PROJECT SIDEWALK: MAPPING THE ACCESSIBILITY OF THE WORLD THROUGH GOOGLE STREET VIEW

@jonfroehlich | Associate Professor | Computer Science | University of Washington

DESIGN USE BUILD

MAKEABILITY LAB

PAUL G. ALLEN SCHOOL OF COMPUTER SCIENCE & ENGINEERING

UNIVERSITY of WASHINGTON


MAKEABILITY LAB


FALL 2013
DC MAKERFAIRE
HCIL
MAKEABILITY LAB


SUMMER 2018
SEATTLE ARBORETUM
MAKEABILITY LAB

Our Mission

DESIGN, BUILD, & STUDY INTERACTIVE TOOLS & TECHNIQUES TO ADDRESS PRESSING SOCIETAL CHALLENGES

MAKEABILITY LAB

FOUR FOCUS AREAS

ENVIRONMENTAL SUSTAINABILITY

HEALTH & WELLNESS

ACCESSIBILITY

STEM EDUCATION

MAKEABILITY LAB

FOUR FOCUS AREAS

ENVIRONMENTAL SUSTAINABILITY

HEALTH & WELLNESS

ACCESSIBILITY

STEM EDUCATION

MAKEABILITY LAB

FOUR FOCUS AREAS

ENVIRONMENTAL SUSTAINABILITY

HEALTH & WELLNESS

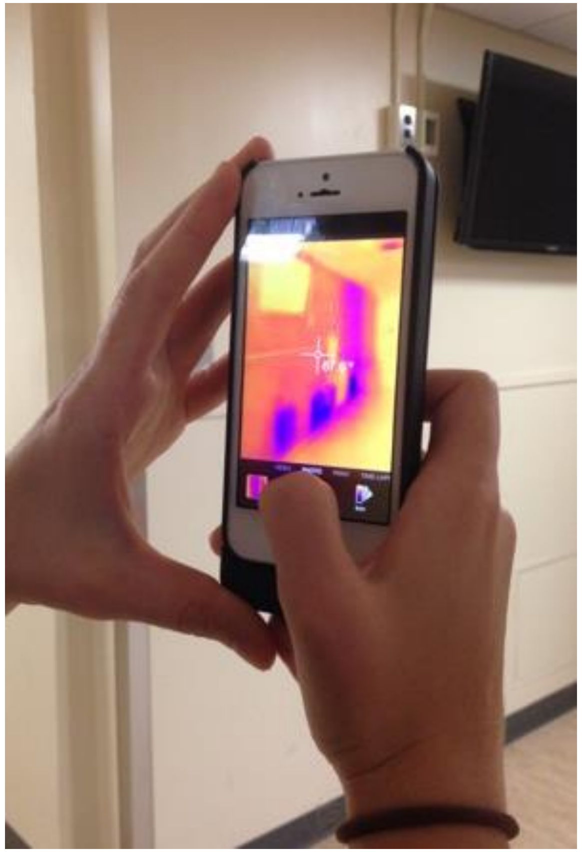
ACCESSIBILITY

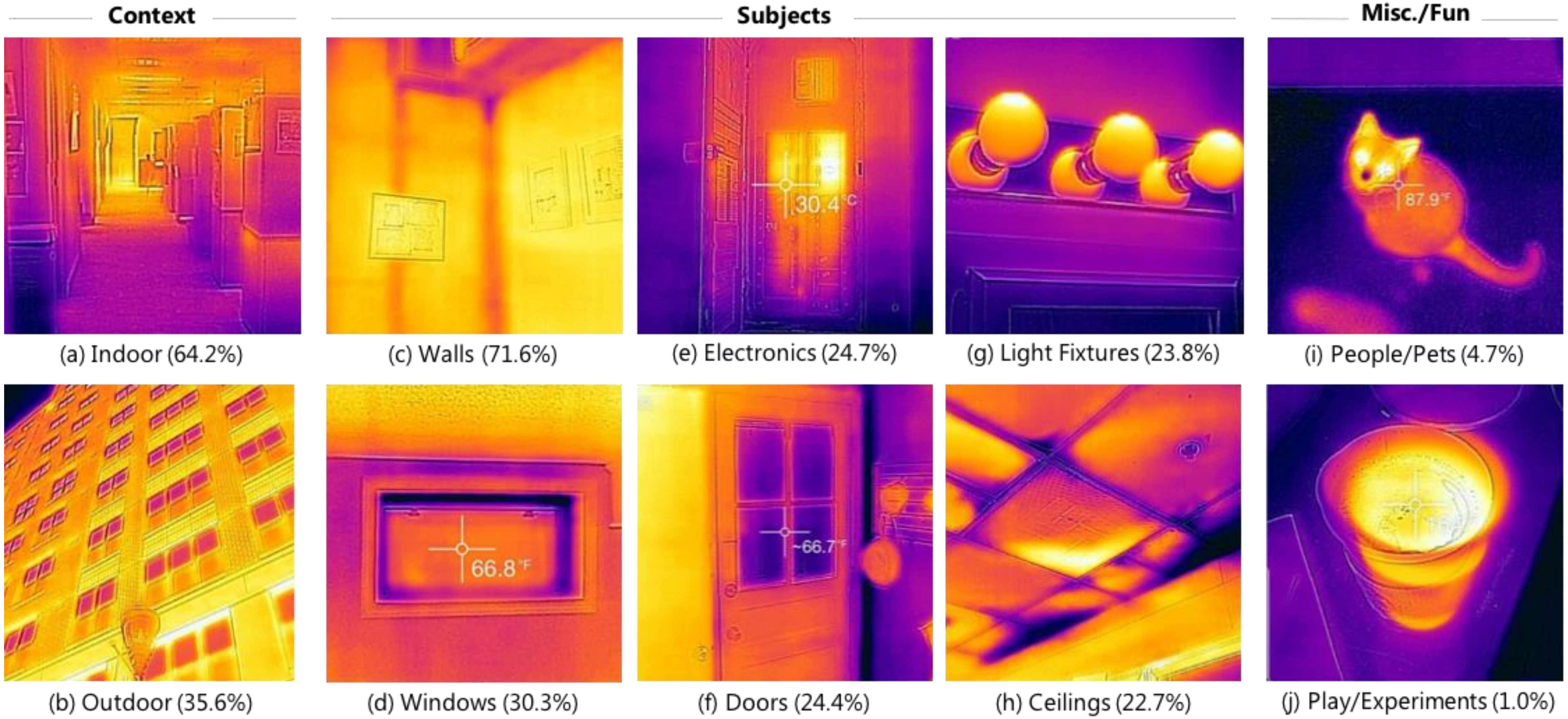
STEM EDUCATION

ENVIRONMENTAL SUSTAINABILITY

PERVASIVE THERMOGRAPHY

With recently graduated UMD CS PhD Student Matt Mauriello, now a post-doc at Stanford





[UbiComp'14, CHI'15 Honorable Mention, HBI'16, CHI'17, UbiComp'17 DC, MobileHCI'18]

MAKEABILITY LAB

FOUR FOCUS AREAS

ENVIRONMENTAL SUSTAINABILITY

HEALTH & WELLNESS

ACCESSIBILITY

STEM EDUCATION

HEALTH & WELLNESS

DESIGNING HEALTH SUPPORT SYSTEMS

[CHI'13 Best Paper, CHI'14]

MAKEABILITY LAB

FOUR FOCUS AREAS

ENVIRONMENTAL SUSTAINABILITY

HEALTH & WELLNESS

ACCESSIBILITY

STEM EDUCATION

HEALTH + STEM

BODYVIS

[IDC’13, CHI’15 Honorable Mention, ICLS’16, IDC’16, CHI’17, ICLS’18]

MAKEABILITY LAB

FOUR FOCUS AREAS

ENVIRONMENTAL SUSTAINABILITY

HEALTH & WELLNESS

ACCESSIBILITY

STEM EDUCATION

MAKEABILITY LAB

FOUR FOCUS AREAS

ENVIRONMENTAL SUSTAINABILITY

HEALTH & WELLNESS

ACCESSIBILITY

STEM EDUCATION

OUR OVERARCHING RESEARCH QUESTION

PROJECT SIDEWALK

[ASSETS'12, CHI'13, HCOMP'13, ASSETS'13 Best Paper, UIST'14, TACCESS'15, SIGACCESS'15, CHI'16, ASSETS'17, ASSETS'18 x2]

How can we…

develop solutions that collect, model, verify, & visualize urban accessibility at scale?


30.6
million U.S. adults
have a mobility impairment
Source: US Census, 210


15.2
million use an assistive aid
Source: US Census, 210


CHANEL
CHANEL
CHANEL
CHANEL
ONE WAY
NO PARKING
DIESEL


NO CURB RAMPS
CHANEL
ONE WAY
DIESEL

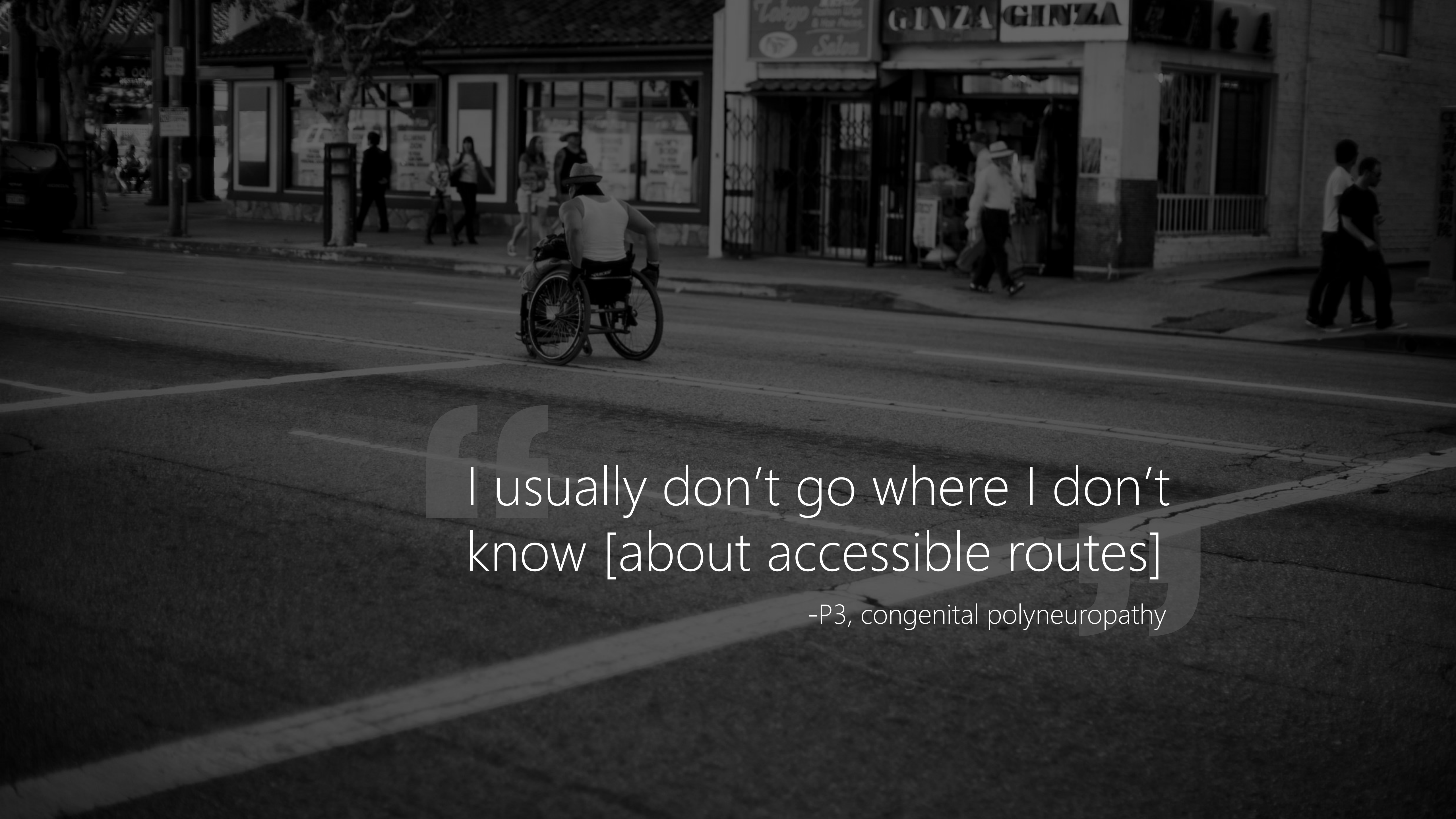

PHYSICAL OBSTACLES


FedEx
INCOMPLETE SIDEWALKS


SURFACE PROBLEMS

PHYSICAL OBSTACLES
NO CURB RAMP
SURFACE DEGRADATION


Accessible infrastructure has a significant impact on the independence and mobility of citizens
[Thapar *et al.*, 2004 ; Nuernberger, 2008]



"I usually don't go where I don't know [about accessible routes]"

-P3, congenital polyneuropathy

The National Council on Disability noted that there is **no comprehensive information** on "the degree to which sidewalks are accessible" in cities.

National Council on Disability, 2007
The impact of the Americans with Disabilities Act: Assessing the progress toward achieving the goals of the ADA

There are many approaches for data collection but they typically require **onsite reporting**, which **limits scalability**

TRADITIONAL ACCESSIBILITY AUDITS

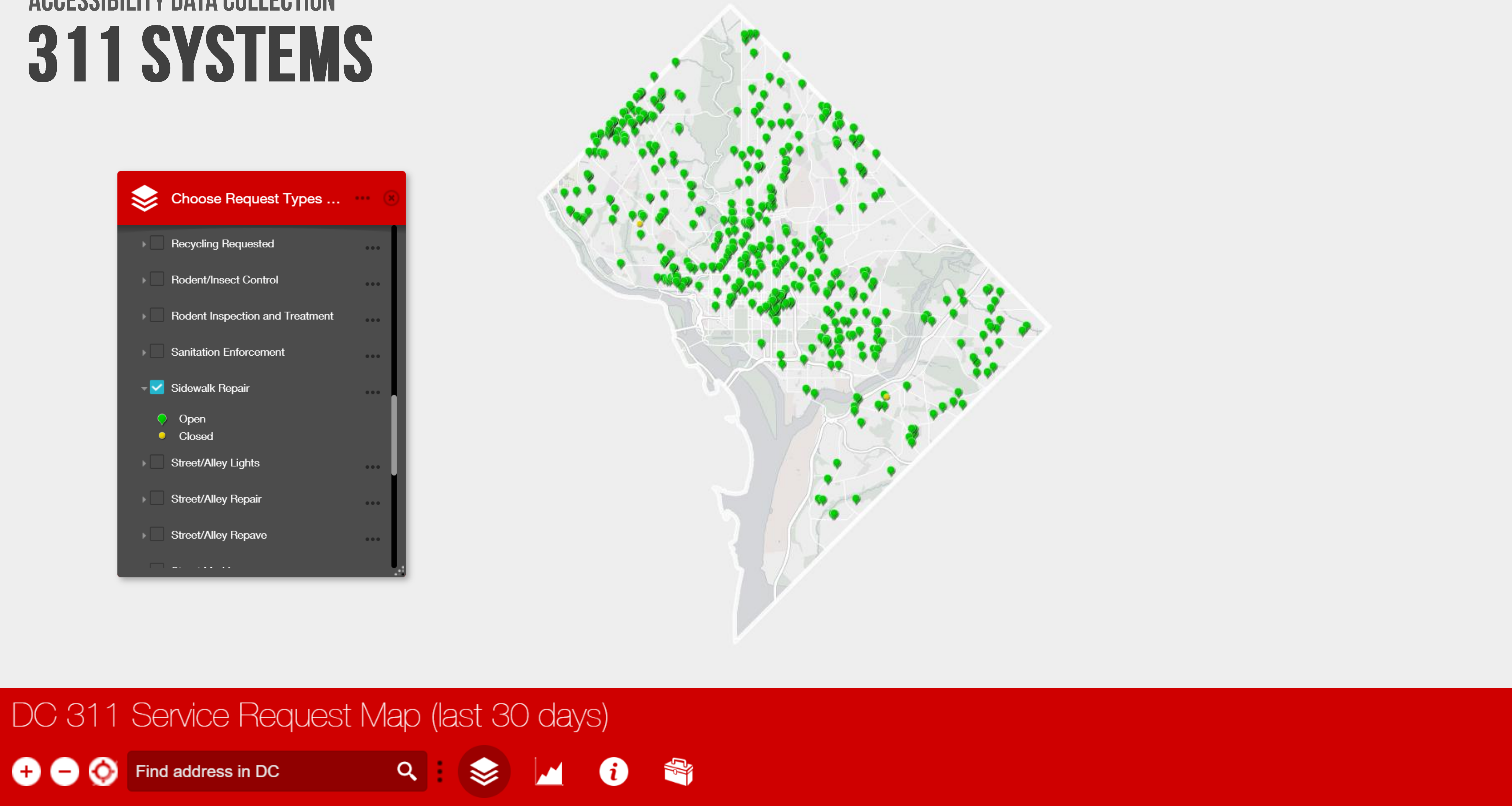
Walkability Audit
Wake County, North Carolina

Walkability Audit
Wake County, North Carolina

Safe Routes to School Walkability Audit
Rock Hill, South Carolina

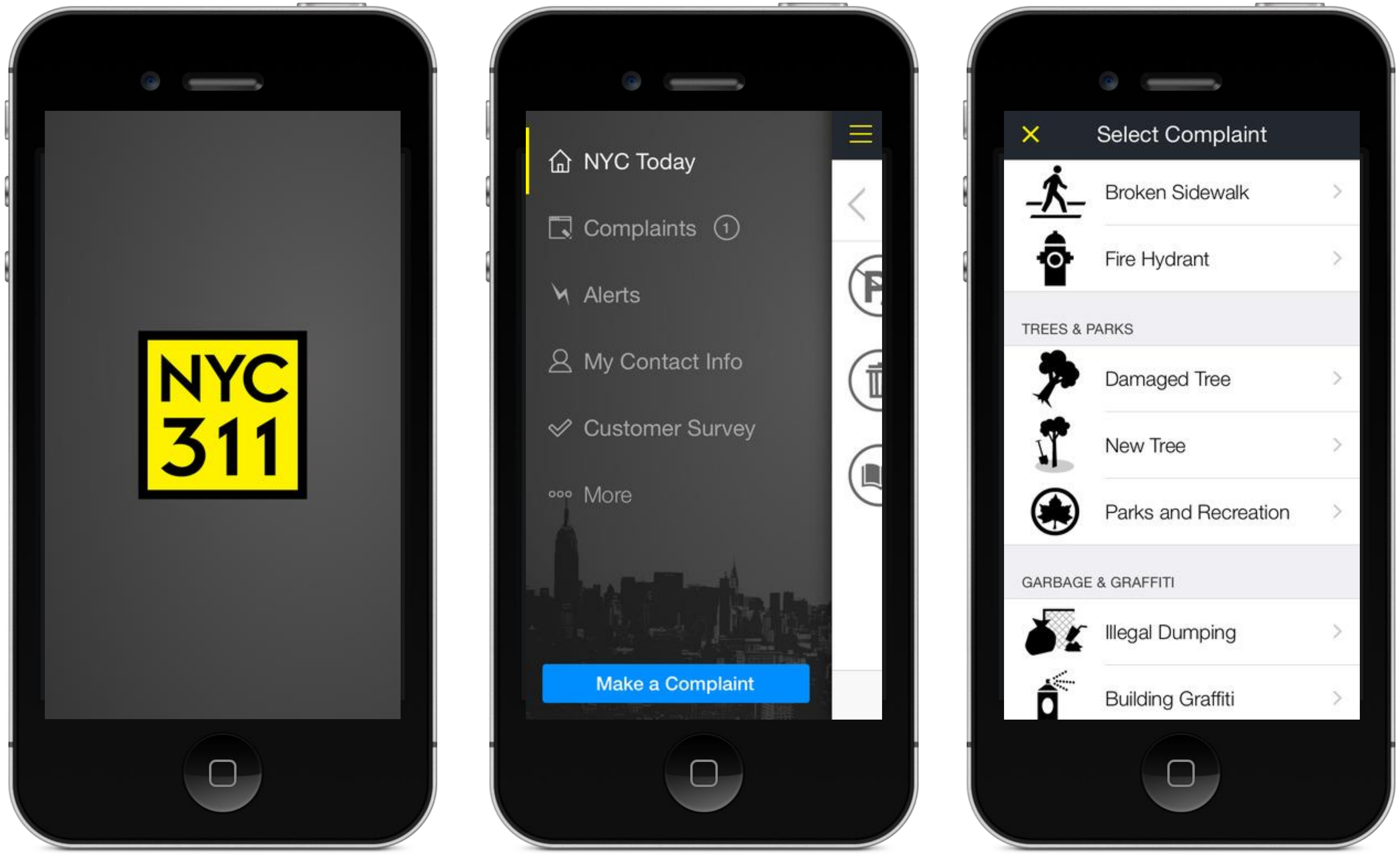
ACCESSIBILITY DATA COLLECTION

311 SYSTEMS



ACCESSIBILITY DATA COLLECTION

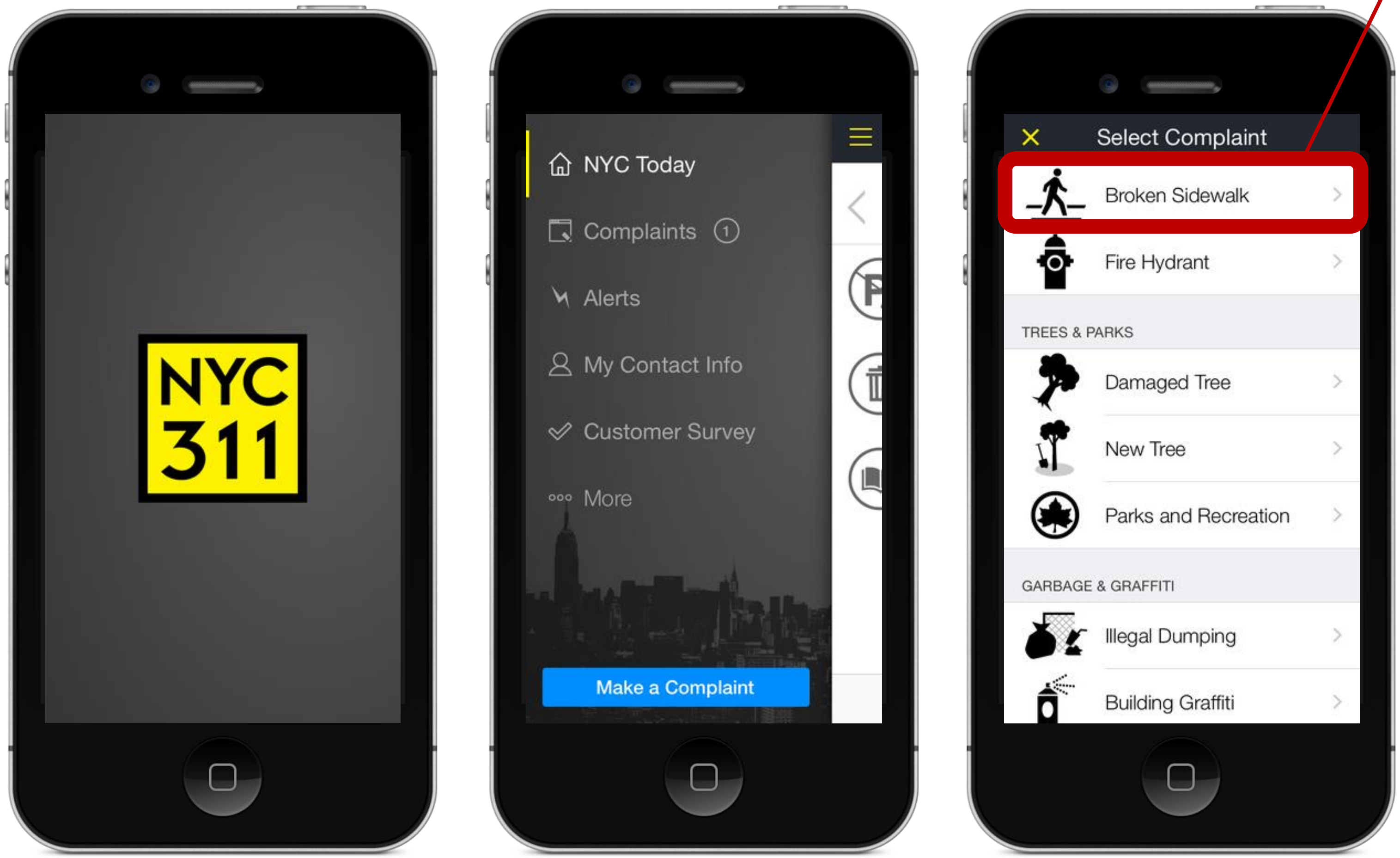
MOBILE REPORTING SOLUTIONS



http://www1.nyc.gov/311/index.page

MOBILE REPORTING SOLUTIONS

The NYC311 app has a specific option for **broken sidewalks**



http://www1.nyc.gov/311/index.page

Get Involved while on-the-go.

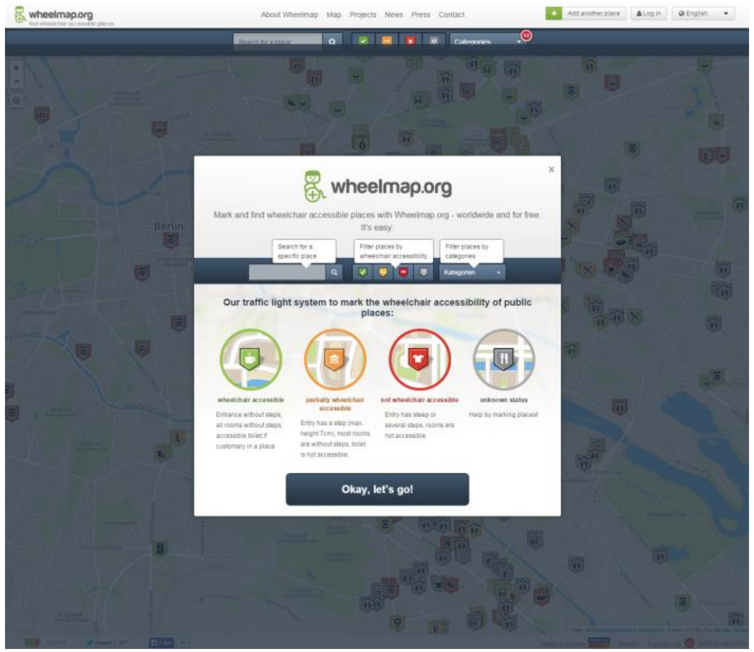
Report, track, and discuss issues in your neighborhood. With just a few clicks, fellow citizens and your government can find and manage 311 issues instantly. Available across devices and on mobile web browsers, anyone can get involved in their community.

Download Now! ▼

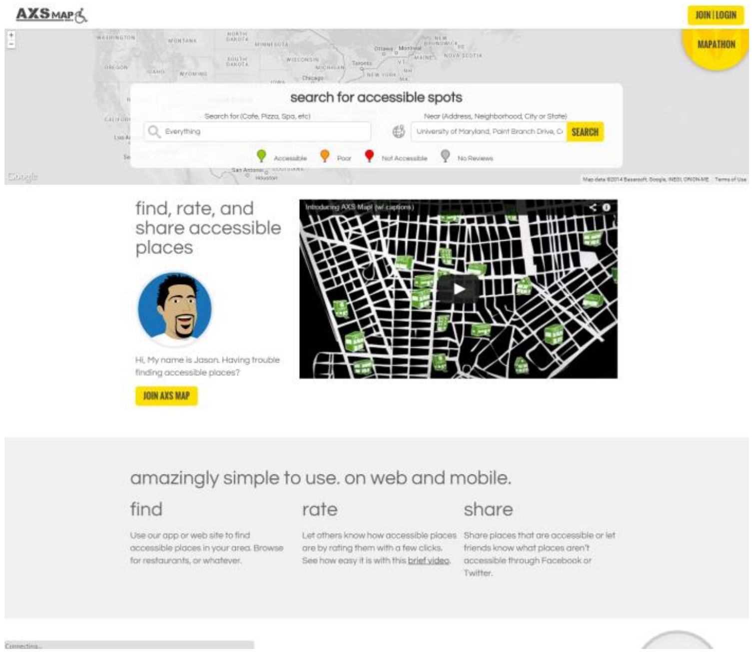
Download using our QR code

Be a good neighbor. Everywhere.

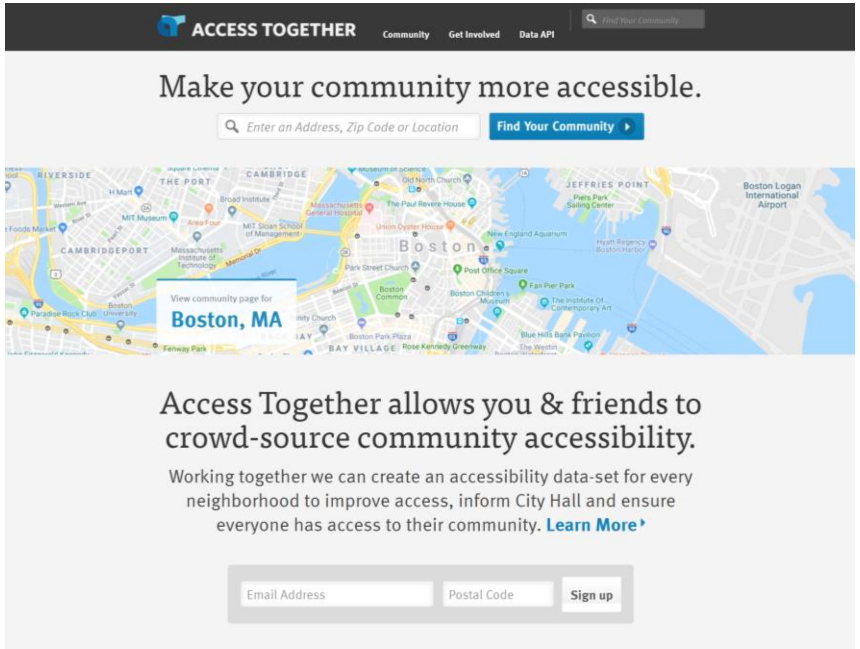
REPORTING ON ACCESSIBILITY OF PLACES



http://wheelmap.org



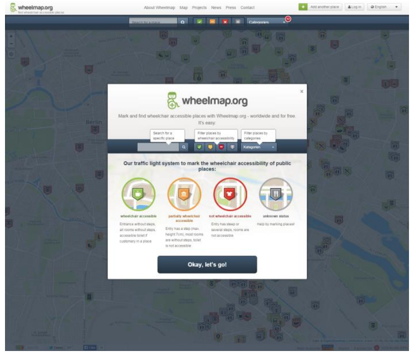
http://axsmap.com



http://accesstogether.org

ACCESSIBILITY DATA COLLECTION

REPORTING ON ACCESSIBILITY OF PLACES



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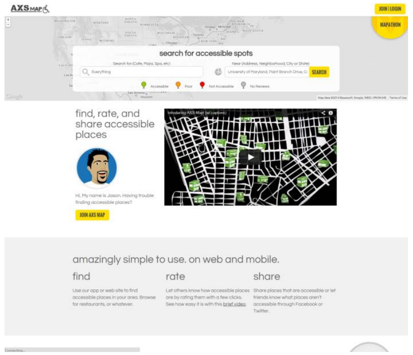

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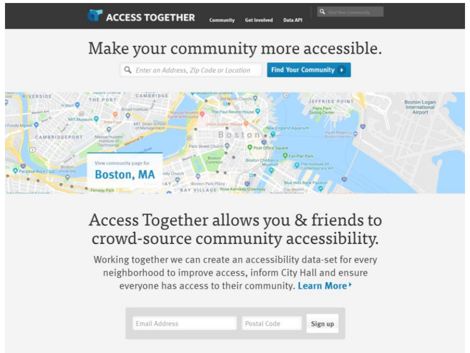


http://accesstogether.org

Important crowdsourcing tools

Reliance on local population for reporting limits *who* can supply data and *how* much they supply

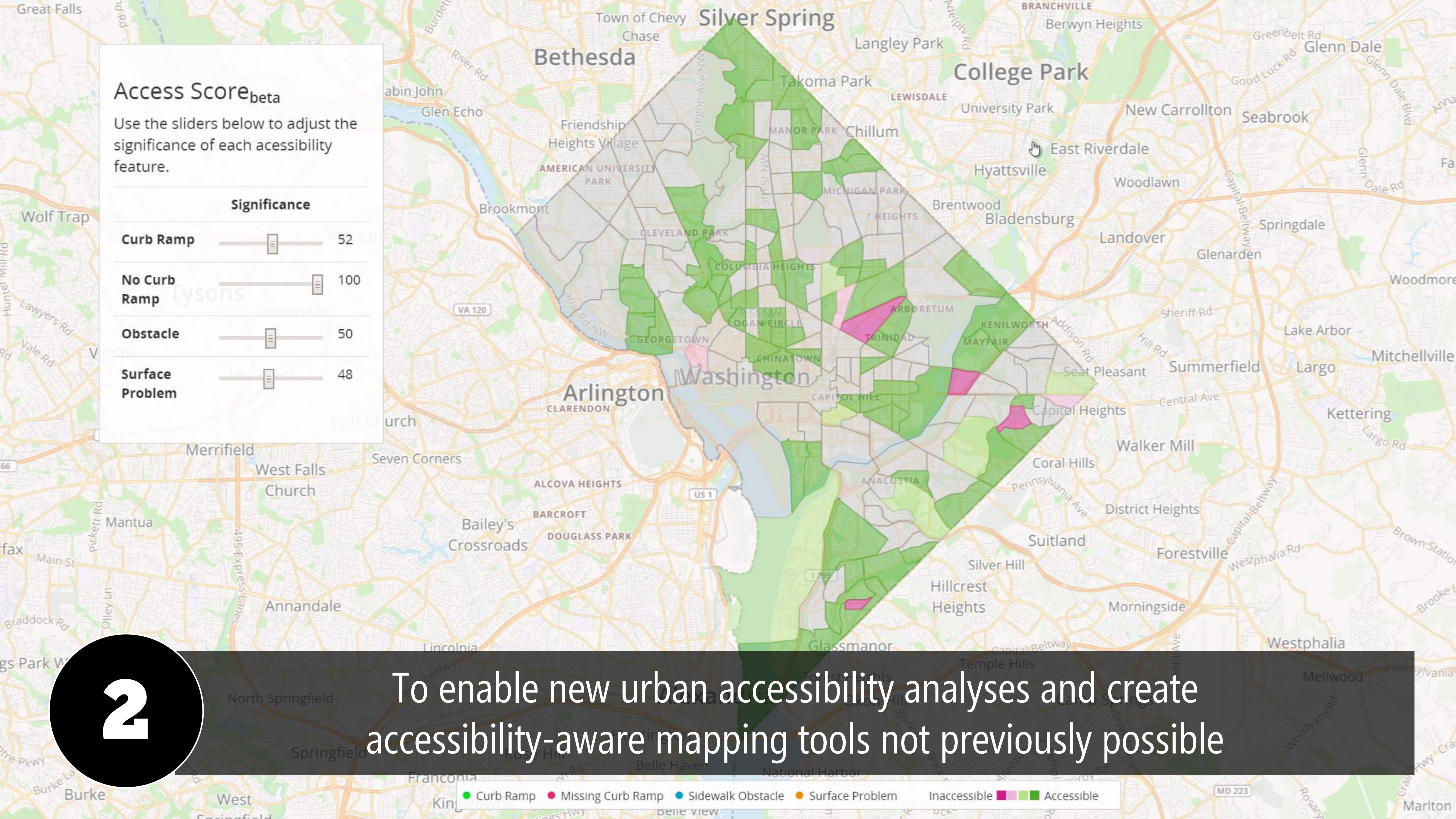
Recent survey by Ding *et al.*, 2014 found that only 1.6% of Wheelmap POIs had data about accessibility

Focus is on *places* rather than *sidewalk infrastructure*

We are pursuing a complementary **two-fold approach**

1

To develop scalable methods that mine massive repositories of online map imagery to identify accessibility problems semi-automatically

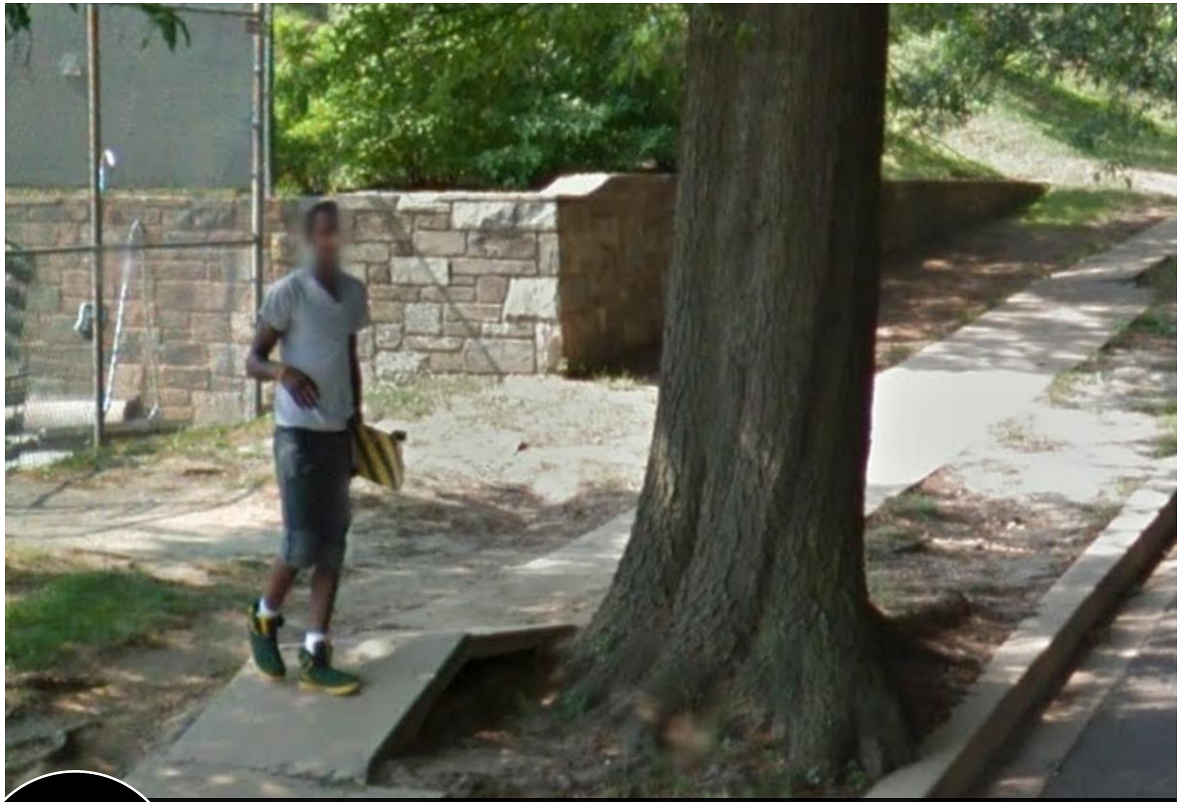


2

To enable new urban accessibility analyses and create accessibility-aware mapping tools not previously possible

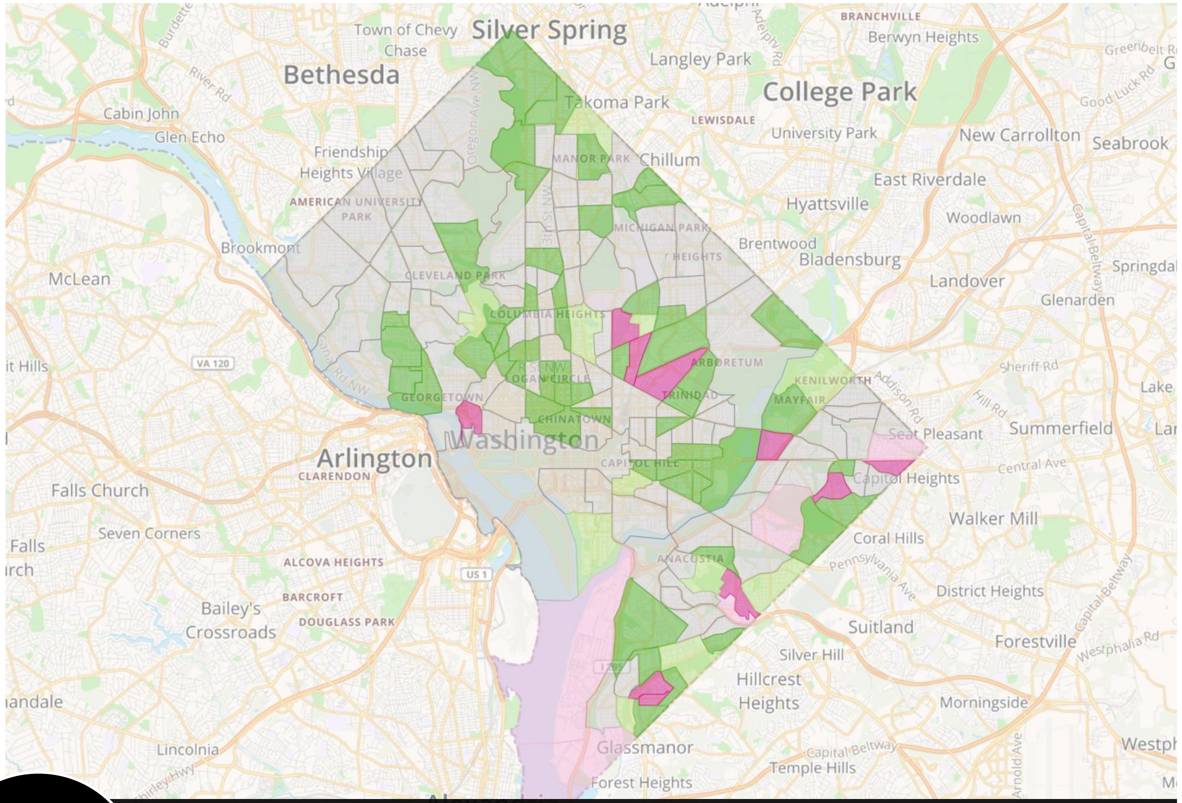
MAPPING THE ACCESSIBILITY OF THE WORLD

TWO FOCUS AREAS



1 SCALABLE DATA COLLECTION METHODS

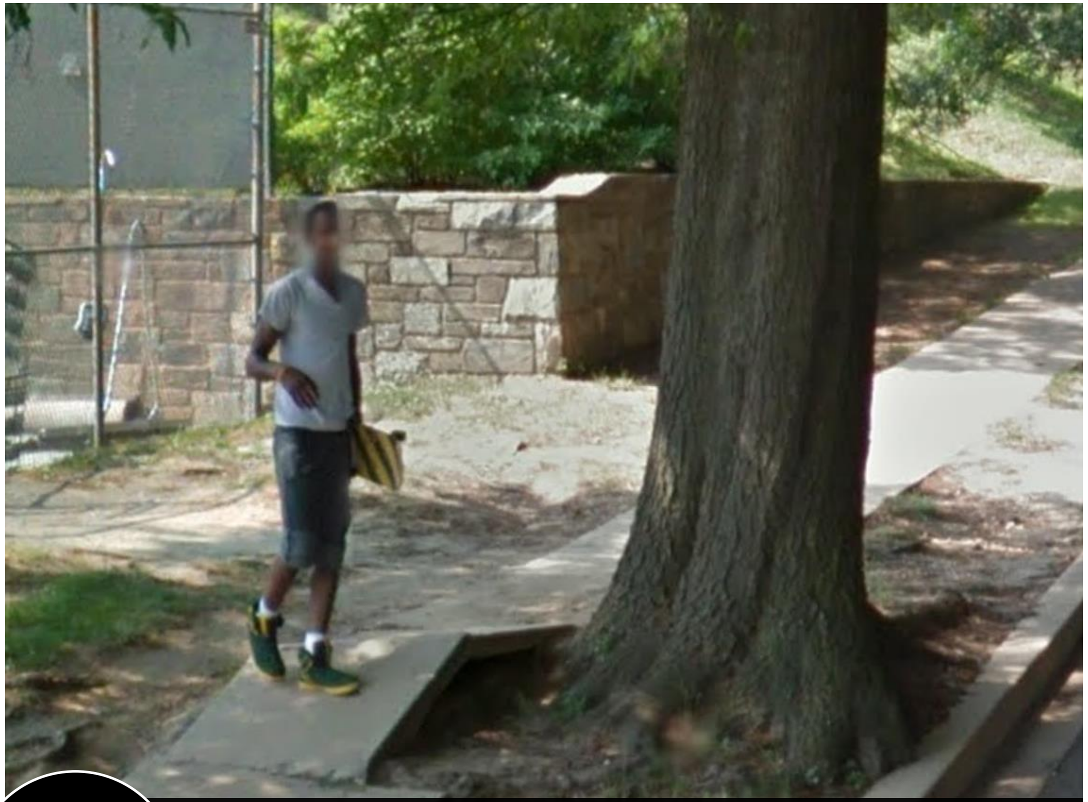
[ASSETS'12, CHI'13, HCOMP'13, ASSETS'13, UIST'14, TACCESS'15, ASSETS'17, ASSETS'18]



2 NEW URBAN ACCESS ANALYTICS & TOOLS

[SIGACCESS '15, CHI'16, ASSETS'18]

KEY RESEARCH QUESTIONS



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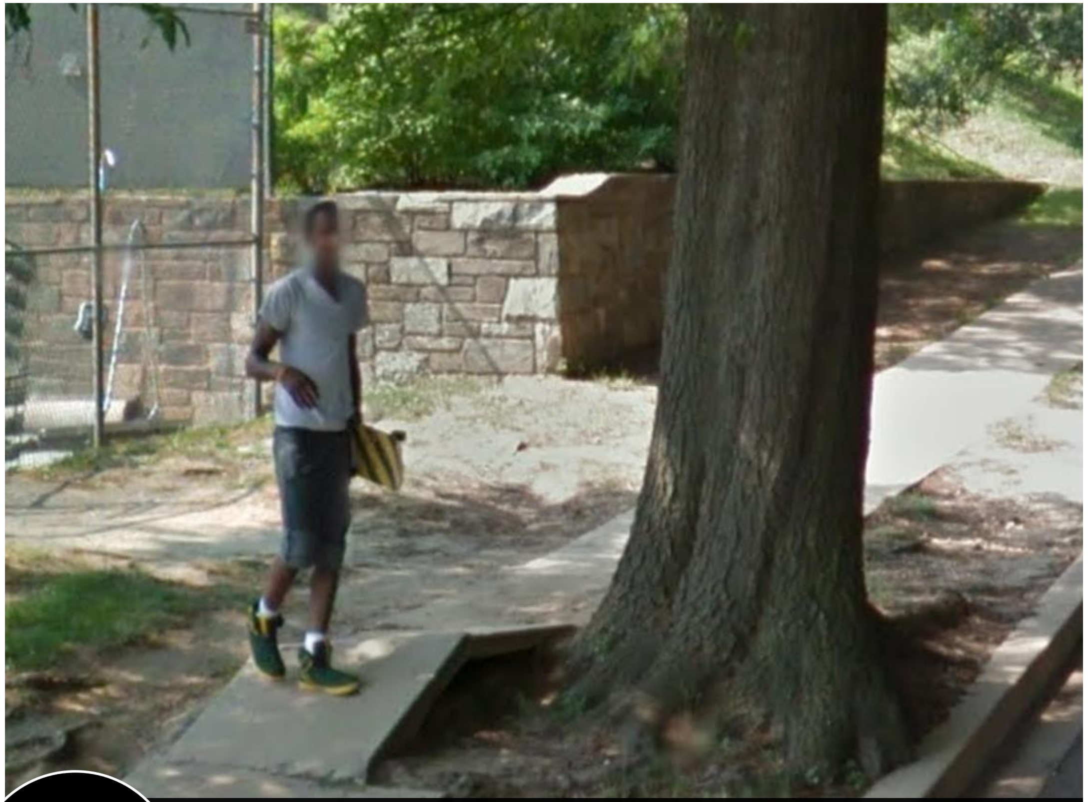
[ASSETS'12, CHI'13, HCOMP'13, ASSETS'13, UIST'14, TACCESS'15, ASSETS'17, ASSSETS'18]

Is **online map imagery** a good source for accessibility data?

