SO CLOSE, YET SO FAR: A NEW METHOD FOR AUTOMATED IDENTIFICATION OF MISSING LINKS IN PEDESTRIAN NETWORKS

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ABSTRACT

Post-war suburban development is often characterized by a disconnected pod-and-collector street pattern. This creates significant barriers to active travel, forcing even short trips to take roundabout routes on busy arterial roads. However, it also creates a network of low-stress neighborhood streets. We hypothesize that there are many opportunities to add short, low-cost pedestrian and bicycle links to these street networks to increase connectivity.

A key challenge is identifying these links. While planners have a good idea of where major infrastructure investments are beneficial, they are unlikely to be familiar with every neighborhood street and potential connections between them. We introduce an algorithm to automatically and efficiently identify potential new links based only on existing network topology, with no need to prespecify potential projects. We score these links based on their contribution to accessibility. We apply this algorithm to the pedestrian network of Charlotte, North Carolina, USA, and find opportunities to improve connectivity through new links and safe crossings of major roads.

Keywords: pedestrian networks, bicycle networks, network design, accessibility

1. INTRODUCTION

There is increasing interest worldwide in active travel, for a variety of reasons. Active travel promotes public health (Glazener et al., 2021; Hansmann et al., 2023). If it replaces motorized travel, it can reduce greenhouse gas emissions (Brand et al., 2021) and other externalities of motorization. One of the most significant challenges to widespread adoption of active travel is a lack of safe infrastructure (Winters et al., 2017). To address this, cities around the world have made investments in both permanent and temporary infrastructure to promote active travel (Combs & Pardo, 2021).

Bicycle and pedestrian plans often focus on large-scale connections—such as new off-street paths or protected bike lanes on major corridors. While these links are valuable, they are also costly, controversial, and slow to implement. We hypothesize that there are additionally many short "low-hanging fruit" links, which would provide critical connectivity between disconnected parts of the network. For instance, these might be a connection between two adjacent neighborhoods, allowing people to safely travel on foot from one neighborhood to the next without using an arterial. They might be connections between a neighborhood and school that otherwise opens only onto an arterial. They might be safe crossings of busy streets. These connections serve a smaller population than large investments, but are also cheaper, faster to implement, and likely to face less public opposition. Since the value of transportation infrastructure is primarily derived from network effects, each of these links increases the value of the rest of the network.

We believe these opportunities exist across American suburbia. The dominant street pattern in developments from the last 60 years is the "pod-and-collector" pattern, where neighborhood streets and culs-de-sac connect to arterial roads (Boeing, 2021; Southworth & Ben-Joseph, 1995). This street design generally discourages active travel. However, on neighborhood streets, traffic volumes are low, increasing comfort for pedestrians and cyclists. Adding pedestrian and bicycle links to connect low-traffic streets could significantly increase the potential for comfortable and safe carless travel.

A key challenge with these types of links is identifying them in the first place. While planners are familiar with where demand for large infrastructure investments exists, this is less likely to be true of small links on side streets that predominantly serve specific neighborhoods.

We present a new algorithm which identifies locations for potential links based only on existing network topology, and scores them based on their contribution to accessibility. Our algorithm overcomes many of the limitations of previous algorithms: we can identify these locations without any prespecified scenarios, and we can identify both links provide new connections, as well as those that greatly shorten existing connections. The identified links can be further assessed by planners for feasibility and usefulness. We apply this method to the pedestrian network of Charlotte, North Carolina, USA, a southeastern city with a largely postwar street and a renewed focus on pedestrian infrastructure.

2. LITERATURE REVIEW

2.1 Street network design

Disconnected street network designs were the norm for North American development for the latter half of the 20th century, but in the 21st there has been renewed interest in more connected street networks. A number of cities adopted design standards restricting culs-de-sac, block sizes, or setting minimum connectivity standards in the 2000's (Handy et al., 2003). Empirical studies confirm that street network connectivity in new developments dropped until the 1990's, before rising again (Barrington-Leigh & Millard-Ball, 2015; Boeing, 2021).

Furthermore, the expansion of freeways starting in the mid-20th-century decreased connectivity by bifurcating street networks, particularly in communities of color (Estrada, 2005). These roads displaced, and continue to displace, scores of residents (Kimble, 2024; Swift, 2012). As early as the 1960's it was recognized that these roads created barriers that harmed cities (Jacobs, 1961). Starting in the 1990's, several San Francisco earthquake-damaged freeways were replaced with boulevards (Henderson, 2013). More recently, there have been grassroots efforts as well as new federal funding to remove freeways or reconnect communities across them (Kimble, 2024).

Most studies of street connectivity do not differentiate by mode. Some authors note the value of differential connectivity, with disconnected streets for autos and connectivity for active travel. This can happen through "living ends" wherein cul-de-sacs have pedestrian or bicycle paths connecting them to pathway networks or other neighborhoods. More systematic proposals include pedestrian superblocks and "fused-grid" layouts, where a system of pedestrian paths provides connectivity within an otherwise disconnected street network (Childs, 1996; Handy et al., 2003; Masoud et al., 2015). Some authors even propose completely separate networks for active or lower-speed travel (Alexander et al., 1977; Delucchi et al., 2010; Doxiadis et al., 1975). Off-street pedestrian connections can significantly increase connectivity in areas with disconnected street networks (Giles-Corti et al., 2008; Tal & Handy, 2012).

While researchers have identified value in a more-connected pedestrian networks paired with less-connected auto networks, the pedestrian and bicycle network is often even more disjointed than the auto network (Mekuria et al., 2012). While many professional organizations recommend a 2:1 ratio of sidewalk to roadway miles (representing sidewalks on both sides of every street), a recent survey of US cities found that many did not even reach a quarter of that ratio (Coppola et al., 2021). That said, in high-density urban areas, the pedestrian network may be far more extensive and connected than the road network, demonstrating the need for high-quality pedestrian network data (Sun et al., 2021).

For a street network to be pedestrian friendly, it needs to not only provide pedestrian infrastructure along the network, but also safe crossings of streets in the network. Unfortunately, crosswalks are also lacking in many US cities. Moran (2022) found that almost half of intersections in San Francisco—one of the more walkable cities in the US—were missing crosswalks. A large proportion of the growing number of pedestrian fatalities in the US occur on arterials, underscoring the importance for safe crossing to connected network (Schmitt, 2020).

Many regions have taken on efforts to map and identify missing sidewalks in their regions (e.g., Philadelphia, Boulan, 2022; Atlanta, Sanders, 2016). The District of Columbia is systematically closing gaps in their sidewalk network, prioritized based on proximity to schools, parks, transit, and the high injury network (District Department of Transportation, 2023).

2.2 Accessibility measurement

Accessibility metrics measure the potential of the transport system to connect people to destinations. They are increasingly used in transportation planning (Committee of the Transport Access Manual, 2020). These metrics most commonly measure how many destinations are accessible from each location in a region; this is known as a location-based accessibility metric (Geurs & van Wee, 2004). These location-based metrics are sometimes aggregated to a single regional metric by summing or averaging the accessibility experienced by each individual in the region (e.g., Bertaud, 2018, ch. 2).

