

Characterizing Physical World Accessibility at Scale

Combining Google Street View, Crowdsourcing, and Automated
Methods to Collect Accessibility Data about the Built Environment

Kotaro Hara



The Americans with Disabilities Act

mandates that new constructions and alterations of the built environment are to be **accessible for everyone.**



1990



2016

25 Years After The A Still Daunting For T Navigating New York City Is

07/27/2015 03:55 pm ET



Savannah OLeary
Multimedia Producer

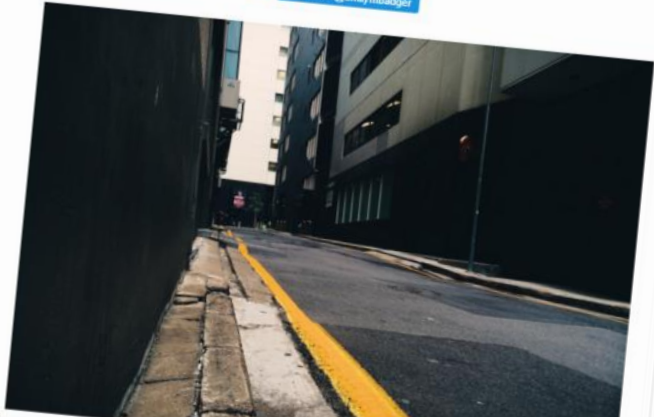


02:15
Lisa's

Wonkblog The inequality of sidewalks

A 9 Save for Later Reading List

By Emily Badger January 15 Follow @emilymbadger



Most Read

- 1 Legal marijuana is finally doing what the drug war couldn't
- 2 The magical thing eating chocolate does to your brain
- 3 The most racist places in America, according to Google
- 4 Georgians form human chain to protest talks with Gazprom
- 5 The key difference between how Trump and Romney made their money