Can we **create interactive tools** that enable crowd workers to find accessibility problems?

How can we **leverage computational techniques** to scale our approach?

KEY RESEARCH QUESTIONS



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How well do accessibility problems found in **Google Street View correspond** with the **real world**?

Can you tell **which image** comes from Google Street View and which image we took ourselves with our iPhone?


503 7th St NW
503 7th St NW
Washington, District of Columbia
Street View - Aug 2014
GOOGLE STREETVIEW
F St NW
9th St NW
8th St NW
6th St NW
E St NW
D St NW
Back to Map

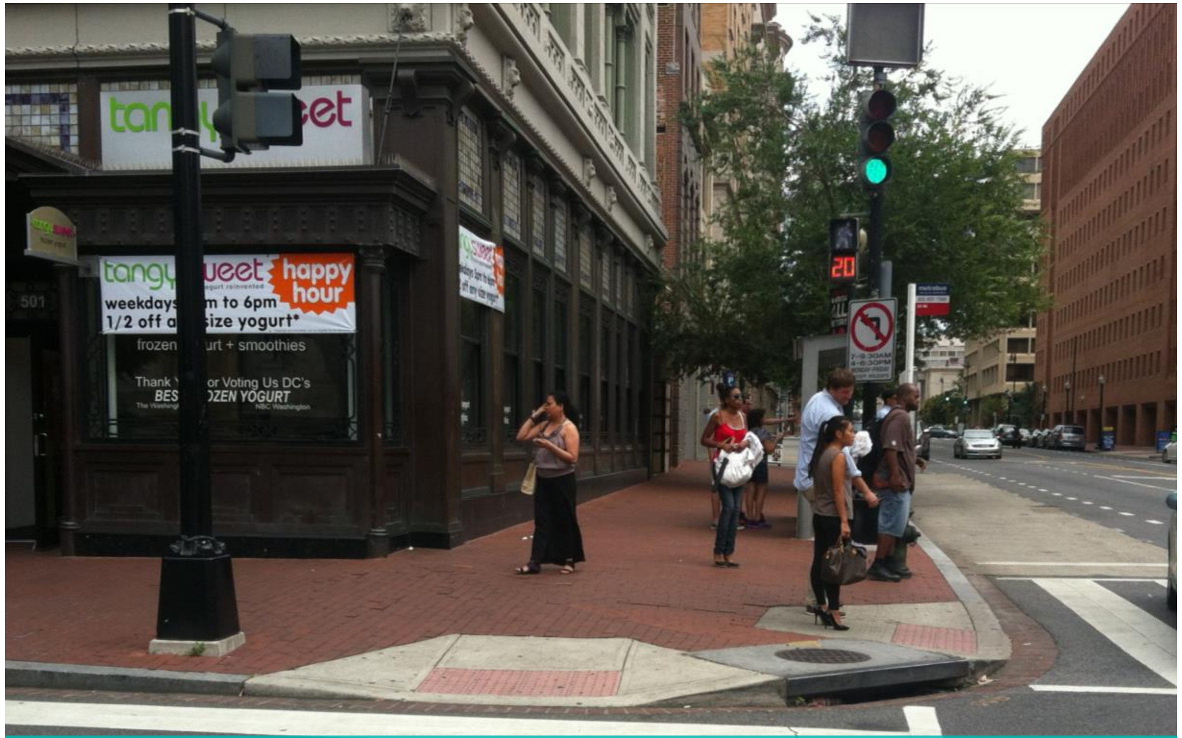

REAL WORLD
happy hour

IS GOOGLE STREET VIEW A REASONABLE DATASET FOR ACCESSIBILITY AUDITS?

PHYSICAL AUDITS VS. GSV: SURVEYED 76KM

179 BUS STOPS

Washington DC & Seattle | 42 km surveyed



273 INTERSECTIONS

Washington DC & Baltimore | 34 km surveyed

IS GOOGLE STREET VIEW A REASONABLE DATASET FOR ACCESSIBILITY AUDITS?

COMPARISON RESULTS: SPEARMAN RANK COEFFICIENTS

BUS STOPS

PHYSICAL AUDIT DATA

vs.

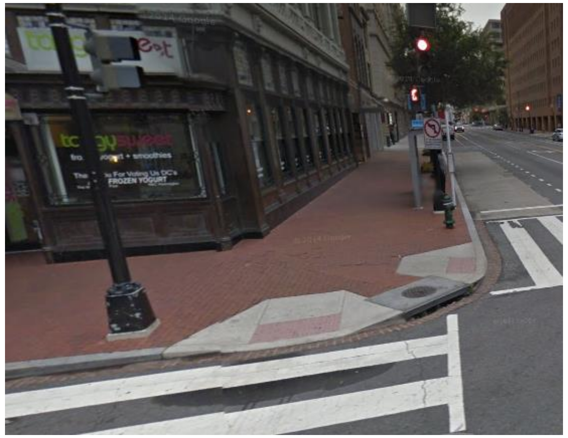
GSV AUDIT DATA

$$\rho = \mathbf{0.88}$$

INTERSECTIONS

PHYSICAL AUDIT DATA

vs.



GSV AUDIT DATA

$$\rho = \mathbf{0.98}$$

All results statistically significant at $p < 0.001$

CONSISTENT WITH FINDINGS IN URBAN STUDIES & PUBLIC HEALTH LITERATURE

JOURNAL OF CHILD PSYCHOLOGY AND PSYCHIATRY
ACAMH
Journal of Child Psychology and Psychiatry 53:10 (2012), pp 1009–1017 doi:10.1111/j.1469-7610.2012.02565.x

Systematic social observation of children's neighborhoods using Google Street View: a reliable and cost-effective method

Candice L. Odgers,[1] Avshalom Caspi,[2,3] Christopher J. Bates,[4] Robert J. Sampson,[5] and Terrie E. Moffitt[2,3]

[1]Center for Child and Family Policy and the Sanford School of Public Policy, Duke University, Durham, NC, USA; [2]Department of Psychology and Neuroscience, and Psychiatry and Behavioral Sciences, and Institute for Genome Sciences and Policy, Duke University, Durham, NC, USA; [3]Social, Genetic, and Developmental Psychiatry Centre, Institute of Psychiatry, King's College London, UK; [4]Department of Psychology and Social Behavior, University of California, Irvine, CA, USA; [5]Department of Sociology, Harvard University, Cambridge, MA, USA

Background: Children growing up in poor versus affluent neighborhoods are more likely to spend time in prison, develop health problems and die at an early age. The question of how neighborhood conditions influence our behavior and health has attracted the attention of public health officials and scholars for generations. Online tools are now providing new opportunities to measure neighborhood features and may provide a cost effective way to advance our understanding of neighborhood effects on child health. **Method:** A virtual systematic social observation (SSO) study was conducted to test whether Google Street View could be used to reliably capture the neighborhood conditions of families participating in the Environmental-Risk (E-Risk) Longitudinal Twin Study. Multiple raters coded a subsample of 120 neighborhoods and convergent and discriminant validity was evaluated on the full sample of over 1,000 neighborhoods by linking virtual SSO measures to: (a) consumer based geo-demographic classifications of deprivation and health, (b) local resident surveys of disorder and safety, and (c) parent and teacher assessments of children's antisocial behavior, prosocial behavior, and body mass index. **Results:** High levels of observed agreement were documented for signs of physical disorder, physical decay, dangerousness and street safety. Inter-rater agreement estimates fell within the moderate to substantial range for all of the scales (ICCs ranged from .48 to .91). Negative neighborhood features, including SSO-rated disorder and decay and dangerousness corresponded with local resident reports, demonstrated a graded relationship with census-defined indices of socioeconomic status, and predicted higher levels of antisocial behavior among local children. In addition, positive neighborhood features, including SSO-rated street safety and the percentage of green space, were associated with higher prosocial behavior and healthy weight status among children. **Conclusions:** Our results support the use of Google Street View as a reliable and cost effective tool for measuring both negative and positive features of local neighborhoods. **Keywords:** Systematic social observation, Google Street View, neighborhood disorder, neighborhood deprivation, antisocial behavior, body mass index.

Introduction

Children who grow up in poor versus affluent neighborhoods are more likely to engage in antisocial behavior, experience mental health problems and become overweight (Chen & Paterson, 2006; Duncan, Brooksgunn, & Klebanov, 1994; Papas et al., 2007). A recent World Health Organization (WHO) Commission reported that individuals living in poor neighborhoods will die earlier than their peers in affluent settings and will spend more of their life – approximately 17 years – suffering from a disability (CSDH, 2008). The Commission concluded that these types of social inequalities are 'killing people on a grand scale' (p. 26) and cautioned that the social environment can have far reaching effects on health even within the most affluent countries. For example, comparisons between socio-demographic and geographically clustered subgroups in the United States reveal average life expectancies ranging from the highest on record to those typically observed in developing countries (Murray et al., 2006). Similarly, a more than twofold difference in mortality rates has been documented between individuals living in the most versus least deprived neighborhoods in the United Kingdom (Romeri, Baker, & Griffiths, 2006).

The robust relationships between social inequalities and health across the social gradient serves as a constant reminder of the need to understand how the settings where we live, work and play affect our health (Marmot, et al., 2008). Exposure to adverse social conditions are believed to have strong effects in childhood and there are now urgent calls for research that integrates assessments spanning from 'neurons-to-neighborhoods' (Shonkoff & Phillips, 2000). Unfortunately, most studies are not

Conflict of interest statement:
The authors declare no conflicts of interest. Candice L. Odgers had full access to all the data and takes responsibility for the integrity of the data and the accuracy of the data analysis.

ann. behav. med. (2013) 45 (Suppl 1):S108–S112
DOI 10.1007/s12160-012-9419-9

BRIEF REPORT

Using Google Street View to Audit the Built Environment: Inter-rater Reliability Results

Cheryl M. Kelly, PhD · Jeffrey S. Wilson, PhD · Elizabeth A. Baker, PhD, MPH · Douglas K. Miller, MD · Mario Schootman, PhD

Published online: 2 October 2012

Abstract
Background Observational field audits are recommended for public health research to collect data on built environment characteristics. A reliable, standardized alternative to field audits that uses publicly available information could provide the ability to efficiently compare results across different study sites and time.
Purpose This study aimed to assess inter-rater reliability of built environment audits conducted using Google Street View imagery.
Methods In 2011, street segments from St. Louis and Indianapolis were geographically stratified to ensure representation of neighborhoods with different land use and socioeconomic characteristics in both cities. Inter-rater reliability was assessed using observed agreement and the prevalence-adjusted bias-adjusted kappa statistic (PABAK).
Results The mean PABAK for all items was 0.84. Ninety-five percent of the items had substantial (PABAK≥0.60) or nearly perfect (PABAK≥0.80) agreement.
Conclusions Using Google Street View imagery to audit the built environment is a reliable method for assessing characteristics of the built environment.

Keywords Physical activity · Measurement · Imagery

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4444 Forest Park Avenue, Ste 6700,
St. Louis, MO, USA

Background

Advocates of physical activity promotion have recognized that interventions must address not only individual-level factors (e.g., lack of time or motivation) but also interpersonal (e.g., social support), community or environmental (e.g., improving sidewalks), and policy (e.g., land use planning) factors [1–4]. Public health researchers and practitioners recognize that interventions at the environmental or policy level provide opportunities, support, and cues to help people engage in physical activity and have the potential to benefit the population exposed to the environment, as potential complements to more individually focused interventions [4–6].

Observational field audits are one method used in public health research to collect data on built environment characteristics that affect health-related behaviors and outcomes, including physical activity [7]. However, field audits are time and resource intensive because they require auditors to travel to each location that must be observed. This limits practicality of implementing field audits across large or geographically dispersed areas (e.g., local, regional, national, or international study

Assessing the Built Environment Using Omnidirectional Imagery

Jeffrey S. Wilson, PhD, Cheryl M. Kelly, PhD, Mario Schootman, PhD, Elizabeth A. Baker, PhD, Aniruddha Banerjee, PhD, Morgan Clennin, MPH, Douglas K. Miller, MD

This activity is available for CME credit. See page A4 for information.

Observational audits commonly are used in public health research to collect data on built environment characteristics that affect health-related behaviors and outcomes, including physical activity and weight status. However, implementing in-person field audits can be expensive if observations are needed over large or geographically dispersed areas or at multiple points in time. A reliable and more efficient method for observational audits could facilitate extendibility (i.e., expanded geographic and temporal scope) and lead to more standardized assessment that strengthens the ability to compare results across different regions and studies. The purpose of the current study was to evaluate the degree of agreement between field audits and audits derived from interpretation of three types of omnidirectional imagery.

Street segments from St. Louis MO and Indianapolis IN were stratified geographically to ensure representation of neighborhoods with different socioeconomic characteristics in both cities. Audits were conducted in 2008 and 2009 using four methods: field audits, and interpretation of archived imagery, new imagery, and Google Street View™ imagery. Agreement between field audits and image-based audits was assessed using observed agreement and the prevalence-adjusted bias-adjusted kappa statistic (PABAK). Data analysis was conducted in 2010. When measuring the agreement between field audits and audits from the different sources of imagery, the mean PABAK statistic for all items on the instrument was 0.78 (archived); 0.80 (new); and 0.81 (Street View imagery), indicating substantial to nearly perfect agreement among methods. It was determined that image-based audits represent a reliable method that can be used in place of field audits to measure several key characteristics of the built environment important to public health research.
(Am J Prev Med 2012;42(2):193–199) © 2012 American Journal of Preventive Medicine

Introduction

Physical inactivity is a leading contributor to the rise of the prevalence of overweight and obesity.[1] Although physical activity is influenced by individual and interpersonal factors, researchers increasingly are examining built environment characteristics as potential determinants of physical activity behavior. For example, a 2008 review[2] suggests that mixed land use, shorter distances to nonresidential destinations, and development density are consistent correlates of utilitarian walking among adults. Researchers[3,4] also have reported associations between children's participation in physical activity and recreational and pedestrian infrastructure. Accumulating evidence[5–7] for built environment effects on physical activity has prompted advocacy for environmental interventions to increase physical activity in communities as a way to counteract the overweight and obesity epidemic.

Despite the emerging evidence base, there are currently several limitations to conducting studies of built environment effects on physical activity. A 2009 review[8] of methods for measuring the built environment identified three general approaches: (1) perceived measures obtained by surveys (e.g., of community residents); (2) extracting objective measures from archival data sets (e.g., census-based GIS data); and (3) systematic observational audits by trained observers. Each of these methods provides different but complementary insight into the built environment. However, studies examining detailed observational characteristics of the built environment from the human perspective currently face several challenges.

When comparing perceived versus objective measures of built environment, fair to low levels of agreement between resident perceptions of environmental supports for physical activity and objective measures of these features have been reported.[9] Perceptions are susceptible

From the Department of Geography (Wilson, Banerjee), Indiana University–Purdue University, the Regenstrief Institute, Inc., and Center for Aging Research (Miller), Indiana University, Indianapolis, Indiana; Beth-El College of Nursing and Health Sciences, University of Colorado, Colorado Springs, Colorado (Kelly); the School of Public Health (Baker, Clennin), Saint Louis University, and the School of Medicine (Schootman), Washington University, St. Louis, Missouri

Cheryl Kelly was with the School of Public Health at St. Louis University when this research was conducted.

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0749-3797/$36.00
doi: 10.1016/j.amepre.2011.09.029

See: Odgers *et al.*, 2012; Wilson *et al.*, 2013; Kelly *et al.*, 2013; Bader, *et al.*, 2017

IS GOOGLE STREET VIEW A REASONABLE DATASET FOR ACCESSIBILITY AUDITS?

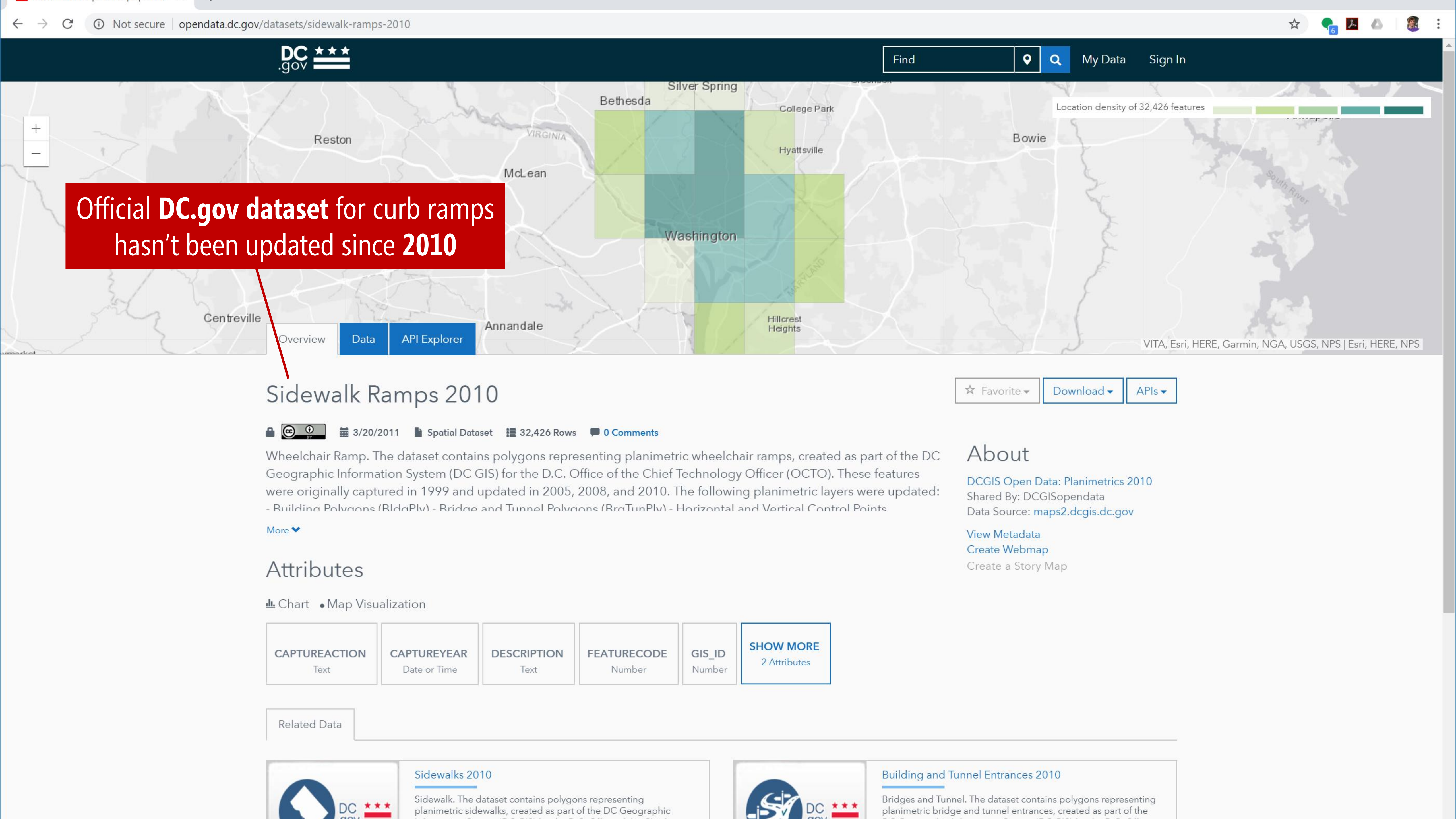
CITY INFRASTRUCTURE CHANGES SLOWLY

AVG IMAGE AGE IN BUS STOP DATASET

1.7 yrs (SD=0.7)

AVG IMAGE AGE IN INTERSECTION DATASET

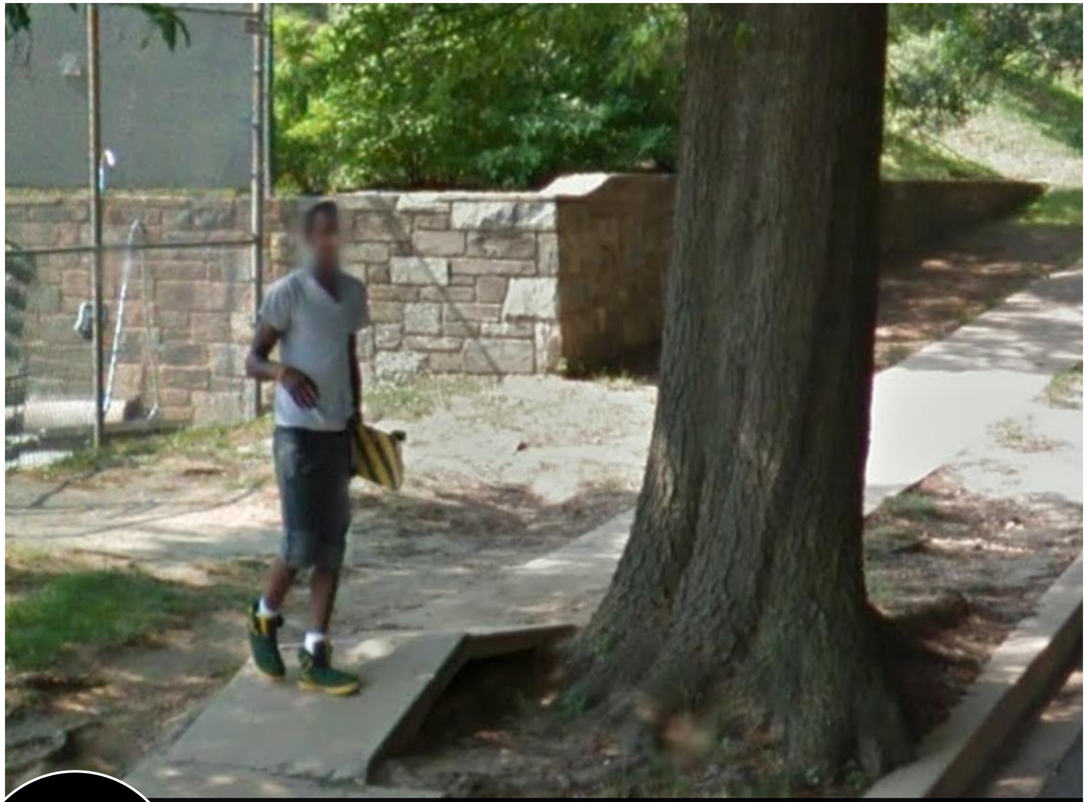
1.5 yrs (SD=0.7)



Not secure
opendata.dc.gov/datasets/sidewalk-ramps-2010
DC .gov
Find
My Data
Sign In
Silver Spring
Bethesda
College Park
Location density of 32,426 features
Reston
VIRGINIA
Hyattsville
Bowie
McLean
Official **DC.gov dataset** for curb ramps hasn't been updated since **2010**
Washington
Centreville
Annandale
Hillcrest Heights
Overview
Data
API Explorer
VITA, Esri, HERE, Garmin, NGA, USGS, NPS | Esri, HERE, NPS
Sidewalk Ramps 2010
Favorite
Download
APIs
3/20/2011
Spatial Dataset
32,426 Rows
0 Comments
Wheelchair Ramp. The dataset contains polygons representing planimetric wheelchair ramps, created as part of the DC Geographic Information System (DC GIS) for the D.C. Office of the Chief Technology Officer (OCTO). These features were originally captured in 1999 and updated in 2005, 2008, and 2010. The following planimetric layers were updated:
More
About
DCGIS Open Data: Planimetrics 2010
Shared By: DCGISopendata
Data Source: maps2.dcgis.dc.gov
View Metadata
Create Webmap
Create a Story Map
Attributes
Chart
Map Visualization
CAPTUREACTION
Text
CAPTUREYEAR
Date or Time
DESCRIPTION
Text
FEATURECODE
Number
GIS_ID
Number
SHOW MORE
2 Attributes
Related Data
Sidewalks 2010
Sidewalk. The dataset contains polygons representing planimetric sidewalks, created as part of the DC Geographic
Building and Tunnel Entrances 2010
Bridges and Tunnel. The dataset contains polygons representing planimetric bridge and tunnel entrances, created as part of the

Google Street View is a reasonable proxy for studying the state of street-level accessibility

KEY RESEARCH QUESTIONS



1 SCALABLE DATA COLLECTION METHODS

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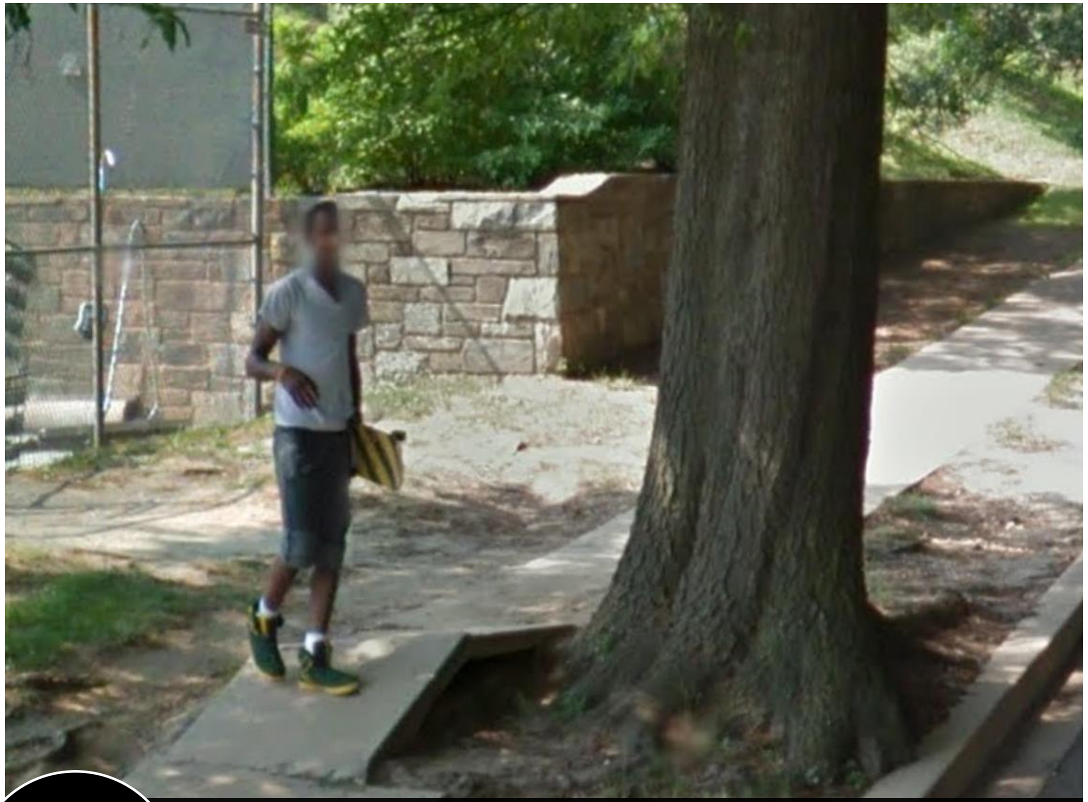

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Is **online map imagery** a good source for accessibility data?

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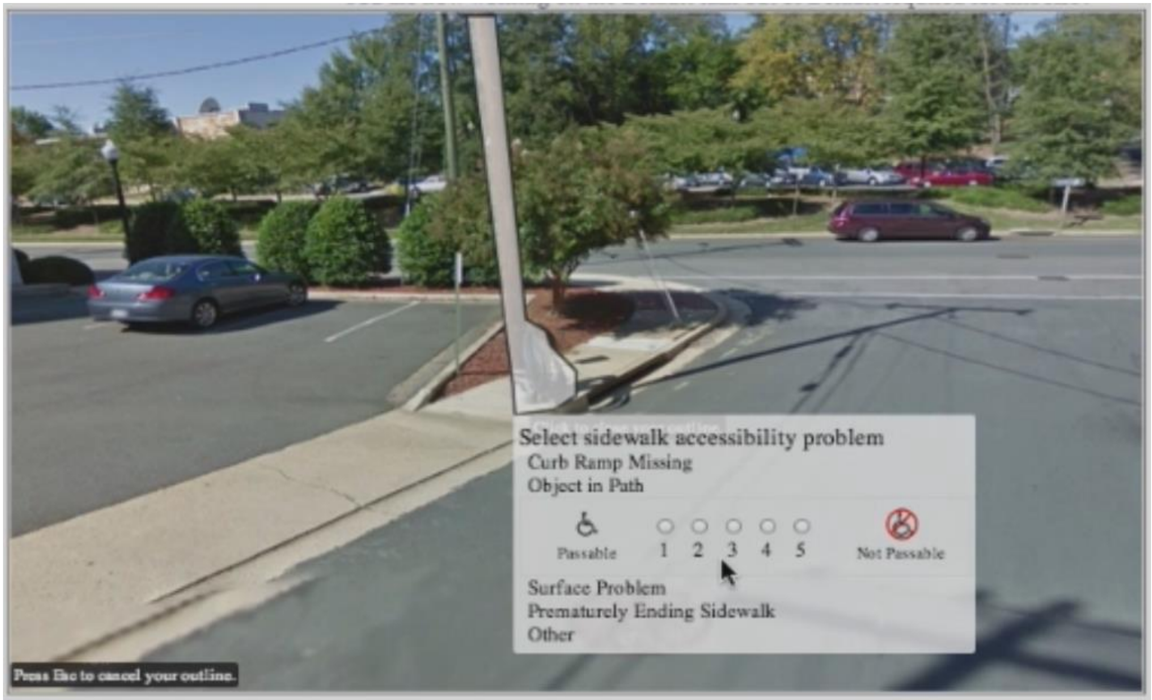
How can we **leverage computational techniques** to scale our approach?

INITIAL CROWDSOURCING SYSTEM



LABELING INTERFACE

VERIFICATION INTERFACE

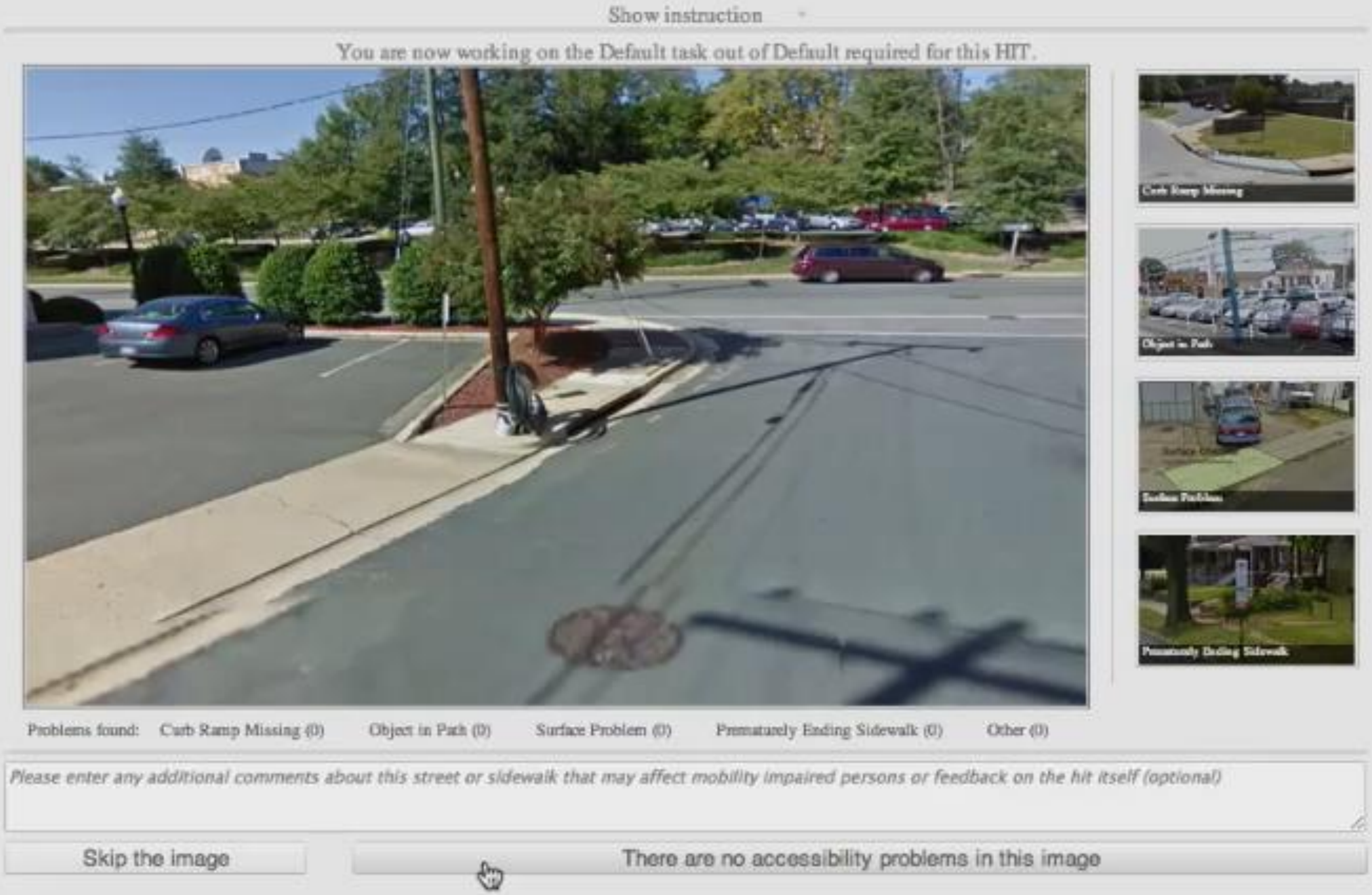
[ASSETS'12 Poster, CHI'13]

