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Identifying and classifying gaps in the bicycle network of Copenhagen

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Abstract

Cycling is a promising solution for making urban transport systems more sustainable. The planning of bicycle networks can be supported with computational concepts from network theory applied to massive crowdsourced data sets, allowing for data-driven and potentially more efficient decision-making. However, there is no consolidated methodology in the application of network analysis to bicycle infrastructure. This study contributes to the consolidation of computational methods for bicycle network planning by tackling the specific task of identifying gaps in a bicycle network. We show how the detection and prioritization of gaps in an urban bicycle network can be automatized by topological network analysis of open source data from OpenStreetMap (OSM). To this end, we develop a four-step procedure (identify, cluster, classify, and prioritize) for finding the most important network gaps based on topological network metrics. We apply our procedure to Copenhagen, Denmark, and report the 101 top priority gaps found in the network. To evaluate our results, we compare our findings with the current Cycle Path Prioritization Plan of the Municipality of Copenhagen, and find considerable overlaps with citizen survey data. Our results show how network analysis with minimum data requirements can serve as a powerful and cost-efficient tool for bicycle network planning. Our procedure takes into account the entire urban bicycle network and can therefore meaningfully complement localized, manual planning processes for effectively consolidating dense urban bicycle networks.

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Acronyms

APSP All-Pair Shortest Paths. 18, 31

BLOS Bicycle Level of Service. 11

CPPP Cycle Path Prioritization Plan. 31, 54, 58, 102

GIS Geographic Information System. 23

IPCC Intergovernmental Panel on Climate Change. 8

LTS Level of Traffic Stress. 21

OSM OpenStreetMap. 10, 23

PCA Principal Component Analysis. 22

PCT Propensity to Cycle Tool. 11

SDGs Sustainable Development Goals. 8

UN United Nations. 8

Chapter 1

Introduction

We start this chapter by outlining, in section 1.1, the overarching goal of this study: supporting a mobility shift towards increased bicycle use by means of data-driven sustainable urban transport planning. This sets the scene for the research question and research plan, described in section 1.2. Section 1.3 gives an overview of previous work on the topic of gaps in bicycle networks. After that, the scope of the present study is outlined in section 1.4, where the spatial and temporal limits of the case study, limitations of the input data and considered infrastructure types are described.

1.1 Motivation: Towards a data-driven sustainable urban transport planning

We live in an era of global change of unprecedented pace. The term *anthropocene*, introduced to describe the current geological epoch [1], is now commonly used in environmental research and policy-making to illustrate the magnitude of human impact on the Earth System [2]. The Brundtland report [3], published in 1987 by the United Nations (UN), sets the goal of achieving sustainable development, i.e. finding a way to meet humanity’s current needs without undermining the wellbeing of future generations. Reaching this goal is one of the greatest challenges of the 21st century and will require substantial systemic shifts on many levels of human activity [4], including the transport sector.

The transport sector (passengers and freight) is accountable for roughly one quarter of global CO₂ emissions and currently represents the fastest-growing energy end use sector with respect to emission quantities [5]. According to the Intergovernmental Panel on Climate Change (IPCC), there is a high mitigation potential within the sector, with a modal shift to more sustainable forms of transportation as one of the key mitigation options. However, it is also clear that this shift will not come about easily, given that both transport emissions and demand for motorized transport are on the rise globally [5]. In the face of an increasing trend in urbanization, with two thirds of the global population projected to live in cities by 2050 [6], urban transportation systems play a decisive role in the context of climate change mitigation and sustainability. This is reflected in the UN’s Sustainable Development Goals (SDGs) as *Goal 11: Make cities inclusive, safe, resilient and sustainable*, where providing a sustainable transport system for all citizens is one of the key targets [7].

As of today, there is not one single clear definition of **sustainable transport** – rather, the implications of this term are still part of an ongoing debate [8]. In order to avoid terminological

complications, and in line with the sustainability concept as introduced by the Brundtland report mentioned above [3], our working definition will be as follows: A **sustainable urban transport system** is one that provides appropriate mobility options to all its citizens without compromising ecosystem health [5]. Although there is a wide range of sustainability indicators which vary from study to study, there is some common ground within sustainable transport research, often referred to as the “triple bottom line” of (transport) sustainability: economy, environment, and social equity [9]. It would be beyond the scope of the present work to further outline the corresponding analytical framework. However, as will be argued below, a data-driven, computational approach to urban transport planning can be beneficial from all three sustainability perspectives.

Calls for a modal shift away from motorized transport towards more “green”, i.e. environmentally friendly, forms of urban mobility such as cycling and walking are becoming more persistent [10]. Arguments brought forward in favour of such a modal shift are manifold, with many of them simultaneously addressing environmental, economic and social equity dimensions. A clear-cut advantage of shifting away from motorized transport is the subsequent reduction both in greenhouse gas emissions and in material use, with a positive impact for climate change mitigation and air quality [11, 12]. From a transport planning perspective, cycling has the beneficial effect of reduced congestion [13]; moreover, cycling is a highly flexible and reliable transport mode, both in time and space, and allows to reach destinations that are not accessible by public transport [14, 15]. In many situations, cycling can be faster than driving [16]. There is also a substantial reduction in land consumption, both for moving and parking vehicles, associated with a shift from car to bicycle [17, 18], as has been conspicuously illustrated by Hermann Knoflachner’s “Gehzeug” [19] shown in figure 1.1, or more recently by the online platform *What the Street!?* [20].



Figure 1.1: Hermann Knoflachner’s “Gehzeug”: a wooden construction carried by a pedestrian to visualize the additional space they would require for themselves if driving a car instead. *Image licensed under CC BY SA 2.0* [21]

urban context [28], as e.g. not everyone can afford to live in an area that is within cycling distance from their workplace. Recently emerging research also indicates potential equity benefits of taking up cycling from a gender perspective [29, 30].

In short, there is enormous potential to be harnessed by “greening” the transportation sector through an increase of the modal share of cycling, both in terms of climate change mitigation and of socioeconomic (co-)benefits. Best practice examples such as the Netherlands, where several

To describe the unequal distribution of urban space amongst pedestrians, cyclists and car users, Colville-Andersen [22] coined the term “arrogance of space”. The allocation of a major part of available space to car infrastructure is prevalent in many contemporary cities all over the world, and its mitigation would in turn bring about an increase in urban livability [23]. Socioeconomic benefits of active mobility modes such as cycling include physical and mental health improvements from increased physical activity and car crash reduction [24, 25], as well as health benefits from reduced air and noise pollution for all residents, independently of their mobility patterns [26]. Bicycle ownership being, in principle, more affordable than car ownership, a modal shift towards cycling can also be beneficial from an equity perspective [14, 27]. This, however, should be thoroughly scrutinized for the given

decades of policy-making and dedicated investment paved the way for a cultural turn of cycling becoming a normalized mobility mode in a previously car-dominated urban context [31], demonstrate that this goal is, in fact, an attainable one. However, it is also clear that the task is far from being trivial. The private car is, as of now, the most frequently used form of transportation worldwide [32]. With the introduction of motorized transport, urban environments have undergone a radical transformation, sometimes referred to as “Modernist revolution” [33], towards a car-centric setup where cycling is marginalized [34]. Already established infrastructure which primarily caters to motorized transport may easily result in a so-called “carbon lock-in” [35] and fostering of car-dependency [36] of the urban transport system. A systemic shift towards a sustainable urban transport system will thus require major joint efforts of citizens, policy-makers and researchers across disciplines [37]. From a research perspective, a structured approach to bicycle network planning along with a stronger theoretical underpinning is often called for as necessary precondition for substantial modality shifts [15, 34, 38, 39]. With the aim of supporting a sustainable transition of the urban transport system, we envision a data-driven systemic approach to urban transport planning which favours cycling as mobility mode. This Master’s thesis aims at contributing to this goal by tackling a specific task, namely identifying and classifying gaps in urban bicycle networks, with the tools of topological network analysis using open source data.

1.2 Research question and research plan

This thesis project will address the following research question:

How can the detection of gaps in an urban bicycle network be automatized by means of topological network analysis of open source data from OpenStreetMap (OSM)?

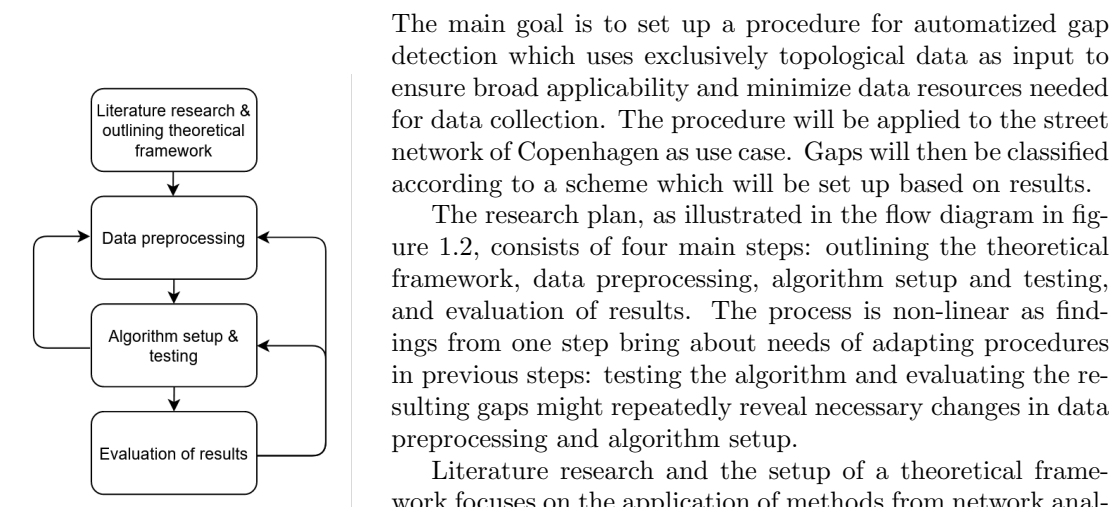


Figure 1.2: Research plan

The main goal is to set up a procedure for automatized gap detection which uses exclusively topological data as input to ensure broad applicability and minimize data resources needed for data collection. The procedure will be applied to the street network of Copenhagen as use case. Gaps will then be classified according to a scheme which will be set up based on results.

The research plan, as illustrated in the flow diagram in figure 1.2, consists of four main steps: outlining the theoretical framework, data preprocessing, algorithm setup and testing, and evaluation of results. The process is non-linear as findings from one step bring about needs of adapting procedures in previous steps: testing the algorithm and evaluating the resulting gaps might repeatedly reveal necessary changes in data preprocessing and algorithm setup.

Literature research and the setup of a theoretical framework focuses on the application of methods from network analysis to bicycle network planning. Data preprocessing includes all steps that are necessary to get from raw OSM data of a city to the street network which the gap-identifying procedure uses as input. The algorithm setup consists of several steps:

first, a formal working definition of a “gap” is outlined, and an algorithm for gap identification is set up. Then, a metric for ranking gaps by relevance is defined. The algorithm and the ranking metric are then tested on the use case of Copenhagen, with a list of most relevant gaps

as preliminary result. Lastly, we visually inspect resulting gaps to evaluate and possibly adjust gap definition, algorithm steps and/or the chosen ranking metric. While the gap-identifying algorithm will be applicable to other input data as well, the resulting classification scheme will require context-dependent adaptation for other cities.

To make the procedure for data processing, algorithm application and analysis available and results reproducible, the code is published on GitHub:

<https://github.com/anastassiavybornova/msc-bikegaps>

1.3 Previous work on gaps in bicycle networks

It is often argued that continuous bicycle infrastructure and visually well distinguishable road categories provide higher safety and lower stress level for all users [15]. Numerous studies have investigated the connectivity of bicycle infrastructure elements; see section 2.4 for terminological definitions and a review of connectivity-related concepts within bicycle planning research. Nevertheless, few attempts have been made so far to explicitly identify the gaps (also often referred to as “missing links”) on an equally high level of spatial resolution as intended in the present study. Without the claim to comprehensiveness, we list below several examples of studies that the present work can be aligned with in terms of motivation, approach or scope.

Ilie, Oprea, *et al.* [40] conducted a case study in the city of Dej in Romania by applying the Bicycle Level of Service (BLOS) concept [41] to a bicycle network planned from scratch and then defining the street segments with the lowest BLOS score as gaps in the planned network [40]. The Propensity to Cycle Tool (PCT) by Lovelace, Goodman, *et al.* [42] identifies high potential for bicycle infrastructure usage on a regional scale by means of origin-destination tables. Oblein [43] recently proposed a heuristic for optimizing bicycle infrastructure upgrading based on cyclist flow estimated from empirical census data. Within the same local context as the present study, Rahbek Vierø [44] applied network analysis concepts to the bicycle network of Copenhagen, aggregating the network data, e.g. by assuming continuous infrastructure if a gap of a length below 3 m is present, and assessing connectivity parameters at neighbourhood level. Lastly, the current Cycle Path Prioritization Plan 2017-2025, published by the Municipality of Copenhagen [45], contains a list of empirically identified missing links on the *Grønne Cykelruter* network, which is aimed at cyclists who prefer quiet and less busy paths (e.g. recreational cyclists, children).

While all of the studies listed above partially overlap with the present work in terms of motivation, methods, and/or scope, no previous study that identifies and prioritizes gaps in an urban bicycle network based solely on topological network data could be found in the literature. A broader review of literature on the application of network analysis to bicycle networks is given in section 2.4.

1.4 Study scope

In this section, we will outline the scope of the work: spatial and temporal limits of the case study, limitations of the input data and considered infrastructure types.

1.4.1 Case study: Copenhagen, Denmark

The municipality of Copenhagen is currently striving to become *verdens beste cykelby* – the “world’s best cycling city” [46]. Indeed, Denmark’s capital is well known for its cycling culture

and often cited as best practice example for bicycle-friendly urban design [17]. The fact that Copenhagen managed to position itself as a role model for bicycle-friendly cities is due both to its favourable cycling policies and to its well-coordinated marketing efforts [31, 47]. The absence of a significant automotive industry in Denmark [48] can be seen as main point in favour, as no major political hurdles need to be overcome when it comes to investment in non-motorized transport [36]. Furthermore, in the case of Copenhagen, considerable parts of today’s bicycle infrastructure were already in place prior to the motorization boom starting in the 1950ies. Over the past decades, an increasing political will to promote a more sustainable urban transport system has allowed for a continuous expansion of the bicycle network in Copenhagen [23]. Other attributes that are often cited as contributing to the high modal share of cycling in Copenhagen are the virtual absence of steep slopes, with hilliness possibly being a major obstacle for cycling in other geographic contexts [15, 49], and the fact that commuter cycling was already widespread historically [50] prior to the rise of car use.

Since the 1990ies, the City of Copenhagen publishes a biennial *Cykelregnskab* (Bicycle Account) and a regularly updated *Cykelsti-Prioriteringsplan* (Cycle Path Prioritization Plan – CPPP). The Bicycle Account contains data on cycling as a mobility mode, citizen surveys, political goals and investment plans for bicycle infrastructure in Copenhagen. In line with the CPH 2025 Climate Plan [51], the latest Bicycle Account from 2018 [46] sets several mobility targets to be reached by 2025: reducing the modal share of cars for all trips to/from/in Copenhagen from 32% to 25% and increasing the modal share of cycling for trips to/from work or education from 49% to 50%. The current Cycle Path Prioritization Plan for the period 2017-2025 [45] contains an overview of foreseen infrastructure improvements and measures, targeted at increasing the modal share of cycling, which are split into five categories:

- Adding bicycle infrastructure (paths, lanes, sharrows) on specified roads
- Improving the traffic conditions for cyclists at specified intersections
- Widening of specified cycle paths
- Improving the *Supercykelstier* network
- Improving the *Grønne cykelruter* network

The last three categories, i.e. the widening of cycle paths, the Supercykelstier, and the Grønne cykelruter networks, are outside of the scope of the present study. For the first two categories, i.e. missing bicycle infrastructure and problematic intersections, the results from a citizen survey that has been conducted in the frame of the Cycle Path Prioritization Plan will be used to qualitatively assess the validity of our findings (see sections 2.5.3 and 3.7).

1.4.2 Defining the bicycle network

The basic spatial limits of the use case network correspond to the boundaries of the municipality of Copenhagen. Frederiksberg, which is formally another municipality, is included out of practical considerations, given that it is enclaved within the city of Copenhagen. From a practical viewpoint, assuming city limits as network boundaries makes sense insofar as cycle network planning is commonly undertaken by local governments or administrative units [15, 52]. However, given that the thus defined network boundaries are administrative rather than physical, and many infrastructural elements do continue across administrative boundaries, this approach might introduce a bias towards the city center, with detrimental consequences for the periphery. Section 2.4.3 provides a more detailed outline of this problem, which is known as “network edge effect”.

We include only protected bicycle infrastructure in our analysis, meaning that the bicycle network consists only of protected infrastructure and does not include e.g. unprotected cycle lanes or sharrows. The rationale behind defining only protected bicycle infrastructure as part of the bicycle network is that a designated cycling infrastructure, including a physical separation from motorized traffic, increases both subjective and objective safety for cyclists [15, 53]. There is a wide agreement on the benefits of protected bicycle infrastructure for utilitarian cycling [50, 54, 55, 56]. Ultimately, the motivation is “planning for the vulnerable” [57]. For our purposes, we will therefore define protected cycling infrastructure as infrastructure that is physically separated from motorized traffic, without distinguishing on-road/off-road subcategories (for a more detailed account on infrastructure types and their impact on cyclist behaviour see e.g. Veillette, Gris e, and El-Genaidy [58]). We shall call this type of infrastructure **cycle path** or **protected bicycle infrastructure** (the terms are to be used interchangeably).

We now give a brief overview of other commonly used terminological distinctions of bicycle infrastructure. The CROW manual [15] describes three layers that can be distinguished within a city from a network perspective: the basic structure, the main bicycle network, and bicycle highways. The basic structure refers to the physical presence of pathways; the main bicycle network is the network of bicycle infrastructure, where “coherence” is a relevant factor (see section 2.4 for a detailed account of terminology); and bicycle highways are strategically placed additional links that are meant to provide for higher cycling speed and thus do not need to be “coherent”. Next, the CROW manual [15] classifies bicycle infrastructure into “cycle lanes”, which are not physically separated from motorized traffic, and “cycle paths”, which are physically separated from cars. Cycle paths are further classified into two subcategories: “segregated cycle path” and “solitary cycle path”; the former is related to an adjacent road while the latter is not. Within OSM data, similarly to the CROW manual, two main categories for bicycle infrastructure are used: “cycle lanes”, which are not physically separated from motorized traffic, and “cycle tracks”, which are physically separated from cars [59]. In line with this, the literature review by Dill and Buehler [60] defines the same broad categories, calling them “cycle lane” (no physical separation from motorized traffic), “cycle track” (physically separated on-road) and “cycle path” (off-road, e.g. running through a park or along a water body).

Whether cycling in mixed traffic (without physical separation from motorized traffic) is acceptable from a safety perspective depends on a variety of external factors: traffic volume of motorized transport, traffic volume of cyclists, maximum speed, street width, slope, road categorization, presence of parking facilities and many more [15]. It also depends, however, on the cyclists themselves: for vulnerable population groups like children, cycling in mixed traffic is not considered to be safe [61]. The mixed traffic option is therefore not included here for three reasons: first, to follow the rationale of planning for the vulnerable; second, because we want to keep data requirements as simple as possible; and third, as further argued in the following section, because we find it reasonable to choose a purely topological approach.

Lastly, although we do assess network growth options by comparing the benefits of adding bicycle infrastructure at identified gaps (see section 3.4), we do not estimate possible cyclist flow changes resulting from changes in the bicycle network, and thus are working with a static network model.

In summary, the bicycle network of Copenhagen that is analyzed in this study is the set of all protected bicycle infrastructure elements as listed in the OSM database within the municipal boundaries of Copenhagen and Frederiksberg municipalities as of February 2021.

1.4.3 Using only topological data

This study aims at developing a procedure for the identification and prioritization of gaps in a bicycle network. In the section below, we briefly present the arguments and benefits of using only topological data for this purpose.

The topology of a network, i.e. its structure, can be seen as its most fundamental property. This is true for any transportation network [62, 63]. The spatial structure of streets and intersections of a city defines the most basic physical limitations for any bicycle network [64]. The corresponding geographic information is nowadays widely available as open-source through platforms such as OSM [65]. Transport network analysis studies often use additional, non-topological data, such as origin-destination tables, census data, or traffic volumes [66, 67, 68, 69]. Incorporating non-topological data into a model has the advantage of fine-tuning the representation of a context-specific reality. At the same time, however, it has the disadvantage of decreasing the model's applicability to contexts other than the one it was originally created for. For example, a model that uses origin-destination tables from a citizen survey on daily trips will allow for a more realistic estimation of urban traffic flow – however, it will do so exclusively for those locations where corresponding data is readily available.

When it comes to cycling data, there are currently not only inconsistencies in data collection methods, but also large inequalities in data availability, both across EU member states [70] and from a global perspective [39]. Therefore, limiting the input data of this study to topological data ensures the broad applicability of its results, both by minimizing data requirements and data acquisition costs and by focusing on properties which can be derived from the network topology independently of its specific geographic location. The limitations arising from the exclusion of non-topological data from the analysis are discussed in section 4.2.

Chapter 2

Methods

After setting the scene for the application of network science in transport studies in section 2.1, this chapter provides an introduction to the basic concepts of graph theory and network statistics in sections 2.2 and 2.3. We then review the most recent network science approaches to the analysis of bicycle networks in section 2.4, and conclude with a description of the data structure of the presented case study in section 2.5.

2.1 Network science for transport studies

Network science can be understood as the application of the mathematical framework of graph theory to a system of interacting entities. It is a powerful tool for (predictive) analysis in a variety of fields – ranging from molecular genetics to social sciences – which partially owes its rising popularity over the last few decades to the increased availability of both computational capacities and data [71]. Independently of the type of system that is being described by a network, the underlying methodology has its foundation in structural characteristics and algorithmic processes of **graphs**, which are the study objects of graph theory [72]. Within transport studies, the applicability of network science might appear particularly obvious, given the ubiquity of maps as visual representations of networks in geographical space. As a matter of fact, within Euler’s solution of the Königsberg problem, which is often cited as the birth of network science, what is formalized as a network is precisely the set of streets and bridges of Kaliningrad [71].