Among the most common applications of accessibility metrics is evaluation of proposed transport projects (e.g., Conway et al., 2017; Lowry et al., 2016; Palmateer et al., 2016; Peralta-Quiros & Mehndiratta, 2015; Pereira, 2019). Generally, accessibility metrics are calculated for some baseline, and then recalculated under a scenario with some change to the network. This is a useful and understandable metric for both policymakers and the general public (Stewart & Zegras, 2016).

This process requires a small number of prespecified scenarios. This works for large infrastructure investments—these are extensively planned, with accessibility evaluation being one part of a larger planning process. However, it does not work well for neighborhood-scale interventions, which are too numerous and insufficiently well-known to list.

2.3 The road network design problem

Algorithms that do not require a small number of prespecified scenarios are known as the *road network design problem* (Farahani et al., 2013). These are optimization algorithms that choose a set of optimal links to build based on some objective (usually minimized travel cost across the population), subject to a budget constraint. The advantage of these algorithms is that they can evaluate many potential projects, or a combination of projects. The downside is that they generally still require possible projects to be prespecified, generally in the form of a network of existing and potential links (e.g., Drezner & Wesolowsky, 2003; Duthie & Unnikrishnan, 2014; Lin & Yu, 2013; Mesbah et al., 2012; Ospina et al., 2022; Zhang & Gao, 2009; Zhu & Zhu, 2020). While more projects can be evaluated, the planner must have knowledge of all potential projects to create this network of potential links.

For neighborhood infrastructure, we need an algorithm that can identify investment locations based on the existing network, without needing to enumerate potential locations *a priori*. One such method is introduced by Natera Orozco et al. (2020), for bicycle network design. Their algorithm partitions the network into *components*—segments of the network which are internally connected but isolated from the rest of the network. They then iteratively connect the largest component to either the closest or the next largest. This algorithm can effectively connect gaps in the bicycle network; however, there are three downsides. First, it cannot guarantee that proposed links will be short. Second, it assumes that the most valuable links are the ones that connect to the largest component, which may not always be the case. Third, it cannot find links within a component that reduce travel distance. In some cases, the most valuable links may not connect parts of the network that were disconnected previously, but provide shortcuts between streets that are already connected in a roundabout fashion. Verma and Ukkusuri (2023) propose using widely-available road centerline network data to identify all possible locations for sidewalks and crossings. The main downside to this method is that it cannot identify off-street links.

3. METHOD

Our method starts from data on an existing pedestrian network, and identifies locations where adding an additional short link could have a large impact. The algorithm has two steps. The first step finds potential links. Each potential link connects two points on the network which are geographically close, but distant (or disconnected) by traveling along the network. The second step scores these potential links based on their contribution to accessibility.

3.1 Finding potential links

We first compute a distance matrix between all nodes, using Dijkstra's algorithm (Dijkstra, 1959). This matrix is used extensively in the following steps.

The next step is to find potential links. We define these as locations that are geographically close together, but far apart on the network (or, potentially, disconnected entirely). We define a potential link as two points on the network that are within 100 meters of each other geographically, but at least 1,000 meters apart via the network. These distances can be adjusted to fit local context. Potential links may occur between points on any two edges; they do not necessarily have to connect existing nodes.

To identify possible locations for new links, we iterate over each edge *g* in the network. Using a spatial index, we iterate over all nearby edges *h*. Most of these edges are closely connected to *g.* To quickly eliminate these from consideration, we calculate an upper bound on the network distance between any two points on edges *g* and *h*. This upper bound is the minimum network distance (from the distance matrix) between the nodes at either end of *g* and either end of *h*, plus the lengths of *g* and *h.* If this upper bound is less than the minimum network distance to consider a potential link (1000m in our case), all points on *g* and *h* are within 1000m of one another, and thus are not eligible to be considered as a potential link because they are already connected. We thus remove the edge pair from consideration as a potential link.

Otherwise, we compute the shortest crow-flies distance between *g* and *h*, as well as the points where they pass most closely together, using the GEOS library. If this distance is short enough to be considered a potential link, we calculate the network distance between the points, using the node-to-node distance matrix computed and the distances from the ends of the edges to the locations where they pass most closely together. This is computed as the minimum of the network distances between all four combinations of the nodes at the ends of *g* and *h*, plus the offsets from the ends of the edges to the point where they pass most closely together. If this network distance is greater than the minimum network distance to consider a link, or if the edges are disconnected entirely, we record this as a potential link.

A simplifying assumption is that we always propose links where two edges pass most closely together. This is not always optimal. For example, the network in Figure 1 has two culs-de-sac that run largely parallel, but curve slightly towards one another at their ends. The closest points are near the ends of the culs-de-sac, but using a link in that location would require a detour to the end of one cul-de-sac and then back up the other. A slightly longer link near the start of the culs-de-sac could be more useful, and cost only slightly more to construct. This problem will be most apparent with long edges. To help ameliorate the issue, we artificially insert intersections such that no edge is longer than 250m.
That said, decisions about exact siting of a link will ultimately be made by humans, not algorithms, as many other factors come into play (e.g. topography, land acquisition, etc.).