CROWDSOURCING ACCESSIBILITY AUDITS

WEB-BASED LABELING INTERFACE

4-STEP PROCESS

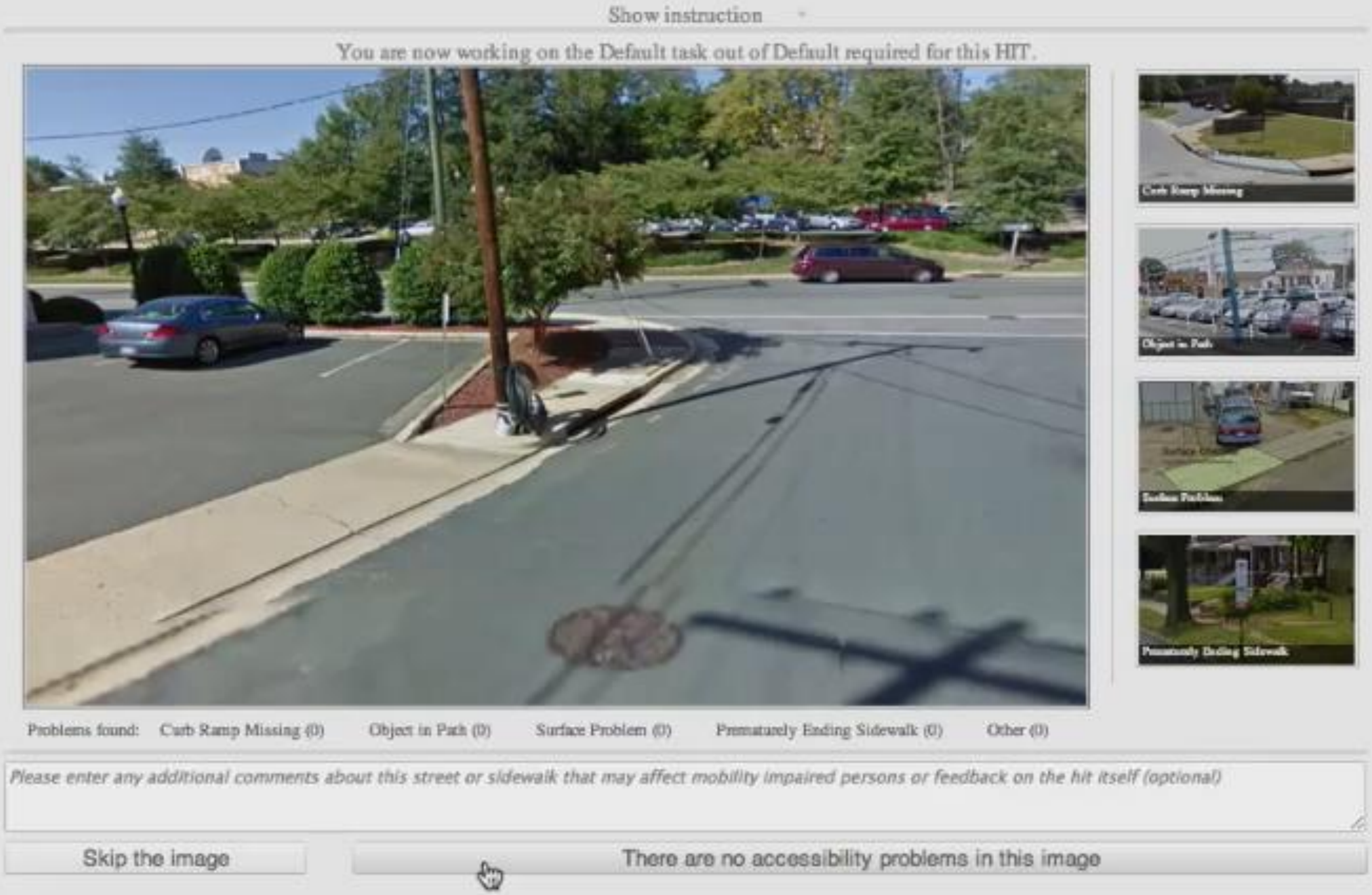
1. Find & label problem



WEB-BASED LABELING INTERFACE

4-STEP PROCESS

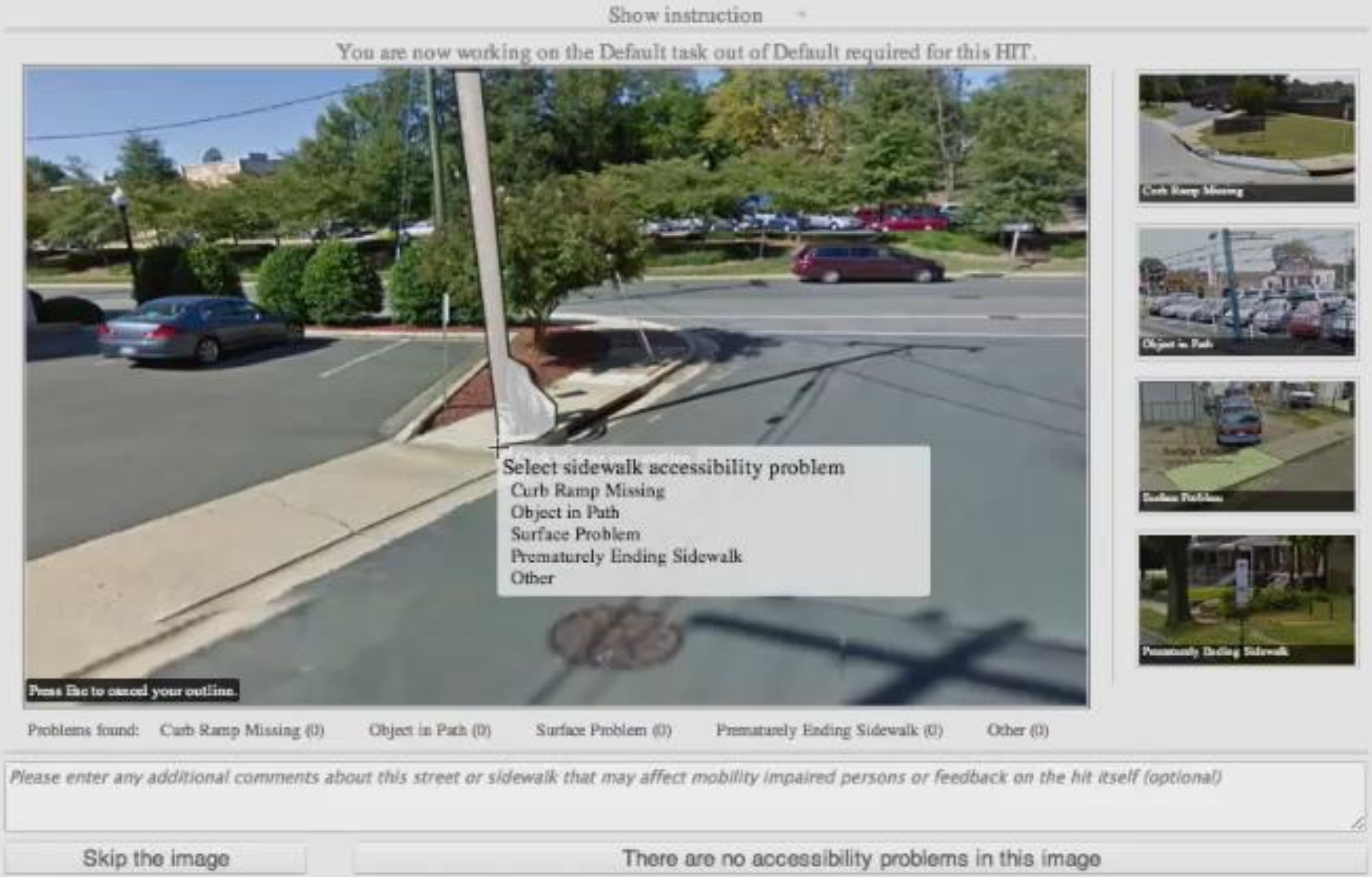
1. Find & label problem



WEB-BASED LABELING INTERFACE

4-STEP PROCESS

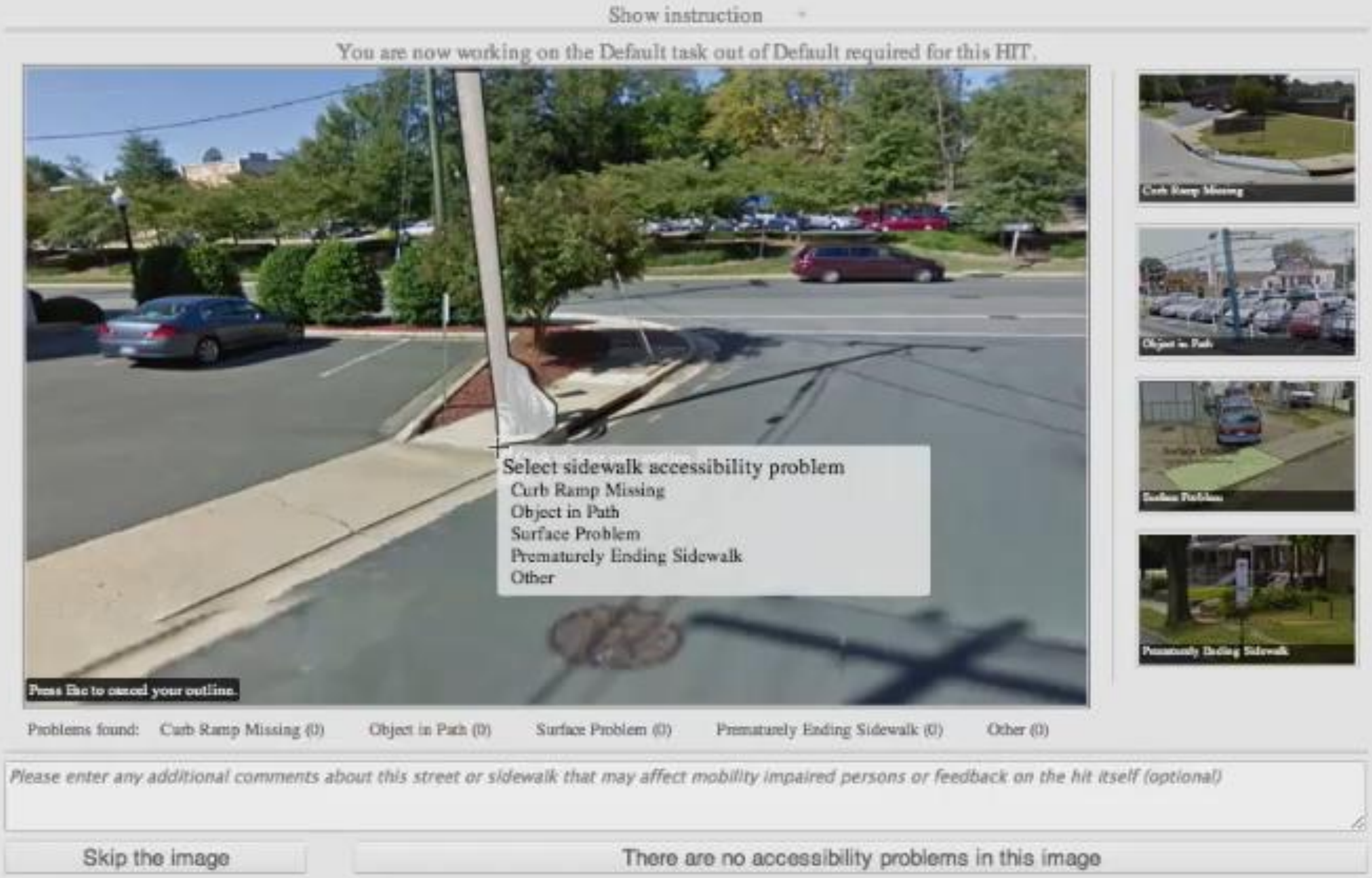
1. Find & label problem
2. Categorize problem



WEB-BASED LABELING INTERFACE

4-STEP PROCESS

1. Find & label problem
2. Categorize problem



WEB-BASED LABELING INTERFACE

4-STEP PROCESS

1. Find & label problem
2. Categorize problem
3. Rate problem severity

WEB-BASED LABELING INTERFACE

4-STEP PROCESS

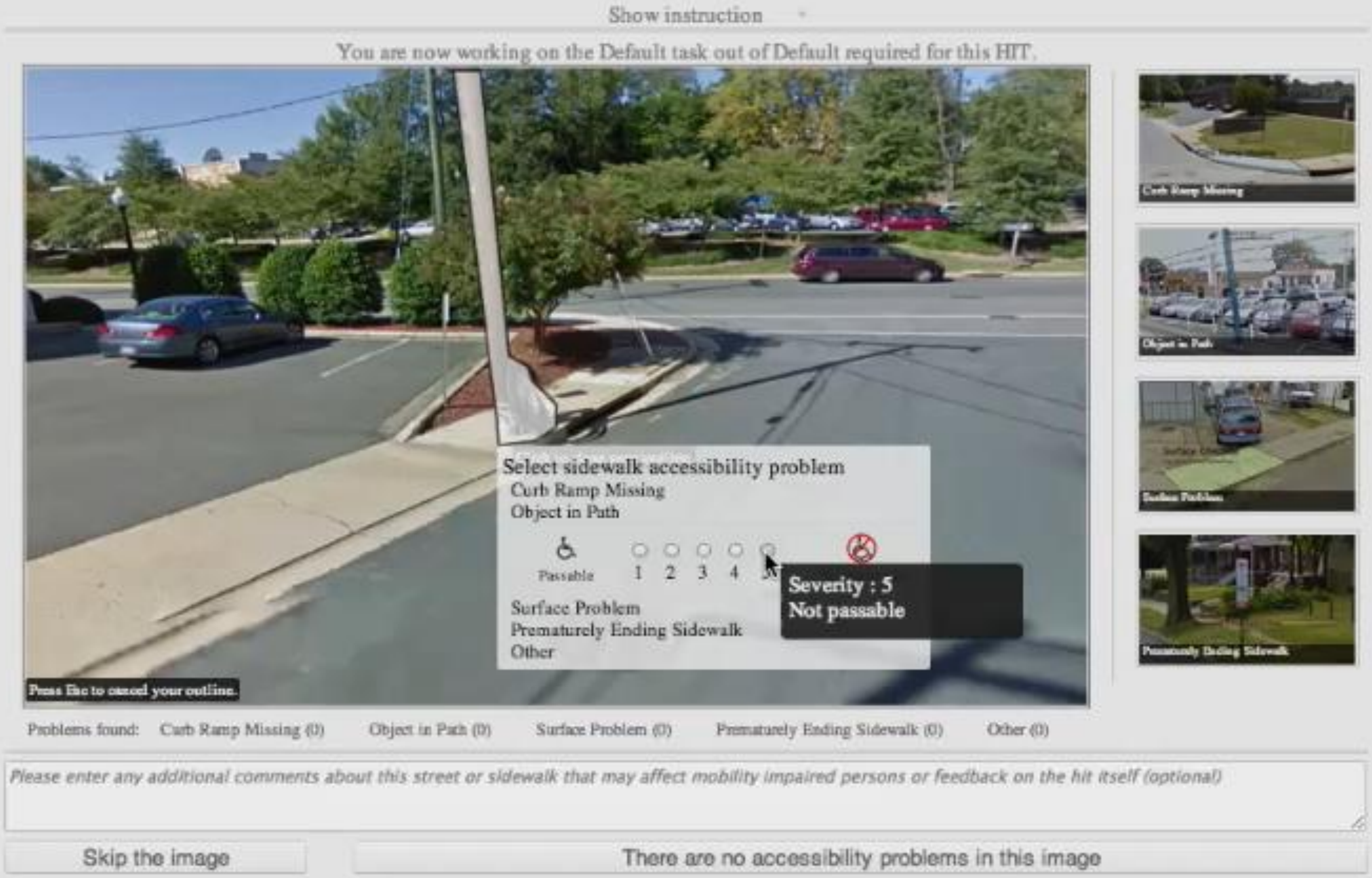
1. Find & label problem
2. Categorize problem
3. Rate problem severity

CROWDSOURCING ACCESSIBILITY AUDITS

WEB-BASED LABELING INTERFACE

4-STEP PROCESS

1. Find & label problem
2. Categorize problem
3. Rate problem severity
4. Submit work



WEB-BASED LABELING INTERFACE

4-STEP PROCESS

1. Find & label problem
2. Categorize problem
3. Rate problem severity
4. Submit work

Receive another image to label & process repeats.

WEB-BASED VERIFICATION INTERFACE

3-STEP PROCESS

1. Verify label

WEB-BASED VERIFICATION INTERFACE

3-STEP PROCESS

1. Verify label

WEB-BASED VERIFICATION INTERFACE

3-STEP PROCESS

1. Verify label
2. Verify rating

WEB-BASED VERIFICATION INTERFACE

3-STEP PROCESS

1. Verify label
2. Verify rating
3. Provide details

WEB-BASED VERIFICATION INTERFACE

3-STEP PROCESS

1. Verify label
2. Verify rating
3. Provide details

Check for false negatives

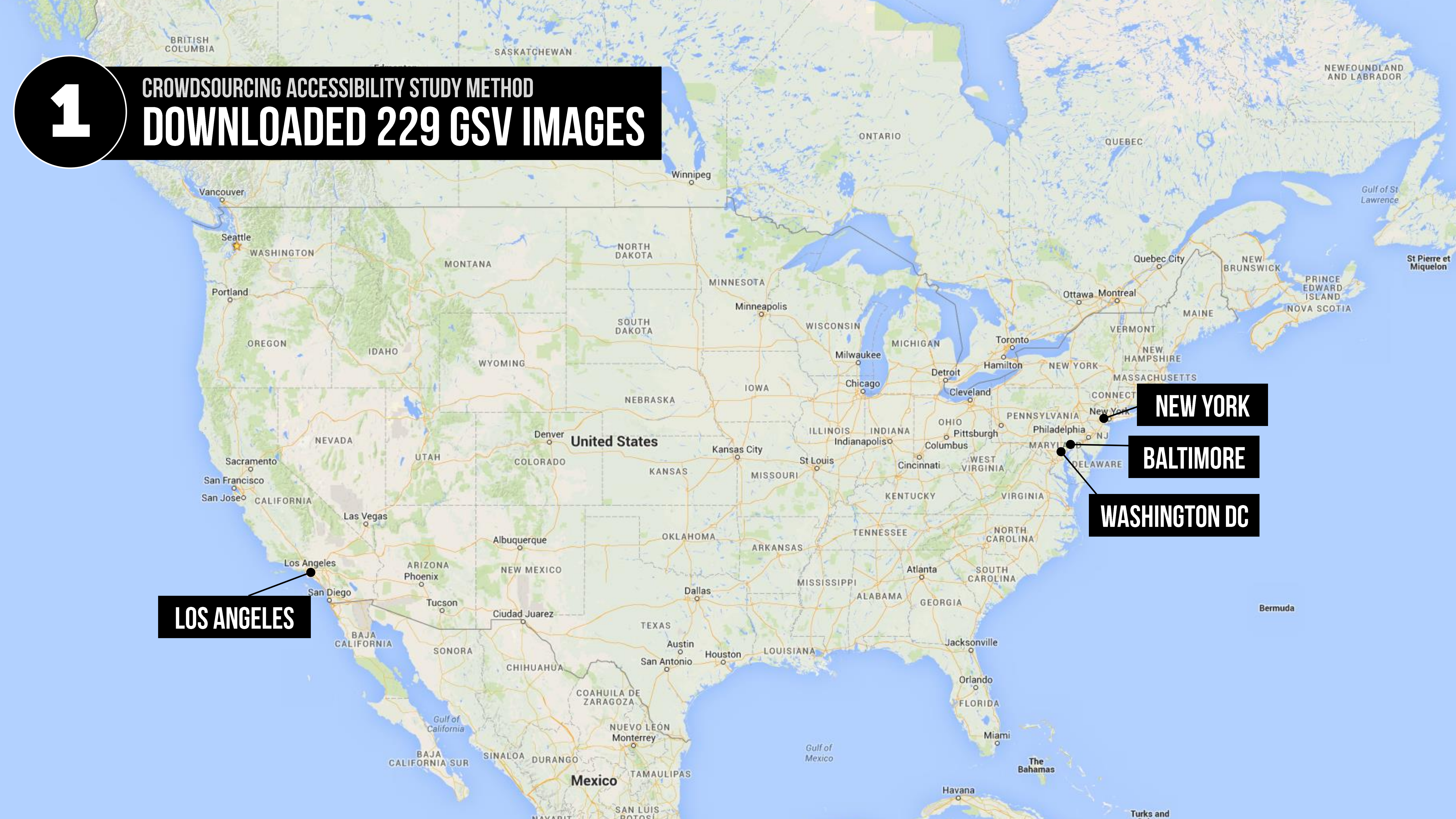
STUDY METHOD

1. Create image dataset
2. Generate ground truth labels
3. Deploy our tools to crowd
4. Compare performance to ground truth

1

CROWDSOURCING ACCESSIBILITY STUDY METHOD

DOWNLOADED 229 GSV IMAGES



50 images
Sidewalk Ending

66 images
Object in Path

67 images
Surface Problems

47 images
Missing Curb Ramps

50 images
No Problems

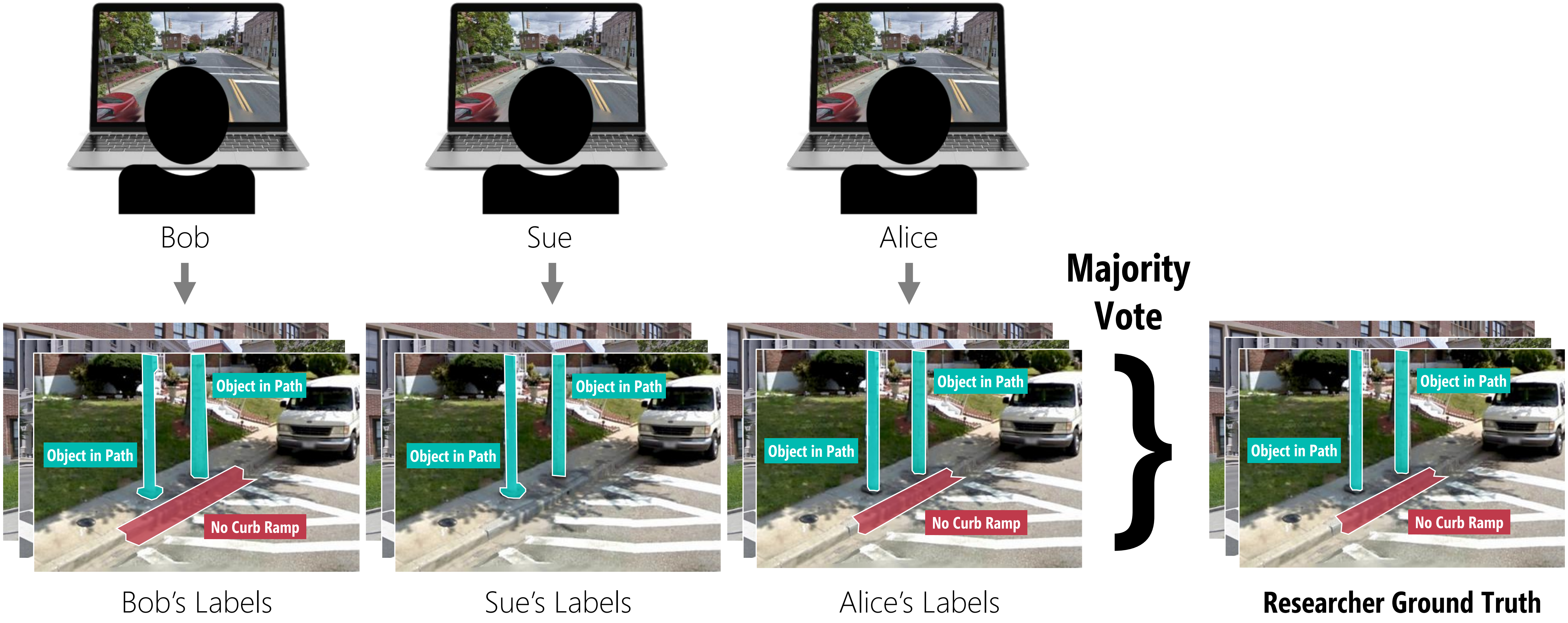
STUDY METHOD

1. Create image dataset
2. Generate ground truth labels

2

CROWDSOURCING ACCESSIBILITY STUDY METHOD

CREATE GROUND TRUTH LABELS



STUDY METHOD

1. Create image dataset
2. Generate ground truth labels
3. Deploy our tools to crowd

3

CROWDSOURCING ACCESSIBILITY STUDY METHOD

DEPLOY TOOLS TO MECHANICAL TURK

CROWDSOURCING ACCESSIBILITY STUDY RESULTS

MTURK STUDY STATISTICS

185
LABELERS

7,517
LABELS

35.2s
LABEL AN IMAGE

273
VERIFIERS

19,189
VERIFICATIONS

10.5s
VERIFY AN IMAGE

CROWDSOURCING ACCESSIBILITY STUDY RESULTS

MTURK STUDY STATISTICS

185
LABELERS

7,517
LABELS

35.2s
LABEL AN IMAGE

273
VERIFIERS

19,189
VERIFICATIONS

3x as fast!

10.5s
VERIFY AN IMAGE

STUDY METHOD

1. Create image dataset
2. Generate ground truth labels
3. Deploy our tools to crowd
4. Compare performance to ground truth

Are crowd workers capable of **finding accessibility problems** in online map imagery?

CROWDSOURCING ACCESSIBILITY STUDY RESULTS

OVERALL LABELING ACCURACY

With one labeler per image

OVERALL LABELING ACCURACY

With one labeler per image

SIDEWALK ENDING

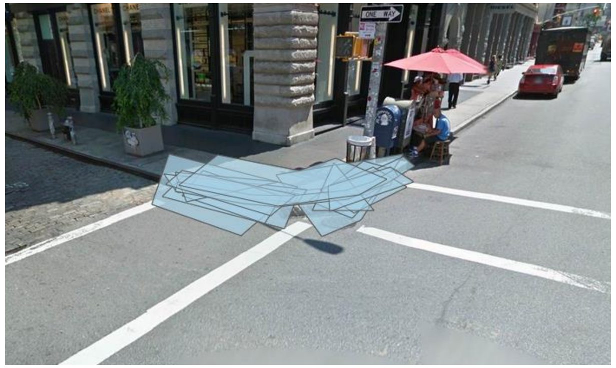
85%

OVERALL LABELING ACCURACY

With one labeler per image

SIDEWALK ENDING

85%



MISSING CURB RAMPS

79%

SURFACE PROBLEM

77%

OBJECT IN PATH

73%

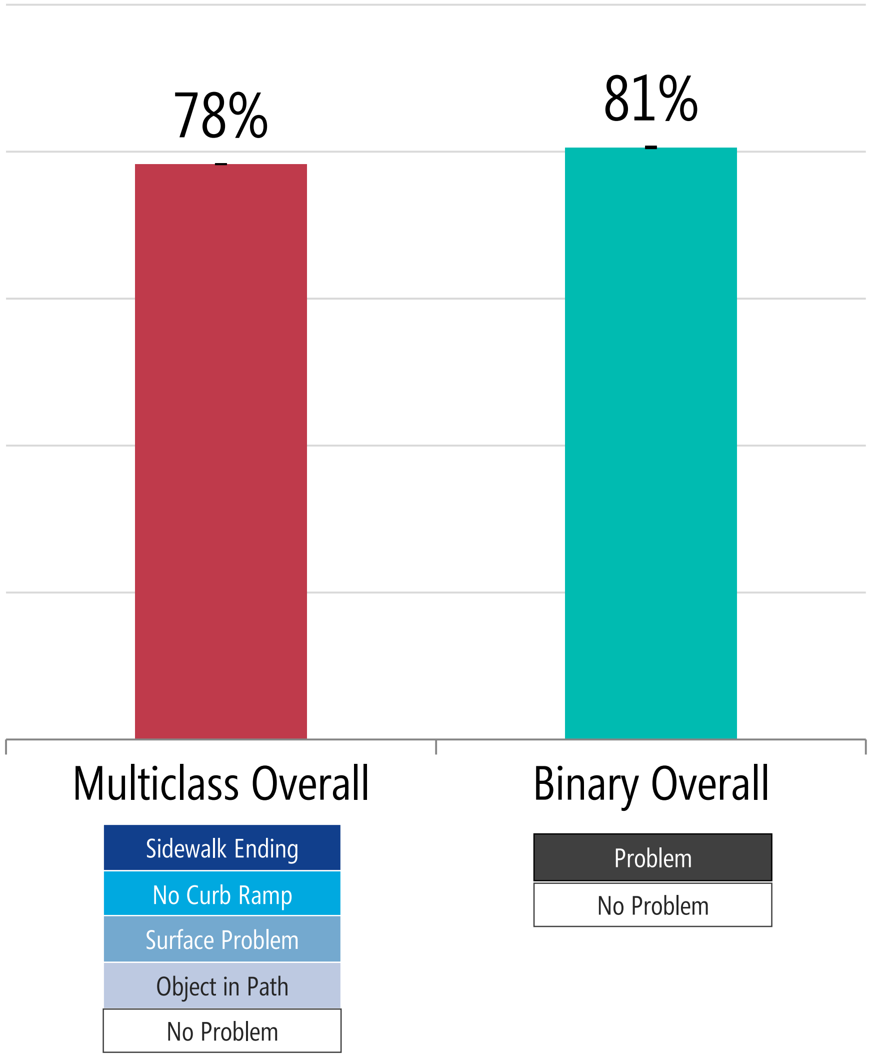
CROWDSOURCING ACCESSIBILITY STUDY RESULTS

OVERALL LABELING ACCURACY

With one labeler per image

SIDEWALK ENDING	MISSING CURB RAMPS	SURFACE PROBLEM	OBJECT IN PATH
85%	**79%**	**77%**	**73%**

AVERAGE OVERALL ACCURACY



COMMON LABELER MISTAKES

CROWDSOURCING ACCESSIBILITY STUDY RESULTS

COMMON LABELER MISTAKES

OVER LABELING

(*i.e.,* tendency towards false positives)

COMMON LABELER MISTAKES

OVER LABELING

(*i.e.,* tendency towards false positives)

RANDOM LABELS

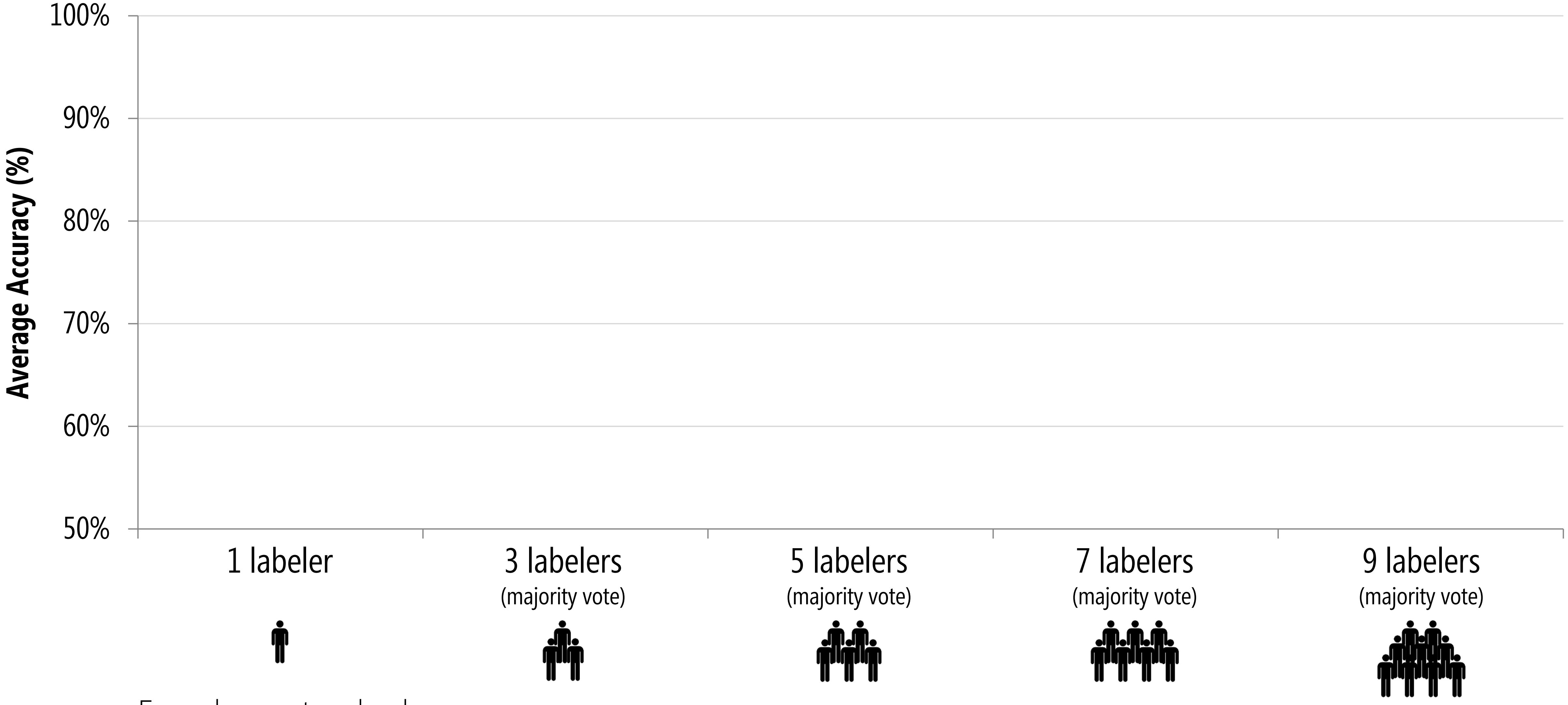
(*e.g.,* misunderstanding, malevolence)

CATEGORY ERRORS

(*i.e.,* ambiguous problem category)

CROWDSOURCING ACCESSIBILITY STUDY RESULTS

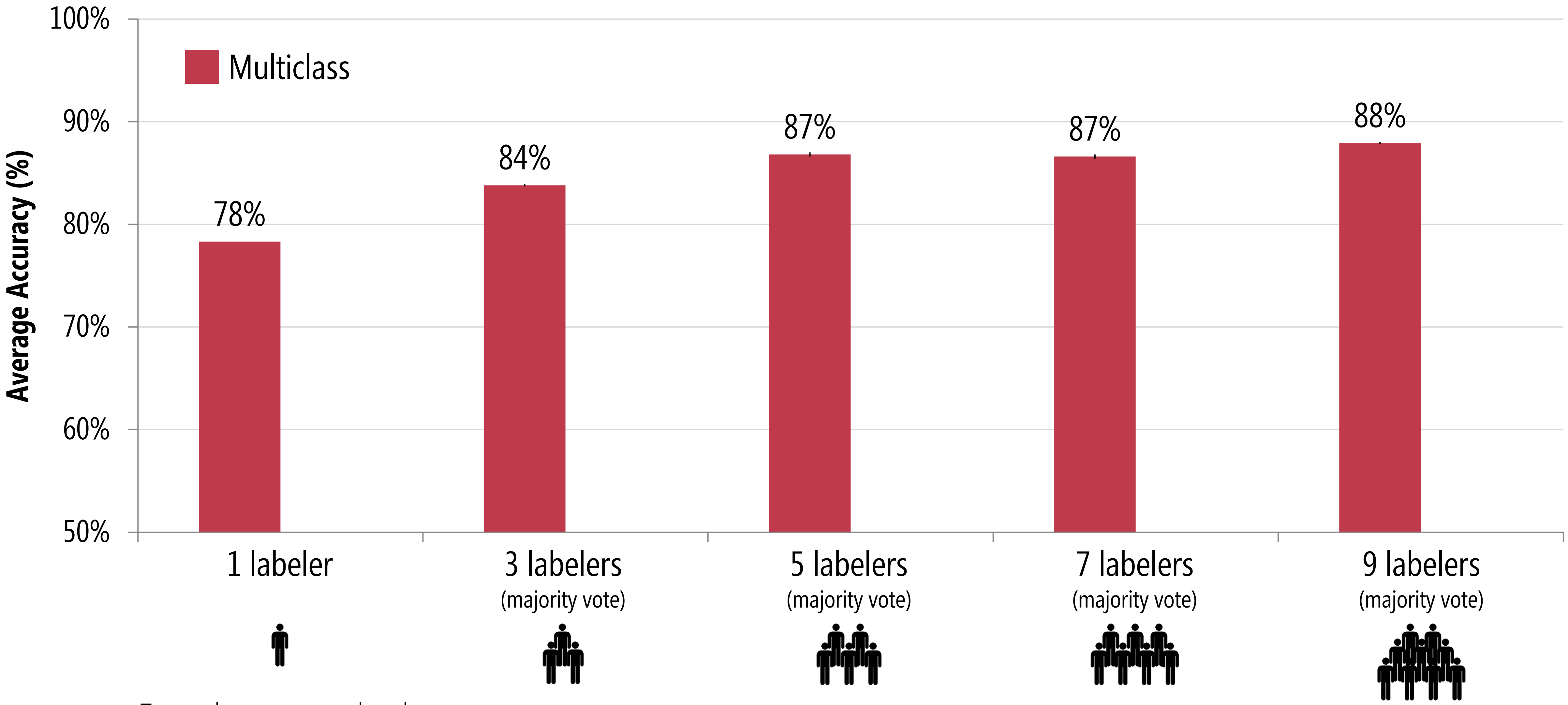
ACCURACY AS A FUNCTION OF LABELERS PER IMAGE



Error bars: standard error

CROWDSOURCING ACCESSIBILITY STUDY RESULTS

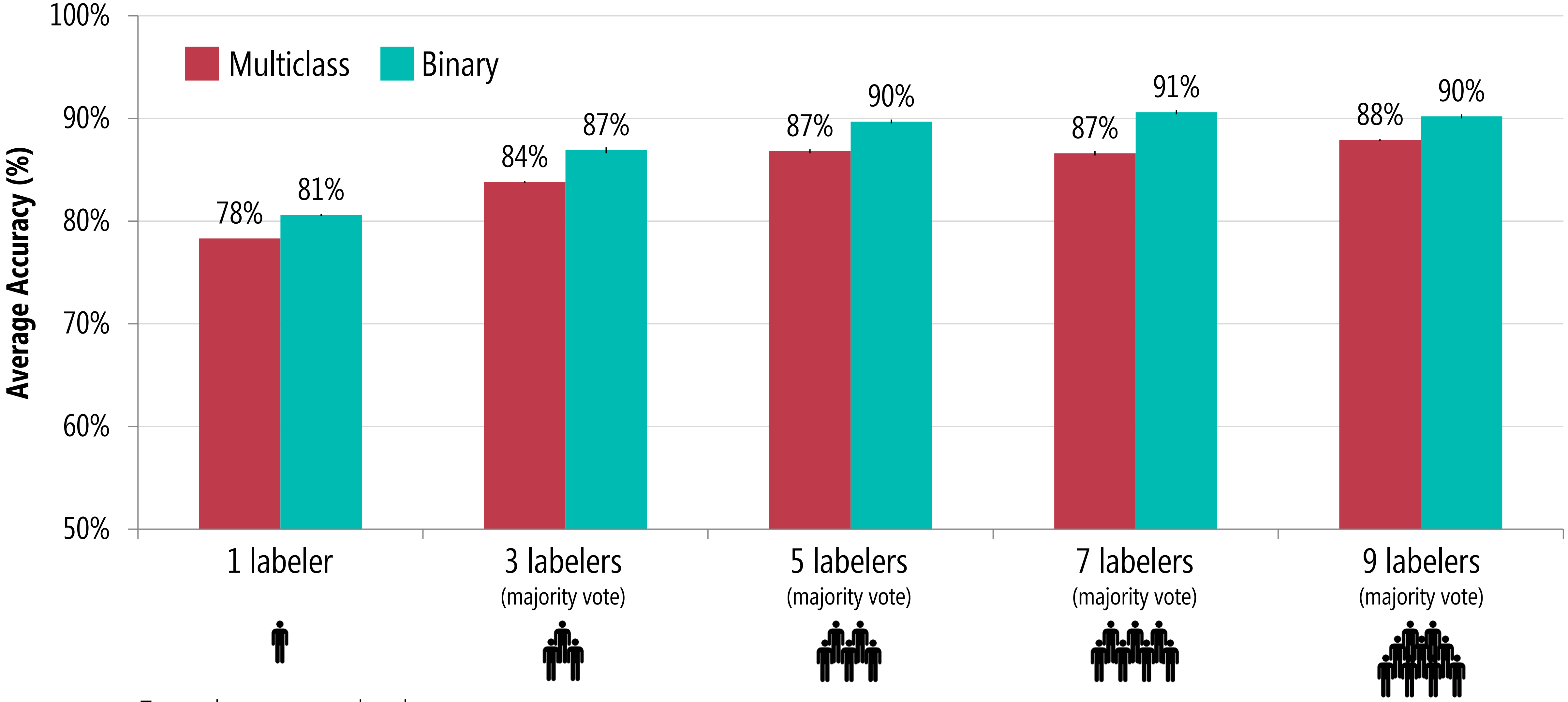
ACCURACY AS A FUNCTION OF LABELERS PER IMAGE



Error bars: standard error

CROWDSOURCING ACCESSIBILITY STUDY RESULTS

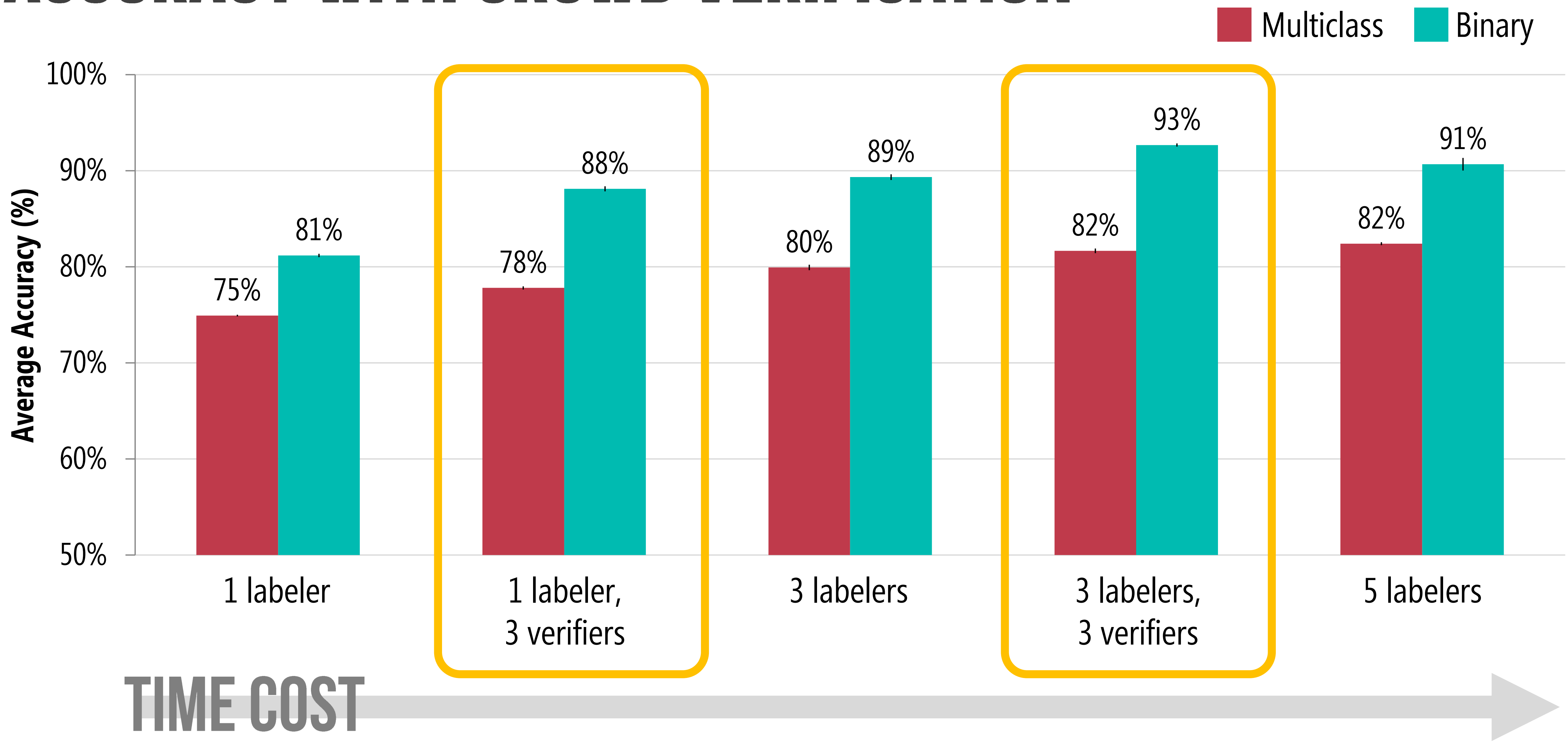
ACCURACY AS A FUNCTION OF LABELERS PER IMAGE



Error bars: standard error

CROWDSOURCING ACCESSIBILITY STUDY RESULTS

ACCURACY WITH CROWD VERIFICATION

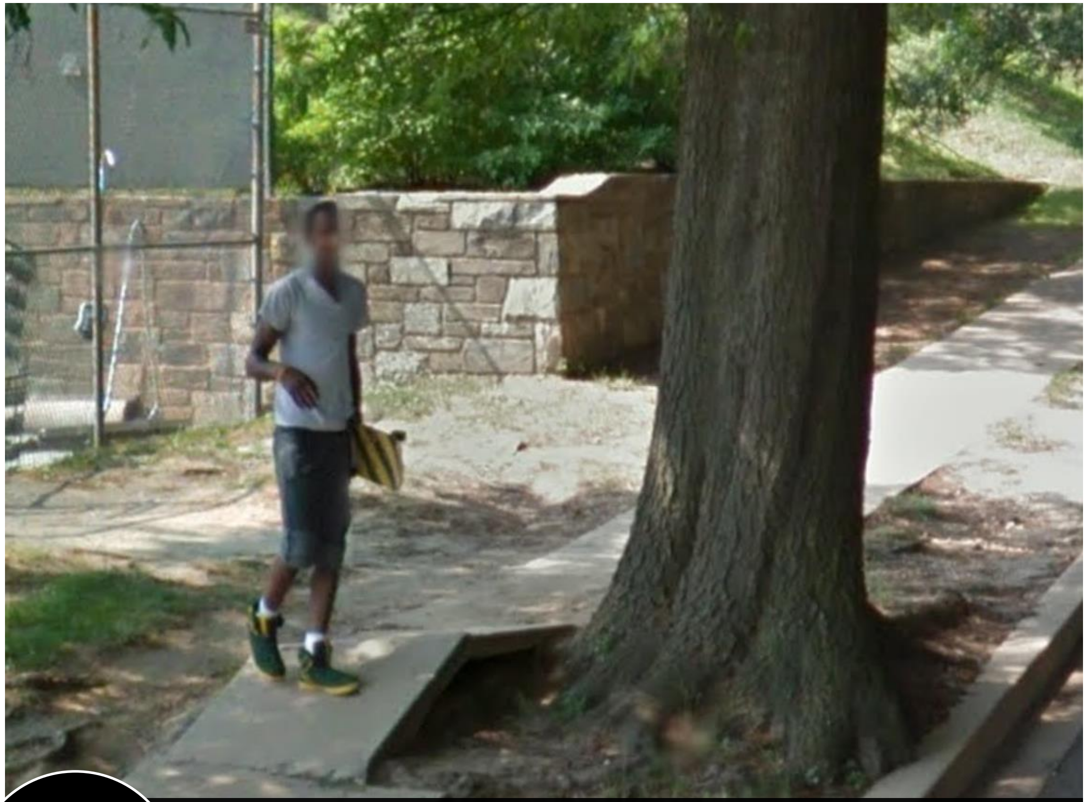


Error bars: standard error; experiments run on subset of data

With basic quality control measures, **minimally trained crowd** workers can find accessibility problems with an accuracy of **~93%**

But this approach relied **purely on manual labor**. Can we do better?

