Catchment Cell Visualization for Multi-Modal Public Transportation Networks

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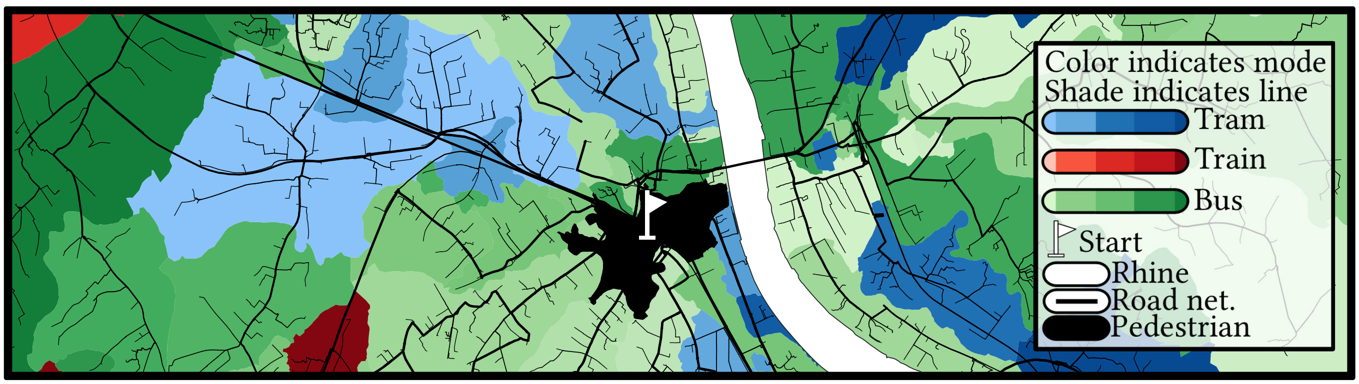

Figure 1: Visualization of *Catchment cells* for the city of Bonn, Germany. The color indicates the travel mode used to reach the road network segments the fastest from the starting location, Bonn Central Station, indicated by a white flag. The start time is Monday 10 a.m.. Different shades of colors represent individual public transportation lines.

ABSTRACT

Mobility is a prerequisite to ensure the access and fair distribution of citizens's basic needs, such as health and social facilities. In this context, assessing the impact of different transit lines and the overall performance of a public transportation network is an important task. Visualizing transit maps is a requirement for diverse fields of application such as spatial decision support systems or tourist navigation. This work focuses on visualizing transit maps for multi-modal public transportation networks with *Catchment cells*. In contrast to previous attempts, our work proposes an approach to estimate the catchment areas of individual transit lines and stations for multi-modal public transportation networks. The accessibility of different parts of the road network is determined by integrating the timetable information of different public transportation modes on a multi-modal, time-expanded network. *Catchment cells* are estimated based on location-dependent contractions of road networks segments and visualized by non-overlapping geometries. The resulting maps turn out to be a good means for the assessment of mobility and accessibility.

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CCS CONCEPTS

• **Public transportation networks** → **Visualization**; *Urban planning*; *Passenger navigation*; • **Computer aided systems** → Computational cartography; • **Networks** → Multi-modal routing.

KEYWORDS

catchment cells, sustainable mobility, transit maps

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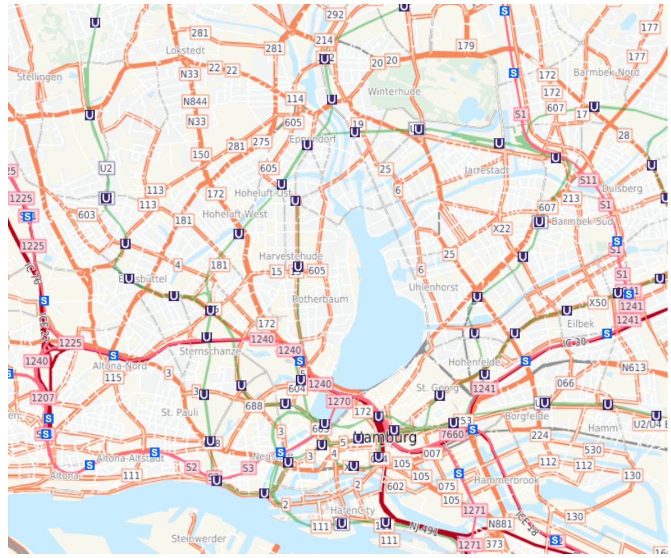
1 INTRODUCTION

