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Applying Human-scale Understanding to Sensor-based Data

Generating Passive Feedback to Understand Urban Space Use

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Civilingenjörsprogrammet i system i teknik och samhälle

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Abstract

The aim of this thesis is to investigate how parametrization of large-scale person movement data can contribute to describing the use of urban space. Given anonymous coordinate and timestamp data from a sensor observing an open-air mall, movement-based parameters are selected according to public life studies, behavioral mapping, and space syntax tools. The thesis aim is operationalized by answering how well the parametrizations perform in capturing urban space use, as well as investigating how the use is described when applying the parameterized data in selected urban space use tools. Also, the parameterized data are evaluated as time series to investigate possible further understanding of urban space use. The parametrization performance is evaluated by accuracy and F_1-score and time series forecasts are evaluated by root mean square error (RMSE) and mean absolute error (MAE). The results indicate a parametrization accuracy of 93% or higher, while a high yet fluctuating F_1-score indicates that the parameterizations might be sensitive to imbalanced data, and that accuracy alone might not be sufficient when evaluating urban data. The parameterized data applied in the selected urban space use tools highlights the granularity achieved from sensor-based data. In the time series analysis, a Facebook Prophet forecast model is implemented, with an MAE of 8.6% and RMSE of 11.7%, outperforming a seasonal naïve forecast implementation with an MAE of 14.1% and RMSE of 18.8%. The thesis finds that time series modelling adds to understanding patterns and changes of use over time and that the approach could be developed further in future studies. In answering how the urban space is used, the thesis develops a new methodology. This methodology combines human-scale understanding of urban space use with large-scale data, generating citizen passive feedback.

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Populärvetenskaplig sammanfattning

Vikten av att förstå hur en plats, eller ett stadsrum, faktiskt används härstammar ur det faktum att användningen ofta avviker från vad som var planerat. Genom en utökad förståelse för användningen av en plats går det exempelvis att anpassa platsens utformning efter faktisk användning. För att uppnå denna djupare förståelse finns flera olika tillvägagångssätt. Ett sätt är att använda de analoga teorier och verktyg som under lång tid har utvecklats av arkitekter och stadsplanerare, med avsikt att förstå sig på människors beteenden i olika stadsrum. Dessa urbana analysverktyg innefattar exempelvis ramverk för att kartlägga människors aktivitet. Ett annat sätt är att analysera stora datamängder för att utvinna generella rörelsemönster eller detaljerade trender.

I denna uppsats presenteras en metod som kombinerar dessa två tillvägagångssätt i syfte att väva in de analoga teoriernas mänskliga utgångspunkt med de möjligheter som uppstår vid analys av stora datamängder. Genom att utveckla algoritmer kan rörelse-baserad information utvinnas, eller parametriseras, ur data från människors rörelse. Metoden innebär i kontexten av denna studie således en parametrisering av rörelse-data från en sensor uppsatt på shoppinggatan Kompassen i Göteborg. Urvalet av parametriseringar har baserats på de urbana analysverktygen. Detta sammanfattas i studiens övergripande syfte: att undersöka hur parametrisering av storskalig rörelsedata kan bidra till att förklara användningen av stadsrum.

För att uppnå detta syfte besvaras tre frågeställningar. Först utvärderas hur väl det parametriserade rörelsedatat kan fånga upp användningen av stadsrum. Sedan undersöks hur användningen gestaltas genom att det parametriserade datat appliceras i utvalda urbana analysverktyg. Till sist analyseras datat som tidsserier i syfte att undersöka hur en förståelse över tid kan öka förståelsen för användningen av stadsrum.

Genom att utgå från rörelsedata utvanns personers hastighet, startpunkt, och destination. Vidare parametriserades klasserna butiksinteraktion, grupptillhörighet, och stillastående i enlighet med de urbana analysverktygen. Vid utvärdering av dessa tre klasser visar studiens resultat att användningen av stadsrummet fångas upp till hög grad och uppnår åtminstone 93% i precision. Dock visar resultaten även att träffsäkerheten minskar ju mer obalanserat datat är. Detta innebär att ju lägre frekvent en klass är i datat desto svårare är den att fånga upp.

När det parametriserade datat används i de urbana analysverktygen, visar resultaten att det utvunna datat bidrar med en högre upplösning som kan bana väg för ny förståelse för hur stadsrum används. Den högre upplösningen möjliggör även för tidsserieanalys av det parametriserade datat. Resultaten pekar på en mer detaljerad förståelse för trender och användningen av stadsrummet över tid. Till exempel implementeras verktyget Facebook Prophet som i detta fall prognostiserar andelen med grupptillhörighet. För en prognos på två veckor uppnås ett genomsnittligt absolutfel på 8.6%, vilket anses vara ett träffsäkert resultat. På så sätt medför möjligheten att prognostisera användning och identifiera avvikelser från trender ett ytterligare bidrag till förståelsen för hur platsen används.

Tidsserieanalysen uppvisar stor potential och tolkningar från såväl tidsserierna som prognosmodeller har utrymme att vidareutvecklas. I framtida studier bör även algoritmer för fler aktivitetsbaserade parametrar, till exempel sittande eller samtalande, utvecklas. Uppsatsens fokus kretsar kring att skapa förståelse för hur ett stadsrum används och lämnar således frågan varför åt framtida studier, där resultat från denna studie kan fungera som viktigt underlag.

Studiens metod tillför ett mänskligt perspektiv till stora datamängder och bidrar på så sätt till ett bredare underlag för hur stadsrum används. Med utgångspunkt i urbana analysverktyg har insamlad sensordata parametriserats till viktiga rörelse-baserade klasser. Detta underlag motsvarar en passiv återkoppling från användarna av stadsrummet som därigenom förklarar hur en plats faktiskt används.

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1. Introduction

As cities are challenged with balancing environmental, social and economic sustainability, smart cities are considered the contemporary solution. With the great promise of smart cities, urban data are leveraged to improve them (Townsend, 2013). Internet of things, digital twins and industry 4.0 use data-centric approaches toward increasing efficiency in many of the city's functions. However, the billion-dollar evaluated smart city industry can prove useful in more cases than in optimization and efficiency (Townsend, 2013). In a critique toward technocratic urban development, Jacobs (1961, p. 566-570) argues that simplifying city complexity, to an optimization problem, marginalizes citizens and local culture. Half a decade later, in an analogous critique, Townsend (2013, p. 314) warns that smart city applications dismissing urban science runs the risk of being deeply misleading.

Urban science disciplines, such as public life studies (Gehl & Svarre, 2013; Whyte, 1980), behavioral mapping (as described by Sommer & Sommer, 1997) and space syntax (introduced by Hiller & Hanson, 1984), have since the 1960s established a collection of urban space use tools. These tools, based on manual observational techniques, highlight important data to understand activity in cities. With new data sources, larger datasets can be ensembled and new applications are found (Arribas-Bel, 2014). Considering that applications solely based on big datasets in general struggle to address the complex nature of cities, the large datasets' strength is providing more granular data to urban science disciplines (Kitchin, 2013). As urban spaces are not always used as intended (Sommer & Sommer, 1997), large amounts of data could help develop new understanding of urban interventions (Matějček & Přibyl, 2020).

With the new data sources, citizen resources can be utilized to a greater extent (Komninos, 2008, p. 248). For example, the European Commission finds that new technology offers novel applications to bolster citizen participation in urban development (EU, n.d.). Citizen participation and feedback is important, not only as a democratic implementation but also as a means of developing cities (Ma, 2017). One restriction on citizen feedback, though, is that citizens' recollections of activity in the city runs the risk of being inaccurate (Fan Ng, 2015). Moreover, there are multiple barriers to address before citizen participation can occur, where unwillingness to participate and lack of resources are two examples (OECD, 2019). However, using observationally collected data, participation unwillingness and inaccurate recollections can be curbed, developing an understanding of how a space is truly used (Vaughan, 2001; Fan Ng, 2015; Gehl, 2010). Further, using new technology, such as sensors, observational data can be continuously collected. In this sense, through leveraging large-scale data with human-scale understanding from the urban space use tools, a citizen passive feedback is generated.

In this thesis, a methodology combining human-scale observational knowledge with large-scale data is developed. This is achieved by parameterizing large-scale person movement data collected by a camera-based sensor observing Kompassen, an open-air shopping mall in Gothenburg, Sweden. The parameterizations are selected in accordance with urban space use tools as a foundation for developing classification algorithms for selected movement patterns, connecting large-scale data to human-scale understanding. Furthermore, time series data are extracted and evaluated to nuance the understanding of how the urban space is used.

1.1 Purpose Statement and Research Questions

The aim of the thesis is to investigate how large-scale movement data can contribute to describing the use of urban space. Using movement data from a camera-based sensor observing an open-air mall, the aim is accomplished by parameterizing the data according to urban space use tools.

The aim is captured in the following three research questions:

- How well can parameterization algorithms describe urban space use?
- How is the use of urban space described when the parameterized data are applied in urban space use tools?
- How can time series modelling aid in understanding the use of urban space?

1.2 Central Concepts

Two central concepts for this thesis are parameterization and urban space use tools. A parameter represents a specific characteristic of a certain use of urban space. Parameters are extracted, or translated, from the large-scale movement data by developing algorithms in what the thesis refers to as parameterization. Urban space use tools are defined in this thesis as an ensemble of tools from urban science disciplines using manual observational methods to understand the use of urban space.

1.3 Thesis Outline

To fulfill the aim and to answer the research questions, the thesis is structured as follows. Section 2 first introduces background on the shopping-mall and the technical characteristics, in order to get an understanding of the urban area and the data. Section 2 then continues with presenting background on urban space use tools which are essential in the thesis methodology. The thesis methodology in section 3 explains the cross-section between human-scale understanding and large-scale data processing, motivating parameterizations and introducing time series forecasting methods. The results and analysis in section 4 are structured according to the research questions; first, by investigating if parameterizations can capture urban space use, then understanding use when applied in the selected tools, and finally by exploring possible new understanding of urban space use over time. In section 5, the answered research questions are discussed in the perspective of the thesis aim. Conclusions are presented in section 6.

2. Background

The background section is divided into three parts. As the thesis data was made available from an AFRY Flowity sensor observing the open-air shopping mall Kompassen, an introduction to the urban space and the sensor is in order. In section 2.1, the open-air shopping mall is introduced as an urban space. A brief background on AFRY Flowity and the movement data gathered from the sensor, used as input data in this thesis, is presented in section 2.2. Further, an introduction to the forecasting framework is presented in the same section. To broaden the understanding of important parameters, section 2.3 presents a theoretical background of urban space use tools.

2.1 Kompassen as an Urban Space

Kompassen is an open-air mall on Fredsgatan in Gothenburg, Sweden. Centrally located, it accommodates multiple stores, a café and a gym. The walk-through mall is covered by a transparent roof. There are two main entrances to Kompassen, both located on Fredsgatan. The stores fill the Kompassen facade on both sides. South of Kompassen is Harry Hjörnes plats, a small plaza with a large bench, some trees, a café and mixed-use buildings. North of Kompassen, Fredsgatan continues as a pedestrian-only shopping street, continuing past more malls until it reaches Brunnsparken. As a part of the city center of Gothenburg, the majority of activity is during store opening hours. Thousands walk on Fredsgatan every day to run errands, take a stroll, or pass by to get to other parts of Gothenburg's city center or transit opportunities.

Figure 1. Kompassen seen from Harry Hjörnes plats. The AFRY Flowity sensor is visible at the top of the image, indicated by the red circle.

2.2 Technical Background & Data

The data used in this thesis is anonymised person movement data collected using an AFRY Flowity sensor observing the open-air mall Kompassen. In section 2.2.1 the camera-based sensor is described. Section 2.2.2 presents the input data retrieved from the sensor. Finally, the time series model implemented in this thesis is briefly overviewed in section 2.2.3.

2.2.1 AFRY Flowity

AFRY Flowity is a machine vision platform used for identifying objects (AFRY, n.d.). For this thesis, the sensor anonymously identifies and tracks person movement patterns as x- and y-coordinates projected on a two-dimensional surface. Illustrated in Figure 2 is a stick-figure representation of a snapshot from sample video footage and how it is projected as coordinate data.

