagram data collection platform to identify different urban features.

This study, carried out over six months, may cover different and wider periods. Different spatial boundaries can be determined if the place where this method is to be implemented is studied in the periods when certain events occur. Data collection period could be extended to one year, to get less temporal biased results in analysis process.

In the thesis, only Instagram photos collected from public user profiles have been analyzed in case areas. Considering that the Instagram users are slightly younger than the user groups using platforms such as Facebook and Twitter, the analysis may lead to generalization. In order to eliminate this, different social media platforms, including different user types can be analyzed by avoiding population bias.The scope of research can be developed on social media platforms such as Instagram and Twitter, which provide better results for temporal data.

4.3 Future Studies

This study introduces the analysis of urban characteristics and many elements in urban scenes that will form the visual archives of cities. Hence, it could be an initial framework for integrating visual social media data into multidisciplinary research. In this thesis research, a different visual data collection platform can be used due to the difficulties encountered in the data collection and extraction process. Alternatively, future studies collected simultaneously from several social media channels may be less biased.

According to the research case studies, two different squares were analyzed. In future studies, this research method can be used to examine and understand one specific city in detail by avoiding spatial bias. In this way, this application may give urban researchers strong clues in understanding the connection between the visual features of a city and human perception.

The relationship with the landmark and proximity to landmark may be analyzed by making predictions according to the post numbers. Especially, user types and the social clusters can be correlated and compared with each other. Urban features may be extracted from city scenes with Google Cloud Vision API or other ML implementations. Moreover, an urban archive can be created by detecting landmarks. Thus, it is possible to discover various urban features which are closely related to the image of the urban scenes.

Lastly, urban design layouts can be obtained by integrating the result data of this study into the research of GIS and 3D city models such as Digital Twin projects for specific cities. This research was only the beginning and I believe that I will pursue the concept of city features in future academic studies.

REFERENCES

Abascal-Mena, R., Lema, R., & Sèdes, F. (2014). From Tweet to Graph: Social Network Analysis for Semantic Information Extraction. *IEEE International Conference on Research Challenges in Information Science*, 1-10.

Abascal-Mena, R., Lema, R., & Sèdes, F. (2015). Detecting Sociosemantic Communities by Applying Social Network Analysis in Tweets. *Social Network Analysis and Mining*, 1-17.

Achanta, R., Shaji, A., Smith, K., Lucchi, A., Fua, P., & Susstrunk, S. (2012). SLIC Superpixels Compared to State-of-the-Art Superpixel Methods. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 74-81.

Agency, W. A., & Hootsuite. (2022). Digital 2022 Global Overview Report. London, United Kingdom.

Andrianaivo, L. N., D'Autilia, R., & Palma, V. (2019). Architecture Recognition By Means of Convolutional Neural Networks. *Remote Sensing and Spatial Information Sciences*.

Arefieva, V., Egger, R., & Yu, J. (2021). A Machine Learning Approach to Cluster Destination Image on Instagram. *Tourism Management*, 1-11.

Augusti, D. (2021). The Clustering of City Images on Instagram: A Comparison Between Projected and Perceived Images. *Journal of Destination Marketing & Management*, 1-12.

Barthelemy, M. (2017). *The Structure and Dynamics of Cities: Urban Data Analysis and Theoretical Modeling.* Cambridge: Cambridge University Press.

Bastian, M., Heymann, S., & Jacomy, M. (2009). Gephi: an open source software for exploring and manipulating networks. *International AAAI Conference on*

Weblogs and Social Media (pp. 361-362). California: PKP Publishing Services.

Batty, M. (2013). *The New Science of Cities.* Massachusetts:: The MIT Press.

Bi, W., Li, H., & Fanb, Z. (2021). Tourism Demand Forecasting with Time Series Imaging: A Deep Learning Model. *Annals of Tourism Research*.

Bokanyi, E., & Kallus, Z. (2021). Collective Sensing of Evolving Urban Structures: From Activity-based to Content-aware Social Monitoring. *Urban Analytics and City Science*.

Bourriaud, N. (2002). *Relational Aesthetics.* Chicago: Les Presses du réel.

Boy, J., & Uitermark, J. (2015). Capture and Share the City: Mapping Instagram's Uneven Geography in Amsterdam. *The Ideal City Between Myth and Reality. Representations, Policies, Contradictions and Challenges for Tomorrows Urban Life.*

Boy, J., & Uitermark, J. (2016). How to Study the City on Instagram. *Public Library of Science*.

Castells, M. (2000). *The Rise of the Network Society* . Malden, MA: Wiley-Blackwell.

Çelik, Z., Favro, D., Ingersoll, R., & Kostof, S. (1996). *Streets: Critical Perspectives on Public Space.* Los Angeles: University of California Press.

Çelikten, E., Le Falher, G., & Mathioudakis, M. (2016). Modeling Urban Behavior by Mining Geotagged Social Data. *IEEE Transactions on Big Data*, 1-27.

Correa Martins, J., Menezes, G., Gonçalves, W., Andre Sant'Ana, D., Osco, L., Liesenberg, V., . . . Marcato, J. (2021). Machine Learning and SLIC for Tree Canopies Segmentation in Urban Areas. *Ecological Informatics*, 1-14.

Cranshaw, J., Schwartz, R., Hong, J., & Sadeh, N. (2021). The Livehoods Project: Utilizing Social Media to Understand the Dynamics of a City. *Proceedings* *of the International AAAI Conference on Web and Social Media* (pp. 58-65). Dublin: AAAI Press.

Date, K., & Allweil, Y. (2021). Towards a New Image Archive for the Built Environment. *Urban Analytics and City Science*, 1-16.

Derrida, J. (1968). La "différance". *Société Française de Philosophie, Bulletin*, 73.

Derrida, J. (1993). *Khôra.* Paris: Galilée.

Dobesova, Z. (2019). The Similarity of European Cities Based on Image Analysis. *Proceedings of 3rd Computational Mehods in Sysems and Software.* Czech Republic: Springer.

Donahuea, M. L., Keelera, B., Wood, S. A., Fisherc, D. M., Hamsteadd, Z. A., & McPhearsone, T. (2018). Using Social Media to Understand Drivers of Urban Park Visitation in the Twin Cities, MN. *Landscape and Urban Planning*.

Dubey, A., Naik, N., Parikh, D., Raskar, R., & Hidalgo, C. (2016). Deep Learning the City: Quantifying Urban Perception At A Global Scale. *European Conference on Computer Vision* (pp. 1-23). Amsterdam: Springer.

Dunkel, A. (2015). Visualizing the perceived environment using crowdsourced photo geodata. *Landscape and Urban Planning*, 173–186.

Fang, Z., Shaw, S. L., Yang, B., Santi, P., & Tu, W. (2021). Integrated Enviromental and Human Observations for Smart Cities. *Urban Analytics and City Science*.

Fassino, G. (2020). Architecture And Urbanism As a Tourist Factor Documenting City change The city and Its Image 1928-1936. In T. M. Sala, & M. Bruzzo, *I-Media-Cities: Inovative e-Environment for Research on Cities and the Media* (pp. 53-61). Barcelona: Universitat de Barcelona Edicions.

Foucault, M. (2008). *The Birth of Biopolitics: Lectures at the Collège de France, 1978–1979.* New York: Palgrave Macmillan.

Frias-Martinez, V., Soto, V., Hohwald, H., & Frias-Martinez, E. (2012). Characterizing Urban Landscapes using Geolocated Tweets. *International Confernece on Social Computing.*

Gatti, F., & Procentese, F. (2021). Experiencing Urban Spaces and Social Meanings Through Social Media: Unravelling the Relationships Between Instagram City-Related use, Sense of Place, and Sense of Community. *Journal of Environmental Psychology*.

