ENABLING A NEW DATA SCIENCE FOR URBAN ACCESSIBILITY FOR ALL

FINAL PROJECT REPORT

by

Jon E. Froehlich
University of Washington

Sponsorship
PacTrans,
UW Center for Research and Education on Accessible Technology and Experiences (CREATE)
Allen School of Computer Science.

for
Pacific Northwest Transportation Consortium (PacTrans)
USDOT University Transportation Center for Federal Region 10
University of Washington
More Hall 112, Box 352700
Seattle, WA 98195-2700

In cooperation with U.S. Department of Transportation,
Office of the Assistant Secretary for Research and Technology (OST-R)

DISCLAIMER

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the U.S. Department of Transportation's University Transportation Centers Program, in the interest of information exchange. The Pacific Northwest Transportation Consortium, the U.S. Government and matching sponsor assume no liability for the contents or use thereof.

TECHNICAL REPORT DOCUMENTATION PAGE		
1. Report No.	**2. Government Accession No.** 01784887	**3. Recipient's Catalog No.**
4. Title and Subtitle Enabling a New Data Science for Urban Accessibility for All		**5. Report Date** July 31, 2022
		6. Performing Organization Code
7. Author(s) and Affiliations Jon E. Froehlich 0000-0001-8291-3353 Allen School of Computer Science and Engineering University of Washington		**8. Performing Organization Report No.** 2021-S-UW-3
9. Performing Organization Name and Address PacTrans Pacific Northwest Transportation Consortium University Transportation Center for Federal Region 10 University of Washington More Hall 112 Seattle, WA 98195-2700		**10. Work Unit No. (TRAIS)**
		11. Contract or Grant No. 69A355174110
12. Sponsoring Organization Name and Address United States Department of Transportation Research and Innovative Technology Administration 1200 New Jersey Avenue, SE Washington, DC 20590		**13. Type of Report and Period Covered**
		14. Sponsoring Agency
15. Supplementary Notes Report uploaded to: www.pactrans.org		

16. Abstract

We are developing new data collection approaches that use a combination of remote crowdsourcing, machine learning, and online map imagery. Our newest effort, called Project Sidewalk, enables online crowdworkers to remotely label pedestrian-related accessibility problems by virtually walking through city streets in Google Street View. Aided, in part, by PacTrans funding, we have now deployed Project Sidewalk into ten cities across the world. Overall, 11,000 users have contributed over 720,000 labels and 400,000 validations. To our knowledge, this is the largest, most granular open dataset on sidewalk accessibility in existence. This unprecedented dataset enables new types of urban accessibility analyses not previously possible, which is the focus of our work and our report. Specifically, we report on the (1) expansion of Project Sidewalk into three additional cities, including La Piedad, Mexico, Oradell, New Jersey, and Amsterdam, The Netherlands; (2) an initial correlative analysis of how sidewalk accessibility/condition corresponds to socioeconomic factors; and (3) tool development and an initial study of combining Crowd+AI techniques to study how sidewalk accessibility is changing over time in cities.

17. Key Words		**18. Distribution Statement**	
A: Transportation; E: Planning and design; J: Environment			
19. Security Classification (of this report)	**20. Security Classification (of this page)**	**21. No. of Pages**	**22. Price**
Unclassified.	Unclassified.	30	N/A

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized.

SI* (MODERN METRIC) CONVERSION FACTORS

Symbol	When You Know	Multiply By	To Find	Symbol
		APPROXIMATE CONVERSIONS TO SI UNITS		
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
tf	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	ml
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^0F	Fahrenheit	5 (F-32)19 or (F-32)11.8	Celsius	^0C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cdlrrf
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/irf	poundforce per square inch	6.89	kilopascals	kPa

Symbol	When You Know	Multiply By	To Find	Symbol
		APPROXIMATE CONVERSIONS FROM SI UNITS		
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	tf
m^2	square meters	1.195	square yards	yd'
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
ml	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	tt'
m•	cubic meters	1.307	cubic yards	yd'
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^0C	Celsius	1.8C+32	Fahrenheit	"F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/irf

•s1 is the syrrbol fa- the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. Revised March 2003)

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF ABBREVIATIONS

ADA:	Americans with Disabilities Act
AI:	Artificial intelligence
API:	Application programming interface
Crowd+AI:	Crowdsourcing + Artificial Intelligence
CV:	Computer vision
GSV:	Google Street View
ML:	Machine learning
MS	Multiple sclerosis
NGO:	Non-governmental organization
PacTrans:	Pacific Northwest Transportation Consortium
SDOT:	Seattle Department of Transportation
WSDOT:	Washington State Department of Transportation

ACKNOWLEDGMENTS

We thank the Project Sidewalk team, including Michael Saugstad, Manaswi Saha, Michael Duan, Shosuke Kiami, and Logan Milandin.

EXECUTIVE SUMMARY

We are developing new data collection approaches that use a combination of remote crowdsourcing, machine learning, and online map imagery. Our newest effort, called [Project Sidewalk](), enables online crowdworkers to remotely label pedestrian-related accessibility problems by *virtually* walking through city streets in Google Street View. Rather than pulling solely from local populations, our potential pool of users scales to anyone with an Internet connection. In 2019, we completed an 18-month deployment in Washington, D.C.: 1,150+ users provided over 200,000 geo-located sidewalk accessibility labels and audited 3,000 miles of D.C. streets. With simple quality control mechanisms (*e.g.,* majority vote), we found that minimally trained remote crowd workers could find and label 92 percent of accessibility problems in street view scenes, including *missing curb ramps*, *obstacles in path*, *surface problems*, and *missing sidewalks*.

Aided, in part, by PacTrans funding, we have now deployed Project Sidewalk into ten cities across the world. Overall, 11,000 users have contributed over 720,000 labels and 400,000 validations. To our knowledge, this is the largest, most granular open dataset on sidewalk accessibility in existence. This unprecedented dataset enables new types of urban accessibility analyses not previously possible, which is the focus of our work and our report. Specifically, we report on the (1) expansion of Project Sidewalk into three additional cities, including La Piedad, Mexico, Oradell, New Jersey, and Amsterdam, The Netherlands; (2) an initial correlative analysis of how sidewalk accessibility/condition corresponds to socioeconomic factors; and (3) tool development and an initial study of combining Crowd+AI techniques to determine how sidewalk accessibility is changing over time in cities.

CHAPTER 1. PROJECT GOALS AND RESEARCH THREADS

Sidewalks provide a safe, off-road pathway for pedestrians, help interconnect mass transportation services like bus and rail, and support commerce and recreation [9,16]. For individuals with a mobility disability, sidewalks play a crucial role in independence [18], quality of life [17], and overall physical activity [6]. However, unlike for their road counterparts, for sidewalks there is a lack of high-quality datasets and fast, inexpensive, and reliable assessment techniques. This limits how sidewalks and sidewalk accessibility can be studied in cities.

Traditionally, sidewalk assessment has been conducted via in-person street audits [30,33,34], which are labor intensive and costly. While crowdsourcing approaches like *SeeClickFix.com, Wheelmap.org*, and *Mapeatón* [7] involve community members in reporting inaccessible infrastructure with smartphone cameras, these tools require conscientious volunteers with on-site knowledge, can be logistically difficult to manage, and limit both *who* can supply data and *how much* data each individual can supply

In our work, we are exploring complementary sidewalk auditing approaches that are fast, reliable, and low-cost and use a combination of remote crowdsourcing, machine learning (ML), and online map imagery. Previously, we received PacTrans funding for *Project Sidewalk*, a web tool that enables online users to remotely label sidewalks and identify accessibility problems by *virtually* walking through city streets [26,27]—similar to a first-person, immersive video game (figure 1.1). For each label, users provide a severity score, mark relevant tags, and also supply open-ended descriptions. Labels are used to create new urban accessibility visualizations, inform government policy and funding decisions, and train deep learning networks to assess sidewalks automatically—further scaling our approach [39]. Rather than relying solely on local populations, our potential user pool scales to anyone with an Internet connection and a web browser. In a 2018 pilot deployment, 1,400 users from across the world virtually audited 2,934+ km of Washington, D.C., streets, providing 255,000 sidewalk accessibility labels with 92 percent accuracy [28].