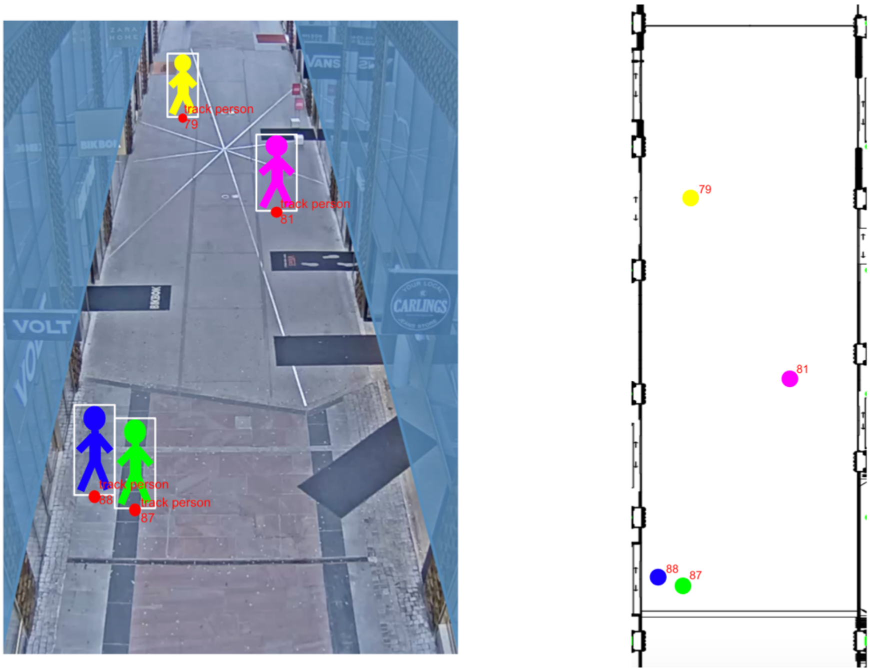

Figure 2. A stick-figure representation of how AFRY Flowity identifies persons and records them as x- and y-coordinates.

The tracking algorithm identifies features in order to synthesize a person’s movement until the person leaves the frame, or tracking is interrupted. For example, one person walking into a store and ten minutes later walking out will be represented as two separate IDs.

2.2.2 Input Movement Data

The input data, retrieved from the sensor, are person IDs, x- and y- coordinates and timestamps. The timestamps give the date and time in a tenth of a second resolution from when the data were collected. The collected data are summarized in Table 1.

Table 1. An overview of the input movement data for this report.

Name	Description	Data Structure	Example value	Unit
Person ID	*Unique ID for a detected person*	*int*	*532001*	*N/A*
x-/y-coordinate	x-/y-*position of the ID on a 2D projection*	*float*	*3.2*	*m*
Timestamp	*Timestamp of collected data*	*datetime*	*2021-03-21T13:03:36.8*	*Year, month, day, hour, minute, second, tenth of a second*

The input data are collected in a ten frame-per-second resolution, generating an average ten values per present ID and second. As the amount of data depends on registered IDs, data size differs from day to day. To illustrate an approximate size, 2.3 million readings are collected on an ordinary Wednesday in March, 2021. Daily movement data are availabe from February 12th, 2021, until April 20th, 2021.

2.2.3 Forecasting Framework

The time series forecasting tool used in this thesis is Facebook Prophet (hereafter referred to as Prophet). Prophet was released as an open-source software in 2017 and was developed with the ambition to be as flexible as more advanced forecasting tools, meanwhile being easy to implement (Taylor & Letham, 2018). In its core, Prophet is an additive regression model, meaning that it sums several components when representing the data (Rafferty, 2021). The choice of components is primarily based on the characteristics and extent of the dataset and could for example be a general trend component, a yearly component, a daily component, a holiday component, etc. (Rafferty, 2021).

Taylor and Letham (2018, p. 17) present Prophet as containing properties for what they call "analyst-in-the-loop modelling". Using some model characteristics, such as changepoints, holidays and smoothing, analysts can apply domain knowledge to improve the model fit. These characteristics and component decomposition are of interest in modelling the parameterized data, visualizing and understanding the time series.

Prophet has been implemented in numerous time series analyses, i.e., for train passengers forecasting (Pontoh et al., 2021), groundwater level forecasting (Aguilera et al., 2019), or for forecasting of the financial markets (Fang et al., 2019). A more in-depth presentation and mathematical formulation of the components, parameters and modifications of the Prophet model used on the urban data in this thesis is presented in the methodology section 3.5.

2.3 Urban Space Use Tools

Multiple theoretical corpuses have analysed, quantified and created tools to understand urban space use. The three main theoretical frameworks also used in this thesis are space syntax, behavioral mapping, and public life studies. All frameworks depend on manual observational studies and are of a similar scale as the urban area, Kompassen. The combination of theories helps identify key parameters in the person movement data, which aid in understanding the use of urban space. The presented theories and tools also serve as a background to how urban space use has been analysed.

The theoretical background section is constructed as follows. First, the space syntax research field is introduced in section 2.3.1. Then, parts of the behavioral mapping research corpus are highlighted in section 2.3.2. Lastly, selected work from the public life studies field are presented in section 2.3.3.

2.3.1 Space Syntax

Hillier and Hanson (1984) introduce space syntax as a framework to analyse the social effects of building compositions creating spaces, highlighting the syntax difference between space and society. In this research area, software and analyses have been developed to quantify movement patterns. The quantitative approach toward understanding the use of urban space makes the research area of interest.

Notable contributions have been aiding the renovation of Tate Modern (Dursun, 2007), and understanding space usage of train stations (van der Hoeven & van Nes, 2013). Space syntax theories and applications are usually of larger scales, such as neighborhood flows or larger indoor environments, than Kompassen. However, some space syntax tools are applicable in the scale of the shopping mall, summarized in the *Space Syntax Observation Manual* (Vaughan, 2001). In the manual, multiple methods for tracking and quantifying human movement in areas or streets are presented.

The *gate method* presented in the Vaughan (2001) manual, suggests counting the amount of people moving in the urban area. Observing different parts of the urban area, the person count can be divided into different classes, such as based on sex or age. It is also of interest to compare findings between different parts of the day and days of the week. Vaughan (2001) suggests that a normal division of the day is splitting it into two-hour observational windows, between 8 am to 10 pm. Further, Vaughan (2001) proposes splitting the days of the week into three categories: Monday - Thursday, Friday, and Saturday - Sunday. The reasoning is that the use is different during working days, the weekend, and the day before the weekend.

The *static snapshot* method maps static urban space use (Vaughan, 2001). Using a map of the urban space, persons' behavior and activity snapshot can be created. Suggested activity classes are standing, sitting, walking and talking; however, categories are to be selected or expanded to fit the location (Vaughan, 2001). To complement *static snapshot*, Vaughan (2001) suggests the *movement traces* method (Vaughan, 2001). Analyzing person movement traces, precise routes taken in the urban space are recorded. The combination of tools indicates preferred movement patterns by understanding user origin and destination and mapped static use of the urban area.

2.3.2 Behavioral Mapping

Behavioral mapping is a research tool developed in the 1970s and is used for systematic observations of people's behavior in specific places and during specific times (Goličnik Marušić & Marušić, 2012, p.115). The tool is used for example within the fields of environmental psychology and urban planning, two areas where understanding space use is of great importance (Sommer & Sommer, 1997). Behavioral maps create a direct connection between the physical and functional attributes of the place and the users of the place (Goličnik Marušić & Marušić, 2012, p.114).

There are two main orientations of behavioral mapping, namely place-centered mapping and individual-centered mapping (Sommer & Sommer, 1997). Place-centered mapping determines if a space is used and which types of activities are performed where, also taking time into consideration (Rigolon, 2013; Sommer & Sommer, 1997). Examples of spaces mapped and understood through this approach include libraries, stores, parks, plazas etc. (Sommer & Sommer, 1997). Individual-centered mapping, instead focuses on an individual's actions through space and time (Sommer & Sommer, 1997), and provides a mapping of individual's behaviors classified in different user groups (Fan Ng, 2015). Using individual-centered mapping, store customer and hospital patient movement are example applications (Rigolon, 2013). The combination of individual-based and place-based mapping offers a nuanced understanding of behaviors in the space.

Behavioral mapping methodology is flexible and is adjusted according to the desired end product. Data collection can be both map-based and table-based, allowing for data to be stored not only on maps (Goličnik Marušić & Marušić, 2012). In behavioral mapping, different classes and activities to study are codified based on research purpose (Sun et al., 2019). Similar to the presented space syntax theory (Vaughan, 2001), data collection at different times is important to understand changing use patterns (Sommer & Sommer, 1997).

Goličnik & Ward (2009) suggest two approaches to collecting data. The first, detailed approach is to record the precise location of each individual on a site plan and through that gain a deeper understanding of how specific urban structures relates to specific behaviors (Goličnik & Ward, 2009). This approach is similar to the *static snapshot* methodology presented in the space syntax manual (Vaughan, 2001). The other, less granular, approach is deciding subspaces and mapping general behavior from the different subspaces (Goličnik & Ward, 2009). To conclude, the result of the behavioral mapping methods should be seen as an empirical illustration of actual behavior, something which might stand in contrast to what was planned for the space or nuance the understanding of space use (Sommer & Sommer, 1997).

2.3.3 Public Life Studies

The third theoretical framework for studying urban space use, is referred to as public life studies. The importance of understanding public life came to light in the 1960s, after Jane Jacobs (1961) critique. Changing the views of many urban planners and pioneering a new perception of the city, Jacobs (1961) expressed rhetoric toward urban planning for active human use of the city, addressing issues such as safety, well-being, and active cities. William H. Whyte (1980) further contributed to the research corpus with new methodology and systemic approaches in understanding public life. Jan Gehl has added to the understanding of public life since the 1970s (Gehl & Svarre, 2013). Several other publications, such as Cooper Marcus & Francis (1976), Project for Public Spaces (n.d.) and Ewing & Handy (2013), have contributed to the public life studies corpus. However, only Whyte's and Gehl's systematic approaches, methods and tools are considered in this thesis.

Both Gehl's and Whyte's research are based on observations of urban spaces. Whyte (1980) uses camera-footage to observe human activity in his *The Social Life of Small Urban Spaces*. Observing different city sceneries, such as plazas, indoor malls and parks, Whyte depicts user behavior and analyses why they are present. Using the quantified material, Whyte finds larger understanding in the use of the urban spaces. This is, for example, applied to understand the use of a plaza's seating opportunities or effective person capacities in urban space. Gehl (2010) has also based his theories on urban use observations. Categorizing different use, Gehl has developed and uses multiple techniques and tools to quantify important user activity in urban space (Gehl & Svarre, 2013). His work has been used to understand and change streets, parks and plazas in Copenhagen, London and New York (Gehl & Svarre, 2013).

Gehl and Svarre (2013) summarize some of the observational tools in four observational themes: *counting, mapping, tracing and tracking*. In the following paragraphs, these themes are introduced and contextualized using all of the presented urban space use tools presented in section 2.3.

Gehl and Svarre (2013) argue that anything can be counted, making the tool universal in public life studies. *Counting*, and thus quantifying, user activity over longer periods of time can illustrate a daily rhythm in the use of the urban space. Activity counting can be used to compare quantified activity over longer periods of time, such as weeks, months or years (Gehl & Svarre, 2013). Whyte (1980) uses counting to present observations, visualizing full day sitting patterns or comparing different park use densities. The space syntax *gate method*, counting users in the urban space, is a method encompassed within the theme *counting* and from now on referenced as a part of this observational theme.

People's activity can also be mapped and plotted, which Gehl and Svarre (2013) call *mapping*, or behavioral mapping, as described in section 2.3.2. For example, finding *good places to stand*, Gehl studies and maps preferred places (Gehl, 2011). He found that people often carefully choose a place to stand at the edge of the public square and gravitate toward built objects such as walls for protection. People standing in the middle of the square are usually talking with someone else, as they tend to stop and talk where they are (Gehl, 2011). Whyte (1980) finds similar observations in his studies.