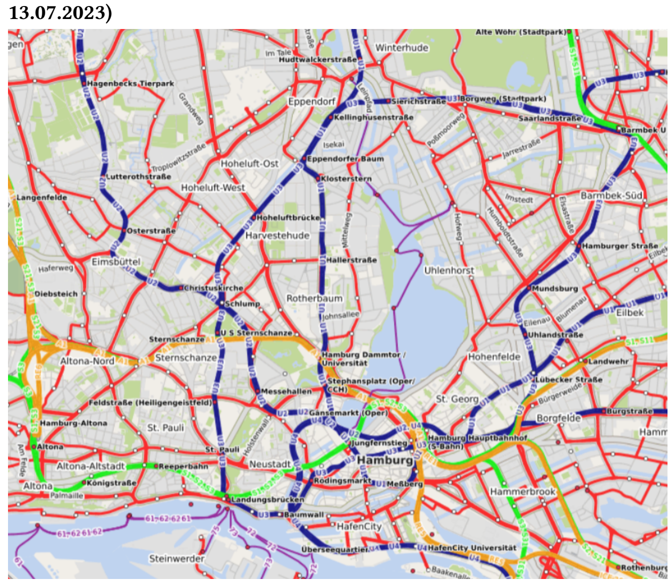
Transit maps provide passengers with a simple and comprehensive visualization of a public transportation network. They help passengers to orient themselves and navigate in a transportation network. Passengers, e.g., tourists, can roam freely through a city and visit different landmarks by taking a transit map as guidance. In order to plan the most satisfying route, passengers often do not necessarily need the exact geography of the transportation network. Instead, it is the topology of the network that provides the most important information [Nöllenburg and Wolff 2010]. As the number of new transportation modes and transit routes is ever-increasing, transit maps become more complex and lose their simplicity at the same time. In this context, passengers might not be able to infer their next departure or arrival by quickly observing a transit map since occlusions due to annotations and station markers or intersecting routes, as depicted in Figure 2, reduce the legibility.Besides, transit maps are a prerequisite in urban planning and can be a valuable tool in spatial decision support systems, e.g., to analyze the accessibility of health and social facilities in different city districts and communities [Forsch et al. 2021].

Given a starting location and starting time, we define a *Catchment cell* as a cluster of the spatial extent on a road network that can be reached the fastest from a distinctive transit station in a public transportation network. We introduce a novel approach to visualize transit maps by employing a clustering technique inspired by *Catchment cells*, as seen in Figure 1. Our clustering technique aims to address the growing complexity in transit maps that is associated with the integration of new modalities and routes in public transportation networks while trying to keep graphical complexity as low as possible, making it a viable tool in urban planning and passenger navigation likewise. The motivation for our approach is to highlight the spatial significance and predominance of individual transportation modes, transit lines, and transit stations, as previous techniques mostly fail at this task. *Catchment cells* provide the necessary analytical capabilities to communicate transportation options and modalities for complex systems by visualizing accessibility in a city as a whole. That way, the fairness in regions lacking supply with basic functionalities can be monitored, or the substitution of personal motorized trips can be encouraged. As it is arguable that most people take a trip that brings them the fastest from their origin to their destination, new simulations that are tailored to develop solutions to mitigate deficiencies can be solved reasonably with a *catchment cell* visualization of a transit map.

Before *Catchment cells* can be clustered the underlying routing component and time-table information are needed to support integrated path finding in the road and public transportation network. To identify the reachable part of the road network, we use the *time-expanded model* introduced by Pyrga et al. [2008].
Applying *Dijkstra's algorithm* [Dijkstra 1959] to calculate the shortest-path tree and clustering the road network segments according to their last transit segment, i.e., a transit station, we can identify segments in the road network which are reachable the fastest by a specific transit station. This way, we treat every transit station as a *representative* resulting in many small and highly detailed



(a) transit map by *flosm* © (https://www.flosm.de/en/, last visited 13.07.2023)



(b) transit map by *öpnvkarte* © (https://www.öpnvkarte.de/, last visited 13.07.2023)

Figure 2: Two examples of digital transit maps for Hamburg, Germany.

Catchment cells reducing the clarity of the transit map drastically. However, using the *ContractTree* algorithm by van Dijk et al. [2016] we are able to identify vertices in the road network that can be contracted due to their *similarity*, allowing a more simplified and clear visualization. Road network segments which share a large *similarity* are less relevant to the user as these segments would lead to the same location in an equivalent amount of time. The strength of their *similarity* is controlled by a parameter that balances the actual representation of the fastest connection and the overall clarity of the visualization by contracting at least two different *representatives* back to one. As a result, we are able to control the overall size and the level of detail of the *Catchment cells*. The aforementioned algorithm has been previously used for other clustering tasks and will be explained in more detail in Section 3. Further, a *Voronoi diagram* is used to ensure an overlapping-free visualization of clustered *Catchment cells*. This measure reduces the visual complexity as the topology between individual *Catchment cells* is highlighted. To further improve a low visual complexity and readability, we generalize the acquired *Catchment cells* by simplifying their boundaries and eliminating smaller catchments.