Global Public Space Programme. (2019). *City-wide Public Space Assessment Toolkit.* Nairobi: UN-Habitat.

Global Public Space Programme. (2020). *Public Space Site-specific Assessment: Guidelines to Achieve Quality Public Spaces.* Nairobi: UN-Habitat.

Goldsmith, S., & Crawford, S. (2014). *The Responsive City: Engaging Communities Through Data-Smart Governance.* San Francisco: Jossey-Bass.

Gonzalez, R., & Woods, R. (2018). *Digital image processing.* New York: Pearson.

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning.* Cambridge: MIT Press.

Hollander, B., Nikolaishvili, G., Adu-Bredu, A., Situ, M., & Bista, S. (2021). Using Deep Learning to Examine the Correlation Between Transportation Planning and Perceived Safety of the Built Environment. *Urban Analytics and City Science*.

Hu, Y., Gao, S., Janowicz, K., Yu, B., Li, W., & Prasad, S. (2015). Extracting and understanding urban areas of interest using geotagged photos. *Computers, Environment and Urban Systems*, 240-254.

Ibrahim, M., Haworth, J., & Cheng, T. (2021). URBAN-i: From Urban Scenes to Mapping Slums, Transport Modes, and Pedestrians in Cities Using Deep Learning and Computer Vision. *Urban Analytics and City Science*.

Iglesias-Sánchez, P., Correia, M. B., Jambrino-Maldonado, C., & Heras-Pedrosa, C. (2020). Instagram as a Co-Creation Space for Tourist Destination Image-Building: Algarve and Costa del Sol Case Studies. *Sustainability*.

Jacobs, J. (1961). *The Death and Life of Great American Cities.* New York: Random House.

Kitchin, R. (2013). Big Data and Human Geography: Opportunities, Challenges and Risks. *Dialogues in Human Geography*, 262–267.

Kitchin, R. (2014). The Real-time City: Big Data and Smart Urbanism. *GeoJournal*.

Koenig, R. (2020). Artificial Intelligence in Architecture and City-Scale Design In AI & Architecture. 1-2.

Kostof, S. (1992). *The City Assembled : The Elements of Urban Form Through History.* Boston: Little, Brown and Company.

Lee, J. M. (2021). Understanding Volume and Correlations of Automated Walk Count: Predictors for Necessary, Optional, and Social Activities in Dilworth Park. *Urban Analytcs and City Science*.

Lefebvre, H. (1991). *The Production of Space.* New York: Wiley-Blackwell.

Li, X. (2021). Examining the Spatial Distribution and Temporal Change of the Green View Index in New York City using Google Street View Images and Deep Learning. *Urban Analytics and City Science*, 39-54.

Lock, O., & Pettit, C. (2020). Social Media as Passive Geoparticipation in Transportation Planning - How Effective are Topic Modelling & Sentiment Analysis in Comparison With Citizen Surveys. *Geo-spatial Information Science*.

Long, Y., Song, Y., & Chen, L. (2021). Identifying Subcenters with a Nonparametric Method and Ubiquitous Point-of-Interest Data: A Case Study of 284 Chinese Cities. *Urban Analytics and City Science*.

Lynch, K. (1960). *The Image of the City.* Cambridge: MIT Press.

Miguel-Rodriguez, J., Galan-Paez, J., Aranda-Corral, A., & Borrego-Diaz, J. (2016). Urban Knowledge Extraction, Representation and Reasoning as a Bridge from Data City towards Smart City. *IEEE Conferences on Ubiquitous Intelligence & Computing.*

Nadai, M. D., Staiano, J., Larcher, R., Sebe, N., Quercia, D., & Lepri, B. (2016). The Death and Life of Great Italian Cities: A Mobile Phone Data Perspective. *Proceedings of the 25th International Conference on World Wide Web.* Montreal: Association for Computing Machinery.

Newman, M. E. (2006). Modularity and community structure in networks. *Proceedings of the National Academy of Sciences*, 1-6.

Nikhil, N., Philipoom, J., Raskar, R., & Hidalgo, C. (2014). Streetscore - Predicting the Perceived Safety of One Million Streetscapes. *IEEE Conference on Computer Vision and Pattern Recognition Workshops* (pp. 1-8). Columbus: Institute of Electrical and Electronics Engineers.

Oguztimur, S., & Akturan, U. (2016). Synthesis of City Branding Literature (1988–2014) as a Research Domain. *International Journal of Tourism Research*, 357–372.

Patterson, G., & Hays, J. (2012). SUN Attribute Database: Discovering, Annotating, and Recognizing Scene Attributes . *IEEE Conference on Computer Vision and Pattern Recognition*, 1-8.

Pettenati, G., Dansero, E., & Calafiore, A. (2019). Researching and Enabling Youth Geographies in the Digital and Material City: The Teencarto Project. In A. Voghera, & L. La Riccia, *Spatial Planning in the Big Data Revolution* (pp. 221-247). Pennsylvania: IGI Global.

Plato, & Lee, H. D. (1977). *Timaeus and Critias* . Harmondsworth: Penguin Books.

Portugali, J. (2011). *Complexity, Cognition and the City.* New York: Springer.

Preotiuc-Pietro, D., Cranshaw, J., & Yano, T. (2013). Exploring Venue-Based City-To-City Similarity Measures. *UrbComp'13*.

Ratti, C., & Offenhuber, D. (2014). *Decoding the City: Urbanism in the Age of Big Data.* Basel: Birkhauser Verlag AG.

Richards, D., & Tunçer, B. (2018). Using Image Recognition to Automate Assessment of Cultural Ecosystem. *Ecosystem Services*.

Roe, J., & McCay, L. (2021). *Restorative Cities: Urban Design for Mental Health and Wellbeing.* Londom: Bloomsbury Publishing.

Salesses, P., Schechtner, K., & Hidalgo, C. (2013). The Collaborative Image of The City: Mapping the Inequality of Urban Perception. *Public Library of Science*.

Shen, Q., Zeng, W., Ye, Y., Muller, S., Schubiger, S., Burkhard, R., & Qu, H. (2018). StreetVizor: Visual Exploration of Human-Scale Urban Forms Based on Street Views. *IEEE Transactions on Visualization and Computer Graphics*.

Sokmenoglu Sohtorik, A. (2016). A Knowledge Discovery Approach to Urban Analysis: Beyoglu Preservation Area As a Data Mine. *A+BE | Architecture and the Built Environment*, 409.

Stavrides, S. (2016). *Common Space: The City as Commons.* London: Zed Books.

Takerngsaksiri, W., Wakamiya, S., & Aramaki, E. (2019). City Link: Finding Similar Areas in Two Cities using Twitter Data. *Web and Wireless Geographical Information Systems*, 15.

Verma, D., Mumm, O., & Carlow, V. (2021). Identifying Streetscape Features Using VHR Imagery and Deep Learning Applications. *Remote Sensing*.

Visser, F., Stappers, P., Lugt, R., & Sanders, E. (2005). Contextmapping: Experiences From Practice. *CoDesign*, 119-149.

Whyte, W. (1980). *The Life of Plazas The Social Logic of Small Urban Spaces.* Washington D.C: Conservation Foundation.

Yao, Y., Wang, J., Hong, Y., Qian, C., Guan, Q., Liang, X., . . . Zhang, J. (2021). Discovering the homogeneous geographic domain of human perceptions from street view images. *Landscape and Urban Planning*.

Ye, C., Zhang, F., Mu, L., Gao, Y., & and Liu, Y. (2021). Urban Function Recognition by Integrating Social Media and Street-Level Imagery. *Urban Analytics and City Science*, 104-125.

You, Q., Bhatia, S., & Luo, S. (2016). A Picture Tell a Thousand Words—About you! User Interest Profiling from User-generated Visual Content. *Signal Processing*.