Tracing depicts person movement in the urban area, making it possible to understand general movement patterns (Gehl & Svarre, 2013). By tracing movement, or *movement traces* as described in section 2.3.1, dominant and subordinate lines can appear, and less trafficked areas of the urban space are highlighted (Gehl & Svarre, 2013). Tracing patterns, like most urban space observations, will shift depending on time, which is similar to the reasoning regarding daily and weekly division as reported by Vaughan (2001).

Tracking can be used to follow individual persons' behavior, understanding specific characteristics such as walking speed, or understanding routes to certain destinations (Gehl & Svarre, 2013). Tracking person movement speed over different times of day, different users with different speeds are observed (Gehl & Svarre, 2013). For example, elderly, families and promenading people generally have slower tempo than goal-oriented pedestrians (Gehl & Svarre, 2013). Further, walking speeds depend on day of the week and weather, where weekdays and harsh weather offer faster tempo and good weather and weekends usually entail slower speed (Gehl & Svarre, 2013). The individual-based mapping tool has many similarities with *tracking*, classifying individual's use and patterns.

To conclude, the four presented observational themes span the three theoretical corpuses presented in this section and provides a representation of the central tools used in understanding how urban space is used.

3. Methodology

Based on the human-scale understanding from section 2.3, large-scale data were parameterized and evaluated as time series. In this section, this methodology is presented and structured in three parts as follows. First, the selected parameters extracted from the movement data are defined in section 3.1. Second, an overview and presentation of the data management and implemented algorithms are summarized in sections 3.2 - 3.4. Third and finally, the time series forecast methodology is presented in section 3.5.

3.1 Parameter Selection

Implemented parameterizations were selected based on the theoretical background in section 2.3. In parameterization selection, the importance within the urban space use literature is considered, as well as the ability to parameterize given the movement data obtained from the sensor, and the limitations of the urban area. As stressed by Sun et al. (2019), an initial site visit was also carried out to get a deeper understanding of the site and its characteristics (Sommer & Sommer, 1997), contributing to the understanding of relevant parameterizations.

The parameter selection follows the four presented observational themes, suggested by Gehl and Svarre (2013): *counting, mapping, tracking* and *tracing*. *Tracing*, suggested in all three research corpuses in section 2.3, is applicable, but is only used as a tool in this thesis. To reiterate, no parameter was extracted from this observational theme. From the observational theme *tracking* the time spent, distance travelled, walking speed, and origin and destination are deemed as important parameters also suitable given the input movement data. Origin and destination are also part of the observational theme *mapping* and highlighted by behavioral mapping and space syntax theories. Both behavioral mapping and space syntax suggest deciding activity classes based on the characteristics of the urban space and its users. Due to the commercial nature of the urban space, the class store interaction was parameterized.

In the case of parameterizing movement data, technical limitations delimit possible user classes to those based on movement-based properties. For example, parameterizing a family class, as implied in section 2.3, cannot be captured by the input data. However, group affiliation can be parameterized and is considered a user class in this thesis. Further, from Gehl (2011), Vaughan (2001) and behavioral mapping, studying a standing still parameter is of interest. As Gehl and Svarre (2013) argue, anything can be counted. From *counting*, parameters such as ID count, count of IDs in a group, number of IDs registered from a specific origin and so on were created.

To summarize, the parameters extracted from the input movement data in this thesis are the following: origin and destination, store interaction, distance, time, speed, standing still and group affiliation. Using these parameters and IDs from the input data, different counting parameters are also presented in the results. The relation between the selected parameters and urban space use tools are presented in Figure 3.

	Counting	Mapping	Tracking
Origin and destination	x	x	x
Store interaction	x	x	x
Time spent, distance travelled and walking speed	x		x
Standing still	x	x	
Group affiliation	x	x	x

Figure 3. The selected parameters in this report connected to the observational themes Counting, Mapping and Tracking from Gehl & Svarre (2013).

3.2 Parameterization Overview

Given parameters to extract from the movement data, a method is deployed to create the parameterization algorithms. In this thesis, validation video was supplied and is described in section 3.4.5. With the validation video, a methodology similar to Whyte's (1980) is followed. Whyte (1980) evaluated recorded video to collect data and analyze scenes for his analyses. In evaluation of the video, he searched for patterns, hypothesized and tried understanding the collected data in new perspectives. The parameterization algorithms were developed in a similar fashion. Through observing the validation video footage, patterns and hypotheses which could be encompassed by the implemented parametrization algorithms are explored. The parameterization algorithms are meant to address general patterns, present in all data, in order not to overfit on the validation data and video. To minimize algorithmic uncertainty, as stressed by Kwan (2016), the parameterization algorithms were developed in a conservative manner, in order to avoid false positive assignments.

Extracting the parameters from the input movement data requires two types of algorithms, one for data cleaning and one for data parameterization. The input dataset was first cleaned for the processing algorithms to extract credible parameters. The data limitations and cleaning are presented in section 3.3. With cleaned data, the parameterization algorithms were implemented, according to the overview in section 3.4. The full process overview with all algorithms is presented in Figure 4.

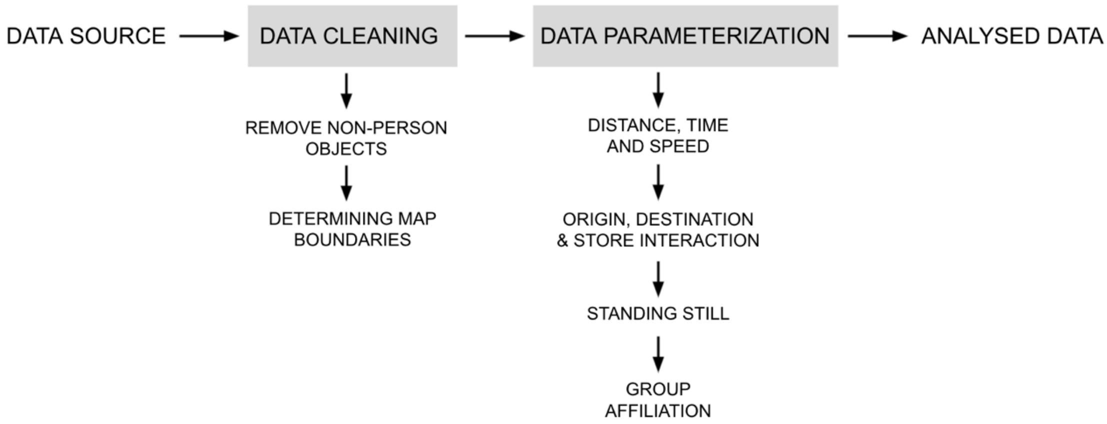

Figure 4. A process overview of the parameterization methodology presented in this thesis. First, the input data is cleaned. Then, the parameters are extracted in data parameterization.

3.3 Data Cleaning

The extent of data cleaning reflects the nature of the input data and the data used in later processes. The data cleaning executed in this study addresses the data limitations presented in the section 3.3.1. The executed data cleaning consists of two steps; first, non-person object IDs were removed, presented in section 3.3.2. Then, map boundaries were enforced on the dataset ensuring that all recorded values were bounded within the defined urban space, presented in section 3.3.3. Finally, a discussion about the remaining data limitations is carried out in section 3.3.4.

3.3.1 Data Limitations

As expected with urban data, the input data has limitations which are briefly explained in this section. In short, three main limitation themes are identified, namely: wrongly identifying non-person objects as persons, loss or change of tracking of persons, and stuttering capture. The three themes are presented below.

The sensor can capture and register non-person objects as persons. Objects can be dogs, trolleys or flowerpots, but are mostly people's reflection or shadows. Reflections and shadows usually occur temporarily, making the capturing of them brief. Similarly, the capturing of other non-person objects is usually short-lived. Another example is that a person recently entering the frame can get two separate IDs registered, where one will have few data and the other will have the full path.

In the input data and validation video, a pattern of loss or change of tracking has been noticed. For example, from the perspective of the camera, if one person is covering the other, the covered person's tracking ID can be disrupted mid-path. When the persons are, for the camera, distinguishable again, a new ID is generated for the previously lost person. Further, the tracking of an individual can also be shortly disrupted, as the tracking ID shortly fixates to another person or non-person object before returning to the original individual, resulting in a recorded jump in the frame. The change of ID can also become permanent, registering two different individual's paths under the same ID.

In a way to optimize performance, the sensor only considers movement in its detection. This can result in persons standing completely still will become a part of the background, and therefore ID tracking would be lost. Further, people who are visually standing still in reference footage are slightly moving in the dataset.

An uncertainty of person size, constantly changing from the perspective of the camera as a person is walking, combined with the high-resolution capture rate creates a stutter-like nature between consecutive data points. Studying every data point consecutively recreates a bobbing effect in the movement patterns. To summarize, these are some non-exhaustive examples which constitute some recorded movement paths as unnatural.

3.3.2 Removing Non-person Objects

The largest data cleaning was removing non-person objects. The majority of objects incorrectly identified as persons, showed to be represented by only a few data points. To remove the non-person object IDs, a threshold value on the number of values for the unique IDs was set. All IDs with recorded values lower than 80, roughly corresponding to eight seconds in frame, were omitted in the cleaned dataset. Naturally, some persons will spend less than eight seconds in the urban area and will with this implementation also be omitted.

3.3.3 Determining Area Boundaries

The physical attributes of the urban space determine the boundaries alongside the building walls while the area border closest to the sensor is determined by identifying where coordinate values begin to register correctly. A similar reasoning is applied for the area border at the opposite end of the sensor location. All collected data points outside the area boundaries were removed. Area boundaries are illustrated in Figure 6 in section 3.4.2.

3.3.4 Further Data Management

Identifying person-to-person ID switches, cleaning large distance jumps and merging broken paths are three main data limitations which are not addressed in the presented data cleaning. The reasons are twofold; they do not harm the overall analysis and no general solutions to clean them were found. Switching IDs are hard to generally identify, because there are no unique triggers for an ID switch. The most common ID switch is at the furthest end of the street, and plots reveal multiple persons walking to the end of a street and back; these are probably two different persons. However, the distance travelled by the persons are recorded correctly, only under one ID. This will affect origin and destination analyses and people counts, but not to a large extent, implying that the results will still represent the movement in general.

Cleaning sudden large distance jumps also proved to be hard. It was concluded that it would be wasted information removing the whole ID for a few uncertain recordings, as other information would be disregarded. Instead of omitting the ID, the IDs were flagged for faulty distance travelled, and not considered in distance and speed analyses.

If a path ends in the middle, it is due to the path being broken which in turn is due to change of ID. Theoretically, another ID should represent the person. Trying to find the new ID was proven to be difficult to generalize, and thus not implemented. Similar to aforementioned reasoning, broken path IDs affect origin and destination analyses, but do not affect other analyses such as distance travelled and speed. The number of paths ending in the middle do not affect the final analyses to such an extent so that the findings could not be generalized.

3.4 Data Parameterization

Using training video and data, parameterization algorithms were developed. In this section, the methodologies used for developing these are presented. The parameterizations were grouped under four categories: distance, time and speed; origin, destination and store interaction; standing still; and group affiliation. This section is split according to the categories, which are shortly described in Figure 5.

	Description	Data Structure	Example value
Origin and destination	*The origin and destination of the ID*	string	*Kyrkogatan*
Store interaction	*Store interaction rate based on origin and destination*	string	*store interactor*
Time spent, distance travelled and walking speed	*The time spent, distance travelled and the average speed of the ID*	float, float, float	*26.6 seconds, 32.3 meters, 1.2 meters per second*
Standing still	*Location and time duration of standing still activity.*	[float, float], float	*[6.4,30.0], 4 seconds*
Group affiliation	*The IDs group affiliation. One group has a unqiue affiliation*	integer	*56*

Figure 5. An overview of parameters extracted from the input movement data, containing a short description, data structure, and example values.

3.4.1 Distance, Time and Speed

Due to the nature of the input movement data, the sum of the distances between all recorded values is not representative for the total distance travelled. Instead, representative points chosen every three seconds showed to represent a smooth, more realistic path. Therefore, the total distance travelled was determined as the sum of differences between the representative, three-second interval, values. As mentioned in section 3.3.3, few data-points with unnatural distance jumps were not cleaned, which affects the distance travelled and average speed. The IDs with faulty data were flagged, and not used in the distance, time and speed analyses.