Given a public transportation network represented as a graph $G = (V, E)$, a starting location $s \in V$, and a starting time τ, a *Catchment cell* C is a cluster of nodes in V. Each cluster is required to induce a connected subtree in the shortest-path tree with root s. Moreover, for any two nodes u, v within the same cluster, it is required that the shortest path P_{su} from s to u and the shortest path P_{sv} from s to v are sufficiently similar with respect to a definition by van Dijk et al. [2016] that we review in Sect. 3.1. The root node x of the connected subtree representing a cluster also serves as the cluster's *representative* node. Traveling in the shortest-path tree starting at s, this representative is reached with a certain line of the transportation system. We visualize this line and its travel mode as the line and travel mode for the entire cluster represented by x.

With this visualization based on clusters we greatly reduce the visual complexity compared to a visualization of the line and travel mode for each individual node of the transportation network. Applying this clustering approach is the crucial contribution of our paper to obtain a legible map even for large multi-modal transportation systems. Accessibility is the most valuable feature of a public transportation system and the direct outcome of the available level of mobility [Saif et al. 2019]. Mobility can be understood as a core service of public interest, interconnecting basic needs and demands of citizens across all social groups [Saif et al. 2019; Wegener 2013; Zhang et al. 2021]. Furthermore, public transportation can be regarded as a key driver of sustainable urban planning and sustainable economic growth [Chen 2019; Zhang et al. 2021]. By improving mobility with public transportation, the accessibility of core services and potentially a decrease in greenhouse gas emissions through the reduction of personal motorized trips is expected [Butler et al. 2021; Wegener 2013]. However, developing the public transportation network of a region is expensive. The outcome of different measures must be maximized in terms of their impact as a large number of planning steps and decision making is involved [Wegener 2013].

Visualizing the accessibility of a public transportation network increases the situational awareness of planners and other decision-makers. A *Catchment cell* inspired visualization is a tool for estimating the *serviceable area* by highlighting the individual performance of transit lines and transit stations as it involves searches in the road and public transportation network [Andersen and Landex 2008].
Transit lines can have different modalities and spatial extents and hence provide valuable information on the overall quality of a transportation network. Since *Catchment cells* reflect which transit lines served their surroundings the fastest from a selected location and starting time, they give key insights into not only the accessibility but also the mobility of a public transportation network. Recently, *Catchment cell* inspired visualizations have been used to analyze how dockless bike-sharing systems change the catchment area around metro stations. According to the authors, the bike catchment areas increase from the city center towards the suburbs and profit from a balanced distribution of metro stations [Lin et al. 2019].
In Hu et al. [2020], the park accessibility with different travel times has been investigated and visualized with *Catchment cells*. A network analysis concerning multi-modes, including public transportation, walking, and motorized individual transport, found that the traditional single-mode model overestimates the park accessibility while the multi-modes can provide a more realistic evaluation for urban park planning.

Before going into the details of the methodology of our *catchment cell* inspired visualization technique (Section 3), we briefly summarize schematics maps for visualizing transit maps and name their strength and weaknesses (Section 2). Following this, we present our experimental results (Section 4) and give an outlook on possible improvements (Section 5).

2 SCHEMATIC MAPS FOR TRANSIT MAP VISUALIZATION

Visualizing a complex transportation network in a single transit map is a challenging task, as can be observed in Figure 2. Until now, several solutions for visualizing transit maps have been proposed. Some tried to solve the problem by schematizing line geometries, and others by schematizing polygons [Forsch et al. 2021].
Metro maps are among the most prominent examples of schematic network maps and frequently used to visualize transit maps [Zeng et al. 2014]. They are inspired by the London underground map style created by Harry Beck in 1933. Metro maps use strong schematics instead of precise geographic locations as they need to have low visual complexity and must be simple to understand [Nöllenburg and Wolff 2010; Zeng et al. 2014]. That the schematics of metro maps help users to accurately and efficiently navigate a public transportation network was empirically confirmed [Bartram 1980; Meilinger et al. 2007; Nöllenburg and Wolff 2010]. During the last two decades, research interest in automating schematic network maps increased heavily, which led to different surveys to be conducted [Nöllenburg 2014; Wu et al. 2022]. Metro maps serve as an overview or visual aid for route planning and navigation even for hundreds or thousands of bus, train, tram, or subway lines, including their transit stations [Nöllenburg and Wolff 2010; Wu et al. 2022]. However, to do so, one usually needs to overcome two major difficulties, namely laying out the map and placing non-overlapping labels [Niedermann and Haunert 2018; Nöllenburg and Wolff 2010].