2016

30.6

million U.S. adults with
mobility impairment





15.2

million use an assistive
mobility aid

Missing Curb Ramp



Obstacle

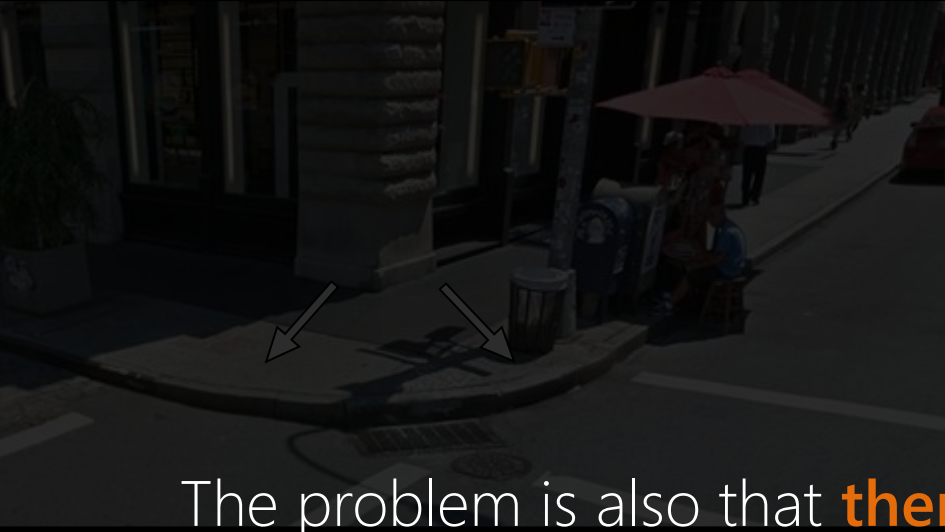


Surface Problem

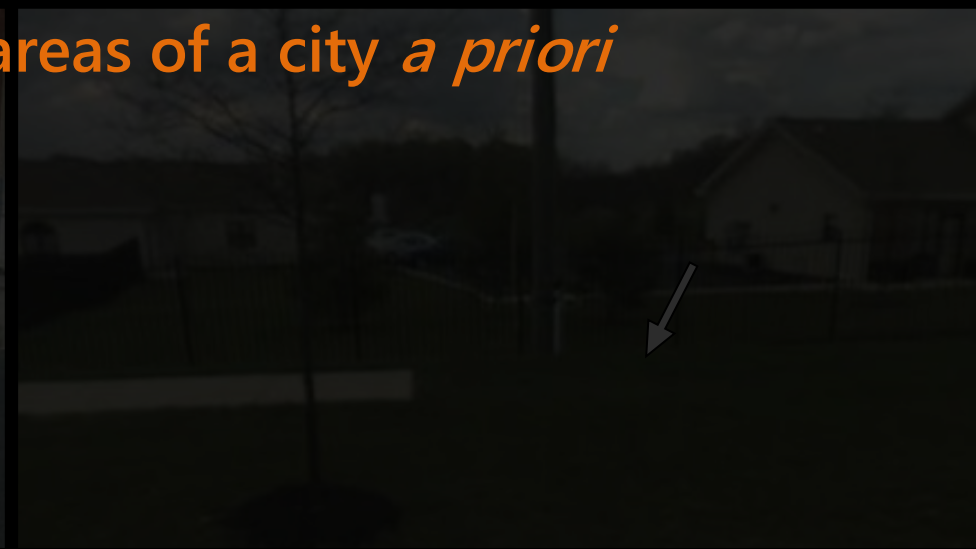


No Sidewalk





The problem is also that **there are few mechanisms to determine accessible areas of a city *a priori***