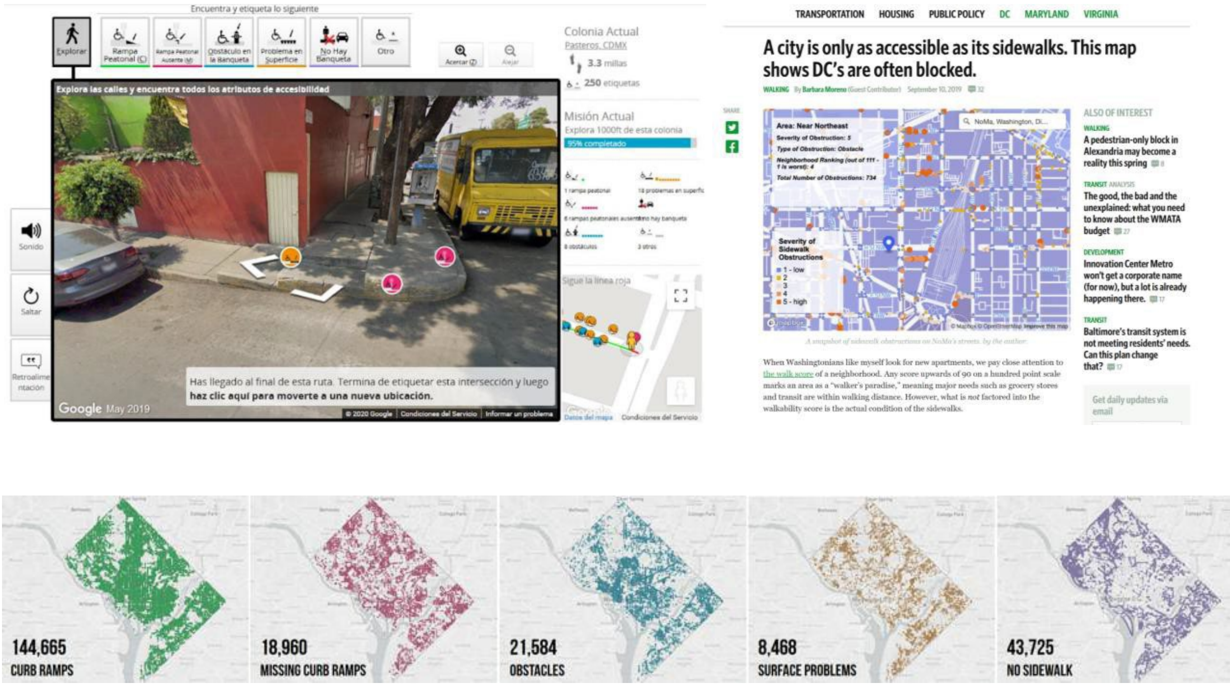

Figure 1.1 (a) A screenshot of Project Sidewalk, which combines crowdsourcing and machine learning to scalably map and assess sidewalk accessibility. Here, a user is virtually inspecting Mexico City and has marked the corner with two *missing curb ramps* (red labels) and the unavoidable stairs as a *surface problem* (orange). **(b)** All of Project Sidewalk data and tools are open source, which has enabled others to create visualizations and perform data analysis. Shown here, a screenshot of a user's own visual analytics tool for Washington, D.C., sidewalks, using our data and APIs. **(c)** Visualizations of the sidewalk accessibility data collected in Washington, D.C.—the scale and scope of Project Sidewalk data across cities enables new urban accessibility analyses not previously possible.

Aided, in part, by an initial *PacTrans Small Proposal* in 2019, we have built on our successful pilot deployment in DC and established new partnerships with local governments and non-governmental organizations (NGOs). At the time of writing our follow-up 2020 PacTrans proposal (the focus of this report), Project Sidewalk was deployed into six cities, including Seattle, Washington, Newberg, Oregon, Columbus, Ohio, Pittsburgh, Pennsylvania, Mexico City, Mexico, San Pedro, Mexico, and had collected 400,000 geo-located sidewalk labels.

1.1. Proposed Work

In our proposal, we outlined a plan to leverage Project Sidewalk's unique cross-regional sidewalk dataset and investigate the following research questions via new data analytics and visualization tools. Our first aim, however, was to deploy Project Sidewalk into additional areas to support our work.

1. **Continue expansion of Project Sidewalk into** two to four additional cities to support our cross-regional work?
2. **What are the geo-spatial patterns and key correlates of urban accessibility?** How does accessible infrastructure correspond to racial and socioeconomic factors or other metrics such as house pricing, school ratings, park density, and transit access.? Who appears to be primarily impacted?
3. **How do sidewalk patterns compare *across* cities?** What are the main accessibility barriers and how can/should we categorize them? How do these barriers reflect the socio-cultural, economic, and political context of those regions?
4. **How does urban accessibility change over time?** We propose adapting our crowdsourcing + machine learning techniques to examine street scene imagery across time, which will enable new temporal analyses focused on *how* and *where* sidewalks and sidewalk accessibility change over time.

Below, we enumerate progress within each thread (one chapter per thread). We have not yet made substantial progress on Thread 3; however, so threads 2 and 3 are combined.

CHAPTER 2. EXPANDING PROJECT SIDEWALK DEPLOYMENTS

Since being awarded this PacTrans grant, we have continued our expansion of Project Sidewalk into additional cities (as originally proposed), including La Piedad, Mexico; Oradell, New Jersey; and Amsterdam, The Netherlands (figure 2.1). Each new deployment has been conducted with a local NGO and/or government and typically initiated by local community members. We have now collected over 720,000 sidewalk labels and 400,000 validations from 11,000 users. To our knowledge, this is the largest and most granular open dataset on sidewalk condition in the world.

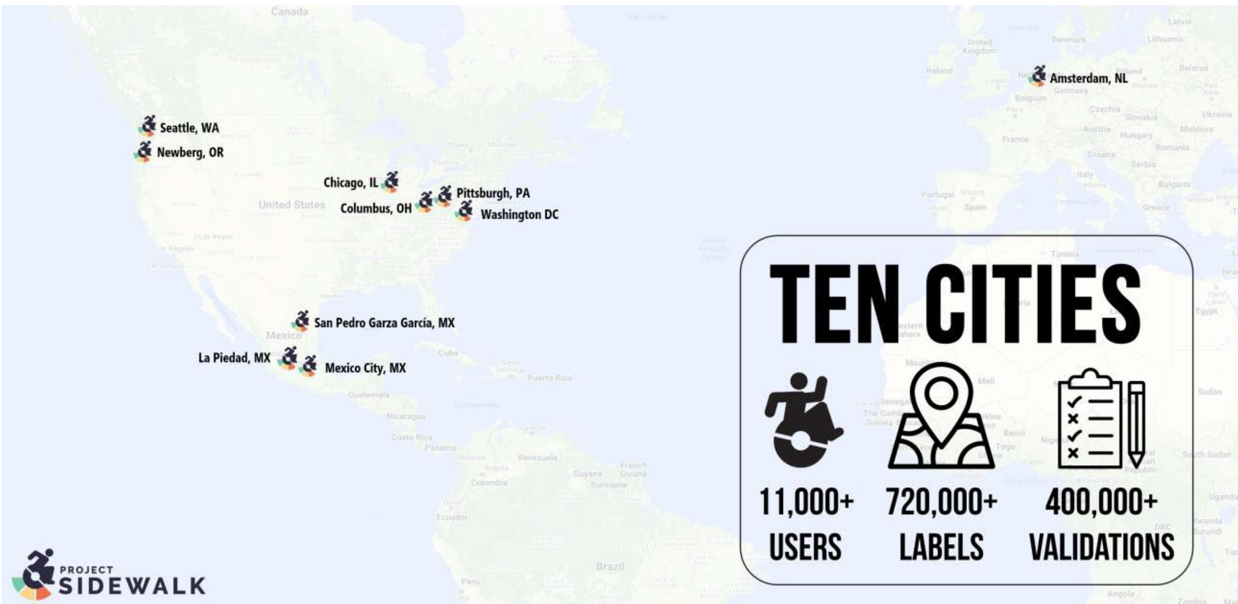

Figure 2.1 Since being awarded this small grant, Project Sidewalk has expanded into additional cities, including La Piedad, Mexico; Oradell, New Jersey; and Amsterdam, The Netherlands. These new deployments are largely being driven by local community members, NGOs, and disability organizations.