3 METHODOLOGY

In their work, van Dijk et al. [2016] generalize routes in a geographic network based on equivalent destinations for focus-and-context visualizations. Their algorithm, named *ContractTree*, identifies sets of paths with an equivalent destination to a root vertex and contracts

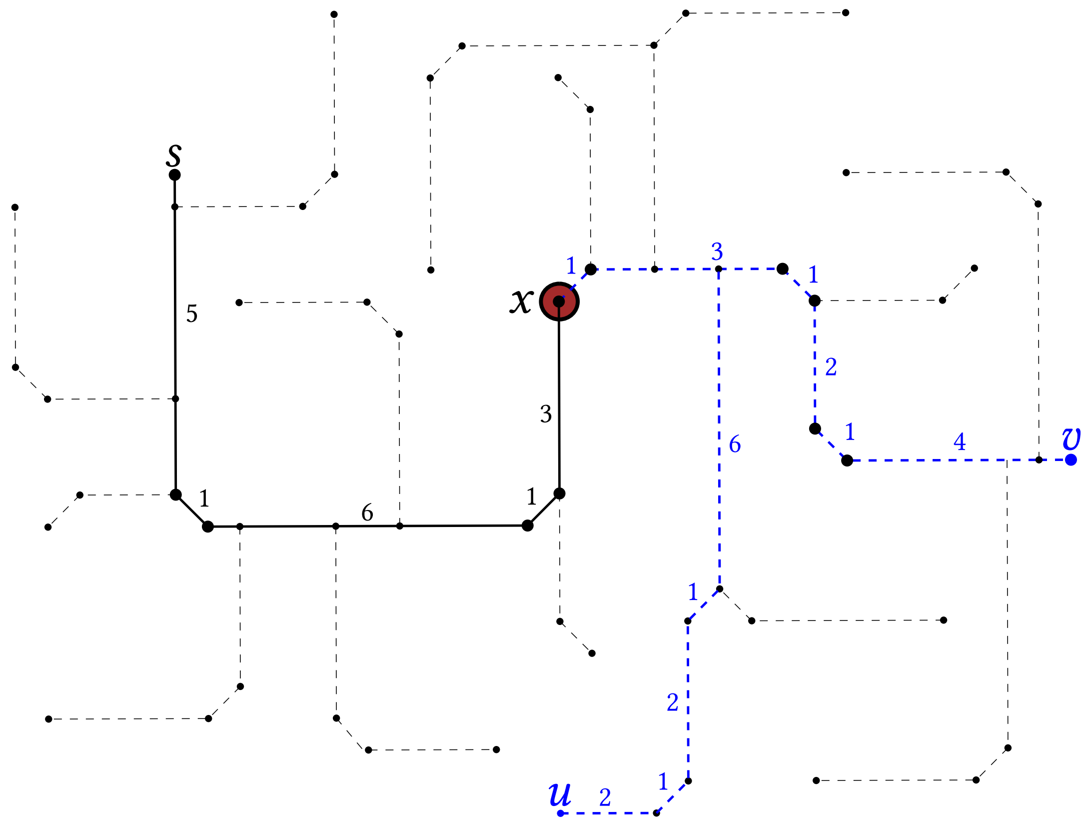


Figure 3: Illustration expressing the *similarity* and *compatibility* after van Dijk et al. [2016]. Note, $\sigma(u,v) = \frac{4}{7}$ and $\sigma(v,u) = \frac{1}{2}$; hence u and v are contractible only for $\alpha \leq \frac{4}{7}$.

them into clusters to reduce the complexity of a network. For this, a prerequisite is to calculate a rooted, edge-weight tree that allows the contraction of vertices based on a least shared fraction of their paths to the root vertex. That way, users receive a high-level representation at the starting location and a detailed representation of the geographic network the closer they get to the desired location [van Dijk et al. 2016].

3.1 Formal definition

Given a shortest-path tree $G = (V, E)$ as the combination of a road and a public transportation network, rooted at a vertex $s \in V$ defining the selected starting location. P_{uv} denotes the unique path that connects u and v in G where $w(P_{uv})$ resembles the sum of the edge-weights representing the remaining travel time. As each cluster is required to induce a connected subtree in the shortest-path tree with root s we introduce a measure of *similarity*. The *similarity* expresses how much of the path to the root between the root vertex s is shared by two different vertices $u, v \in V$ as denoted in Figure 3. In a more formal way, the *representative* vertex x can be defined as the lowest common ancestor of the vertices $u, v \in V$. Now the *similarity* for both combinations of $u, v \in V$ can be modeled with the following equation:

$$\sigma(u,v) = \frac{w(P_{sx})}{w(P_{su})} \quad \textit{and} \quad \sigma(v,u) = \frac{w(P_{sx})}{w(P_{sv})} \tag{1}$$