The total time spent in frame was decided as the difference between the first and last timestamp for the unique ID. Average speed was defined as the total distance travelled divided by the total time spent in the area.

3.4.2 Origin, Destination and Store Interaction

To classify origin and destination, area zones were constructed. The zones are determined by the area boundaries, described in section 3.3.2, as well as coordinate values characteristic for each specific zone. Five different zones were created based on location and function; these are plaza, kyrkogatan, left, right and middle zones as illustrated in Figure 6.

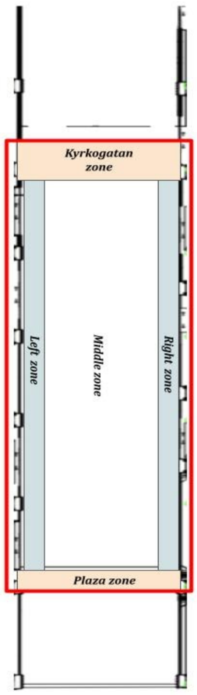

Figure 6. Illustration of the five area zones as well as area boundaries defined by the red rectangle.

The two entrance zones (plaza and kyrkogatan) are bounded by the area boundaries as well as the right and left zones start/end coordinate values. The kyrkogatan zone is larger than the plaza zone due to the sensor location and perspective. The right and left zones contain the shopping street's stores located along the facade. The store zones' boundaries toward the street are determined by studying coordinate values for persons entering or exiting different stores, validated by looking at supplied video footage. The store zones cover multiple store entrances as this implementation was the most generalizable. This means, however, that a more detailed view of specific store interactions is lost. Finally, the middle zone is the area enclosed by the other four zones, as presented in Figure 6.

Based on the different area zones, the origin was determined by the zone containing the first recorded coordinate value of the ID. Analogously, the destination was determined by the last recorded coordinate value. This information provides the possibility to assign an individual store interaction status based on origin and destination. The possible statuses are no store interactor, store interactor or store-to-store interactor. To be assigned as a store interactor the ID needs to have either origin or destination in one of the two store zones. To be assigned as a store-to-store interactor the origin as well as the destination has to be within the store zones. Every other combination is classified as a no store interactor.

3.4.3 Standing Still

The developed algorithm for parameterizing standing still movement was influenced by the data limitations discussed in section 3.3.1. Because of the scarce zero movement data, the algorithm treats very low movement over a certain time as an ID standing still. This means that to be classified as standing still, an ID must have repeatedly low movement until it reaches a threshold indicating the minimum standing still time. Using pseudo code, the first part of the algorithm is described in Figure 7.

```
ALL STANDING STILL LOCATIONS (movement dataframe, ID)
all movement = movement dataframe[ID]
still locations = []
still movement = low movement threshold
still counter = 0
standing still threshold = threshold
for movement in all movement
     if movement <= still movement
          still counter + 1
          if still counter == standing still threshold
               add location to still locations
               still counter = 0
          end
     else
          still counter = 0
     end
end
return still locations
```

Figure 7. Pseudo-code for identifying standing still locations of an ID.

The above algorithm returns a list of all the IDs standing still locations based on the standing still threshold, not taking unique locations into account. To visually understand where and for how long IDs are registered standing still, the algorithm in Figure 8 determines unique locations. Depending on a same-location threshold, the algorithm determines if a location in `still locations` is a unique location or the same location as the next location.

```
STANDING STILL UNIQUE LOCATIONS (still locations)
standing still unique locations = []
same location threshold = small distance
for i in index of still locations
     delta location = abs still locations[i] – still locations[i+1]
     if delta location > same location threshold
          add location to standing still unique locations
     end
end
return standing still unique locations
```

Figure 8. Pseudo-code for identifying unique locations given the standing still locations of an ID.

Due to the fact that the algorithm was designed to compare the current location to the next, the case where a person moves from one still location to another and then back to the first location would result in three different unique standing still locations. However, if two consecutive standing still locations are considered the same, only one unique location is saved. This itself is not a problem since the recorded standing still time per unique location is summed and therefore the standing still intensity would be the same.

3.4.4 Group Affiliation

The group affiliation parameter was defined as two persons being close to each other in multiple frames. In short, the group affiliation parametrization is an algorithm creating a snapshot every five seconds and recording all pairs close to each other. If pairs are close to each other in multiple snapshots, according to a threshold value, they are determined to be an affiliated pair. The resulting data structure is a list of affiliated pairs. The affiliated pairs are then combined into groups of connected IDs. The group affiliation algorithm is presented in more detail below.

First, all pairs close to each other are identified, presented in pseudo code in Figure 9. A list of all sets passing the threshold is created. The snapshot data frame is defined as the average position of all recorded IDs at that second. The distances between average positions are returned as a triangular matrix.

```
ALL PAIRS CLOSE TO EACH OTHER (movement df)
distance threshold = threshold value
all pairs = []
for every fifth second in all seconds of the day:
     snaphshot_df = get_average_positions_at_second(movement df,
                                                    every fifth second)
     distances between IDs = get_distances_between_IDs(snaphshot_df)
     for pair and distance in distances between IDs:
          if distance < distance threshold:
               add pair to all pairs
          end
     end
end
return all pairs
```

Figure 9. Pseudo-code for identifying all ID-pairs close to each other in the five-second snapshots.

When all pairs are saved in the list, an occurrence threshold decides if the recorded pairs are affiliated, or in other words in a group with each other, described in the pseudo code in Figure 10.

```
ALL PAIRS IN GROUP (all pairs)
occurrence threshold = threshold value
pairs in group = []
for pair in unique(all pairs):
     if occurrence of pair in all pairs >= occurrence threshold:
          add pair to pairs in group
     end
end
return pairs in group
```

Figure 10. Pseudo-code for identifying ID-pairs which are considered to be in a group, according to an occurrence threshold.

When all pair group affiliations are decided, pair sets are interpreted as edges and IDs as nodes in a graph, a visual example is presented in Figure 11. All connected nodes, or

IDs, in the graph are assigned the same group to all connected IDs. The IDs not present in a group are assigned to a singles group.

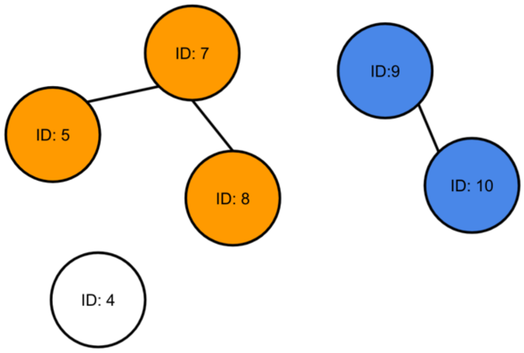

Figure 11. An example image of deciding group affiliation, where the nodes of the graph are IDs and the identified pairs are edges. In this example, IDs 5,7 and 8 as well as 9 and 10 are connected and create two groups (orange and blue, respectively). The ID 4 has no connections and is therefore assigned part of the singles group (white).

This parametrization methodology requires per design that IDs need to be close to each other in multiple snapshots. Using a large occurrence threshold will unfavorably affect short times in frame. For example, an occurrence threshold of three close occurrences in different snapshots requires the two IDs to be present in frame for at least ten seconds.

3.4.5 Evaluating Parameterizations

To evaluate the implemented parameterizations, sample video footage was supplied. A total of 48 minutes of reference video footage was supplied divided into four parts from different months and time of day. Two sections of a total of 17 minutes of footage was used as combined training and validation data including movement data for 228 unique IDs. The remaining two sections containing 31 minutes of footage and 284 unique IDs, were used as test data. The reference video was annotated, creating test data for the parameters standing still, group affiliation and store interaction.

The classification parametrization algorithms were evaluated using two metrics based on the confusion matrix as suggested by He & Ma (2013). The confusion matrix is visualized in Table 2 where true positives (TP) represent the correctly classified positive instances, false negatives (FN) are the positive instances classified as negatives, false positives (FP) is the number of negatives incorrectly classed as positives, and true negatives (TN) are negative instances correctly classified.

The true values were determined by annotating the video footage test data. In a conservative attempt to not inflate the parameterizations, the algorithms presented in this section were designed with minimizing generating false positives in mind.

Table 2. Confusion matrix of predictive and true values.

	Predicted positive	Predicted negative
True positive	TP	FN
True negative	FP	TN

Through the confusion matrix framework, numerous evaluation metrics can be constructed (Ha & Ma, 2013). The most commonly used metric is $accuracy$, given by equation (1) in accordance with He & Ma (2013):

$$accuracy = \frac{TN+TP}{TN+TP+FN+FP}. \tag{1}$$

In an attempt to nuance the parametrization evaluation, based on the understanding that $accuracy$ might be misleading for imbalanced data, the F_1-score was also used as an evaluation metric (Ha & Ma, 2013). This metric builds upon the concepts $precision$ and $recall$, where $precision$ indicates how often a positive classification is truly positive and is given by equation (2) (Ha & Ma, 2013):

$$precision = \frac{TP}{FP+TP}, \tag{2}$$

and $recall$ explains how often a true positive instance is classified as positive and given by equation (3) (Ha & Ma, 2013):

$$recall = \frac{TP}{TP+FN}. \tag{3}$$

The F_1-score metric combines these two concepts to provide a single value indicating how well a classifier performs when less frequent classes are present (Ha & Ma, 2013).

$$F_1 = 2 * \frac{precision * recall}{precision + recall} \tag{4}$$

There are several versions of the F-score metric with different weights on precision, but the most commonly used is the F_1 version (Ha & Ma, 2013), resulting in a value between zero and one where one signifies perfect classification.

3.5 Time Series Forecast Methodology

Based on the parameterized data, a time series forecasting method was implemented. Two models, Prophet and seasonal naïve, forecasted a new parameter, namely group affiliation ratio. The forecast models are presented in section 3.5.1, data used in the time series forecasting are introduced in section 3.5.2, and model implementations are covered in section 3.5.3.

3.5.1 Compared Models

The two compared models in this thesis were Prophet and a seasonal naïve. In this section, the mathematical formulations of the two models are introduced.

Because there is a weekly trend and the time series was not randomly shuffled, a simple persistence model, forecasting a value as the previous one, was expanded to forecast the same value of the previous occurrence of the weekday. The weekly seasonal naïve is described in equation (5) below, according to Hyndman and Athanasopoulos (2018):

$$\hat{y}_{D,W+1|W}(t) = y_{D,W}(t), \tag{5}$$

where $\hat{y}_{D,W+1|W}$ is the prediction of a point at the time t of day D in week W. This means that predicted values of a certain day are the same as the values from the week before. Forecasts of multiple weeks are copies of the most previous week (Hyndman & Athanasopoulos, 2018).

Prophet is based on a decomposable time series model, fit according to the three summed components: trend $g(t)$, seasonality $s(t)$ and holidays $h(t)$ (Taylor & Letham, 2018).

$$y(t) = g(t) + s(t) + h(t) + \epsilon, \tag{6}$$

where ϵ is the error not fit by the model (Taylor & Letham, 2018). The trend component $g(t)$ fits non-periodic changes, the seasonality component $s(t)$ covers the periodic changes, from sub-daily to yearly seasonality. The holiday component $h(t)$ represents the effects of holidays on the time series (Taylor & Letham, 2018). Given historic training data and hyperparameter selection, the components are fit to trend, seasonality and holiday. Forecasted values are the sum of the fitted components.

The trend component in this application was set as piecewise linear, due to the non-growth nature of the time series data, as reported by Taylor & Letham (2018) in equation (7):

$$g(t) = (k + \boldsymbol{a}(t)^{\mathrm{T}}\boldsymbol{\delta})t + m(\boldsymbol{a}(t)^{\mathrm{T}}\boldsymbol{\gamma}), \tag{7}$$

where k represents the growth rate, $\boldsymbol{\delta}$ is a vector with rate adjustments, m is an offset parameter, $\boldsymbol{\gamma}$ is set to enable function continuity, and $\boldsymbol{a}(t)$ is a vector of defined changepoints in the trend component $g(t)$. Changepoints are set automatically, with the prior hyperparameter s_{CP}, or 'changepoint_prior_scale', was set using forward-chaining cross validation, covered in section 3.5.3.