2.1. La Piedad, Mexico

The La Piedad, Mexico, (http://la-piedad.projectsidewalk.org) deployment was initiated by local geographer Jesus Medina Rodriguez from the Centro de Estudios en Geografía Humana at El Colegio de Michoacán, A.C. Rodriguez originally contacted us via our Project Sidewalk Twitter account. Together with the NGO Liga Peatonal—which is a pedestrian advocacy organization based in Mexico that has helped with all of our other Mexican-based deployments—we have begun an initial pilot deployment in La Piedad, Mexico (figure 2.2). La Piedad is a municipality located at the northwest corner of the Mexican state of Michoacán and has a population of 99,837.

Figure 2.2 A map of our pilot deployment in La Piedad, Mexico. Each circle represents a geo-located accessibility label color-coded by label type. For example, orange is a "*surface problem*" and purple is "*no sidewalk*." Thirty-five users have audited 8.3 miles of the 11.3-mile pilot neighborhood (73 percent), contributing 3,006 labels and 800 validations

Rodriguez is also leading our efforts to work with the local La Piedad government. With Rodriguez, local city officials, and Liga Peatonal, we have met together to better understand how Project Sidewalk can serve them. Thus far, 35 users have audited 8.3 miles of the 11.3-mile pilot neighborhood (73 percent), contributing 3,006 labels and 800 validations.

One ongoing concern has been about the Google Street View car drive-through rate. As Project Sidewalk is completely dependent on Google Street View (GSV) for streetscape images used to evaluate sidewalks, the timeliness of capture is important. We wrote a custom Python script to examine GSV capture dates and found that 50 percent of La Piedad streets have GSV imagery from 2019 or later. The most recent capture date was June 2021, and the least recent was December 2008. We plan to study GSV availability and how frequently it is updated in a future project along with UW epidemiologist Stephen J. Mooney.

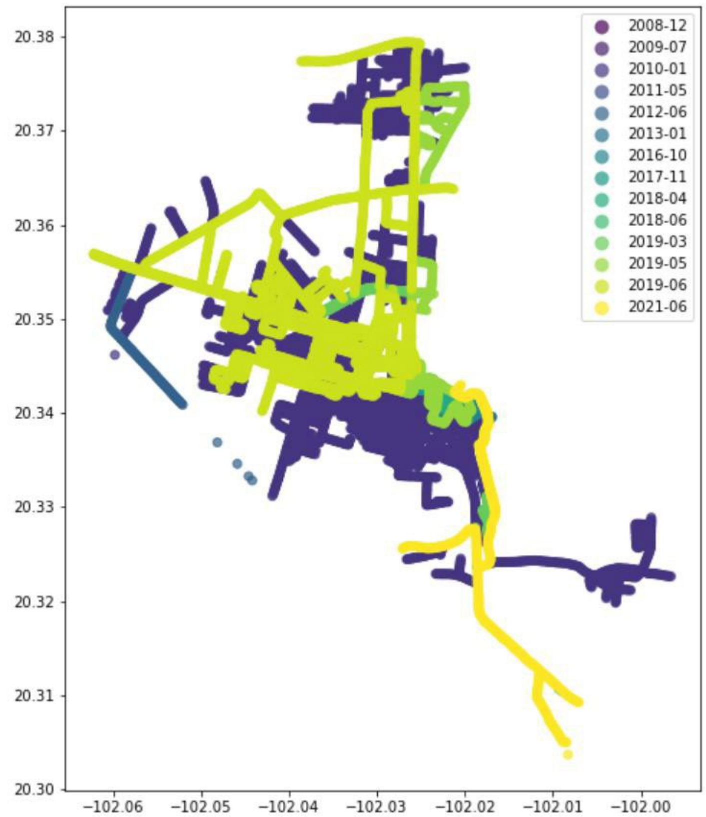

Figure 2.3 A spatio-temporal analysis of Google Street View panorama capture dates in La Piedad, Mexico, showing that over 50 percent of the images captured were from 2019 or later; however, some images dated back to 2011 or before.

2.2. Oradell, New Jersey

Together with the Oradell New Jersey Girl Scouts, the Bergen County Community Council of the National Multiple Sclerosis Society, and Hackensack Meridian School of Medicine, we deployed Project Sidewalk into Oradell, New Jersey (http://oradell.projectsidewalk.org/) (figure 2.4). Here, we have used Project Sidewalk as a service-learning platform for the Girl Scouts and local community to learn about urban design, human mobility, and disability and equity while contributing valuable data. We have hosted both virtual and in-person mapathons. This collaboration was initiated by a medical student and wheelchair user Kie Fujii.

Thus far, in Oradell, 72 users have audited 100 percent of the community (35.9 miles of streets), contributing over 8,800 geo-located sidewalk accessibility labels and 7,841 validations. The next stage is to have the Girl Scouts perform some basic analyses and present their results to the city council. We plan to publish a paper examining Project Sidewalk as a service-learning vehicle and platform to learn about urban design and disability, and to provide data science-related skills.

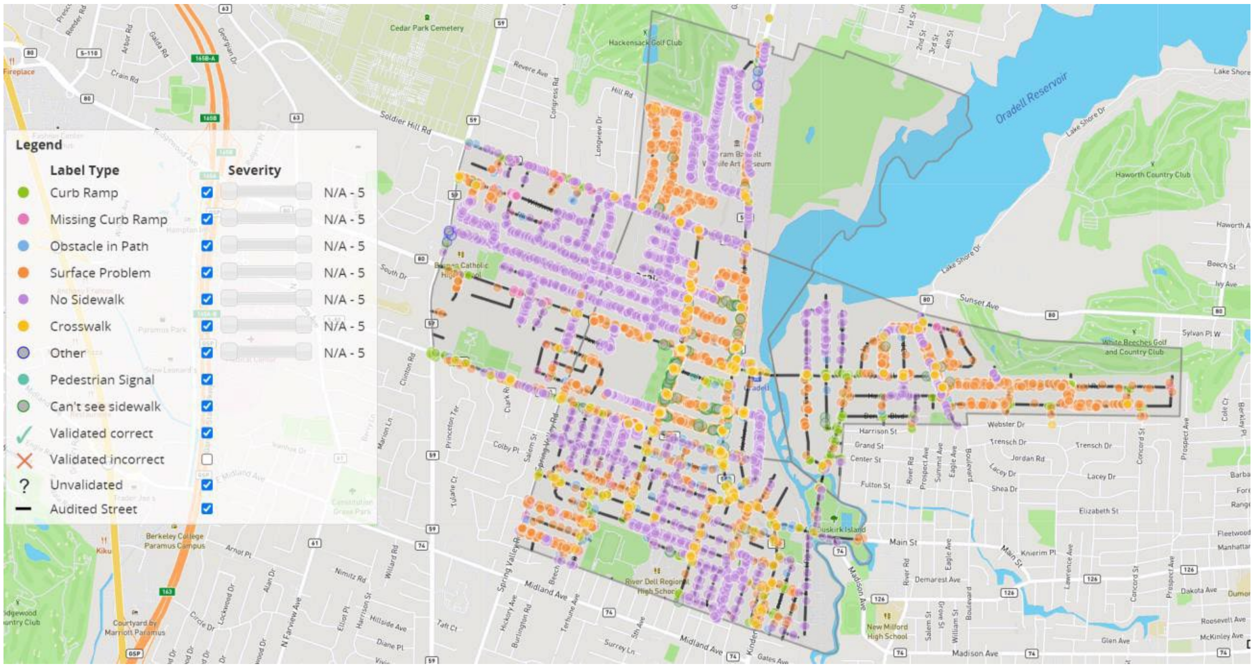

Figure 2.4 A map of our Project Sidewalk deployment in Oradell, New Jersey, which is in collaboration with the Oradell New Jersey Girl Scouts, the Bergen County Community Council of the National MS Society, and the Hackensack Meridian School of Medicine. Thus far, 72 users have audited 35.9 miles of streets, contributing over 8,800 geo-located sidewalk accessibility labels and 7,841 validations.