Knowing to which extent $u, v \in V$ share a common path towards the vertex s is insufficient for a contraction of both induced subtrees in G. Additionally, the resulting coefficient σ expressing the *similarity* needs to be compared against a parameter α selected by the user as shown in Figure 3. The parameter α expresses the level of *compactness* of the desired clusters and therefore directly impacts the legibility for large multi-modal transportation systems [van Dijk et al. 2016]. Whether $u, v \in V$ are compatible and therefore contractible, is expressed by the following equation:

$$\sigma(u,v) \geq \alpha \quad \textit{and} \quad \sigma(v,u) \geq \alpha \tag{2}$$

The *ContractTree* algorithm examines all children of each vertex in the shortest-path tree in post-order. It verifies whether the deepest vertex of the *Catchment cell* that a child belongs to is compatible with its parent vertex. If they are compatible, both subtrees including all their vertices are merged into the *Catchment cell* of the child, as visualized in Figure 3 [van Dijk et al. 2016].

3.2 Voronoi diagram and post-processing

A non-overlapping visualization of *Catchment cells* is realized with a *Voronoi diagram*. The *Voronoi diagram* partitions a plane into overlapping-free regions defined by a given set of points, resulting in *Voronoi cells*. Each vertex stores the information to which transit station and thereby to which travel mode and transit line it belongs.

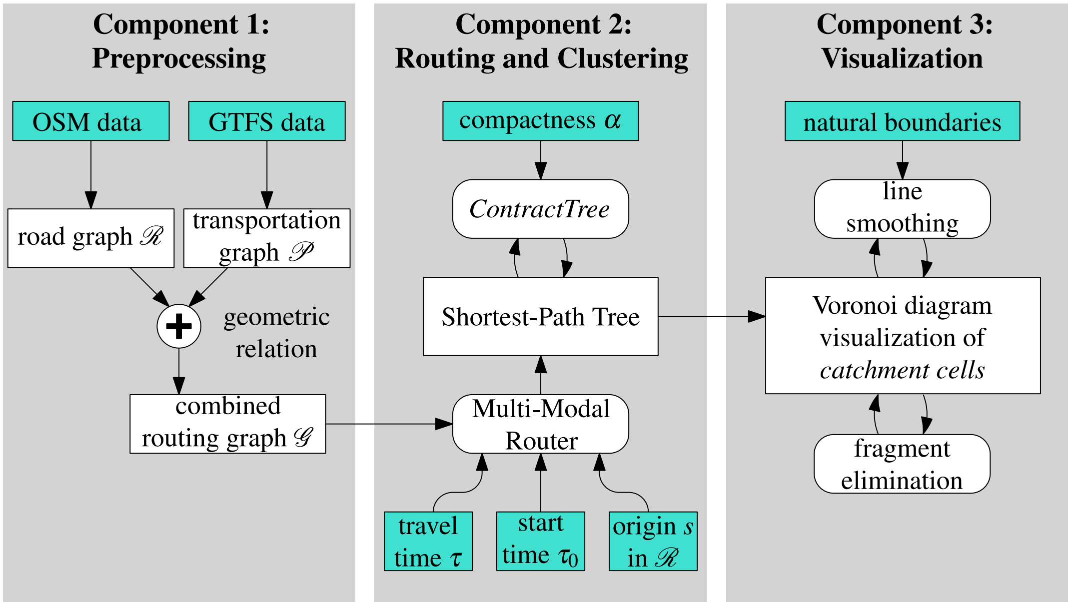


Figure 4: Pipeline developed to calculate and visualize *Catchment cells*.

This information is later used to aggregate the calculated *Voronoi cells* to topological persistent polygons representing *Catchment cells*. Since the boundaries of the aggregated *Voronoi cells* are too detailed and uneasy to observe, the boundaries of the resulting *Catchment cells* are simplified to improve the aesthetics and readability. In our work, the sliding averaging algorithm by McMaster and Shea [1992] is used to smooth the boundaries of *Catchment cells*. The algorithm calculates a smoothed boundary by taking the average coordinate values of a point p_i w.r.t. to the coordinate values of a set of neighboring points n_p and then sliding the averaged point p_{avg} towards the original point p_i according to a specified displacement value [McMaster and Shea 1992].