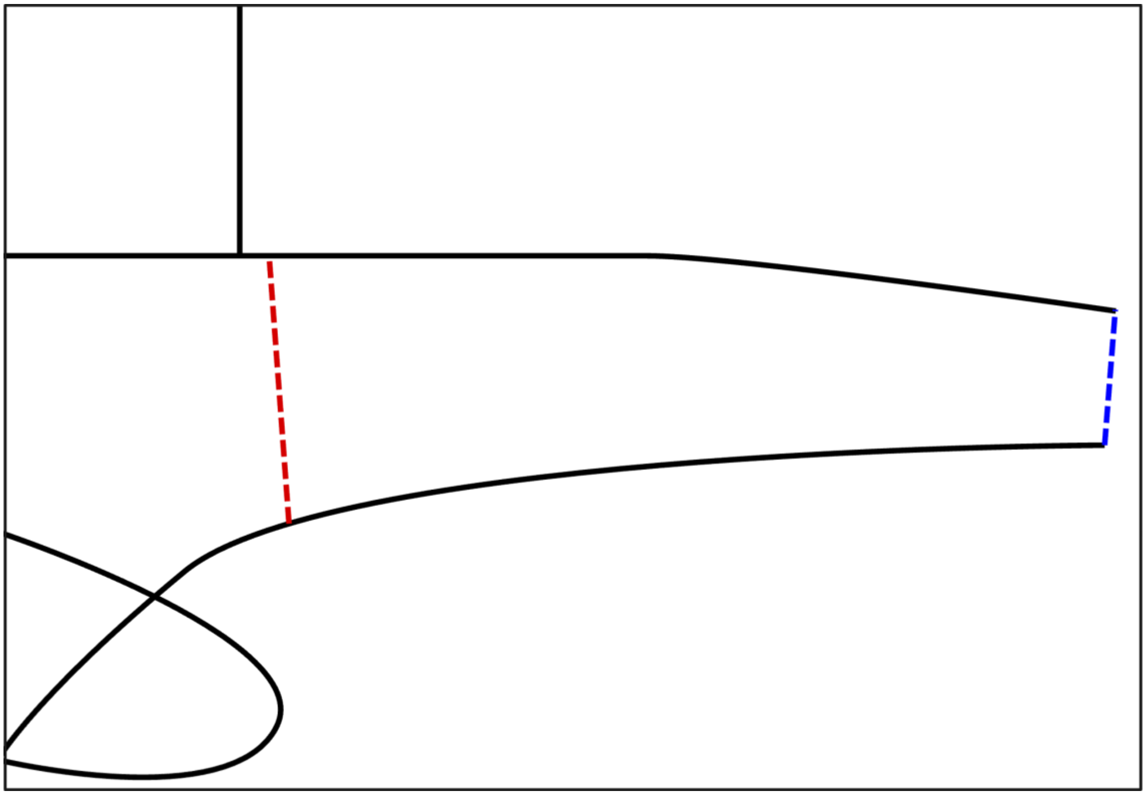

Figure 1: A hypothetical portion of a network where the location where the edges pass most closely (blue) has a lower accessibility impact than a longer link between the same edges (red)

3.2 Link deduplication

This process finds many potential links, but most of them are almost completely duplicative of one another. We consider two potential links to be duplicates if both ends of one link are within 100m network distance of one of the ends of the other. To identify duplicate links, we use the following greedy algorithm.

For the first potential link, we identify the "sphere of influence" of that link; the sphere of influence is all nodes that are within 100m of either end of the potential link. We calculate this using the node-to-node distance matrix and the distances of the link from the start and end of the edges it connects. For subsequent potential links, we check to see if one of the ends of each of the edges it connects is in an existing sphere of influence. If it is, we further check to see if the network distances between the ends of this potential link and the ends of potential link that defined the sphere of influence are less than the threshold for both ends of the links. If these network distances are both less than the radius of the sphere of influence, we add the link to this sphere of influence. If a potential link is not within any existing sphere of influence, we define a new sphere of influence based on the potential link. We then retain the potential link with the shortest geographic distance from each sphere of influence.

The deduplication algorithm is demonstrated in Figure 2. The potential links in blue are identified by the algorithm. There are several clusters of links that provide basically the same connectivity. After deduplication, only the potential links shown in red are retained. While these remain somewhat duplicative, and not all make logical sense, the situation can be handled by human planners reviewing the results.

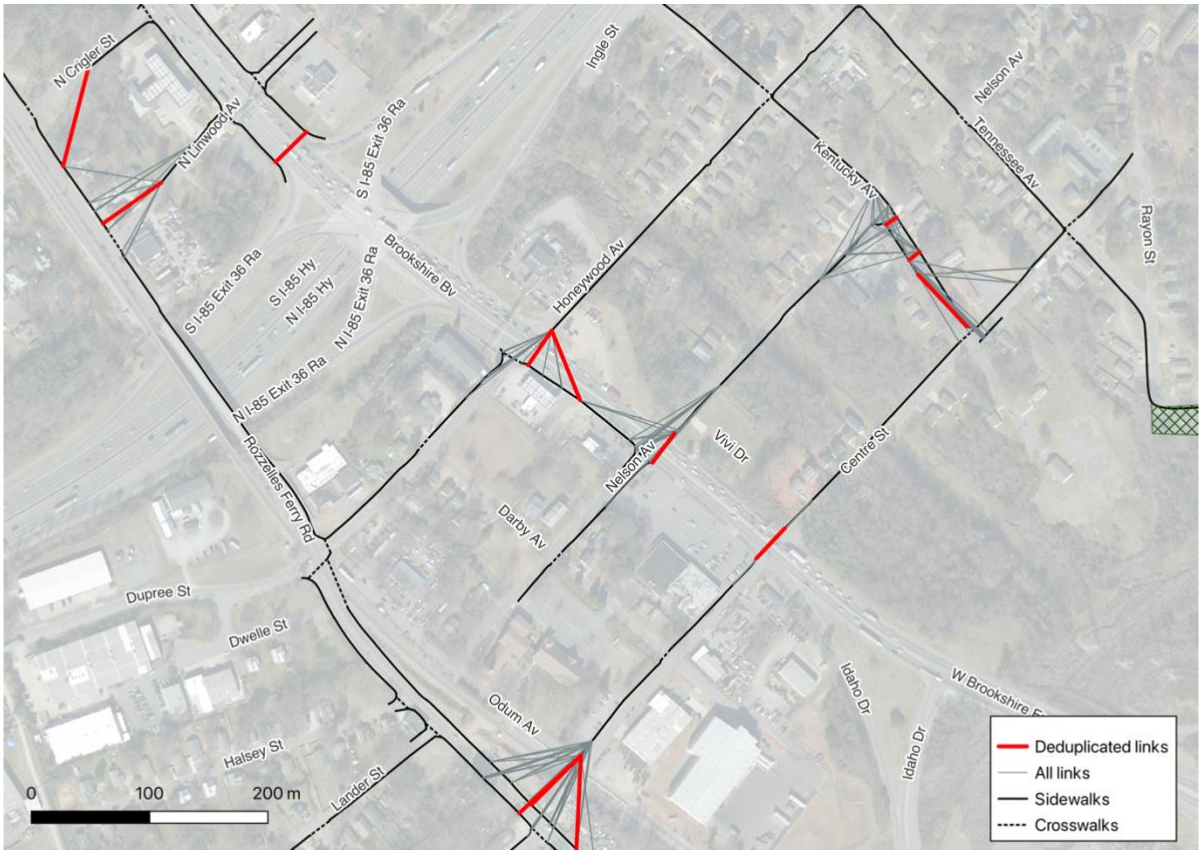

Figure 2: Results of link deduplication algorithm (Imagery: NC OneMap/NC 911 Board, sidewalk data: City of Charlotte, street name data © OpenStreetMap contributors)

3.3 Scoring potential links

Even after deduplication, the process described above will identify thousands of potential links in a city-scale network. The second part of our algorithm scores each of the potential links by their contribution to aggregate accessibility. We define aggregate accessibility as the sum of the accessibility experienced by all members of the population. This is an appropriate metric for evaluating missing links, as it accounts for both the magnitude of the accessibility increase and the number of people affected by it. Links that improve accessibility for many people, or that greatly improve accessibility for a few people, will score highly. This is closely related to the average-accessibility measures of labor market access used by Bertaud (2018). Mathematically, we define aggregate accessibility *a* as

$$a = \sum_{i=1}^{n} o_i \sum_{j=1}^{n} w_j f(d_{ij}) \quad (1)$$

where o_i is the number of origins (people in our case) at node i, w_j is the number of destinations at location j, and d_{ij} is the network distance from i to j.