Network science has a wide range of applications within transport studies, such as optimizing a route or a facility location, or the prediction and analysis of travel demand [73]. Shortest path problems, which include finding the safest or the fastest path between two points, are of particular interest for transportation networks [74]. Applications of network analysis to street networks for motorized transport and air transportation networks have a long-standing history. When it comes to the bicycle as a mode of transport, however, the picture is different. In spite of recent advances [75], bicycle traffic is still often left out of the equation in transportation modeling [32]. Network analysis applied specifically to bicycle networks, which we will review in section 2.4, is a newly emerging field that has a high potential for the application of computational tools [76], but still suffers a lack of consolidated methodological approaches [77, 78, 79].

2.2 Graph theory: Definitions and Terminology

This section gives a condensed introduction into the basic concepts and terms of graph theory, which will be used within our analysis.

A **graph** is the mathematical object that represents a network. It consists of two sets: a set of nodes (also called vertices) and a set of links (also called edges). Within graph theory, the more common terminology is *vertices* and *edges*, while in network science, it is *nodes* and *links* [71]; the terms are, however, interchangeable in their meaning, and we shall use *nodes* and *links*.

A **link** is a pair of 2 nodes and represents a connection between them. Links can be directed, if the link has a defined direction from node u to node v , or undirected otherwise. Two nodes u and v are called **adjacent** (also: **neighbours**) if there is a link $l = (u, v)$ connecting them; if l is an ordered pair, the link is said to be **directed** (from u to v); if l is not an ordered pair, the link is said to be **undirected**. In the former case, l is said to be **incident** on v ; in the latter, l is incident on both u and v .

The **degree** of a node is the number of links it is part of; in the case of directed networks, in-degree d_{in} and out-degree d_{out} must be distinguished. **Undirected networks** are networks whose links are all undirected. For undirected networks, $d_{in} = d_{out}$ for all nodes and we can simply speak of node degrees [71, 80, 81].

Two links are called **parallel** if both their origin and their destination nodes coincide. A graph that contains no parallel links is called **simple**. A link whose origin node is identical with its destination node is called a **loop**. A graph that contains no loops is called **loop-free** [72].

Links can be assigned a **weight**, which is a real number that quantifies the strength of the connection between two nodes that this link represents [71]. Depending on the context, the strength of the connection can be expressed, for example, as cost or physical distance. A **weighted network**, thus, is a network with weighted links. In an unweighted network, all links have unit weight [72].

A **walk** on a network is an ordered sequence of nodes where each ordered pair (u_i, u_{i+1}) belongs to the link set of the network. If the first and the last node of the sequence are identical, the walk is called **closed**; if not, the walk is called **open**. If the node sequence of the walk contains no node more than once, the walk is called **simple**. A simple walk is also called a **path**. A path is thus an (open) simple walk from a source node to a target node. It can be represented by the sequence of nodes or by the sequence of links it contains.

Based on this definition of a path, we can define the network property of **connectedness**: a network is called **connected** if for any pair of nodes u and v , there exists a path between u and v , and **disconnected** otherwise. A connected network consists of one single component that contains all nodes and links of the network; a disconnected network consists of more than one component.

We now briefly give the formal definition of a network component, which requires some further terminological clarifications. A graph H is said to be the **subgraph** of a graph G if all nodes and links of H are also elements of G . A connected subgraph H of G is called **maximal** if there is no other connected subgraph H' of G that contains all nodes from H as well as further nodes from G . Finally, a **component** of a network is a maximal connected subgraph of a network. A **disconnected network** thus consists of at least two disconnected components, where each component is a maximal connected subgraph of the network [72]. In other words, and referring back to the notion of paths: for any pair of nodes belonging to the same component, there is always a path between them; and for any pair of nodes belonging to different components, there is never a path between them and their distance is said to be **infinite** [71].

The **length** of a path can be defined as the number of links for an unweighted network or as a function (usually the sum) of the weights of the links for a weighted network. The **shortest**

path is defined as the path with the smallest total weight [72]. Through the shortest path length, a distance metric on the network can be defined. Distance metrics on a network, based on the computation of shortest paths, form the basis of many **centrality measures**, which are a set of possible metrics to quantify the importance of particular nodes or links in the network by assessing the underlying network statistics.

2.3 Graph theory: Network Statistics

Information on properties of individual network elements (nodes and links) can be aggregated on network scale by analyzing the corresponding probability distributions. This procedure, known as **network statistics**, allows for a definition of properties of the network as a whole. Thus, network statistics provide a means for classification, comparison and algorithmic analysis of networks, as well as for the simulation of dynamic processes on networks [72]. Metrics derived from network statistics, by aggregating available information on network scale, allow for an understanding of the network structure and function [71]. Out of the wide range of tools within network statistics, here we will describe only those that are relevant for the purpose of the present study: degree distribution, centrality (in particular edge betweenness centrality) and connectivity.

2.3.1 Degree distribution

One of the most basic and frequently used network statistics is the degree distribution of a network, i.e. the distribution of its node degrees (see figure 2.6). In the case of planar networks, particularly street networks, the degree distribution is mainly of interest for a sanity check of the data. With intersections represented as nodes and streets as links, the degree distribution of a street network will in most cases peak at $d = 4$, and will hardly have any outliers of $d > 4$. For the purposes of the present study, this measure is mainly relevant within the context of data preprocessing. Section 2.5.2 takes a closer look at the degree distribution of the case study network.

2.3.2 Centrality measures

There are different approaches to the assessment of the centrality (relative importance) of a node or link within a network, or in other words: to the quantification of the intuitive concept of some nodes/links being more relevant than others for a given network [72]. Depending on which characteristics they are based on, these centrality measures can roughly be classified into three groups: importance based on the number of associated links (degree centrality); importance based on reducing distance between other parts of the network (straightness, closeness and betweenness centralities); and importance stemming from dynamic processes (especially random walks). For the purpose of our analysis, we will focus on edge betweenness centrality as most relevant measure (see section 2.4.3 on the application of this measure to bicycle networks).

The concept of **node straightness centrality** emerged in the context of network flow efficiency computations applied to transport networks, from the closely related concept of information (flow) efficiency [82, 83]. It is particularly applicable for networks in geographical space as it evaluates the length of a shortest path in relation to the Euclidean distance (“as the crow flies”) covered. For a given node i on a graph G , with d_{ij}^G as the length of the shortest path between i and j on the network and d_{ij}^E as the Euclidean distance between i and j , straightness centrality $c_S(i)$ is calculated as the inverse of shortest path length to Euclidean distance for all possible destination nodes $j \neq i$, normed to total destination node number:

$$c_S(i) = \frac{\sum_{j \in G, j \neq i} \frac{d_{ij}^E}{d_{ij}^G}}{N-1} \quad (2.1)$$

For the definition of **node betweenness centrality** $c_B(i)$ of a node i , which quantifies the relevance of a node for the connections between other nodes, let $\sigma(j, k)$ be the number of all shortest paths between j and k , as computed by an All-Pair Shortest Paths (APSP) algorithm. Furthermore, let $\sigma_i(j, k)$ be the number of all shortest paths between u and v which contain the node i . Then, for the node i , we define its node betweenness centrality $c_B(i)$ as the sum, over all possible node pairs, of the fraction of shortest paths that contain the node i :

$$c_B(i) = \sum_{j, k \neq i} \frac{\sigma_i(j, k)}{\sigma(j, k)} \quad (2.2)$$

Using the expressions introduced above, we analogously define the **edge betweenness centrality** $c_B(l)$ of a link l , which quantifies a link's relevance for the connection between other links. Let again $\sigma(i, j)$ be the number of all shortest paths between all possible node pairs (i, j) in the network, and let $\sigma_l(i, j)$ be the number of all shortest paths that contain the link $l = (u, v)$; then the edge betweenness centrality of the link l is defined as the fraction of these two values,

$$c_B(l) = \sum_{i, j} \frac{\sigma_l(i, j)}{\sigma(i, j)} \quad (2.3)$$

The betweenness centrality of a node indicates the number of node pairs whose distance would increase if the node was removed from the network. Thus, nodes with a higher edge betweenness centrality have a higher relevance for (information) flow to parts of the network. In other words, the network would become less connected if the node was removed, which is particularly well illustrated in the so-called “bottleneck” pattern (see figure 2.1). The same applies to edge betweenness centrality of a link, which can be understood as the number of link pairs whose distance would increase if the link was removed from the network [71, 72].

2.3.3 Connectivity measures

Lastly, we want to define the term connectivity and several related concepts. Thurner et al. [71] differentiate between connectivity and connectancy. The **connectivity** κ of a network is defined simply as the ratio of the number of existing links, L , to the number of existing nodes, N :

$$\kappa = \frac{L}{N} \quad (2.4)$$

Connectancy ν , as synonym for **network density**, is defined as the ratio of existing links to possible links (which depends on the number of existing nodes – the binomial factor accounts for the number of ways to connect two out of N nodes):

$$\nu = \frac{L}{\binom{N}{2}} \quad (2.5)$$

This is not to be mixed up with the average degree $\langle k \rangle = 2L/N$, which differs from network connectivity by a factor of 2 because each link contributes to the degree of two nodes.

The **edge connectivity** of a network, denoted simply as “**connectivity**” by some authors [74], is the smallest number of links upon the removal of which the number of disconnected

components in the network increases [80]. In other words, it quantifies the strength of connection between nodes on a network by the number of links that have to be removed so that two nodes that were either randomly chosen or specified become disconnected [72].

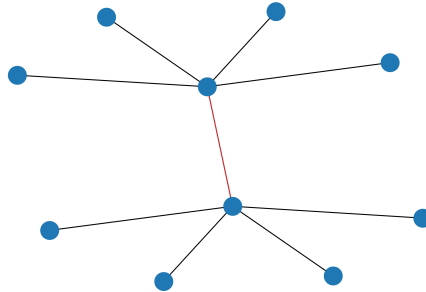


Figure 2.1: Example network with $N = 10$ and $L = 9$. The red link is a “bottleneck”; if removed, the network gets disconnected into two components.

The example network in figure 2.1 illustrates several of the concepts explained above. It has $N = 10$ nodes and $L = 9$ links. The red link has the highest edge betweenness centrality, and the two nodes adjacent to it have the highest node betweenness centrality. For this network, connectivity and connectancy are $\kappa = 0.9$ and $\nu = 0.2$, respectively. Removing just the red link would disconnect the network into two separate components, so the edge connectivity is equal to 1. The bottleneck link is therefore crucial for walks (flow) between the network parts.

2.4 Bicycle network analysis

This section shows how the concepts from graph theory, as introduced above, are used to conceptualize bicycle infrastructure elements as networks, and concludes with an overview of the state of the art in the field of network analysis applied to bicycle networks.

The formal description of geospatial data of infrastructure as a network usually represents **intersections as nodes** and **streets** (that connect the intersections) **as links**. The same approach is taken by the majority of studies on bicycle network metrics that are included in the literature review below. The so-called **dual approach**, which does the opposite – representing intersections as links and streets as nodes – has also been used within transportation studies and urban planning [33, 84, 85, 86] but will not be investigated further here, as its applications do not intersect with the scope of the present study.

Although studies on the topic of bicycle network planning have flourished within academic research in the past decade, and cities around the world are increasingly interested in promoting cycling as mobility mode [53], there is, as of now, no consolidated methodological approach to quantitative network analysis and assessment of bicycle networks [79]. Decision-making support for the development of bicycle infrastructure still lacks a solid scientific foundation [87]. Many studies take a so-called “ad-hoc” approach [15], looking into one specific case study and relying on data availability which cannot be generalized (e.g. from stated preference surveys), which makes it difficult to extrapolate results to other planning contexts. Furthermore, as will become more evident from the review of metrics below, there is no consolidated set of quantitative indicators for the quality assessment of bicycle networks. Additionally, commonly used concepts, such as connectivity, have no standard definition and are interpreted in manifold ways. For example, according to the CROW manual [15], requirements for bicycle network design are comprised by four factors: cohesion, directness, attractiveness and safety. Cohesion and directness can in

principle conceptually be linked to the graph theoretical terms of connectivity and straightness centrality, respectively, as defined in section 2.3.2, but no quantitative definition of the terms is given within the manual itself. There is, thus, a high potential for computational-based methods from network analysis to contribute to the consolidation of concepts.

There is, however, also some solid common ground within bicycle network studies. The most relevant concepts as identified from the literature, namely directness, connectivity and centrality, are reviewed in detail below. In addition, given that connectivity is one of the key concepts for network quality assessment, two major trends within the literature can be broadly outlined by differentiating how the definition and computation of connectivity is approached (see section 2.4.2). One stream of research focuses on the level of traffic stress as main variable, which is also used for defining network connectivity. Another stream of research assesses connectivity on the basis of network measures such as detour and percentage of time spent on bicycle facilities.

Lastly, before moving on to the description of metrics commonly applied to bicycle networks, it shall be acknowledged that in spite of calls for a more consolidated and structured network analysis approach, some degree of context-dependence will not be avoidable. Let us give two illustrative examples of metrics, connectedness and degree distribution, which both require a context-specific interpretation for the case of bicycle networks. First, what does it mean for two network components to be “disconnected”? In graph theory, this implies an infinite distance between them; in the context of bicycle networks, there is, of course, no such thing as an infinite distance – two components that are formally disconnected in the bicycle network, because there is no bicycle path between them, might in fact be very well connected by a car link in the physical street network. Second, within the data structure of OSM, a curved path is represented by a sequence of auxiliary nodes connected by straight links (see section 2.5.2 and figure 2.5). The degree distribution of a non-simplified OSM dataset will consequently be strongly biased towards the degree of 2 due to the auxiliary nodes and can therefore not be used to derive information about e.g. intersection density. Therefore, the choice of applicable metrics will depend both on the system characteristics and the purpose of the analysis.

2.4.1 Directness measures for bicycle networks

Several of the bicycle network connectivity definitions include **route directness** (also associated with the terms “route diversion” and “maximum detour”) as one of the factors determining connectivity. **Diversion** (or detour) of a path from A to B is defined as percentage of additionally travelled distance with respect to the shortest path from A to B. In the context of bicycle networks, the “shortest path” usually means the shortest possible path regardless of road type, while the actually chosen route might include a detour if the cyclist is willing to travel a longer distance for a better cycling experience, e.g. on a path with less motorized traffic or more protected bicycle facilities. The concept of route directness is closely related to the concept of straightness centrality (see section 2.3.2). They differ in that straightness centrality compares the shortest path to the connection between two points “as the crow flies” (Euclidean distance), while route directness compares the chosen path to the shortest path.

2.4.2 Connectivity measures for bicycle networks

In the context of urban planning and transportation networks, the term **network connectivity** has been subject to a wide range of interpretations. The common denominator of connectivity measures for transportation networks is the underlying question – *How easy is it to get from A to B?* – or as Twaddell and Rose [88] put it: *Can I get where I want to – quickly and safely?*. Each connectivity measure is yet another attempt to provide a quantitative answer. Dill [89] offers a

detailed account of the manifold connectivity measures found in urban planning literature. Those measures contain, but are not limited to, concepts defined by graph theory (such as “link-node ratio”, which is the same as connectivity as defined in section 2.3.3). It is noteworthy, though certainly not surprising, that several of the connectivity measures as applied in urban planning include parameters that describe the topography of the physical space within which the network is situated, e.g. intersection density that gives the number of intersections per square unit of area.

In the view of the diversity of approaches, offering an exhaustive list of connectivity measures for bicycle networks would not be possible here. We therefore outline several selected connectivity measures, aiming to demonstrate methodological and terminological variety of recent studies on the topic.

Low traffic stress (LTS) connectivity

The concept of Level of Traffic Stress (LTS) connectivity has been introduced by Mekuria, Furth, and Nixon [90], refined by Furth, Mekuria, and Nixon [67] and taken up by many subsequent studies [78, 91, 92]. It builds upon the **Four Types of Cyclists** typology, as introduced by Geller [93] and further scrutinized by Dill [94, 95], which classifies traffic participants into four groups depending on their willingness to cycle in mixed traffic (see table 2.1).

Street segments, crossings and intersection approaches with right-turn lanes are assigned an LTS level. The LTS ranges from 1 to 4 (see table 2.2) and is a summary measure derived from various factors (such as speed limit, street width, vicinity to parking lane etc.), based on the CROW manual design criteria for safe cycling facilities [15]. The stress level of a path is defined as the stress level of its most stressful element (street, crossing or intersection approach). Two points on the network are then said to be connected at stress level X if there is a path of maximum stress level X between them that at the same time satisfies empirically found maximum detour criteria [67].

LTS connectivity of a path or an origin-destination pair, at each of the 4 different traffic stress levels, is a binary measure (yes/no). Furth et al. [67] suggest the aggregation of LTS connectivity on network scale by computing the connectivity ratio for each of the stress levels, which is the fraction of origin-destination pairs (u, v) that are connected at the given stress level, weighted by the number of daily trips undertaken between u and v .

Type of Cyclist	Description
strong and fearless	will cycle regardless of traffic conditions
enthused and confident	will share road with cars, but prefer to cycle on bicycle facilities
interested but concerned	will cycle, but will not share road with cars
no way, no how	will not cycle under any circumstances

Table 2.1: Four Types of Cyclists, adapted from Dill and McNeil [94]

The strength of the concept of LTS connectivity lies in its quantification of the extent to which heavy motorized traffic hinders or even completely impedes a gradual modal shift towards utilitarian cycling: if it is practically life-threatening to cycle to work, large infrastructural changes are a necessary precondition for any noticeable modal shift to take place. However, LTS connectivity is particularly well applicable in the context of cities whose urban structure consists of residential area “islands” separated by bottlenecks of transport arterials with high traffic stress. This is the case for many North American cities, where the LTS connectivity concept was originally developed and applied. However, it will be of less relevance in urban contexts where traffic

load is less, cycling is already more frequent and/or infrastructural elements supporting cycling are already in place.

LTS	Description
LTS4	highest level of traffic stress; regular negotiation with moderate-speed traffic or proximity to high-speed traffic; crossings perceived as dangerous
LTS3	regular negotiation with low-speed differential traffic or near to moderately-high speed traffic; crossings stressful, but perceived as safe by most adults
LTS2	physically separated from traffic or near to well-confined traffic; crossings easy for most adults
LTS1	lowest level of traffic stress; physically separated from, or only occasionally dealing with low-speed traffic; crossings safe for children who were trained to cross intersections

Table 2.2: Four Levels of Traffic Stress, adapted from Furth, Mekuria, and Nixon [67]

Other connectivity measures

Boisjoly, Lachapelle, and El-Geneidy [79] base their definition of connectivity on two variables: diversion from the shortest path, which should be minimized; and trip percentage spent on a bicycle facility, which should be maximized. Within the routing algorithm, a cost reduction coefficient is applied to bicycle facilities. Two points on the network are then said to be connected if a path exists that complies with thresholds for both variables, and disconnected otherwise. An aggregated connectivity value for the whole network is then computed based on the percentage of connected trips from an origin-destination table. Thresholds for maximum detour and minimum trip percentage on a bicycle facility, as well as the cost reduction coefficient, are derived from empirical cycle route choice data.

In the CROW manual [15], the attribute “cohesion” is defined as cycle infrastructure “*linking all origins and destinations that cyclists may have*” [p. 31]. The same concept is also referred to as “coherence” [15, p. 63], and conceptually related to the term “connectivity” as used in this section. However, no quantitative definition of network connectivity is given within the manual.

Schoner and Levinson [96] apply Principal Component Analysis (PCA) to a set of 21 topological network variables and obtain 5 factors with eigenvalues larger than 1. One of the 5 factors is defined as “connectivity”. The two variables κ and ν from equations 2.4 and 2.5, which we have defined as “connectivity” and “connectancy”, respectively, obtain the highest loadings for the PCA factor termed “connectivity”.

To give a last and recent example, Olmos, Tadeo, *et al.* [97] define “global connectivity” of a bicycle network as the condition of all nodes of the city street network being connected by bicycle infrastructure. Nodes are defined as locations from an origin-destination survey on census block level. Percolation theory is then used to optimize the location of new bicycle infrastructure; the giant connected component of a percolating network is said to be globally connected.

2.4.3 Centrality measures for bicycle networks

Within the context of transport network analysis, centrality measures from network theory are often subsumed into the set of so-called “network criticality measures”. Centrality indices are commonly used to estimate flow on transport networks, and have been recently applied to bicycle networks mainly from the viewpoint of cyclist safety. Zhang, Bigham, *et al.* [98] set up a statistical model to correlate metrics derived from edge betweenness centrality with observed data of traffic crashes involving pedestrians or cyclists. Ye, Wu, and Fan [99] incorporated travel demand data into network betweenness centrality computations to estimate traffic flow. Their

approach is similar to the one taken by McDaniel, Lowry, and Dixon [100], who set up a method to estimate specifically bicycle traffic flow from counting station data, using edge betweenness centrality measures derived from trip tables. More recently, Kamel and Sayed [101] examined the correlation of topological network measures, including node and edge betweenness centralities of the bicycle network, with the number of traffic crashes and the number of kilometers cycled, as proxies for the overall quality of the bicycle network.

A city’s physical street network is rarely limited by its municipal boundaries. Defining the limit of the network to be analyzed is a context-dependent and potentially ambiguous task. The so-called “network edge effect” [102], also known as “border effect” [86], refers to the non-trivial dependence of network measures on changes in network boundaries. Gil [103] reviews the implications of the network edge effect for the analysis of transport networks, focusing on how centrality measures are impacted. A possible way of smoothing the network edge effect is to introduce a cut-off radius for the set of shortest paths based on which the edge betweenness centralities are computed [103]. Yamaoka, Kumakoshi, and Yoshimura [104] demonstrate the applicability of this approach, which they refer to as “local betweenness centrality”, for the use case of 30 different urban street networks.

The tools of network theory might appear sufficient to describe and possibly mitigate the network edge effect on the level of network topology. However, Jafino, Kwakkel, and Verbraeck [105] point out that there are, in addition, some deeper implications to the concept of centrality itself, when applied as prioritization metric for transportation networks. The choice of a specific centrality measure implies a moral decision, which can be roughly summarized as utilitarian vs. egalitarian. Jafino [106] proposes a framework for equity-based transport network analysis, where the main idea is to introduce weight factors from equity considerations in each of the betweenness centrality computation steps.