KEY RESEARCH QUESTIONS



1 SCALABLE DATA COLLECTION METHODS

[ASSETS'12, CHI'13, HCOMP'13, ASSETS'13, UIST'14, TACCESS'15, ASSETS'17, ASSSETS'18]

Is **online map imagery** a good source for accessibility data?

Can we **create interactive tools** that enable crowd workers to find accessibility problems?

How can we **leverage computational techniques** to scale our approach?

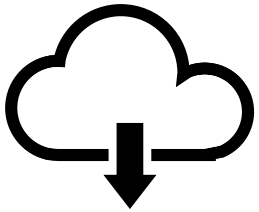
Tohme

遠目 ·*Remote Eye*

[HCOMP'13, UIST'14]

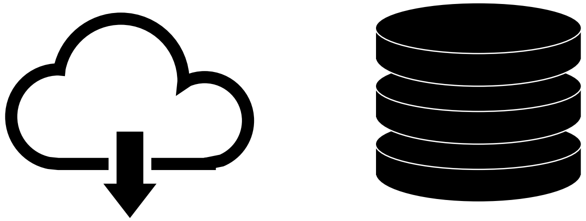
TOHME
遠目 Remote Eye

1 svCrawl
Web Scraper



TOHME
遠目 Remote Eye

1 svCrawl
Web Scraper

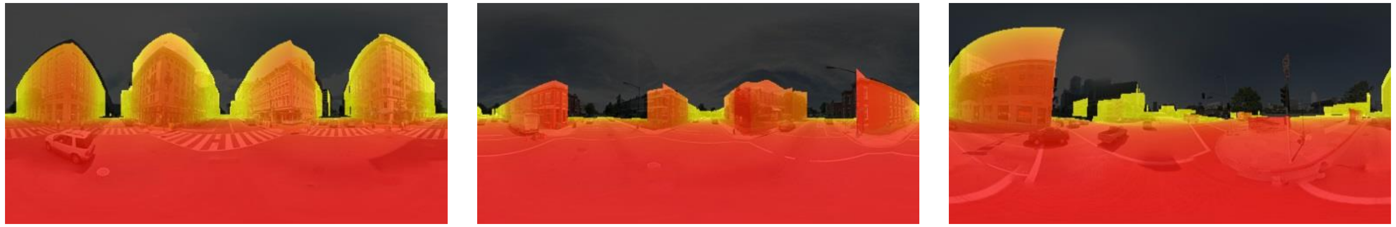


Street View images
3D-depth maps
Top-down map images
GIS metadata

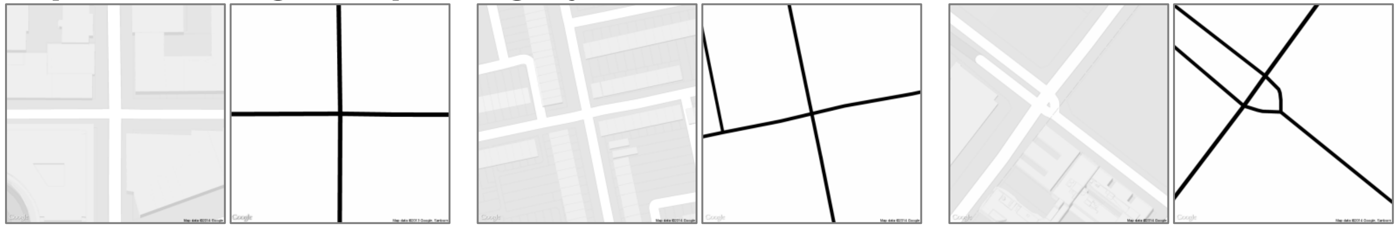
2 **Street Dataset**

Google Street View Panoramas

3D Point-cloud Data



Top-down Google Maps Imagery



GIS Metadata

<Latitude & longitude/>
<GSV image age/>
<Street & city names/>
<Intersection topology/>

TOHME

遠目 Remote Eye

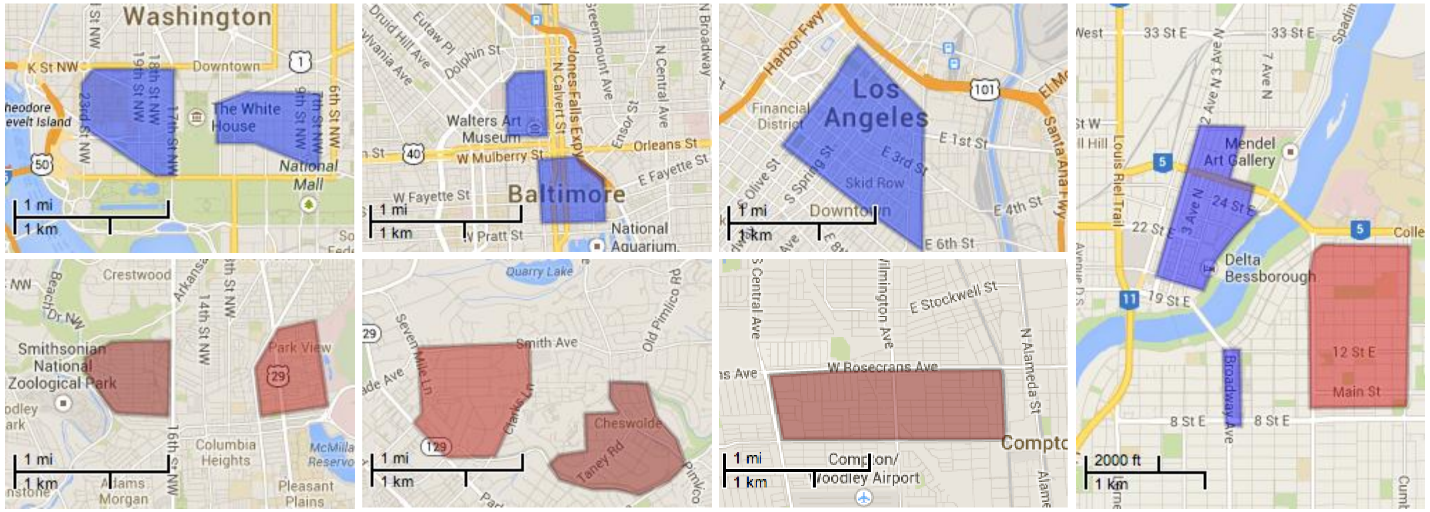
1 svCrawl
Web Scraper

Street View images
3D-depth maps
Top-down map images
GIS metadata

2 **Street Dataset**

Scraped Area: 11.3 km^2

Urban   Residential



D.C.   Baltimore   Los Angeles   Saskatoon

Dataset Statistics

1,086
intersections

2,877
curb ramps

647
missing curb ramps

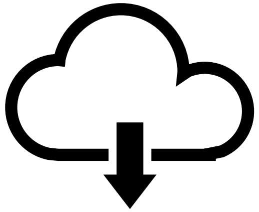
2.2 yrs (SD=1.3)
average GSV image age

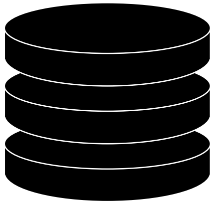
TOHME

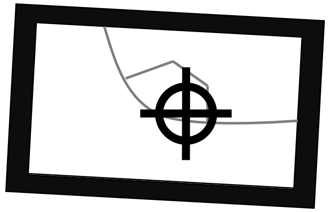
遠目 Remote Eye

① svCrawl
Web Scraper

③ svDetect
Automatic Curb Ramp Detection







Street View images
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GIS metadata

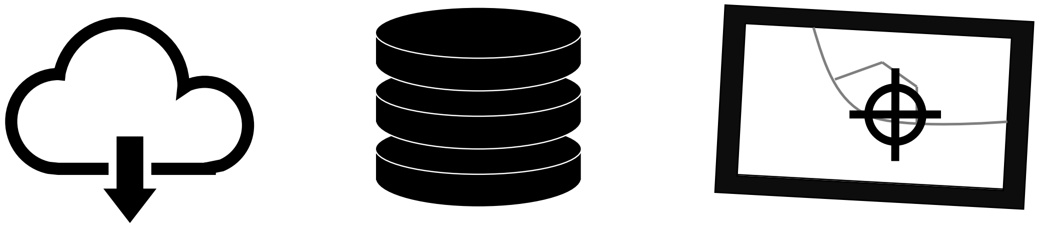
② **Street Dataset**

TOHME

遠目 Remote Eye

1 svCrawl
Web Scraper

3 svDetect
Automatic Curb Ramp Detection



Street View images
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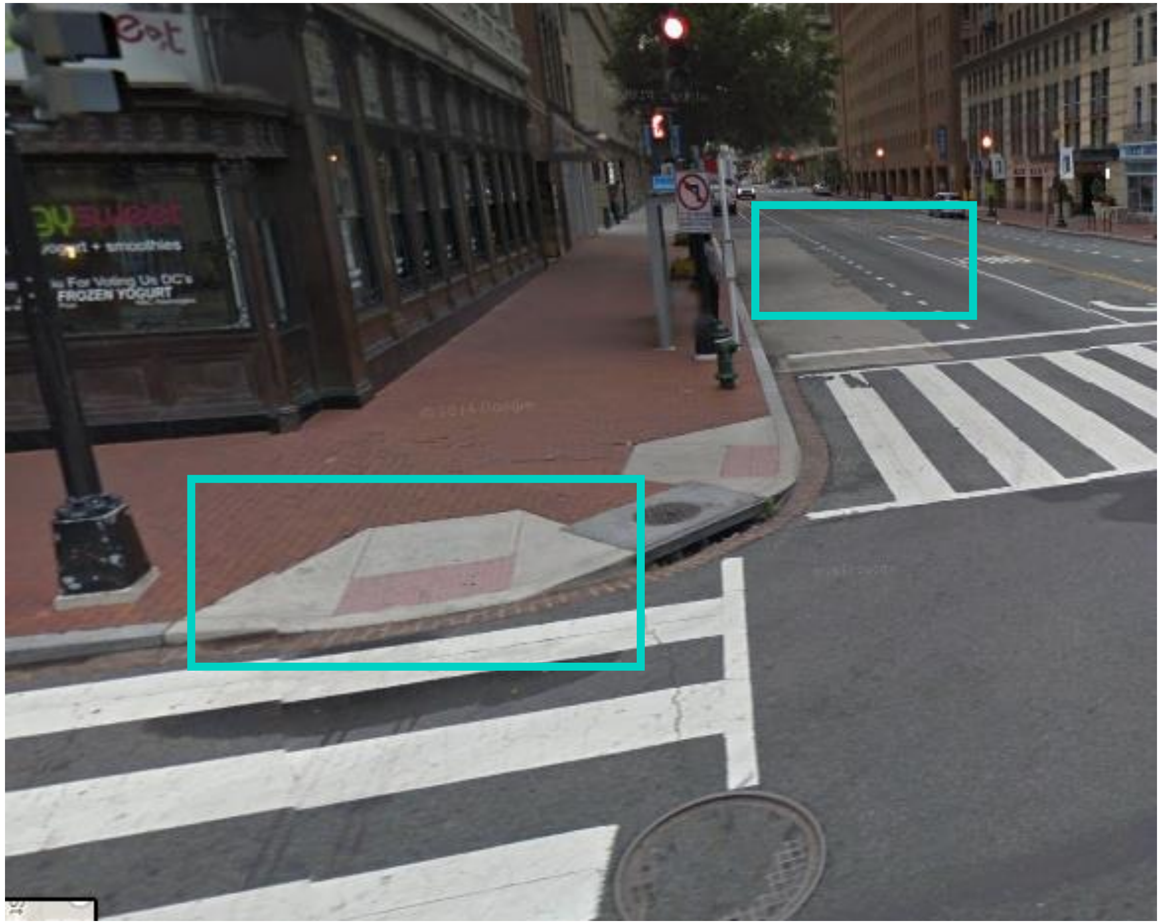
2 **Street Dataset**



TOHME
遠目 Remote Eye

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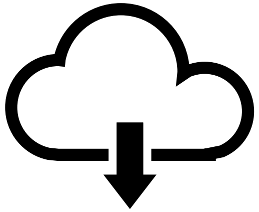
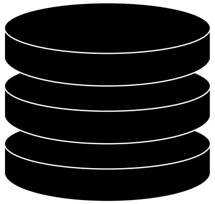
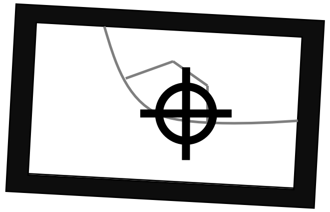
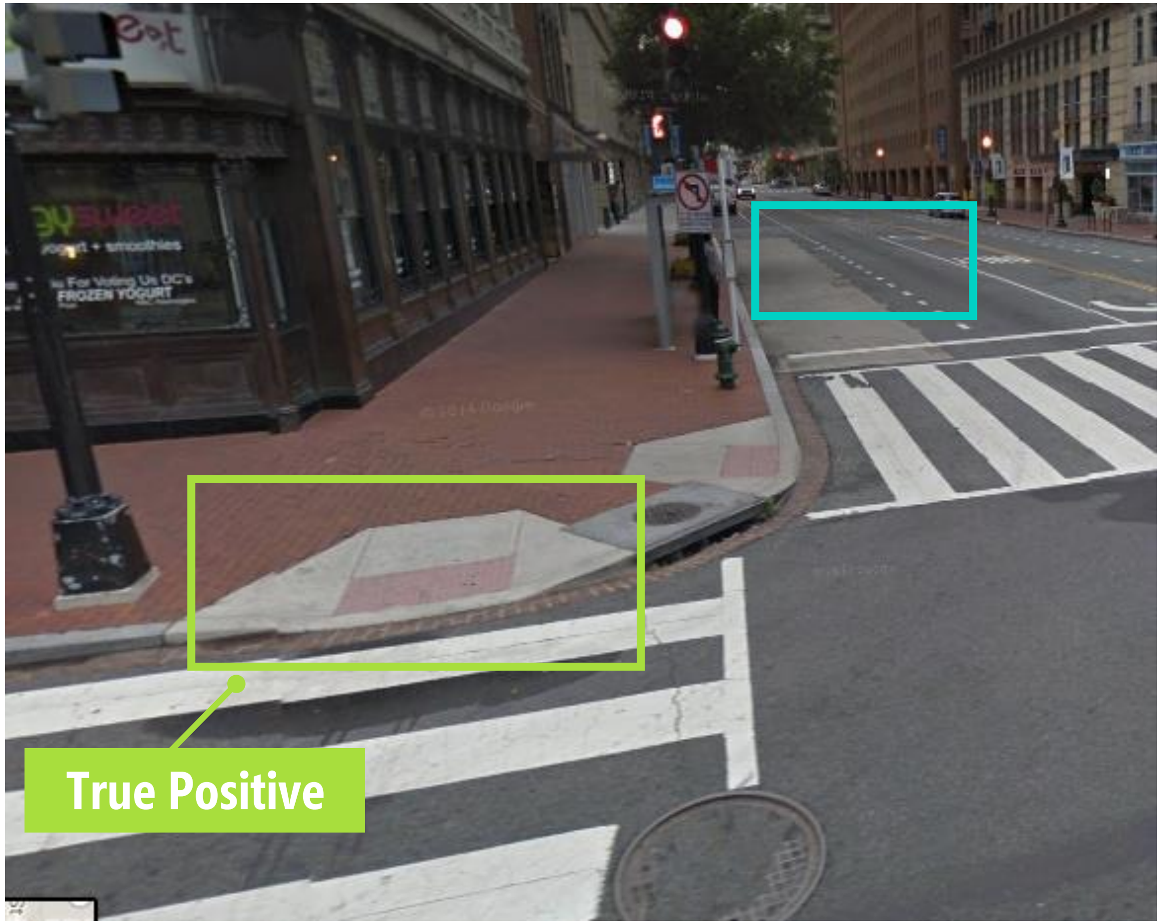
Web Scraper





3 svDetect
Automatic Curb Ramp Detection





Street View images
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Top-down map images
GIS metadata
2 **Street Dataset**

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遠目 Remote Eye

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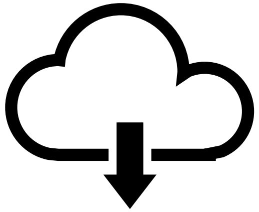

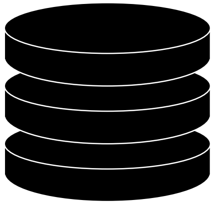

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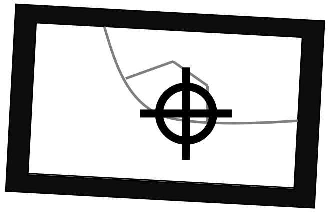
Automatic Curb Ramp Detection



Street View images
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GIS metadata

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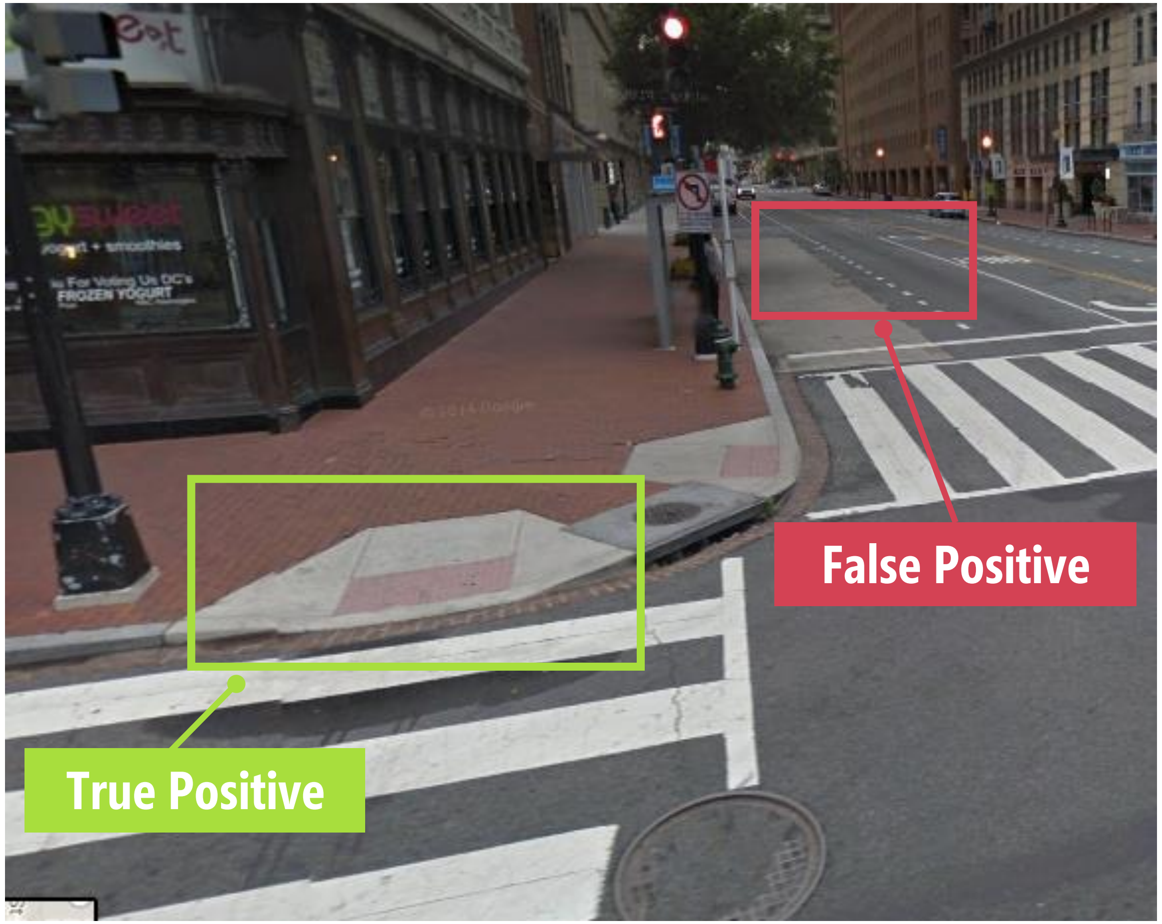
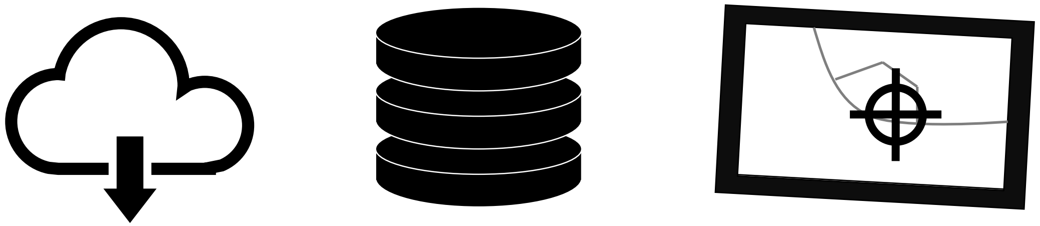


TOHME
遠目 Remote Eye

1 svCrawl
Web Scraper

3 svDetect
Automatic Curb Ramp Detection



Street View images
3D-depth maps
Top-down map images
GIS metadata

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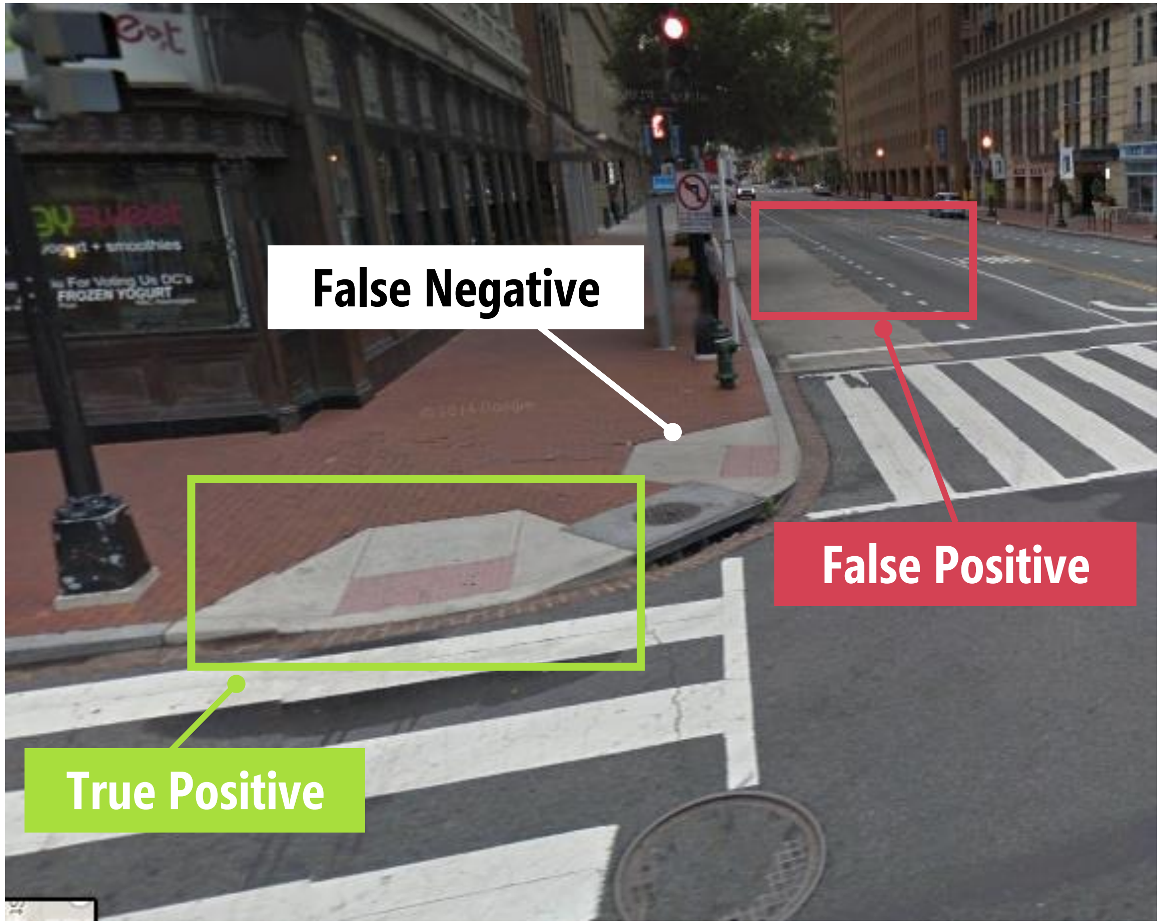
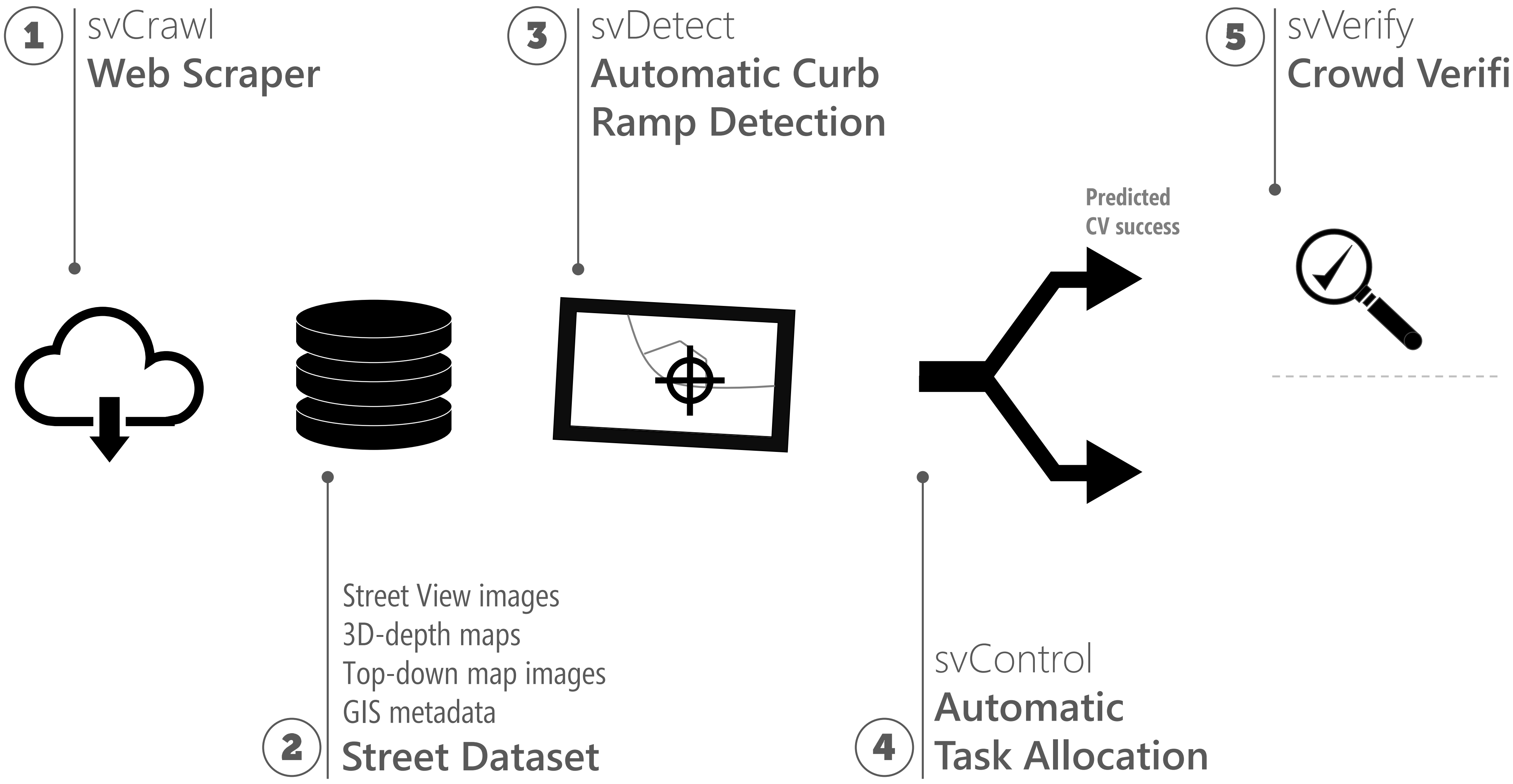
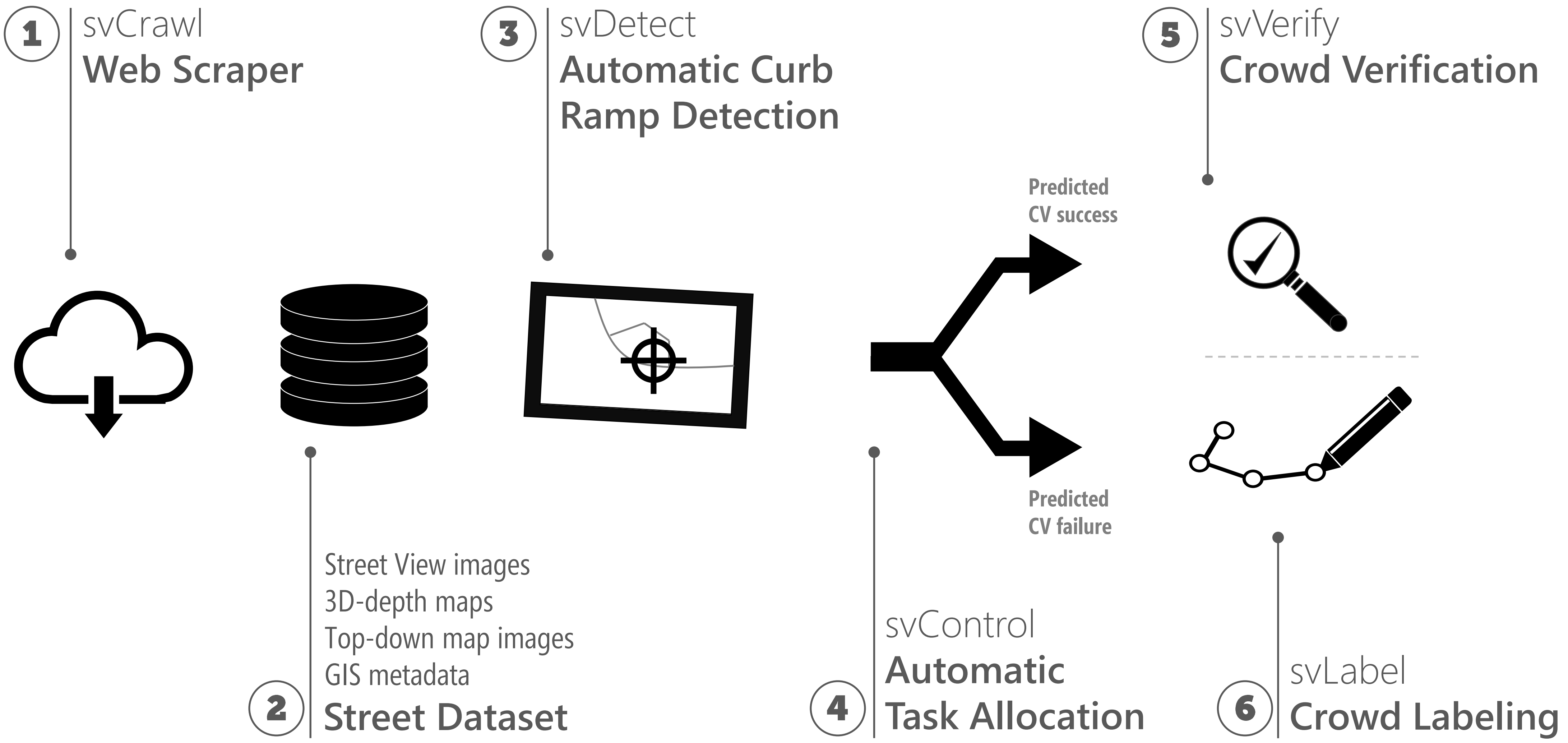


TOHME

遠目 Remote Eye



TOHME
遠目 Remote Eye



TOHME
遠目 Remote Eye

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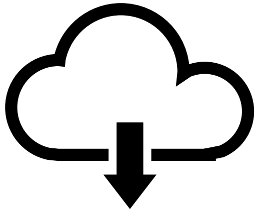
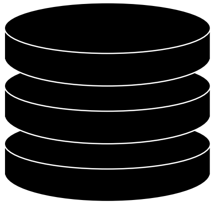
Web Scraper

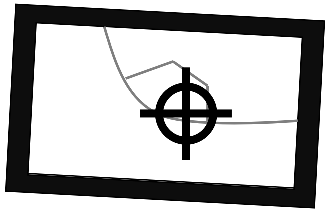


2 **Street Dataset**

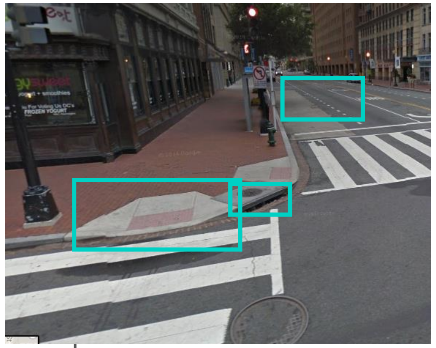


Street View images
3D-depth maps
Top-down map images
GIS metadata

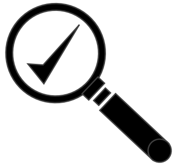
3 svDetect
Automatic Curb Ramp Detection



4 svControl
Automatic Task Allocation



5 svVerify
Crowd Verification

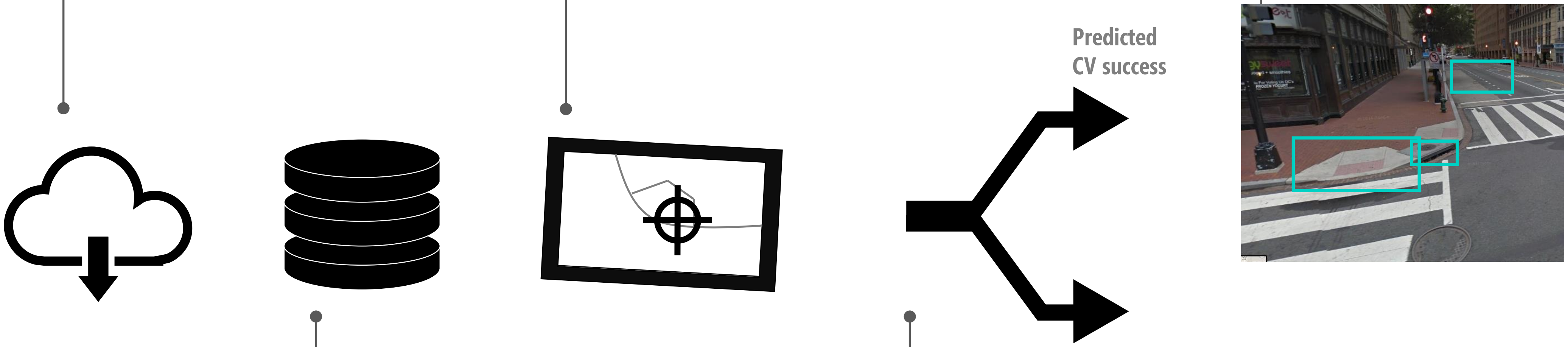


TOHME
遠目 Remote Eye

1 svCrawl
Web Scraper

3 svDetect
Automatic Curb Ramp Detection

5 svVerify
Crowd Verification



Street View images
3D-depth maps
Top-down map images
GIS metadata

2 **Street Dataset**

4 svControl
Automatic Task Allocation

TOHME

遠目 Remote Eye

1 svCrawl

Web Scraper

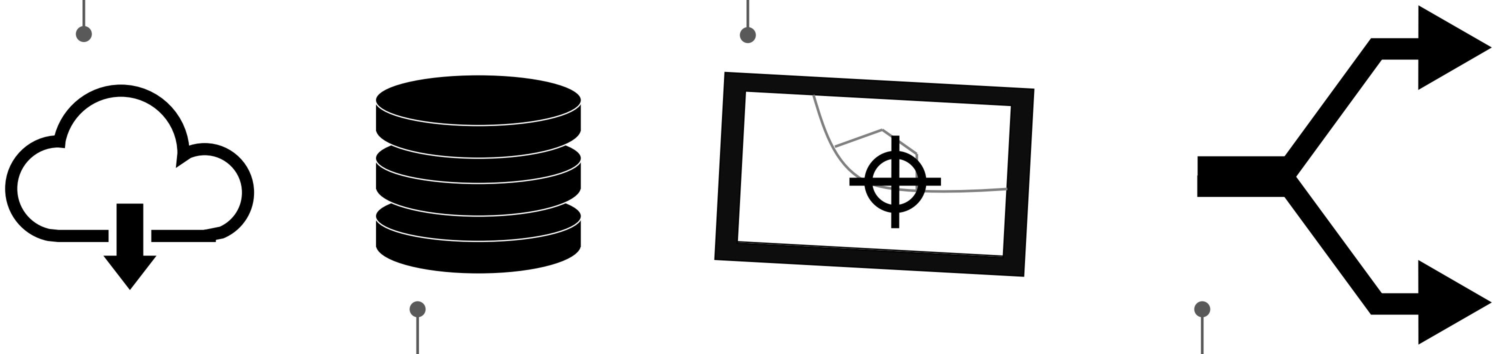
3 svDetect

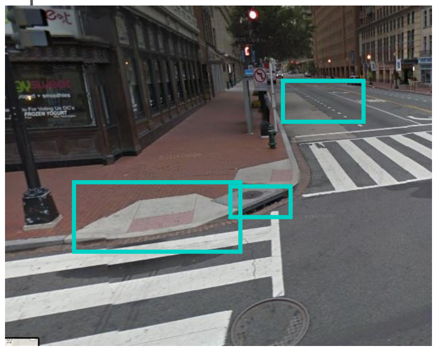
Automatic Curb Ramp Detection

5 svVerify

Crowd Verification

Predicted CV success





Street View images

3D-depth maps

Top-down map images

GIS metadata

2 **Street Dataset**

4 svControl

Automatic Task Allocation

TOHME

遠目 Remote Eye

1 svCrawl
Web Scraper

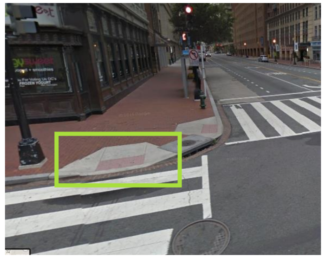
2 Street View images
3D-depth maps
Top-down map images
GIS metadata
Street Dataset