$f(d_{ij})$ is a distance decay function that controls how much less attractive destinations further away are. There are number of distance decay functions used in accessibility measurement (Geurs & van Wee, 2004), and our method can use a variety of them. However, for simplicity, in this research we primarily use a cumulative-opportunities metric:

$$f(d_{ij}) = \begin{cases} 1 \; if \; d_{ij} < c \\ 0 \; otherwise \end{cases} \quad (2)$$

where c is a distance cutoff (we primarily use 3.2 km/2 mi). With this distance decay function, we can interpret accessibility as the number of destinations reachable within the cutoff distance. Aggregate accessibility is this value summed across the population. We additionally perform sensitivity tests with 1 mile and 3 mile cutoffs, as well as a negative exponential functional form in the results section.

3.4 Scoring links

We score each link by the change the aggregate accessibility it provides. The naïve approach of recalculating the distance matrix separately for each potential link and then calculating accessibility is not computationally feasible, so we use the following more efficient algorithm.

For each link, we arbitrarily set one end as p_1 and the other as p_2, without loss of generality. We then define our origin set I as all nodes within $c - l$ meters network distance of p_1, and our destination set J as all nodes within $c - l$ meters network distance of p_2. Since our accessibility metric only includes distances less than c, and the link itself has length l, any node that is more than $c - l$ meters from either end of the new link cannot be affected by the new link.

If using a distance-decay function other than cumulative opportunities, c is defined as the point at which that distance decay function goes to zero. Many decay functions asymptotically approach zero. In these cases, we modify the function to be piecewise, and drop to zero at some defined point when the distance decay is near enough zero that further destinations are immaterial to accessibility.

For any pair of nodes $i \in I$ and $j \in J$, we can calculate the distance between them using the new link as

$$d_{ip_1p_2j} = d_{ip_1} + l + d_{p_2j} \tag{3}$$

where d_{ip_1} is calculated as the minimum distances between i and each end of the edge containing p_1, plus the offsets from the respective end to p_1. d_{p_2j} is calculated similarly.

The process is illustrated in Figure 3. The blue line shows the path between nodes i and j using the existing network. i and j are existing nodes in the network. The proposed link is shown in red, connecting p_1 and p_2, which are points on edges in the existing street network, but not necessarily at nodes. $p_1$occurs on the edge between existing nodes k and k', and p_2 occurs between m and m'. The path from i to j via the new link is shown in dark green. The distance is calculated as the distance from i to k (labeled [1]), plus the distance from k to p_1 (labeled [2]), plus the length of the link (labeled [3]), plus the distance from p_2 to m (labeled [4]), and from m to j (labeled [5]). All possible combinations of paths containing k or k' and m or m' are considered.

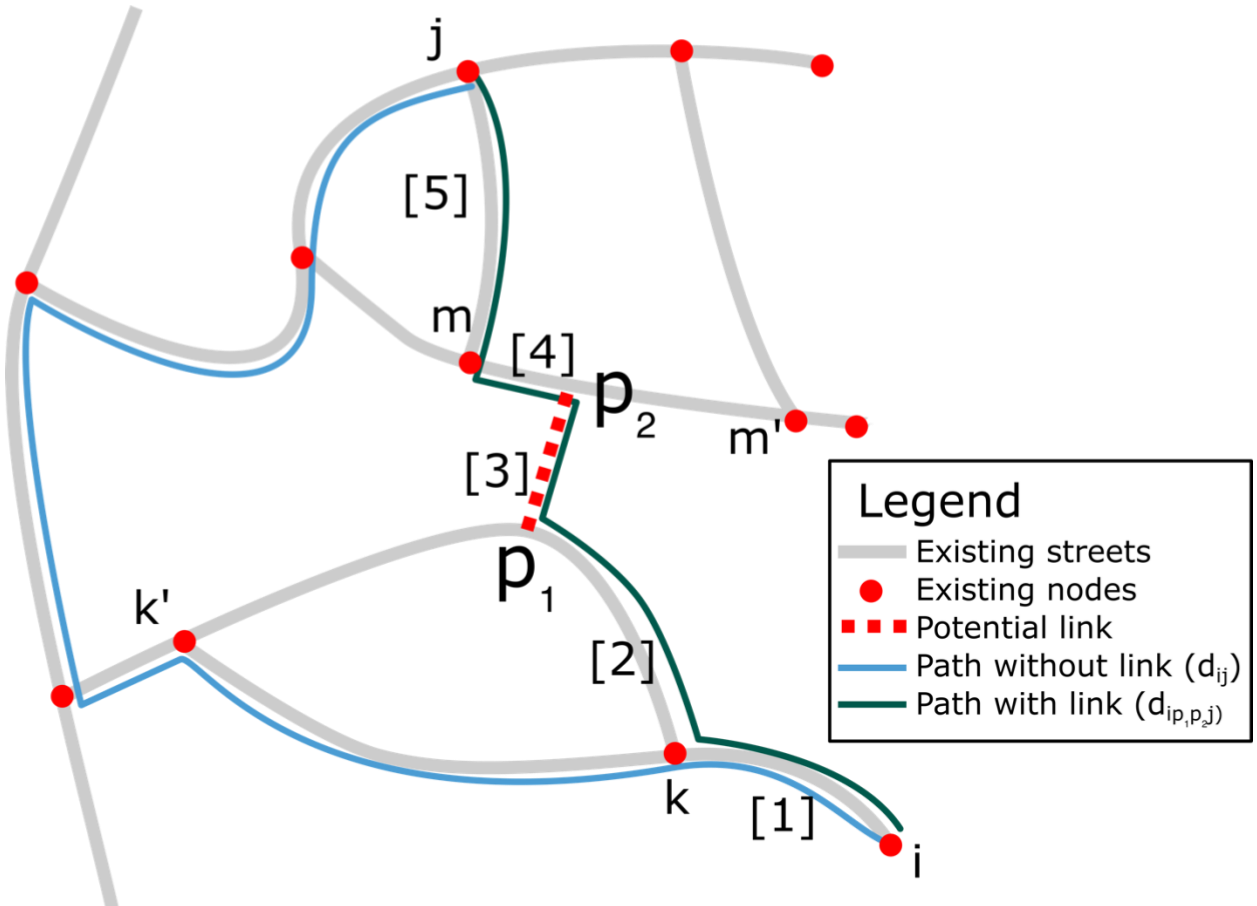

Figure 3: A hypothetical street network displaying how distances using a new link are calculated

We then take the minimum of this and the original distance between *i* and *j* to calculate the shortest distance d'_{ij} between *i* and *j* in the network with this link added. This assumes that adding a link cannot increase distances. This is always true for physical distance. In uncongested networks, it holds for travel time if the new links do not introduce intersection penalties. For congested networks, Braess' paradox may apply, where an additional link increases travel times by concentrating more travelers on a link (Braess et al., 2005).