2.5 Data

2.5.1 OSM datasets: definition and acquisition

The main data source for the present study is OpenStreetMap (OSM). OSM provides global map data for free use under the OSM licence. The map data is crowdsourced, i.e. built and maintained by volunteers [65]. A review of implications of OSM data quality for the present study can be found in section 4.3. The basic structure of the data used in this study is Geographic Information System (GIS) vector data of geographic objects which together form the street network of Copenhagen - mainly streets and intersections, but also bridges, roundabouts, parking lots, paths through green areas etc. In the data, intersections are represented as points in geographic coordinates, and street segments are represented as sequences of points. In our network derived from the data, intersections are interpreted as network nodes, and street segments are interpreted as links.

All input data was downloaded from OSM in February 2021 in csv file format. Datasets were acquired separately for two partially overlapping networks, which, when combined, form the **street network** of the municipalities of Copenhagen and Frederiksberg: the network of car infrastructure and the network of protected bicycle infrastructure. From now on, we will refer to these two networks simply as **car network** and **bicycle network**. It is important to point out that the limits of the two networks in physical space therefore coincide with the municipality boundaries, which introduces an arguably arbitrary cut into the continuous fabric of the street network of the Greater Copenhagen area. The consequences of this limitation for the validity of our findings are discussed in more detail in section 4.2.

For each of the two networks, two csv files were generated through OSMnx: one for the nodes and one for the links. Each row of the datasets contains attributes that belong to one specific node/link of the network: geocoordinates and OSM ID; for links additionally: length, street name, oneway/two-way indication; furthermore, several attributes which have not been used within the scope of this study, such as type of highway and speed limit.



Figure 2.2: The street network of Copenhagen from OSM data. The largest connected component is shown in grey. Disconnected components with number of nodes $n > 1$ and $n = 1$ (i.e. single nodes with no incident links) are shown in red and purple, respectively.



Figure 2.3: The largest connected component of the street network of Copenhagen. Car links are shown in grey, bicycle links in green, multi links (car *and* bicycle) in blue. The bicycle and multi links (green and blue) together form the bikeable network of protected bicycle infrastructure.

2.5.2 Data preprocessing

For data acquisition and data processing we used Python and OSMnx. The data on car and bicycle nodes was combined into one dataset and the parameter “node type” was added. Nodes that appeared only in the bicycle dataset were assigned the type “bicycle” and nodes that appeared only in the car dataset were assigned the type “car”. Nodes that appeared in both datasets were assigned the type “multi”. After this, duplicates were removed. The same procedure was applied to the car and bicycle link datasets: they were merged into one dataset with the “link type” parameter set to bicycle, car, or multi. Figure 2.3 illustrates the resulting distinctions in

the network. For the sake of further simplification, in order to create an undirected network, the oneway vs. twoway attribute was dropped, after which duplicated links, i.e. links with same length and type but opposite origin/destination nodes, were removed.

The link type was used as parameter for the definition of gaps (see section 3.2). Given that for the purposes of the present study we were only interested in protected bicycle infrastructure while disregarding the presence or absence of car infrastructure, we further simplified the data by dropping the distinction between bicycle and multi links, and subsuming them under the link type **bikeable** (see figure 2.3 for the illustration of the resulting network coloured by link type). As for the node types, the distinction between bicycle, car, and multi nodes was preserved because it is needed for the definition of gaps (see section 3.2 and figure 3.2).

A graph object was created from the resulting dataset using the Python’s networkx library. The resulting network had 77 disconnected components, out of which only the largest connected component was kept, while all other disconnected components were dismissed as negligible for the sake of simplicity (see figures 2.2 and 2.4). In the real street network of the city, disconnected components, i.e. street segments that are not accessible from any other street segment, are quite rare. The appearance of disconnected components in our dataset is mostly due to data quality issues, e.g. missing street segments that should have been classified as bicycle links (see figure 2.4). Future analysis could take a more thorough approach and connect the disconnected components to the largest connected component of the network by manually adding the missing links to the dataset.

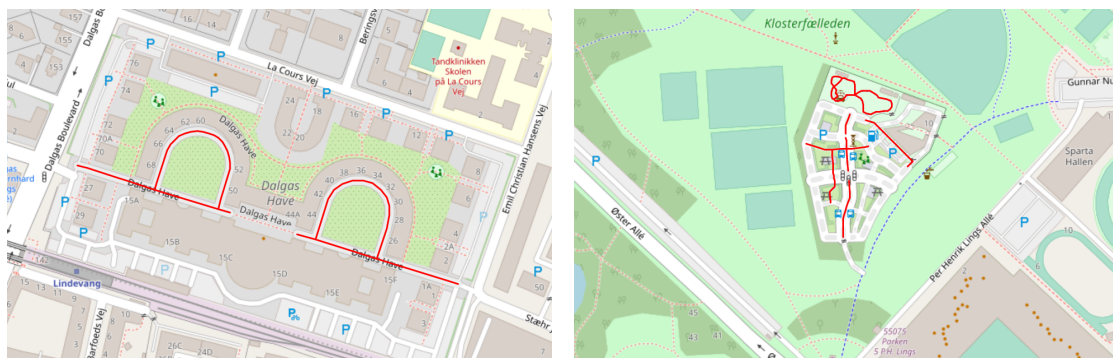


Figure 2.4: Two examples of disconnected network components, shown in red. Left: Copenhagen Business School parking lots. Right: Trafiklegeplads in Fjaelledsparken. [107]

Within OSM data, prior to further processing, a curved street is represented by a sequence of several points in geocoordinates, which are connected by straight lines, as is illustrated in figure 2.5. We shall call the corresponding degree-two nodes, which are introduced only for the sake of preserving the physical shape of an link, “auxiliary”. The presence of auxiliary nodes in the dataset strongly biases the degree distribution of the network towards $d = 2$ (see figure 2.6). The network can be simplified by replacing a sequence of straight links and their corresponding auxiliary nodes by a single polygon link, while preserving the data on length and coordinates of the aggregated links. OSMnx has a built-in function to export already simplified datasets. For our purposes, however, the simplification had to be done for the combined car and bicycle network. This is because nodes which are auxiliary in only one of the two networks would otherwise disappear from the dataset, and information on connections and partial overlaps between the car and bicycle networks would be lost if simplification was carried out within OSMnx. Therefore, a network was created from the merged dataset of car/bikeable links and

car/bicycle/multi nodes. Then, a simplification algorithm (see box “Algorithm 1”) was created and applied to the network to remove all auxiliary nodes.

```

Input: Network  $H$  with auxiliary nodes
Output: Network  $H'$  without auxiliary nodes

while auxiliary nodes in  $H$  do
  for node in  $H$  do
    if node degree  $d(n) = 2$  and links incident on node have the same type then
      | place node in stack
    end
  end
  while stack is not empty do
    take random node  $n$  from stack;
    if neighbours of  $n$  are neighbours themselves then
      | remove node  $n$  from stack;
    else
      | remove two links incident on node  $n$  from link set of network  $H$ ;
      | add new link connecting two neighbours of  $n$  to the link set of network  $H$ ;
      | set length attribute of new link to sum of lengths of removed links;
      | add geocoordinates of removed links to geocoordinate attribute of new link;
      | remove node  $n$  from node set of network  $H$ ;
      | remove node  $n$  and, if applicable, its two neighbours from stack;
    end
  end
end

```

Algorithm 1: Removal of auxiliary nodes from the OSM dataset

At each step, all degree-two nodes of the modified network H' that have two same-type links incident on them are placed in the stack. Nodes are then taken out from the stack one by one. If the two neighbours of the node are neighbours themselves, resulting in a triangular pattern within the network, the node is not auxiliary; then the node is simply removed from the stack, and no further action is taken. In the contrary case, i.e. if the two neighbours of the node are not neighbours themselves, the node is an auxiliary node. Then the auxiliary node itself, as well as the two links incident on it, are removed from the network and replaced by a new link that connects the auxiliary node’s neighbours. The length attribute of the new link is calculated as the sum of lengths of the two replaced links. The information about coordinates is preserved in the coordinate attribute of the link. Lastly, the endpoints of the new link (neighbours of the removed node) are, if present, removed from the stack as well. The process is repeated until the stack is empty. At the next run of the algorithm, the steps are repeated to create a new stack and empty it again, as described above. The algorithm terminates when the stack contains no auxiliary nodes, i.e. when the only degree-two nodes with same-type links incident on them left in the network are nodes that form part of a triangle.

For the dataset used in the present study, the algorithm terminates after seven runs; the highest number of auxiliary nodes associated with a link in the final, simplified network is 54. The only degree-two nodes that appear in the dataset after simplification are either meeting points of two links of different types or nodes that are kept to represent loops on the network while maintaining the network simple, i.e. without parallel links (see figure 2.7). As expected, the

degree distribution of the simplified network significantly differs from the original one, shifting from a high to a low percentage of degree-two nodes (see figure 2.7).



Figure 2.5: Auxiliary nodes in OSM data: Vejlands Allé as example of a curved street. Left: Before simplification, the path between the two black nodes consists of a sequence of 16 auxiliary nodes of degree 2 (red), connected by 17 straight links (blue). Right: After simplification, the path consists of one link, whose curvature in physical space is preserved in the link attribute. [107]

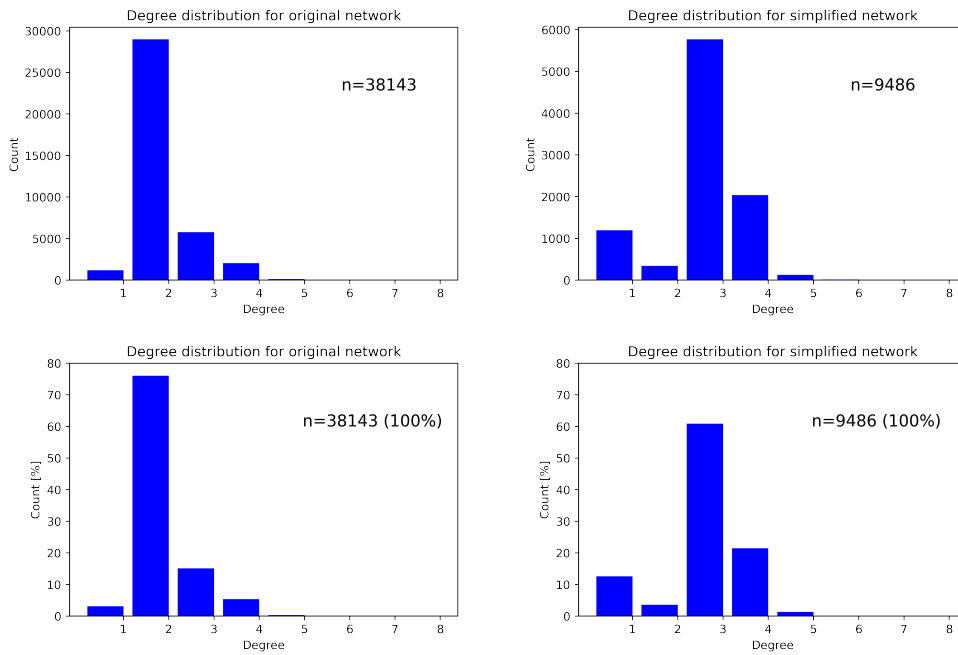


Figure 2.6: Node degree distributions before and after simplification

The final outcome of the data preprocessing, as visualized in figure 2.3, is the car and bicycle network of Copenhagen, represented by a simple, loop-free, undirected graph with no auxiliary nodes, where each link has two attributes: *type* (car or bikeable) and *length*, and each node has the attribute *type* (car, bicycle, or multi). The type distinctions of nodes and links are illustrated in figure 2.8. This network will be the input for all further analysis.



Figure 2.7: Preserved nodes of degree 2 in the simplified network. Car links are shown in orange, multi links in green and bicycle links in blue. Only nodes of degree 2 (black circles) are shown. All preserved nodes of degree 2 are either meeting points of links of two different types (as the three nodes in the upper left part of the figure) or belong to a loop (remaining nodes). [107]

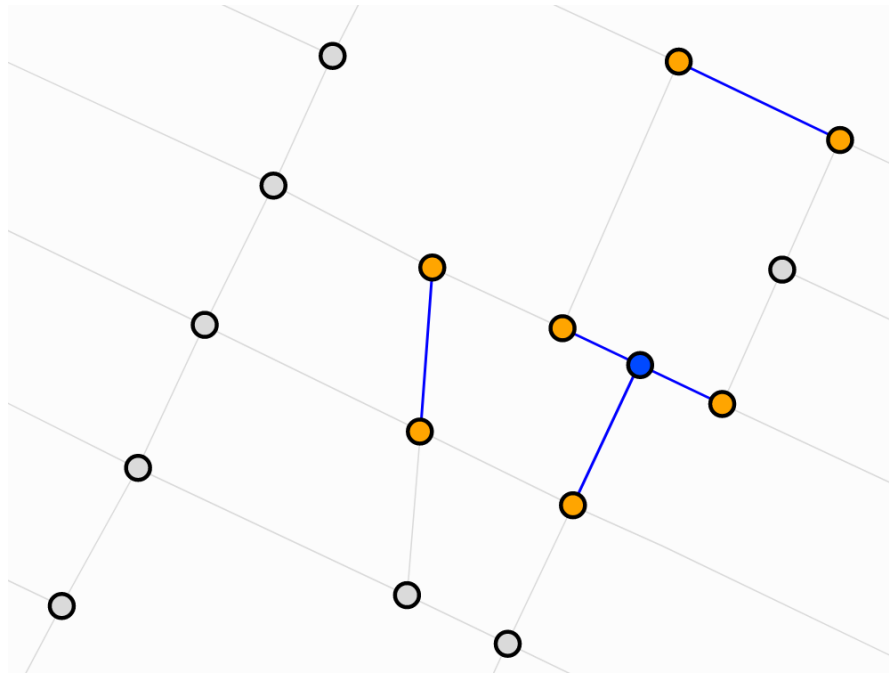


Figure 2.8: A part of the Copenhagen street network illustrating distinctions of node and link types. Links of the type “car” are plotted in grey; links of the type “bikeable” are plotted in blue. Nodes between links of the same type are either car nodes, plotted in grey, or bicycle nodes, plotted in blue. Nodes between links of different types are multi nodes, plotted in orange.

2.5.3 Citizen survey data from Copenhagen’s Cycle Path Prioritization Plan

For a qualitative assessment of result validity, gaps as identified in section 3.3 are plotted together with results from a citizen survey conducted by the Municipality of Copenhagen in September and October 2016, as presented in the document “Cykelsti-Prioriteringsplan 2017-2025” [45]. Data was provided to us by the Municipality of Copenhagen in shapefile format and consists of a set of geocoded locations, indicated by survey respondents through clicking on a digital map, for each of the following categories: “Cykelsti mangler” (cycle path missing), “Cykelsti for smal” (cycle path too narrow) and “Kryds med stor traengsel” (busy intersection). The data on too narrow cycle paths was discarded, given that street width was not accounted for in the present study. The data on missing cycle paths and problematic intersections was processed and plotted as separate layer on all maps that show the gaps identified in this study. Figure 2.9 gives an overview of the processed data from the citizen survey. The data is compared with results from our procedure in section 3.7. Detail maps of all gaps identified within the case study that showed an overlap with citizen survey results are found in appendix B.

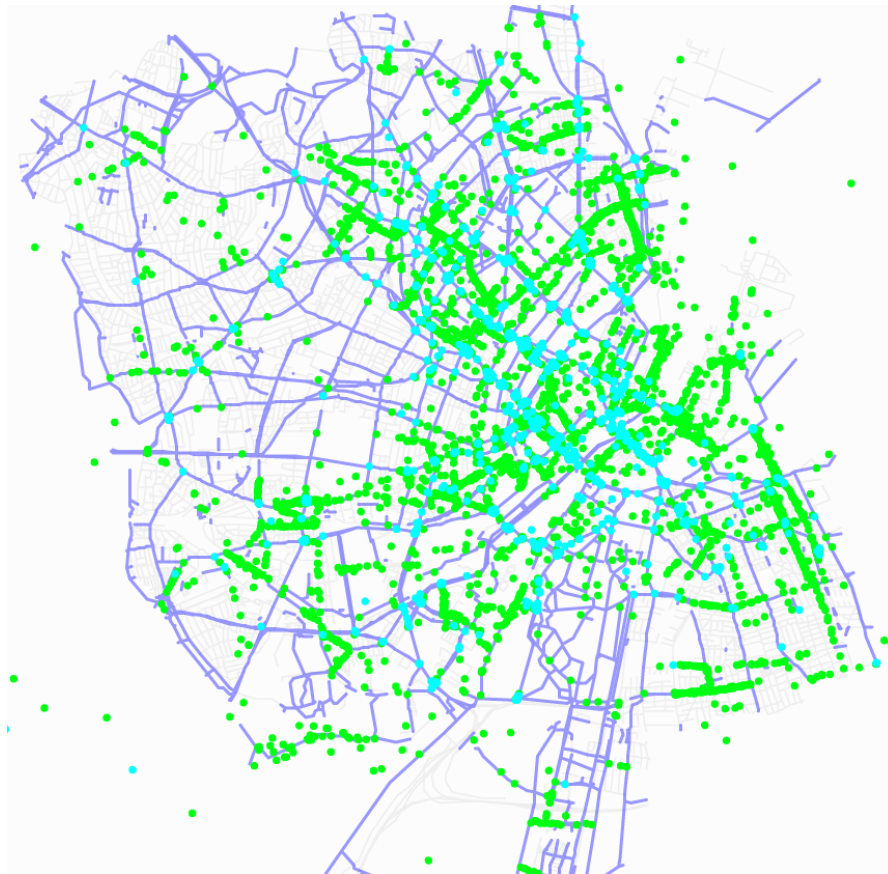


Figure 2.9: Overview map of citizen survey data. The car network is shown in grey, the bicycle network in dark blue. Green dots show citizen input on missing cycle paths; light blue dots show citizen input on problematic intersections.

Chapter 3

Results

In the following chapter, we present the two main results of this thesis project: the procedure for gap detection, and its application to the case of Copenhagen. The corresponding code is published on GitHub:

<https://github.com/anastassiavybornova/msc-bikegaps>

We start by presenting, at one glance, the procedure steps that lead from the preprocessed dataset to the list of top-ranked gaps in section 3.1. The procedure steps are then outlined in detail, using the street network of Copenhagen as application example. In section 3.2, the concept of “gap” is defined. Section 3.3 describes the identification of all gaps in the bicycle network of Copenhagen. Section 3.4 defines a ranking metric and describes its application to the list of identified gaps. The process of visual analysis and clustering is described in section 3.5. Section 3.6 gives an overview of identified gaps grouped by class. Lastly, we compare our findings to the contents of the Cycle Path Prioritization Plan (CPPP) in section 3.7.

3.1 Procedure steps: Overview

Figure 3.1 summarizes the procedure steps, described in the following sections, that lead from the preprocessed dataset to the final list of prioritized and classified gaps. The final outcome of preprocessing raw OSM data, as it has been described in section 2.5.2, is a simple, loop-free, undirected graph representing the street network, with no auxiliary nodes, with links classified by type (car, bicycle, or multi) and weighted by their physical length. This preprocessed dataset is used as input for the procedure described in this chapter.

An All-Pair Shortest Paths (APSP) algorithm with a defined cut-off length c_{gap} is applied to the network to obtain set of shortest paths. Paths that do not fit the gap definition are discarded, rendering a list of gaps to be clustered and ranked. Edge betweenness centrality values are computed for all network links, applying a cut-off radius r_{max} within the APSP

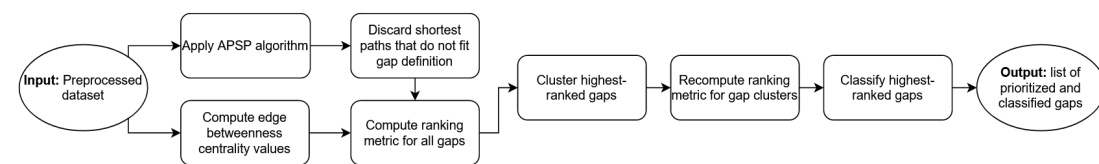


Figure 3.1: Procedure steps

algorithm. The ranking metric \bar{m}_c is defined and computed for all gaps, and the gap list is sorted accordingly. Gaps are then analyzed and overlapping gaps are manually clustered. The value of \bar{m}_c is recalculated for gap clusters, rendering the final ranking of prioritized gaps. A classification scheme is derived from visual inspection of the prioritized gaps.

3.2 Gap definition

A cyclist on their way through the well-connected and dense bicycle network of Copenhagen might find themselves surprised by suddenly having to share the road with cars for a while, or by having to cross unprotected intersections with a high traffic load. To formalize this intuitive concept, we start out by defining a **gap** on the street network as a **car segment between two protected bicycle infrastructure elements**. This is visualized in figure 3.2. In network terminology, a

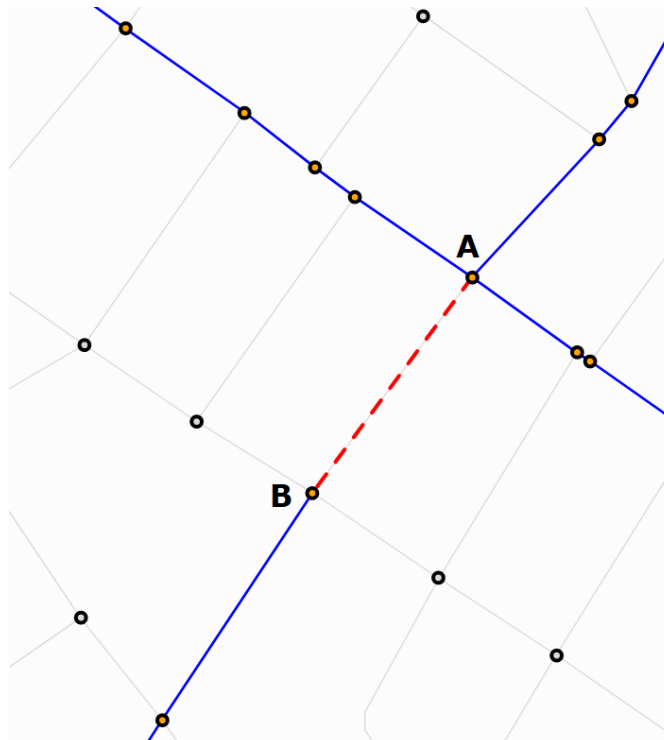


Figure 3.2: Example of a gap X on Mågevej. Car links are plotted in grey, bikeable links in blue. Car nodes are plotted in grey and multi nodes in orange. The dashed red line shows the gap, which is a sequence of car links of total length 130 m $<$ c_{gap} as shortest path between the two multi nodes A and B.

gap in the protected bicycle infrastructure of the street network is a **shortest path between two multi nodes which consists only of car links**. Not all street segments that fit this formal definition are equally suitable for the construction of new bicycle infrastructure, nor are they equally relevant for the overall performance of the bicycle network. Therefore, after finding all gaps which fit the above definition, the next step is to evaluate how beneficial it would be for the overall performance of the bicycle network if a protected bicycle infrastructure element was added along a gap. In other words, we need to quantify how much “closing the gap” would

improve the bicycle network. The evaluation of gap relevance is carried out in section 3.4. The most relevant gaps are then classified by type in section 3.6.