3 svDetect
Automatic Curb Ramp Detection

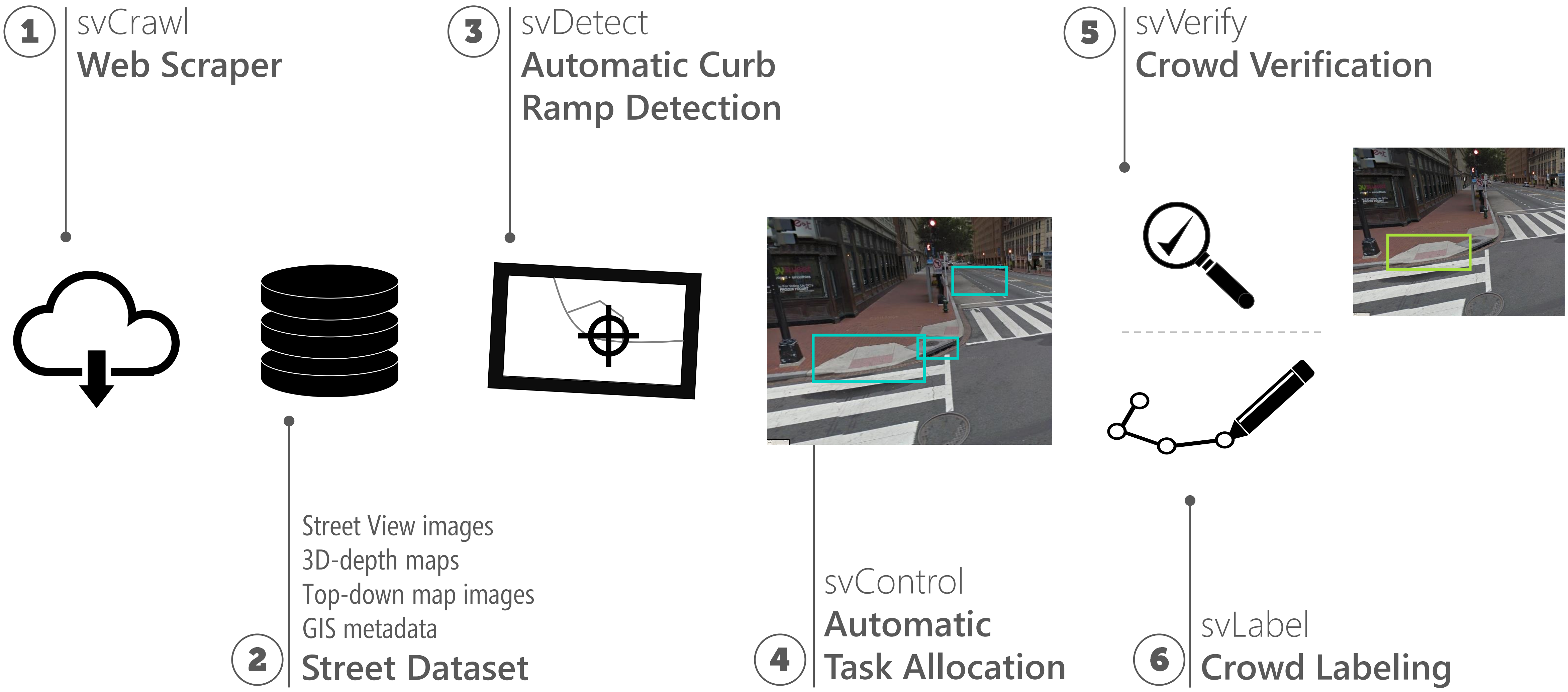
4 svControl
Automatic Task Allocation

Predicted
CV success

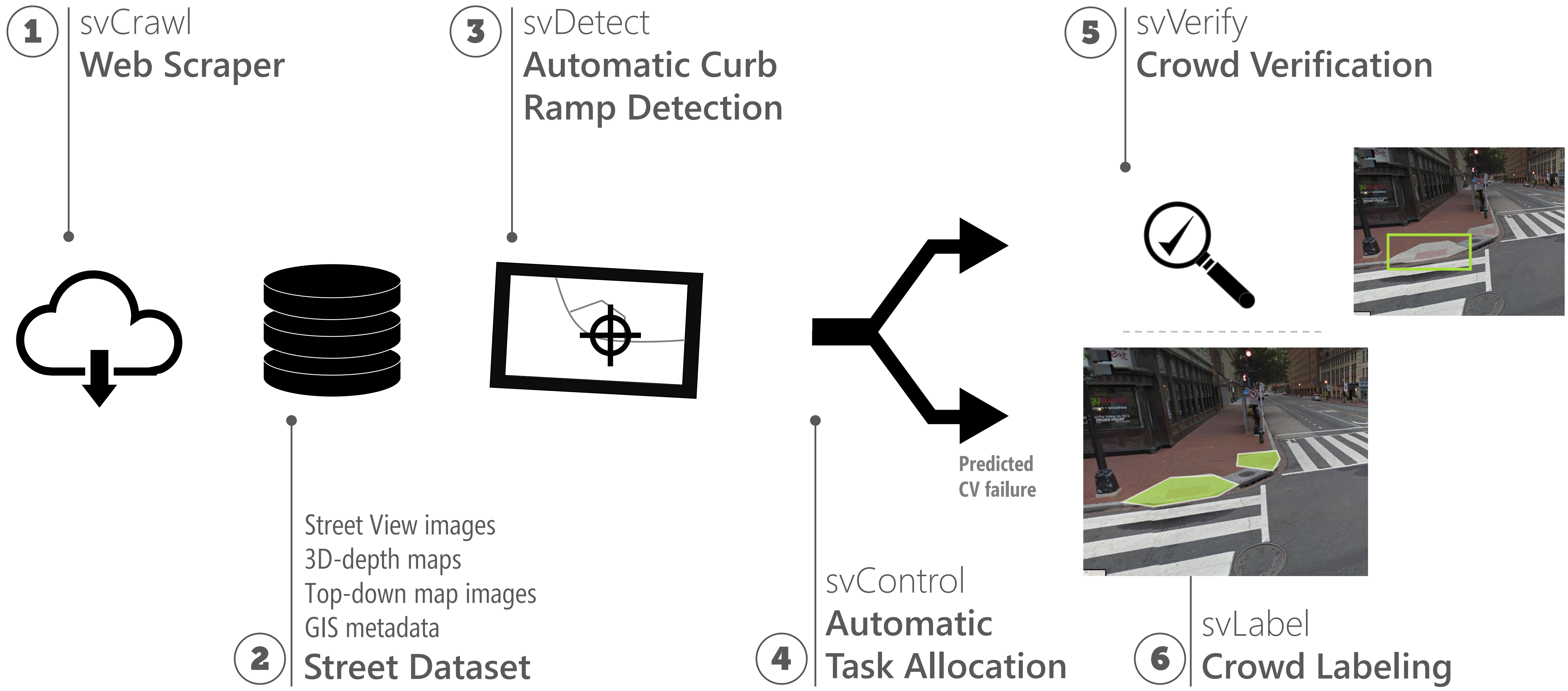
5 svVerify
Crowd Verification

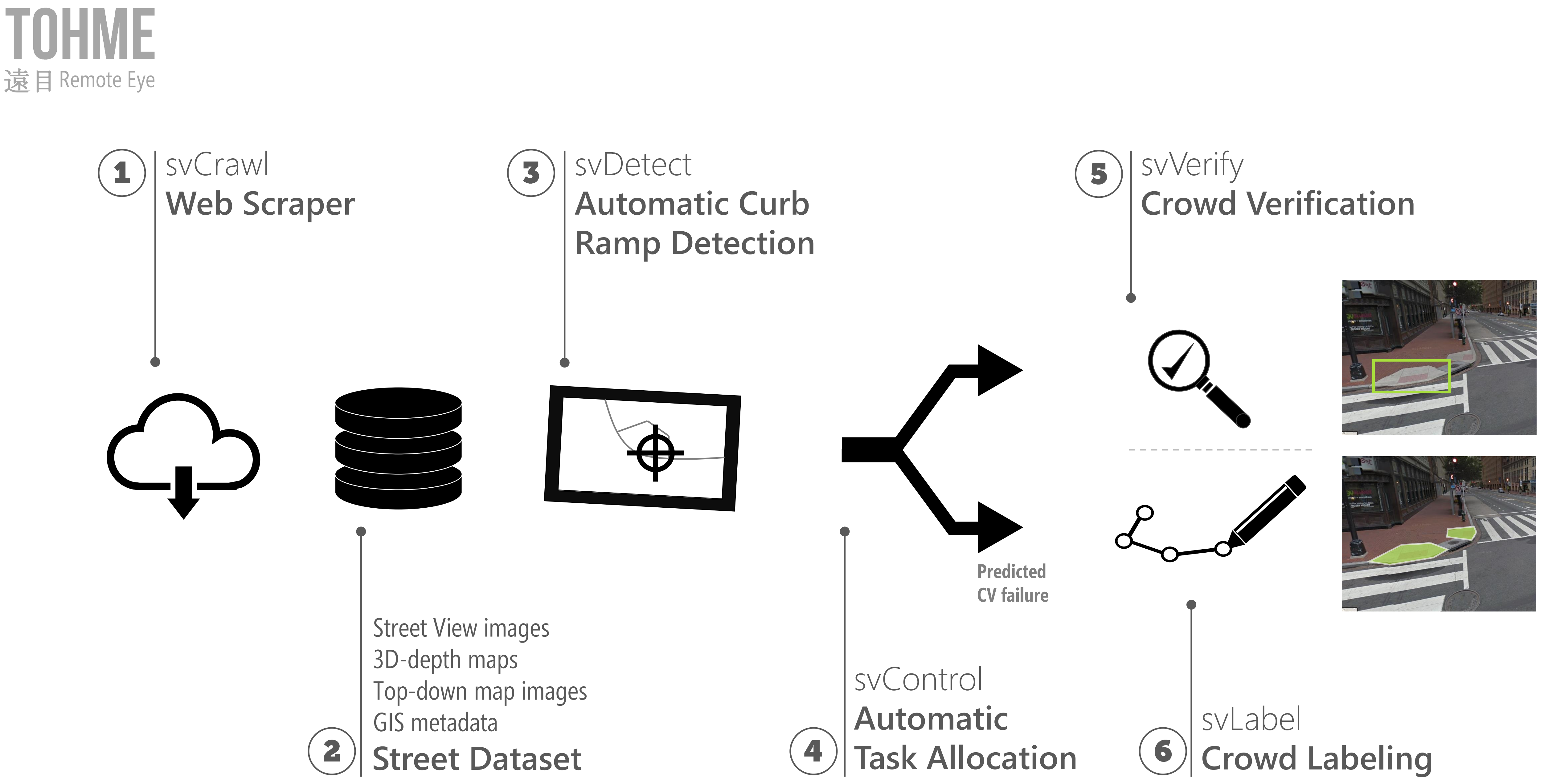


TOHME
遠目 Remote Eye



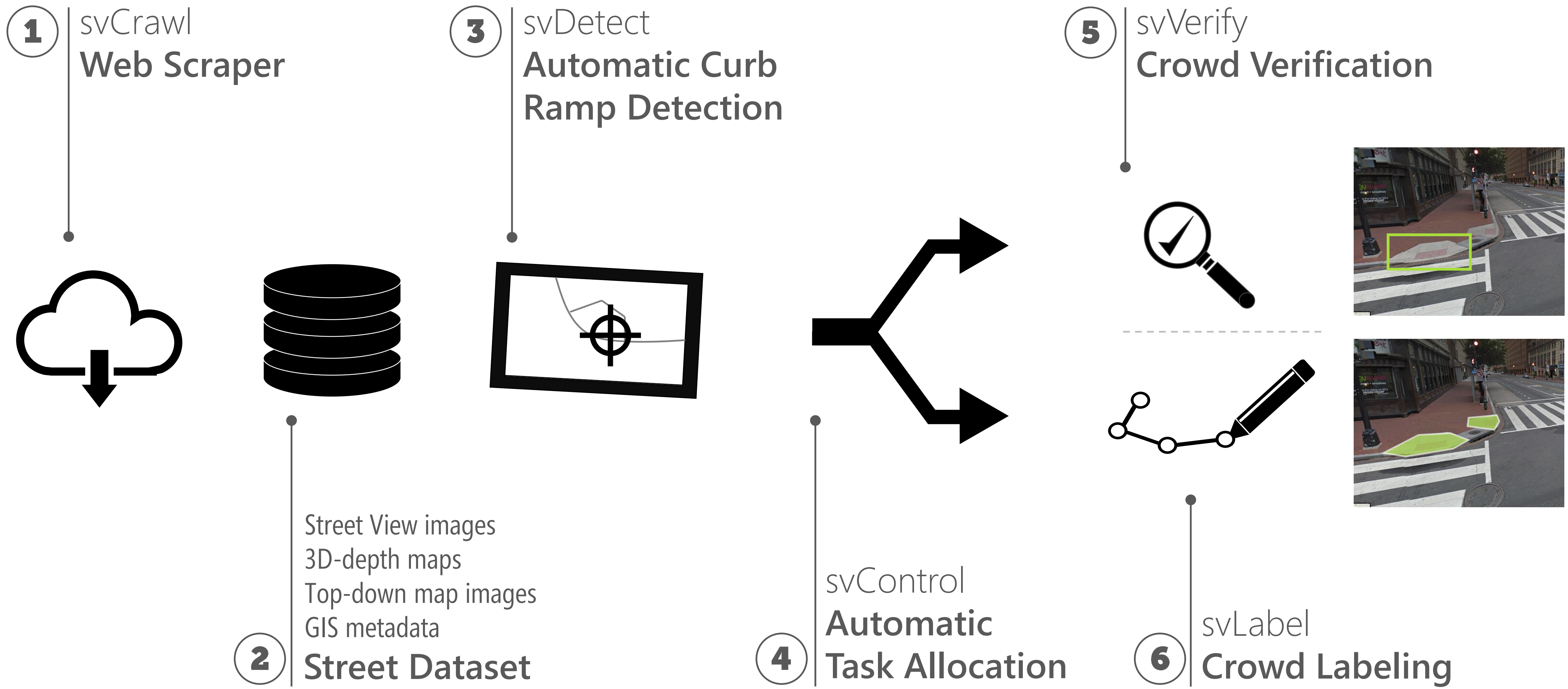
TOHME
遠目 Remote Eye

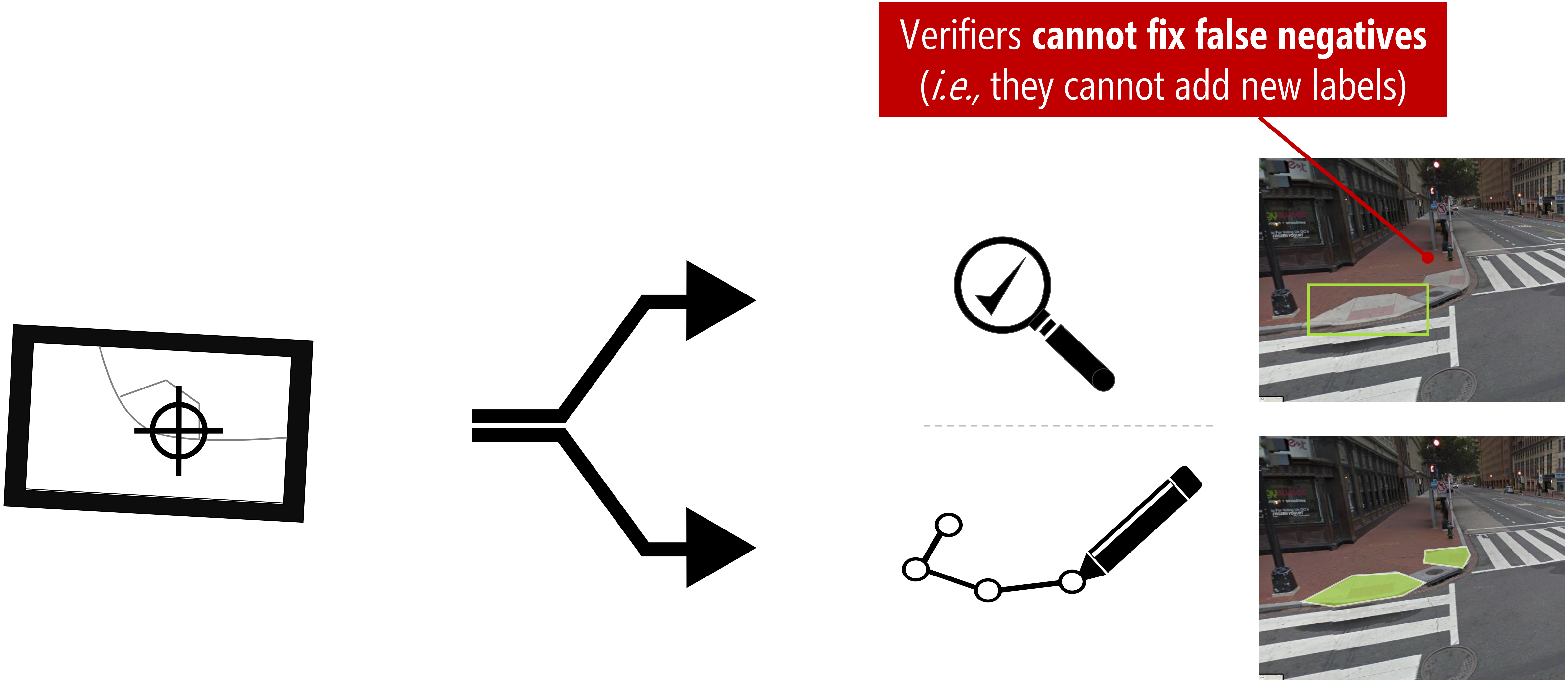




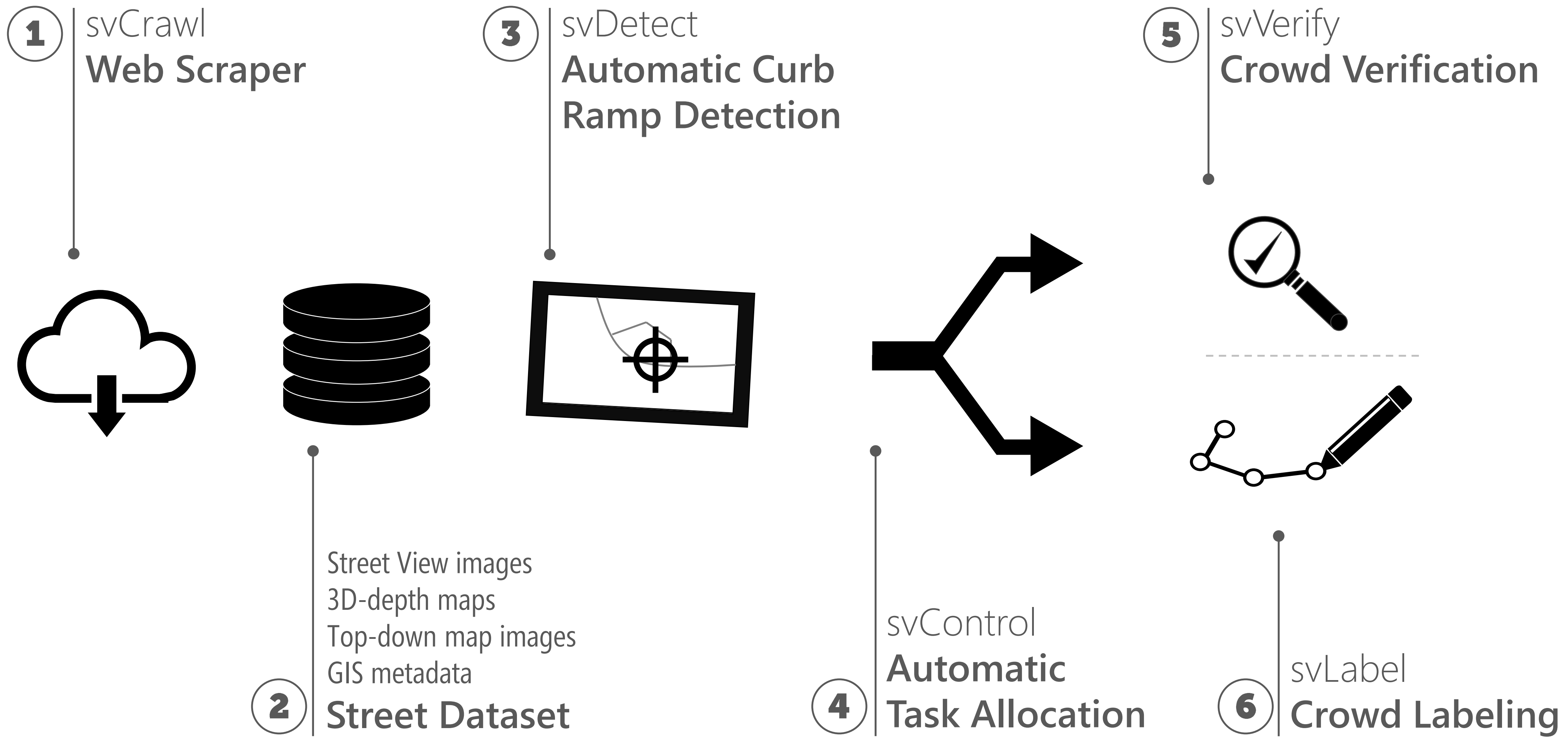
TOHME
遠目 Remote Eye
1 svCrawl
Web Scraper
2 Street View images
3D-depth maps
Top-down map images
GIS metadata
Street Dataset
3 svDetect
Automatic Curb
Ramp Detection
4 svControl
Automatic
Task Allocation
Predicted
CV failure
5 svVerify
Crowd Verification
6 svLabel
Crowd Labeling

TOHME
遠目 Remote Eye



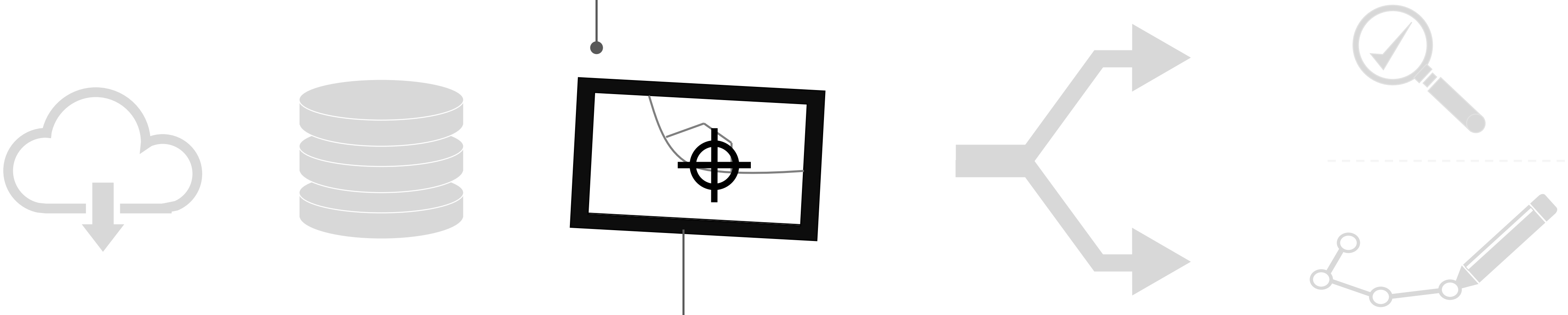

Verifiers **cannot fix false negatives**
(*i.e.*, they cannot add new labels)

TOHME
遠目 Remote Eye



3 svDetect

Automatic Curb Ramp Detection

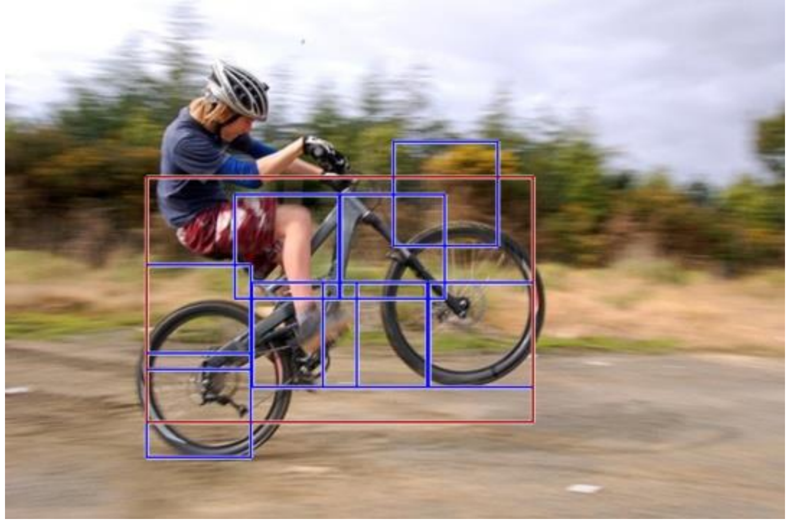


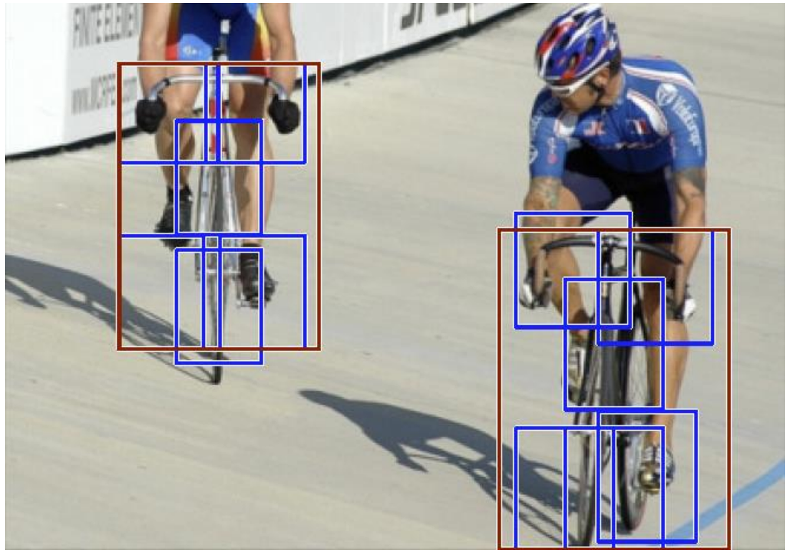
1. Deformable part model (DPM)
2. Post-processing DPM
3. SVM-based classifier

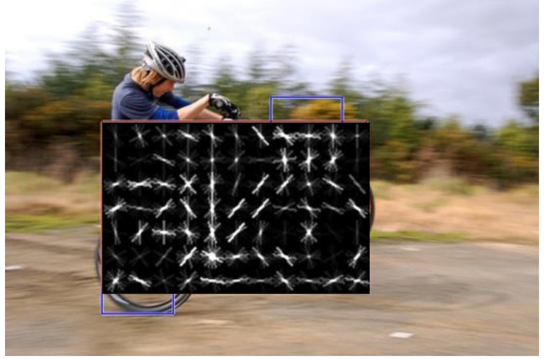
1

AUTOMATIC CURB RAMP DETECTOR

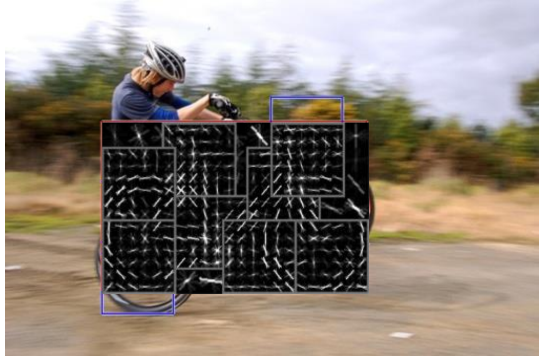
DEFORMABLE PART MODEL



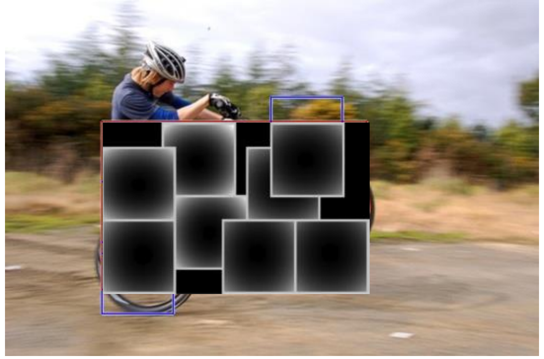




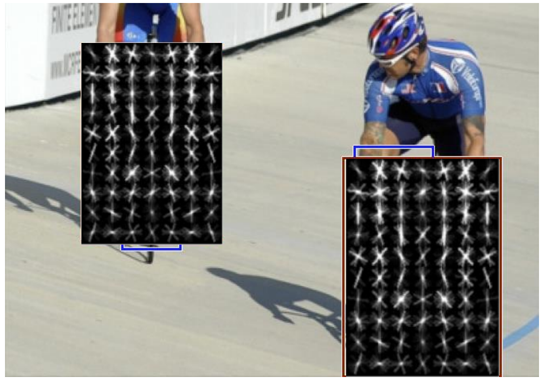
Root filter



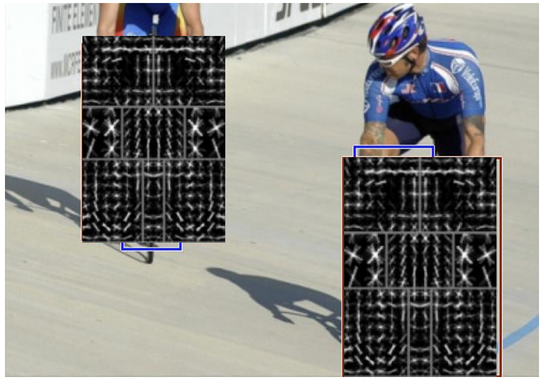
Parts filter



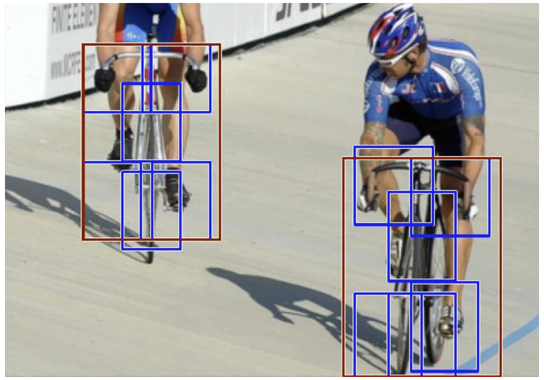
Displacement cost



Root filter



Parts filter



Displacement cost

Felzenszwalb *et al.*, CVPR'08, CVPR'10

1

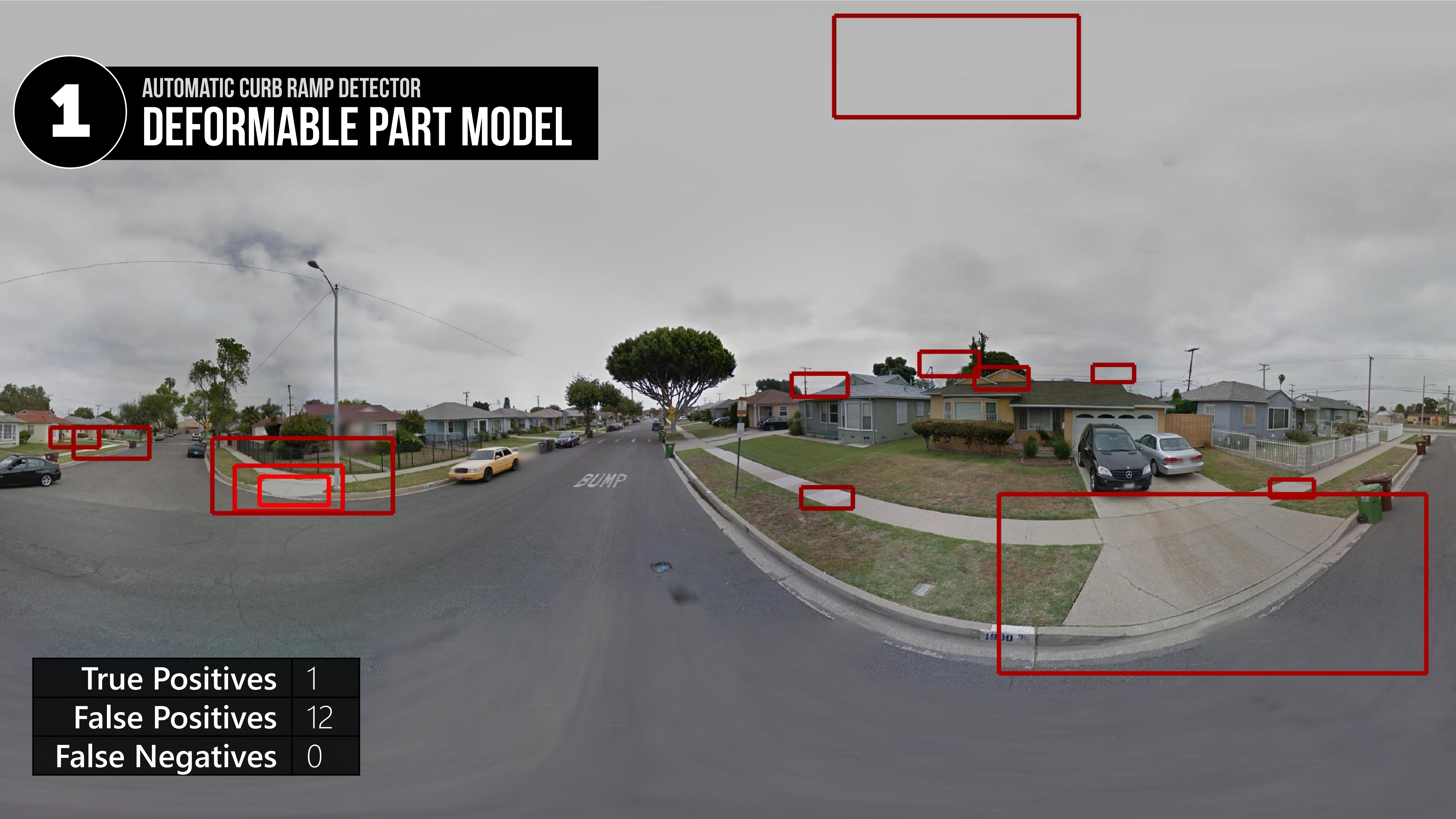
AUTOMATIC CURB RAMP DETECTOR

DEFORMABLE PART MODEL

1

AUTOMATIC CURB RAMP DETECTOR

DEFORMABLE PART MODEL

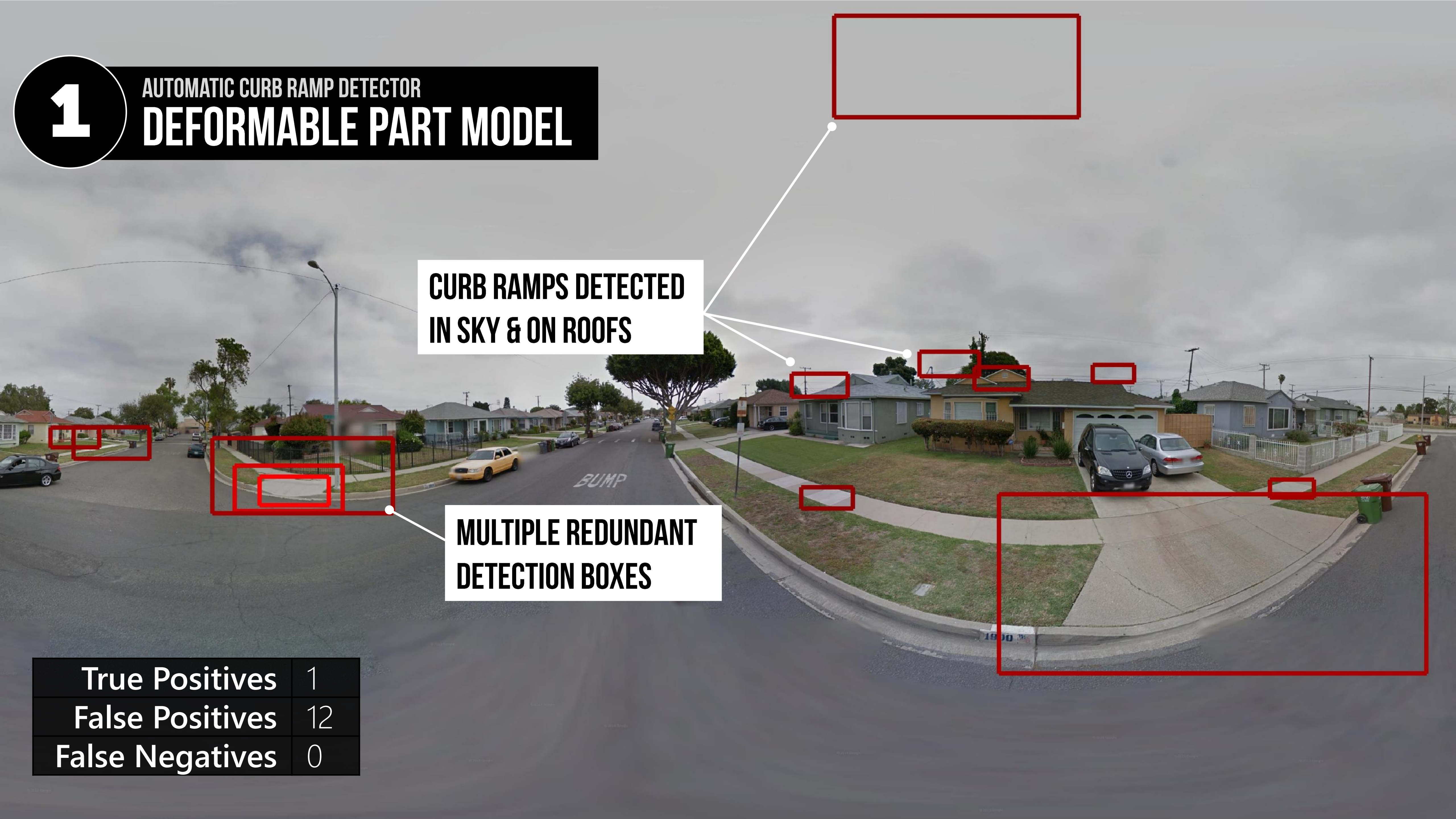


True Positives	1
False Positives	12
False Negatives	0

1

AUTOMATIC CURB RAMP DETECTOR

DEFORMABLE PART MODEL

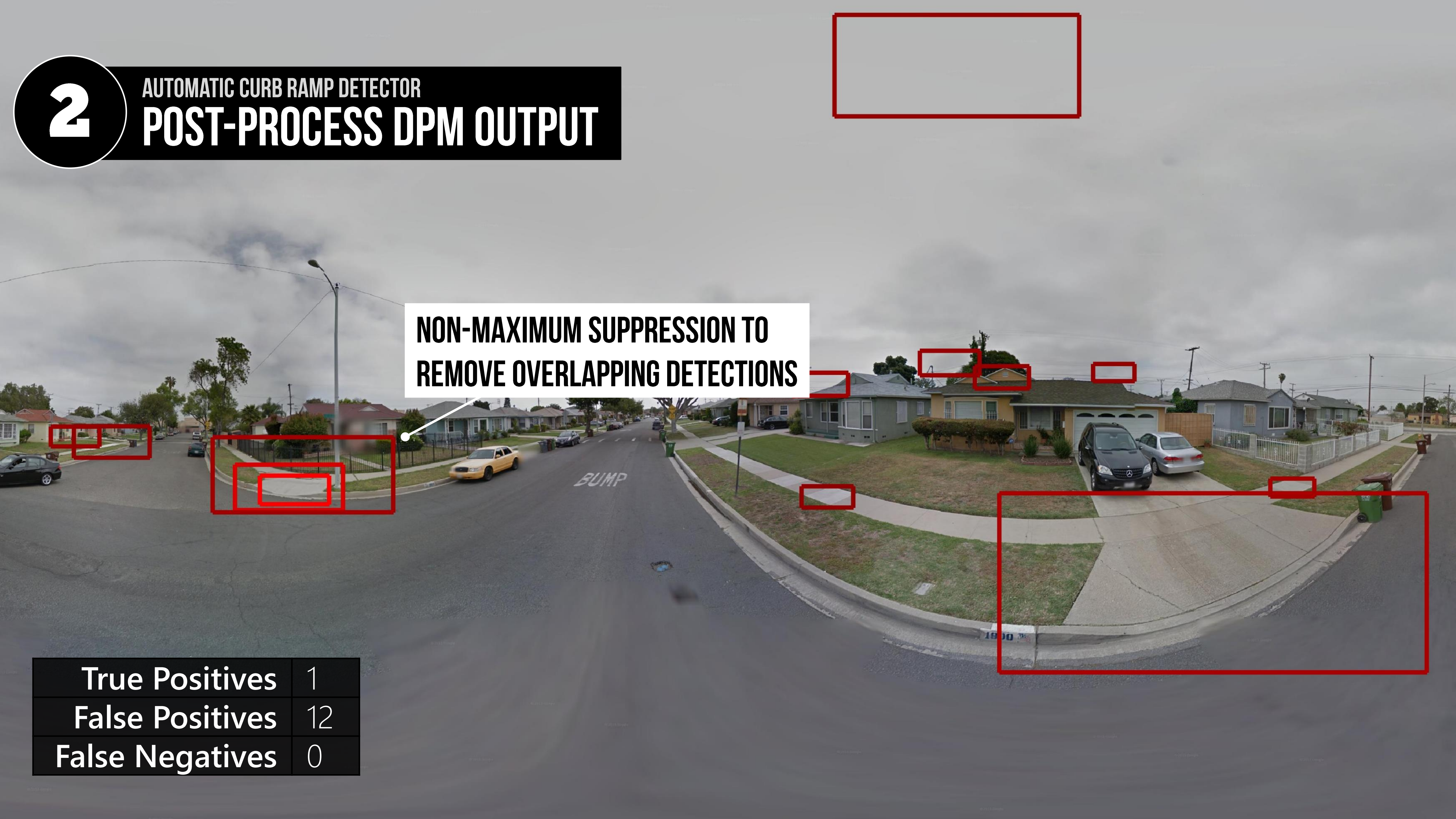


True Positives	1
False Positives	12
False Negatives	0


2
AUTOMATIC CURB RAMP DETECTOR
POST-PROCESS DPM OUTPUT
3D-POINT CLOUD TO REMOVE CURB RAMPS ABOVE GROUND
BUMP

2 AUTOMATIC CURB RAMP DETECTOR

POST-PROCESS DPM OUTPUT



True Positives	1
False Positives	12
False Negatives	0

2 AUTOMATIC CURB RAMP DETECTOR

POST-PROCESS DPM OUTPUT

True Positives	1
False Positives	5
False Negatives	0

3

AUTOMATIC CURB RAMP DETECTOR

SVM-BASED REFINEMENT

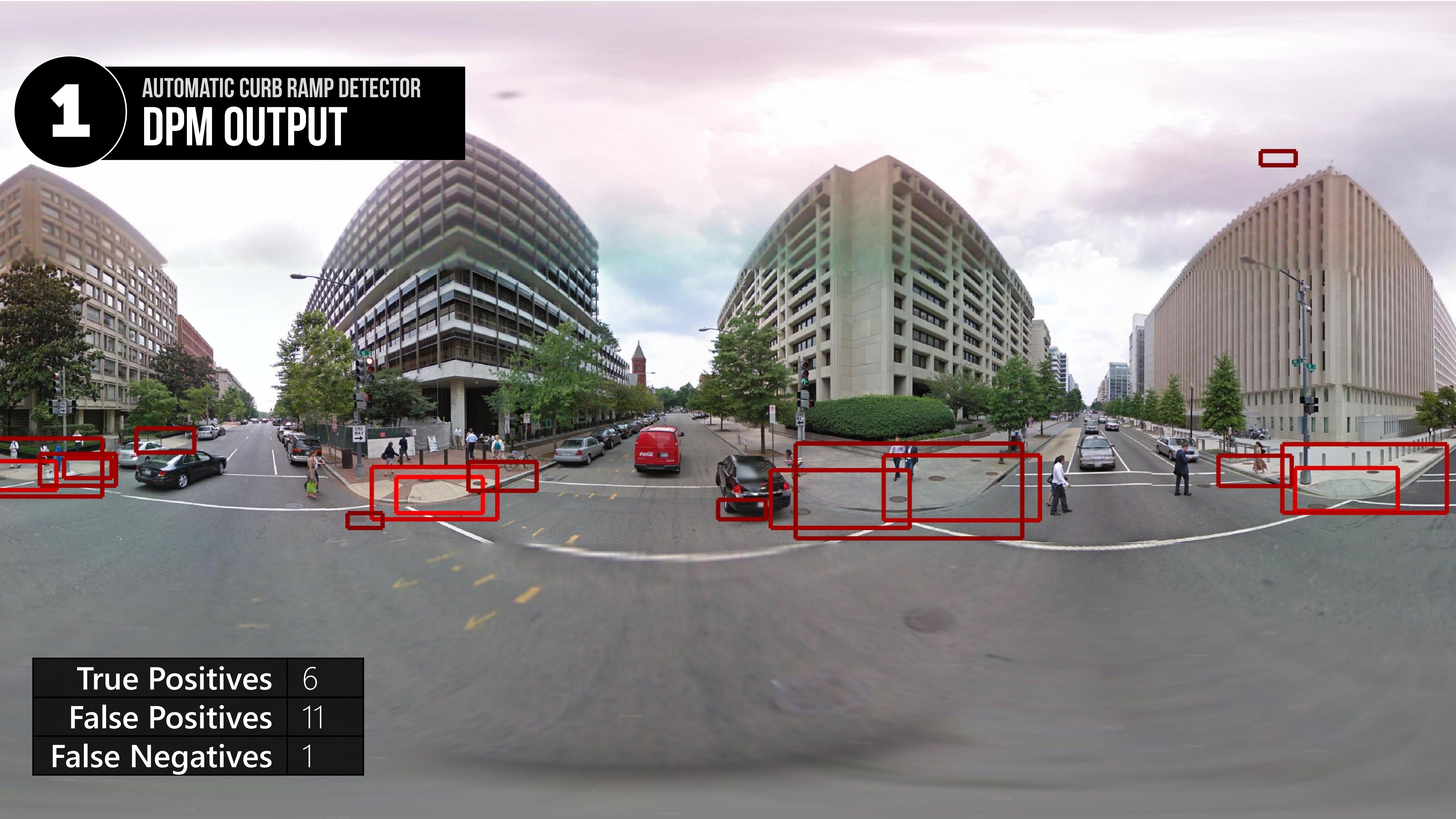
True Positives	1
False Positives	5
False Negatives	0