We then calculate the contribution of *i* and *j* to the change in aggregate accessibility as the number of origins at node *i,* multiplied by the number of destinations at *j*, multiplied by the difference in distance decay functions from the network with and without the potential link. To calculate the total contribution to aggregate accessibility of the link from p_1 to p_2, we sum across our origin and destination sets:

$$\Delta a_{p_1 p_2} = \sum_{i \in I} \sum_{j \in J} o_i w_j \left[f\left(d'_{ij}\right) - f\left(d_{ij}\right) \right] \quad (4)$$

Finally, since the link can be used in either direction, we reverse p_1 and p_2, and likewise calculate $\Delta a_{p_2 p_1}$. We add these results to get the final aggregate accessibility impact of the link.

Thus, we calculate the difference in aggregate accessibility directly, without recalculating the distance matrix or overall aggregate accessibility. The entire process of computing the change in accessibility relies only on the precomputed distance matrix; new shortest-path calculations are not needed.

The heuristic nature of the deduplication algorithm means that it is possible the optimal link will not be retained. For instance, if a link retained by the deduplication algorithm supplanted one that was slightly closer to a destination—particularly if it was near a cutoff distance in a cumulative-opportunities metric—the retained link could have a lower accessibility impact than the "duplicate" it supplanted. We recommend experimenting with several cutoff distances if using a cumulative-opportunities metric.

3.5 Computational details

For performance, all algorithms are implemented in Julia (Bezanson et al., 2017), making heavy use of the Graphs package (Fairbanks et al., 2021), among others. All the code used in this project is at [link removed for review], along with instructions on how to apply it to other street networks. We parallelize the slowest parts of the algorithm, calculating distances and scoring. Both are "embarrassingly parallel," meaning there is no dependence between different starting nodes (for the shortest path algorithm) or potential links (for the scoring algorithm). This allows results for different nodes or links to be computed simultaneously, without needing any synchronization between computations. We store the distance matrix from the shortest path algorithm in a memory-mapped file, allowing fast access even if the machine does not have sufficient memory to hold the full matrix. To preserve memory and maximize speed, we store distances in this matrix as unsigned 16-bit integer meters, allowing us to represent distances up to 65.5 km, far longer than any reasonable daily bicycle or pedestrian trip.

4. CASE STUDY: CHARLOTTE, NORTH CAROLINA

We applied our method to the pedestrian network of Charlotte, North Carolina, USA. The population and economy of the Charlotte area are growing rapidly. Mecklenburg County is increasingly racially diverse, and the financial gap between income groups continues to widen (Mecklenburg County Board of Commissioners, 2023). Roadway fatalities have increased almost every year since 2012. Mecklenburg County is the deadliest in the state for roadway users. Roadway fatalities in the area disproportionately affect pedestrians and bicyclists. Charlotte adopted a Vision Zero plan to eliminate traffic fatalities in 2016, and created a task force in 2018. Traffic safety is a key component of the city's Strategic Mobility Plan and 2050 Metropolitan Transportation Plan (Charlotte Regional Transportation Planning Organization, 2022; City of Charlotte, 2022; North Carolina Division of Motor Vehicles, 2022).

Government entities acknowledge the lack of a cohesive multimodal transportation network (City of Charlotte, 2022), but according to independent advocacy organizations, such as Sustain Charlotte and the Charlotte Urbanists, little is being done to actively address the gaps. In Mecklenburg County, nearly 70 percent of homes are within a half mile of a transit stop, however, only 44% of paved roads have sidewalks (Mecklenburg County et al., n.d.). The continued prioritization of interstate travel through I-77, I-85, and I-277 exacerbates multimodal transportation challenges.

4.1 Data

Developing a sidewalk network is challenging and requires many assumptions (Rhoads et al., 2023). The City of Charlotte collects and publishes data about the locations of sidewalks and greenways within their jurisdiction. Unfortunately, these data are not designed to support routing. Sidewalks in the dataset often do not connect with one another at corners, and crosswalks are not digitized. We created a routable dataset by manually connecting disconnected portions of sidewalks and greenways using aerial imagery from 2019, as well as automatically connecting nodes within 3.5 meters.[1] We digitized all marked crosswalks. For residential/local streets that were one lane each way and flanked by houses, we assume safe unmarked crosswalks exist in all directions. For all others, we consider unmarked crosswalks connecting sidewalks along roadways across side streets, but not crossing through traffic on major roads. When we ran the algorithm, a number of locations identified had pedestrian infrastructure installed since 2019. We digitized infrastructure in these locations based on a variety of sources (primarily Google Maps/Street View).

The decisions around what links to include in the pedestrian network can have significant implications for accessibility results (van Eggermond & Erath, 2016). We did not include low-traffic streets without pedestrian infrastructure. While many people may feel safe walking on such streets, in Charlotte they be dangerous. The Charlotte Department of Transportation maintains a High Injury Network dataset, calculated using five years of fatal and serious injury crashes (City of Charlotte, 2023). Even some residential streets are considered part of the high-injury network. We also did not include informal pedestrian connections, which can be significant contributors to connectivity but are not maintained by municipal governments and thus have more limited policy relevance (Cambra et al., 2019).

One challenge when working with any network dataset is "islands"—walkable areas disconnected from the rest of the network. These may be due to data quality issues, or actual disconnected pieces of infrastructure. To balance fixing data quality issues and retaining data on infrastructure quality, we remove all islands with fewer than 10 nodes.

Calculating accessibility contributions of new links requires detailed spatial data on population and destinations. For population data, we use 2020 US Census population counts at the block level. We disaggregate these data to parcels, based on the number of units on each parcel from the Mecklenburg County Assessor, and the proportion of the parcel within the block. We assign each parcel to a network edge within 20 meters; if there are multiple, we divide the population evenly among them. The algorithm requires data at the node rather than edge level, so we assign half of each edge's population to the node at either end. Only 65% of the city's population is assigned to the network. Much of the remaining population lives in locations without sidewalks or pedestrian infrastructure. A small portion lives in areas with private sidewalk infrastructure not included in the data from the City of Charlotte.

The Charlotte Regional Transportation Planning Organization provides a scoring guide for bicycle and pedestrian projects, which identifies high, medium, and low priority destinations (Charlotte Regional Transportation Planning Organization, 2021). We used high and medium priority destinations, giving high-priority destinations a weight of three and medium-priority destinations a weight of two. We created the dataset of destinations by aggregating information from Data Axle, Mecklenburg County, the City of Charlotte, the US Department of Agriculture, the US Department of Education, the Centers for Medicare and Medicaid Services, and the North Carolina Department of Health and Human Services. In most cases, these are point data, which we assign to parcels and then link to the network as described above. For some destinations that are polygons (e.g. parks) or adjacent to streets (e.g. bus stops) we

[1] Automatically closing gaps in the network is a two-step process; first we ensure nodes exist any place the end of one line segment passes within 3m of another line segment, and create them if there is not a node with 0.5m of the closest point on the second segment. Then we add edges between all nodes less than 3.5m apart, to ensure that all of the nodes we created are connected, even if they are slightly more than 3m apart.

assign them directly to nearby edges. Details of how the destination data was constructed, and from what sources, are in the Supplemental Materials.

4.2 Results

Our final network has 140,289 nodes and 161,745 edges. Calculating shortest paths, deduplicating links, and scoring them took 26 minutes using Julia 1.11.4 with four threads on an Apple MacBook Pro with 16GB of RAM, a solid-state disk, and an Apple M1 processor.