Small fragments of catchments can be produced when calculating the *Voronoi diagram*. Such fragments can, however, interfere with the clarity of the visualization, e.g., if they are contained within each other. For *Catchment cells*, topological persistence must be ensured since gaps or large distortions that emerge from deleting these artifacts have a much worse effect on the structural logic of the map. The beforementioned algorithm selects *Catchment cells* whose size is below a certain threshold ϵ and dissolves them with the neighboring *catchment cell* with which they share the largest common boundary. Formally, we determine two sets of *Catchment cells* where the first set S_c contains all selected *Catchment cells* that have an area smaller than ϵ. The other set C_o contains the remaining non-selected *Catchment cells*. While iterating over all selected *Catchment cells* $\{c_1, ..., c_n\}$ in the set S_c, we test whether the boundary of the current *catchment cell* intersects the boundary or the interior of a non-selected *catchment cell*. Finally, the selected *catchment cell* is dissolved with the neighboring non-selected *catchment cell* it shares the largest common boundary with.

3.3 Implementation

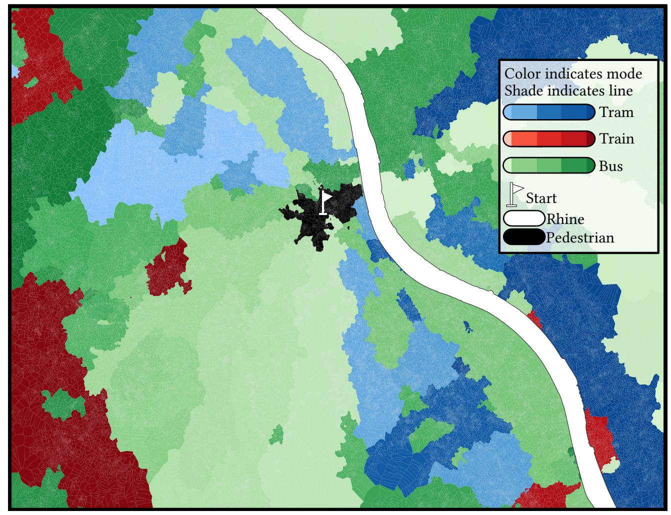
The flexibility of our approach has been demonstrated for the region of the city of Bonn, Germany. The data sets for the public transportation network for the city of Bonn are provided by the VRS (Verkehrsbund Rhein-Sieg) [VRS 2023] while the geometries for the road network are provided by OpenStreetMap (OSM) [OpenStreetMap 2023]. Both data sets have a geometric relation, making it possible to combine them into one routing graph as highlighted in Figure 4.

We use the time-expanded model developed by Pyrga et al. [2008] to identify the underlying time-table information and provide it for integrated pathfinding in the combined routing graph. Integrated pathfinding is conducted in our *multi-modal router*, which uses *Dijkstra's algorithm* [Dijkstra 1959], to successfully determine which part of the road network is reachable with a remaining travel time which we treat as our edge-weight. The outcome is a shortest-path tree on which we apply the *ContractTree* algorithm of van Dijk et al. [2016] after selecting a value for the compactness parameter α as can be seen in Figure 4. The resulting vertices store a reference to the last vertex they have been contracted with. This reference is expected to resemble a transit station and identify a specific transit line in the public transportation network since this would be the only possibility to enter or leave the public transportation network. The resulting vertices containing the reference to the transit stations are visualized as non-overlapping geometries with *Voronoi cells*. Additionally, they are aggregated and simplified by line smoothing and fragment elimination as described in Section 3.