3

AUTOMATIC CURB RAMP DETECTOR

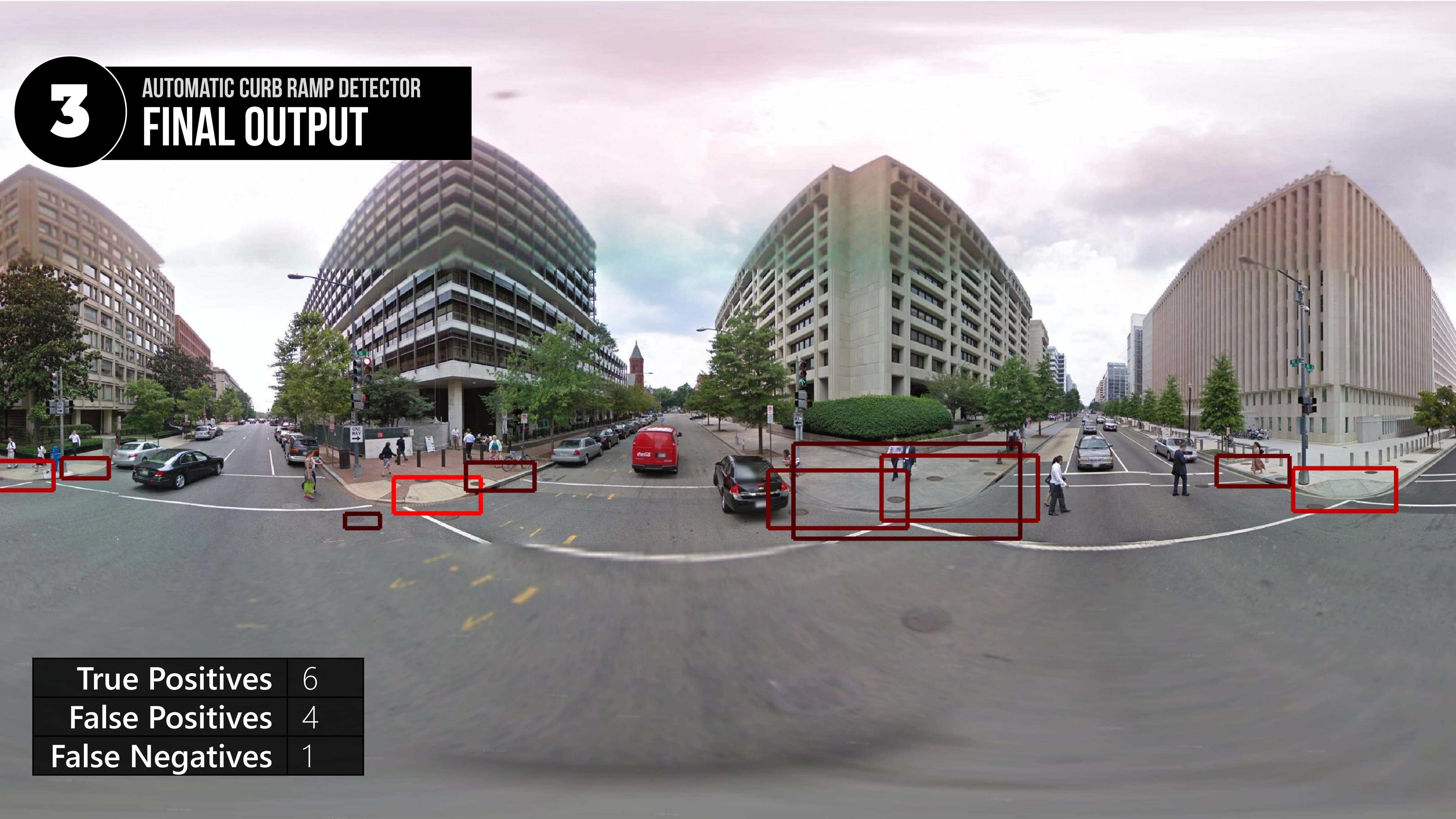
FINAL OUTPUT

True Positives	1
False Positives	3
False Negatives	0



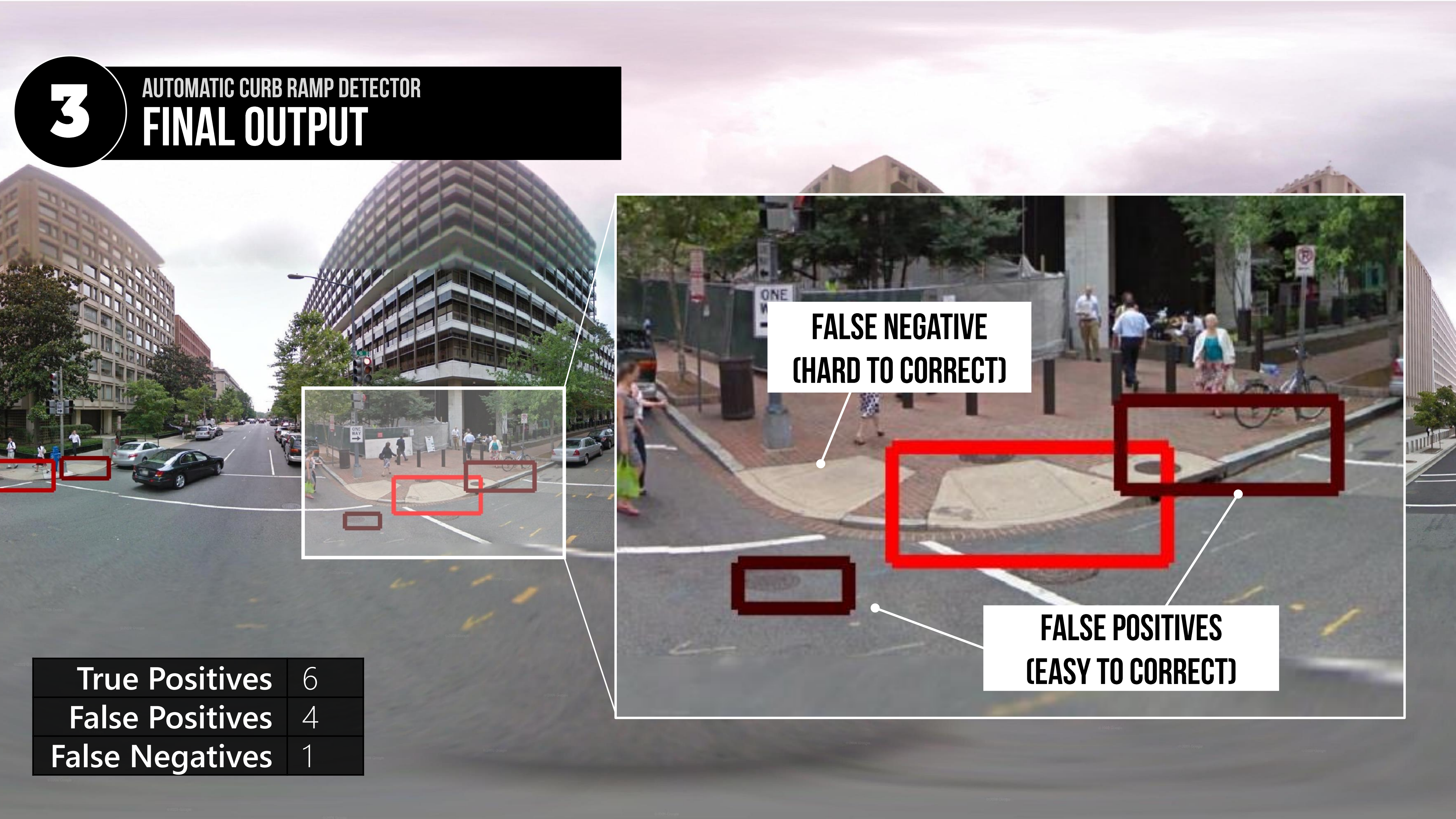
1 AUTOMATIC CURB RAMP DETECTOR
DPM OUTPUT

True Positives	6
False Positives	11
False Negatives	1

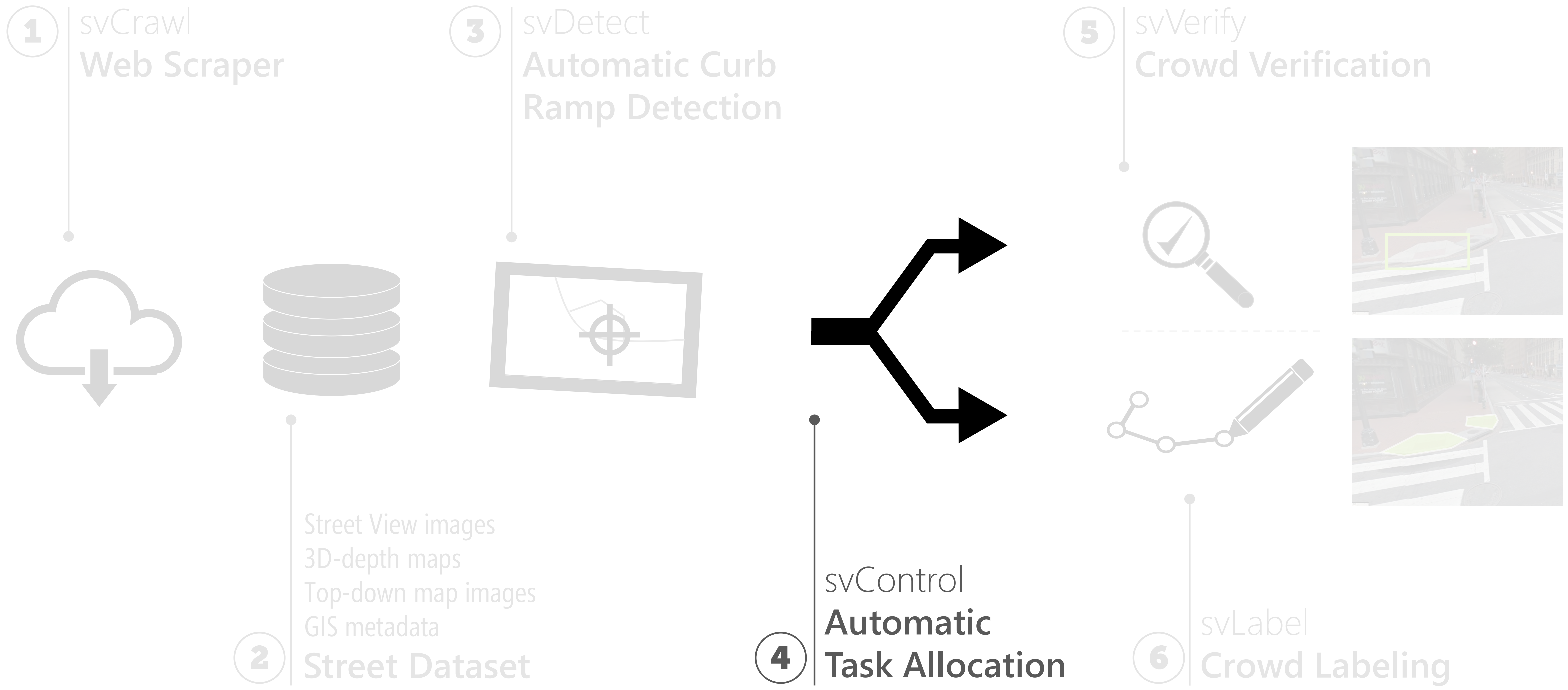


3 AUTOMATIC CURB RAMP DETECTOR
FINAL OUTPUT

True Positives	6
False Positives	4
False Negatives	1


3
AUTOMATIC CURB RAMP DETECTOR
FINAL OUTPUT
FALSE NEGATIVE
(HARD TO CORRECT)
FALSE POSITIVES
(EASY TO CORRECT)
True Positives 6
False Positives 4
False Negatives 1

TOHME
遠目 Remote Eye



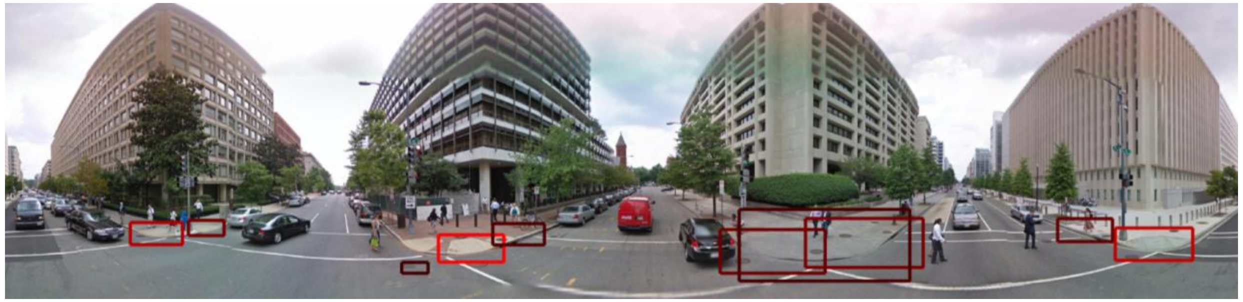
SMART TASK ALLOCATOR

SVM TRAINED WITH 23 INPUT FEATURES

Binary classifier trained to predict occurrence of false negatives from svDetect stage

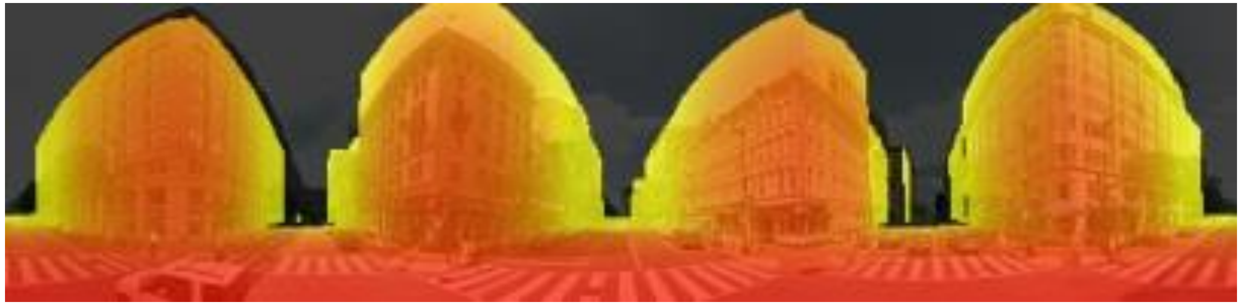
svControl
Automatic
4 **Task Allocation**

Curb Ramp Detector Output (16 Features)



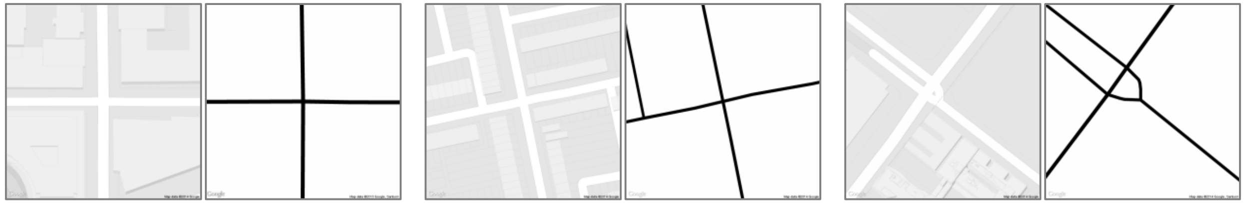
Raw # of bounding boxes
Descriptive stats of confidence scores
Descriptive stats of XY-coordinates

3D-Point Cloud Data (5 Features)



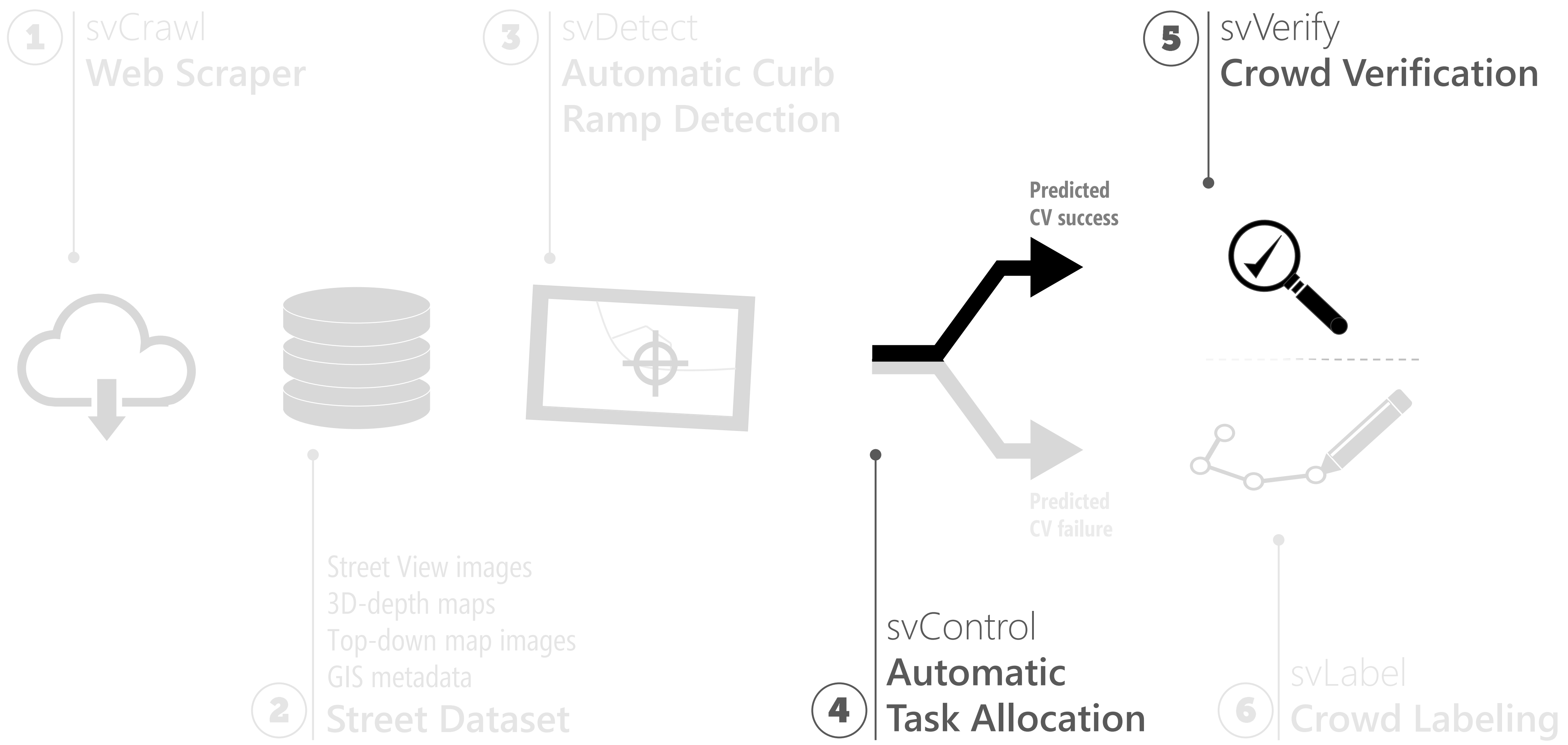
Descriptive stats of depth information (*e.g.,* average, median, variance) of pixel depth

Intersection Complexity (2 Features)



Cardinality (# of connected streets)
Amount of road

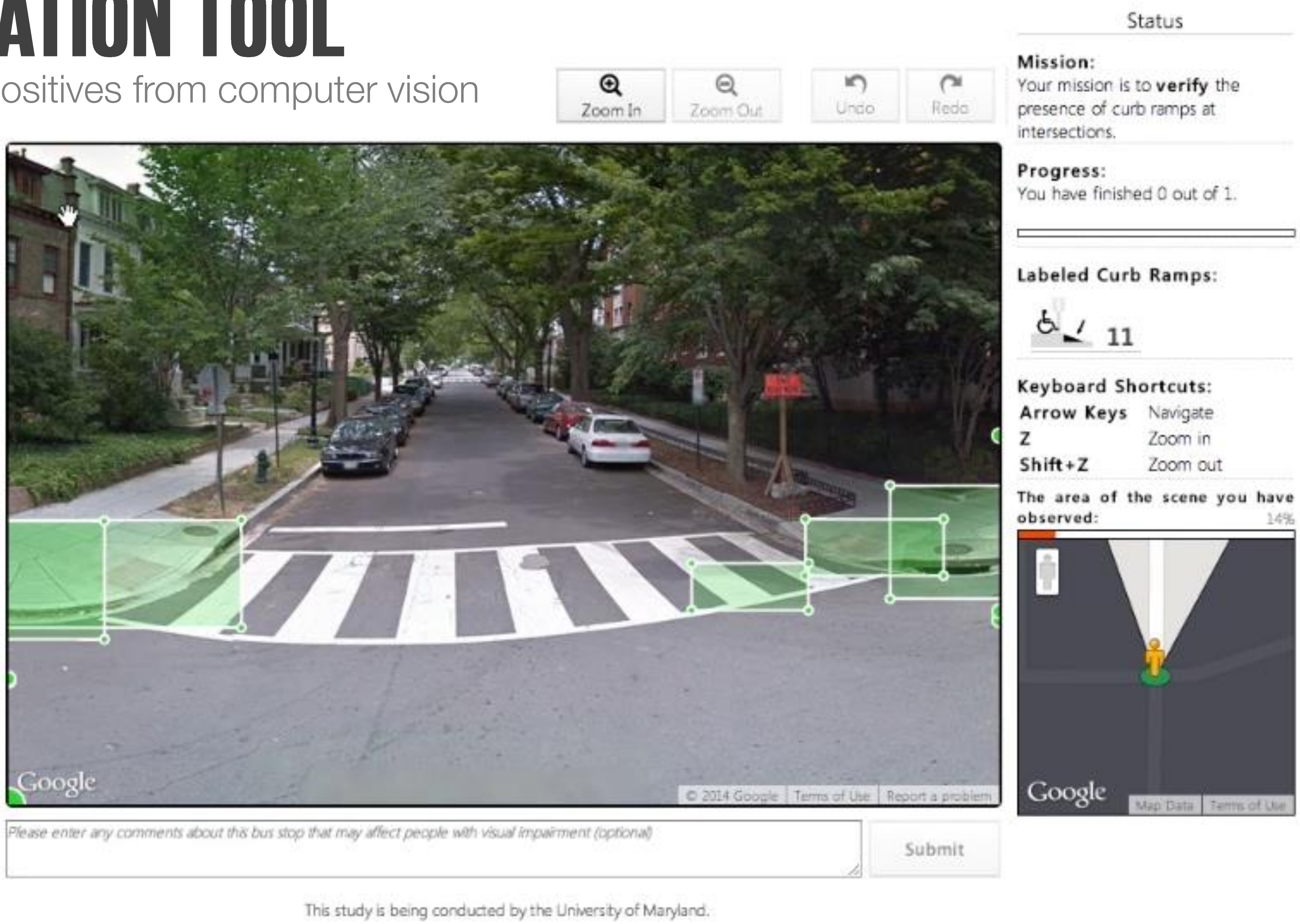
TOHME
遠目 Remote Eye



CROWD INTERFACES

VERIFICATION TOOL

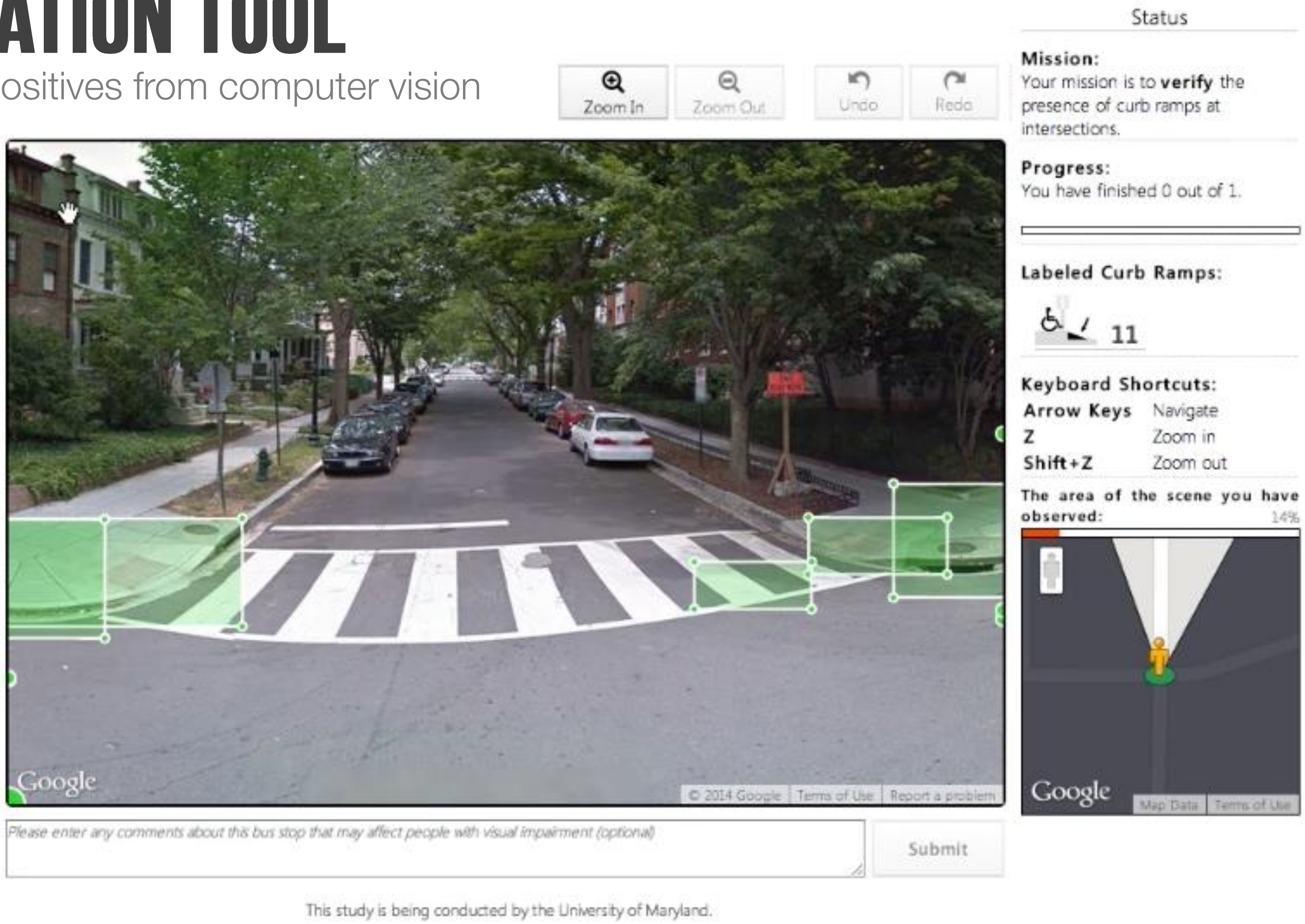
Correct false positives from computer vision



CROWD INTERFACES

VERIFICATION TOOL

Correct false positives from computer vision



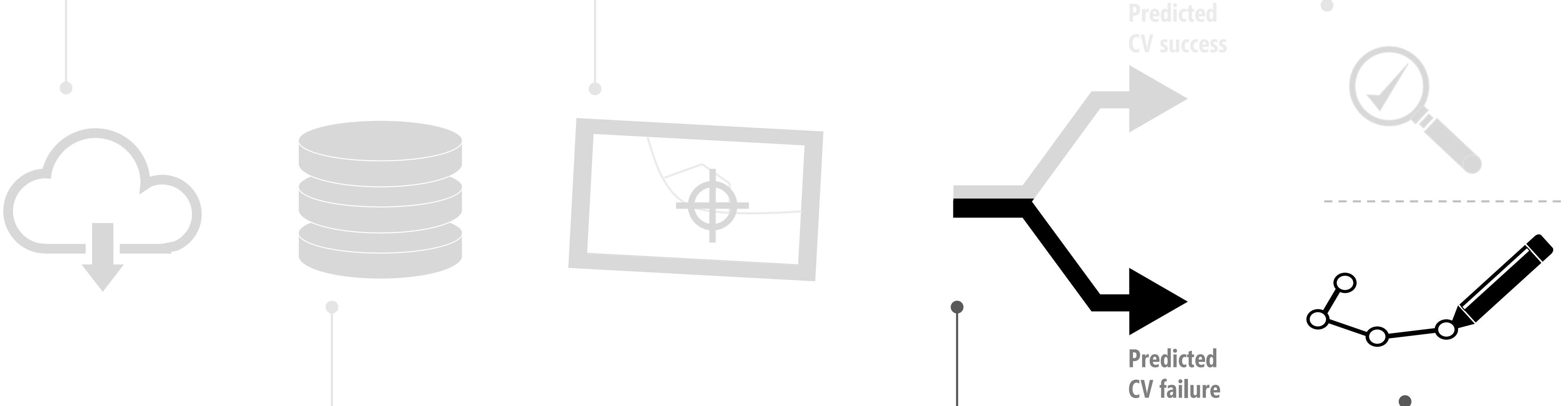
Playback Speed: **2x**

TOHME
遠目 Remote Eye

1 svCrawl
Web Scraper

3 svDetect
Automatic Curb Ramp Detection

5 svVerify
Crowd Verification



Street View images
3D-depth maps
Top-down map images
GIS metadata

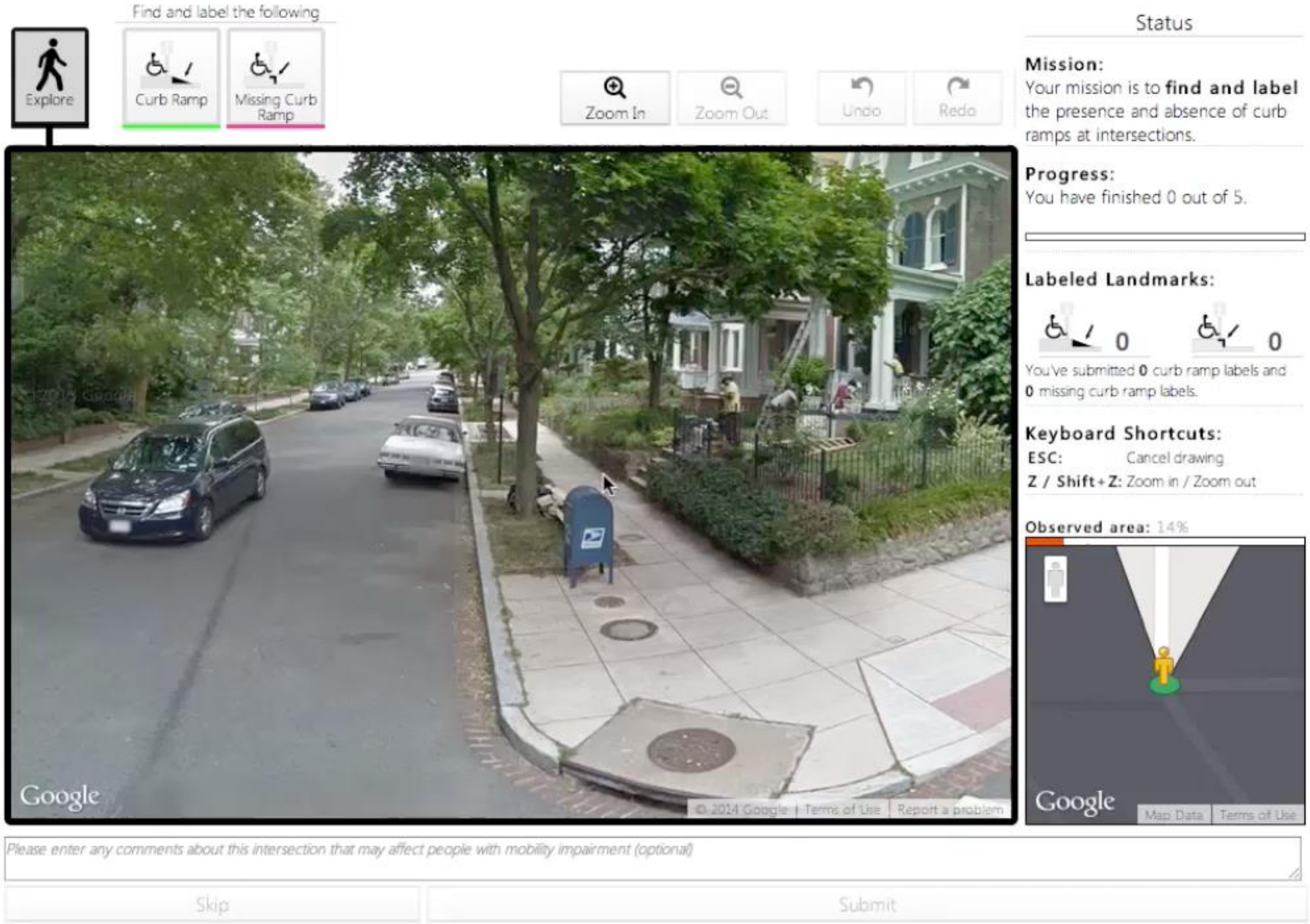
2 **Street Dataset**

4 svControl
Automatic Task Allocation

6 svLabel
Crowd Labeling

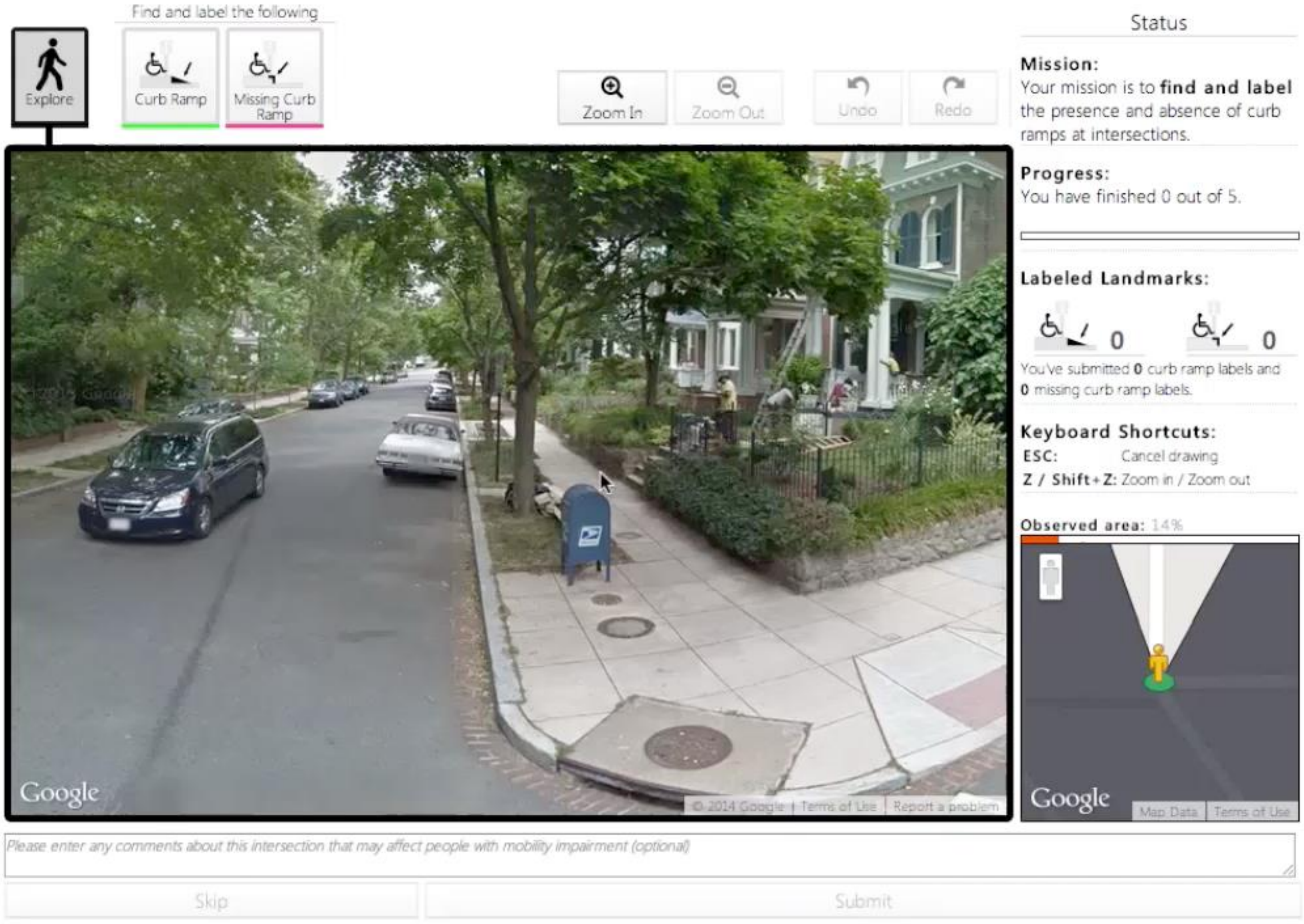
CROWD INTERFACES

LABELING TOOL



CROWD INTERFACES

LABELING TOOL



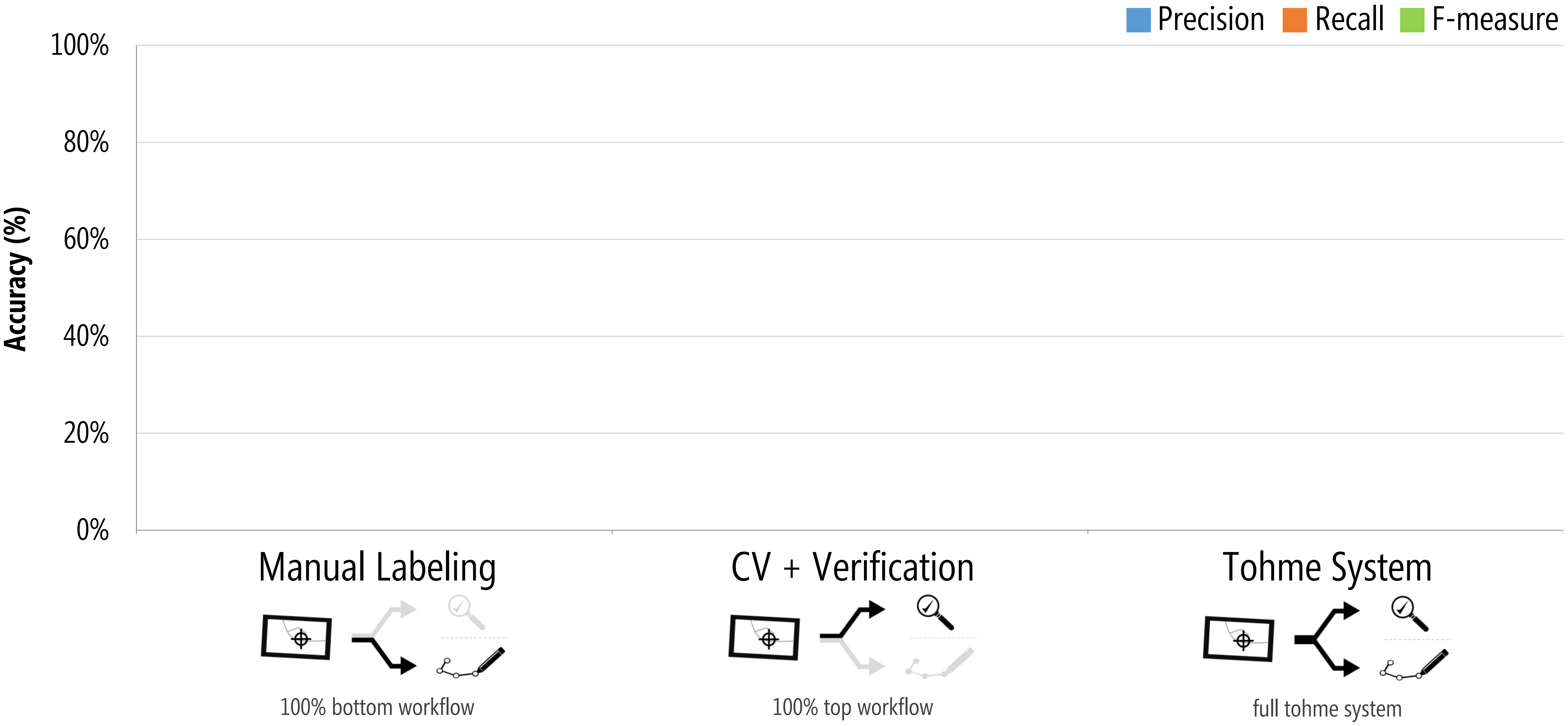
Playback Speed: **2x**

STUDY METHOD

1. Generate ground truth labels
2. Train computer vision & task controller
3. Deploy Tohme to Mechanical Turk
4. Compare Tohme to baseline