Yu, J., & Egger, R. (2021). Color and Engagement in Touristic Instagram Pictures: A Machine Learning Approach. *Annals of Tourism Research*.

Zasina, J. (2018). The Instagram Image of the City: Insights from Lodz, Poland. *Bulletin of Geography: Socio-economic Series*.

Zhang, F., Zhou, B., Ratti, C., & Liu, Y. (2019). Discovering Place-informative Scenes and Objects Using Social Media Photos. *Royal Society Open Science*, 1-15.

Zhang, J., Fukuda, T., & Yabuk, N. (2020). A Large-Scale Measurement and Quantitative Analysis Method of Facade Color in the Urban Street Using Deep Learning. *Proceedings of the 2020 DigitalFUTURES.*

Zhang, K., Chen, Y., & Li, C. (2019). Discovering the Tourists' Behaviors and Perceptions in a Tourism Destination by Analyzing Photos' Visual Content with a Computer Deep Learning Model: The Case of Beijing. *Tourism Management*.

Zhou, B., Liu, L., Oliva, A., & Torralba, A. (2014). Recognizing City Identity via Attribute Analysis of Geo-tagged Images. *Computer Vision – ECCV* . Zurich: Springer.

Retrieved from https://github.com/arc298/instagram-scraper, 12/20/2021.

Retrieved form https://developer.foursquare.com/docs/legacy-venue-categories, 10/20/2021.

Google Cloud Vision, 2017. Documentation for the Google Cloud Vision API. Retrieved from https://cloud.google.com/vision/docs, 12/01/2021.

Retrieved form https://www.publicspace.org/ , 01/06/2022.

APPENDICES

A. Top Sights in Istanbul According to Google Maps Places Data

Top Sights	Likes Score	Reviews	Categories
Suleymaniye Mosque	4.9	(37078)	Storied 16th-century Ottoman mosque
Yoros Castle	4.9	(8)	Castle and history
Hagia Sophia	4.8	(88265)	Byzantine basilica museum with mosaics
Rahmi M. Koc Museum	4.8	(17847)	Array of industrial artifacts & vehicles
Eyup Sultan Mosque	4.8	(49211)	Historic mosque with a mausoleum
Fatih Mosque	4.8	(27746)	Massive multi-domed place of worship
Camlica Mosque	4.8	(45711)	Massive mosque with a museum & a gallery
Mihrimah Sultan Mosque	4.8	(3421)	Grand mosque dating from 16th century
Zeyrek Mosque	4.8	(1438)	Medieval mosque dating from 12th century
Sokollu Mehmet Pasha Mosque	4.8	(1443)	Scenic 16th-century Ottoman mosque
Yavuz Sultan Selim Mosque	4.8	(4680)	Ottoman architecture & Golden Horn views
The Blue Mosque	4.7	(75611)	Iconic Blue Mosque with 6 minarets

Topkapi Palace Museum	4.7	(66161)	Historic Ottoman-era palace complex
Galata Tower	4.7	(111366)	67-meter Byzantine tower & restaurant
Dolmabahce Palace	4.7	(49401)	Museum in ornate Ottoman sultan's palace
Bosphorus	4.7	(3520)	Landmark waterway & continental boundary
Ciragan Palace Kempinski	4.7	(7863)	Palatial hotel with a spa & a helipad
Sultanahmet Square	4.7	(21780)	Public square where hippodrome stood
Maiden's Tower	4.7	(16266)	Iconic islet tower with boat trips
Büyük Mecidiye Mosque (Ortaköy Mosque)	4.7	(26786)	Baroque mosque built to capture light
Beylerbeyi Palace	4.7	(7488)	Historical summer palace with gardens
Gülhane Park	4.7	(42900)	Serene city park with gardens & a museum
New Mosque	4.7	(8303)	Iconic, landmark 17th-century mosque
Sabancı University Sakıp Sabancı Museum	4.7	(3312)	Fine arts museum in a historic mansion
Little Hagia Sophia	4.7	(3545)	Iconic Byzantine-style domed mosque
Yıldız Park	4.7	(25103)	City park with an Ottoman palace museum
Belgrade Forest	4.7	(1314)	Forest, camping, nature, running and park and garden

Istanbul Toy Museum	4.7	(5285)	Museum with antique toys & miniatures
Burgaz Island	4.7	(349)	Remote island with a museum & ruins
Kılıç Ali Paşa Hamami	4.7	(1302)	Renovated, 16th-century bathhouse
Harbiye Military Museum and Cultural Site	4.7	(3012)	Huge museum of Turkey's military history
Beyazit Mosque	4.7	(3392)	Mosque complex completed in 1506
St. Stephen’s Bulgarian Orthodox Church	4.7	(370)	Ornate 19th-century place of worship
Sadberk Hanım Museum	4.7	(570)	Ancient relics in distinctive buildings
Nuruosmaniye Mosque	4.7	(7922)	Large, 18th-century Ottoman mosque
German Fountain	4.7	(983)	Late 19th-century Ottoman fountain
Elgiz Museum	4.7	(109)	Exhibitions of contemporary art
Istanbul Archaeological Museums	4.6	(9784)	Museum of Turkish archaeological finds
İstiklal Street	4.6	(1147)	Busy city avenue with shops & cafes
Taksim AKM	4.6	(550)	Civic Center
Galata Bridge	4.6	(25023)	Modern bridge spanning the Golden Horn
Rumeli Fortress	4.6	(9821)	Ancient fortress with panoramic views

Museum of Turkish and Islamic Arts	4.6	(2681)	Turkish & Islamic arts in a palace
Golden Horn	4.6	(782)	Prominent inlet with commerce & parks
Pera Museum	4.6	(3710)	Painting, ceramics & modern art exhibits
Miniaturk	4.6	(25957)	Park showing Turkey in miniature format
Rustem Pasha Mosque	4.6	(3542)	Historic mosque famous for its tile work
Emirgan Park	4.6	(33808)	Picturesque park with play areas & paths
Anatolian Fortress	4.6	(4821)	14th-century fortress over the Bosphurus
Cağaloğlu Turkish Bath	4.6	(1262)	Historic 300-year-old hammam
St. Antuan Church	4.6	(10596)	Catholic church dating from 1912
Maritime Museum	4.6	(5430)	Showcase for Turkish naval heritage
Küçüksu Kasrı	4.6	(3508)	Historic sultan's palace with tours
Panorama 1453 History Museum	4.6	(9597)	Panoramic painting of historic siege
Obelisk of Theodosius	4.6	(1746)	Transplanted ancient Egyptian obelisk
Column of Constantine	4.6	(6730)	Ancient Roman column built of stone
Fatih Sultan Mehmet Bridge	4.6	(1126)	Suspension bridge linking Asia & Europe

Borusan Contemporary	4.6	(449)	Museum, art, art museum and modern art
Tiled Pavilion Museum	4.6	(329)	Palace pavilion & museum
Arter	4.6	(1157)	Modern art in a historical space
Ataturk Museum	4.6	(1177)	Photos & paintings in house museum
Basilica Cistern	4.5	(30565)	Restored 542 A.D. waterworks
Mısır Bazaar	4.5	(115896)	Historic covered spice & textiles market
Bosphorus Bridge	4.5	(8106)	Suspension bridge from Europe to Asia
Büyükada	4.5	(2962)	Charming island with historic homes
Heybeliada	4.5	(724)	Small inhabited island with a monastery
SALT Galata	4.5	(669)	Gallery, library & coffee shop
Bagdat Avenue	4.5	(287)	Lively destination for shopping & dining
The Museum of Innocence	4.5	(1641)	Museum-home with an accompanying novel
Galata Mevlevihanesi Müzesi	4.5	(2440)	Museum known for whirling dervish shows
Ataturk Arboretum	4.5	(10897)	Natural area for quiet walks & photos
Santralistanbul	4.5	(3024)	Historic power plant turned museum
Serpent Column	4.5	(375)	Remains of anancient Greek monument
Grand Bazaar	4.4	(94571)	Labyrinth of colorful covered markets