The algorithm identified 133,246 potential missing links; after the deduplication process, 2,777 were retained, with a maximum aggregate accessibility impact of 350,000 households multiplied by destinations within two miles walk, a mean of 15,000, and a median of 4,300. The full distribution of accessibility impacts is shown in Figure 4. There are a few very high-value links, and many more of medium value.

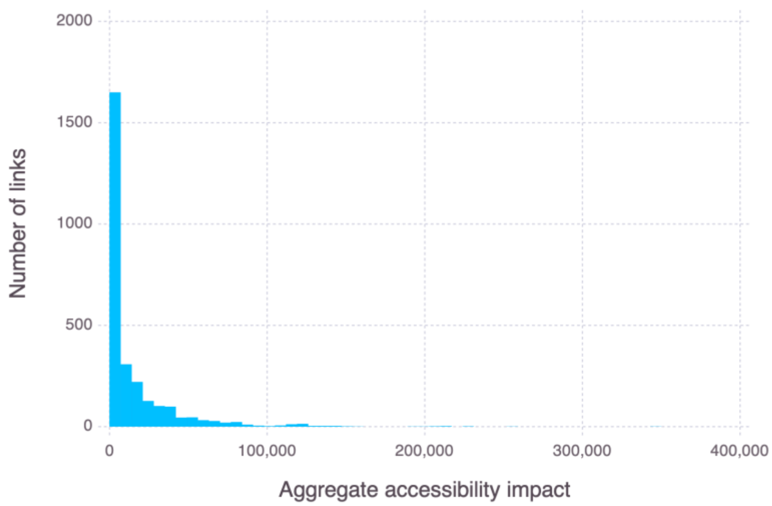

Figure 4: Histogram of aggregate accessibility impact of each link

Figure 5 shows the top 100 links identified in the region. The links are spread regionally, but many are approximately 1–2 miles from Uptown Charlotte (the Charlotte central business district). This is unsurprising, given that our accessibility metric accounts for destinations within 2 miles, though it does suggest that the algorithm is sensitive to the distance cutoff chosen.

Quite a few links are effectively duplicates, but were not filtered by the deduplication algorithm as they were not part of the same sphere of influence (for example, the links shown in red in Figure 2). We manually reviewed the top-ranked 100 links, and grouped them into 41 groups of links that provide approximately the same access. Of these, 31 represented gaps best closed by new crossings, and 11 represented gaps in sidewalks. Four represented new off-street paths. Two links would require bridges or other vertical infrastructure. Some links fell into multiple categories.

All but one fell within existing public right-of-way. Four crossed railroad infrastructure, potentially making planning and permitting more difficult.

While we initially expected the algorithm to find a higher proportion of off-street paths, Charlotte has a clear problem with safe crossings. While off-street paths may provide shortcuts, missing pedestrian connections may completely bifurcate the city, making their importance relatively higher. It is also possible that many potential off-street links do not fall below our 100 meter threshold.

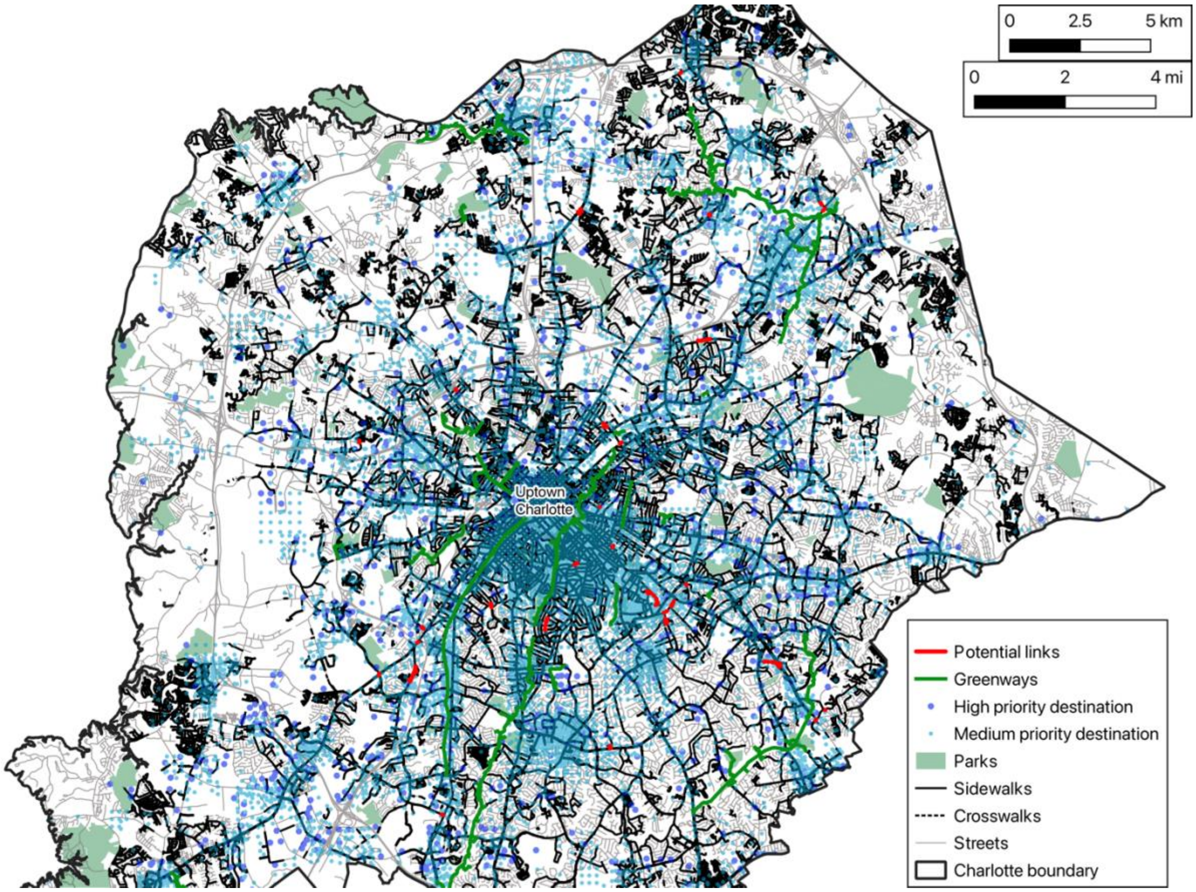

Figure 5 Top 100 links identified by the algorithm

The most highly ranked road crossing is at a railroad crossing on Louise Avenue, just outside uptown, and is shown in Figure 6a. On the south side of the tracks, the sidewalk is on the west side of the street; it transitions to the east side north of the tracks. There is no marked crossing of the street or the tracks. Closing this gap would connect residents north of the tracks with significant opportunities in the uptown area to the south. This link has an accessibility score of 350,000.