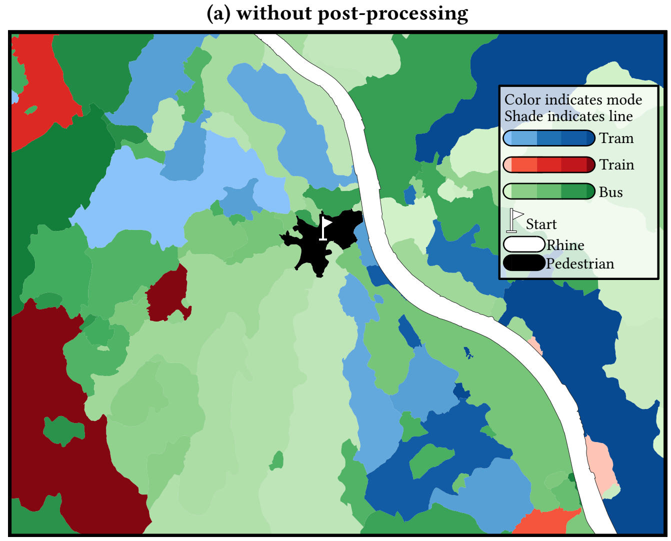
4 EXPERIMENTS

Our experiments aim to discover to which degree *Catchment cells* can be used as a visualization technique for understanding the impact of individual lines, transit stations and the overall accessibility of a public transportation network. For all experiments, the starting point is Bonn Central Station, indicated by a white flag. The starting time for all experiments is Monday at 10 a.m.. In the following, the transportation modes: tram, train, bus, and walking are represented in the combined routing graph and visualized in the following Figures 6a, 6b, 6c. After carefully tuning the α-compactness, a value of $\alpha < 0.5$ was found to result in more detailed but scattered *Catchment cells* as highlighted in Figure 5a. A sweet spot between a satisfying level of detail without too much scatter was found for $\alpha = 0.3$ and has been chosen for the following experiments. Note that other values might also be suitable, depending on the desired level of detail. This sweet spot was only determined by visual inspection and not quantitatively. That smaller values for α result in finer structures follows from the principles of the algorithm of van Dijk et al. [2016] as explained in Section 3. Throughout the figures the Rhine is represented by a white polygon that winds from north to south. In the following, the performance of our approach is analyzed. We choose the best liability for our *Catchment cells* by creating a non-overlapping visualization with a *Voronoi diagram.* As shown in Figure 5a, topological relations between individual transit lines and the overall accessibility are well reflected. *Voronoi cells* aid with a clear analysis of the public transportation network w.r.t. to the catchment areas of individual lines and transit stations. However, they also create sharp and complex border geometries between cells, degrading the visualization's simplicity as seen in Figure 5a. To improve the simplicity, we apply a post-processing pipeline as described in Figure 4. The *average sliding* smoothing algorithm of McMaster and Shea [1992] is applied to smoothen out the border of *Catchment cells* as can be seen in Figure 5b. Additionally, smaller fragments of *Catchment cells* resulting from the computation of the *Voronoi diagram* were eliminated using a rule-based system that preserves topological persistence, as explained in Section 3. While removing fragments of a certain size, the topological persistence must be ensured as the visualization would otherwise be distorted and introduce gaps, resulting in an incorrectly displayed topology of the reality. The results of the fragment elimination can be seen in Figure 5b.

Our *catchment cell* visualization, gains a deeper understanding of the accessibility and pronounces the importance of certain transit lines and transit stations. One example is the Tram Line 66, reflected by the dark blue color in Figure 6a. As can be seen, this tram line serves the area east of the Rhine sufficiently but does not play an important role in the area west of the Rhine. The reason for that is that bus lines allow for more mobility in this area, as highlighted in Figure 6c. A rather obvious observation is that *Catchment cells* form around transit stations and stops in the public transportation network, as can be seen in Figure 5b. This can be explained by the fact that a transit station is at an equivalent distance for all other vertices that are reachable by walking after arriving at the pertaining transit station. Furthermore, a transit station is usually the only possibility to enter or leave a transit line of a public transportation network. For passengers navigating in a public transportation network, it is rather desired to comprehend which line to take or where the closest transit station to the current location is. On the contrary, the area in the southwest of the city of Bonn is most accessible by Train Line S23, indicated in dark red as can be seen in Figure 6b.