3.3 Gap identification

We first define a cutoff length c_{gap} for the maximum gap length. The number of identified gaps on the network grows supralinearly with cutoff length. For the purpose of this study the parameter was set to $c_{\text{gap}} = 1200$ m. We found this parameter choice to offer a fair trade-off between several constraining factors (see section 4.1 for a sensitivity check). We then apply the Dijkstra all-pair-shortest-path algorithm [108, 109, 110] to the street network, with links weighted by link length in meters, using the cutoff path length of c_{gap} . From the set of paths obtained, we discard all paths except those that meet the following two criteria:

- All links in the path are car links
- Both start and end nodes of the path are multi nodes

We also discard all duplicates, given that the shortest path algorithm returns directed paths, i.e. for each origin-destination node pair (u, v) two shortest paths are found. For the given gap cutoff length of $c_{\text{gap}} = 1200$ m, a total number of 8141 unique gaps was identified in our dataset.

A problem that the shortest path algorithm, as presented above, does not yet account for, is the fact that in many cases, when a street does provide protected bicycle infrastructure and the cycle path runs along the car lane, the shortest path algorithm applied to a pair of car nodes will choose the car path over the bicycle path due to its slightly smaller length (see figure 3.3), and therefore falsely detect a gap located on the car lane, in spite of a bicycle path running next to it. We shall refer to these falsely identified gaps as **parallel paths**. Out of the list of most relevant gaps as identified by our algorithm, the ones that are actually parallel paths coincide with some of the busiest bicycle corridors in the city, such as Gyldenløvesgade. This is an encouraging observation as a proof of concept for our use of edge betweenness centrality as a proxy for bicycle traffic flow – or, to put it simply, for the parallel paths on figure 3.3, “*indeed, if there was no bicycle path yet, you’d better place one there*”.

The parallel paths problem is a consequence of applying the shortest path algorithm to a relatively high-resolution network layer. However, lowering the resolution is not an option, because using map data with a high resolution of the street segments is a necessary precondition for identifying the gaps that we are looking for. This is a well-know problem in transportation network modeling: if a high-resolution layer is given as input, solving a routing problem at a lower resolution is a non-trivial task [111, 112]. After experimenting with a cost factor approach for individual link length, which was then discarded (see section 4.4 for a detailed account), we applied the following mitigation strategy for parallel paths:

For all identified gaps of length x_{gap} , the distance between their endpoints on the bikeable network, x_{bike} , was computed. The distance range, as expected, was found to be $x_{\text{gap}} < x_{\text{bike}} \leq \infty$, with infinite distance indicating that the two points were not connected on the bicycle network, as explained in section 2.2. The detour factor d was then computed as ratio of distances on bicycle vs. multi network:

$$d = \frac{x_{\text{gap}}}{x_{\text{bike}}} \quad (3.1)$$

We then defined a maximum detour value, d_{max} , assuming that most “gaps” of length x_{gap} that are connected on the street network with a maximum detour of 50% are likely to be parallel paths. The choice of $d_{\text{max}} = 1.5$ was arrived at empirically through a first manual analysis of identified gaps. In the thus acquired final list of gaps prior to clustering (see section 3.5), only 6%

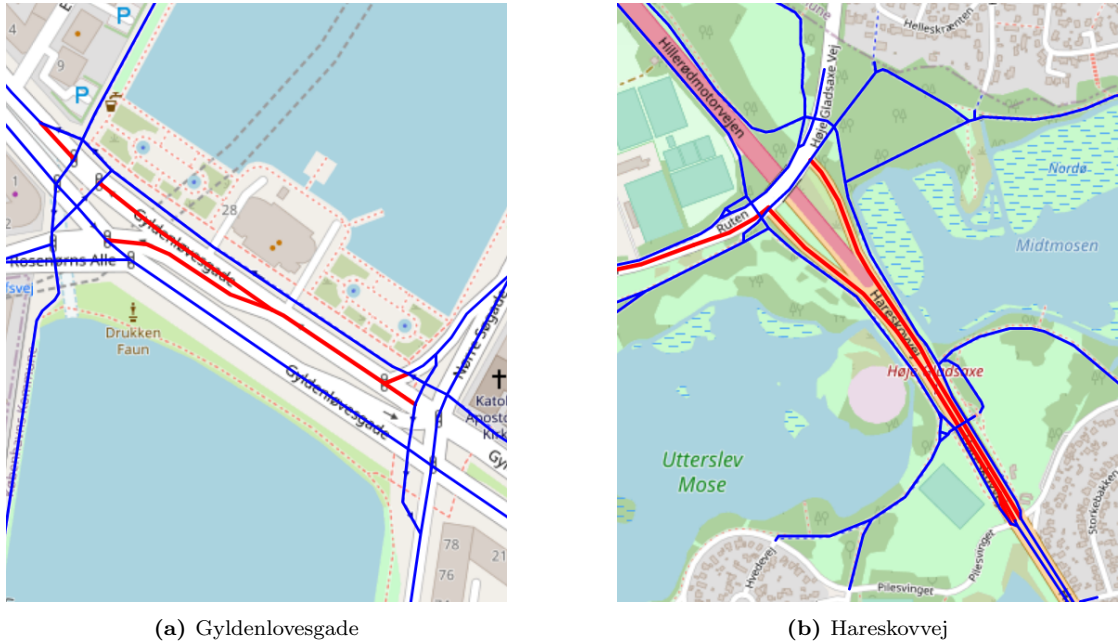


Figure 3.3: Two examples of parallel paths. The bicycle network is shown in blue. The parallel paths along the car network are shown in red. [107]

were found to be parallel paths that had to be excluded from the analysis manually (see section 3.6.6). Gaps with a detour factor of less than 1.5, i.e. gaps identified between endpoints that were connected on the bicycle network with a detour of up to 50%, were consequently excluded from the analysis. The thus assumed maximum detour of 50% might seem quite high in the Copenhagen context, but appears reasonable given that the main purpose of the present study is to identify gaps of smaller length, rather than to investigate optimal network growth by adding substantial amounts of longer links.

In this way, 2573 gaps were discarded and a final list of 5568 gaps was obtained. Each gap was labeled with a unique gap ID. The next step, ranking of gaps by relevance, is outlined in section 3.4 below.

3.4 Gap prioritization

While making their way through the street network of Copenhagen, a cyclist will quite likely have to ride at least part of the time in mixed traffic with cars and/or use unprotected bicycle infrastructure to some extent. The rationale behind the positive impact of “closing gaps” by providing certain street segments with protected bicycle infrastructure is that by reducing the number of meters that cyclists have to bike in the same space as motorized traffic, we will reduce the number of crashes and increase both objective and subjective cyclist safety. We will moreover increase inclusiveness of the bicycle network through facilitating its use by more vulnerable population groups, such as children, who should not under any circumstances cycle in mixed traffic [61]. This idea, as explained below, is quantitatively expressed through computing the edge betweenness centrality for each gap and further weighing each gap by its length. We illustrate this with a simple example before passing on to the formal definition. Let us assume

that gap A has a length of 10 m and a traffic volume of 50 cyclists in a time unit (e.g. during one day); and gap B has a length of 20 m and a traffic volume of 15 cyclists. Then, by multiplying the numbers, we obtain a total of 500 m for gap A and 300 m for gap B, with the values indicating how many meters less would be cycled in mixed traffic if this gap was to be provided with a protected bicycle path. In other words, by “closing” gap A, we would avoid more meters cycled in mixed traffic. Gap A is therefore ranked as more relevant than gap B.

As explained above, edge betweenness centrality is derived from an all-pair shortest path algorithm. In practical terms, calculating the edge betweenness centrality of the street or bicycle network can be interpreted as assuming that for each possible origin-destination combination, there is one cyclist making their way through the network by choosing the shortest possible path between origin and destination. Then, for one specific link, the number of cyclists that use it on their way through the network, divided by the total number of cyclists on the network, will render the fraction of cyclists that we expect to find on this link. Thus, the edge betweenness centrality indicates how “central” or relevant a link is for the flow of – in our case – cyclists through the network. Similar approaches based on edge betweenness centrality have previously been used to estimate bicycle and motorized traffic flow [99, 100, 113]. Note that we do not include the temporal (e.g seasonal) variations in cycle traffic volume, assuming for simplicity a temporally uniform distribution of cyclist numbers.

To decrease the bias towards the center of the network (see section 2.4.3), we adjust the all-pair shortest path algorithm: for each origin node i , instead of including all other nodes on the network as possible destinations, we only include nodes j within the Euclidean distance of $r_{\max} = 2500$ m. On a side note, this reduction in considered origin-destination pairs also has the beneficial effect of reducing computation time, which was not an obstacle in our case, but can be a limiting factor for larger datasets. From the set of shortest paths obtained in this way, we then compute the modified edge betweenness centrality $\tilde{c}_B(l)$ for each link l from the number of times p_l this link appears in the set:

$$\tilde{c}_B(l) = \sum_{|i,j| < r_{\max}} p_l(i,j) \quad (3.2)$$

The modified edge betweenness centrality $\tilde{c}_B(l)$ provides us with a simple proxy of traffic flow, i.e. the number of cyclists expected on a certain link of the network. As expected, the distribution of edge betweenness centrality values becomes much narrower for the modified shortest path algorithm (see figure 4.2). While this approach does not do away with the network edge effect, as it is inherent to the centrality approach, we do expect it to speed up the identification of relevant gaps in outer city districts.

By multiplying the modified edge betweenness centrality $\tilde{c}_B(l)$ by the length $x(l)$ of link l , we obtain the total number of meters cycled on this link, m_c . Since a gap g can consist of several links, the final value of meters cycled on a gap, $m_c(g)$, is obtained from adding up the meters cycled on each of the links l .

$$m_c(g) = \sum_{l \in g} \tilde{c}_B(l) \cdot x(l) \quad (3.3)$$

As a last step, we want to account for cost-efficiency. We assume for simplicity, and in line with previous studies [68], that construction costs are proportional to facility length. We norm the meters cycled on a gap to the total length of that gap and thus obtain $\bar{m}_c(g)$: the meters cycled *per investment unit* that would be avoided if the gap was to be “closed”.

$$\bar{m}_c(g) = \frac{\sum_{l \in g} \tilde{c}_B(l) \cdot x(l)}{\sum_{l \in g} x(l)} \quad (3.4)$$

Not assigning any further weights apart from the total physical length of the gap corresponds to the assumption that for each cyclist, every meter cycled jointly with motorized traffic equally contributes to the risk of getting injured or killed.

The parameter $\bar{m}_c(g)$ will be used for gap prioritization. Summing up the above explanations, it expresses, for each gap, how many meters cycled in mixed traffic could be per investment unit. It has to be noted that by estimating cyclist traffic flow in this way, the absolute value of the “number” of cyclists on a certain link is not meaningful in itself, given that it is derived from the number of paths, and not from the number of actual network users. The values of the modified edge betweenness centrality $\tilde{c}_B(l)$ of a link l and of the derived ranking parameter $\bar{m}_c(g)$ of a gap g (defined below) are therefore only meaningful either in comparison to other links/gaps, which is carried out in the present study, or alternatively after norming to the total number of paths considered to obtain percentages rather than absolute values.

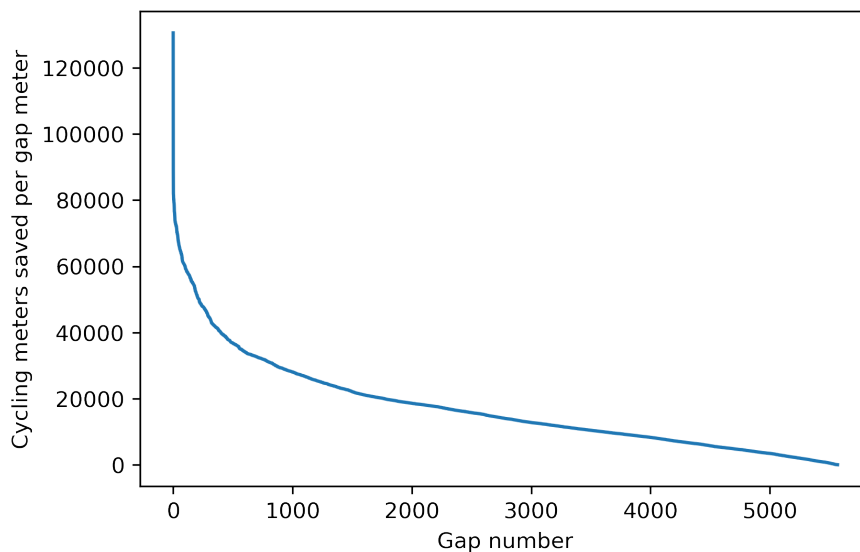


Figure 3.4: Distribution of the ranking parameter $\bar{m}_c(g)$ in the final gap list

To rank the gaps by relevance, we compute $\bar{m}_c(g)$ for each gap g and sort the list of gaps by descending value of \bar{m}_c . Figure 3.4 shows the distribution of $\bar{m}_c(g)$ within the list of 5568 gaps that were found with a cutoff length of $c_{\text{gap}} = 1200$ m and a maximum detour of $d_{\text{max}} = 1.5$. We then proceed to visual analysis, clustering and classification of the gaps ranked as most relevant, i.e. with the highest \bar{m}_c values, as described in the next sections.

3.5 Visual analysis and gap clustering

Interactive maps were created for visual analysis and manual clustering, with separate layers for the city map, the street network, the car and bikeable networks, the identified gaps and the citizen survey results, respectively. The gaps were then either manually verified as actual gaps in the bicycle network, or classified as errors (see section 3.6.6), by means of visual comparison with data from the online platform Mapillary [114] and by on-site visits. Verified gaps were categorized according to an empirical classification scheme described in detail in the next section.

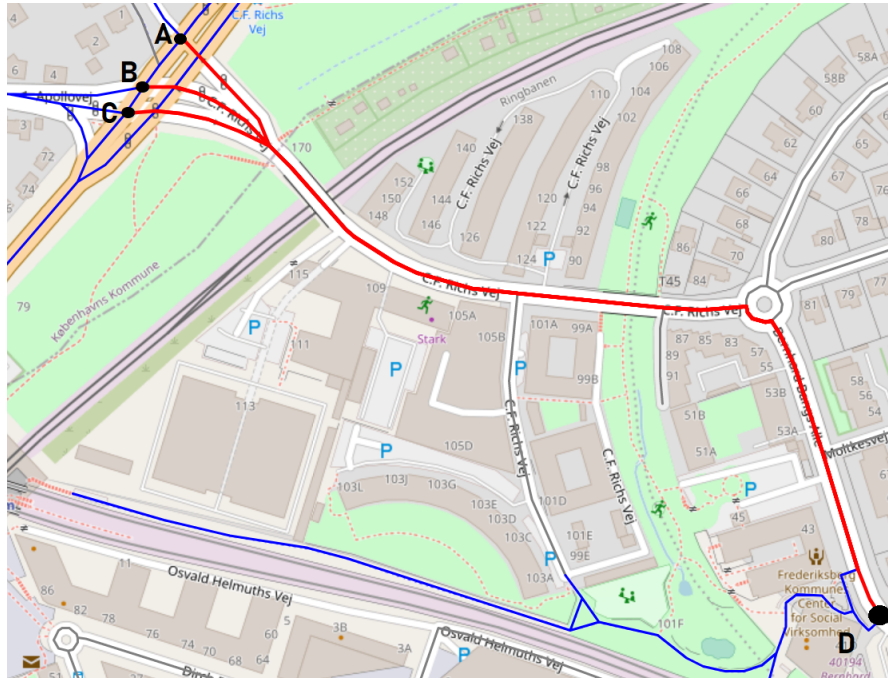


Figure 3.5: Gap 28: Cluster on C.F. Richs Vej. The street network is shown in grey, the bicycle network in blue, the gap cluster in red. The three gaps AD, BD and CD partially overlap and have similar \bar{m}_c . Therefore, the three gaps are bundled into one cluster. [107]

Visual analysis of the maps revealed that in many cases, several unique gaps with similar \bar{m}_c values partially overlap, thus forming a structure which we shall call **gap cluster**. This is partially explained by the fact that an all pairs shortest path algorithm is applied to a network with an inherently dense spatial clustering of nodes at street intersections. An example to illustrate gap clustering is shown in figure 3.5: the intersection of C.F. Richs Vej and Grøndals Parkvej is represented by several network nodes. All shortest paths to destination node D from any of the origin nodes A, B, C will be classified as gaps and display similar \bar{m}_c values. Obviously, as further outlined in section 4.2, it would not always be meaningful to provide *all* street segments constituting a gap cluster with protected bicycle infrastructure. However, the task of identifying the exact location for the construction of infrastructure to “close the gap” is beyond the scope of the present study. Therefore, wherever this clustering appeared, gap clusters were treated as one single element: all gaps constituting the cluster were merged by assigning a new gap ID and computing the corresponding \bar{m}_c value for the whole cluster for further analysis. Unless otherwise indicated, we shall from now on use the term “gap” both for single gaps and for gap clusters.

3.6 Gap classification

The gap classification scheme presented in this section was determined empirically by means of visual analysis. The first 600 gaps identified as most relevant by our procedure according to the ranking parameter $\bar{m}_c(g)$ were inspected and overlapping gaps were manually clustered, as outlined in sections 3.4 and 3.5, which reduced the number of gaps to 141. The value for $\bar{m}_c(g)$ was recomputed for each gap after clustering, and ranking was adjusted accordingly. Then, the top 141 gaps were grouped into categories by similarity from a transport planning perspective, resulting in the following gap classes: missing link; intersection; right-turn lane; bridge; roundabout; and data issue. This classification scheme is meant to facilitate both the interpretation of results from bicycle network analysis, and the decision-making within a subsequent planning process. However, given its empirical nature, the classification scheme is adjusted to the Copenhagen context and might need to be adapted for other urban contexts in future research.

Acronym	Gap type	Color	Count	Percent	See section
ML	Missing link	Red	67	48%	3.6.1
IS	Intersection	Yellow	23	16%	3.6.2
RT	Right-turn lane	Pink	7	0.5%	3.6.3
BR	Bridge	Orange	3	0.2%	3.6.4
RA	Roundabout	Brown	1	0.07%	3.6.5
DI	Data issue	Black	40	28%	3.6.6

Table 3.1: Gap class distribution within the final list of top 141 gaps. Color coding refers to maps and detail plots.

The distribution of gap classes in the top 141 gaps is shown in figure 3.6. Corresponding numbers are listed in table 3.1. Discarding gaps classified as data issues resulted in a final list of 101 confirmed gaps. The map in figure 3.7 gives an overview of all 101 gaps, with classes plotted by color. Sections 3.6.1 to 3.6.6 provide, for each of the gap classes, a gap class definition, an overview map, and a summary of results together with few selected examples. A list of all 101 confirmed gaps with detail maps and addresses can be found in appendix A.

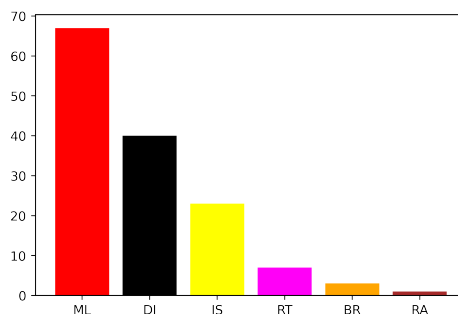


Figure 3.6: Distribution of gap classes in top 141 gaps. Red: missing links (ML), black: data issues (DI), yellow: intersections (IS), pink: right-turn lanes (RT), orange: bridges (BR), brown: roundabouts (RA)



Figure 3.7: Overview map of top 101 gaps by class: missing links in red, bridges in orange, intersections in yellow, right-turn lanes in pink, roundabouts in brown. Data issues are not shown. The street network is shown in grey, the bicycle network in blue.

3.6.1 Missing links

The gap class **missing link** is the most frequent type of gap in our dataset. Alongside an intuitive understanding of what might be considered as “gap in the bicycle network” by the general public, i.e. a street segment without protected bicycle infrastructure, we define as missing link all mixed-traffic street segments with a length of up to 1200 m whose both ends connect to protected bicycle infrastructure and that do not correspond to any of the other gap classes (bridge, intersection, roundabout, right-turn lane, or data issue).

The map in figure 3.8 gives an overview of all 67 missing links within the top 101 gaps as identified by our procedure. The numbers correspond to gap ranking by the parameter \bar{m}_c . Detail maps of all gaps sorted by rank are found in appendix A.