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

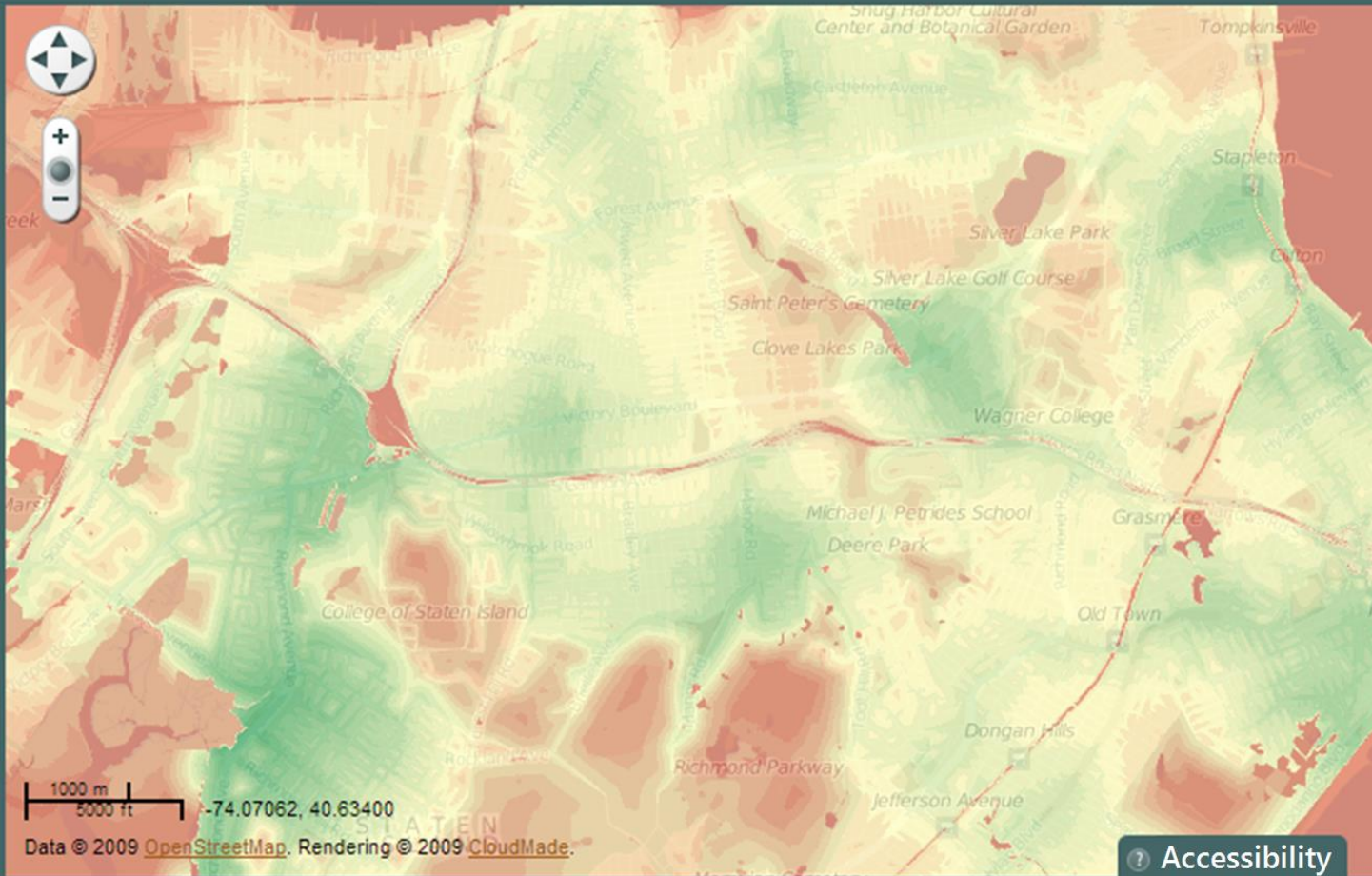
Enter a New York Address

Map Layers

Settings

Adjust Mobility Factors

Recalculate Score



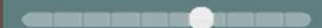
Rate Your Mobility Level



Rate No Curb Cuts Importance



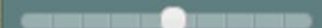
Rate Object in Path Importance



Rate Sidewalk Coverage Importance



Rate Accessible Grocery Importance



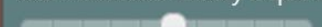
Rate Accessible Transit Importance



Rate Crosswalk Importance



Rate Accessible Library Importance



Rate Accessible Cafes Importance

Accessibility

1000 m / 5000 ft -74.07062, 40.63400

Data © 2009 OpenStreetMap. Rendering © 2009 CloudMade.

123 Broadway Ave NW

Map Layers ▾

Adjust Mobility Factors

Settings

Recalculate Score

Address: 123 Broadway Ave NW

This address received an accessibility score of **67** primarily because **28%** of nearby intersections lack curb cuts, **20%** roads lack sidewalks on both sides, and a lack of an accessible grocery store within **0.5 miles**.



1000 m
5000 ft
-74.07062, 40.63400

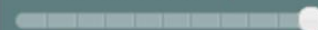
Data © 2009 [OpenStreetMap](#). Rendering © 2009 [CloudMade](#).

Accessibility

Rate Your Mobility Level



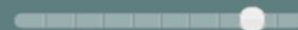
Rate No Curb Cuts Importance



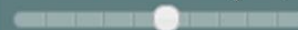
Rate Object in Path Importance



Rate Sidewalk Coverage Importance



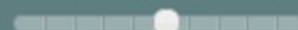
Rate Accessible Grocery Importance



Rate Accessible Transit Importance



Rate Crosswalk Importance



Rate Accessible Library Importance



Rate Accessible Cafes Importance

Accessibility-aware Navigation



Our vision is to design methods to **scalably collect street-level accessibility data** that enables technologies that support mobility impaired people to navigate the physical environment



Traditional Walkability Audits



Walkability Audit
Wake County, North Carolina



Walkability Audit
Wake County, North Carolina



Safe Routes to School Walkability Audit
Rock Hill, South Carolina

Community Audits

Take a walk and use this checklist to rate your neighborhood's walkability. How walkable is your community?

Location of walk _____
Rating Scale: 1 2 3 4 5 6
awful many problems some problems good very good excellent

1. Did you have room to walk?

- Yes Some problems:
 - Sidewalks or paths started and stopped
 - Sidewalks were broken or cracked
 - Sidewalks were blocked with poles, signs, shrubbery, dumpsters, etc.
 - No sidewalks, paths, or shoulders
 - Too much traffic
 - Something else _____

Rating: (circle one)
1 2 3 4 5 6 _____

2. Was it easy to cross streets?

- Yes Some problems:
 - Road was too wide
 - Traffic signals made us wait too long or did not give us enough time to cross
 - Needed striped crosswalks or traffic signals
 - Parked cars blocked our view of traffic
 - Trees or plants blocked our view of traffic
 - Needed curb ramps or ramps needed repair
 - Something else _____

Rating: (circle one)
1 2 3 4 5 6 _____

3. Did drivers behave well?

- Yes Some problems: Drivers...
 - Backed out of driveways without looking
 - Did not yield to people crossing the street
 - Turned into people crossing the street
 - Drove too fast
 - Sped up to make it through traffic lights or drove through traffic lights?
 - Something else _____

Rating: (circle one)
1 2 3 4 5 6 _____

4. Was it easy to follow safety rules?

- Could you and your child...
- Yes No Cross at crosswalks or where you could see and be seen by drivers?
 - Yes No Stop and look left, right and then left again before crossing streets?
 - Yes No Walk on sidewalks or shoulders facing traffic where there were no sidewalks?
 - Yes No Cross with the light?