The seasonality component $s(t)$ is modelled as Fourier series, using different periods to represent different seasonality, such as weekly, monthly and sub-daily (Taylor & Letham, 2018). The functions for different periods P are described in equation (8) (Taylor & Letham, 2018).

$$s(t) = \sum_{n=1}^{N} \left(a_n \cos\left(\frac{2\pi nt}{P}\right) + b_n \sin\left(\frac{2\pi nt}{P}\right)\right), \tag{8}$$

where $N,$ a_n and b_n are set in the model fit. Holiday effects add to the model by defining a set of L dates $D_{1\cdots L}$ and creating a matrix of regressors $Z(t)$ where t is time:

$$Z(t) = [\mathbf{1}(t \in D_1), \cdots, \mathbf{1}(t \in D_L)]. \tag{9}$$

As explained by Taylor and Lehtam (2018), the holiday component $h(t)$ is described in equation (10):

$$h(t) = Z(t)\boldsymbol{\kappa}, \tag{10}$$

where $\boldsymbol{\kappa}$ is set in the model fit, with prior $\boldsymbol{\kappa} \sim Normal(0, \nu^2)$.

3.5.2 Time Series Data

With data from February 12th to April 20th, 68 days of parameterized data were combined to create a time series dataset. In this section, the data used in the implemented models are presented.

The parameter considered in the time series data is the group affiliation ration, r_{GA}, meaning the proportion of persons in frame that are registered to be in a group, explained by equation (11):

$$r_{GA} = \frac{ID_{GA}}{ID_{tot}}, \tag{11}$$

where ID_{GA} constitutes the number of IDs with a group affiliation and ID_{tot} is the total amount of IDs. Before creating the new parameter, the two extracted parameters ID_{GA} and ID_{tot} are processed according to the following. The parameter studied as a time series is only relevant for when there are people in the area. As there is consistent activity between 10.00 and 20.00, the forecast data consists only of the ten active use hours every day. To avoid duplicate registrations, parameters were registered according to the entry timestamps of the ID and were aggregated into a lower resolution five minute interval data. This results in 12 values per hour and 120 values per day. After this, the group affiliation ratio r_{GA} was processed according to equation (11).

The 68 days were split into 54 days of training data and 14 days of test data, rendering ≈20.5% of the data as test. The training and test data thus consists of 6480 and 1680 values respectively as presented in Table 3.

Table 3. Training and test data split for the time series forecast implementations.

	Training data	Test data
Days	54	14
Values	6480	1680

3.5.3 Model Implementations

The two models presented in section 3.5.1 were implemented as follows. The seasonal naïve model forecasts the 14-day test set as the last week of the training set, twice repeated. For example, the first Monday and second Monday in the test set were forecasted to have the same values as the last Monday in the training set.

As explained in section 3.5.1, the Prophet model has a holiday component. In Gothenburg, three sets of holidays were present while the data were collected. First, there was a school sports break between February 15th and February 21st. Then, Easter occurred between April 1st and April 4th. Following Easter, school had an Easter break the preceding week, from April 5th until April 10th. These holidays were added to the Prophet model holiday component.

Hyperparameters s_{CP} and s_{SP} ('seasonality_prior_scale') were set using a forward-chaining cross validation for the time series, as described by Rafferty (2021). Using the Prophet module, the dates March 2nd, March 9th, March 16th, March 23rd and March 30th were selected as cut-off points. With a 7-day forecast horizon, the models were validated on five validation splits, presented in Figure 12 below.

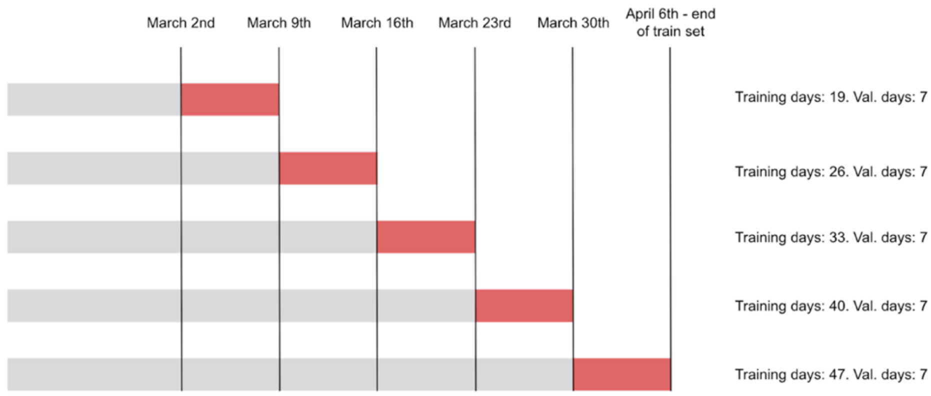

Figure 12. The training and validation split of the training data in the forward-chaining cross validation.

Adding flexibility to the model, changepoints are points of abrupt changes in the trend of the time series (Rafferty, 2021). The hyperparameter s_{CP} regularizes changepoints in order to not overfit. Lowering the value increases regularization. The default value is 0.05 and was in the implemented model set as 0.001. Similarly, s_{SP} is a hyperparameter regularizing the seasonality component (Rafferty, 2021). Lowering the hyperparameter increases regularization and reduces the complexity of the seasonality component. The default value is 10 and was in the implemented model set as 1.

Except for the hyperparameters presented in this section, and excluding the yearly seasonality, default values were assumed in the model.

To evaluate the implemented models, the metrics Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were applied, as implemented by Bolin et al. (2020), presented in equations (12) and (13). The two metrics assess different performance; MAE presents the absolute residual error between prediction $\hat{y}$ and test value y, and RMSE highlights outliers and model variability (Hyndman & Athanasopoulos, 2018).

$$MAE = \frac{\sum_{i=1}^{N} |\hat{y}_i - y_i|}{N} \tag{12}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (\hat{y}_i - y_i)^2}{N}} \tag{13}$$

4. Results and Analysis

Reflecting the three different research questions, the results and analysis section is divided into three main parts. First, in section 4.1, the evaluation of the parametrization performance is presented. Section 4.2 presents the results gathered from applying the parameterized data in the urban space use tools. The final part is the time series modelling and forecasting results, which are presented in section 4.3.

4.1 Parameterization Performance

Answering the first research question regarding how well parameterization algorithms can describe urban space use, this section presents the parametrization performance results based on the two evaluation metrics $accuracy$ and F_1-score. The parametrization results presented are standing still analysis, group affiliation and store interaction. Due to the binary requirement of the F_1-metric, the store interactor and store-to-store interactor classes were grouped. This works well with the sparseness of test data of the store interactor classes. Table 4 presents the standing still parameterization result.

Table 4. Standing still parameterization results from the two test sets.

Standing Still	True negatives (TN)	True positives (TP)	False negatives (FN)	False positives (FP)	Accuracy (%)	F_1-score
Test set 1	123	16	7	1	94.6%	0.800
Test set 2	133	2	2	-	98.5%	0.666
Total test set	256	18	9	1	96.5%	0.782

In terms of accuracy the results indicate a high capture of standing still. However, in the second test set only four IDs were actually standing still which entails imbalanced data. Observing the fact that the F_1-score was substantially lower for this specific test set; the performance of the standing still algorithm might be considered lower compared to the other parametrized analyses. On the other hand, this kind of imbalanced data was not present in the other parametrizations, which makes a direct comparison difficult. Another interpretation of the overall lower F_1-score in Table 4 is that standing still movement was in this case harder to parametrize. This interpretation is supported by the fact that the standing still parametrization performed accurately in terms of accuracy while the second evaluation metric indicated a less accurate result. It might also be a reflection of the data limitations affecting the standing still parameter. A final observation is that there was a low amount of false positives. The group affiliation results are presented in Table 5.

Table 5. Group affiliation parameterization results from the two test sets.

Group Affiliation	True negatives (TN)	True positives (TP)	False negatives (FN)	False positives (FP)	Accuracy (%)	F_1-score
Test set 1	74	60	13	-	91.2%	0.902
Test set 2	98	32	7	-	94.9%	0.901
Total test set	172	92	20	-	93.0%	0.901

The two evaluation metrics indicate that the group affiliation parameterization captures the urban movement accurately. The group affiliation algorithm generated no false positive assignments, instead, false negatives constitute all the misclassifications of the group affiliation analysis, indicating a similar trend as found in the standing still parameterization results. This was in the majority of the cases the result of the characteristics of the constructed algorithms, or more precisely, the time condition of the algorithms. Both algorithms have conservatively set time conditions to avoid generating false positives. In the case of group affiliation, this means that the time required for two IDs to be registered as affiliated was long. Consequently, persons walking in groups for a short time, as for example fast-walking groups traversing the urban area or broken IDs paths, generated false negatives. Table 6 presents the store interaction class results.

Table 6. Store interaction parameterization results from the two test sets.

Store interaction	True negatives (TN)	True positives (TP)	False negatives (FN)	False positives (FP)	Accuracy (%)	F_1-score
Test set 1	104	33	6	4	93.2%	0.868
Test set 2	92	41	3	0	97.8%	0.965
Total test set	196	74	9	4	95.1%	0.919

In terms of performance the store interaction class performed well based on the two metrics. Accuracy was higher for test set 2 compared to test set 1 which is a result also present in the results of the other two parameterizations. An observation is that the F_1-score was lower for the more imbalanced test sets which indicates that these parametrizations also might struggle with imbalanced data. Regarding false positives and negatives, the store interaction class follows the desired trend in terms of keeping the false positives lower compared to false negatives, although with a slightly higher number of false positives.

To conclude the parametrization performance results, some general patterns should be highlighted. Looking only at accuracy as an evaluation metric, the overall results were good. An observation is that test set 1 generally contained less accurate performance than the second test set. This is assumed to be due to an increase of faulty non-person object IDs due to sunshine in the first test set. Unfortunately, the training data did not cover the sunny weather condition and therefore, the developed algorithms and data cleaning were agnostic to similar input data patterns. Furthermore, the training dataset was similar to the second dataset, in regards to weather, making the second test set optimal conditioned for the parameterizations.

Considering the F_1-score evaluation metric, the test set trend affecting the performance was related to imbalanced data in terms of how often the parametrization in question occurs. In the presented results, a lower occurrence is followed by a lower F_1-score which signifies that the parametrized analysis performs less accurately the more imbalanced the data are. A conclusion based on this result is that the constructed algorithms detected the true negative class more easily than true positives. In other words, identifying a standing still ID was harder than identifying a moving ID which should be considered a reflection of the conservative approach used in developing the algorithms, rather identifying false negatives than false positives.

4.2 Applying Urban Space Use Analysis

The results presented in this section describe how the urban space is used when the parameterized data was applied in the urban space use tools. In answering the second research question, this section first presents a standing still analysis in section 4.2.1, followed by movement tracing results in section 4.2.2. Finally, daily and weekly analysis results are presented in section 4.2.3.

4.2.1 Good Places to Stand

In one of the Gehl (2011) tools, *good places to stand*, the architect highlights the importance of understanding where people like to stand. Gehl (2011) focuses on finding where people find it comfortable to stand and wait, usually close to walls or other protected areas. Standing still is also one of the activities often mapped in behavioral mapping and the space syntax method *static snapshot*. The illustration in Figure 13 might be considered a high resolution standing still activities map as gained from the theoretical frameworks in section 2.3

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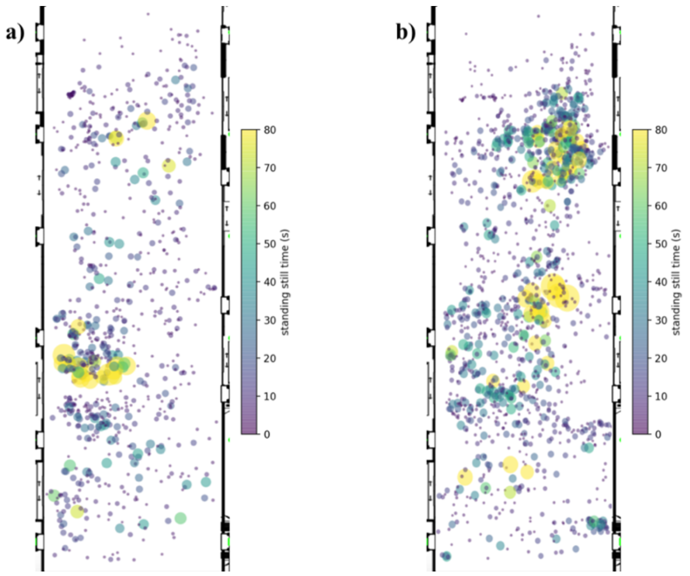

Figure 13. Standing still locations and times for Monday, February 15th, (a), and Wednesday, February 17th, (b), of this year. Brighter colored and bigger circles indicate longer standing still times.