2.3. Amsterdam, The Netherlands

For our first city in Europe, we worked with the disability advocacy organization WorldEnabled.org, led by Victor Pineda, and the city of Amsterdam (Gemeente Amsterdam) to deploy into Amsterdam (figure 2.5). They are also working with community members and, specifically, a disability organization for workforce development to help collect data. Thus far, 320 users have assessed 255.6 mi of city streets, collecting 27,000 labels and 21,472 validations

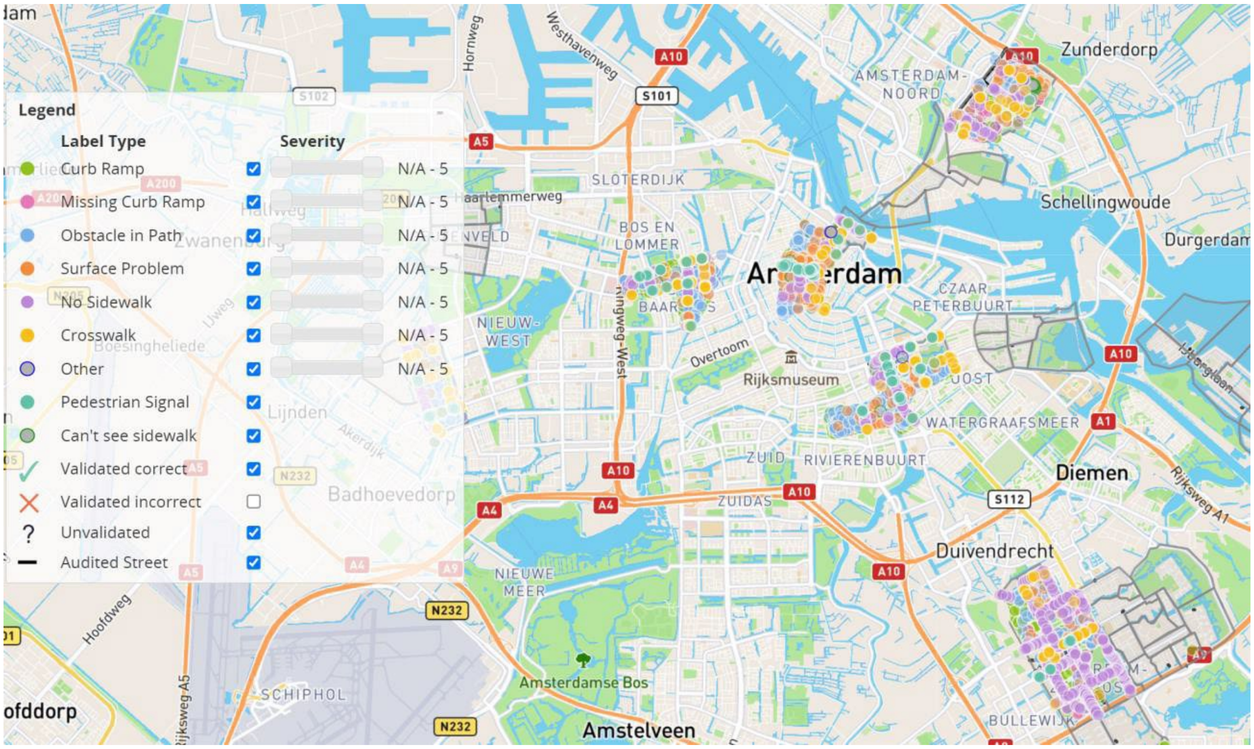

Figure 2.5 A map of our Project Sidewalk deployment in Amsterdam, The Netherlands, which is in collaboration with the disability advocacy organization WorldEnabled.org, led by Victor Pineda, and the city of Amsterdam itself (Gemeente Amsterdam).

CHAPTER 3. SPATIAL PATTERNS OF SIDEWALK INACCESSIBILITY

Building on our growing Project Sidewalk dataset, we proposed to examine key correlates of sidewalk availability, connectivity, and quality as measured by our Project Sidewalk techniques, combined with secondary datasets including population density, road type, land use, census tracts, real estate pricing, and building age. We also proposed to extend previous work examining socioeconomic and racial disparities in pedestrian safety and physical activity [22,42] by incorporating our enhanced sidewalk-related measures.

In preliminary work, we created a heatmap density plot of sidewalk accessibility problems in our Project Sidewalk Washington, D.C., dataset (see figure 3.1). We incorporated both label frequency and label severity via weighted scaling, which was parameterizable to accommodate different mobility disabilities. We found a higher density of surface problems and sidewalk obstacles along the southeastern corridor of the city along the Anacostia River, a historically Black neighborhood. Interestingly, we also found a higher precedence of accessibility problems in one of the most affluent D.C. neighborhoods, Georgetown, perhaps because of policies aimed at preserving historic cobblestone walkways—but at a cost of accessibility. Other models of assessing urban accessibility are also possible. Figure 3.1b, for example, shows that we scored street-level accessibility based on both problem density and street slope.

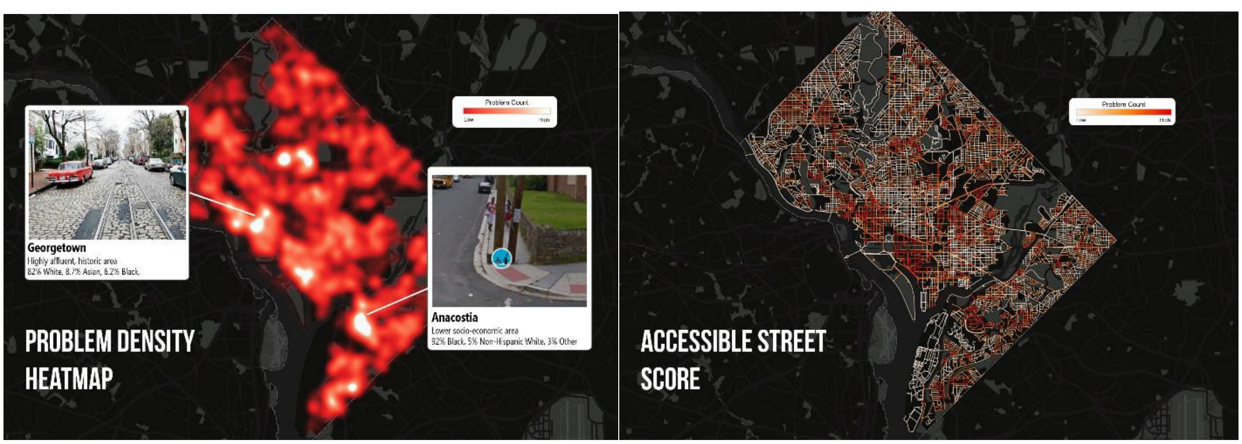

Figure 3.1 (a) A heatmap visualization of sidewalk problem density allowing for a glanceable overview of hotspots (lighter areas are worse). The two callouts highlight problematic areas: Anacostia, a historically lower socioeconomic area that is 92 percent Black, and Georgetown, an affluent, historic area that is 82 percent White. **(b)** A street-level visualization of the same data (here, darker is worse), which better highlights topological information.

We have now shifted to more quantitative methods. However, this work is ongoing and yet to be published. As a pilot study, PhD student Chu Li examined Project Sidewalk data from Seattle, Washington (https://seattle.projectsidewalk.org/api), which includes 207,726 labels and 182,695 validations from 4,163 users (see figure 3.2). For external datasets, we used the following:

- Sidewalk Geometry Data from the City of Seattle GIS Program
- Seattle Census Block Groups Geometry from the Seattle City GIS Program
- Market Profile Data 2020 from Social Explore.