Rating: (circle one)
1 2 3 4 5 6 _____

5. Was your walk pleasant?

- Yes Some unpleasant things:
 - Needed more grass, flowers, or trees
 - Scary dogs
 - Scary people
 - Not well lighted
 - Dirty, lots of litter or trash
 - Something else _____

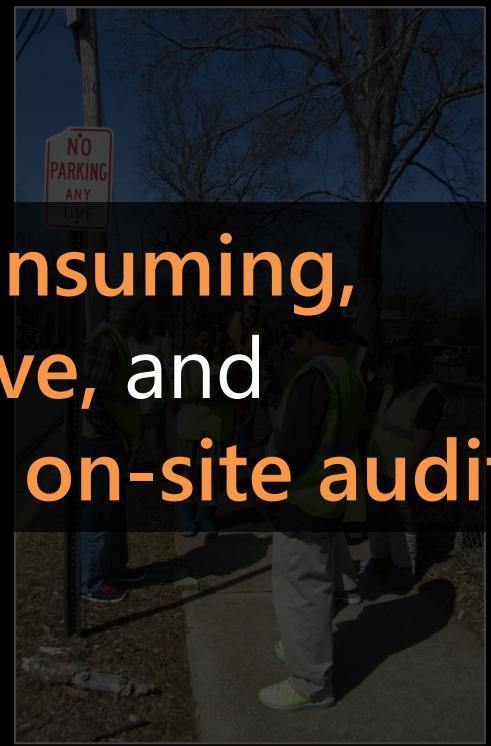
Rating: (circle one)
1 2 3 4 5 6 _____

How does your neighborhood stack up?

Add up your ratings and decide.

- 1. _____ 26-30 Celebrate! You have a great neighborhood for walking.
- 2. _____ 21-25 Celebrate a little. Your neighborhood is pretty good.
- 3. _____ 16-20 Okay, but it needs work.
- 4. _____ 11-15 It needs lots of work. You deserve better than that.
- 5. _____ 5-10 Call out the National Guard before you walk. It's a disaster area.