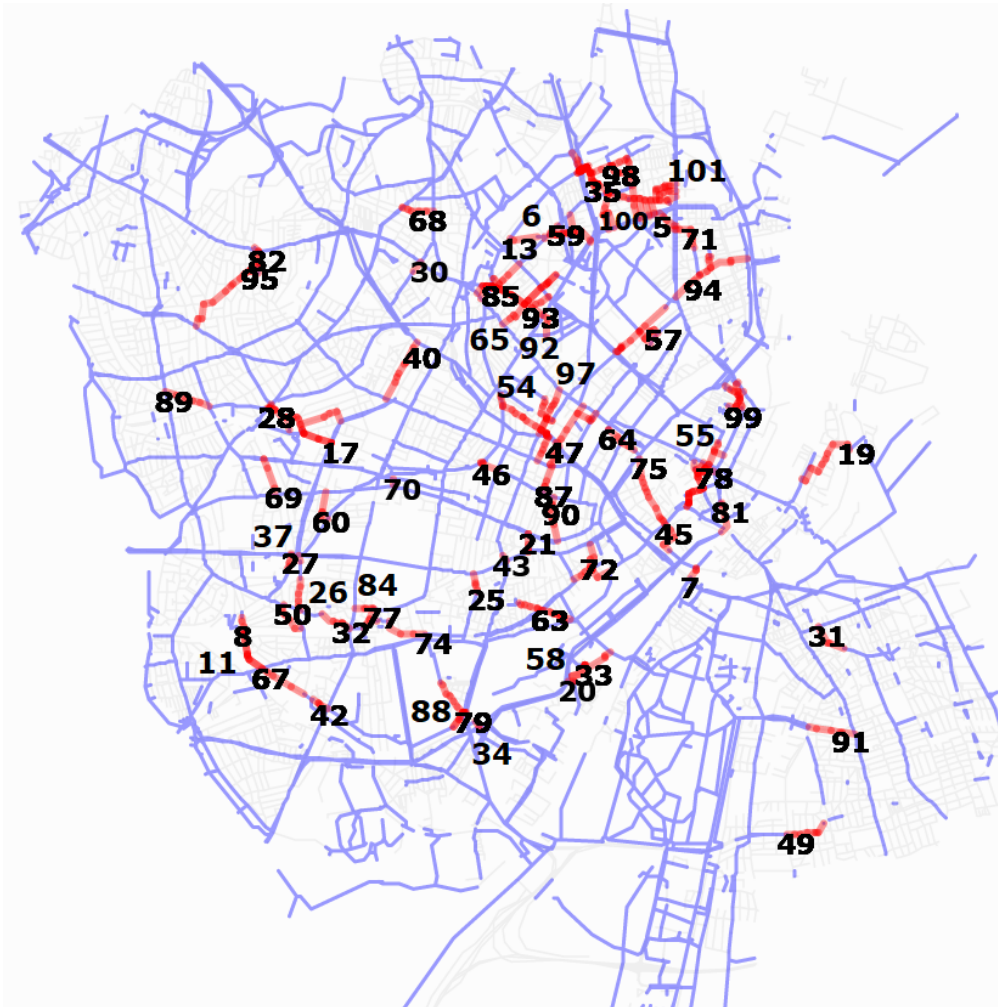


Figure 3.8: Overview map of the 67 missing links. The street network is shown in grey, the bicycle network in blue, and the missing links in red. Numbers correspond to gap ranking. Detail maps of all gaps by rank are found in appendix A.

We estimate that several of the identified missing links might be confirmed as relevant by transport planning practitioners. Four examples from the neighbourhoods of Amager, Vesterbro, Østerbro and Islands Brygge are shown: gap 31 on Ålandsgade and Frankrigshusene (figure 3.10), gap 43 on Kingosgade (figure 3.11), gap 94 on Nordre Frihavns-gade (figure 3.12) and gap 7 on Langebrogade (figure 3.9). Other examples are gap 8 on Værnedamsvej, gap 32 on Rantzausgade, gap 38 on Valby Langgade, gap 60 on Thorvaldsensvej and gap 97 on Vognmandsmarken (see appendix A for detail maps). A comparison with Copenhagen’s current Cycle Path Prioritization Plan (see section 3.7) shows that several of the locations listed there as high priority for the construction of new bicycle infrastructure coincide with gaps identified by our procedure.

Some of the missing links that have been identified are situated on residential streets with presumably low traffic speed and volume, so they would probably not be prioritized from a transport planning perspective in spite of their estimated local relevance indicated by high edge betweenness centrality values. An example of a gap in a residential area is shown in figure 3.13. Further examples are gap 10 on Solvej, gap 47 on Jyllandsvej, and gap 83 on Gåsebæksvej (see appendix A). These missing links illustrate the need of non-topological data to be included in decision-making and possibly already in the network analysis process; see section 1.4.3 on the use of only topological data, and section 4.2 on a possible refinement of methods.

Several missing links come to lie within a locally sparse area of the network and are initially considered by the algorithm as gaps due to the presence of small, isolated bicycle infrastructure elements in their vicinity, as can be seen for gap 8 on Tschernings Allé and gap 95 on Valløvej in figure 3.14. Other examples are gap 11 on Stadfeldtsvej and Ole Borchs Vej, and gap 69 on Krabbesholmvej (see appendix A). This is a direct consequence of our initial definition of a gap as a path between two bicycle infrastructure elements; hence, in areas where no bicycle infrastructure is present, no gap will be identified. While this definition has the advantage of never increasing the number of disconnected components, the missing links found in sparse network areas illustrate that the procedure gives meaningful results particularly for locally dense networks, and is not equally suitable for identifying optimal locations for bicycle infrastructure for locally sparse networks. For a refinement of the procedure, a further distinction of subcategories within the missing link class, both by road conditions (e.g. speed limit) and by actual traffic flow, would be recommended, as it might help to estimate whether these links can be considered bikeable in spite of their lack of designated infrastructure [15].

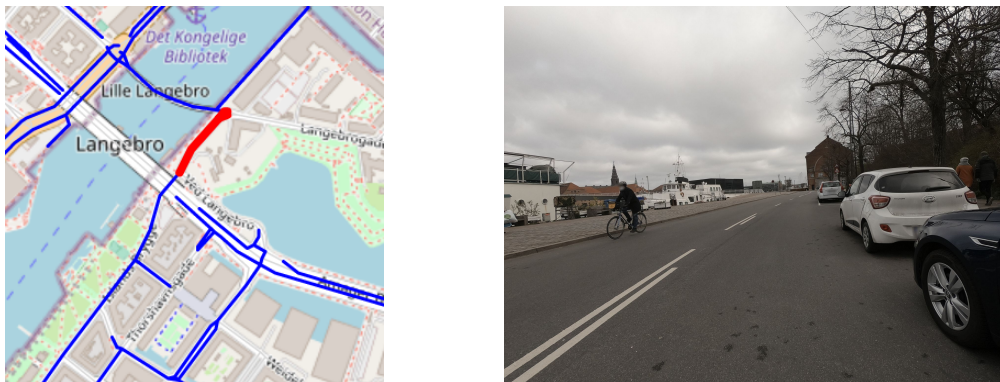


Figure 3.9: Missing link: Gap 7 on Langebrogade [107, 114]



Figure 3.10: Missing link: Gap 31 on Ålandsgade and Frankrigshusene [107]



Figure 3.11: Missing link: Gap 43 on Kingsgade [107, 114]



Figure 3.12: Missing link: Gap 94 on Nordre Frihavns-gade [107]



Figure 3.13: Missing link in residential area: gap 11 on Stadfeldtsvej and Ole Borchs Vej [107, 114]



Figure 3.14: Missing links connecting isolated bicycle infrastructure elements: gap 8 on Tschernings Allé (left) and gap 95 on Valløvej (right). [107]

3.6.2 Intersections

The gap class **intersection** is the second most frequent type in the dataset. The map in figure 3.15 gives an overview of all 23 intersections within the top 101 gaps as identified by our procedure. Detail maps for all gaps are found in appendix A.

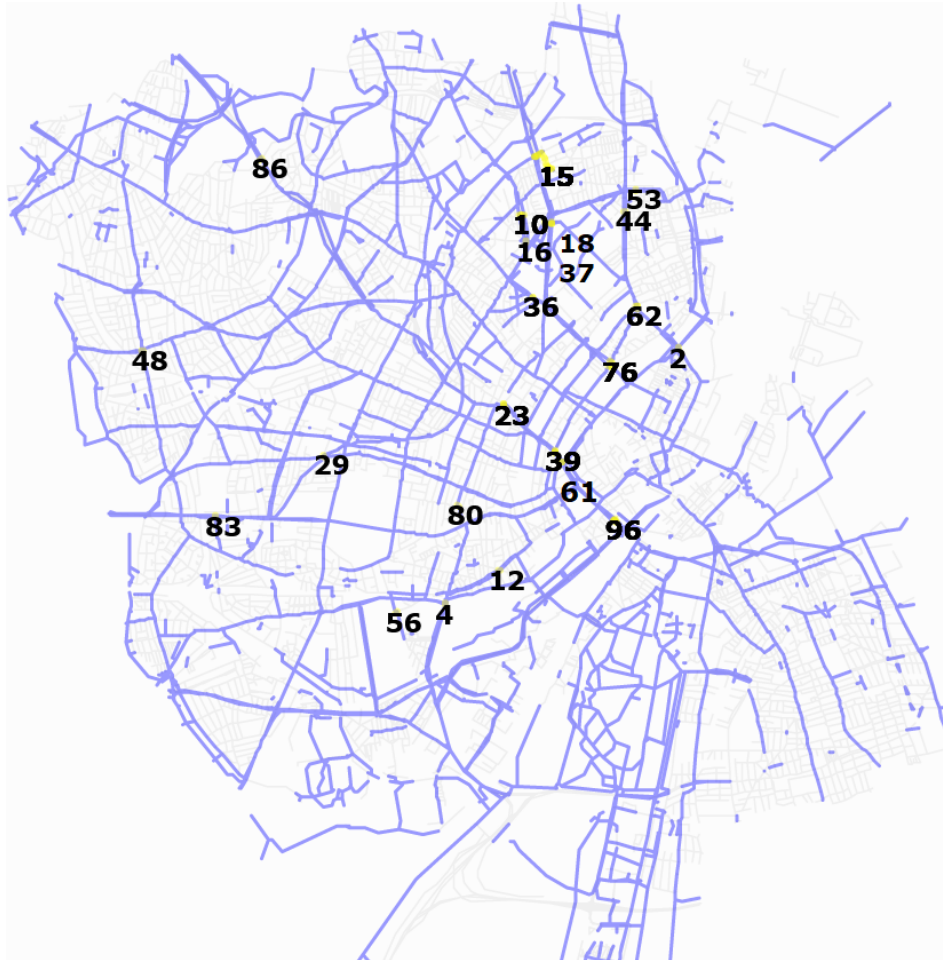


Figure 3.15: Overview map of the 23 intersections. The street network is shown in grey, the bicycle network in blue, and the intersections in yellow. Numbers correspond to gap ranking. Detail maps of all gaps by rank are found in appendix A.

Intersection design is crucial for cyclist safety. A high proportion of traffic collisions occur there. By the very nature of an intersection, a potential for conflict between traffic participants cannot be brought to zero; however, it can be minimized with appropriate planning [15]. Intersection design deserves to be considered a discipline of its own right, and different network analysis methods than the one used in this study might need to be applied to explicitly identify problematic intersections from a bicycle network planning perspective [67]. Here, we do not model intersections separately, but rather identify them as gap class in the last step of the procedure.

From the perspective on network modeling, within the OSM data structure, intersections of smaller spatial extent appear as single nodes (a node representing the crossing of two streets),

while larger ones appear as a set of nodes and links (each node representing the intersect of two or more lanes – see the example in figure 3.5, where nodes A, B and C are all part of the same intersection). As a rule, but not exclusively, this is the case when at least one of the intersecting streets is bidirectional. The fact that this representation of larger intersections was kept within the data structure allows for the identification of unprotected crossings, that lie on an otherwise protected bicycle path, as gaps in the bicycle network. However, this method of identifying unprotected crossings is by far not exhaustive. This has several reasons. First, due to the data structure, our procedure does not recognize unprotected intersections that are represented by single nodes in the network model as gaps. Second, even with a clearly outlined set of intersection design criteria at hand which would enable us to discard protected intersections from the gap list, the incoherence of intersection tagging in OSM results in numerous false negatives and false positives: intersections with a protected crossing for cyclists are often tagged as unprotected bicycle infrastructure; intersections without any bicycle infrastructure are often tagged as part of the cycle path they are actually interrupting. Further research is recommended to determine the magnitude of these data quality issues within OSM (see section 4.5).

The results presented here should be seen in the light of the issues outlined above, additionally considering that it would go beyond the scope of the present study to outline the criteria by which an intersection counts as sufficiently well protected. The list of gaps classified as intersections can therefore be understood as a non-exhaustive list of locations where checking for appropriate intersection design is recommended. Four examples are shown below: gap 96 at the intersection of H. C. Andersens Boulevard with Rysensteensgade (figure 3.19), gap 2 at the intersection of Øster Voldgade with Grønningen (figure 3.16), gap 29 at the intersection with Peter Bangs Vej with Lindevangs Allé, which forms part of the green cycle route *Den Grønne Sti* (figure 3.17), and gap 62 at the intersection of Øster Søgade with Østerbrogade (figure 3.18). Further noteworthy examples are gap 23 at the intersection of Rantzausgade with Aboulevard, gap 26 at the intersection of Kingosgade with Frederiksberg Allé and gap 37 at the intersection of Nørre Allé with Øster Allé (see appendix A for detail maps).



Figure 3.16: Intersection: gap 2 on Øster Voldgade with Grønningen [107, 114]



Figure 3.17: Intersection: gap 29 on Peter Bangs Vej with Lindevangs Allé [107, 114]



Figure 3.18: Intersection: gap 62 on Øster Søgade with Østerbrogade [107, 114]



Figure 3.19: Intersection: gap 96 on H. C. Andersens Boulevard with Rysensteensgade [107]

3.6.3 Right-turn lanes

A common feature of Copenhagen’s bicycle network is that at many locations, a right-turn car lane merges with the adjacent bicycle path [115]. In such cases, the bicycle path ceases to be part of the protected bicycle network as it approaches an intersection, and cyclists are forced to mix with motorized traffic. We classify this type of gap as **right-turn lane**. The map in figure 3.20 gives an overview of all 7 right-turn lanes within the top 101 gaps as identified by our procedure. Detail maps for all of these gaps are found in the appendix A.

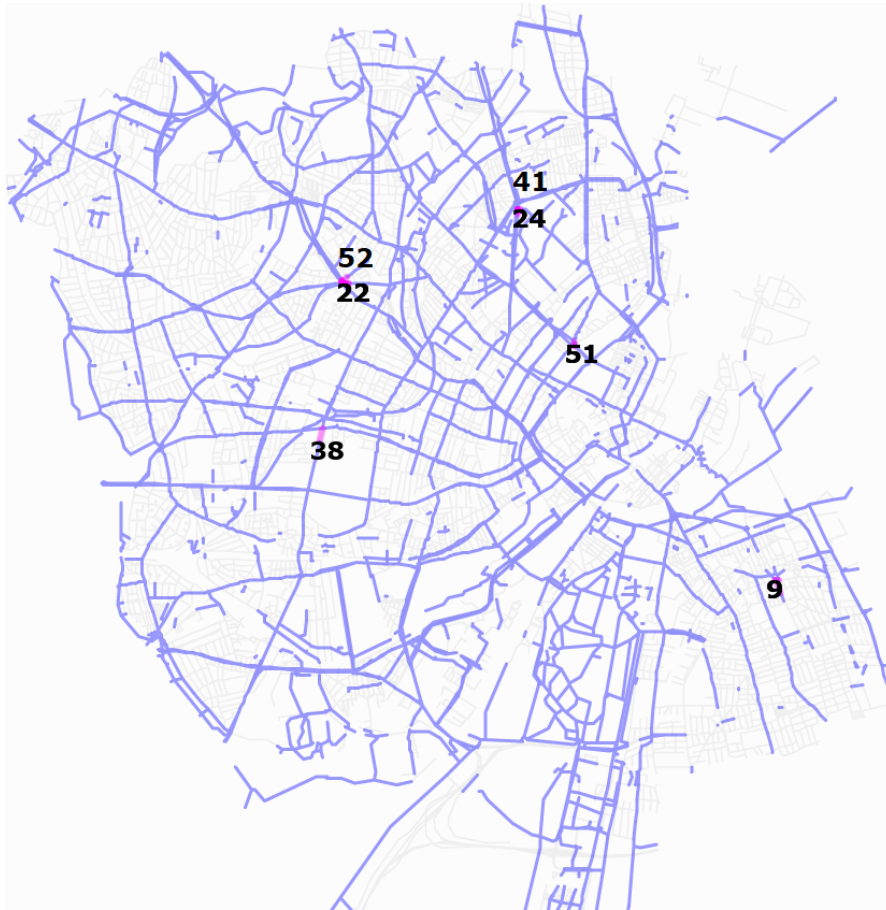


Figure 3.20: Overview map of the 7 right-turn lanes. The street network is shown in grey, the bicycle network in blue, and the right-turn lanes in pink. Numbers correspond to gap ranking. Detail maps of all gaps by rank are found in appendix A.

Gaps that are classified as right-turn lanes are less frequent in our dataset, which might be in part attributed to a potentially high number of false positives (i.e. erroneously tagged as protected bicycle infrastructure) in the OSM tags. Although some studies cite the merging of right-turning vehicles with a bicycle path as acceptable in case of low traffic volume and low speed [67], these situations can imply lethal danger for cyclists, particularly when leading up to busy intersections [15, 115]. There are several design alternatives to right-turn lane merging that increase cycling safety [116, 117, 118]. Much in line with what has been said about intersections, overcoming the data inconsistencies from OSM, identifying right-turn lane merging locations in the Copenhagen

bicycle network and suggesting a possible design change to avoid mixing of vehicles and cyclists calls for a research project of its own. The results presented below should therefore be considered a non-exhaustive list of illustrative examples.

Figure 3.21 shows gap 9 at the right turn from Backersvej to Øresundsvej. The intersection of Nørre Allé with Øster Allé, which has already been cited as an example of an unprotected intersection in section 3.6.2, in addition renders two gaps classified as right-turn lanes: gap 41 from Nørre Allé to Øster Allé (see figure 3.24) and gap 24 from Øster Allé to Nørre Allé (see appendix A). The right-turn from Hillerødgade to Borups Allé also causes two gaps: one before and one after the right turn (gaps 22 and 52 as illustrated in figures 3.22 and 3.23, respectively). Lastly, figure 3.25 shows gap 51 at the right turn from Sølvgade to Øster Farimagsgade.



Figure 3.21: Gap 9 at right turn from Backersvej to Øresundsvej [107]

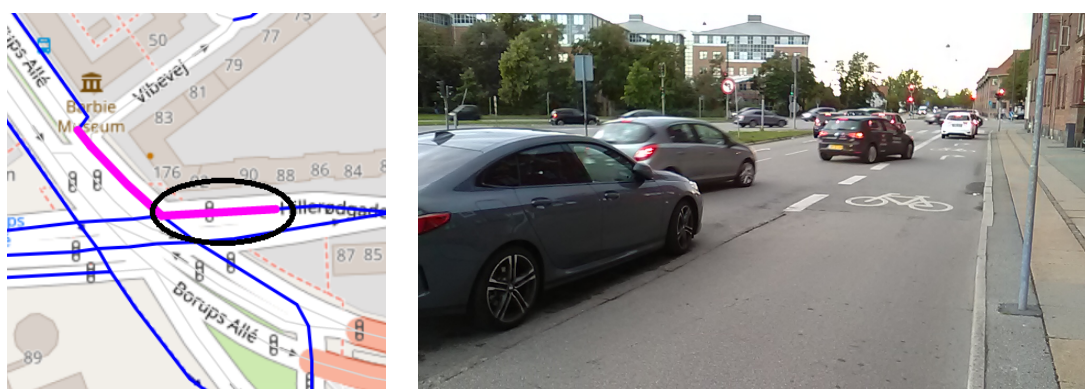


Figure 3.22: Gap 22 before right turn from from Hillerødgade to Borups Allé [107]



Figure 3.23: Gap 52 after right turn from Hillerødgade to Borups Allé [107]



Figure 3.24: Gap 41 at right turn from Nørre Allé to Øster Allé [107, 114]



Figure 3.25: Gap 51 at right turn from Sølvgade to Øster Farimagsgade [107, 114]

3.6.4 Bridges

The map on figure 3.26 shows the three gaps from our dataset that were classified as **bridges**. In locations where there are physical barriers such as water bodies or railway tracks that have to be crossed, bridges play a particularly important function for connecting parts of the network and often constitute bottlenecks for traffic flow. At the same time, there are often inherent constraints to placing additional infrastructural elements on bridges due to limited physical space available [119]. In the case of Copenhagen, bridges play a particularly relevant role as the city is situated on the two islands of Amager and Zealand, and harbours an extensive canal system.



Figure 3.26: Overview map of the 3 bridges. The street network is shown in grey, the bicycle network in blue, and the bridges in orange. Numbers correspond to gap ranking. Detail maps of all gaps by rank are found in appendix A.

As a matter of fact, according to Copenhagen’s latest Bicycle Account, 7 of the top 10 most heavily trafficked cycling stretches in the city are bridges [46]. The first three stretches on that list are Dronning Louises Bro, Langebro and Knippelsbro. While Dronning Louises Bro is provided with protected bicycle infrastructure, Langebro and Knippelsbro are not. In this regard, the numbers from the Bicycle Account align well with the results of our procedure, given

that Knippelsbro (gap 1) and Langebro (gap 3) were ranked first and third by relevance on our list of 101 gaps.

Physical separation from motorized vehicles is a desirable feature for bridges [120]. As shown in figure 3.27 for gap 1 on Knippelsbro and in figure 3.28 for gap 3 on Langebro, the cycle lanes on these bridges are not physically separated from the motorized traffic in spite of space availability. The Højbro bridge, where gap 66 is located, features no bicycle infrastructure at all, as can be seen in figure 3.29.



Figure 3.27: Bridge: Gap 1 on Knippelsbro [107, 114]



Figure 3.28: Bridge: Gap 3 on Langebro [107, 114]



Figure 3.29: Bridge: Gap 66 on Højbro [107]

3.6.5 Roundabouts



Figure 3.30: Overview map of the roundabout. The street network is shown in grey, the bicycle network in blue, and the roundabout in brown. The number corresponds to the gap ranking.

consists of only one lane where vehicles and bicycles mix. Same as in the case of intersections, future work might consider the set of all roundabouts in the city and examine their design from a cyclist safety perspective (see section 4.5).