The units of this score are persons multiplied by destination points, with high priority destinations receiving three points and medium priority destinations receiving two. This large score is driven by a combination of the relatively high residential density in this neighborhood, and the proximity to many destinations in uptown Charlotte. It is most useful to evaluate this score relative to other scores, rather than on its own.

Constructing this link may not be feasible, however, due to the need to involve the railroad. Furthermore, traffic volumes on this street are relatively low—2700 vehicles/day—potentially making the crossing less of a priority than its accessibility score would indicate (North Carolina Department of Transportation, 2024). For these reasons, it is critical that planners be involved to assess the feasibility and value of any links identified.

The most highly ranked sidewalk gap is on Mallard Creek Church Road west of Tryon Street (Figure 6b), with an accessibility score of 254,400—i.e. 73% as much accessibility impact as the highest scoring project. There is a large apartment complex directly north of the link; the link would provide access to commercial destinations along Tryon Rd without a 2.7 km detour to use existing sidewalks.

There are already many people walking here, as evidenced by a dirt path worn in the grass. This places pedestrians directly next to high-speed traffic, and is not accessible for people with disabilities. A drainage ditch along the side of the road might mean that constructing a sidewalk here requires some earthmoving, but does not make it infeasible.

The most highly ranked new off-street connection that is not better served by a sidewalk on a parallel street is a connection between Commonwealth Avenue and the intersection of Wendover and Independence Avenues, a connection that was previously present but removed when a cloverleaf interchange was installed. This link has an accessibility score of 121,900 (i.e. 35% as much as the highest scoring project). This location is shown in Figure 6c; the photographer is standing at the end of the existing sidewalk.

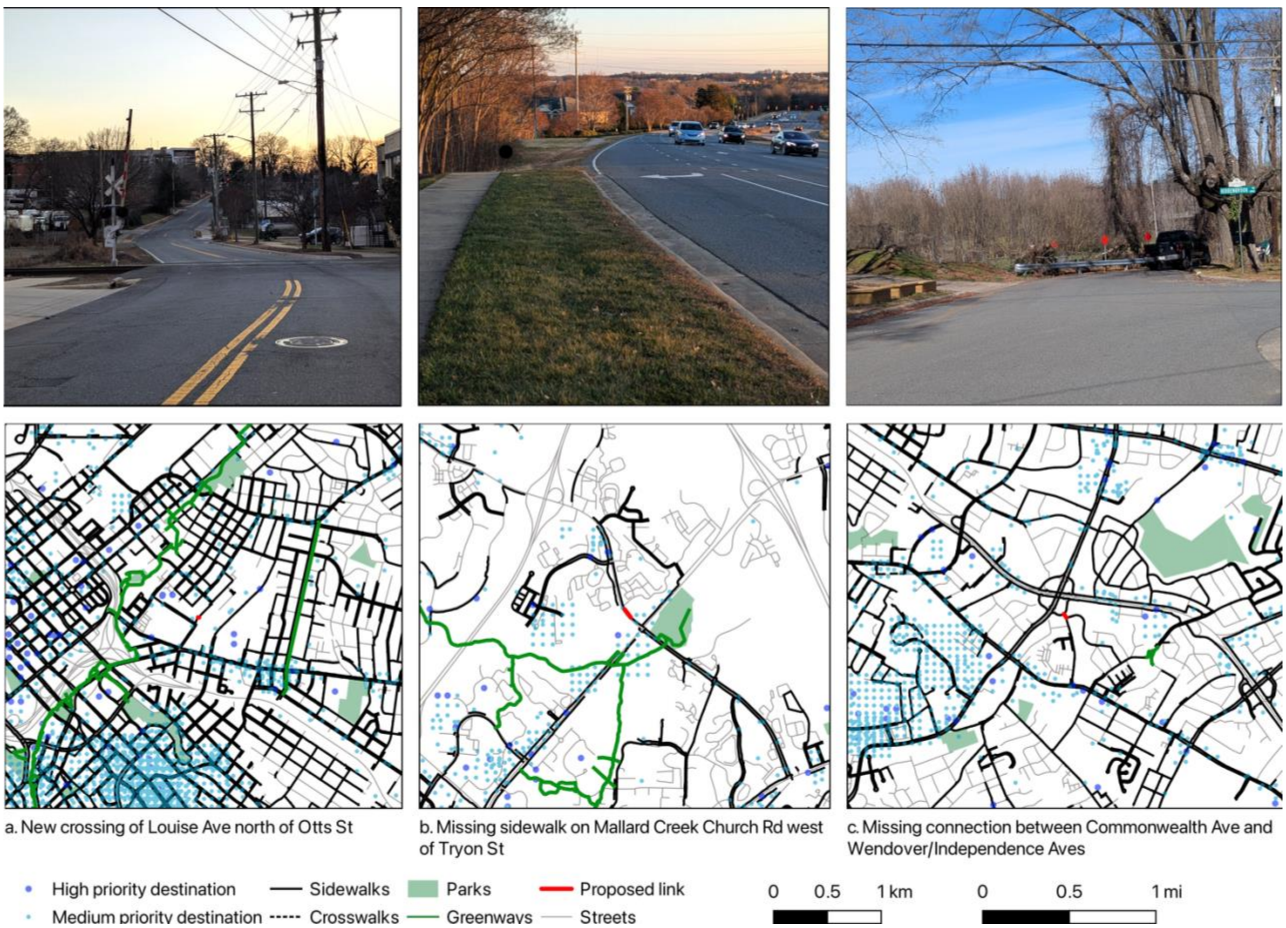

Figure 6 Photographs and maps of most highly ranked road crossing (left), sidewalk gap (center), and new off-street connection (right). Photographs © Google Street View. Basemap data © OpenStreetMap contributors.

As a sensitivity test, we also ran the algorithm with distance cutoffs of one and three miles, as well as a negative exponential decay function $e^{-0.00132d_{ij}}$, d_{ij} in meters; the coefficient -0.00132 was calculated using the formula from Östh et al. (2014) so that the decay function would be 0.5 at 526 meters, the median non-loop walking trip distance in North Carolina (calculated from Federal Highway Administration, 2018). This function reaches 0.01 at 5.25 km, after which we assume additional destinations do not affect accessibility. Running the scoring portion of the algorithm with longer distance cutoffs is slower, even though link identification and deduplication results are reused; scoring links using the negative exponential took the longest at 55 minutes.

The results are somewhat sensitive to the choice of functional form, an unfortunate but well-known challenge of accessibility metrics (Pereira, 2019). The first example given above (the crossing of Louise Ave) ranks as the highest access improvement by the one and two mile metrics, as well as the negative exponential, but ranks 59th by the three-mile metric. This is likely because detouring around this location is only a 1.5km walk, and for the three-mile metric you can still reach the busy uptown area even if you detour.

Of the top 100 links identified by the two-mile cutoff, 43, 63, and 62 were in the top 100 for the one-mile, three-mile, and negative exponential forms, respectively. Pairwise Spearman rank correlations between the scores for all links were 0.63 or higher. Several functional forms should be evaluated when applying the algorithm. Local context should be taken into account. The reason for the low overlap with between the 1- and 2-mile metrics is likely that, in most places in Charlotte, valuable clusters of destinations are more than 1 mile away.