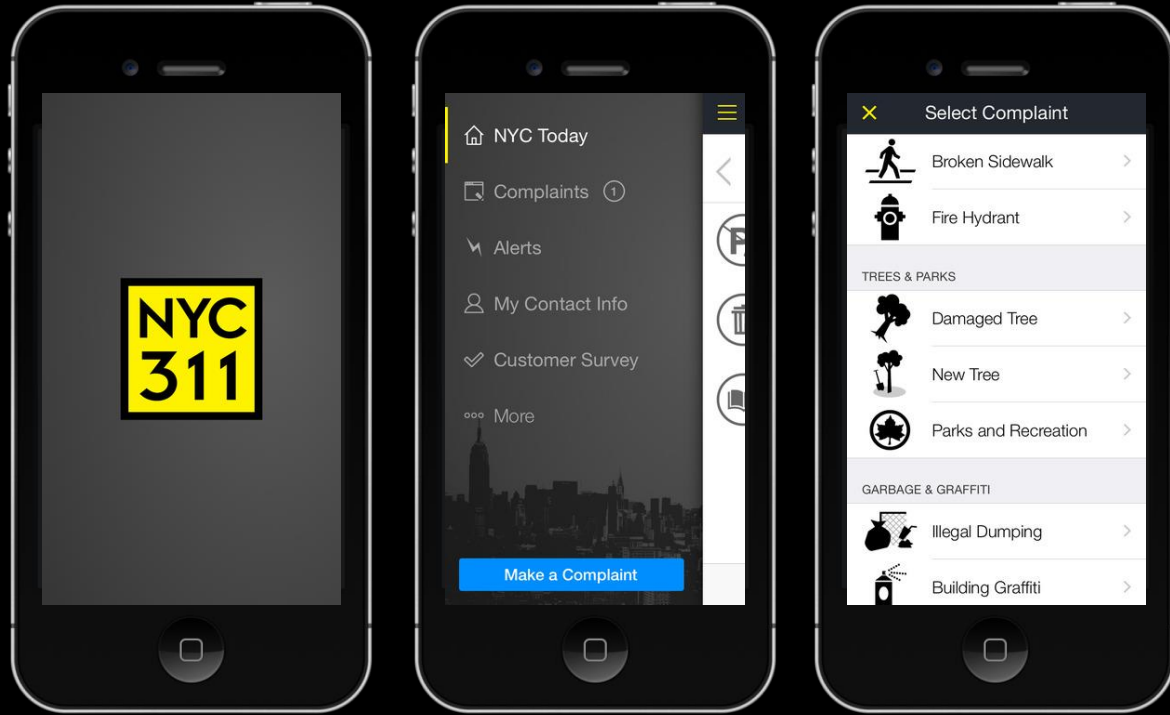
Total _____



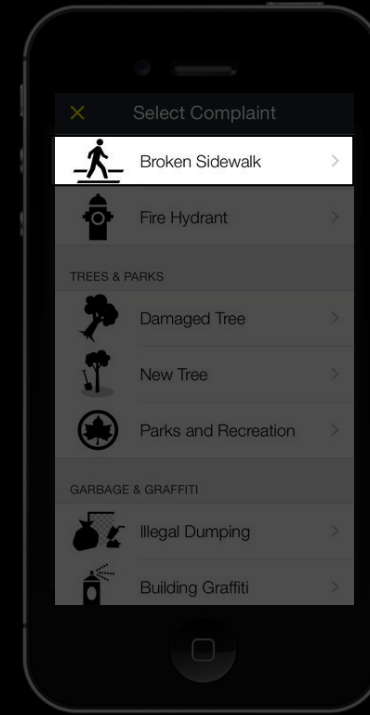
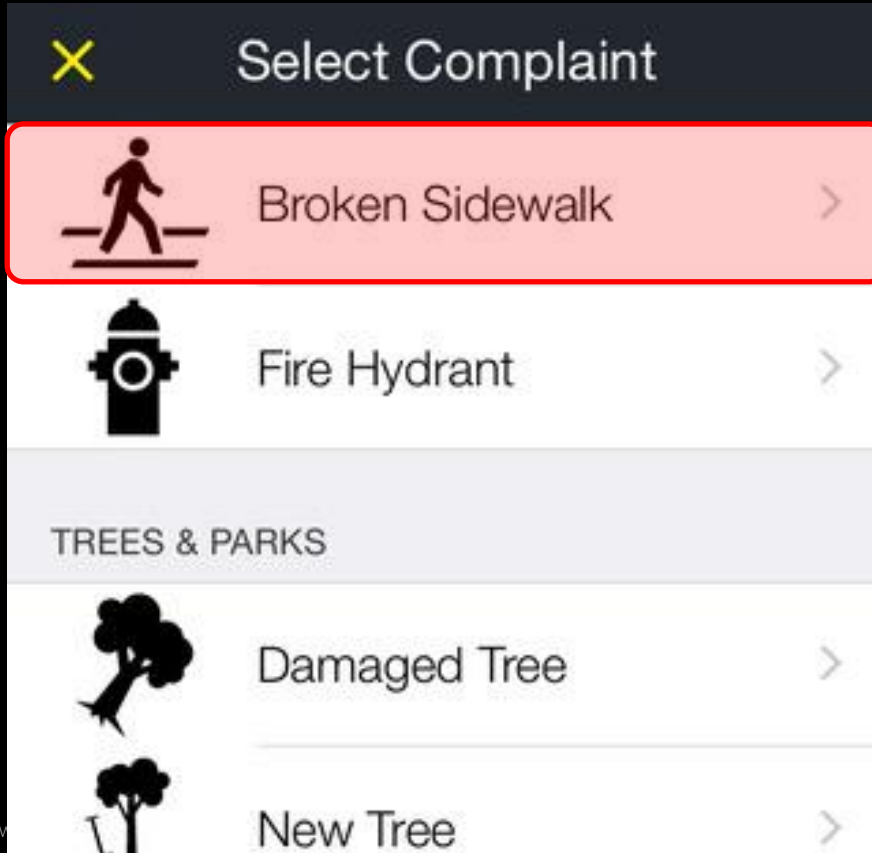
Time consuming, expensive, and requires on-site audit

Now that you've identified the problems, go to the next page to find out how to fix them.