An initial observation from Figure 13 is that the amount of standing still IDs was somewhat larger during Wednesday, February 17th (Figure 13 (b)), compared to Monday, February 15th, (Figure 13 (a)). Another general finding was that standing still locations occur almost everywhere on the Kompassen shopping street during the two days. This finding also exists for longer standing still times since the turquoise and yellow circles are distributed across the whole street.

One interesting aspect to study is the clustering patterns of standing still IDs. One could argue that the Monday (Figure 13 (a)) contained a clustering trend in connection to the yellow, long recorded standing-still-time, circles. This conclusion would be supported by observing Figure 13 (b) which appears to have a similar clustering tendency for the same area. On the other hand, the fact that persons were standing at this place for a long time might in itself magnify the clustering trend because of extra IDs generated as a consequence of the sensor tracking algorithm, described in section 3.3.1. Though this might generate too many unique IDs it might also be considered a fair representation of the actual time spent standing still at a specific location. The most prominent clustering of standing still individuals during the two days is found in the top right corner of Figure 13 (b). The size and diversity of this cluster entails that it was in fact a popular place to stand.

Because of the characteristics of the Kompassen shopping street and the results presented in Figure 13, it is hard to say why one place would be more attractive in regard to standing still compared to another. These results are interesting for future studies since a new trend of urban space use might be observed. Gehl (2011) argues that people tend to look for protected places to stand, the studied area provides relatively equal protection throughout the street. That is, a roof covering for rain and snow. This could also be flowerpots close to the store entrances. Based on these physical attributes, distinctively good places according to the protection aspect of the Gehl framework are hard to argue for.

Observing the results from a behavioral mapping perspective, the standing still algorithm and maps in Figure 13 might be considered too general. Standing still for two seconds or for two minutes are two different behaviors which would need two separate behavioral maps and analyses. This is also reflected in Gehl's (2011) tool, which intends to identify places where people like to stand and wait for longer periods. A short stop, the most common duration in the middle of the street, does not imply that these places are good for standing and waiting. In this sense, the standing still analysis obtains general results, and specifying characteristics could clarify a nuanced understanding.

4.2.2 Movement Traces

Presented in the space syntax *movement traces* method as well as a core theme in Gehl & Svarre (2013), tracing people's movement in the urban space helps describe the use of urban space. Visualizing movement patterns therefore also answers one of the key objectives within the space-based behavioral mapping framework: to determine if and how the space is used. In the urban space use tools, tracing means to represent sample walking routes in the urban space. In Figure 14, the movement patterns of the different store interaction classes are visualized during a whole day.

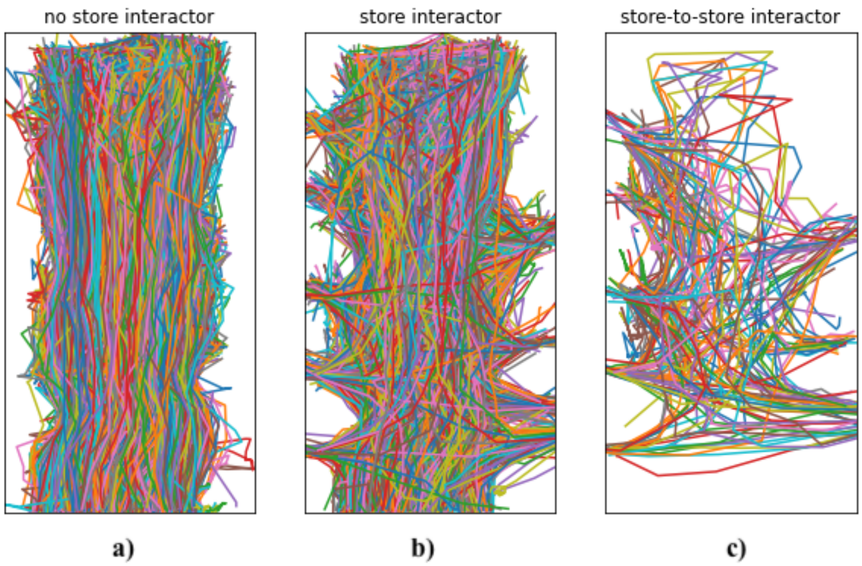

Figure 14. Traced and visualized movement patterns of the three store interaction classes: no store interactors in (a), store interactors in (b), and store-to-store interactors in (c).

The perhaps most intuitive difference in space use between the different classes in Figure 14 was that the no store interaction class, Figure 14 (a), did not use the space directly in connection to the store entrances. This might seem obvious but at the same time implies a level of certainty of the Kompassen visitors: there was generally no hesitation whether to interact with a store or not. This is also supported by looking at the store-to-store class, Figure 14 (c), and realizing that they seldomly used the street entrance area zones. Looking closer, though, there were some tendencies of uncertainty at the top of the store-to-store class (Figure 14 (c)) where persons seem to have turned around and go back shopping. However, this pattern might also be explained by jumping IDs as explained in section 3.3.1.

Due to the urban space characteristics of Kompassen, the dominant lines of flow - as studied by Gehl & Svarre (2013) - are naturally influenced by the physical setting connected to each class. The no store interaction class, plotted in Figure 14 (a), was dominated by relatively straight vertical flow lines while more mixed patterns were identified in the two store interaction classes, visualized in Figure 14 (b) and Figure 14 (c). In the store-to-store class more horizontal flow lines were present and influence the dominant flow patterns, indicating that IDs often moved from a store at one side of the street to a store on the opposite side.

Visualizing tracings of a whole day provides substantial information for identifying the, according to Gehl & Svarre (2013), important dominant flow lines. The general walking patterns of the day become apparent. As shown in Figure 14, most of the urban area of this day was used. However, there is a pattern that very few IDs in the store-to-store class use the upper right part of the Kompassen shopping street. This reflects that the store in the upper right part of Kompassen was closed for renovation.

As Vaughan (2001) and Gehl and Svarre (2013) suggest manual tracing, sample lines are an expected result. In Figure 14, all recorded movement patterns of the day were visualized. Therefore, the thesis methodology showcases a more detailed distribution of urban space use. The visualization also creates a tool which can present movement tracings of different groups, such as store interactors or slow walkers, or different times of the day. This would relate to understanding what Gehl & Svarre (2013) call subdominant flows. Furthermore, dividing the tracing based on different times might facilitate the identification of less used areas which are central in the space-based behavioral mapping framework.

4.2.3 Daily and Weekly Summaries

As all research areas in section 2.3 highlight, there are differences in urban space use during the different hours of the day. In Figure 15, ID count, amount in group and amount standing still of two days are plotted every five minutes. The amount standing still and amount in group depend on ID counts, naturally creating a similar trend. Person ID count peaked during early afternoon. The amount in group count represents the number of IDs with a group affiliation. The parameter aligned with the ID count toward the end of the day, signifying people in the urban space were travelling in groups to a larger extent as the day goes on.

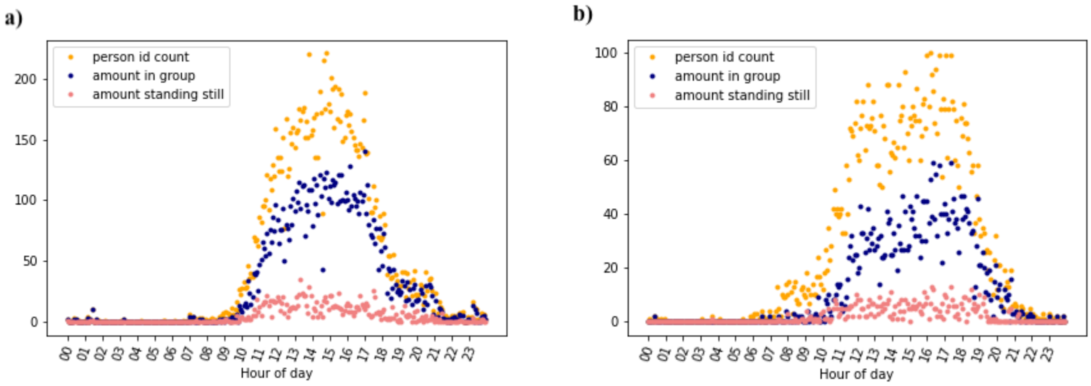

Figure 15. Daily values of parameters person id count, amount in group and amount standing still for March 20th in (a), and April 14th in (b).

As space syntax and behavioral mapping theory suggests, there were differences between weekdays and weekends. Urban space use differed not only on an hourly scale, but also on a daily scale. Observing aggregated information in daily summaries can allow for classifying different use from day to day. In Table 7, example full-day summary data are presented for Tuesday, March 16th, and Saturday, March 20th. Table 7 illustrates that the two days show differences in all parameters presented.

Table 7. Daily summaries of March 16th and March 20th.

	2021-03-16	2021-03-20
Day	Tuesday	Saturday
ID count	8339	14431
Shopper status distribution (no store/one store/two stores)	80.5% / 17.8% / 1.6%	74.4% / 22.7% / 2.8%
Average speed	1.26 m/s	1.23 m/s
Amount in group (%)	46.2%	63.6%
Amount standing still (%)	8.3%	10.4%

On Saturday, there was a larger ID count, a higher percentage of IDs walking into stores, larger amount in group and standing still compared to the Tuesday data. The two days put in the context of the whole week are visualized in Figure 16.

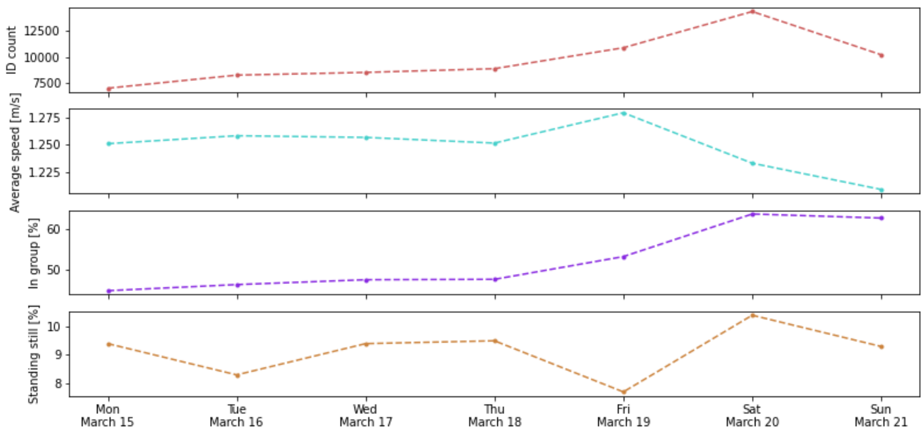

Figure 16. Daily summaries of person count, average speed, amount in group and amount standing still, from Monday, March 15th, to Sunday, March 21st. Please note the broken y-axes.

The results in Figure 16 reflect the different urban space use over days. For example, more people had group affiliation and more IDs were registered during the weekend. Using similar plots over larger datasets, the parameters can be used to classify different general urban space use on different days.

The level of granularity is notable when the parameterized data were applied in the urban space use tools. With more detail, the data are in line with the urban space use tools. As presented in Figure 16, observing data in a continuous manner opens up for studying patterns over time. In other words, a time series approach.

4.3 Time Series Data

Given that the parameterized dataset is granular, time series modelling is available for understanding the use of urban space. Studying changes over time, the results presented in this section answer the third and final research question in this thesis. In section 4.3.1, a time series analysis of the weekly trend in section 4.2.3 is presented. This is followed by a time series analysis of the store interactor average speeds in section 4.3.2. To conclude this section, a forecast implementation of the parameter group affiliation ratio is presented in section 4.3.3.