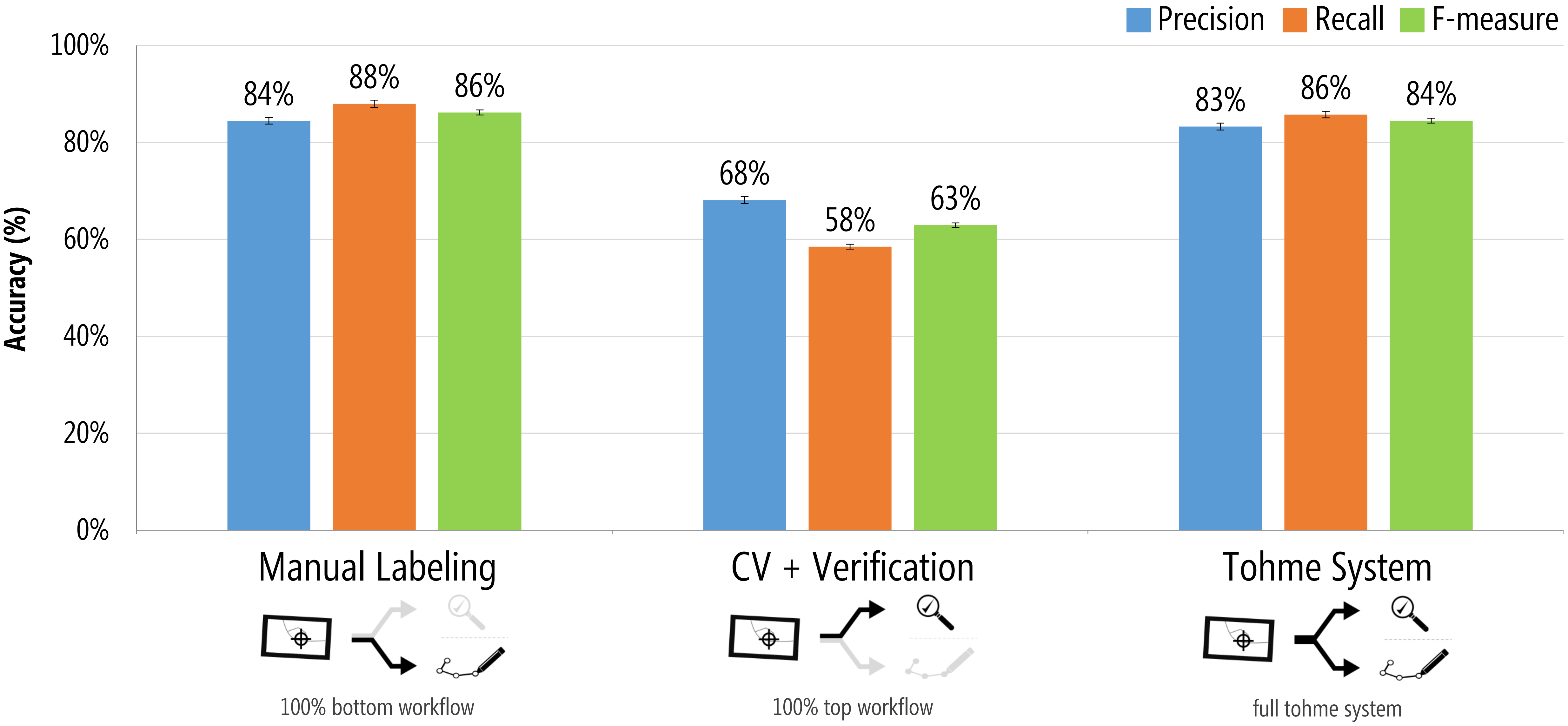
TOHME EVALUATION

OVERALL RESULTS



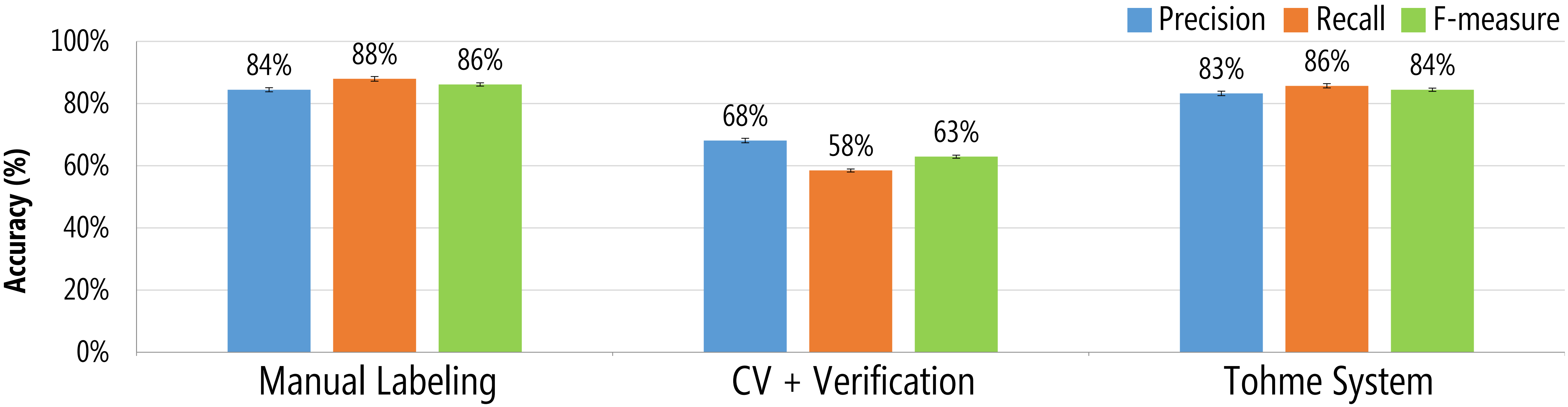
TOHME EVALUATION

OVERALL RESULTS



TOHME EVALUATION

OVERALL RESULTS



100% bottom workflow

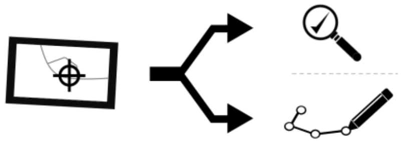
94s

PER SCENE

100% top workflow

42s

PER SCENE



full tohme system

14% faster

81s

PER SCENE

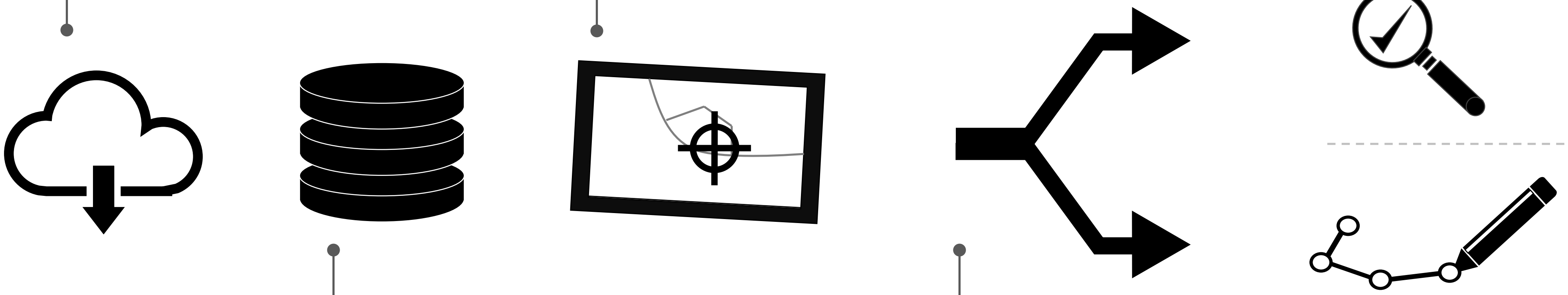
TOHME EVALUATION

TASK CONTROLLER PERFORMANCE

1 svCrawl
Web Scraper

3 svDetect
Automatic Curb Ramp Detection

5 svVerify
Crowd Verification



80%
SCENES CORRECTLY ROUTED

50%
SCENES CORRECTLY ROUTED

Street View images
3D-depth maps
Top-down map images
GIS metadata

2 **Street Dataset**

4 svControl
Automatic Task Allocation

6 svLabel
Crowd Labeling

TOHME EVALUATION

SIMULATED PERFECT TASK CONTROLLER

rb
on

5 svVerify
Crowd Verification

Simulated perfect task controller

100%
SCENES CORRECTLY ROUTED

100%
SCENES CORRECTLY ROUTED

OVERALL SPEEDUP INCREASES OVER MANUAL BASELINE

14% SPEEDUP → **27%** SPEEDUP

4 svControl
Automatic Task Allocation

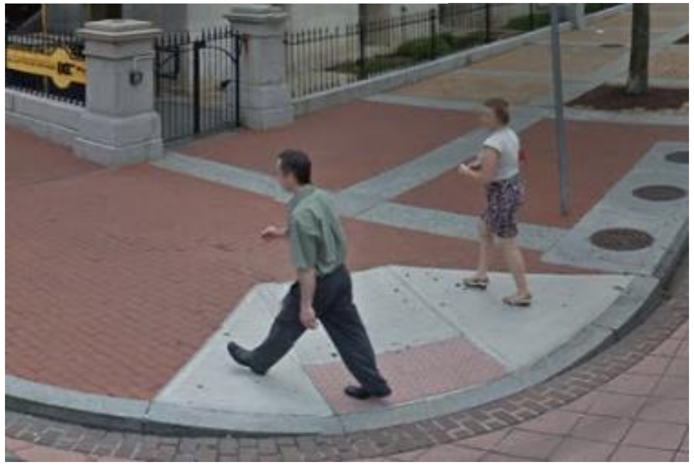
6 svLabel
Crowd Labeling

AUTOMATIC DETECTION IS HARD

IMPROVING DETECTION ALGORITHMS

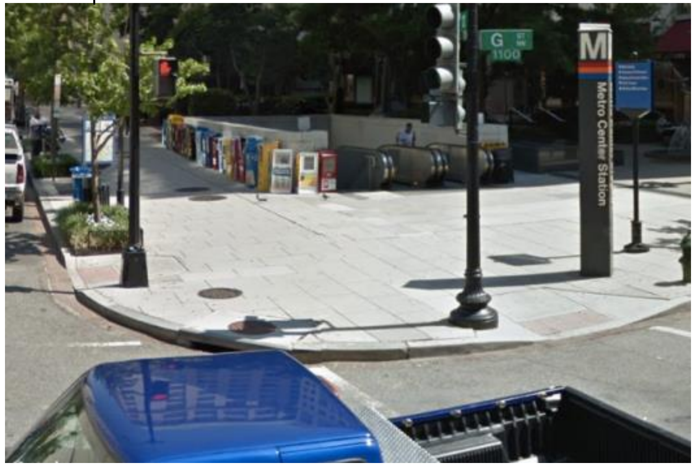
AUTOMATIC DETECTION IS HARD

Occlusion



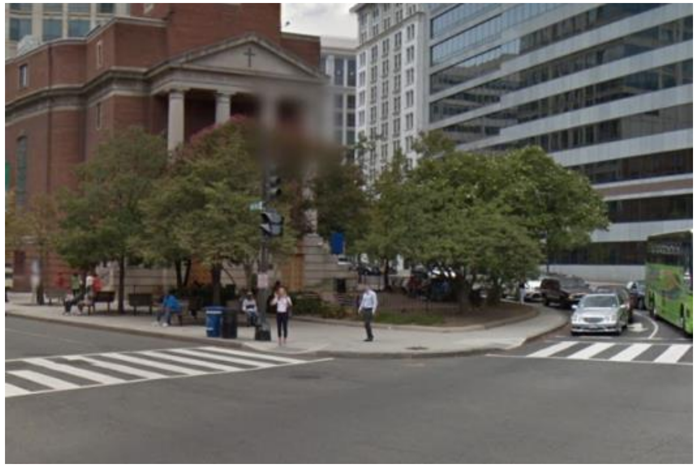
Illumination

Viewpoint Variation



Structures Similar to Curb Ramps

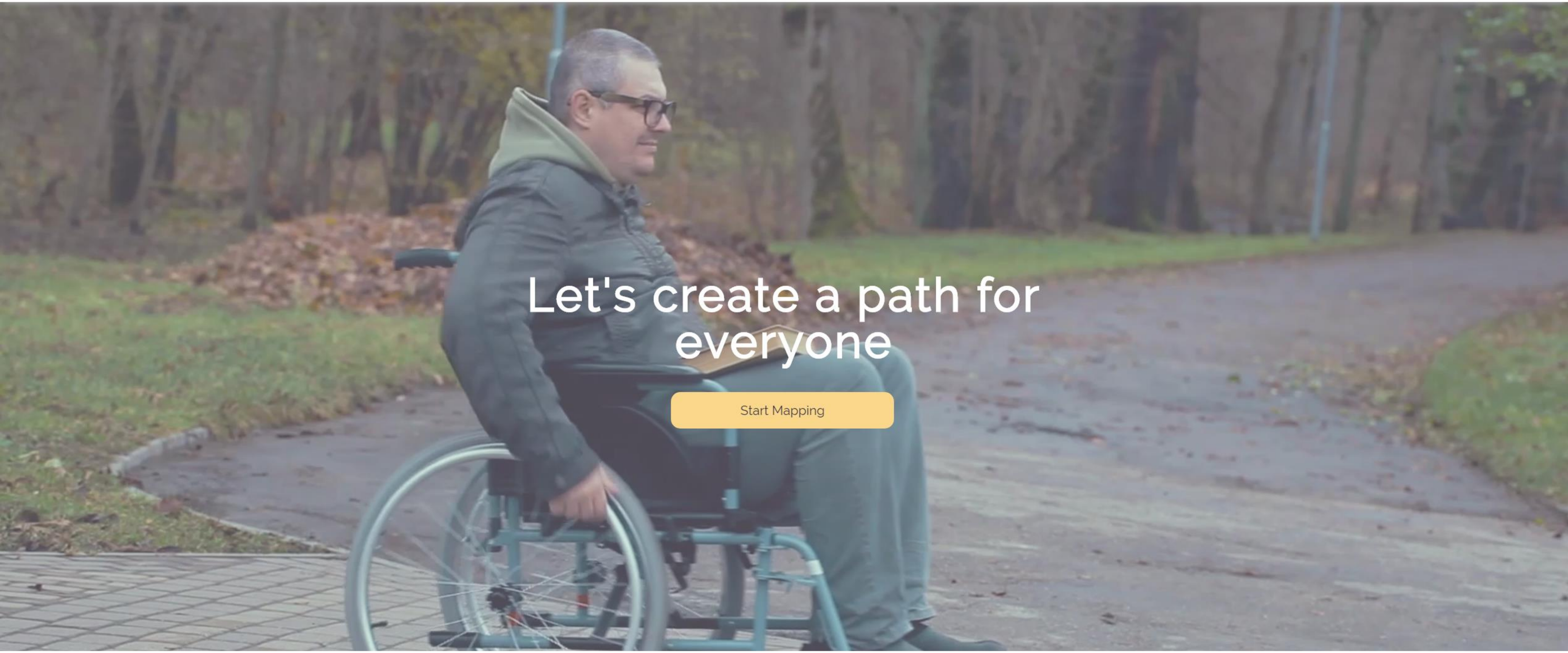
Scale



Curb Ramp Design Variation

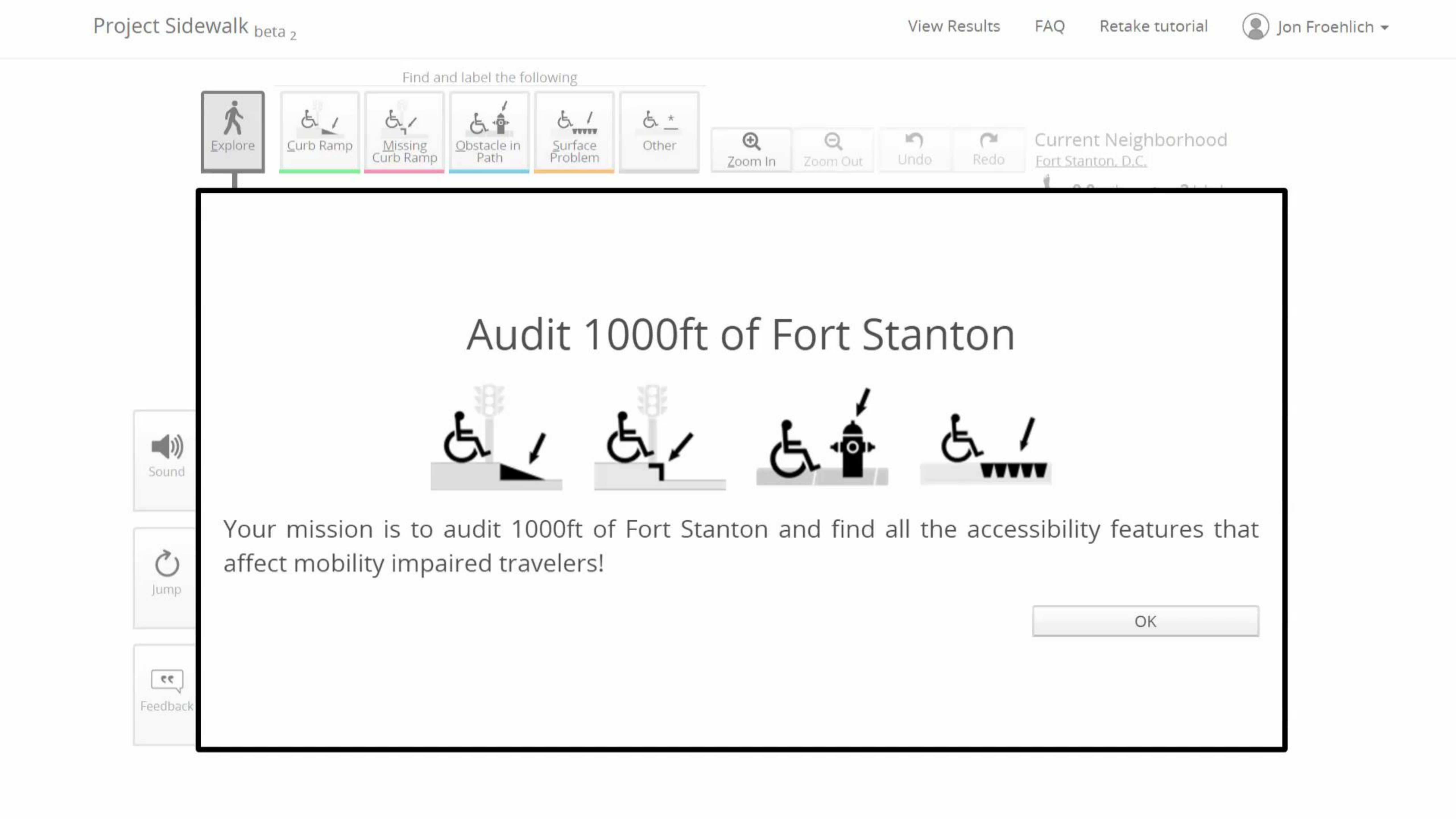
PROJECT
SIDEWALK

HTTP://PROJECTSIDEWALK.IO



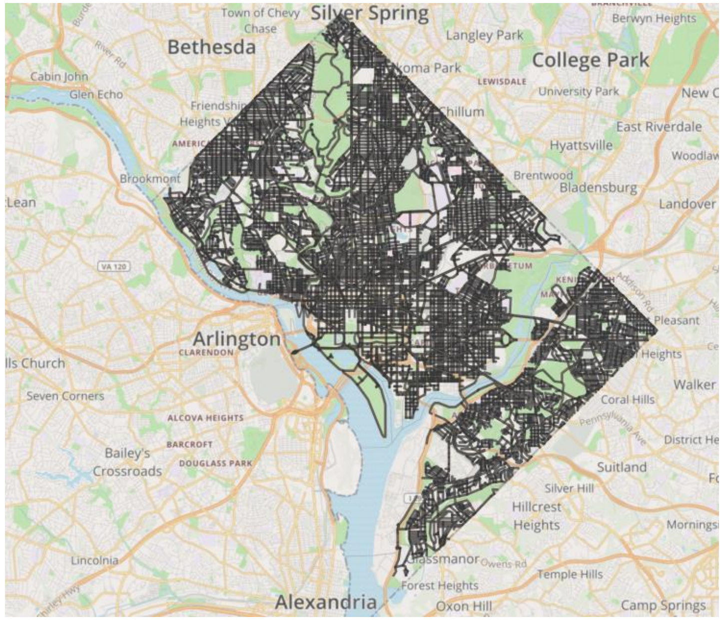
How you can help

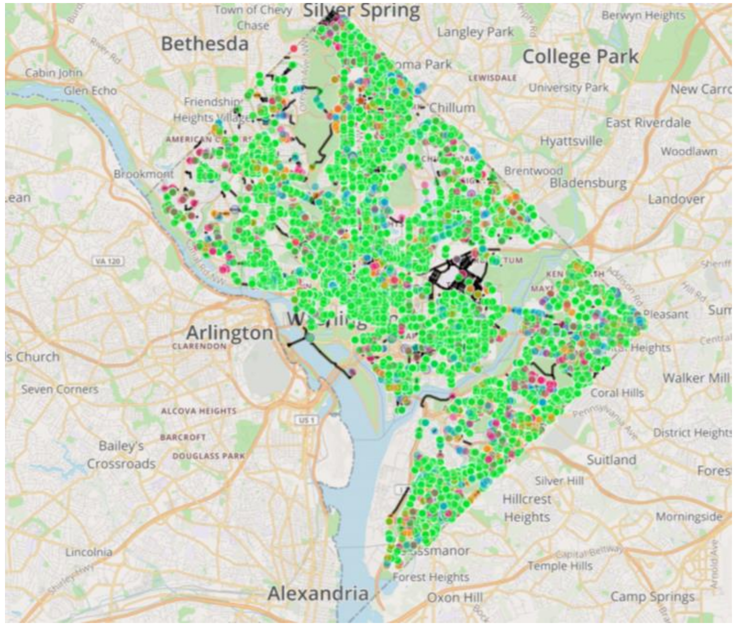
Virtually explore city streets to find and label accessibility


Project Sidewalk beta 2
View Results
FAQ
Retake tutorial
Jon Froehlich
Find and label the following
Explore
Curb Ramp
Missing Curb Ramp
Obstacle in Path
Surface Problem
Other
Zoom In
Zoom Out
Undo
Redo
Current Neighborhood
Fort Stanton, D.C.
Sound
Jump
Feedback
Audit 1000ft of Fort Stanton
Your mission is to audit 1000ft of Fort Stanton and find all the accessibility features that affect mobility impaired travelers!
OK

PROJECT SIDEWALK CONTRIBUTIONS

PROJECT SIDEWALK
HTTP://PROJECTSIDEWALK.IO





3600+
USERS

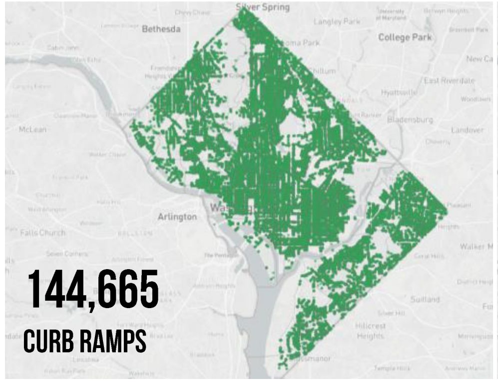
1,075
MILES

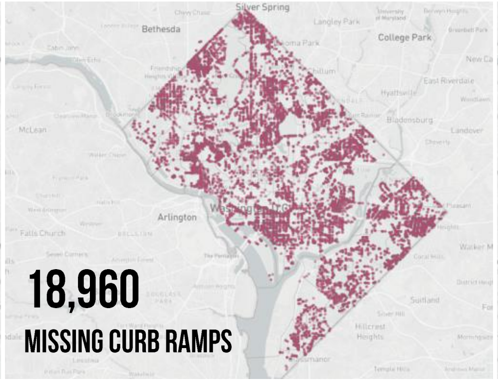
255,000+
LABELS

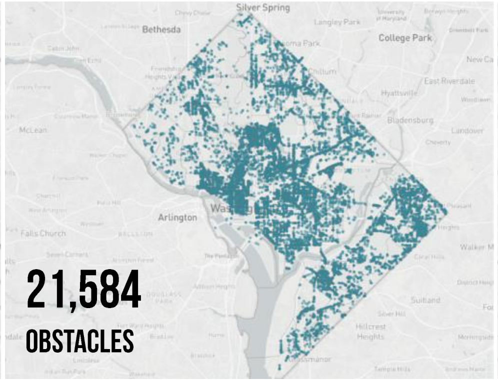
PROJECT SIDEWALK

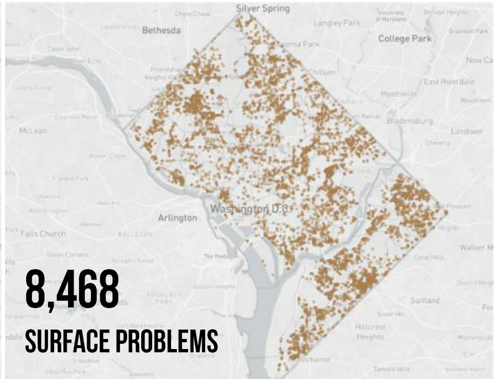
WHERE ARE THE (IN)ACCESSIBLE AREAS OF DC?

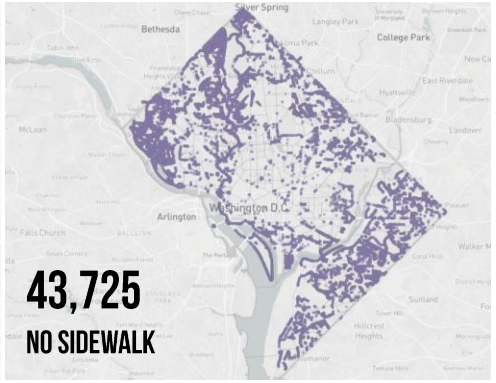
What are the correlates to accessibility? Census tract data, real estate pricing, school quality, park density?





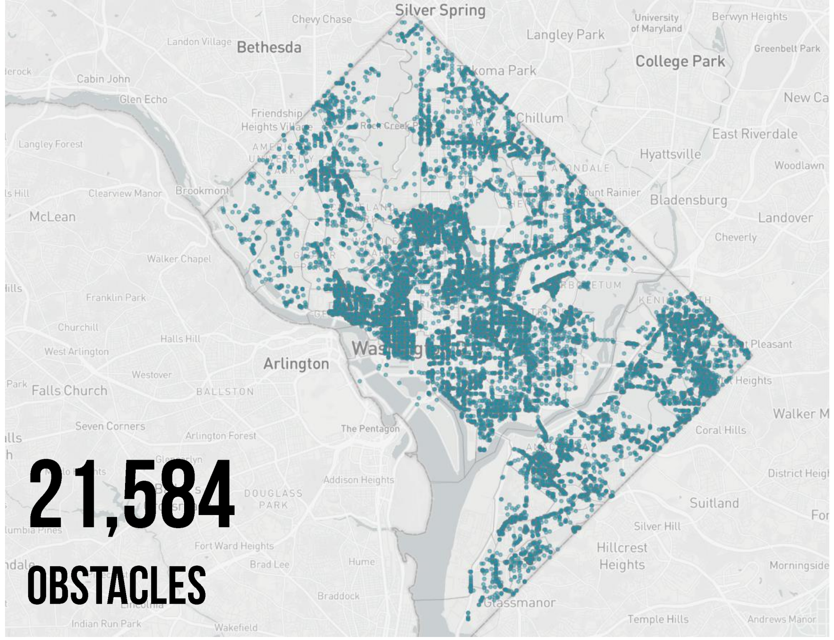


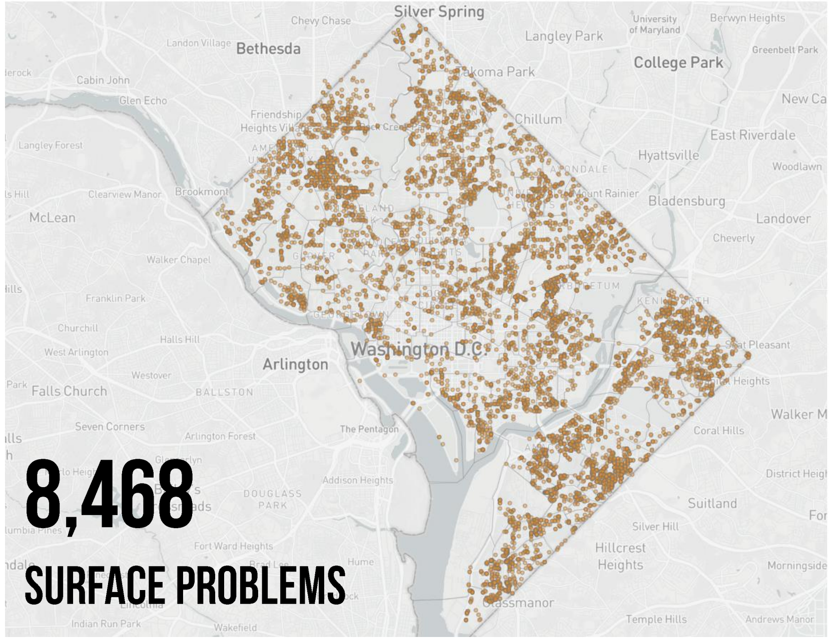


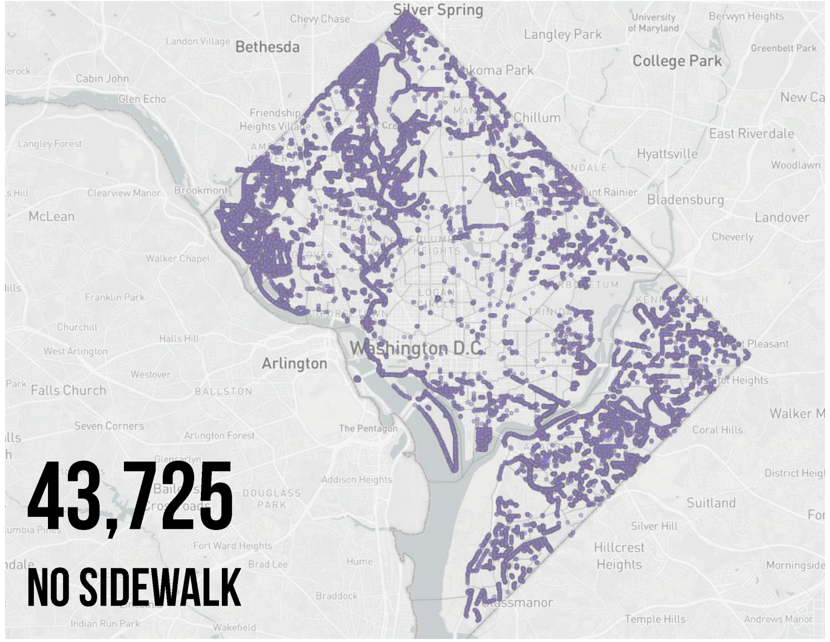


PROJECT SIDEWALK

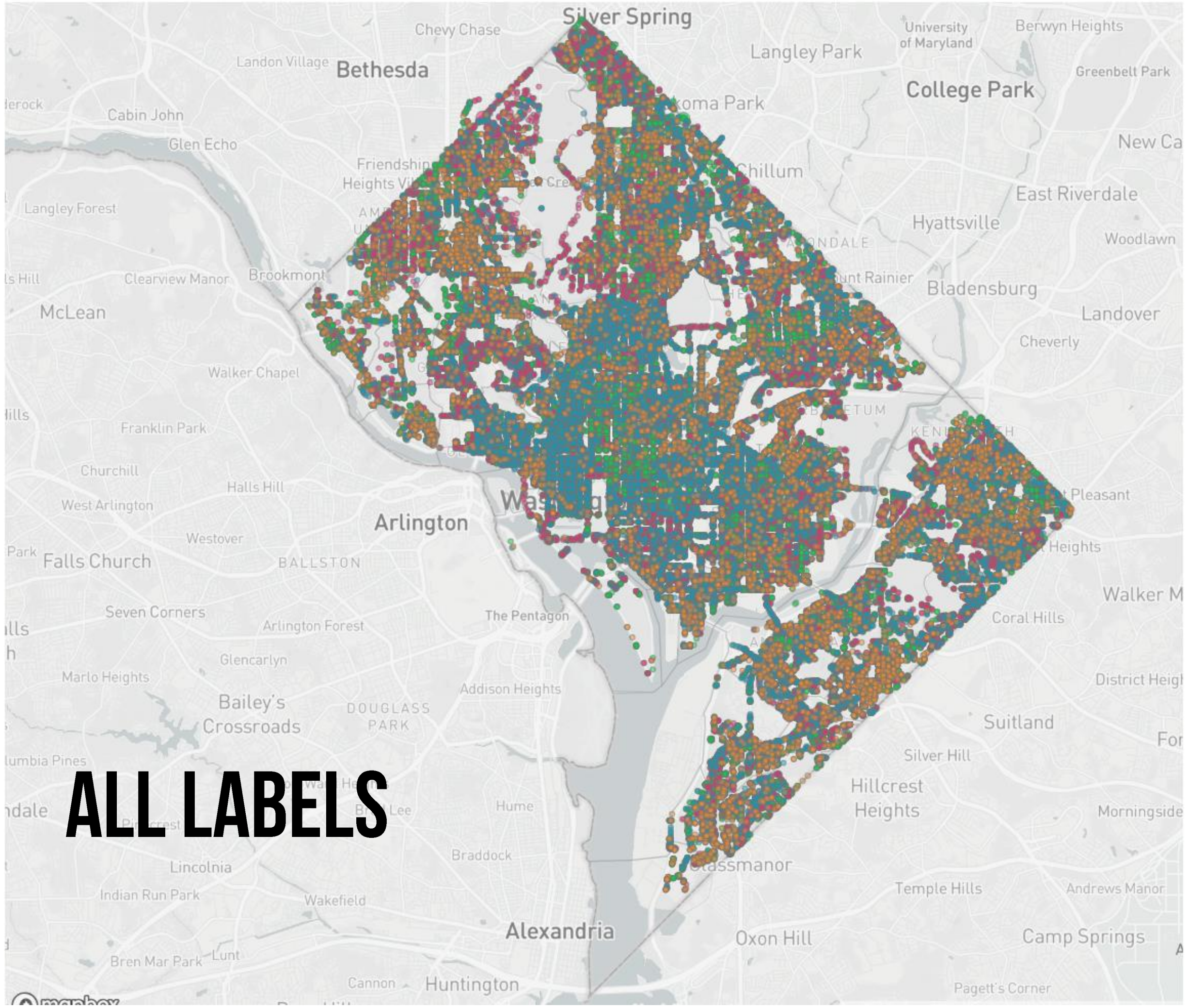
WHAT DO YOU SEE?

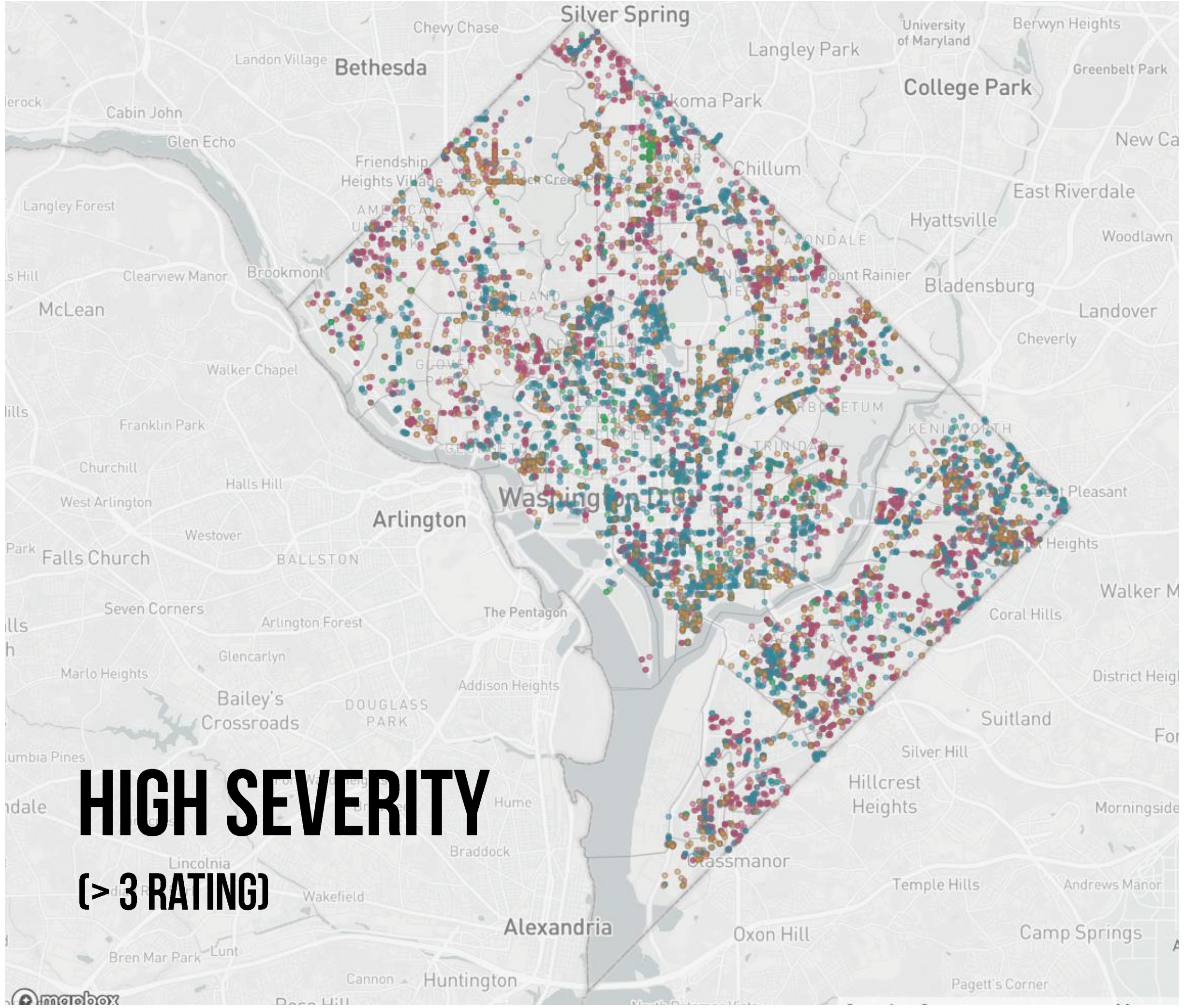






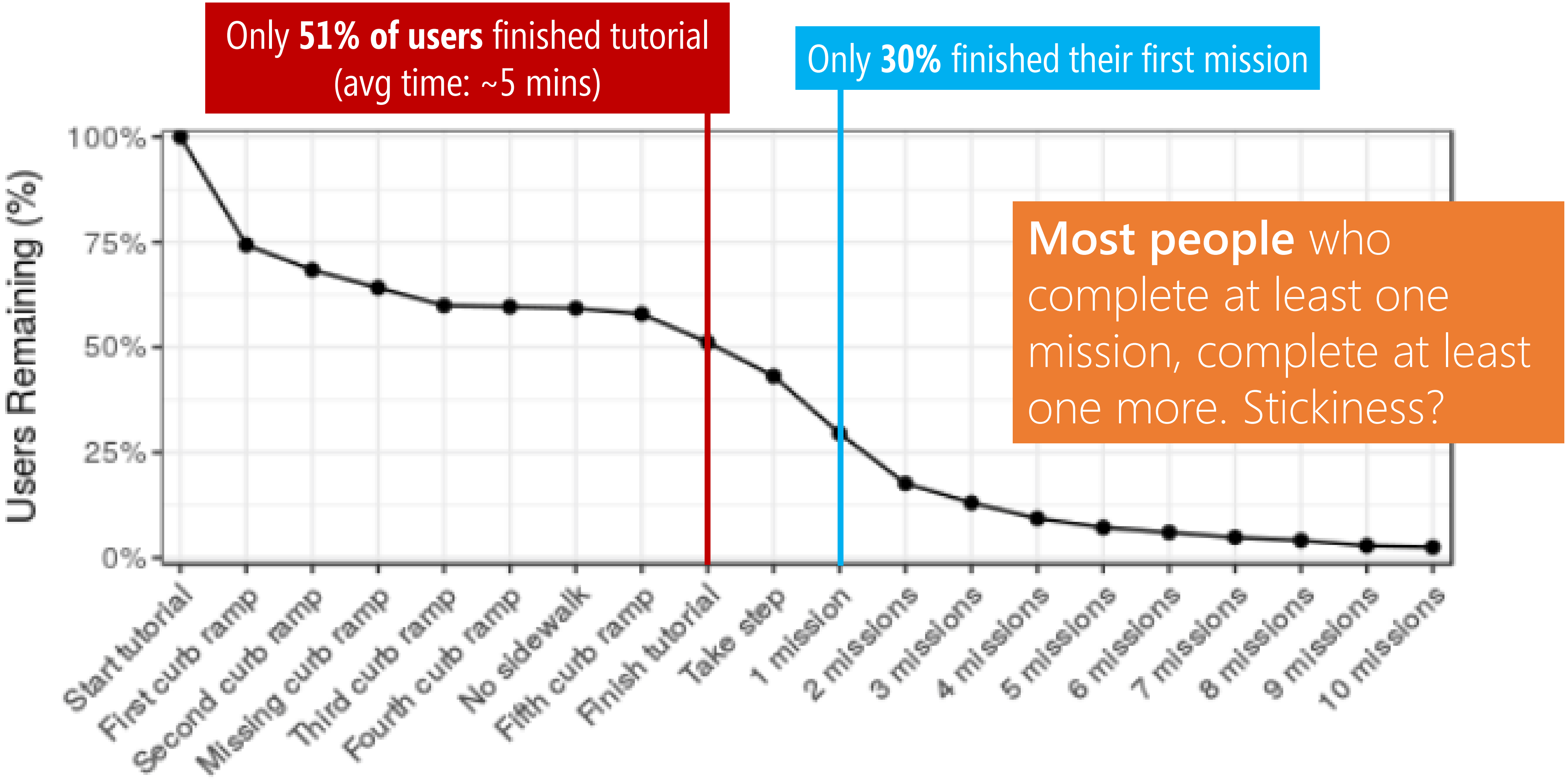
WHERE ARE THE HIGH SEVERITY ISSUES?