Mobile Reporting Solutions



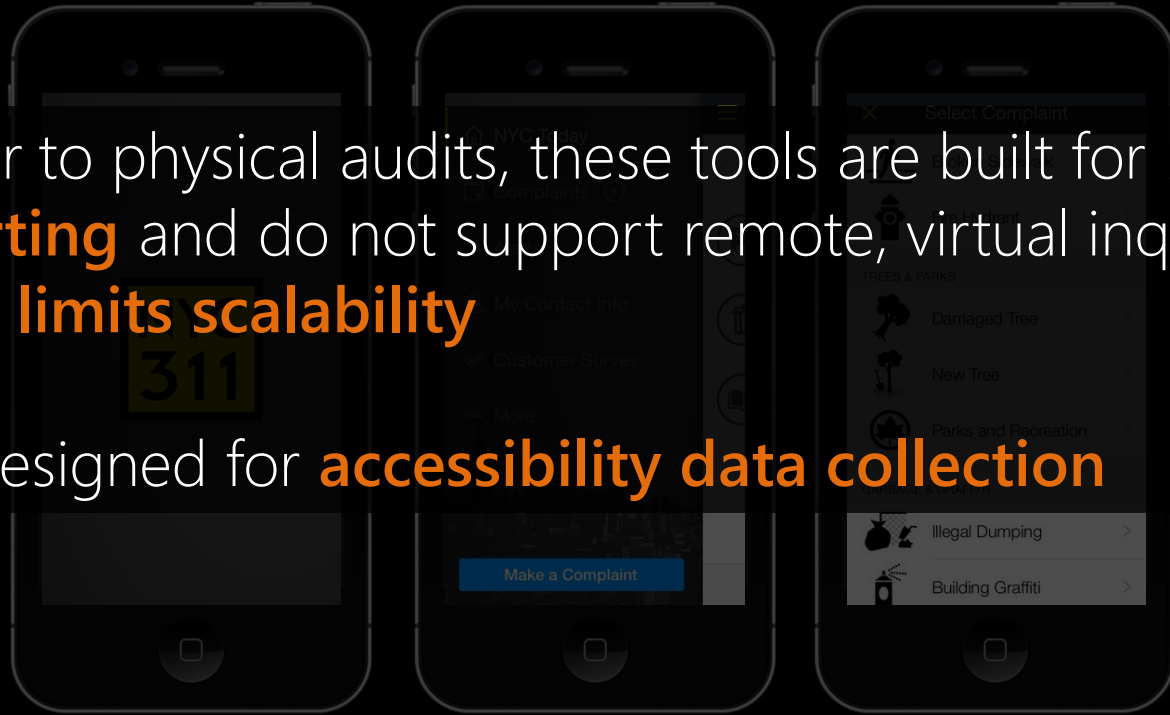
Mobile Reporting Solutions



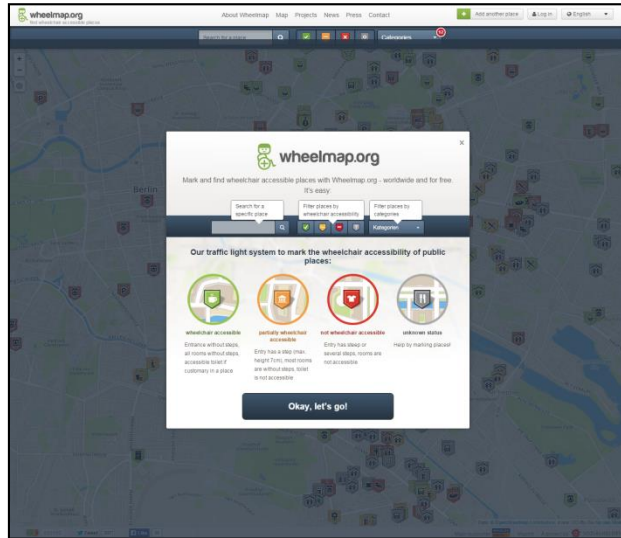
Mobile Reporting Solutions

Similar to physical audits, these tools are built for *in situ* **reporting** and do not support remote, virtual inquiry—which **limits scalability**

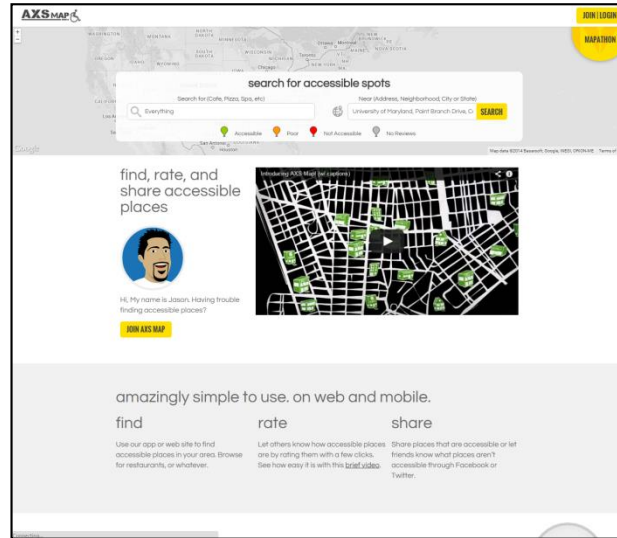
Not designed for **accessibility data collection**