We separately define the gap class **roundabout**, although, as can be seen on figure 3.30, only one such gap was found within the top 101 gaps. There are several arguments for considering roundabouts a gap class of their own. Requirements for roundabout design are not the same as for intersections. Roundabouts are often considered to be the safer option for cyclists [121, 122, 123]. However, this should not be considered a generally applicable rule. According to the recommendations of the CROW manual, whether additional bicycle infrastructure is needed at a roundabout depends on the traffic volume [15]. A roundabout with more than one single lane puts cyclists at danger [123]. According to a recent literature review by Poudel and Singleton [124], data from Northern Europe suggests that the number of bicycle crashes might actually be higher for roundabouts than for intersections. There are several roundabout design options focusing on cyclist safety [125], such as the Zwolle roundabout, named after the Dutch city that first introduced it [15, 126].

Gap 14 is the roundabout on Sankt Kjelds Plads. As can be seen on figure 3.31, it consists of only one lane where vehicles and bicycles mix.



Figure 3.31: Roundabout: Gap 14 on Sankt Kjelds Plads [107]

3.6.6 Data issues

Gaps that were identified by the procedure but were not confirmed as such by visual inspection are classified as **data issue**. There are two types of data issues: **parallel paths** and **OSM errors**. Parallel paths are errors stemming from the routing problem in high resolution networks, while data issues are errors stemming from incorrect information on OSM.

Parallel paths

The problem of parallel paths is explained in detail in section 3.3. Figure 3.32a shows a map of all gaps that were identified as parallel paths and therefore discarded from the list of relevant gaps. Many of the parallel paths occur at large intersections, such as Frederikssundsvej with Borups Allé or Lyngbyvej with Rovsingsgade, or along streets with multiple lanes and bicycle infrastructure on both sides, such as H. C. Andersens Boulevard or Tagensvej. As can be seen from the map, there is also a partial overlap with actual gaps, e.g. Rantzausgade (gap 32) or Nordre Frihavnsgade (gap 94). These gaps were excluded from the corresponding gap cluster because they contained parallel paths.

OSM errors

There are several reasons for errors in the OSM data: segments might be missing, mistagged, or outdated. Figure 3.32b gives an overview of all gaps that were discarded from the analysis as OSM errors. Many of the wrongly identified gaps correspond to relatively new bicycle infrastructure elements which have not yet been tagged as such in OSM. Several gaps that have been discarded from the analysis for this reason were actually just recently “closed”, as part of Copenhagen’s either current or previous Cycle Path Prioritization Plan, as can be seen from the respective lists of high-priority locations for the construction of new bicycle infrastructure [45, 127]. This is the case e.g. for the bicycle paths on Øresundsvej, Ved Langebro, Jernbane Allé, Christian IV’s bro and Nørre Farimagsgade, as well as the intersection of Skelbækgade with Dybbølsgade. This fact, while raising the issue of outdated tags in OSM, at the same time showcases the applicability of our procedure, as results partially align with the city’s bicycle planning strategy.



Figure 3.32: Data issues: Overview map

3.7 Comparison with Copenhagen’s Cycle Path Prioritization Plan

With the aim of showcasing the potential applicability of our results, in this section we briefly compare and contrast our top 101 prioritized gaps with Copenhagen’s current Cycle Path Prioritization Plan (CPPP). As outlined in section 1.4.1, the CPPP contains five fields of action: new bicycle infrastructure; controlled (i.e. traffic light regulated) intersections; widening of cycle paths; the *Supercykelstier* network; and the *Grønne cykelruter* network [45]. A set of prioritized locations for each of the action fields is given as list of street names and/or as map plot in the CPPP. Data from the citizen survey that was conducted within the framework of the CPPP was provided to us by the Municipality of Copenhagen (see section 2.5.3). The comparison of our results with the CPPP’s priorities will be carried out in the following way: we first list all prioritized gaps from the results of this study that overlap with locations prioritized in the CPPP. Next, we qualitatively describe the overlap of our results with data from the citizen survey. Lastly, we discuss the implications and possible pitfalls of both overlaps and divergences found.

Before we proceed to the comparison, it shall be noted that this study is not aiming at a perfect overlap with transportation planning outputs. Rather, one of the aims is precisely to shed some light on potentially problematic parts of the bicycle network which have so far been overlooked. The CPPP contents provide for some valuable insights and allow a first qualitative assessment of our procedure. However, they should not be considered as “ground truth”. This is particularly relevant for the evaluation of the citizen survey results. While participatory approaches can improve the equity impact of transportation plans [128], a failure to adequately design them might introduce biases and undermine the applicability of the findings. For example, (self-)selection bias might lead to more affluent citizens being overrepresented in the survey results [129, 130]. Therefore, while we do not have access to information on how this particular citizen survey was designed, we want to stress that there are several equity considerations to be accounted for, such as survey language, used medium, distribution channels and socio-demographic variables of respondents.

Comparison with high priority locations in CPPP

Several items from our list of top 101 prioritized gaps coincide with locations listed as high priority in the CPPP [45]. Table 3.2 summarizes these overlaps. Geocoded data of prioritized locations as listed in the CPPP was not available, so no plots are provided at this point.

Comparison with citizen survey in CPPP

From the gap class **missing link**, 49 out of 67 identified gaps had at least one mention within the citizen survey in the category “cycle path missing”. The same is true for all gaps from the classes **bridge** and **roundabout**. Detail plots of all gaps from the classes missing link, bridge and roundabout which showed an overlap with citizen survey inputs can be found in appendix B. Figure 3.33 shows four examples of gaps with a particularly high number of mentions within the citizen survey.

Apart from these encouraging overlaps, there is also a significant number of locations where results diverge. There are several potential reasons for this; figure 3.34 shows two examples. From the street segments with a high number of mentions in the citizen survey, some are located in neighbourhoods where the protected bicycle infrastructure is very sparse, as is the case for Husum (figure 3.34a); other street segments exceed the gap cut-off length of 1200 m which was used in the present study, as is the case for Strandboulevarden in the neighbourhood of Østerbro (figure 3.34b). Furthermore, some preferential patterns of cyclist flow which appear to be discernible from the citizen input survey were not recognized by the procedure. This might in

Location	Gap number	Gap class	CPPP
Knippelsbro	1	BR	upgrade from cycle lane to cycle path
Langebros	3	BR	upgrade from cycle lane to cycle path
Dybbølsgade	12 & 63	IS & ML	cycle street
Ålandsgade	31	ML	contra-flow cycling
Gyldenløvesgade	39	IS	problematic intersection
Borgergade	55	ML	contra-flow cycling
Høffdingsvej	67	ML	Missing link on a <i>Grønne Cykelrute</i>
Birkedommervej	68	ML	contra-flow cycling
Guldbergsgade	92	ML	Planned <i>Grønne Cykelrute</i>
Mimersgade	93	ML	Planned <i>Grønne Cykelrute</i>
Backersvej	-	DI	upgrade from cycle lane to cycle path
Skelbækgade	-	DI	listed as already planned

Table 3.2: Overlap of identified gaps with priority locations from the CPPP [45]. In the column *Gap class*: BR - bridge, DI - data issue, IS - intersection, ML - missing link. In the column *CPPP*, the type of action foreseen by the CPPP for the corresponding location is indicated.

part be due to the presence of non-protected bicycle infrastructure, as is the case for the cycle lane along Sonnerupvej and Gaunøvej on figure 3.34a. Therefore, including unprotected bicycle infrastructure in the analysis might give more nuanced results in future studies.

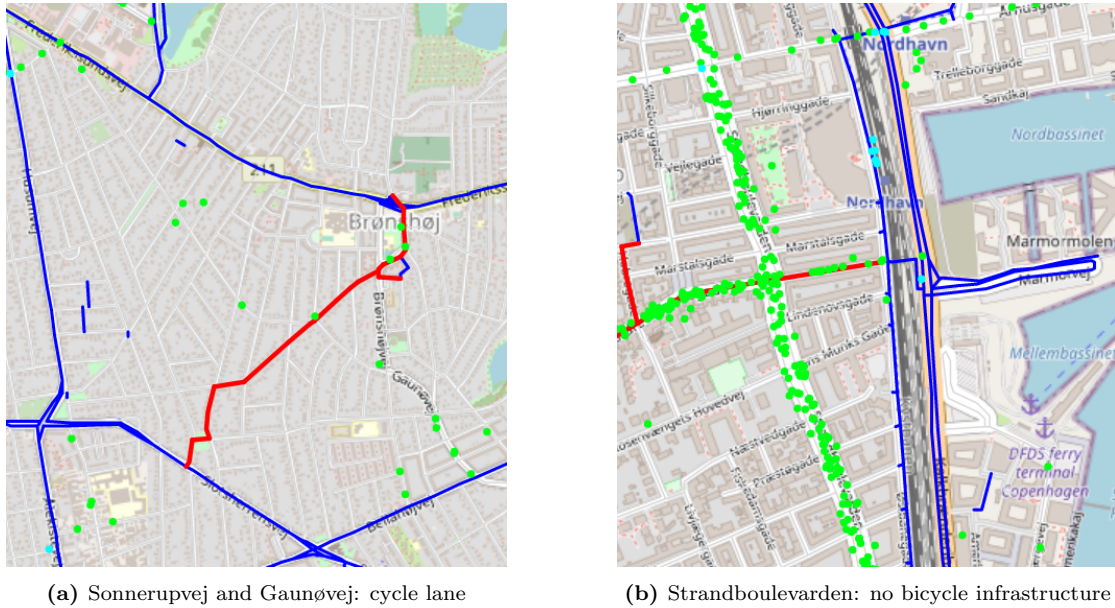


Figure 3.34: Two examples of street segments with a high number of mentions in the citizen survey which are not on our list of top 101 gaps. The street network is shown in grey, the bicycle network in dark blue. Light blue dots represent citizen input on problematic intersections. Green dots represent citizen input on missing cycle paths. [107]

Out of the 23 gaps classified as **intersections**, 10 had at least one mention within the citizen survey in the category “problematic intersection”. Figure 3.35 shows detail maps of all gaps classified as intersections that overlap with citizen input on controlled intersections with high

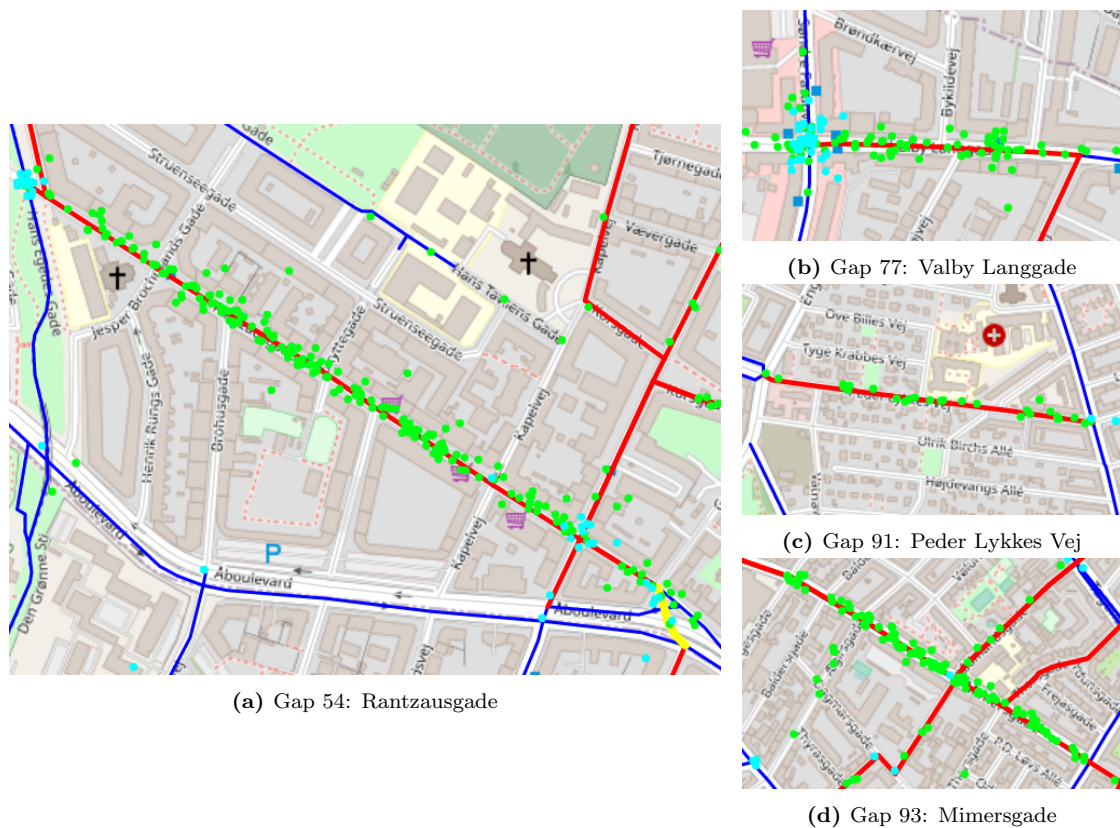


Figure 3.33: Four examples of overlap of citizen survey results with missing links from the list of top 101 gaps. The street network is shown in grey, the bicycle network in dark blue. Gaps from the missing link class are highlighted in red. Gaps from the intersection class are highlighted in yellow. Light blue dots represent citizen input on problematic intersections. Green dots represent citizen input on missing cycle paths. [107]

cyclist volumes. A visual inspection of the citizen input shows that most of the intersections perceived as problematic either appear as coherent pieces of bicycle infrastructure in the OSM data, or are found in places where no protected bicycle infrastructure is present at all. Such intersections are not identifiable as gaps by our procedure, which motivates a reiterated call for a network analysis study focusing on intersection design, with a corresponding review of OSM data quality and adaptation of methods.

All 7 gaps classified as right-turn lanes had at least one mention in the citizen survey in the categories “problematic intersections” and/or “cycle path missing”. Figure 3.36 shows detail maps of right-turn lane gaps overlapping with citizen survey inputs. It goes beyond the scope of the study to determine how many right-turn lanes have not been identified by our procedure but are present in the citizen survey inputs. Further research is recommended as citizen survey results could be used to assess to what extent right-turn lane merging is perceived as problematic by cyclists in Copenhagen.

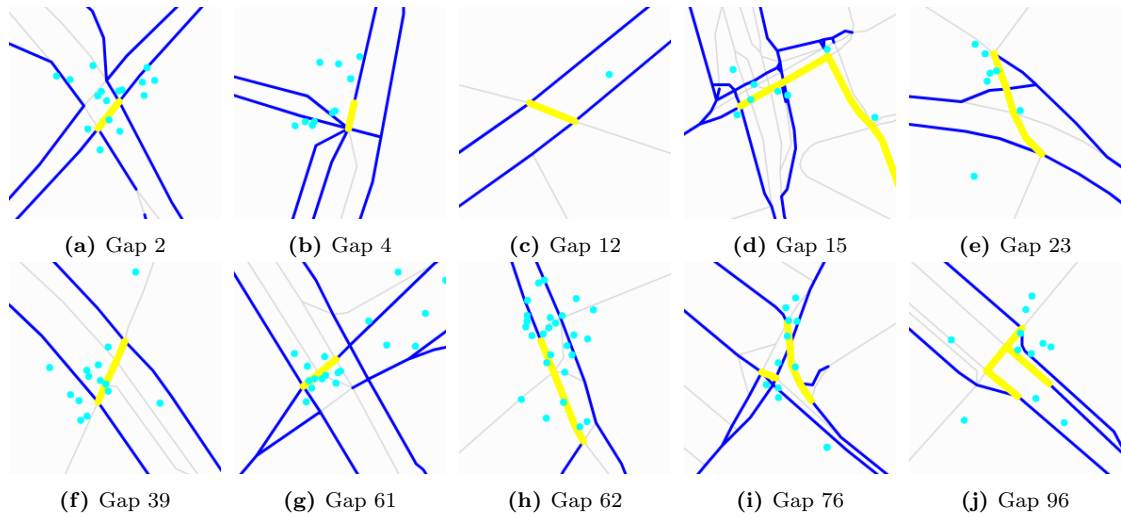


Figure 3.35: Overlap of gaps classified as intersections with citizen survey results on controlled intersections with high cycle traffic volume. The street network is shown in grey, the bicycle network in dark blue. Gaps are highlighted in yellow. Light blue dots represent citizen input. For detail maps with the city map as background layer, see appendix A.

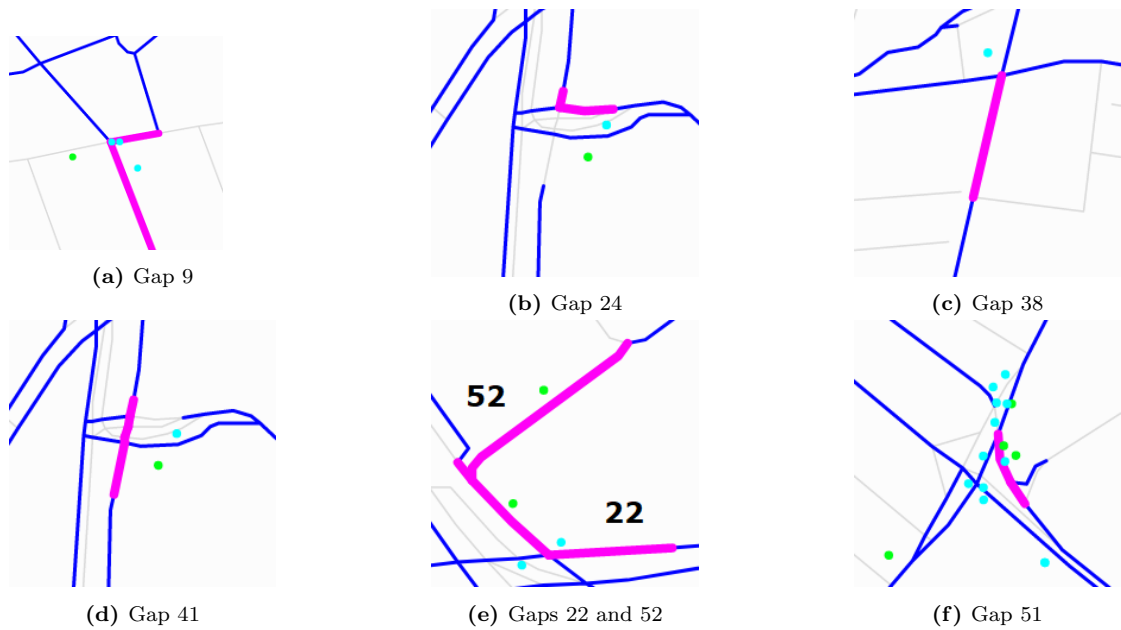


Figure 3.36: Overlap of gaps classified as right-turn lanes with citizen survey results. The street network is shown in grey, the bicycle network in dark blue. Gaps are highlighted in pink. Light blue dots represent citizen input on problematic intersections. Green dots represent citizen input on missing cycle paths. For detail maps with the city map as background layer, see appendix A.

Chapter 4

Discussion

In this chapter, we discuss the results presented in chapter 3. We first conduct an algorithm sensitivity check and discuss implications of applied parameters in section 4.1. Then, applicability and limitations of our procedure are outlined and suggestions for future improvements are given in section 4.2. Section 4.3 briefly discusses data quality issues. We include an overview of discarded approaches and lessons learned from trial and error in section 4.4, and conclude with future research needs in section 4.5.

4.1 Validation of results and algorithm sensitivity check

Both the definition and the identification of gaps in a bicycle network as results of this study are difficult to validate quantitatively since there is no “ground truth” to compare them to. A qualitative validation of the applicability of results by means of comparison of our case study with Copenhagen’s current Cycle Path Prioritization Plan (CPPP) has been carried out in section 3.7. Visual inspection of the identified top 101 gaps showed diverse results. Some of the gaps were also part of the CPPP and/or indicated as problematic by many citizen survey respondents. The overlap with CPPP contents could be interpreted as proof of concept. Furthermore, some of the gaps that were not mentioned in the CPPP could turn out to be of actual interest to bicycle network planners. At the same time, the relevance of some gaps was most likely overestimated within our procedure, as is the case for gaps on residential streets with supposedly low traffic volume. Suggestions on how results could be improved are found in section 4.2.

Similarly, a quantitative sensitivity analysis for any introduced algorithm parameter constitutes a challenge within the scope of the present study due to the lack of “ground truth”. At the same time, comparability of results from applying the algorithm in other contexts is negatively affected by a high number of parameters. It was therefore our intention to keep the number of algorithm parameters as low as possible. Table 4.1 offers an overview of the 3 parameters that were used.

Parameter	Description	Value	Sensitivity Check
c_{gap}	Cut-off gap length	1200 m	Figure 4.1
r_{max}	Cut-off radius in shortest path algorithm	2500 m	Figure 4.2
d_{max}	Maximum detour on bicycle network	150%	none

Table 4.1: Algorithm parameters and values used in this study

The parameter c_{gap} is the cut-off length for gaps. The number of found gaps will increase with an increasing c_{gap} value and plateau for $c_{\text{gap}} > D$, where D is the network diameter, i.e. the longest of all possible shortest paths. For $c_1 < c_2$, the set of gaps found with c_1 is a subset of the set of gaps found with c_2 . This is illustrated in figure 4.1. Gaps for $c_{\text{gap}} = 1200$ m are plotted in black. Gaps for $c_{\text{gap}} = 500$ m are plotted on top, in white and with a thinner line style, to visualize the fact that they form a subset of the gaps found with a higher c_{gap} value. This study uses a value of $c_{\text{gap}} = 1200$ m. For less dense bicycle networks than the one of Copenhagen and/or for networks with a larger spatial extent, higher values for c_{gap} might be appropriate.



Figure 4.1: Gaps for $c_{\text{gap}} = 1200$ m are plotted in black. Gaps for $c_{\text{gap}} = 500$ m are plotted on top, in white and with a thinner line style. All white gaps (smaller cutoff) are contained in the set of black gaps (larger cutoff). Other map details are omitted and the background color is set to grey for the sake of readability.