PROJECT SIDEWALK

HOW DO WE BETTER ENGAGE & SUSTAIN PARTICIPATION?

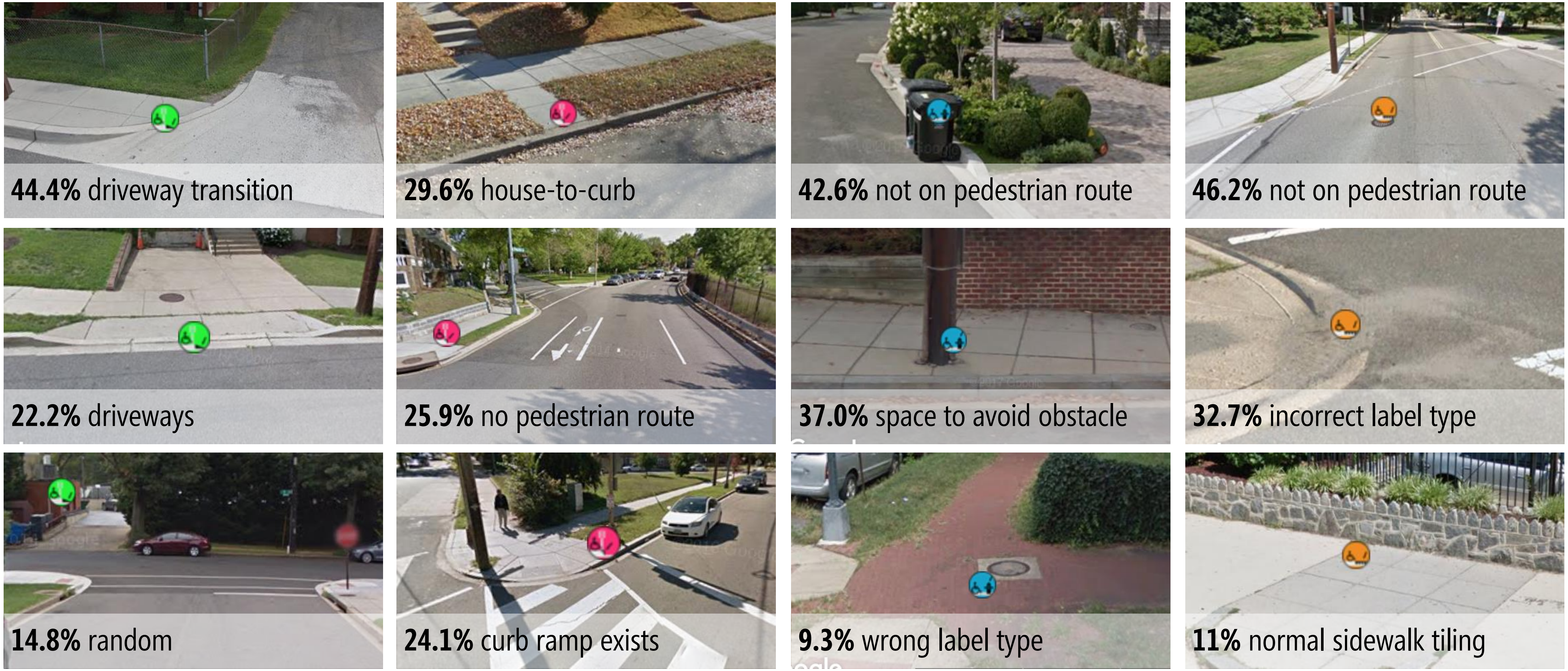


PROJECT SIDEWALK

HOW DO WE HELP USERS LABEL MORE ACCURATELY?

Randomly sampled 54 false positives and 54 false negatives for each label type (432 total error samples analyzed). False positives shown below.

Curb Ramps | Missing Curb Ramps | Obstacles | Surface Problems



FUTURE WORK

We are actively seeking collaborators on this work!

Improving data collection methods.

Predicting work quality, better integration with computer vision, more sophisticated feedback and training

Data/urban science questions.

What factors correlate with urban accessibility? How can we create models that allow us to compare across cities?

New applications of method.

How can we track urban accessibility changes over time? Could we create a reusable GSV-based platform to support other studies?

Creating new interactive tools.

Interactive visualizations of neighborhood accessibility, 'smart routing' that takes into account accessibility obstacles


19393.jpg
7915.jpg
19395.jpg
19394.jpg
19392.jpg
19390.jpg
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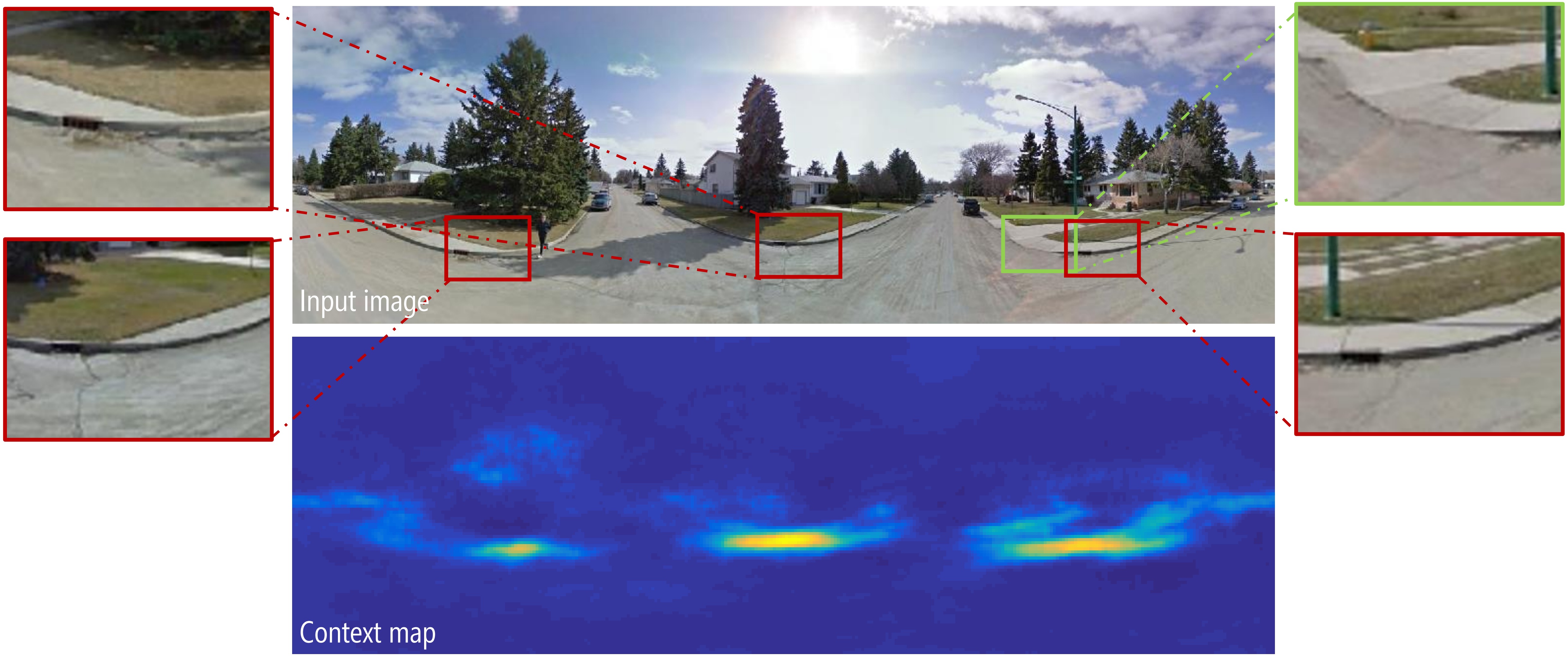
FUTURE WORK: IMPROVING DATA COLLECTION METHODS

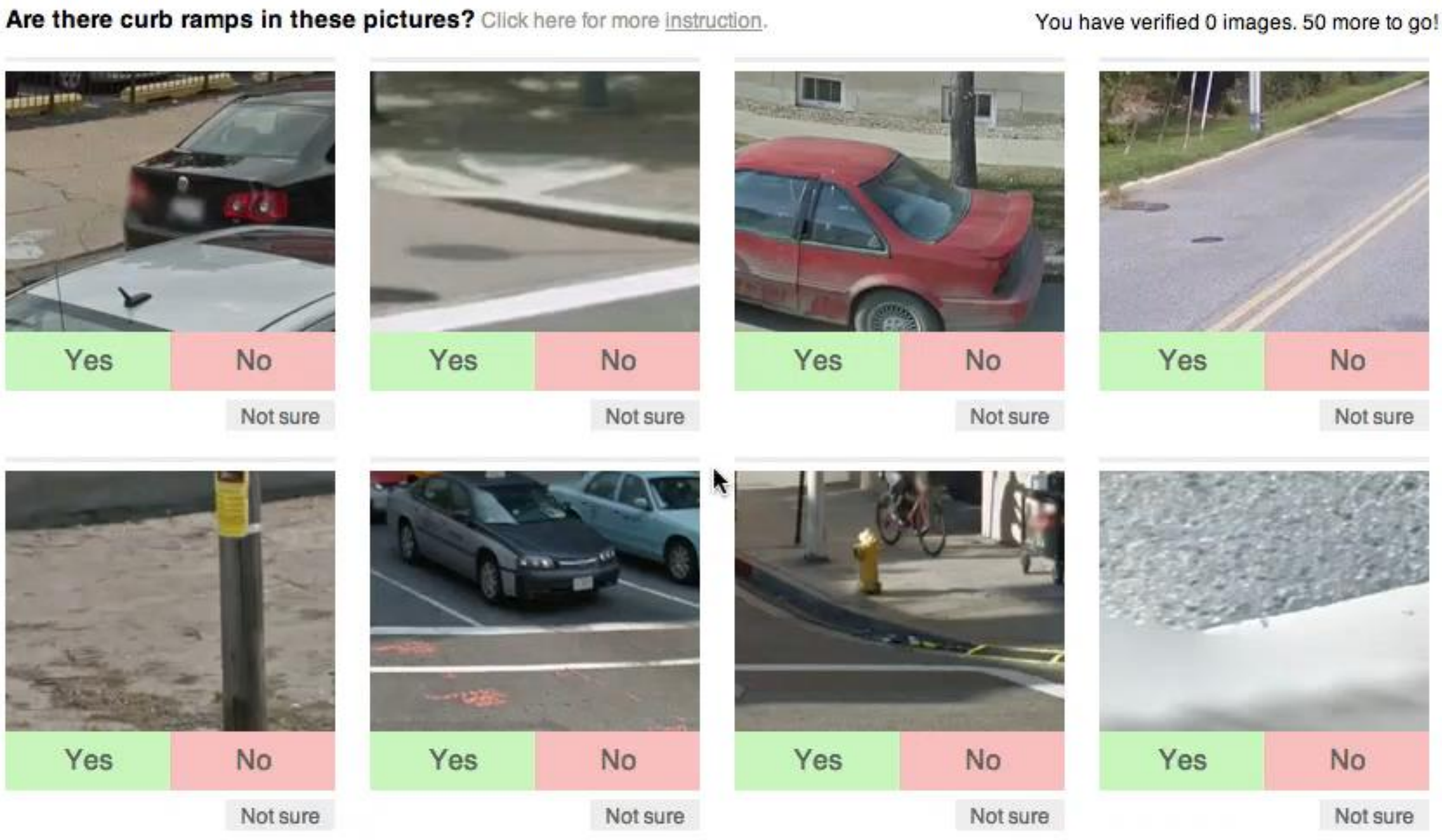
APPLYING DEEP LEARNING METHODS TO AUTOMATIC DETECTION

Follow-up to UIST'14, published at CVPR'17.

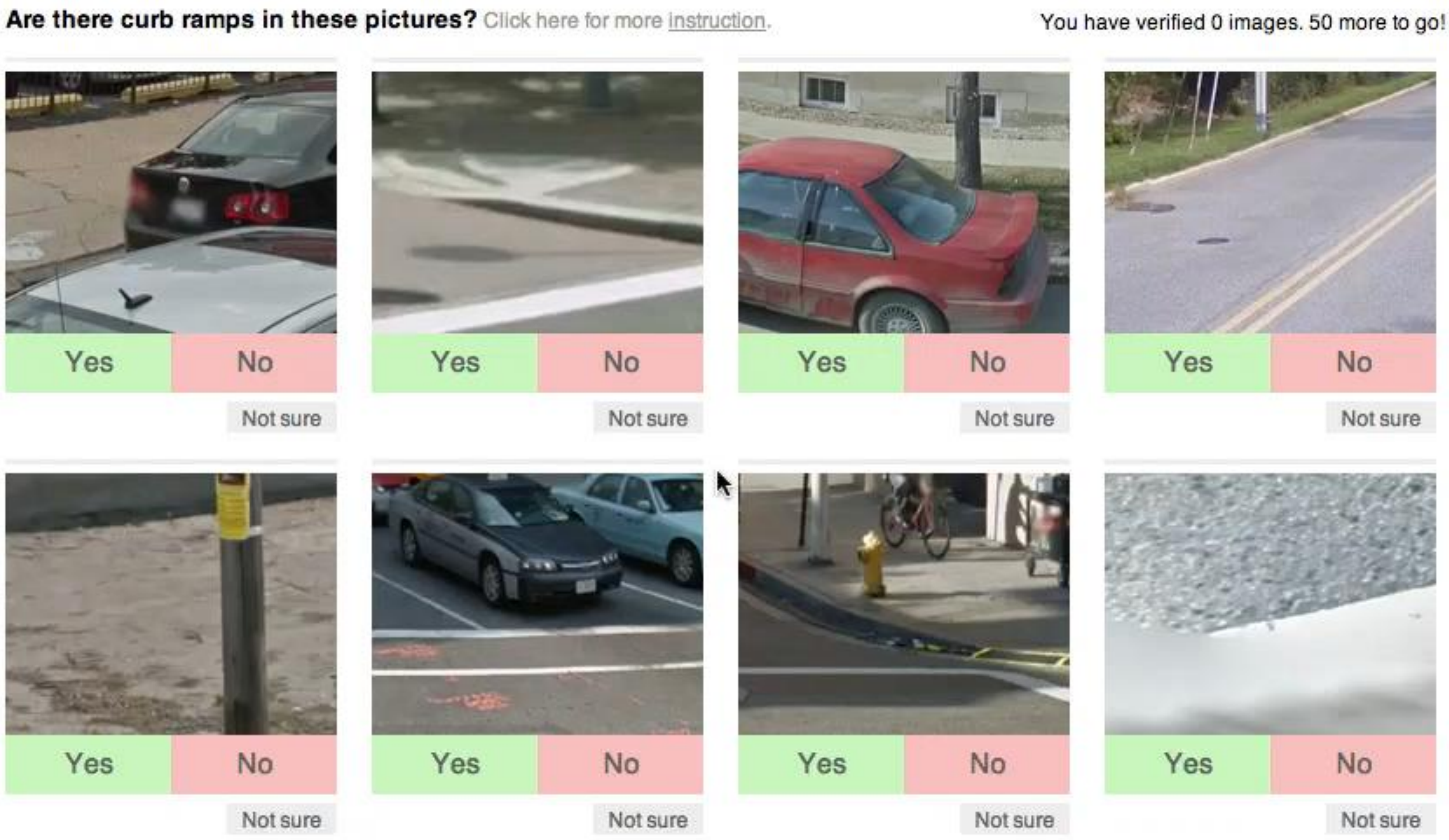


FUTURE WORK: IMPROVING DATA COLLECTION METHODS

NEW HYBRID WORKFLOWS & INTERFACES



NEW HYBRID WORKFLOWS & INTERFACES

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Washington, District of Columbia
Street View - Sep 2007
34th St NW
St Albans School for Boys
Garfield St NW
Cleveland
Back to Map
Google
Image capture: Sep 2007
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FUTURE WORK: NEW APPLICATIONS OF METHOD

TRACKING ACCESSIBILITY INFRASTRUCTURE OVER TIME

A Feasibility Study of Using Google Street View and Computer Vision to Track the Evolution of Urban Accessibility

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Figure 1. In this paper, we examine the feasibility of using Google Street View's "time machine" feature [4] and basic computer vision algorithms to track changes in urban accessibility over time. For each location, accessibility problems are manually labeled in the most recent Street View image (blue outline) then are automatically back propagated through time (red outlines) to track and discover potential changes. In the example here, an object in the pedestrian path has persisted over time to the most recent data (2014), while a sidewalk surface problem from 2007 was resolved by 2009.

ABSTRACT

Previous work has explored scalable methods to collect data on the accessibility of the built environment by combining manual labeling, computer vision, and online map imagery. In this poster paper, we explore how to extend these methods to track the evolution of urban accessibility over time. Using Google Street View's "time machine" feature, we introduce a three-stage classification framework: (i) manually labeling accessibility problems in one time period; (ii) classifying the labeled image patch into one of five accessibility categories; (iii) localizing the patch in all previous snapshots. Our preliminary results analyzing 1633 Street View images across 376 locations demonstrate feasibility.

Author Keywords

Urban accessibility; computer vision; Google Street View

ACM Classification Keywords

H.5.m. Information interfaces and presentation (e.g., HCI)

INTRODUCTION

Recent work has explored scalable methods to identify and characterize accessibility features in the built environment using remote crowdsourcing, machine learning, and online map datasets (*e.g., Google Street View* (GSV) [5, 7, 11], satellite photographs [1]). For example, *Tohme* [7] combines computer vision with web-based crowd work to semi-automatically label curb ramps in GSV. While accurately finding and assessing accessibility features in map imagery is still an active research area, in this poster paper, we begin to explore a related but even more data-intensive process—how to semi-automatically track the evolution of urban accessibility over time using historical map data (Figure 1).

Our work builds on decades of past research in urban studies, geography, and ecology, which analyze temporal changes in land use from remote sensors. Typically, however, the focus is on macroscopic trends (*e.g.,* urbanization [8, 14, 18], deforestation [13]), which do not require the detailed sensing of small entities that our work requires (*e.g.,* light poles, curb ramps). In addition, rather than rely on satellite images, we use the historical omnidirectional panoramic imagery found in GSV's "time machine" [4]. With the emergence of large-scale image sets and an interest in vision algorithms to support autonomous vehicles, computer scientists have also begun to develop techniques to detect and model urban change [2, 9, 12]. Our techniques are informed by these approaches but with a distinct focus on tracking accessibility.

Our contributions include: (i) a preliminary examination of using GSV's "time machine" as a data source for tracking (in)accessible pedestrian infrastructure over time; (ii) an initial three-stage classification framework for labeling and categorizing accessibility features through time; (iii) a preliminary study validating our approach.

FEASIBILITY STUDY

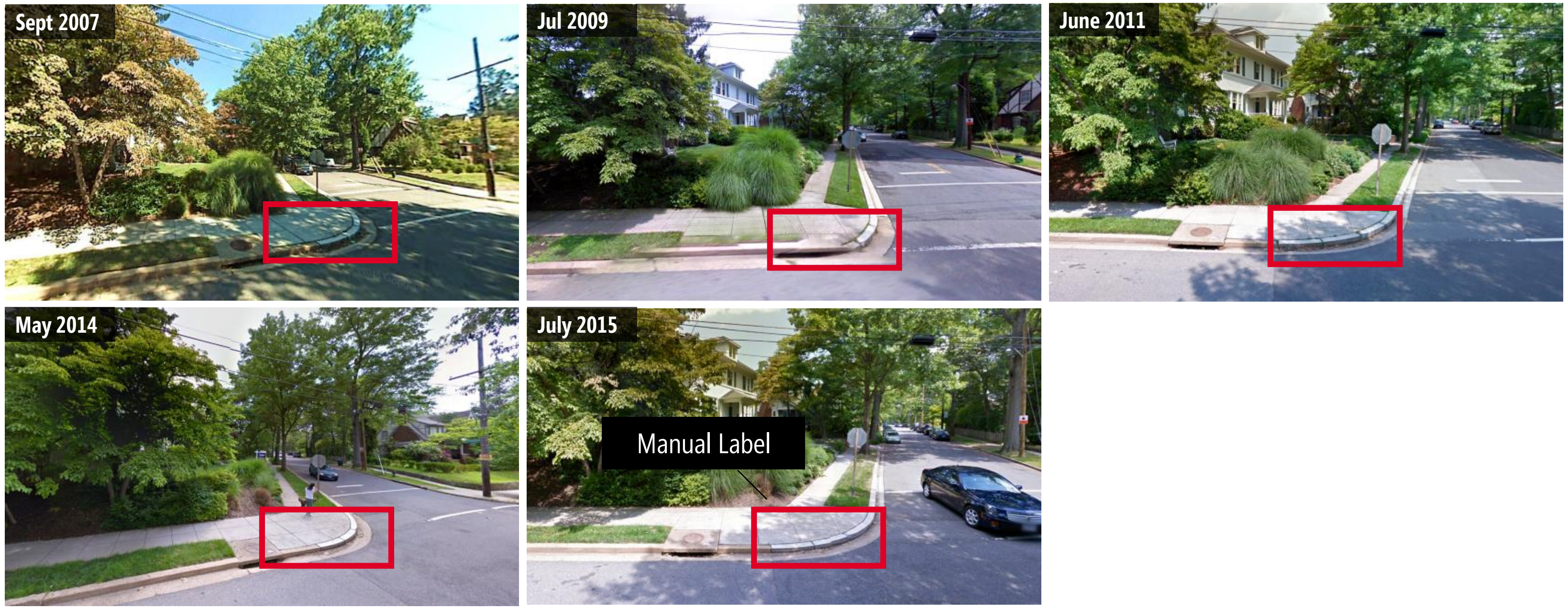
To examine the feasibility of our approach, we created a test dataset, implemented a classification framework, and performed initial validation. Based on [6, 11], we track five classes of sidewalk features: *accessible sidewalks* (*i.e.*, no problems), *accessible curb ramps*, *missing curb ramps*, *objects in path*, and *surface problems.*

Dataset

We built our dataset by randomly selecting locations in Washington DC and Maryland, examining the GSV imagery to identify accessibility features, and then using "time machine" to capture historical panoramas. As we are primarily interested in how accessibility features change over time, we iteratively diversified the dataset to include locations where features: (i) changed over time; (ii) persisted over time; or (iii) were occluded in at least one time period (*e.g.*, by a passing car), making it difficult to track temporal changes. For each location, we captured a screenshot of all available images across time and recorded GPS coordinates, Street View URL, capture timestamp, and the camera's yaw, pitch, and field-of-view.

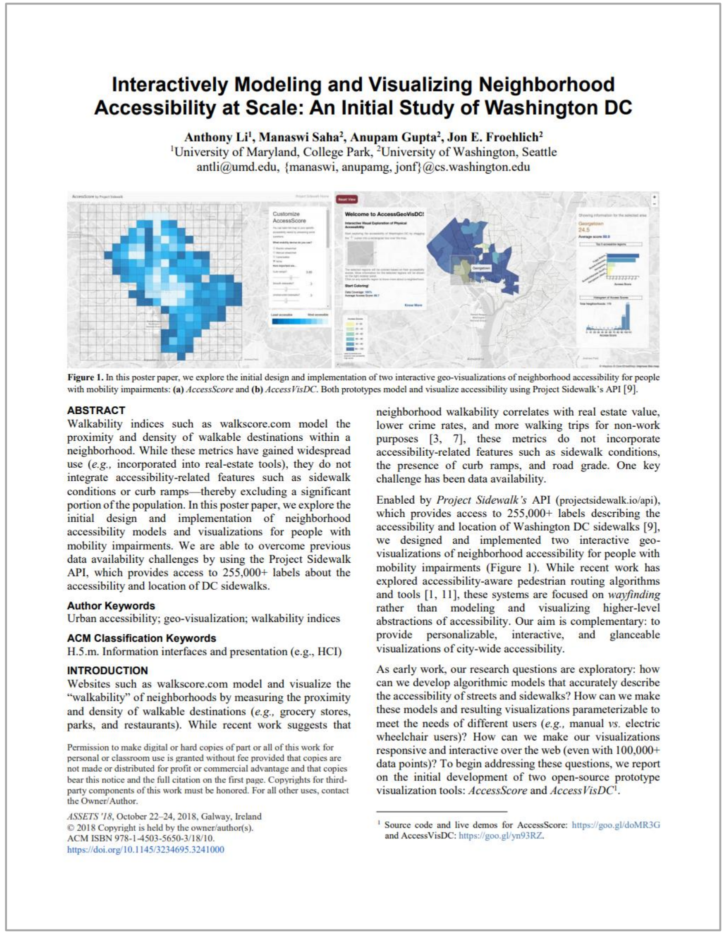
ASSETS '18, October 22–24, 2018, Galway, Ireland

ACM ISBN 978-1-4503-5650-3/18/10.
https://doi.org/10.1145/3234695.3240999



FUTURE WORK: CREATING NEW INTERACTIVE TOOLS

INTERACTIVELY MODELING & VISUALIZING ACCESSIBILITY



Interactively Modeling and Visualizing Neighborhood Accessibility at Scale: An Initial Study of Washington DC

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Figure 1. In this poster paper, we explore the initial design and implementation of two interactive geo-visualizations of neighborhood accessibility for people with mobility impairments: **(a)** *AccessScore* and **(b)** *AccessVisDC*. Both prototypes model and visualize accessibility using Project Sidewalk's API [9].

ABSTRACT
Walkability indices such as walkscore.com model the proximity and density of walkable destinations within a neighborhood. While these metrics have gained widespread use (*e.g.*, incorporated into real-estate tools), they do not integrate accessibility-related features such as sidewalk conditions or curb ramps—thereby excluding a significant portion of the population. In this poster paper, we explore the initial design and implementation of neighborhood accessibility models and visualizations for people with mobility impairments. We are able to overcome previous data availability challenges by using the Project Sidewalk API, which provides access to 255,000+ labels about the accessibility and location of DC sidewalks.

Author Keywords
Urban accessibility; geo-visualization; walkability indices

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI)

INTRODUCTION
Websites such as walkscore.com model and visualize the "walkability" of neighborhoods by measuring the proximity and density of walkable destinations (*e.g.*, grocery stores, parks, and restaurants). While recent work suggests that neighborhood walkability correlates with real estate value, lower crime rates, and more walking trips for non-work purposes [3, 7], these metrics do not incorporate accessibility-related features such as sidewalk conditions, the presence of curb ramps, and road grade. One key challenge has been data availability.

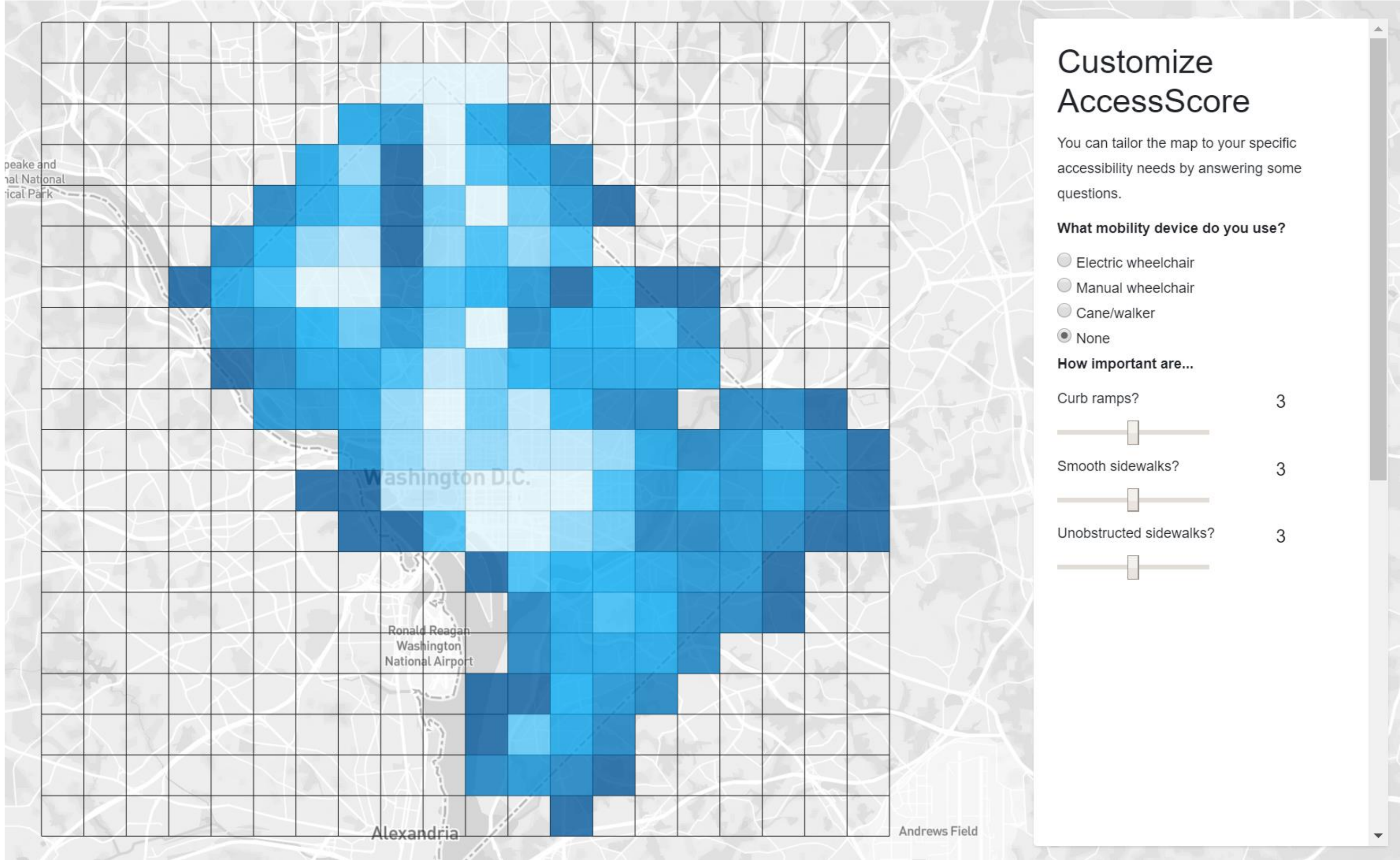
Enabled by *Project Sidewalk's* API (projectsidewalk.io/api), which provides access to 255,000+ labels describing the accessibility and location of Washington DC sidewalks [9], we designed and implemented two interactive geo-visualizations of neighborhood accessibility for people with mobility impairments (Figure 1). While recent work has explored accessibility-aware pedestrian routing algorithms and tools [1, 11], these systems are focused on *wayfinding* rather than modeling and visualizing higher-level abstractions of accessibility. Our aim is complementary: to provide personalizable, interactive, and glanceable visualizations of city-wide accessibility.

As early work, our research questions are exploratory: how can we develop algorithmic models that accurately describe the accessibility of streets and sidewalks? How can we make these models and resulting visualizations parameterizable to meet the needs of different users (*e.g.*, manual *vs.* electric wheelchair users)? How can we make our visualizations responsive and interactive over the web (even with 100,000+ data points)? To begin addressing these questions, we report on the initial development of two open-source prototype visualization tools: *AccessScore* and *AccessVisDC*[1].

ASSETS '18, October 22–24, 2018, Galway, Ireland

ACM ISBN 978-1-4503-5650-3/18/10.
https://doi.org/10.1145/3234695.3241000

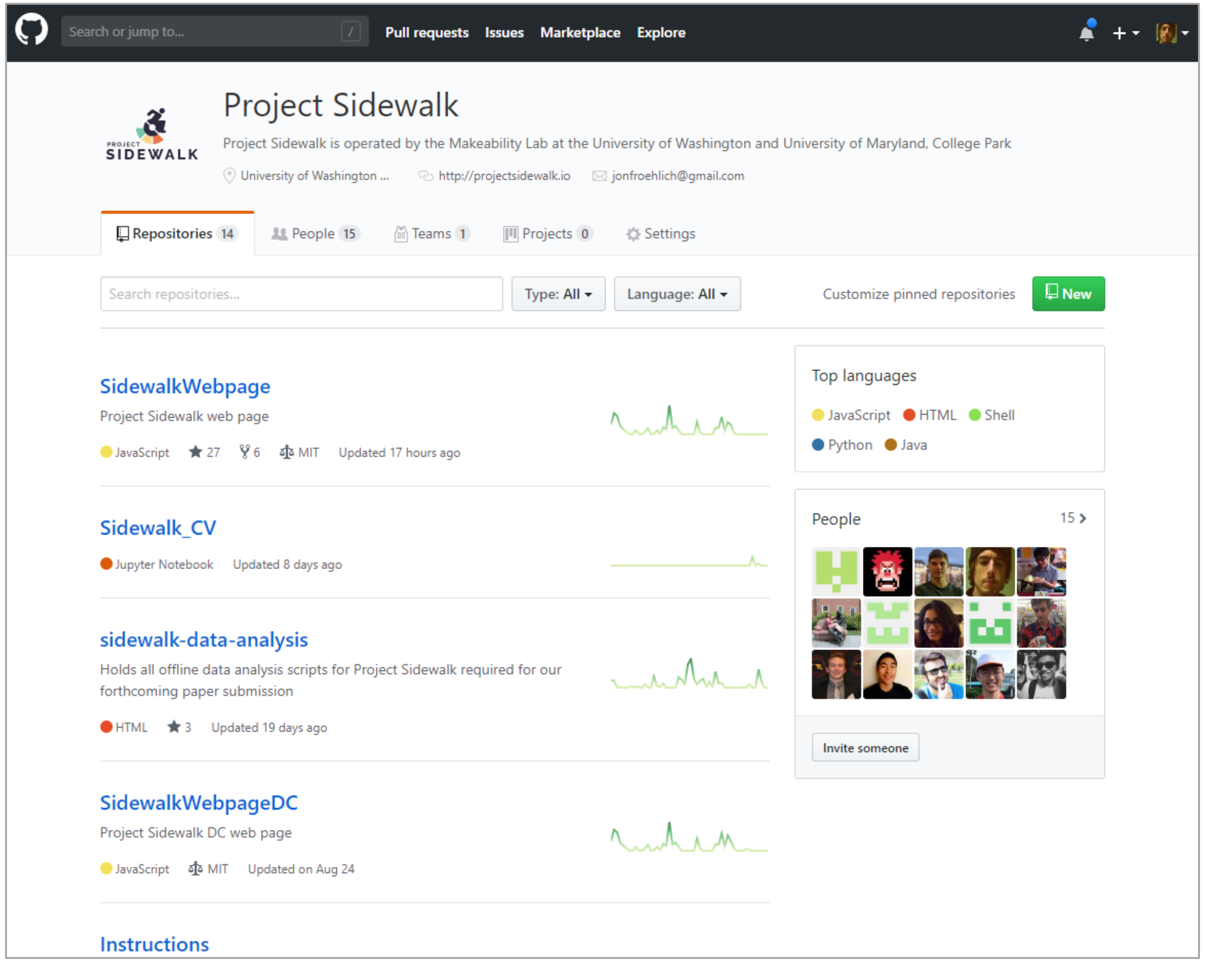
[1] Source code and live demos for AccessScore: https://goo.gl/doMR3G and AccessVisDC: https://goo.gl/yn93RZ.

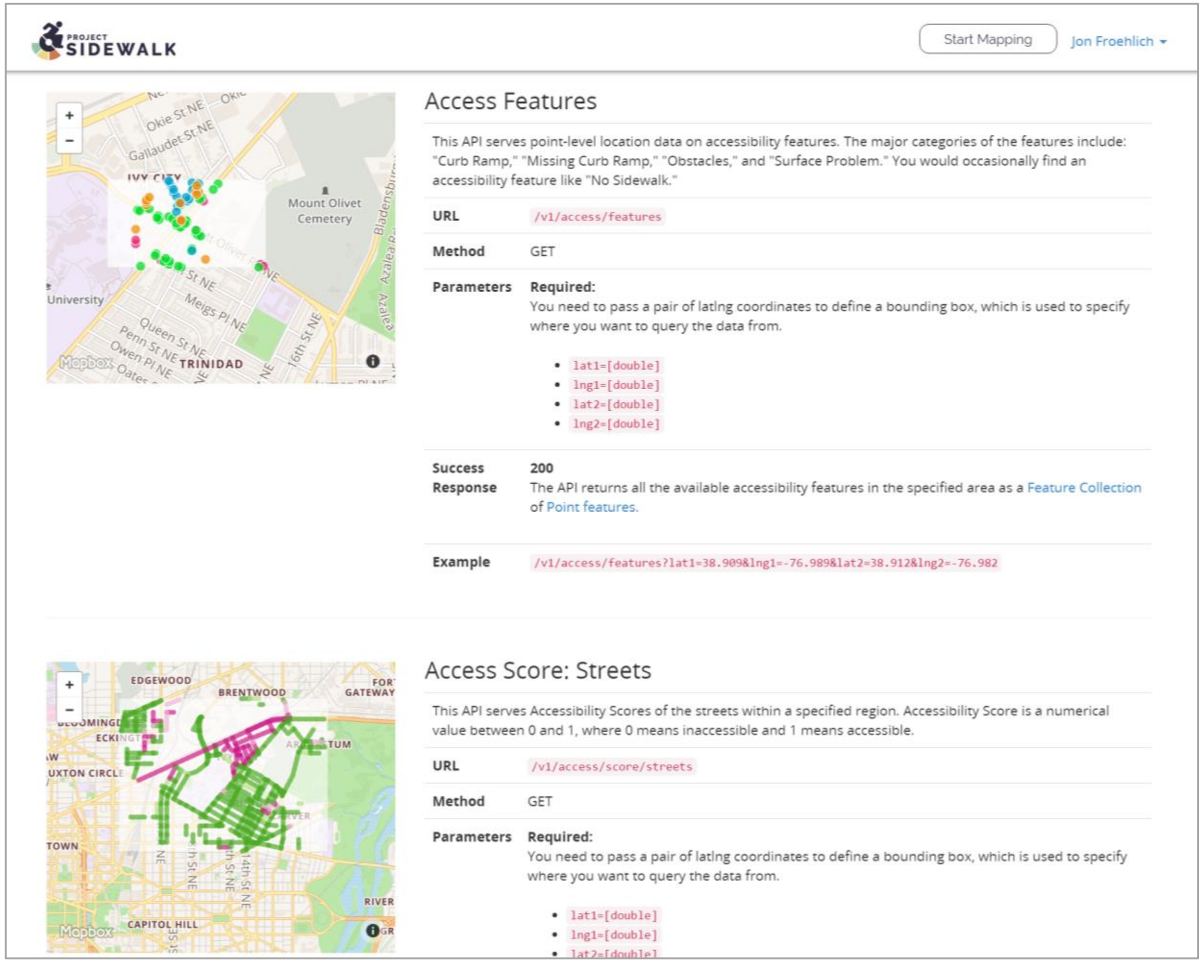


[ASSETS'18 Poster]

PROJECT SIDEWALK

OPEN SOURCE & OPEN DATA





https://github.com/ProjectSidewalk

http://projectsidewalk.io/api

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UNIVERSITY of WASHINGTON

ACKNOWLEDGEMENTS

FUNDING SOURCES

NSF #1302338, Google, IBM

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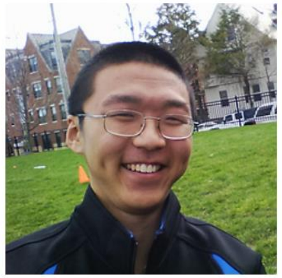

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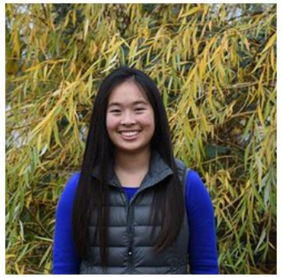

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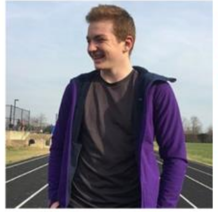

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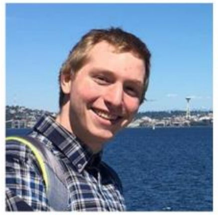

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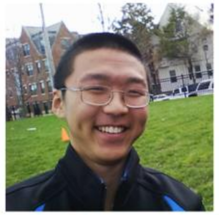

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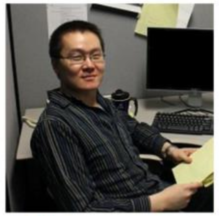

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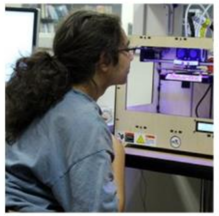

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