Mark & Find Accessible Businesses



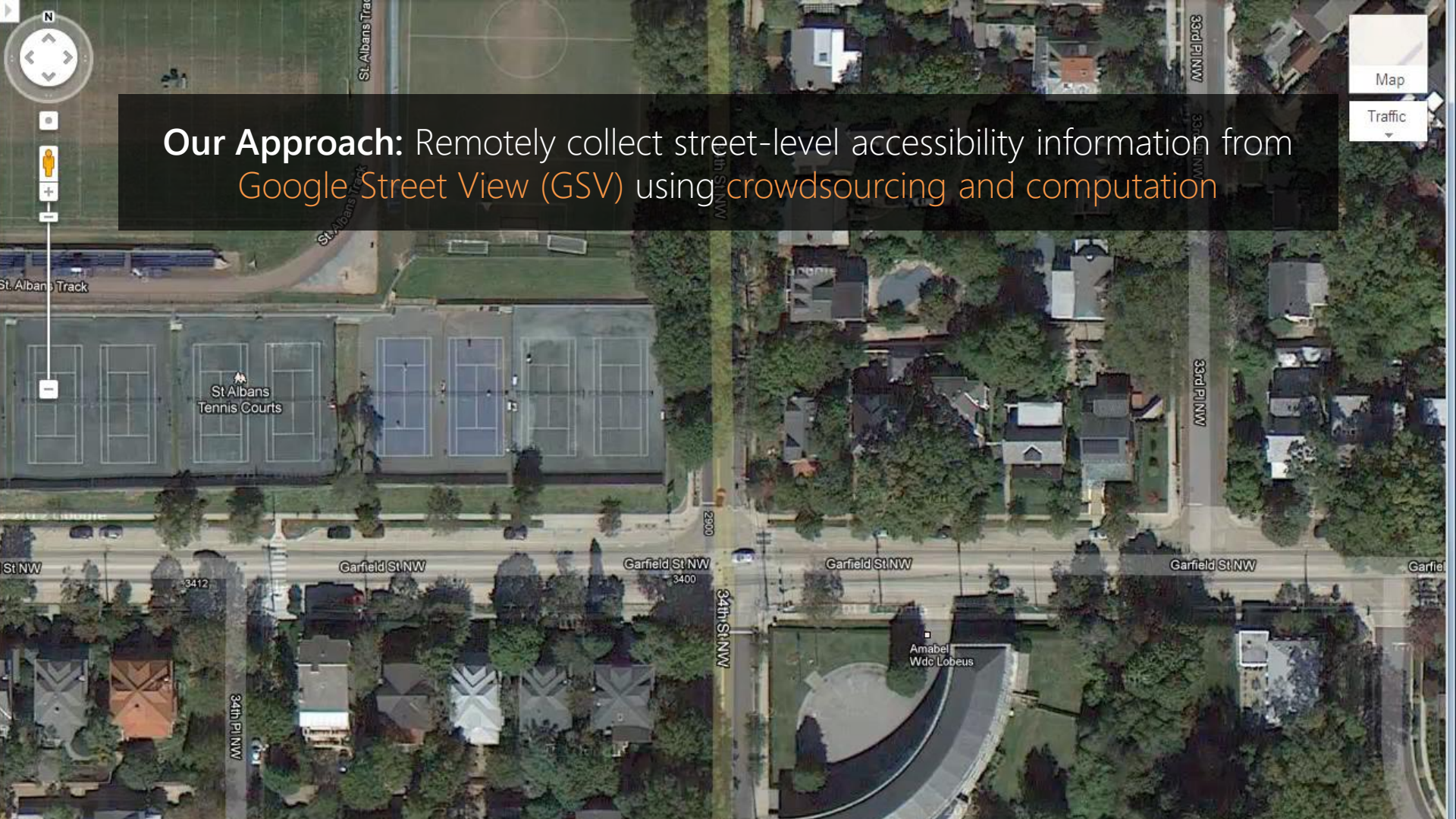
wheelmap.org



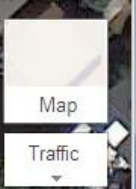
axsmap.com

Focuses on businesses rather than streets/sidewalks

Model is still to report on places you've visited



Our Approach: Remotely collect street-level accessibility information from Google Street View (GSV) using crowdsourcing and computation



A Feasibility Study of Crowdsourcing View to Determine Sidewalk

Kotaro Hara, Victoria Le, and Jon E. Froehlich
Human-Computer Interaction
Computer Science Department, University of Maryland, College Park, MD 20742
{kotaro, jonf}@cs.umd.edu; vln@umd.edu



Figure 1. Using crowdsourcing and Google Street View images, we examined the way to locate and assess sidewalk accessibility problems: (a) Point, (b) Rectangle, and (c) Surface.