Kariye Mosque	4.4	(5960)	Museum with Muslim & Christian artworks
Museum of Great Palace Mosaics	4.4	(970)	Collection of Byzantine-era mosaics
Istanbul Aquarium	4.4	(23127)	Large aquarium with a gift shop & cafes
The Aqueduct of Valens	4.4	(70)	Imposing remains of a Roman-era aqueduct
The Walls of Constantinople	4.4	(262)	Ruins, history, mehmed ii, palace and ancient history
Yıldız Sarayı Müzesi	4.4	(80)	Lavish 1800s Ottoman palace
Kınalıada	4.4	(282)	Scenic spot with beaches & ferry service
Çiçek Pasajı / Cité de Péra	4.4	(10223)	Landmark passage with shops & eateries
Suleymaniye Bath	4.4	(414)	Historic baths since the 16th century
Palace of the Porphyrogenitus	4.4	(1187)	Remains of a Byzantine imperial palace
Macka Park	4.4	(2558)	Laid-back park with a dark past
Istanbul Museum of the History of Science and Technology in Islam	4.4	(1862)	Exhibits in former royal stables
Istanbul Museum of Modern Art	4.3	(5267)	Modern & contemporary art museum
Hagia Irene	4.3	(1427)	4th-century Byzantine church museum
Sea Life	4.3	(11159)	Oceanic exhibits for all ages
Madame Tussauds Istanbul	4.3	(9225)	Sculpture, museum, michael jackson and wax museum

Yavuz Sultan Selim Bridge	4.3	(4385)	One of the world's tallest bridges
Contemporary Istanbul	4.3	(71)	Art, sculpture, art gallery and modern art
Istanbul Theme Park	4.2	(34542)	Family amusement & shopping complex
MAC - Kanyon Shopping Mall	4.2	(156)	Shopping, canyon and architecture
Yedikule Dungeons Museum	4.2	(1772)	Old fortress with towers & a dungeon
Çemberlitaş Turkish Bath	4.1	(1781)	1584 Turkish baths with spa treatments
Faruk Yalçın Zoo	4.1	(14767)	Zoo with diverse animals & plants
ViaSea Aquarium	4.1	(2317)	Marine museum with sea creatures
Aqua Club Dolphin	3.7	(6918)	Sizable waterpark with pools & slides
Historical Galatasaray Bath	3.7	(632)	Traditional Turkish bath facility

B. Top Sights in Turin According to Google Maps Places Data

Top Sights	Likes Score	No.s of Reviews	Categories
Val Sangone	5	(2)	Mountain
Piazza Castello	4.8	(1924)	Palace, history and architecture
Colline del Po	4.8	(6)	Hillwalking routes with landmark castles
Basílica de María Auxiliadora	4.8	(2963)	Frescoes & the remains of John Bosco
Las habitaciones de don Bosco	4.8	(23)	Museum
Museo del Grande Torino e della Leggenda Granata	4.8	(274)	Museum
Egyptian Museum	4.7	(34185)	Sphinxes, mummies & ancient papyrus
Royal Palace of Turin	4.7	(3966)	Royal residence with armory & museum
Piazza San Carlo	4.7	(19042)	Historical city square & events site
Castello del Valentino	4.7	(894)	Historic mansion & architecture campus
Musei Reali di Torino	4.7	(515)	Art & history museums in a grand palace
Mont dei Cappucini	4.7	(3050)	Hilltop church dating to the 1580s
Cappella della Sacra Sindone	4.7	(3924)	Guarini chapel within Turin Cathedral
Iglesia de San Lorenzo	4.7	(512)	17th-century baroque Catholic church
Royal Armoury of Turin	4.7	(539)	Lavishly decorated arms & armor museum
Museo Civico Pietro Micca e dell'Assedio di Torino del 1706	4.7	(956)	History museum with underground tunnels

Santuario della Consolata	4.7	(2363)	Baroque basilica & sanctuary
Collezione Cerruti	4.7	(37)	Art and museum
Parco della Maddalena	4.7	(115)	Park and garden and lighthouse
Colle della Maddalena	4.7	(100)	0
Superga	4.7	(95)	Hilltop basilica with sweeping views
Free Walking Tour Turin	4.7	(86)	0
Madama Palace	4.6	(5536)	Grand museum with antique & applied arts
Basilica of Superga	4.6	(9944)	1700s hilltop church overlooking Alps
Museo Nazionale dell'Automobile	4.6	(10519)	Museum tracing automotive history
Parco del Valentino	4.6	(34426)	Park & castle with medieval origins
Palazzo Carignano	4.6	(2605)	Ornate Baroque palace & museum
Galleria Sabauda	4.6	(618)	Spacious gallery of Italian & Dutch art
Chiesa della Gran Madre di Dio	4.6	(5355)	Historic neoclassical Catholic church
Accorsi - Ometto Museum	4.6	(832)	Museum, decorative arts and art
Juventus Museum	4.6	(3862)	Football memorabilia & stadium tours
Musée Lavazza	4.6	(1648)	Longstanding coffee factory with tours
Chiesa di San Carlo Borromeo	4.6	(135)	Church and architecture
Via Po	4.6	(59)	Historic street with shops & landmarks
Faro Della Vittoria	4.6	(2189)	Lighthouse and history
Centro Storico Fiat	4.6	(394)	Museum

Palazzo Falletti di Barolo	4.6	(538)	Opera house & community cultural hub
Adventure Three Oaks Park	4.6	(1009)	Amusement park
Casa Fenoglio-Lafleur	4.6	(99)	Art nouveau, architecture, belle Époque, art and art deco
La Venaria Reale	4.5	(9989)	Vast restored palace & garden complex
Cathedral of Saint John the Baptist	4.5	(4245)	Historic 15th-century cathedral
Palazzina di Caccia di Stupinigi	4.5	(7606)	Renovated rococo hunting palace
Museum of Eastern Art	4.5	(2727)	Asian art museum in 17th-century palace
Medieval Village	4.5	(8619)	Recreated medieval village & workshops
Museum of the Risorgimento	4.5	(1741)	Museum of Italy's 19th-century history
La Mandria Park	4.5	(7864)	Trails & royal castle in nature reserve
CAMERA - Centro Italiano per la Fotografia	4.5	(1430)	Museum and art
Castello de La Mandria	4.5	(1316)	Park and garden and history
Giardini Reali di Torino	4.5	(3586)	Landscaped royal gardens with statues
Museum of the Resistance	4.5	(293)	Museum
Villa Tesoriera or Sartirana	4.5	(2095)	Grand 1700s mansion & music library
Civic Gallery of Modern and Contemporary Art	4.4	(3813)	Museum of modern & contemporary art
Fondazione Sandretto Re Rebaudengo	4.4	(498)	Art, museum, sculpture, installation art and art museum