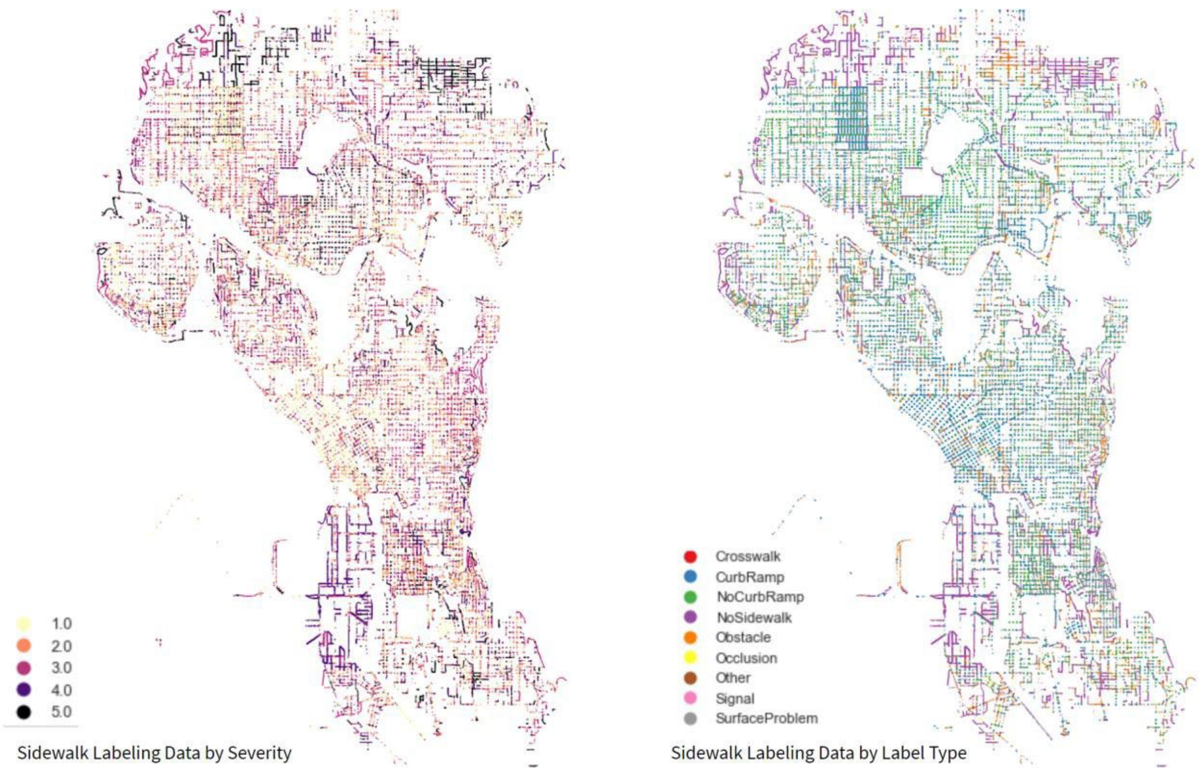

Figure 3.2 The spatial distribution of collected sidewalk labels by **(a)** severity and **(b)** label type.

For our analysis approach, we associated Project Sidewalk labels with the sidewalk geometries published by Seattle Department of Transportation (SDOT). We then normalized label counts by dividing label counts by total sidewalk lengths. To examine statistical relationships between sidewalk quality and socioeconomic factors, including population, income, rent, mode of transit, and quality of life (these factors were all pulled from Market Profile Data from Social Explore), we used the Pearson's correlation coefficient,. Below, we present some initial results showing correlations between sidewalk quality and population characteristics (figure 3.3) and modes of transportation (figure 3.4), respectively.

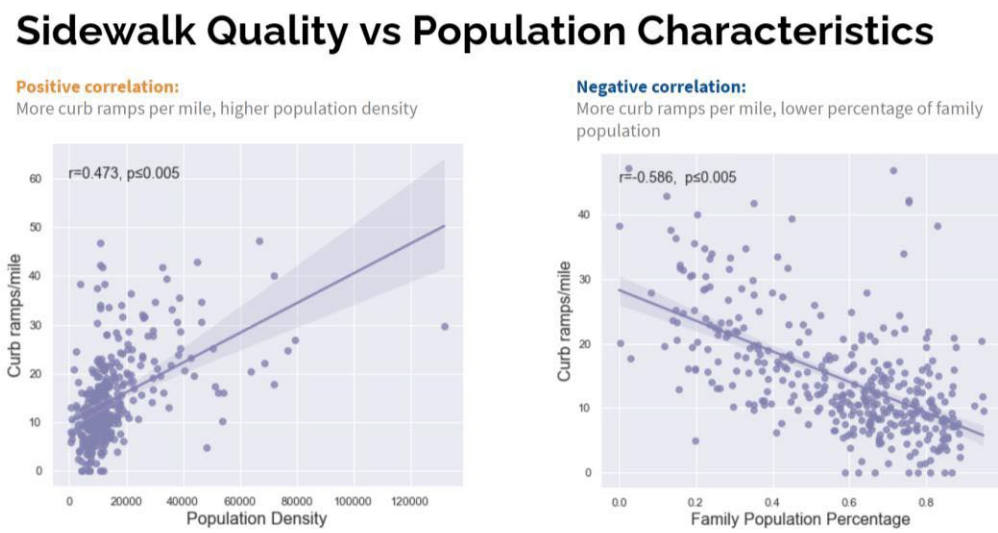

Figure 3.3 Scatter graphs showing more curb ramps per mile in areas of higher population density.

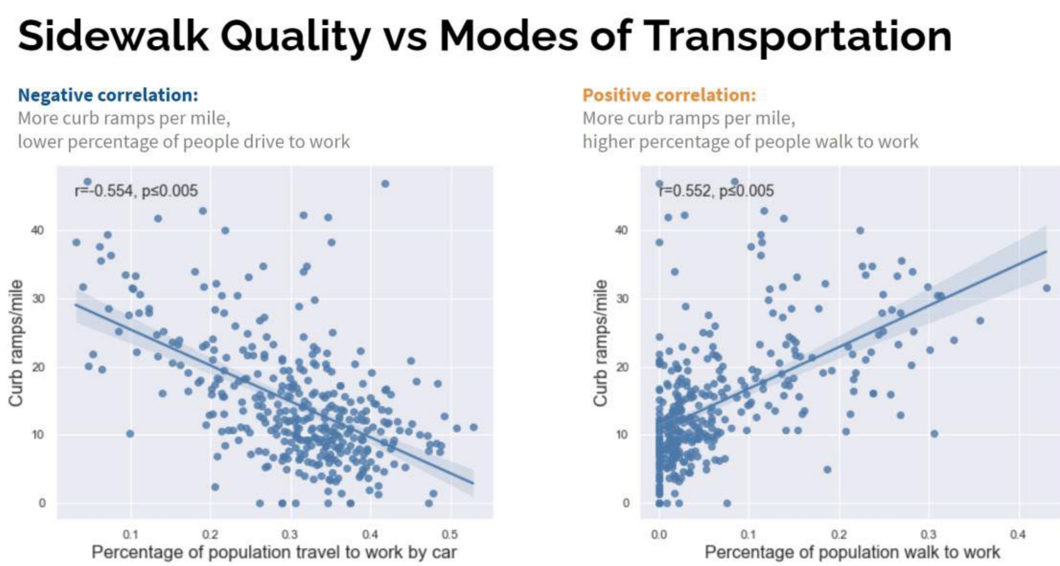

Figure 3.4 Scatter graphs showing a positive correlation between the availability of curb ramps and the number of people who reported walking to work.

Unsurprisingly, there were more curb ramps per mile in areas of higher population density. We also found a positive correlation between the availability of curb ramps and the number of people who reported walking to work. This work is preliminary. We would like to incorporate severity-weighted counts, examine more label types, and repeat our analyses across Project Sidewalk cities (partially addressing Thread 3).

CHAPTER 4. TRACKING URBAN ACCESSIBILITY OVER TIME

Thread 4's focus is on adapting and creating new Crowd+AI tools to study how sidewalk accessibility is changing over time in US cities.