To compute modified edge betweenness centralities, a cut-off radius r_{max} was used within the shortest paths algorithm (see section 3.4 for details). Figure 4.2 shows the distributions of edge betweenness centrality values with and without the cut-off radius. As expected, introducing a cut-off radius in the shortest paths algorithm leads to a much narrower distribution of edge betweenness centralities and less extreme outliers. This partially, but not entirely reduces the

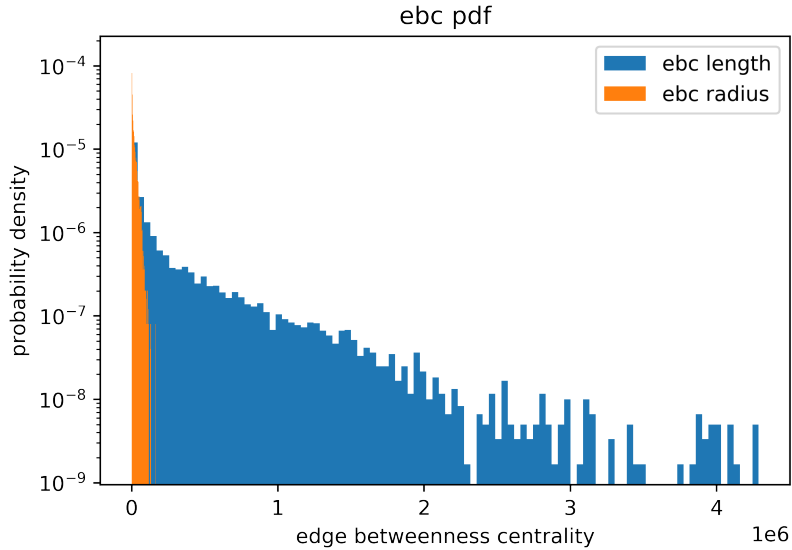


Figure 4.2: Probability distributions of edge betweenness centrality values with (orange) and without (blue) cutoff of 2500m for maximum path length in APSP algorithm

bias towards the center of the network. This is also visualized in the map plots of edge betweenness centrality values in the figures 4.3 and 4.4: the application of a cut-off radius results in a more dispersed pattern of most central links, revealing locally relevant connections. Since edge betweenness centralities were used as a proxy for cyclist flow, the need of choosing an arbitrary parameter value for r_{\max} could be partially remediated if origin-destination tables are available to be included in the analysis.

Lastly, the parameter d_{\max} represents the maximum allowed detour on the bicycle network. This parameter was used to exclude gaps that were potentially parallel paths (see section 3.3). Given that only 20 of the top 141 gaps were discarded as false negatives, i.e. parallel paths, the chosen value of 1.5 appears to be an appropriate upper limit for d_{\max} . However, no estimation of false positives, i.e. the percentage of gaps that are not parallel paths but were discarded as such, was conducted due to the high number (2573) of discarded gaps which would have required manual revision. A quantitative sensitivity analysis for this parameter would contribute to the non-trivial task of route finding algorithms on high-resolution networks (see section 3.3), but goes beyond the scope of the present study.

4.2 Applicability and limitations

This section reviews the implications of our findings for bicycle network planning practitioners and outlines the limitations of the chosen approach together with improvement suggestions.

We elaborated a procedure for the identification and prioritization of gaps in bicycle networks, with the advantage of minimal data requirements thanks to the purely topological approach taken. While there are still some issues to be resolved, we are cautiously optimistic that the procedure could in the future become the basis for a broadly applicable computational tool for decision-making support in bicycle network planning. However, it absolutely does not replace human-steered and human-centered decision making within the planning process. Visual

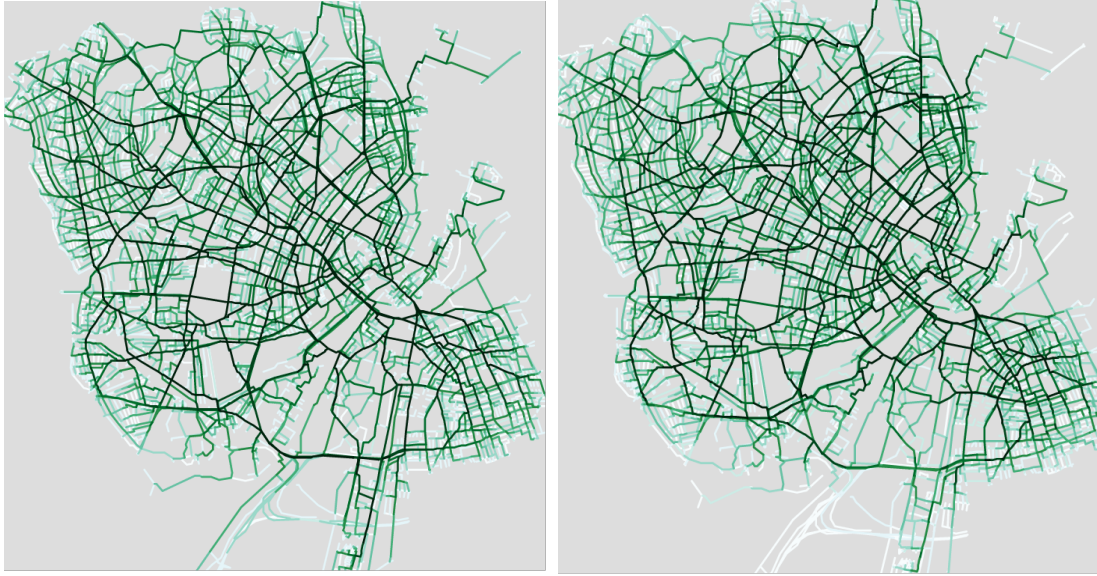


Figure 4.3: Left: edge betweenness centrality values without cutoff radius; the maximum value is in the order of 10^6 . Right: edge betweenness centrality values with a cutoff radius of r_{\max} ; the maximum value is in the order of 10^5 . Values for both figures are plotted in 10 bins of equal width, with a darker color indicating a higher value. The corresponding probability distributions are shown in figure 4.2.

inspection and contextualization of identified gaps forms an integral part of the analysis. Even more importantly, such factors as financial constraints, political framework conditions and equity considerations [131] play a decisive role in the planning process but cannot be meaningfully integrated within a computation tool.

There are several possibilities to obtain a more detailed network representation. Several factors that are directly available in OSM, but have been discarded for the sake of simplicity, could be integrated in the analysis, namely direction of traffic, road type, speed limit, and number of lanes. If available, data on traffic volume could also be added to each of the street segments. Furthermore, including different types of bicycle infrastructure in the network definition might be of interest for further studies. Lastly, including other transport modes (e.g. considering the interconnection of bicycle paths with public transport) would help to account for multimodal mobility.

There are also several ways of improving the estimation of cyclist traffic flow which was used for gap prioritization. In the all-pair shortest path algorithm, the number of cyclists starting from each of the nodes could be weighted by the length of links adjacent to this node, which would more closely approach the assumed spatially uniform population distribution in the city. Depending on the resolution, census data and origin-destination tables might offer an even more realistic picture. Data collected from bicycle counting stations might be used for validating the estimated cyclist flow numbers. However, spatial resolution of such data will most likely not be sufficient for a meaningful inclusion in the network model. Furthermore, in the case of setting up more fine-grained bicycle traffic model, the simplified assumption of preference for the shortest path could be modified to include variables such as hill slope and traffic stress.

Clustering and classification of gaps, which were both conducted manually in the case study, could partially be automatized. Setting up a network of gaps and detecting all disconnected components within this network would offer a first estimation of gap clusters, however manual

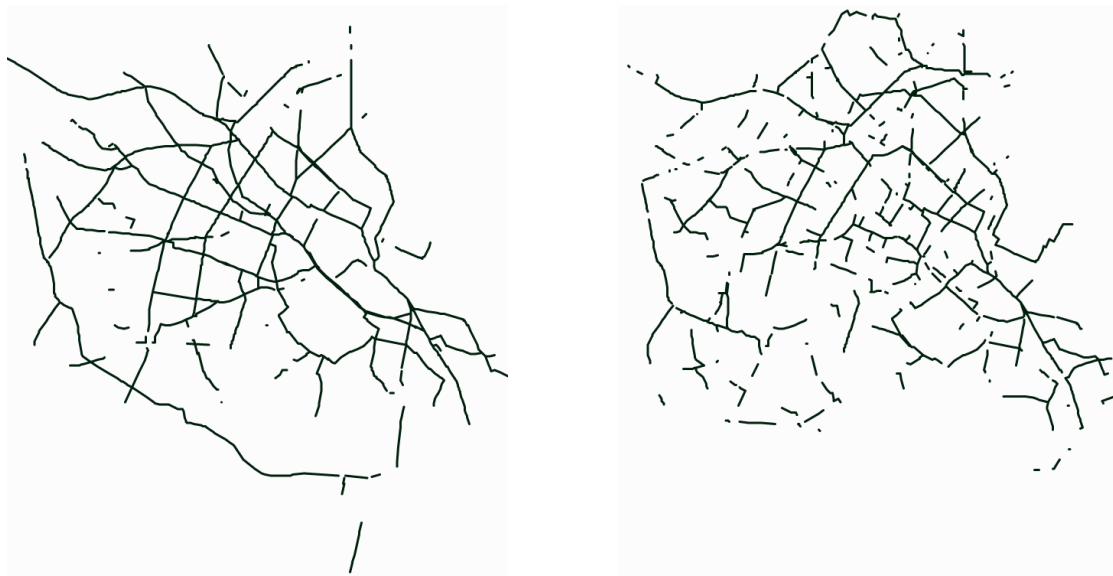


Figure 4.4: The upper 10% of links ranked by edge betweenness centrality values without (left) and with (right) a cutoff radius of $r_{\max} = 2500m$)

inspection would still be required, both because smaller gaps might get wrongly discarded as they get covered by larger clusters, and because in areas with high gap density, clustering might be less meaningful. In addition, OSM tags and network link attributes such as length could be used for an automatized estimation of gap classes, which however would still require a manual revision to confirm the results.

There is also a large potential for improving the integration of citizen input into the analysis. In particular, allocating map points of citizen input to corresponding network links representing street segments would make it possible to include feedback from the general public into the ranking procedure. In addition, data on traffic crashes could also be included in the priority ranking.

Lastly, given that the procedure was designed to be applied to a relatively dense network, as is the case for Copenhagen, its applicability to sparser networks should be evaluated separately in future studies.

4.3 Data quality issues in OSM

Data quality issues within OSM present a further relevant limitation. There are both advantages and disadvantages to the use of crowdsourcing for mapping purposes. It enables the provision of open source data and the integration local knowledge, however different skill levels within the mapping community and a lack of coherence in tag criteria applications lead to data quality issues [132]. Furthermore, OSM data quality varies by location [133]. For example, Haklay [134] found a coverage bias of British OSM data towards wealthier areas. However, the quantitative assessment of OSM data quality is still an open research question [135, 136]. OSM data quality specifically for bicycle infrastructure has been reviewed by Ferster, Fischer, *et al.* [137] for the case of six Canadian cities. Good concordance for most common bicycle infrastructure categories and relatively low concordance for less common ones was found.

In our results, many of the identified gaps which were discarded as data issues were due to outdated OSM tags, with significant portions of recently built bicycle infrastructure not yet included as such in the OSM data. While the number of tagging edits might potentially be used as a workaround for estimating whether the tag is up-to-date [138], ideally the implementation of new bicycle infrastructure elements would go hand in hand with the corresponding update in OSM. Another issue is the lack of coherence in bicycle infrastructure tagging. For example, right-turn lanes where the bicycle path merges with a car lane are sometimes marked as protected bicycle infrastructure; the same goes for unprotected intersections which separate two stretches of protected bicycle infrastructure. Therefore, the definitions of bicycle infrastructure categories within OSM [59] might be scrutinized from the viewpoint of intelligibility in order to enhance correct and coherent identification of bicycle infrastructure by mappers across differing local contexts.

4.4 Discarded approaches and caveats

Many helpful takeaways can be derived from what has not worked well. In this section, we briefly describe approaches that were discarded during the work process, as well as several caveats of data processing.

Cost factors are commonly applied in the modelling of cyclist behaviour. It is a way to account for the fact that cyclists are often willing to take a certain detour in order to e.g. avoid traffic lights, busy intersections or streets with high traffic volume, as many studies have shown [60, 69, 139]. For example, Boisjoly, Lachapelle, and El-Geneidy [79] empirically derived a cost factor of 1.4 for Montreal, Canada, from survey results on the average maximum detour cyclists were taking. However, as the Montreal study also points out, the maximum detour a cyclist is actually willing to take is both subjective (depending e.g. on personal preferences, health condition, weather etc.) and highly context-dependent. Moreover, the empirical derivation of such a cost factor requires survey data on revealed preferences, which cannot be assumed to be readily available in most of the contexts. Furthermore, in case of applying a cost factor to the shortest path algorithm, some actual gaps in the network might remain undiscovered or ranked as less relevant (and the more so, the larger the cost factor is chosen). This is especially true for gaps of smaller length, which are of particular interest for this study.

We experimented with applying different cost factors f_{car} within the value range $1 < f_{car} < 2$ to the car-only links by defining the cost for each link as equal to either its length (for bikeable links) or its length multiplied by the cost factor (for car links), and then computing the shortest paths based on cost instead of length. Applying a cost factor was also considered as possible **solution to the parallel paths problem** (see section 3.3 for a detailed description). However, due to the considerations above, we decided to refrain from using a cost factor within the shortest path algorithm for the computation of edge betweenness centralities. This can be interpreted as the assumption that cyclists always take the physically shortest path, independently of the type of bicycle infrastructure available on that path. To exclude potential parallel paths from the analysis, the detour factor d_{max} was applied instead.

Another factor which we initially tried to integrate in our analysis is the **“bicycle percentage” factor**. The bicycle percentage factor is an attribute of path on a street network and describes the percentage of path length that is provided with bicycle infrastructure. This approach is used by several studies on bicycle network planning [69, 79, 140], e.g. to define a minimum percentage of facility length in order for a route to be acceptable for the “average” cyclist, and also forms part of some definitions of connectivity. However, the computation time imposes serious limitations on deriving the bicycle percentage factor for all paths on the net-

work, while limiting the number of paths for which the factor is computed necessarily introduces some arbitrariness into the results. Moreover, deriving a bicycle percentage factor as stated or revealed preference of cyclists is both data intensive and highly context-dependent. We therefore decided to discard this approach in order to reduce the number of variables and to ensure broader applicability of our procedure.

One of the first approaches for gap identification involved the **attempt to connect disconnected components of the bicycle network**. This approach has been used by studies on network growth algorithms which build upon a dynamic network model [64]. However, in this way we would have not been able to identify any segments between two bicycle infrastructure elements belonging to the same network component as gaps. We therefore decided to consider all bicycle network components as embedded in, and connected by, the multi network, and to look for gaps on the multi network. Our definition of “gap” as a sequence of links which connect two nodes on the bicycle network implies that the number of disconnected components after “closing a gap” will either be decreased (if the nodes belong to disconnected bicycle network components) or stay the same (if the nodes belong to the same component).

Another discarded approach to the “gap” definition included **putting a cut-off value on the number of links in a gap**, instead of defining a maximum gap length. The study by Rosvall, Trusina, *et al.* [85] takes a similar approach for the analysis of information handling on transportation networks. Limiting a gap by its link number was found not to be meaningful in the given context, because the number of links in a gap is a feature of OSM data structure rather than of the actual path a cyclist takes in the real world. However, including the number of links or nodes as network topology attribute of a path might be of interest for future studies on motif identification [141], as well as for studies on intersection safety or route directness.

A further working definition of a “gap” on a bicycle network was based on the idea of looking for **bicycle-car-bicycle patterns in shortest paths**, i.e. selecting sequences of car-only links which are framed by bicycle links from both sides, from the set of shortest paths. In other words, the idea was to look for car segments *between bicycle links*, as opposed to car segments *between multi nodes*, as the final definition goes. This approach was discarded because it erroneously excluded all gaps of length x whose adjacent bicycle links were connected by a path shorter than x from the analysis.

Lastly, the simplification algorithm described in section 2.5.2 was significantly improved by using Python’s `geopandas` package for handling network link attributes which contained geocoordinates imported from OSM data, because this allowed to preserve the order of link sequences throughout the iteration steps of the algorithm.

4.5 Future research needs

We have already outlined potential improvements of the present study’s approach in section 4.2 above. This section takes a broader look at future fields of research, where the present study could be meaningfully embedded.

First off, better quality and availability of relevant data would be highly beneficial for bicycle network planning. This applies both to OSM data, where the main issues within the case study were outdated and inconsistent map tags, and to data that is made publicly available by local governmental institutions. This particularly applies to countries in the Global South, which are currently underrepresented in bicycle planning research [14] and related data collection [39] in spite of their pivotal role for a sustainability shift of the transport sector [142, 143].

Next, as outlined in section 2.4, the development of a solid computational methodology for the analysis of bicycle networks is still in its early stage. Although there has been a significant

rise in studies on bicycle network planning over the last years, cross-study comparability is still fairly low, due to the ad hoc approach often taken. As argued above, we believe that first, an approach based on topological network characteristics is a potential way forward; and second, forces should be joined for the development of strategies that allow a consistent integration of non-topological data in the analysis process. This would enhance cross-study comparability and allow to account for different data availability use cases.

There are several street network elements that would require the adaptation of network analysis methods for a more thorough study. Within our case study, these are intersections, roundabouts, and bridges; in other local contexts, further relevant elements might emerge. We see a particularly large potential for the further development of network analysis applications to intersection design on bicycle networks.

Equity considerations should be an integral part of any plan for a sustainable transport system. The recently emerging concept of cycling equity has been so far mostly applied in case studies for particular cities, and predominantly in a North American context [66, 144]. Moreover, there are substantial knowledge and methodology gaps related to the integration of cycling equity perspectives into policy-making [145].

Chapter 5

Conclusion

Bicycle network planning has become an increasingly popular topic of academic research in recent decades. A variety of methods and metrics for bicycle network analysis grounded in network theory can be found in the literature. However, they are mostly based on labour-intensive case studies whose applicability to other contexts strongly depends on data availability. At the same time, the overwhelming majority of cities worldwide, Copenhagen included, are still far away from displaying modal shares of cycling which would characterize a truly sustainable urban transport system.

In order to achieve substantial modal shifts towards cycling, a well-structured, data-driven framework to bicycle network planning is urgently needed. For such an approach to be applicable in practice and to benefit society, we will need to bridge the gap between the computational methods of network theory and the urban design practices of bicycle network planning. Instead of treating those approaches as separate disciplines, we believe that they way forward is a cooperation that does away with disciplinary boundaries and hierarchies.

This study aimed at contributing to the consolidation of computational methods applied to bicycle network planning by developing a broadly applicable method for the identification of network gaps. We therefore chose an approach that relies solely on topological characteristics of the network, and requires only OSM data which is available openly for many locations. We demonstrated the application of the developed procedure for the case of Copenhagen, and gave an example of how results can be categorized and evaluated. We are cautiously optimistic that the method proposed in this study can be used, with some adequate refinements, as a broadly applicable tool for decision-making support in bicycle network planning.

On an ending note, we want to point out that the object of the present study, i.e. gaps on an already existing and relatively dense bicycle network, can be considered “low-hanging fruits”: to close those gaps, no major political or financial hurdles have to be overcome. A sustainability shift of the transport sector, however, will require much more substantial efforts, including not only an increase in cycling, but also – and much more importantly – a drastic global reduction of car use.

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Appendix A


Appendix A: Detail maps of top 101 gaps

Table A.1 contains close-up maps of all 101 prioritized gaps from the Copenhagen case study, with the city map as background layer. Gaps are sorted by ranking, from highest to lowest value of the ranking metric \bar{m}_c . The parameter \bar{m}_c indicates the number of meters cycled in motorized traffic that can be avoided per investment unit if a gap is “closed”. The street network is shown in grey, the bicycle network in dark blue. Gap classes are indicated by abbreviations and distinguished by plotting color:

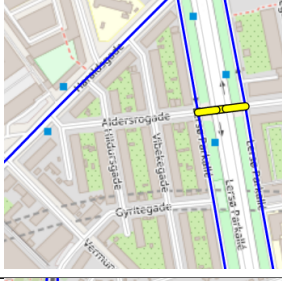
- **BR** Bridge (orange)
- **IS** Intersection (yellow)
- **ML** Missing link (red)
- **RA** Roundabout (brown)
- **RT** Right-turn lane (pink)

For maps showing the overlap between gaps and citizen survey results, see appendix B.