Museum of Contemporary Art	4.4	(3104)	Art museum in 17th-century castle
Pinacoteca Giovanni e Marella Agnelli	4.4	(1040)	Art masterpieces in a rooftop gallery
Villa della Regina	4.4	(3098)	17th-century palace & gardens
Café Al Bicerin	4.4	(1612)	Quaint spot for chocolate-based fare
Palatine Gate	4.4	(1003)	Historic Roman-period city gate
MEF Ettore Fico Museum	4.4	(719)	Museum and art
Castillo de Moncalieri	4.4	(2019)	Palace & former fortress with gardens
Piazza Statuto	4.4	(9194)	Neoclassical square completed in 1865
Botanical Garden of Turin - University of Turin	4.4	(780)	Garden with an arboretum & greenhouses
Palazzo Fetta di Polenta	4.4	(637)	Narrow house built by a famed architect
Stupinigi Natural Park	4.4	(1386)	Conserved historic hunting & farm land
Parc Europa	4.4	(2812)	Terraced park with views of the city
Ciudadela de Turín	4.4	(305)	History and architecture
Fondazione Merz	4.3	(229)	Museum with art by Mario & Marisa Merz
Royal Library of Turin	4.3	(66)	Leonardo da vinci, palace, dante alighieri, michelangelo
Parco della Pellerina	4.3	(6177)	City park with lakes & sports facilities
Musée d'Antiquité	4.3	(104)	Museum of antiquities & Roman theater
QC Termetorino	4.3	(4255)	Spa center with pools & treatments

MUSEUM OF HUMAN ANATOMY LUIGI ROLANDO	4.3	(419)	Museum
Promotrice delle Belle Arti	4.3	(594)	Art, edgar degas, vincent van gogh
MAU - Museum of Urban Art	4.3	(200)	Museum and art
MACA - Museo A come Ambiente	4.3	(432)	Museum
Parco Ruffini	4.3	(7781)	Shady park with a train & sports stadium
Cavalieri di Vittorio Veneto Park	4.3	(4858)	Vast park with play & sports areas
Church of Santo Volto	4.3	(556)	Modern landmark with a striking design
Stura di Lanzo	4.3	(69)	River, fossil and fishing
Porta Palazzo	4.2	(18031)	Indoor-outdoor bazaar for food
Museum of Criminal Anthropology	4.2	(1261)	Inmate artwork & anatomical models
Museo Nazionale della Montagna "Duca degli Abruzzi" CAI - Torino	4.2	(347)	Permanent exhibition on mountain culture
Infini.to Planetario di Torino	4.2	(255)	Planetarium, museum
Ecomuseo Sogno di Luce	4.2	(68)	Museum
Dora Riparia	4.2	(333)	River and canyon
Regional Museum of Natural Science	4.1	(74)	Natural sciences in a former hospital
Museo della Sindone	4.1	(762)	Museum housing the Holy Shroud
Museo del Risparmio	4.1	(256)	Museum
Museum of Fruit Francesco Garnier Valets	4.1	(100)	Museum
Blu Paradise	4.1	(2072)	Water slides, pools & beach volleyball
MUFANT - Museo lab del fantastico e della fantascienza di Torino	4.1	(419)	Museum
Acquajoy	4	(1787)	Water park and amusement park
Parco d'Arte Vivente	3.9	(311)	Outdoor installations
Palazzo Nervi, già Palazzo del Lavoro	3.3	(24)	Modern architecture

C. Nodes in Castello Square

Place_Name	Category	Total_Posts	Lat	Long
Piazza Castello	public	206500	45.07127	7.685101
Mole Antonelliana	cultural	134300	45.06912	7.693346
Museo Egizio	cultural	109000	45.06854	7.68477
Piazza San Carlo	public	58900	45.06799	7.682766
Porto Nuova	travel	58900	45.06242	7.678781
Palazzo Reale	cultural	27900	45.07288	7.686467
Giardini Reali	public	25000	45.07238	7.689457
Teatro Regio Torino	performance	16900	45.07084	7.687496
Camera Centro Italiano	cultural	13700	45.06426	7.691674
Musei Reali Torino	cultural	12900	45.07293	7.686166
Paratissima	cultural	12800	45.07002	7.688768
Circola dei Lettori	cultural	12400	45.06862	7.687985
Palazzo Madama	cultural	11000	45.07116	7.686569
Del Cambio	food	10100	45.06955	7.685096
Caffé Al Bicerin dal 1763	food	10100	45.07634	7.679761
Piazza Carignano	public	7000	45.06913	7.684767
Bar Cavour	food	5000	45.06955	7.685132
Porta Palatina	cultural	5000	45.07508	7.684842
Palazzo Carignano	cultural	5000	45.069	7.685989
Blah Blah	food	5000	45.06894	7.689825
Sweet Lab	food	5000	45.06646	7.691848
Mercato Centrale	shop	5000	45.07708	7.68341
Principi di Piemonte Hotel	travel	5000	45.06524	7.682328
MiaGola Caffe	food	5000	45.06587	7.680214
Hotel NH Piazza Carlina	travel	5000	45.06583	7.689816
Scuola Holden	education	5000	45.08137	7.684072
Jazz Club Torino	performance	5000	45.06539	7.687186
Open Baladin Torino	food	5000	45.06461	7.68746
Centralino Club	nightlife	5000	45.06453	7.690955
Duomo di Torino	religion	3300	45.07341	7.685423
Teatro Stabile Torino	performance	2500	45.06933	7.691598
Teatro Carignano	performance	2500	45.06941	7.685329
Cinema Massimo	cultural	2500	45.06844	7.692857
Artiglieria Contemporary Art Center	cultural	2000	45.07056	7.689123
Caffe Mulsassano Torino	food	2000	45.07009	7.68741
Risorgimento Italiano National Museum	cultural	1800	45.06851	7.685976
Palazzo Barolo	cultural	1700	45.07481	7.679162
Cinema Romano	cultural	1600	45.06995	7.68701

Caffe Barratti & Milano	food	1500	45.06991	7.687007
Torre Littoria	travel	1500	45.07046	7.684312
Palazzo Cisterna	public	1500	45.06737	7.685831
Palazzo Chiablese	cultural	1500	45.07288	7.685588
Teatro Gobetti	performance	1300	45.06941	7.691408
Chiesa di San Lorenzo	religion	1300	45.07216	7.685331
Starbucks	food	1300	45.06636	7.681985
Palazzo Del Rettorato	education	1200	45.06928	7.688766
Da Cianci piola Caffe	food	1200	45.07342	7.683138
Royal Library of Turin	cultural	1100	45.07178	7.686961
Galleria Sabauda	cultural	1100	45.07418	7.686888
Cinema Lux	cultural	1100	45.06921	7.683209
Cappella della Sacra Sindone	religion	1000	45.07342	7.686503
Pescaria	food	1000	45.06971	7.685843
Arcadia Torino Ristorante	food	1000	45.06966	7.686995
Liberty a Deco Alessandro Macri	shop	1000	45.06934	7.686817
Sfashion Café Torino Ristorante	food	1000	45.06919	7.68652
Galleria Supalpina	shop	1000	45.06952	7.686705
Purple	shop	1000	45.06965	7.691001
Melissa	shop	1000	45.06968	7.692579
Gaudenzio Vino e Cucina	food	1000	45.06987	7.693001
Caroe Diem Coffee and Food	food	1000	45.06739	7.691447
Moi. To	shop	1000	45.06641	7.692582
Museo di Arti Decorative	cultural	1000	45.06637	7.693581
Ristorante Tre da Tre	food	1000	45.06824	7.693375
Galleria San Federico	shop	1000	45.06913	7.6837
Roses and Tea	food	1000	45.07323	7.678112
Dash Cocktail Bar	nightlife	1000	45.0586	7.678695
Scannabue Ristorante	food	1000	45.05849	7.679426
Exm	food	1000	45.06534	7.679481
Sushi del Maslé	food	1000	45.06127	7.69001
Bar Zucca	food	1000	45.0646	7.681411
Piazza Palazzo Citta	public	1000	45.07324	7.681711
La Casa del Demone	food	1000	45.0744	7.682007
Mago di Oz	nightlife	1000	45.06662	7.688328
Giardini Sambuy	public	1000	45.0638	7.680312
Piazza carlo felice	public	1000	45.06337	7.678877
L'Enoteca	food	1000	45.06581	7.680318
Rossopomodoro Torino	food	1000	45.06532	7.6789
E Cucina	food	1000	45.07215	7.678736