4.1. Introduction

In 1990, the U.S. passed the *Americans with Disabilities Act* (ADA) requiring that public infrastructure—including sidewalks and street crossings—be accessible. Yet, more than 30 years later, cities struggle to meet accessibility requirements, often only pursuing large-scale sidewalk renovations in response to civil rights litigation, such as in New York [14], Seattle [11], and Los Angeles [24]. Observing these challenges and to help stimulate and structure ADA renovations and city planning, in 2015, the U.S. Federal Highway Administration requested that local governments develop sidewalk ADA transition plans, including an inventory of accessibility barriers and descriptions of accessible renovations [37]. However, in a recent study of 401 municipalities only 54 (13 percent) had published plans, and only seven had met the minimum ADA criteria [10].

Such findings reflect the challenges of making infrastructure accessible. Viable solutions require substantial political, economic, and technical investment—training, resources, community involvement, specialized tools, and the work and coordination of multiple governmental agencies [25]. In addition, there is a lack of open tools, techniques, and datasets to track how urban infrastructure is becoming more or less accessible.

4.1.1. Overarching Questions and Scope of Work

To help understand *how* sidewalks are changing, *where* resources are being invested, and *whether* governments are acting on ADA requirements, our research group is developing new spatiotemporal tracking tools to analyze, visualize, and study changes in urban accessibility over time. With our tools, we hope to support overarching research questions such as the following:

- How does sidewalk infrastructure change over time?
- What are the spatiotemporal patterns of change?
- How do these changes correspond to socioeconomic and demographic factors?
- Where does inaccessibility persist?

As a preliminary step toward addressing these questions, we introduced three new experimental Crowd+AI (artificial intelligence) prototypes for semi-automatically tracking changes in street intersections, specifically curb ramps (or "curb cuts")—figures 4.1 through 4.3. While curb ramps are only one part of accessible urban infrastructure, they are critical to mobility and required by the ADA. Moreover, previous work has found that trained computer vision (CV) models can detect curb ramps at higher accuracy than surface degradations or sidewalk obstacles [13,40], making curb ramps a good starting place for initial crowd+AI work.

4.1.2. Crowd+AI Solutions

Studying and characterizing spatiotemporal patterns of urban change from remote imagery is a longstanding area of interest in the urban- and geo-sciences [15,32,41]. Recent developments in CV, specifically deep learning, and the widespread availability of historic street-level imagery have enabled new urban change detection techniques [3,5,20,29,38]. However, limited work has been done on applying these techniques to urban accessibility to characterize *how* and *where* sidewalks are changing. Below, we describe design considerations for tracking accessibility-related changes in street intersections, three preliminary Crowd+AI prototypes, and results from a pilot usability study with five users that was published as a poster paper at ASSETS'21 in October 2021.

4.2. UI Design Considerations for Tracking Changes in Sidewalks

In brainstorming and working on initial prototypes, we developed the following design considerations:

- **Humans struggle with change detection.** Studies in perceptual psychology have consistently found that humans perform poorly in identifying differences between images [23,31]. How can we create tools that help humans identify and label accessibility features in time-series imagery while mitigating these perceptual effects [31]?
- **Leveraging temporal similarity**. Unlike general street scene labeling tasks [8,21], we are interested not just in identifying objects in a single snapshot but in tracking these objects over time. How can we leverage structural similarities in time-series photography to create efficient and accurate labeling interfaces?
- **Combining AI + human labeling.** Similarly, how can humans + machine learning work together to maximize labeling efficiency and accuracy [4,19]? How should AI-based detections and uncertainty be represented to humans? Can the underlying ML model also leverage similarities across time-series images?
- **Interactive training.** Ultimately, to scale our approach, we will deploy our interfaces to crowdworkers who likely have minimal experience with sidewalks, curb ramps, and advanced labeling interfaces. How can we develop interactive training user interfaces that allow our users to quickly learn and perform accurately in our tasks?

4.3. Three Crowd+AI Interfaces for Tracking Curb Ramps Over Time

Given the above considerations, we have developed three early-stage interactive prototypes for tracking changes in street intersections over time. These differ in the amount of simultaneous time-series imagery shown, how labels propagate from one time-series snapshot to the next (using a derivation of linked editing [35]), and how we incorporate a deep learning model for automatic curb ramp detection (from [40]). Rather than ask users to detect *changes*, users find and label curb ramps in each image. To improve labeling efficiency, we leverage similarities across time shots to auto-propagate labels through linked editing and CV. Each prototype begins with a step-by-step tutorial to train users on the task and the interface.

For our historic street scene dataset, we have used Google Street View's "time machine" feature, which provides high-resolution street-level panoramas dating back to 2007 captured approximately every one to three years. Our test set consists of 100 intersections drawn from Washington, D.C., and Seattle (50 each). The D.C. dataset contains an average of 6.4 time-series images per location (*SD*=1.7), while Seattle has 7.8 (*SD*=2.6). The first capture dates are 2008 and the last are 2019 (while our research is ongoing, this initial test dataset was created in 2019).

The three prototypes are listed and described below.

4.3.1. Prototype 1: Single View

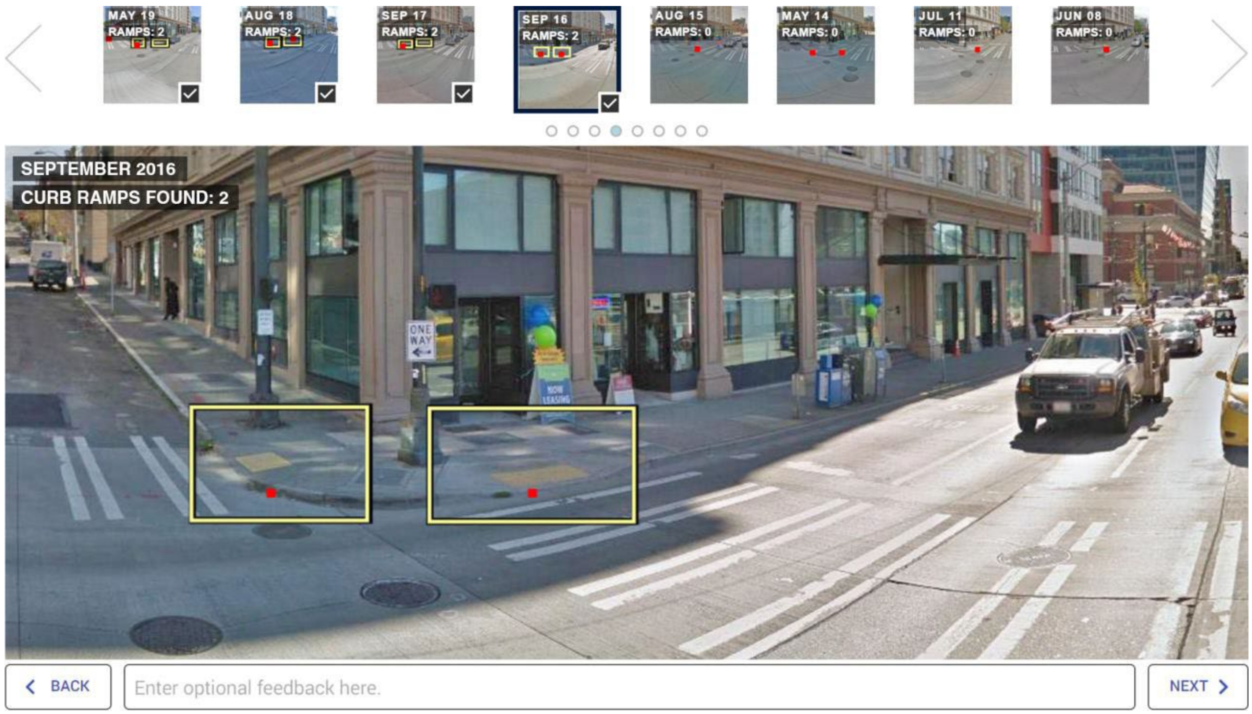

Figure 4.1. With **Prototype 1 (P1): Single View**, users label time-series images of individual street corners (in this case, from May 2019 to June 2008). The thumbnail menu shows available time-series images at the selected corner, which update in real time as users draw bounding-box labels with their mouse. Checkboxes indicate a completed (labeled) time snapshot. Automatically detected ramps are indicated with small red squares, which we can be turned on/off. We plan to conduct experiments to examine the potential benefits of these automatic detections, particularly given that they are not always accurate.