Table A.1: Top 101 gaps: Details

Detail map	Ranking	\bar{m}_c	Class	Address
 A detailed map of the Knippelsbro bridge in Copenhagen. The bridge is highlighted with a thick orange line, indicating it is a Bridge (BR) class gap. The map shows the bridge crossing a canal, with surrounding streets and buildings visible. The text 'Knippelsbro' is written on the map.	1	130 587	BR	Knippelsbro




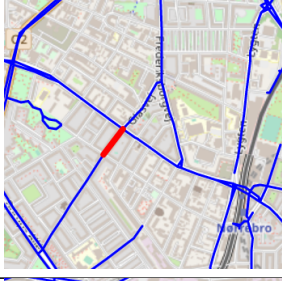

Detail map	Ranking	\bar{m}_c	Class	Address
	2	79 396	IS	Øster Voldgade with Grønningen
	3	71 659	BR	Langebro
	4	69 925	IS	Enghavevej with Vigerslev Allé
	5	61 961	ML	Jacob Erlandsens Gade
	6	60 164	ML	Vermundsgade

Detail map	Ranking	\bar{m}_c	Class	Address
	7	59 289	ML	Langebrogade
	8	58 997	ML	Tschernings Allé
	9	58 298	RT	from Backersvej to Øresundsvej
	10	57 585	IS	Aldersrogade with Lersø Parkallé
	11	56 540	ML	Stadfeldtsvej and Ole Borchs Vej


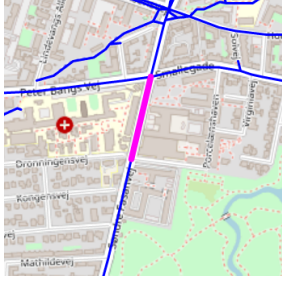

Detail map	Ranking	\bar{m}_c	Class	Address
	12	56 067	IS	Dybbølsgade with Sønder Boulevard
	13	55 883	ML	Sigtungsgade
	14	55 862	RA	Sankt Kjelds Plads
	15	55 298	IS	Rovsinggade with Lynbyvej
	16	54 114	IS	Rådmandsgade with Lersø Parkallé

Detail map	Ranking	\bar{m}_c	Class	Address
	17	52 462	ML	Bernhard Bangs Allé
	18	51 910	IS	Teglværksgade with Jagtvej
	19	50 168	ML	Kongebrovej
	20	49 729	ML	Kortløb
	21	48 951	ML	Værnedamsvej


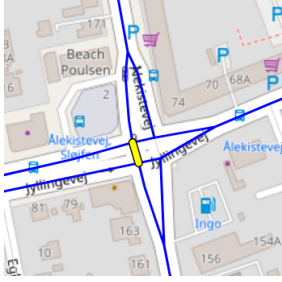


Detail map	Ranking	\bar{m}_c	Class	Address
	22	48 797	RT	from Hillerødsgade to Borups Allé (on Hillerødsgade)
	23	48 713	IS	Rantzausgade with Aboulevard
	24	47 758	RT	from Øster Allé to Nørre Allé
	25	47 303	ML	Vesterfælledvej
	26	46 980	ML	Gåsebæksvej

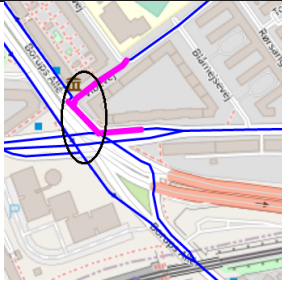




Detail map	Ranking	\bar{m}_c	Class	Address
	27	45 751	ML	Sofus Francks Vænge
	28	44 743	ML	C. F. Richs Vej
	29	44 456	IS	Peter Bangs Vej with Lindevangs Allé
	30	44 400	ML	Mågevej
	31	43 964	ML	Ålandsgade and Frankrigshusene

Detail map	Ranking	\bar{m}_c	Class	Address
	32	43 330	ML	Annexstræde
	33	43 086	ML	Havneholmen
	34	42 636	ML	Gamle Vasbygade
	35	42 412	ML	Kristeneberg
	36	42 220	IS	Fensmarkgade with Tagensvej

Detail map	Ranking	\bar{m}_c	Class	Address
	37	41 597	ML	Borgmester Fischers Vej
	38	41 475	RT	from Søndre Fasanvej to Smallegade
	39	41 229	IS	Gyldenløvesgade with Nørre Farimagsgade
	40	40 568	ML	Drosselvej
	41	40 424	RT	from Nørre Allé to Øster Allé


Detail map	Ranking	\bar{m}_c	Class	Address
	42	40 407	ML	Ib Schønbergs Allé
	43	40 300	ML	Kingosgade
	44	40 011	IS	Koldinggade with Østerbrogade
	45	39 525	ML	Ny Kongensgade and Frederiksholms Kanal
	46	39 363	ML	Thorvaldsensvej

Detail map	Ranking	\bar{m}_c	Class	Address
	47	39 305	ML	Blågårdsgade
	48	39 203	IS	Alekistevej Jyllingevej with
	49	39 079	ML	Vejlands Allé
	50	39 044	ML	Christen Bergs Allé
	51	38 927	RT	from Sølvgade to Øster Farimagsgade




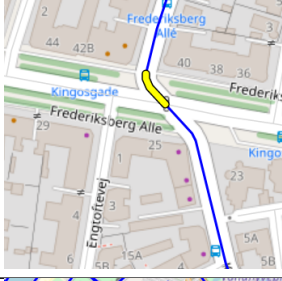

Detail map	Ranking	\bar{m}_c	Class	Address
	52	38 754	RT	from Hillerødgade to Borups Allé (on Borups Allé)
	53	38 590	IS	Randersgade with Strandboulevarden
	54	38 199	ML	Rantzausgade
	55	38 069	ML	Borgergade
	56	37 827	IS	Vestre Kirkegårds Allé

Detail map	Ranking	\bar{m}_c	Class	Address
 A street map showing a red highlighted section of Blegdamsvej in the Triangeln area. The map includes labels for 'Blegdamsvej', 'Triangeln', and 'Øst'.	57	37 776	ML	Blegdamsvej
 A street map showing a red highlighted section of Skibbroen near the harbor. Labels include 'Skibbroen', 'Havneengen', 'Leriks Brygge', and 'Laghave Brygge'.	58	37 747	ML	Skibbroen
 A street map showing a red highlighted section of Aldersrogade and Teglværksgade. Labels include 'Aldersrogade', 'Teglværksgade', 'Leriks Brygge', and 'Laghave Brygge'.	59	37 708	ML	Aldersrogade and Teglværksgade
 A street map showing a red highlighted section of Jyllandsvej. Labels include 'Jyllandsvej', 'Solbjerg Parkkirkegård', and 'Zoologisk Have'.	60	37 694	ML	Jyllandsvej
 A street map showing a yellow highlighted section of Hammerichsgade and H. C. Andersens Boulevard. Labels include 'H.C. Andersens Boulevard', 'Bryderne', 'Jarmers Plads', and 'Jarmers Tårn'.	61	37 209	IS	Hammerichsgade with H. C. Andersens Boulevard

Detail map	Ranking	\bar{m}_c	Class	Address
	62	36 659	IS	Øster Søgade with Østerbrogade
	63	36 598	ML	Dybbølsgade
	64	36 539	ML	Vendersgade
	65	36 537	ML	Rådmandsgade
	66	36 523	BR	Højbro




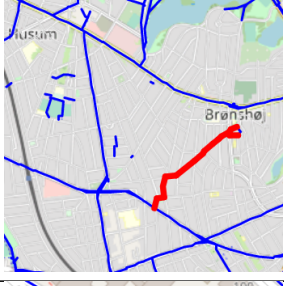

Detail map	Ranking	\bar{m}_c	Class	Address
	67	36 523	ML	Høffdingsvej
	68	36 502	ML	Birkedommervej
	69	36 440	ML	Gustav Johannsens Vej
	70	36 280	ML	Solvej
	71	36 263	ML	Koldinggade and Randersgade




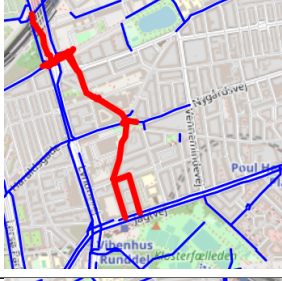

Detail map	Ranking	\bar{m}_c	Class	Address
	72	36 163	ML	Tietgensgade, Halmtorvet and Colbjørnsensgade
	73	35 971	IS	Nørre Allé with Øster Allé
	74	35 895	ML	Banevolden
	75	35 892	ML	Nørregade
	76	35 866	IS	Sølvgade with Øster Voldgade

Detail map	Ranking	\bar{m}_c	Class	Address
	77	35 830	ML	Valby Langgade
	78	35 827	ML	Kristen Bernikows Gade and Nikolaj Plads
	79	35 747	ML	Tranehavevej
	80	35 644	IS	Kingsgade with Frederiksberg Allé
	81	35 224	ML	Niels Juels Gade

Detail map	Ranking	\bar{m}_c	Class	Address	
	82	35 026	ML	Krabbesholmvej	
	83	35 001	IS	Skellet with Roskildevej	
	84	34 955	ML	Gammel Jernbanevej	
	85	34 803	ML	Hamletsgade	
	86	34 641	IS	Pilesvinget Hareskovvej	with

Detail map	Ranking	\bar{m}_c	Class	Address
 A street map showing a red highlighted segment of Julius Thomsens Gade in a city grid. The map includes labels for 'Forum' and 'Sankt Jørgens Sø'.	87	34 623	ML	Julius Thomsens Gade
 A street map showing a red highlighted segment of Ernst Kapers Vej. The map includes labels for 'Johann Kapers Vej' and 'Vand'.	88	34 400	ML	Ernst Kapers Vej
 A street map showing a red highlighted segment of Herlufsholmvej. The map includes labels for 'Vanløse' and 'Damhusvej'.	89	34 321	ML	Herlufsholmvej
 A street map showing a red highlighted segment of Vodroffsvej. The map includes labels for 'København' and 'Vesterbro'.	90	34 320	ML	Vodroffsvej
 A street map showing a red highlighted segment of Peder Lykkes Vej. The map includes labels for 'Vand'.	91	34 283	ML	Peder Lykkes Vej

Detail map	Ranking	\bar{m}_c	Class	Address
	92	34 276	ML	Guldbergsgade
	93	34 035	ML	Mimersgade
	94	33 053	ML	Nordre Frihavnsgade
	95	32 743	ML	Valløvej
	96	31 104	IS	H. C. Andersens Boulevard with Rysensteensgade

Detail map	Ranking	\bar{m}_c	Class	Address
	97	30 528	ML	Griffenfeldsgade
	98	30 160	ML	Vognmandsmarken
	99	28 888	ML	Store Kongensgade
	100	28 473	ML	Tåsingegade
	101	22 565	ML	Æbeløgade

Appendix B

Appendix B: Detail maps of gap overlaps with citizen survey results

Out of the top 101 prioritized gaps (see appendix A), 71 showed at least one overlap with the citizen survey from the Cycle Path Prioritization Plan (CPPP). Table B.1 contains close-up maps of all 71 overlap cases. Gaps are sorted by ranking, from highest to lowest value of the ranking metric \bar{m}_c . The parameter \bar{m}_c indicates the number of meters cycled in motorized traffic that can be avoided per investment unit if a gap is “closed”. The street network is shown in grey, the bicycle network in dark blue. Gap classes are indicated by abbreviations and distinguished by plotting color:

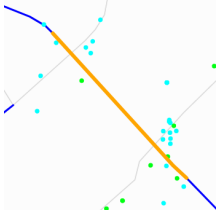
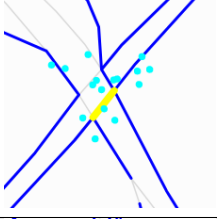
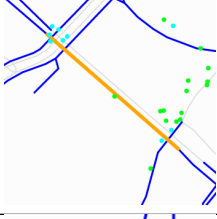
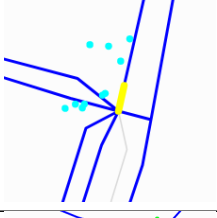
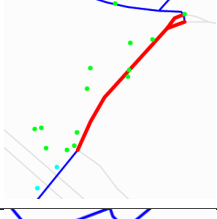
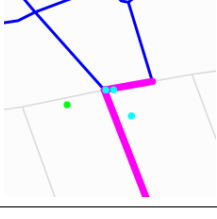
- **BR** Bridge (orange)
- **IS** Intersection (yellow)
- **ML** Missing link (red)
- **RA** Roundabout (brown)
- **RT** Right-turn lane (pink)

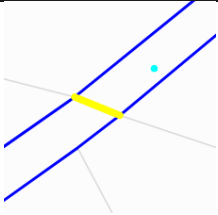
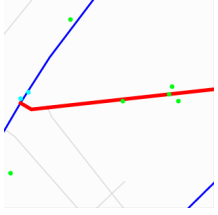
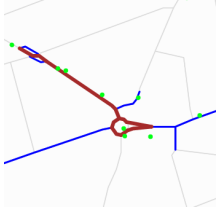

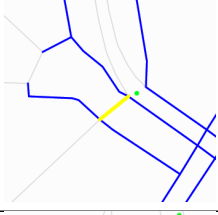
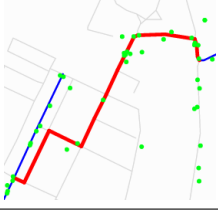
Citizen survey inputs have two categories and are distinguished by plotting color:


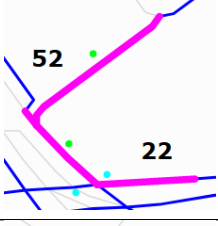
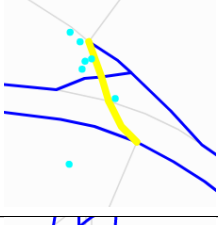

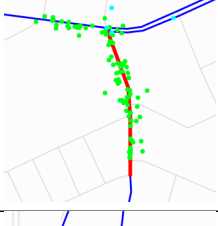

- “Cycle path missing” (green dot)
- “Problematic intersection” (light blue dot)

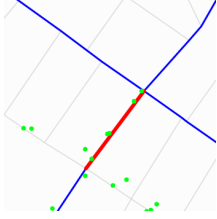
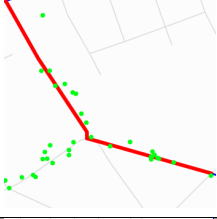
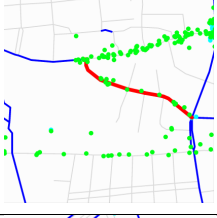
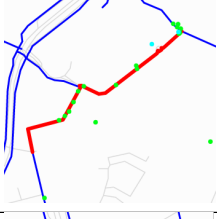
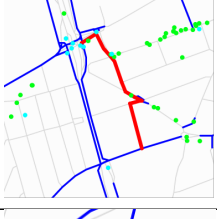
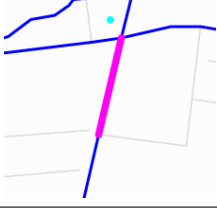
Plots do not include the city map as background layer for better visibility. For detail maps of all gaps with the city map as background layer, see appendix A.

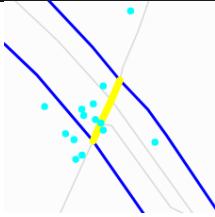

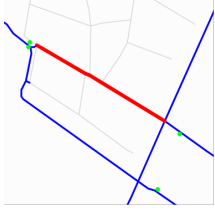
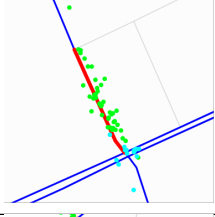
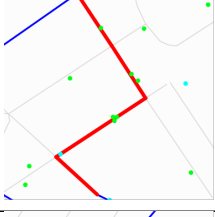
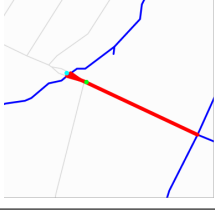
Table B.1: Overlap of gaps with citizen survey: Details


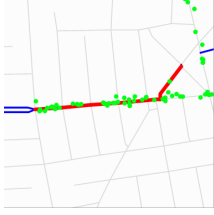
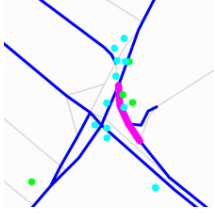
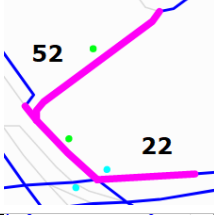
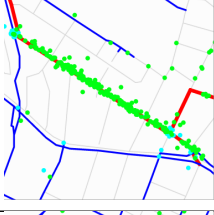
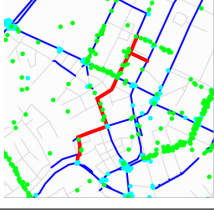
Detail map	Ranking	\bar{m}_c	Class	Address
	1	130 587	BR	Knippelsbro
	2	79 396	IS	Øster Voldgade with Grønningen
	3	71 659	BR	Langebro
	4	69 925	IS	Enghavevej with Vigerslev Allé
	7	59 289	ML	Langebrogade
	9	58 298	RT	from Backersvej to Øresundsvej




Detail map	Ranking	\bar{m}_c	Class	Address
	12	56 067	IS	Dybbølsgade with Sønder Boulevard
	13	55 883	ML	Sigynsgade
	14	55 862	RA	Sankt Kjelds Plads
	15	55 298	IS	Rovsingsgade with Lyn-gbyvej
	16	54 114	IS	Rådmandsgade with Lersø Parkallé
	19	50 168	ML	Kongebrovej

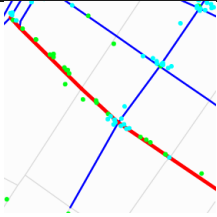
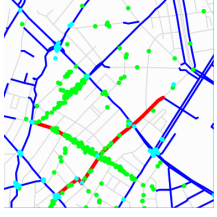

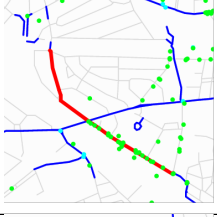
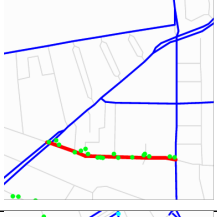
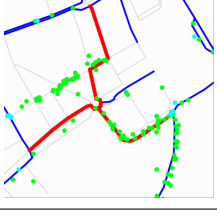
Detail map	Ranking	\bar{m}_c	Class	Address
	21	48 951	ML	Væredamsvej
	22	48 797	RT	from Hillerødgade to Borups Allé (on Hillerødgade)
	23	48 713	IS	Rantzausgade with Åboulevard
	24	47 758	RT	from Øster Allé to Nørre Allé
	25	47 303	ML	Vesterfælledvej
	26	46 980	ML	Gåsebæksvej

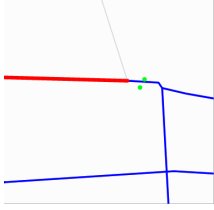


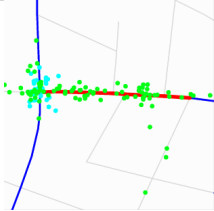

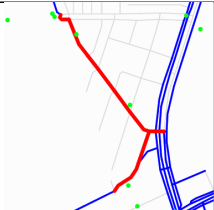
Detail map	Ranking	\bar{m}_c	Class	Address
	30	44 400	ML	Mågevej
	31	43 964	ML	Ålandsgade and Frankrigshusene
	32	43 330	ML	Annexstræde
	33	43 086	ML	Havneholmen
	35	42 412	ML	Kristeneberg
	38	41 475	RT	from Søndre Fasanvej to Smallegade

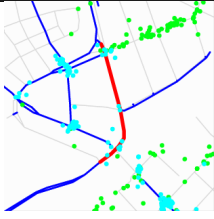
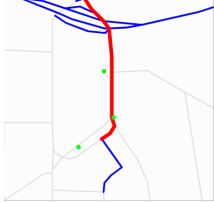
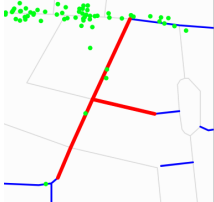
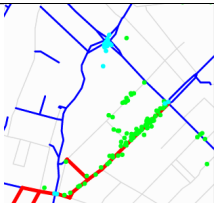


Detail map	Ranking	\bar{m}_c	Class	Address
	39	41 229	IS	Gyldenløvesgade with Nørre Farimagsgade
	41	40 424	RT	from Nørre Allé to Øster Allé
	42	40 407	ML	Ib Schønbergs Allé
	43	40 300	ML	Kingosgade
	45	39 525	ML	Ny Kongensgade and Frederiksholms Kanal
	46	39 363	ML	Thorvaldsensvej



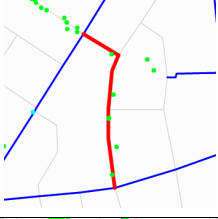
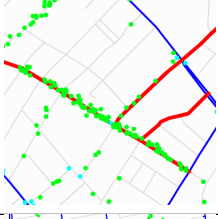
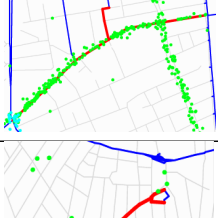
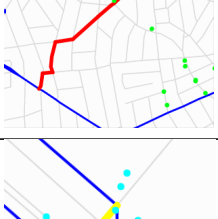
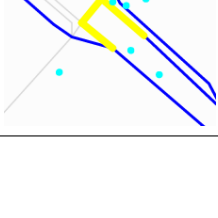
Detail map	Ranking	\bar{m}_c	Class	Address
	47	39 305	ML	Blågårdsgade
	49	39 079	ML	Vejlands Allé
	51	38 927	RT	from Sølvgade to Øster Farimagsgade
	52	38 754	RT	from Hillerødgade to Borups Allé (on Borups Allé)
	54	38 199	ML	Rantzausgade
	55	38 069	ML	Borgergade


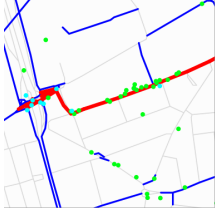

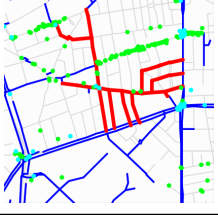
Detail map	Ranking	\bar{m}_c	Class	Address
	57	37 776	ML	Blegdamsvej
	58	37 747	ML	Skibbroen
	59	37 708	ML	Aldersrogade and Teglværksgade
	61	37 209	IS	Hammerichsgade with H. C. Andersens Boule- vard
	62	36 659	IS	Øster Søgade with Østerbrogade
	63	36 598	ML	Dybbølsgade

Detail map	Ranking	\bar{m}_c	Class	Address
	64	36 539	ML	Vendersgade
	65	36 537	ML	Rådmandsgade
	66	36 523	BR	Højbro
	67	36 523	ML	Høffdingsvej
	68	36 502	ML	Birkedommervej
	72	36 163	ML	Tietgensgade, Halmtorvet and Colbjørnsensgade

Detail map	Ranking	\bar{m}_c	Class	Address
	74	35 895	ML	Banevolden
	75	35 892	ML	Nørregade
	76	35 866	IS	Sølvgade with Øster Voldgade
	77	35 830	ML	Valby Langgade
	78	35 827	ML	Kristen Bernikows Gade and Nikolaj Plads
	79	35 747	ML	Tranehavevej

Detail map	Ranking	\bar{m}_c	Class	Address
	81	35 224	ML	Niels Juels Gade
	82	35 026	ML	Krabbesholmvej
	84	34 955	ML	Gammel Jernbanevej
	85	34 803	ML	Hamletsgade
	87	34 623	ML	Julius Thomsens Gade
	88	34 400	ML	Ernst Kapers Vej

Detail map	Ranking	\bar{m}_c	Class	Address
	90	34 320	ML	Vodroffsvej
	91	34 283	ML	Peder Lykkes Vej
	92	34 276	ML	Guldbergsgade
	93	34 035	ML	Mimersgade
	94	33 053	ML	Nordre Frihavnsgade
	95	32 743	ML	Valløvej
	96	31 104	IS	H. C. Andersens Boulevard with Rysensteensgade

Detail map	Ranking	\bar{m}_c	Class	Address
	97	30 528	ML	Griffenfeldsgade
	98	30 160	ML	Vognmandsmarken
	100	28 473	ML	Tåsingegade
	101	22 565	ML	Æbeløgade