Ristorante Urbani Torino	food	1000	45.06168	7.681173
Koi Restaurant	food	1000	45.06701	7.681316
Libreria Luxemburg	shop	1000	45.06959	7.685804
Greenwich Village Cinema	cultural	1000	45.06718	7.692673
Signorvino	food	1000	45.06638	7.683634
Galeria Umberto I	shop	1000	45.07532	7.683735
Sibiriaki Torino	food	1000	45.07441	7.680853
Poormanger	food	1000	45.073	7.681494
Mondadori Megastore	shop	1000	45.07026	7.684011
Armeria Reale	cultural	1000	45.07178	7.686319
Dual	food	1000	45.06904	7.687577
Piazza San Giovanni	public	1000	45.07361	7.684686

D. Edges in Castello Square

Source	**Target**	**Type**	**Weight**
Scuola Holden	Palazzo Del Rettorato	undirected	1
Duomo di Torino	Cappella della Sacra Sindone	undirected	1
Chiesa di San Lorenzo	Cappella della Sacra Sindone	undirected	2
Duomo di Torino	Chiesa di San Lorenzo	undirected	1
Piazza Castello	Piazza Carignano	undirected	2
Piazza San Carlo	Piazza Castello	undirected	3
Piazza Carignano	Piazza Castello	undirected	2
Piazza Palazzo Citta	Piazza Castello	undirected	2
Giardini Sambuy	Piazza carlo felice	undirected	3
Piazza Carlo Felice	Piazza Castello	undirected	1
Giardini Reali	Giardini Sambuy	undirected	3
Piazza Castello	Giardini Reali	undirected	1
Piazza San Giovanni	Duomo di Torino	undirected	3
Mole Antonelliana	Piazza Castello	undirected	1
Museo Egizio	Piazza Castello	undirected	1
Palazzo Reale	Palazzo Madama	undirected	3
Camera Centro Italiano	Mole Antonelliana	undirected	1
Musei Reali Torino	Palazzo Reale	undirected	3
Paratissima	Artiglieria Contemporary Art Center	undirected	1
Circola dei Lettori	Palazzo Barolo	undirected	1
Palazzo Madama	Palazzo Reale	undirected	3
Porta Palatina	Piazza San Giovanni	undirected	1
Palazzo Carignano	Piazza Carignano	undirected	2
Cinema Massimo	Mole Antonelliana	undirected	3
Artiglieria Contemporary Art Center	Museo di Arti Decorative	undirected	1
Museo Nazionale del Risorgimento Italiano	Palazzo Cisterna	undirected	1
Palazzo Barolo	Artiglieria Contemporary Art Center	undirected	1
Cinema Romano	Cinema Lux	undirected	1
Palazzo Cisterna	Piazza San Carlo	undirected	1
Palazzo Chiablese	Musei Reali Torino	undirected	1
Galleria Sabauda	Palazzo Reale	undirected	3
Cinema Lux	Cinema Massimo	undirected	2

Royal Library of Turin	Armeria Reale	undirected	3
Museo di Arti Decorative	Armeria Reale	undirected	1
Greenwich Village Cinema	Cinema Massimo	undirected	1
Armeria Reale	Palazzo Reale	undirected	1
Del Cambio	Bar Cavour	undirected	2
Caffé Al Bicerin dal 1763	Piazza San Giovanni	undirected	1
Bar Cavour	Piazza Carignano	undirected	1
Blah Blah	Piazza Castello	undirected	1
Sweet Lab	Blah Blah	undirected	1
MiaGola Caffe	Sweet Lab	undirected	1
Open Baladin Torino	Signorvino	undirected	1
Caffe Barratti & Milano	Piazza Castello	undirected	1
Starbucks	Piazza San Carlo	undirected	1
Da Cianci piola Caffe	Piazza San Giovanni	undirected	2
Pescaria	Piazza Carignano	undirected	1
Caffe Mulsassano Torino	MiaGola Caffe	undirected	1
Arcadia Torino Ristorante	Galleria Supalpina	undirected	2
Sfashion Café Torino Ristorante	Caroe Diem Coffee and Food	undirected	1
Gaudenzio Vino e Cucina	Caffe Barratti & Milano	undirected	1
Caroe Diem Coffee and Food	Piazza Castello	undirected	1
Ristorante Tre da Tre	Roses and Tea	undirected	1
Roses and Tea	Piazza Castello	undirected	1
Scannabue Ristorante	Giardini Sambuy	undirected	1
Exm	Piazza San Carlo	undirected	1
Sushi del Maslé	Koi Restaurant	undirected	1
Bar Zucca	Piazza San Carlo	undirected	1
La Casa del Demone	Mercato Centrale	undirected	1
L'Enoteca	Signorvino	undirected	1
Rossopomodoro Torino Centro	Piazza carlo felice	undirected	1
E Cucina	Piazza Castello	undirected	1
Ristorante Urbani Torino	Giardini Sambuy	undirected	1
Koi Restaurant	Piazza San Carlo	undirected	1
Signorvino	Piazza San Carlo	undirected	1
Sibiriaki Torino	Da Cianci piola Caffe	undirected	1
Poormanger	Starbucks	undirected	1
Dual	Piazza Castello	undirected	1
Starbucks	Piazza Carignano	undirected	1
Starbucks	Piazza carlo felice	undirected	1

Dual	Giardini Sambuy	undirected	2
Mercato Centrale	Galleria Supalpina	undirected	1
Liberty a Deco Alessandro Macri	Galleria Supalpina	undirected	2
Galleria Supalpina	Galleria San Federico	undirected	1
Purple	Moi. To	undirected	1
Melissa	Purple	undirected	1
Moi. To	Melissa	undirected	1
Galleria San Federico	Piazza Castello	undirected	1
Libreria Luxemburg	Piazza Castello	undirected	2
Galeria Umberto I	Galleria San Federico	undirected	2
Mondadori Megastore	Libreria Luxemburg	undirected	2
Centralino Club	Dash Cocktail Bar	undirected	1
Dash Cocktail Bar	Mago di Oz	undirected	1
Porto Nuova	Starbucks	undirected	1
Principi di Piemonte Hotel	Hotel NH Piazza Carlina	undirected	1
Hotel NH Piazza Carlina	Porto Nuova	undirected	1
Torre Littoria	Piazza Castello	undirected	1
Teatro Regio Torino	Teatro Carignano	undirected	1
Jazz Club Torino	Teatro Carignano	undirected	1
Teatro Stabile Torino	Teatro Gobetti	undirected	2
Teatro Carignano	Teatro Gobetti	undirected	2
Teatro Gobetti	Teatro Stabile Torino	undirected	2
Mole Antonelliana	Cinema Massimo	undirected	1
Palazzo Madama	Mole Antonelliana	undirected	1
Porta Palatina	Duomo di Torino	undirected	1
Duomo di Torino	Torre Littoria	undirected	1
Torre Littoria	Chiesa di San Lorenzo	undirected	1