4.3.2. Prototype 2: Grid View

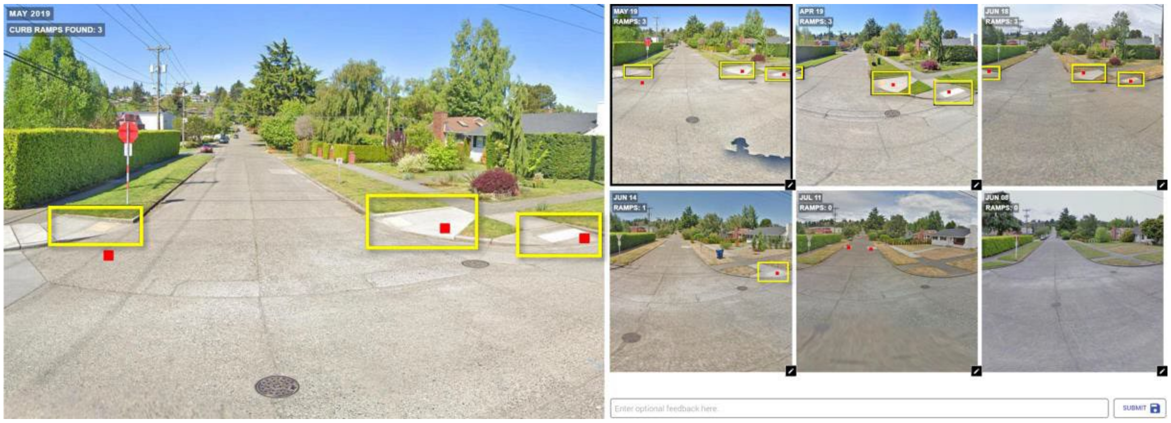

Figure 4.2. With **Prototype 2 (P2): Grid View**, thumbnails are larger and presented in a grid, allowing us to show up to nine time-series images simultaneously. Unlike P1, P2 uses linked editing [36] to leverage structural similarities across time. When users draw or edit a bounding box on the most recent time snapshot (always shown as the top-left thumbnail, which in this case is May 2019), these annotations are auto-propagated to all previous time shots using x,y pixel location similarity. If CV detections are turned on (red squares), we attempt to auto-align propagated boxes based on inferred curb ramp locations; however, these alignments are not always accurate because of noise in the ML model (e.g., there are two incorrect CV detections on the July 2011 time shot above). The user can make micro-edits or deletions, as necessary, on the propagations.

4.3.3. Prototype 3: Panorama View

Figure 4.3. Similar to P2, **Prototype 3 (P3): Panorama View** also includes linked editing [36] and auto-propagation of labels across time. However, unlike P1 and P2, which serve segmented intersections cropped into four individual images (one corner per image), P3 presents full panorama views. The benefits of panoramas include greater context for the user and potentially faster overall labeling. However, the curb ramps themselves are small, and only about three to four time-series panoramas can fit on a laptop screen, so users need to scroll to access older images. To help users more closely examine panorama parts, we have an always-available zoom inset of the mouse location (shown currently at the May 2019 panorama above). In this particular example, the intersection was renovated between June 2008 (bottom pano) and July 2011 with ADA compliant ramps and three ramp additions. These changes are identified with our techniques.

4.4. Pilot Usability Study

To assess the usability and understandability of our prototypes and to prepare for larger web-based deployments, we conducted an in-person "think aloud" usability study with five participants (ages 20 to 45; all had technical backgrounds). Sessions were ~50 minutes. To simulate the experience of using the prototypes in an online deployment, we provided limited instruction and, instead, asked participants to follow the interactive tutorials.

While users were appreciative of the step-by-step tutorials, some aspects of label propagation, and the promise of CV-assisted labeling, we found important areas for future work. First, participants wanted more information on how they should *label*—the size of their bounding boxes, pixel-level precision, *etc.* Second, participants were confused about *label propagations*—should they trust them or modify them? Because auto-propagations only work in one direction (labeling is propagated backward but *not* forward through time) and because only some operations are supported (additions but not deletions), users did not have a strong understanding or confidence in this feature. Finally, though the automatic CV detections (visualized as red squares) were deemed helpful in drawing attention to curb ramps, participants felt that it was too often incorrect and thus distracting (though one participant enjoyed “outperforming” the AI).

4.5. Future Work

In this preliminary study, we introduced three novel Crowd+AI tools aimed at rapidly labeling and tracking changes in sidewalk accessibility features over time. In addition to addressing results from our usability study, we aim to support richer qualitative labels about how curb ramps are changing (*e.g.,* tactile strips, flares, steepness) and other accessibility-related labels for crosswalks [1,2], accessible pedestrian signals [12], and street/sidewalk surfaces. We also plan to conduct a larger-scale deployment study to further assess our tools and progress toward public deployment, like Project Sidewalk, for tracking changes in urban accessibility infrastructure across cities and creating open “change tracking” datasets.

CHAPTER 5. REFERENCES

1. Dragan Ahmetovic, Roberto Manduchi, James M. Coughlan, and Sergio Mascetti. 2015. Zebra Crossing Spotter: Automatic Population of Spatial Databases for Increased Safety of Blind Travelers. In *The 17th International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS 2015)*.

2. Dragan Ahmetovic, Roberto Manduchi, James M. Coughlan, and Sergio Mascetti. 2017. Mind Your Crossings: Mining GIS Imagery for Crosswalk Localization. *ACM Transactions on Accessible Computing* 9, 4: 1–25. https://doi.org/10.1145/304679

3. Pablo F. Alcantarilla, Simon Stent, Germán Ros, Roberto Arroyo, and Riccardo Gherardi. 2018. Street-view change detection with deconvolutional networks. *Autonomous Robots*: 1–22. https://doi.org/10.1007/s10514-018-9734-5

4. Saleema Amershi, Kori Inkpen, Jaime Teevan, Ruth Kikin-Gil, Eric Horvitz, Dan Weld, Mihaela Vorvoreanu, Adam Fourney, Besmira Nushi, Penny Collisson, Jina Suh, Shamsi Iqbal, and Paul N Bennett. 2019. Guidelines for Human-AI Interaction. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems - CHI '19*, 1–13. https://doi.org/10.1145/3290605.3300233

5. Kuan-Ting Chen, Fu-En Wang, Juan-Ting Lin, Fu-Hsiang Chan, and Min Sun. 2017. The World Is Changing: Finding Changes on the Street. . 420–435. https://doi.org/10.1007/978-3-319-54407-6_28

6. Keith M Christensen, Judith M Holt, and Justin F Wilson. 2010. Effects of perceived neighborhood characteristics and use of community facilities on physical activity of adults with and without disabilities. *Preventing chronic disease* 7, 5: A105.

7. ciudatamx.wordpress.com. Mapeatón, la vigilancia ciudadana a pié.

8. Marius Cordts, Mohamed Omran, Sebastian Ramos, Timo Rehfeld, Markus Enzweiler, Rodrigo Benenson, Uwe Franke, Stefan Roth, and Bernt Schiele. 2016. The Cityscapes Dataset for Semantic Urban Scene Understanding. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

9. Renia Ehrenfeucht and Anastasia Loukaitou-Sideris. 2010. Planning Urban Sidewalks: Infrastructure, Daily Life and Destinations. *Journal of Urban Design* 15, 4: 459–471. https://doi.org/10.1080/13574809.2010.502333

10. Yochai Eisenberg, Amy Heider, Rob Gould, and Robin Jones. 2020. Are communities in the United States planning for pedestrians with disabilities? Findings from a systematic evaluation of local government barrier removal plans. *Cities* 102: 102720. https://doi.org/https://doi.org/10.1016/j.cities.2020.102720

11. David Gutman. 2017. Seattle may have to spend millions making sidewalks more accessible to people with disabilities. *The Seattle Times*.