4.3.1 Weekly Summary

Longer time series data provide an opportunity to continually nuance and evaluate the weekly results as obtained from the urban space use tools and presented in section 4.2.3. Figure 17, similar to Figure 16, shows the weekly patterns for four different parameters for nine weeks plotted in the same graph.

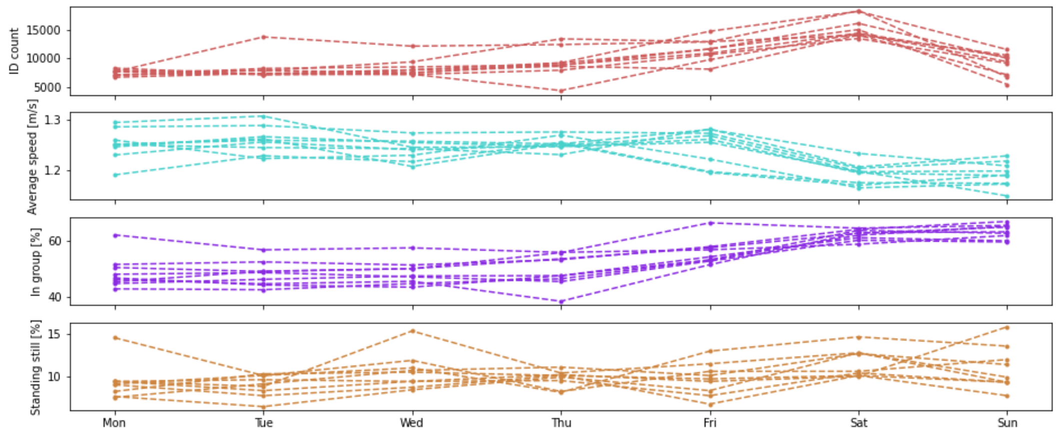

Figure 17. Daily summaries of nine weeks, presented in the same plot. Please note the broken y-axis.

Several results were gathered from the time series approach of the weekly trend. First, patterns were fairly repetitive from week to week, indicating that the different days of the week could be classified differently and thus, following the space syntax theoretical framework presented in section 2.3.1. From Figure 17 it is also possible to identify anomalies. As an example, for one week the amount of IDs present in Kompassen was substantially higher during the weekdays compared to other weeks. In addition, looking only at trends between the parameters, identifying an exceptionally large ID count in itself provides information on the other parameters. For example, given a large ID count, studying Saturday data, a reasonable prediction would be that the average speed is lower and group affiliation ratio is higher.

4.3.2 Average Speed as a Time Series

The results presented in 4.3.1 identify trends for a specific time window and can be used for identifying anomalies and correlations. However, identifying patterns over time might be better presented as a continuous time series. Given the observation that people that walk into stores walk slower, compatible with what Gehl & Svarre (2013) call promenading people, makes it interesting to analyze walking speeds over time. In Figure 18, average walking speeds of the three different store interaction classes are plotted.

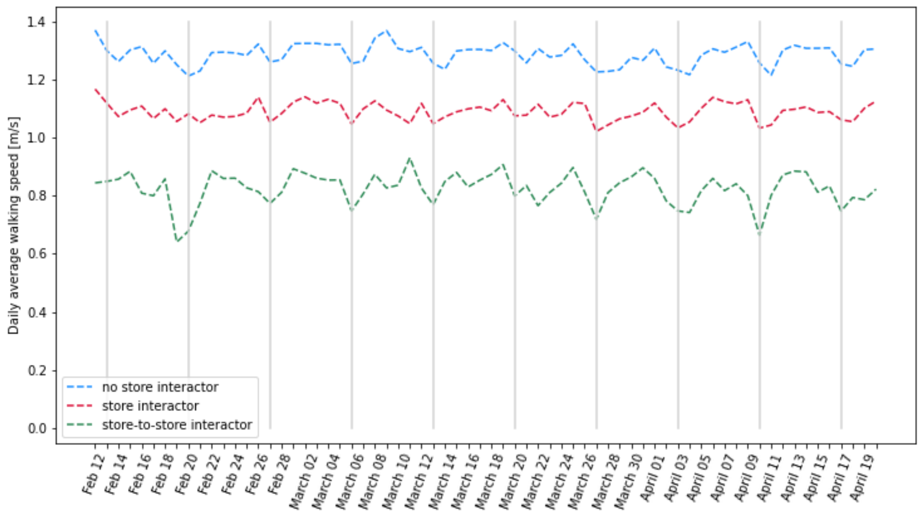

Figure 18. Average speed of the different store interaction classes between February 12th and April 20th. Saturdays are highlighted with gray bars.

The three classes had distinctly different average speeds, a result which could nuance the explanation of how the urban space is used. Users coming from a store and walking into another one had lower average speed than users either coming from or walking into one store, which in turn had lower average speed than the no store interaction class. Furthermore, an interesting finding is that fluctuations usually were similar between the classes. As gathered from the weekly trend, the walking speed decreases during weekends, especially during Saturdays (gray bars in Figure 18) which corresponds to the lowest values in the time series. This weekly trend is repeated and further entails a correlation between day of the week and average walking speed. Continuing the same reasoning of section 4.3.2, given Figure 18, predicting a high ID count and group affiliation would be plausible.

Detailed fluctuations were harder to interpret but since the fluctuations between the different store interaction classes were similar, the weekly trend seems stronger than the user class trends with exception of the clearly distributed average speeds based on store interaction class. One observation, however, is that the slowest, store-to-store, user class presented the largest fluctuations within a class. This could be explained by characteristics of the specific class, but could also be explained by the fact that the group has the least amount of data and therefore is more sensitive to fluctuations compared to the other classes.

As presented in section 2.3.3, Gehl & Svarre (2013) suggest that the average walking speed declines as the weather improves. As temperatures rise from mid-February to mid-April in Gothenburg, no clear trend shows a steady decrease in movement speed in any of the user groups. However, the dataset did not encompass multiple seasons, and more data are needed to evaluate Gehl's and Svarre's (2013) hypothesis. Similarly, larger time series can be used to identify longer trends in the use of urban space.

4.3.3 Forecasting Group Affiliation Ratio

From studying the day-summary plots in Figure 15, one can observe that the amount in group parameter aligned with the ID count, meaning that group affiliation ratio increased later in the day. In Figure 19, the group affiliation ratio between 10.00 and 20.00 are plotted for a time series of seven consecutive days.

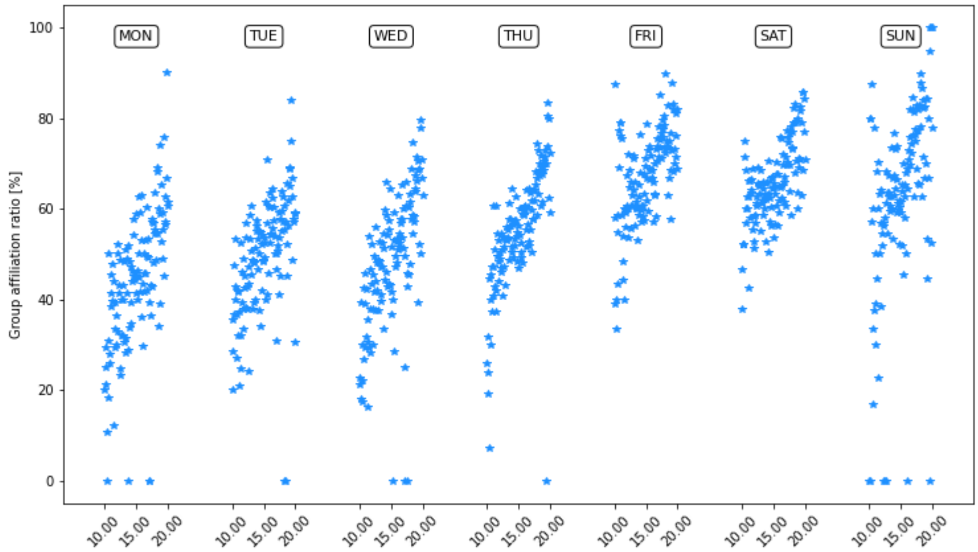

Figure 19. One week of the parameter group affiliation ratio, aggregated in five minute interval data between 10.00 and 20.00.

This time series data signifies that the people in Kompassen were to a larger extent walking in groups at later hours of the day, which reflects the trend observed in Figure 15. During Friday, Saturday and Sunday, the group affiliation ratio parameter starts at a higher base with a similar increasing trend.

The creation of time series paves the way for further understanding of the urban space through the use of forecasts. Using Prophet and the seasonal naïve models, the forecasting results of the parameter group affiliation ratio are presented as follows.

Described in equation (6), the Prophet output is decomposed in three main components. There is a general trend component, a seasonal component (in this case weekly and daily seasonality) and a holiday component. The sum of the three components gives the output value. In the component decomposition plot in Figure 20, the three components are individually clarified. The general trend showed a slight decrease over the time series. The added sports break, Easter and Easter break holidays added to an increased group affiliation ratio. The impact of the sports break was not large compared to Easter and the Easter break, which could imply different activity during the two breaks. There was also a weekly trend with a higher percentage during weekends. The daily trend showed an incremental rise during the studied hours, 10.00 to 20.00. Worth noting is that hours not between 10.00 and 20.00 were not considered in the model train or test data and is why they are faded in the daily seasonal component in Figure 20.

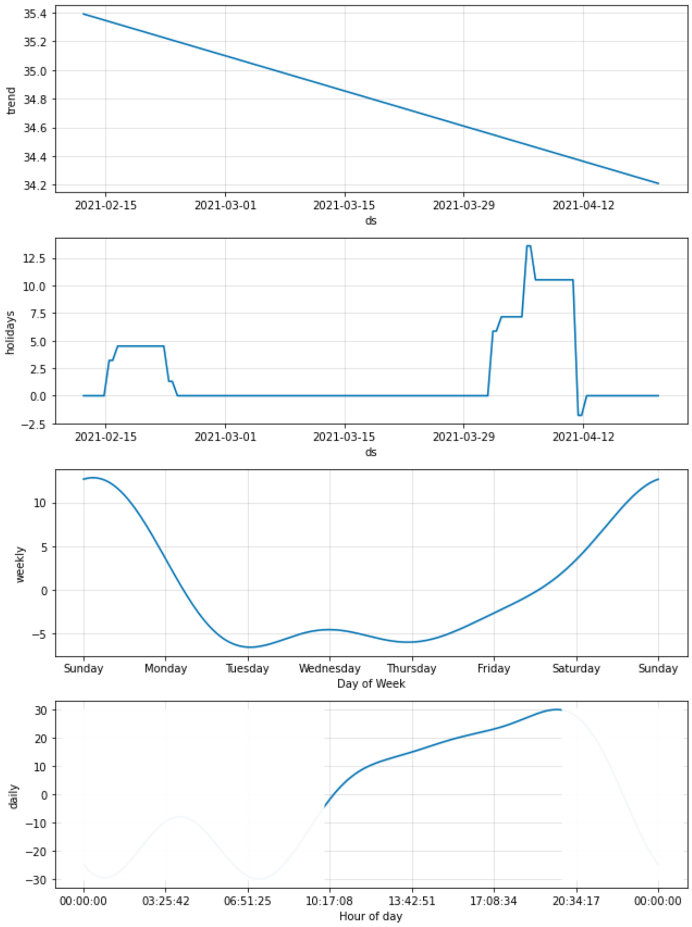

Figure 20. The component decomposition of the Prophet implementation, with a trend component, a holiday component and daily and weekly seasonal components. The hours not between 10 and 20 in the daily component are faded as they are not considered in the implemented model.

The summed components create a forecast visualized in Figure 21. The forecast identified and followed the general pattern of the increase of group affiliation ratio. A zoom-in of one day in the forecast data is presented in Figure 22 (a). Also, in Figure 22 (b), the seasonal naïve forecast is plotted against the same day as in Figure 22 (a). The Prophet model outperformed the seasonal naïve in both MAE and RMSE as shown in Table 8.