5. LIMITATIONS AND FUTURE RESEARCH

There are several avenues for future research. The scoring process does not consider the feasibility of constructing links. Links that score highly may be bifurcated by rivers, railroads, highways, buildings, or cliffs. They may cross private property. Depending on the owner and the configuration of the property, construction may or may not be feasible. The key concern with adding an automated feasibility step is that it may declare links infeasible when a slight reconfiguration would be feasible. For example, a direct link between two points might pass through a house, but a curved link could skirt the property and provide effectively the same access. We believe these feasibility issues are best addressed by a human planner reviewing the highest rated potential links, and determining any changes that could be made to improve feasibility.

We evaluate the accessibility contribution of each potential link independently. In many cases, a critical connection might consist of two or more links. For instance, there are two potential links in the neighborhood in Figure 7. The one shown in red, linking a neighborhood to the strip mall with a grocery and drugstore, is already fairly valuable. The link shown in blue is not particularly valuable on its own—it links two neighborhoods, but neither contains non-residential destinations. However, if the red link were built as well, the blue link would become much more valuable, as it would now provide access to both the neighborhood and the strip mall.

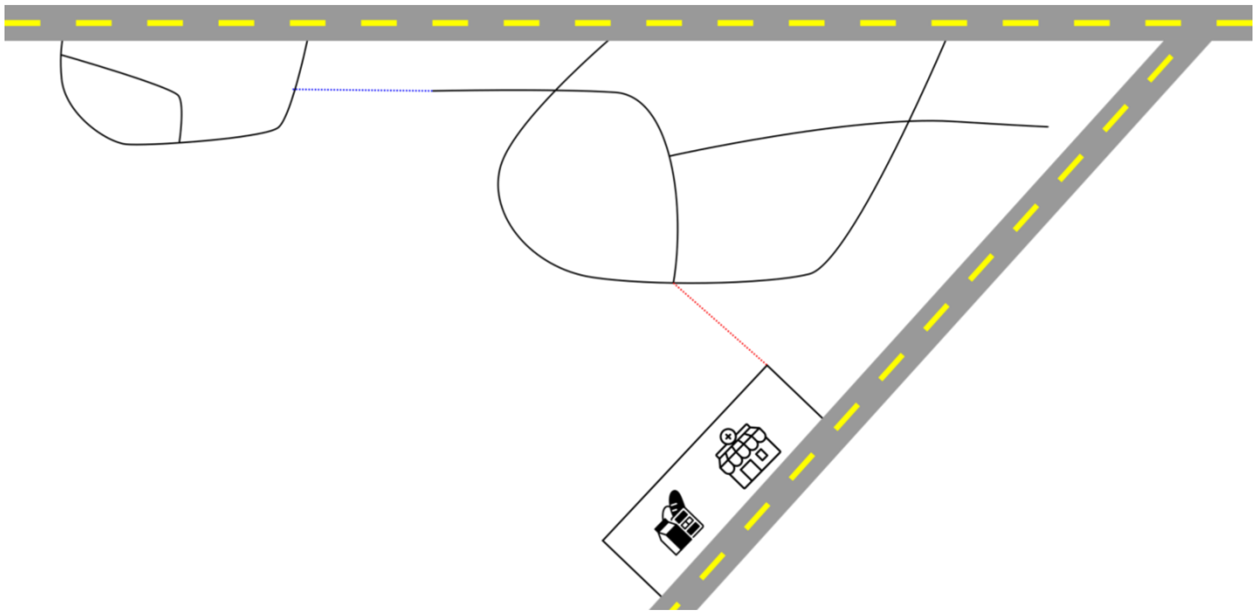

Figure 7: Links may be more valuable when considering multiple links simultaneously

Considering the contribution of multiple links in concert, however, greatly increases computational burden. The number of calculations increases combinatorically with the number of links considered together. That said, choosing the best subset of a set of potential links is exactly the road network design problem. Combining algorithms for that problem with the potential links identified by our algorithm could find the best groups of links.

6. DISCUSSION AND CONCLUSION

In this article, we introduced an algorithm for finding the “low-hanging fruit” potential links in the pedestrian network. We found that there are numerous opportunities to provide missing connections in Charlotte. We anticipate similar findings in suburban locations across the US and around the world.

The algorithm is open-source, and can run on mid-range desktops or laptops. For these reasons, we hope that it will find broad applicability. Identifying and closing missing links in the pedestrian network is a relatively low-cost way to open up safe walking opportunities to a larger population.

There are many ways the algorithm can be productively applied. It can work in concert with scenario planning. For example, it could be applied to a network dataset including a proposed multi-use path, to identify ancillary links that could increase the value of the path. These might be connections between the path and adjacent streets, or links that do not connect to the path at all but connect neighborhoods that do not have access with neighborhoods that do. Similarly, the algorithm could be applied to the proposed street network of new subdivisions, to understand where the proposed network could be better connected while there is still time to make changes. Coordinating construction of the potential links identified with larger projects maximizes the value of investments in the network and promotes efficient use of funds due to economies of scale.

Just because there is pedestrian infrastructure does not mean it is comfortable to walk on, especially for children. For instance, we considered unsignalized marked crosswalks across arterials to be pedestrian infrastructure, but they are not particularly useful if people do not feel safe using them. The algorithm could also be applied to a subset of a pedestrian network that is considered safe (e.g., using the pedestrian stress definitions of Hardy et al., 2019), to identify where links need to be added or improved to increase safe accessibility.

The algorithm proposed can use many different definitions of origin and destination weights. In our case study, we used disaggregated population data for origins. This treats every person equally, but pedestrian infrastructure is more important for low-income or zero-vehicle households with fewer mobility choices. Adjusting the origin weights to weight these households more heavily would allow prioritizing investment based on equity considerations. A significant funding source for bicycle and pedestrian infrastructure in the US are Safe Routes to School programs (Stewart et al., 2014). Using schools as the destination weights would allow the algorithm to identify links that most improve access to schools, supporting investment decisions for Safe Routes to School programs.

We have focused on pedestrian networks in this article, but the same algorithm could be applied to bicycle networks as well, with a slight algorithmic modification to support directed (one-way) links. In low-density areas, providing safe, connected bicycling infrastructure may be more likely to promote non-motorized travel than safe, connected pedestrian networks. In the US, the median auto trip is 5.1 miles, and the 25th percentile is 2.2 miles (Federal Highway Administration, 2022, and author calculations). These trips lengths are long for walking, but are reasonable distances to travel by bike.

The biggest challenge to applying the algorithm is data. A comprehensive and connected sidewalk dataset is required, something most municipalities do not have. For this project, significant effort went into cleaning the existing Charlotte sidewalk dataset. OpenStreetMap is a global, open-access alternative, but its sidewalk data is inconsistently coded and often incomplete (Omar et al., 2022). In particular, it often does not differentiate which side of the street the sidewalk is on.

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SUPPLEMENTARY DATA

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compenvurbsys.2025.102290.

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