12. Richard Guy and Khai Truong. 2012. CrossingGuard: exploring information content in navigation aids for visually impaired pedestrians. In *Proceedings of the SIGCHI*

Conference on Human Factors in Computing Systems (CHI '12) (CHI '12), 405–414. https://doi.org/10.1145/2207676.2207733

13. K. Hara, J. Sun, R. Moore, D. Jacobs, and J.E. Froehlich. 2014. Tohme: Detecting curb ramps in Google Street View using crowdsourcing, computer vision, and machine learning. In *UIST 2014 - Proceedings of the 27th Annual ACM Symposium on User Interface Software and Technology*, 189–204. https://doi.org/10.1145/2642918.2647403

14. Winnie Hu. 2017. For the Disabled, New York's Sidewalks Are an Obstacle Course. *The New York Times*.

15. Wei Ji, Jia Ma, Rima Wahab Twibell, and Karen Underhill. 2006. Characterizing urban sprawl using multi-stage remote sensing images and landscape metrics. *Computers, Environment and Urban Systems* 30, 6: 861–879. https://doi.org/10.1016/j.compenvurbsys.2005.09.002

16. Annette M. Kim. 2012. The Mixed-Use Sidewalk. *Journal of the American Planning Association* 78, 3: 225–238. https://doi.org/10.1080/01944363.2012.715504

17. Corinne E. Kirchner, Elaine G. Gerber, and Brooke C. Smith. 2008. Designed to Deter: Community Barriers to Physical Activity for People with Visual or Motor Impairments. *American Journal of Preventive Medicine* 34, 4: 349–352. https://doi.org/10.1016/J.AMEPRE.2008.01.005

18. Christopher Mitchell. 2006. Pedestrian Mobility and Safety: A Key to Independence for Older People. *Topics in Geriatric Rehabilitation* 22, 1: 45–52.

19. Vikram Mohanty, David Thames, Sneha Mehta, and Kurt Luther. 2019. Photo Sleuth: Combining Human Expertise and Face Recognition to Identify Historical Portraits. In *Proceedings of the 24th International Conference on Intelligent User Interfaces*, 547–557. https://doi.org/10.1145/3301275.3302301

20. Ladan Najafizadeh and Jon E. Froehlich. 2018. A Feasibility Study of Using Google Street View and Computer Vision to Track the Evolution of Urban Accessibility. In *Poster Proceedings of ASSETS'18*.

21. Gerhard Neuhold, Tobias Ollmann, Samuel Rota Bulo, and Peter Kontschieder. 2017. The Mapillary Vistas Dataset for Semantic Understanding of Street Scenes. In *2017 IEEE International Conference on Computer Vision (ICCV)*, 5000–5009. https://doi.org/10.1109/ICCV.2017.534

22. Robert B. Noland, Nicholas J. Klein, and Nicholas K. Tulach. 2013. Do lower income areas have more pedestrian casualties? *Accident Analysis & Prevention* 59: 337–345. https://doi.org/10.1016/j.aap.2013.06.009

23. Ronald A. Rensink. 2002. Change Detection. *Annual Review of Psychology* 53, 1: 245–277. https://doi.org/10.1146/annurev.psych.53.100901.135125

24. Emily Alpert Reyes. 2015. L.A. agrees to spend $1.3 billion to fix sidewalks in ADA case. *Los Angeles Times*.

25. Manaswi Saha, Devanshi Chauhan, Siddhant Patil, Rachel Kangas, Jeffrey Heer, and Jon E. Froehlich. 2021. Urban Accessibility as a Socio-Political Problem. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW3: 1–26. https://doi.org/10.1145/3432908

26. Manaswi Saha, Kotaro Hara, Soheil Behnezhad, Anthony Li, Michael Saugstad, Hanuma Maddali, Sage Chen, Jon E. Froehlich, and J. Behnezhad, S., Li, A., Saugstad, M., Maddali, H., Chen, S., & Froehlich. 2017. A Pilot Deployment of an Online Tool for Large-Scale Virtual Auditing of Urban Accessibility. In *Poster Proceedings of ACM ASSETS 2017*, To appear. https://doi.org/10.1145/3132525.3134775

27. Manaswi Saha, Michael Saugstad, Hanuma Maddali, Aileen Zeng, Ryan Holland, Steven Bower, Aditya Dash, Sage Chen, Anthony Li, Kotaro Hara, and Jon E. Froehlich. 2019. Project Sidewalk: A Web-based Crowdsourcing Tool for Collecting Sidewalk Accessibility Data at Scale. In *Proceedings of CHI 2019*.

28. Manaswi Saha, Michael Saugstad, Hanuma Maddali, Aileen Zeng, Ryan Holland, Steven Bower, Aditya Dash, Sage Chen, Anthony Li, Kotaro Hara, and Jon E. Froehlich. 2019. Project Sidewalk: A Web-based Crowdsourcing Tool for Collecting Sidewalk Accessibility Data at Scale. In *Proceedings of CHI 2019*.

29. Ken Sakurada, Daiki Tetsuka, and Takayuki Okatani. 2017. Temporal city modeling using street level imagery. *Computer Vision and Image Understanding* 157: 55–71. https://doi.org/10.1016/j.cviu.2017.01.012

30. Seattle Department of Transportation. Seattle Sidewalk Survey Update. *2017*.

31. Daniel J. Simons and Michael S. Ambinder. 2005. Change Blindness. *Current Directions in Psychological Science* 14, 1: 44–48. https://doi.org/10.1111/j.0963-7214.2005.00332.x

32. Xiao-Peng Song, Joseph O. Sexton, Chengquan Huang, Saurabh Channan, and John R. Townshend. 2016. Characterizing the magnitude, timing and duration of urban growth from time series of Landsat-based estimates of impervious cover. *Remote Sensing of Environment* 175: 1–13. https://doi.org/10.1016/J.RSE.2015.12.027

33. Edward R. Stollof and Janet M. Barlow. 2008. *Pedestrian Mobility and Safety Audit Guide*.

34. Streets Wiki. Walk Audit.

35. M Toomim, A Begel, and S L Graham. 2004. Managing Duplicated Code with Linked Editing. In *2004 IEEE Symposium on Visual Languages - Human Centric Computing*, 173–180. https://doi.org/10.1109/VLHCC.2004.35

36. M Toomim, A Begel, and S L Graham. 2004. Managing Duplicated Code with Linked Editing. In *2004 IEEE Symposium on Visual Languages - Human Centric Computing*, 173–180. https://doi.org/10.1109/VLHCC.2004.35

37. US Department of Transportation Federal Highway Administration. 2015. ADA Transition Plan.

38. Jan D. Wegner, Steve Branson, David Hall, Konrad Schindler, and Pietro Perona. 2016. Cataloging Public Objects Using Aerial and Street-Level Images — Urban Trees. In *2016*

IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 6014–6023. https://doi.org/10.1109/CVPR.2016.647

39. Galen Weld, Esther Jang, Anthony Li, Aileen Zeng, Kurtis Heimerl, and Jon E Froehlich. 2019. Deep Learning for Automatically Detecting Sidewalk Accessibility Problems Using Streetscape Imagery. In *The 21st International ACM SIGACCESS Conference on Computers and Accessibility* (ASSETS '19), 196–209. https://doi.org/10.1145/3308561.3353798

40. Galen Weld, Esther Jang, Anthony Li, Aileen Zeng, Kurtis Heimerl, and Jon E. Froehlich. 2019. Deep Learning for Automatically Detecting Sidewalk Accessibility Problems Using Streetscape Imagery. In *The 21st International ACM SIGACCESS Conference on Computers and Accessibility*, 196–209. https://doi.org/10.1145/3308561.3353798

41. Jianguo Wu, G. Darrel Jenerette, Alexander Buyantuyev, and Charles L. Redman. 2011. Quantifying spatiotemporal patterns of urbanization: The case of the two fastest growing metropolitan regions in the United States. *Ecological Complexity* 8, 1: 1–8. https://doi.org/10.1016/J.ECOCOM.2010.03.002

42. Chia-Yuan Yu, Xuemei Zhu, and Chanam Lee. 2022. Income and Racial Disparity and the Role of the Built Environment in Pedestrian Injuries. *Journal of Planning Education and Research* 42, 2: 136–149. https://doi.org/10.1177/0739456X18807759