E. Nodes in Taksim Square

Place_Name	**Category**	**Total_Posts**	**Lat**	**Long**
Vodafone Park	sport	450000	41.0395	28.99488
Galata Tower	landmark	276000	41.02566	28.97416
Taksim Nevizade	public	150000	41.03478	28.97763
Istanbul Modern	cultural	149000	41.02998	28.97336
Madame Tussauds Istanbul	cultural	120000	41.03471	28.97987
Hilton Istanbul Bosphorus	travel	115000	41.04461	28.99023
Soho House Istanbul	food	81600	41.03033	28.97315
CVK Park Bosphorus	travel	70800	41.03505	28.98868
Pera Museum	cultural	68900	41.0321	28.97565
Pera Palace Hotel	travel	56500	41.03107	28.97382
Saint. Anthony's Cathedral	religion	48300	41.03241	28.97696
InterContinental Istanbul	travel	46600	41.04036	28.98843
Midpoint Beyoglu	food	32400	41.03165	28.97621
Duble Meze Bar Pera	nightlife	29200	41.03082	28.97418
The Marmara Hotel	travel	27200	41.03634	28.98637
Grand Hyatt Istanbul	travel	27100	41.04065	28.98872
Arter	cultural	26400	41.03054	28.97669
Galataport Istanbul	shop	24700	41.02813	28.98513
Salt Beyoglu	cultural	22400	41.03228	28.97657
Rixos Pera	travel	19900	41.0334	28.97526
Taksim Gezi Park	public	17300	41.03835	28.98689

Asmalimescit/ Tunel	nightlife	17000	41.0299	28.97484
Mikla Restaurant	food	14500	41.03113	28.97408
Nomads Istanbul	food	14300	41.03608	28.98506
Ara Kafe	food	14000	41.03298	28.9771
People Istanbul	food	12900	41.04015	28.98869
Radisson Blu Hotel, Istanbul pera	travel	12900	41.03047	28.97212
Arada Café	food	12100	41.0266	28.97816
Starbucks Coffee, Taksim	food	11500	41.0358	28.98268
Istanbul Barosu	public	11300	41.03043	28.97553
Narmanli Han Beyoglu	shop	11200	41.02928	28.97492
Divan Hotel	travel	10000	41.04127	28.98737
Hakki Zade 1864	food	6000	41.03446	28.97984
Kasimpasa Stadium	sport	6000	41.03281	28.97306
Buyuk Londra Hotel	travel	6000	41.03257	28.97523
Taksim Camii	religion	5000	41.03697	28.9843
Point Hotel Taksim	travel	5000	41.04078	28.98614
Akbank Sanat	cultural	5000	41.03611	28.98313
Mask Live Pera	performance	5000	41.03025	28.97506
Zubeyir Ocakbasi	food	5000	41.03659	28.98304
Balkon Restaurant & Bar	food	5000	41.03005	28.9744
Adahan Istanbul	travel	5000	41.02913	28.97332
Cecconi's	food	5000	41.03034	28.97314
Palazzo Donizetti	travel	5000	41.03058	28.97364
Salon	performance	5000	41.02835	28.97193
Monkey Istanbul	nightlife	5000	41.02836	28.97213
Tren Pera Istanbul	nightlife	5000	41.03151	28.97495
Klein.garten	nightlife	5000	41.03175	28.97516
Ravouna 1906	food	5000	41.03087	28.97625
Mesher	cultural	5000	41.03047	28.97591

Turk Alman Kitabevi Café	food	5000	41.0292	28.97544
Galatasaray Meydani	public	5000	41.03349	28.97735
Ficcin	food	5000	41.03253	28.97602
Peymane	food	5000	41.03247	28.97528
Anna Laudel	cultural	5000	41.0339	28.98756
Elyisum Hotel	travel	5000	41.04177	28.98495
Emek Sahnesi	cultural	3900	41.03481	28.97986
Taksim AKM	landmark	3600	41.03677	28.98783
Institut francais de Turquie	cultural	2000	41.03622	28.98393
ITU Faculty of Architecture	education	2000	41.04129	28.98951
Yapi kredi Kultur Sanat	cultural	2000	41.03322	28.97715
Istanbul Illusion Museum	cultural	2000	41.02919	28.97498
Cite De Pera / Cicek Pasaji	food	1500	41.03395	28.97813
Tarihi Galatasaray Hamami	cultural	1500	41.03284	28.97992
Tatavla Tiyatro	cultural	1000	41.03177	28.98245
Minimuzikhol	nightlife	1000	41.03263	28.98508
Hayalhane - Mahser-i Cumbus	cultural	1000	41.03417	28.98152
Taksim Maksemi Cumhuriyet Sanat Galerisi	cultural	1000	41.03661	28.98508
Kizilkayalar Taksim	food	1000	41.03629	28.98535
Hagia Triada Greek Orthodox Church	religion	1000	41.03589	28.98494
RX Istanbul	nightlife	1000	41.03365	28.98448
Swiss Hotel Bosphorus	travel	1000	41.04123	28.99859
Rika Cihangir	food	1000	41.03061	28.98399
Gezi Hotel Bosphorus	travel	1000	41.03878	28.98909
Avantgarde Hotel	travel	1000	41.03837	28.98854
City Lights Bar	nightlife	1000	41.04013	28.98811
Cafe Italiano	food	1000	41.03969	28.98583
Taxim Hill Hotel	travel	1000	41.03663	28.98587
Gezi Istanbul Brasserie	food	1000	41.03627	28.98741

Al Madina Restaurant Istanbul	food	1000	41.036	28.98371
Czn Burak	food	1000	41.0356	28.9835
Zencefil	food	1000	41.03665	28.98281
Muaf Beyoglu	food	1000	41.03663	28.98277
Bova	performance	1000	41.03615	28.98179
Ses Tiyatrosu	cultural	1000	41.03447	28.97909
Kastel	nightlife	1000	41.03482	28.97702
Kumsaatiblues	performance	1000	41.02973	28.97388
Asmali Sahne	performance	1000	41.02955	28.97363
Slope	nightlife	1000	41.02992	28.97405
Kulp	nightlife	1000	41.02991	28.97421
Baylo	food	1000	41.02935	28.97318
Asmali Saki Meyhanesi	food	1000	41.03028	28.97449
Grand Hotel Halic	travel	1000	41.02919	28.9723
Galata Times Boutique Hotel	travel	1000	41.028	28.97224
IKSV	cultural	1000	41.02843	28.97205
Firuze- Beyoglu	nightlife	1000	41.02833	28.97193
Kitchenette Taksim	food	1000	41.0367	28.9866
Borusan Sanat	cultural	1000	41.03048	28.97587
Istanbul Sanayi odasi Odakule	public	1000	41.03202	28.9752
Mado	food	1000	41.03394	28.9781
Zilberman Gallery	cultural	1000	41.03266	28.97694
Misir Apartmani	shop	1000	41.03263	28.97723
Galeri Nev	cultural	1000	41.0329	28.97702
Versus Art Project	cultural	1000	41.03413	28.98048
Art On Istanbul	cultural	1000	41.03117	28.97519
Galerist	cultural	1000	41.03191	28.97532
Cokcok Thai	food	1000	41.03287	28.97574

Trt Istanbul Radio	food	1000	41.03288	28.97457
IBB Ek Hizmet binasi	public	1000	41.03157	28.97422
Galatasaray Lisesi	education	1000	41.033	28.97915
Ataturk Kitapligi	education	850	41.03919	28.98946
Saint Esprit Cathedral	religion	600	41.04477	28.98682
Tiyatro Pera	cultural	500	41.03399	28.98439
Beyoglu Lisesi	education	500	41.03174	28.97626
ITU Gumussuyu Campus	education	3000	41.03818	28.9919
Macka Park	public	5000	41.04491	28.99341