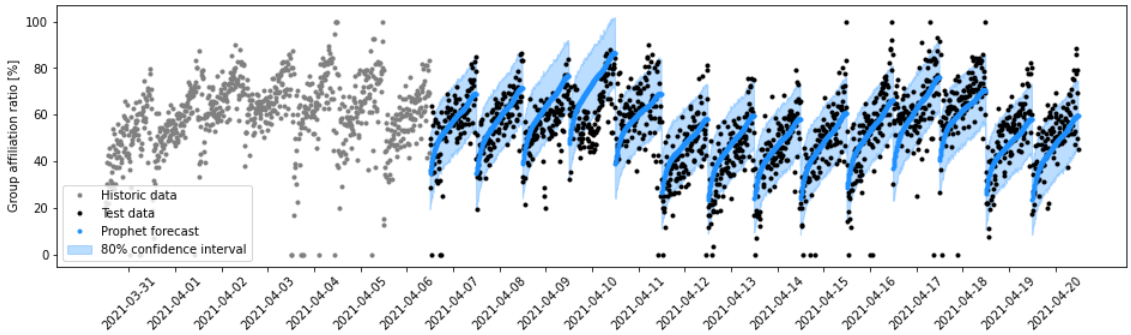

Figure 21. The implemented Prophet model forecast and test data from April 7th to April 20th, and historical data from March 31st to April 6th.

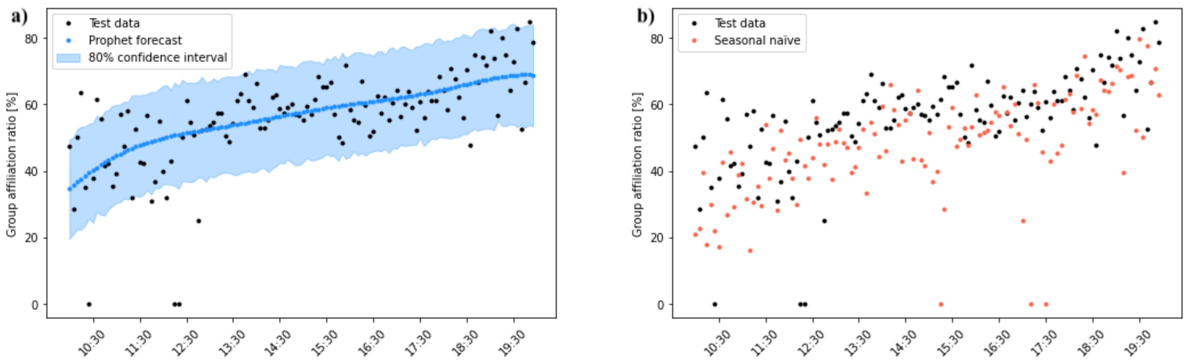

Figure 22. The implemented Prophet model (a) and seasonal naïve (b) forecast and test data from April 7th.

Table 8. RMSE and MAE of the implemented Prophet and Seasonal Naïve models.

	Prophet	Seasonal Naïve
MAE	8.64%	14.07%
RMSE	11.75%	18.83%

The implemented Prophet model, outperforming the seasonal naïve model, added to explaining the use of Kompassen in two ways. First, it predicted future use of the urban space, allowing for a forecast-based understanding of how the urban space will be used. If the actual behavior deviates from the predicted one, understanding that behavior would also be of interest, signaling a shift of user activity or use of the urban space. Identifying long-term inflections of usage would complement the parametrized analyses to further understand the continuous use of the urban space. Second, the component decomposition aided with a general trend overview of the parameter. As urban data usually is noisy, decomposing general trends can present simplified tools toward better understanding the use of the urban space.

5. Discussion

When it comes to understanding urban space use, many different approaches are applied. On the one side of the spectrum, often in the context of smart cities, technical implementations based on data collected from sensors are studied, allowing for a large dataset but without considering urban space use tools. On the other side, architects and urban planners instead base their understanding on experience and intuition and through that gather more qualitative understanding. Meanwhile, the intuition-based studies bring a human scale to understanding cities, they fail to gather large amounts of urban data. On the contrary, the data-driven approach allows for large-scale data collection and understanding patterns over time.

In this thesis, a methodology combining human-scale observational knowledge with large-scale data collection is developed. By identifying key features in the urban space use tools, large-scale movement data are parameterized and thus projected to human-scale understanding. Through this interdisciplinary methodology, further nuance in understanding of how urban space is used is investigated.

As presented in section 4, the nuanced understanding is presented by detailed visualizations as well as the creation of a time series analysis. In section 4.1, the results of the parameterization algorithms are presented, and the evaluation metrics provide an understanding of the parametrization performance. Observing the tables in section 4.1, it is noted that the more imbalanced the dataset is, the lower the F_1-score. The fact that the standing still parameterization has the highest accuracy yet the lowest F_1-score, indicates that accuracy alone is not enough as an evaluation metric for urban data analysis.

As mentioned in section 3.3.4, all identified faults in the data are not cleaned. Instead, the parameterized data reflects the general patterns of urban space use. Worth deliberating is what accuracy and F_1-scores human observers would have. Many of the methods suggested in section 2.3 simplify observations of the urban space use, focusing on certain data collection. A human observer trying to simultaneously collect all parameterized data would probably not outperform the parameterization algorithms. By only collecting certain data at a time, the human observer most likely outperforms the developed algorithms, but data granularity suffers. The human observer can afford to observe the studied area only at certain times. Here, mapping frameworks and observational-based intuitions from the urban space use tools allow for the human observer to strategically carry out observation studies during key times to record important data. Still, the parameterized data encompasses a continuous time span, including the recordings of a human observer.

In summary, the parameterized data outperforms the human observer in terms of data granularity and time span. However, the algorithms are probably not as exact as a human observer but can be used for identifying general patterns. This opens for what value the more detailed and continuous data entails.

In answering the second research questions, the parameterized data are applied according to existing urban space use tools. The results presented in section 4.2 offer a detailed description of the use of Kompassen. However, comparing the results to conclusions in the theoretical literature in section 2.3, it is noticeable that these analyses are not applied in case-studies. This reflects the ambition of this report to highlight tools for understanding how the space is used, leaving answering the question of why for other applications. Diving deeper into answering the question why, using the parameterized data and investigating what understanding can be enhanced, is therefore of interest in further studies.

Furthermore, results from section 4.2 bring an interesting and important discussion regarding the balance between how place-specific and generalizable the thesis results and methodology are. Important to keep in mind is that the results are tested only on two test sets and that the different algorithms have been developed through input data from one sensor at a specific location. From one perspective, considering the standing still parametrization as an example, the algorithm itself could be considered general, provided a similar movement dataset. A comparable urban space with a similar dataset would render analogous results. On the other hand, the characteristics of standing still at a shopping street might be different compared to standing still in a park or plaza. This would be apparent for the human eye but not for the developed algorithm and would therefore need other time and movement constraints making the parametrization more place specific.

Another factor to consider is the limited amount of test data which in itself results in making the results more place specific. Also, parameters suggested in this thesis may not suit other urban spaces. For example, a store interaction class could be abundant when studying a park, where other movement-based user activities are of interest. In short, given that a space has similar functions and characteristics, the parameterization algorithms would be considered transferable. Applying the data cleaning and data parameterization to other urban spaces with new characteristics, performance cannot be ensured, as shown with the sunny conditions of the first test dataset.

To further develop the suggested approach in section 2.3, in understanding how an urban space is used, time series modelling approaches are implemented and analyzed. The results in section 4.3 are in line with the theoretical background. For example, categorizing Kompassen's different use by Monday - Thursday, Friday, and Saturday - Sunday is plausible. Also, slower walking speeds are found for store interactors in the urban space. This could be a further confirmation of the urban space use tools, that they also work with more granular data. It can also contribute as a basis for new tools to be developed, possibly more place-specific or aimed at understanding the urban space use in new light.

An example in line with this discussion is the finding by Sommer & Sommer (1997), who noted that the most interesting behavior information was sometimes recorded at times where no recorded behavior was expected. In this case, a playground was used more frequently by young adults during night than children during the day (Sommer & Sommer, 1997). The time series analysis of the parametrized data in this thesis can capture this unexpected urban space use and contribute with a broader understanding of how the actual use is. This kind of anomaly detection is an important contribution to understanding urban space use and is visualized in Figure 17 in section 4.3.1.

Another example of a broader understanding of urban space use is the Prophet component decomposition. The holiday component $h(t)$ shows a fit where the school breaks and holidays have different impacts on the use of the urban space. As the results highlight, the sports break shows a smaller added impact on the fitted model than Easter and Easter break. One could speculate why this is, but understanding a difference in use between the breaks, using the methodology of this thesis, is an example contribution to the basis for new tools to be developed. The parameterized, granular, data can thus give insights toward creating new analyses and tools.

As the parameterized data is similar to the data used in observational studies, it is accessible for professionals already using this kind of data. However, many of the theories stress the importance of being on-site and getting an intuition for the place, and understanding which data are of interest. Therefore, this methodology most likely serves best as a complement to the observational studies presented in section 2.3, aiding with more and detailed data. The intention of the methodology is to complement architectural practice, and never to replace it.

Looking further, the parameterized data in this report can be supplemented. For example, data identifying sitting or talking, suggested by all tools presented in section 2.3, would be of interest. Collecting data such as gender or age are also suggested by the urban space use tools but requires ethical considerations. Moreover, auxiliary information such as weather data would add to understanding the use of urban space. With a larger parameter scope, new features can be engineered, and activity can be classified in a more detailed manner. The augmented data could enhance the understanding of urban space use but at the same time potentially be overwhelming, considering the large amounts of information. Nevertheless, developing the methodology in further studies would be of interest.

The parameterization methodology presented in the thesis renders a discussion of potential use cases. Traditionally, urban space use tools are conducted by urban planners to understand how an urban space is used, on both a small and large scale. The thesis results indicate a possibility to further deepen the understanding of urban space use through, among other contributions, identifying detailed changes over time. This provides an opportunity for analyzing transformations in urban space directly and over longer timespans, which would be useful in, for example, placemaking.

To summarize, this thesis has contributed with an interdisciplinary methodology, creating passive feedback from urban space users. By parameterizing movement data, humans-scale and granular data for understanding urban space use are extracted. In analyzing the high-resolution dataset as a time series, urban space use tools are complemented. By focusing on answering the question how urban space is used, the thesis results constitute a base for further studies. Preferably, future studies further develop parameterization methods to understand how urban space is used and aid in understanding why behavioral changes occur.

6. Conclusion

The aim of this thesis was to investigate how parametrization of large-scale person movement data can contribute to describing the use of urban space. The thesis aim was operationalized through answering and evaluating three research questions and a methodology combining human-scale observational knowledge with large-scale sensor data collection was developed. Based on observational urban space use tools, movement-based parameter algorithms were developed and analyzed.

Answering the first research question, the parameterization of group affiliation, standing still and store interaction had an accuracy of 93% or higher. A fluctuating F_1-score indicates that the parameterizations might be sensitive to imbalanced data and that accuracy alone might not be sufficient when evaluating urban data. These results are also discussed in the context of how a human observer would perform in terms of the two evaluation metrics.

In the second research question, the parameterized data were applied in selected urban space use tools. By mapping good places to stand, tracing movement, and tracking daily and weekly summaries, a detailed description of how the urban space is used was obtained. Analyzing these results from a generalizability perspective, it is found that the parameterization algorithms capture general behavior in the studied urban space. It is also highlighted that the thesis answers how an urban space is used, leaving answering the question of why an urban space is used for future studies and applications.

Finally, in answering the third research question, time series analyses were developed and distinct patterns of the use of Kompassen over time were crystallized. One example of this was that the group affiliation ratio steadily increases over the day in the full time series. Evaluating this parameter in forecast modelling, the implemented Prophet model, outperformed a seasonal naïve implementation, with an MAE of 8.6% compared to an MAE of 14.1%. By identifying anomalies and forecasting future use, time series modelling aids in understanding change of urban space use over time. Further developing the forecasting implementations would be of interest, adding parameterized user activity such as sitting and talking or other parameters reflecting the highly complex nature of urban space.

With the realization that citizen feedback is important for urban development, this thesis has suggested an interdisciplinary methodology to make use of citizen movement data, to give a detailed description of how an urban space is used. In this sense, the combination of human-scale knowledge of urban space use and the magnitude of large-scale data generates a citizen passive feedback.

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