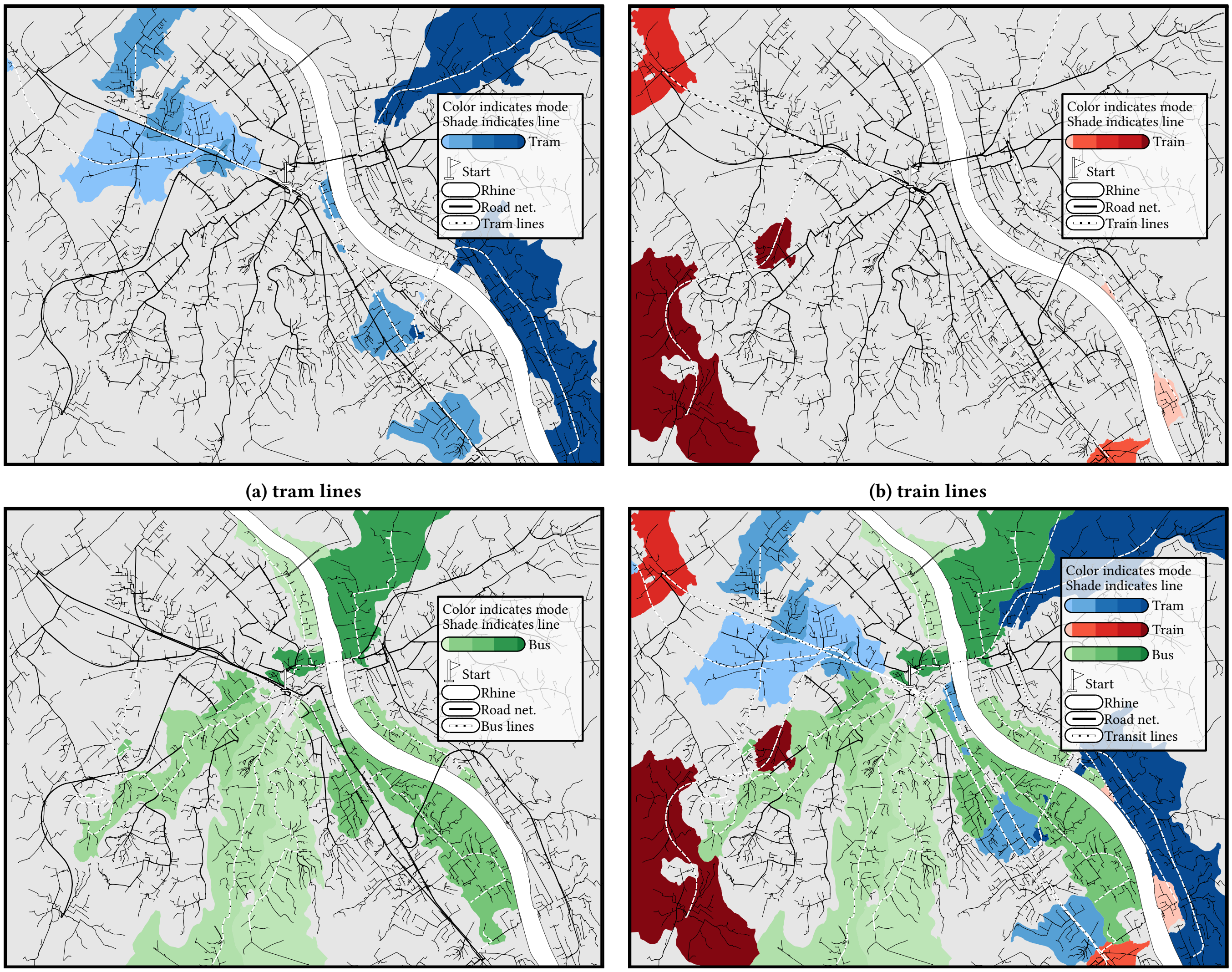
(a) without post-processing



(b) with post-processing

Figure 5: *Voronoi diagram* with and without post-processing representing our *catchment cell* inspired visualization technique of the individual transit lines of the public transportation network of the city of Bonn. Boundary of individual *Catchment cells* indicated by white color. Color indicates different travel modes while color shade indicates different transit lines. The start time is Monday at 10 a.m..

As visualized by Figure 6b, the *catchment cell* for Train Line S23 far exceeds the road network around the transit stations, indicating that it is the most performant transit line for this area. Although the train line *S*23 stops much closer to the city center, it has far fewer stops than competitive bus lines in the close vicinity of its tracks, as highlighted in Figure 6d. As indicated by the color shift, most tram and bus lines are north-south oriented, i.e., they run from the north of the city to the south of the city as indicated by Figure 6a and 6c.



(a) tram lines

(b) train lines

(c) bus lines

(d) all selected transit lines combined

Figure 6: A selection of the largest and most prominent *Catchment cells* representing individual transit lines and their corresponding routes per transit mode. Color represents the travel mode. Not selected cells are depicted in gray color. Different shades of color represent the different transit lines, and white dashed lines represent the corresponding routes in the geographic road graph.

5 CONCLUSION AND OUTLOOK

This paper introduced an approach for visualizing transit maps based on *Catchment cells*. From a start location and start time, a *catchment cell* is a cluster defining the spatial extent on a road network that can be reached the fastest from a distinctive transit station in a public transportation network. The strength of our visualization is that the actual representation of the fastest connection and the overall clarity of the visualization can be balanced. As a result, we are able to control the overall size and the level of detail of *Catchment cells*. Our approach turns out to be suitable for visualizing the accessibility and the capacity of a public transportation network, allowing decision-makers to assess the coverage and quality and simulate the impact of new transit lines and transit stations. Our *catchment cell* based visualization has the potential to improve the understanding of mobility and accessibility in a public transportation network. It can be used as a tool for decision support systems or help passengers navigate in unfamiliar environments. A first follow up to this work could be an evaluation to determine the benefits and weaknesses of our visualization technique for the sake of urban planning and passenger navigation. As yet, both the starting time and location for all experiments are fix. The assessment of how the visualization changes depending on the starting time and location will be subject of future investigation. Additionally, starting points like different transit stations could be aggregated to create and analyze their joined accessibility. Lastly, a combination of our *Catchment cells* with further information is deemed as advantageous. In this context, schematized metro maps could be added on top of *Catchment cells* to improve their potential for passenger navigation.

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