F. Edges in Taksim Square

Source	Target	Type	Weight
Taksim Nevizade	Galatasaray Meydani	undirected	3
Taksim Gezi Park	Galatasaray Meydani	undirected	2
Asmalimescit/ Tunel	Taksim Nevizade	undirected	2
Istanbul Barosu	Istanbul Sanayi odasi Odakule	undirected	2
Galatasaray Meydani	Asmalimescit/ Tunel	undirected	1
Istanbul Sanayi odasi Odakule	IBB Ek Hizmet binasi	undirected	2
IBB Ek Hizmet binasi	Istanbul Barosu	undirected	2
Hilton Istanbul Bosphorus	InterContinental Istanbul	undirected	2
CVK Park Bosphorus	InterContinental Istanbul	undirected	2
Pera Palace Hotel	Galata Times Boutique Hotel	undirected	2
InterContinental Istanbul	The Marmara Hotel	undirected	2
The Marmara Hotel	Point Hotel Taksim	undirected	1
Grand Hyatt Istanbul	The Marmara Hotel	undirected	1
Rixos Pera	Radisson Blu Hotel, Istanbul pera	undirected	1
Radisson Blu Hotel, Istanbul pera	Rixos Pera	undirected	2
Divan Hotel	Grand Hotel Halic	undirected	1
Buyuk Londra Hotel	Adahan Istanbul	undirected	2
Point Hotel Taksim	Elyisum Hotel	undirected	2
Adahan Istanbul	Palazzo Donizetti	undirected	2
Palazzo Donizetti	Galata Times Boutique Hotel	undirected	1
Elyisum Hotel	Point Hotel Taksim	undirected	1
Swiss Hotel Bosphorus	Gezi Hotel Bosphorus	undirected	1
Gezi Hotel Bosphorus	Taxim Hill Hotel	undirected	1
Avantgarde Hotel	Grand Hotel Halic	undirected	1
Taxim Hill Hotel	Avantgarde Hotel	undirected	1
Grand Hotel Halic	Galata Times Boutique Hotel	undirected	1
Galata Times Boutique Hotel	Adahan Istanbul	undirected	1
Duble Meze Bar Pera	Asmalimescit/ Tunel	undirected	3
Asmalimescit/ Tunel	Duble Meze Bar Pera	undirected	3
Monkey Istanbul	Klein.garten	undirected	2
Tren Pera Istanbul	Firuze- Beyoglu	undirected	1
Klein.garten	Minimuzikhol	undirected	2
Minimuzikhol	RX Istanbul	undirected	2
RX Istanbul	Klein.garten	undirected	2

City Lights Bar	Kulp	undirected	1
Kastel	Monkey Istanbul	undirected	1
Slope	Kulp	undirected	1
Kulp	Firuze- Beyoglu	undirected	1
Firuze- Beyoglu	Slope	undirected	1
Vodafone Park	Kasimpasa Stadium	undirected	2
Kasimpasa Stadium	Vodafone Park	undirected	2
Saint. Anthony's Cathedral	Saint Esprit Cathedral	undirected	2
Taksim Camii	Hagia Triada Greek Orthodox Church	undirected	1
Hagia Triada Greek Orthodox Church	Saint. Anthony's Cathedral	undirected	2
Soho House Istanbul	People Istanbul	undirected	3
Midpoint Beyoglu	Ara Kafe	undirected	1
Mikla Restaurant	Cite De Pera / Cicek Pasaji	undirected	1
Nomads Istanbul	People Istanbul	undirected	3
Ara Kafe	Turk Alman Kitabevi Café	undirected	2
People Istanbul	Cite De Pera / Cicek Pasaji	undirected	2
Arada Café	Al Madina Restaurant Istanbul	undirected	3
Starbucks Coffee, Taksim	Peymane	undirected	1
Hakki Zade 1864	Al Madina Restaurant Istanbul	undirected	3
Zubeyir Ocakbasi	Al Madina Restaurant Istanbul	undirected	2
Balkon Restaurant & Bar	Ficcin	undirected	1
Cecconi's	Ravouna 1906	undirected	2
Ravouna 1906	Soho House Istanbul	undirected	2
Turk Alman Kitabevi Café	Cite De Pera / Cicek Pasaji	undirected	1
Ficcin	Cite De Pera / Cicek Pasaji	undirected	1
Peymane	Ficcin	undirected	1
Cite De Pera / Cicek Pasaji	Starbucks Coffee, Taksim	undirected	2
Kizilkayalar Taksim	Al Madina Restaurant Istanbul	undirected	3
Rika Cihangir	Baylo	undirected	1
Cafe Italiano	Starbucks Coffee, Taksim	undirected	1
Gezi Istanbul Brasserie	Cafe Italiano	undirected	2
Al Madina Restaurant	Cite De Pera / Cicek Pasaji	undirected	2
Czn Burak	Kizilkayalar Taksim	undirected	2
Zencefil	Kizilkayalar Taksim	undirected	1
Muaf Beyoglu	Baylo	undirected	1
Baylo	Ravouna 1906	undirected	1
Asmali Saki Meyhanesi	Starbucks Coffee, Taksim	undirected	1
Kitchenette Taksim	Starbucks Coffee, Taksim	undirected	2

Mado	Starbucks Coffee, Taksim	undirected	2
Cokcok Thai	Cite De Pera / Cicek Pasaji	undirected	2
Trt Istanbul Radio	Istanbul Sanayi odasi Odakule	undirected	1
Istanbul Modern	Pera Museum	undirected	2
Madame Tussauds Istanbul	Istanbul Illusion Museum	undirected	3
Pera Museum	Tiyatro Pera	undirected	1
Arter	Salt Beyoglu	undirected	2
Salt Beyoglu	Pera Museum	undirected	3
Akbank Sanat	Salt Beyoglu	undirected	3
Mesher	Anna Laudel	undirected	1
Anna Laudel	Salt Beyoglu	undirected	2
Emek Sahnesi	Taksim AKM	undirected	2
Taksim AKM	Taksim Maksemi Cumhuriyet Sanat Galerisi	undirected	3
Institut francais de Turquie	Taksim AKM	undirected	2
Yapi kredi Kultur Sanat	Taksim AKM	undirected	3
Istanbul Illusion Museum	Tarihi Galatasaray Hamami	undirected	2
Tarihi Galatasaray Hamami	Madame Tussauds Istanbul	undirected	2
Tatavla Tiyatro	Tiyatro Pera	undirected	2
Hayalhane - Mahser-i Cumbus	Tatavla Tiyatro	undirected	2
Taksim Maksemi Cumhuriyet Sanat Galerisi	Yapi kredi Kultur Sanat	undirected	2
Ses Tiyatrosu	Emek Sahnesi	undirected	1
IKSV	Emek Sahnesi	undirected	2
Borusan Sanat	IKSV	undirected	3
Zilberman Gallery	Galerist	undirected	2
Galeri Nev	Zilberman Gallery	undirected	2
Versus Art Project	Galerist	undirected	2
Art On Istanbul	Versus Art Project	undirected	2
Galerist	Versus Art Project	undirected	2
Tiyatro Pera	Hayalhane - Mahser-i Cumbus	undirected	1
Mask Live Pera	Asmali Sahne	undirected	1
Salon	Kumsaatiblues	undirected	2
Bova	Kumsaatiblues	undirected	3
Kumsaatiblues	Asmali Sahne	undirected	1
Asmali Sahne	Salon	undirected	1
ITU Faculty of Architecture	Ataturk Kitapligi	undirected	3

Galatasaray Lisesi	Ataturk Kitapligi	undirected	2
Ataturk Kitapligi	Taksim AKM	undirected	3
Beyoglu Lisesi	Galatasaray Lisesi	undirected	2
Galata Tower	Taksim AKM	undirected	3
Taksim AKM	Galata Tower	undirected	3
Beyoglu Lisesi	Ataturk Kitapligi	undirected	2
Taksim AKM	ITU Faculty of Architecture	undirected	1
Taksim AKM	Ataturk Kitapligi	undirected	2
Taksim AKM	IKSV	undirected	1
Borusan Sanat	Taksim AKM	undirected	1
Taksim Maksemi Cumhuriyet Sanat Galerisi	Taksim AKM	undirected	1
Macka Park	Gezi Park	undirected	2
ITU Faculty of Architecture	Macka Park	undirected	2
ITU Faculty of Architecture	ITU Gumussuyu Campus	undirected	3