ABSTRACT

We explore the feasibility of using crowd workers from Amazon Mechanical Turk to identify and rank sidewalk accessibility issues from a manually curated database of 100 Google Street View images. We examine the effect of three different interactive labeling interfaces (*Point*, *Rectangle*, and *Outline*) on task accuracy and duration. We close the paper by discussing limitations and opportunities for future work.

Categories and Subject Descriptors: Social Issues-Assistive technologies for persons with disabilities

Keywords: Crowdsourcing accessibility, Google Street View, accessible urban navigation, Mechanical Turk

1. INTRODUCTION

The availability and quality of sidewalks can significantly impact how and where people travel in urban environments. Sidewalks with surface cracks, buckled concrete, missing curb ramps, or other issues can pose considerable accessibility challenges to those with mobility or vision impairments [2,3]. Traditionally, sidewalk quality assessment has been conducted via in-person street audits, which is labor intensive and costly, or via citizen street audits, which is done on a reactive basis. As an alternative, we explore the use of crowdsourcing to

Combining Crowdsourcing and Google Street View to Identify Street-level Accessibility Problems

Kotaro Hara, Victoria Le, Jon E. Froehlich
Human-Computer Interaction Lab (HCIL)
Computer Science Department, University of Maryland, College Park, MD 20742
{kotaro, jonf}@cs.umd.edu; vln@umd.edu



Figure 1: In this paper, we propose and investigate the use of crowdsourcing to find, label, and assess sidewalk accessibility problems in Google Street View (GSV) imagery. The GSV images and annotations above are from our experiments.

ABSTRACT

Poorly maintained sidewalks, missing curb ramps, and other obstacles pose considerable accessibility challenges; however, there are currently few, if any, mechanisms to determine accessible areas of a city *a priori*. In this paper, we investigate the feasibility of using untrained crowd workers from Amazon Mechanical Turk (turkers) to find, label, and assess sidewalk accessibility problems in Google Street View imagery. We report on two studies: Study 1 examines the feasibility of this labeling task with six dedicated labelers including three wheelchair users; Study 2 investigates the comparative performance of turkers. In all, we collected 13,379 labels and 19,189 verification labels from a total of 402 turkers. We show that turkers are capable of determining the presence of an accessibility problem with 81% accuracy. With simple quality control methods, this number increases to 93%. Our work demonstrates a promising new, highly scalable method for acquiring knowledge about sidewalk accessibility.

Author Keywords

Crowdsourcing accessibility; accessible urban navigation; Google Street View; Mechanical Turk; image labeling

ACM Classification Keywords

H.5.m. Information interfaces and presentation

INTRODUCTION

According to the U.S. Census Bureau, 30.6 million people in the United States have a disability that affects their ability to perform common tasks. This number is projected to increase to 40 million by 2020. Despite the high prevalence of disability, the built environment is often not designed to be accessible. The built environment is often not designed to be accessible. The built environment is often not designed to be accessible.

Categories and Subject Descriptors

H.5 (Information Interfaces and Presentation): User Interfaces; K.4.2 (Social Issues): Assistive tech for persons with disabilities

General Terms

Measurement, Design, Experimentation, Human Factors

Keywords

Crowdsourcing accessibility; accessible bus stops; Google Street View; Mechanical Turk; low-vision and blind users

1. INTRODUCTION

For people who are blind or low-vision, public transportation is vital for independent travel [1,7,25,32]—particularly because their visual impairment often prevents driving. In previous studies, changes in using public transportation [2], but accessibility issues were frequently a preferred mode of transit. Our work demonstrates a promising new, highly scalable method for acquiring knowledge about sidewalk accessibility.

Improving Public Transit Accessibility for Blind Riders by Crowdsourcing Bus Stop Landmark Locations with Google Street View

Kotaro Hara¹, Shiru Azenkot², Megan Campbell², Cynthia L. Bennett², Vicki Le¹, Sean Pannella¹, Robert Moore¹, Kelly Minckler², Rochelle H. Ng², Jon E. Froehlich¹
¹Makeability Lab | HCIL
Department of Computer Science
University of Maryland, College Park
{kotaro, jonf}@cs.umd.edu
²DUB Group
Computer Science and Engineering
University of Washington, Seattle
{shiru, meganca}@cs.uw.edu



Figure 1. Visually impaired travelers use landmarks to find and verify transit locations [2,14]. In this paper, we examine the feasibility of using Google Street View (GSV) and crowdsourcing to collect detailed information on bus stop locations and surrounding landmarks. The image above shows actual labels from crowdworkers in our Mechanical Turk study (Study 3). From left to right: blue circular icon=bus stop sign, magenta=bus stop shelter, yellow=bench, green=bus stop seating area.

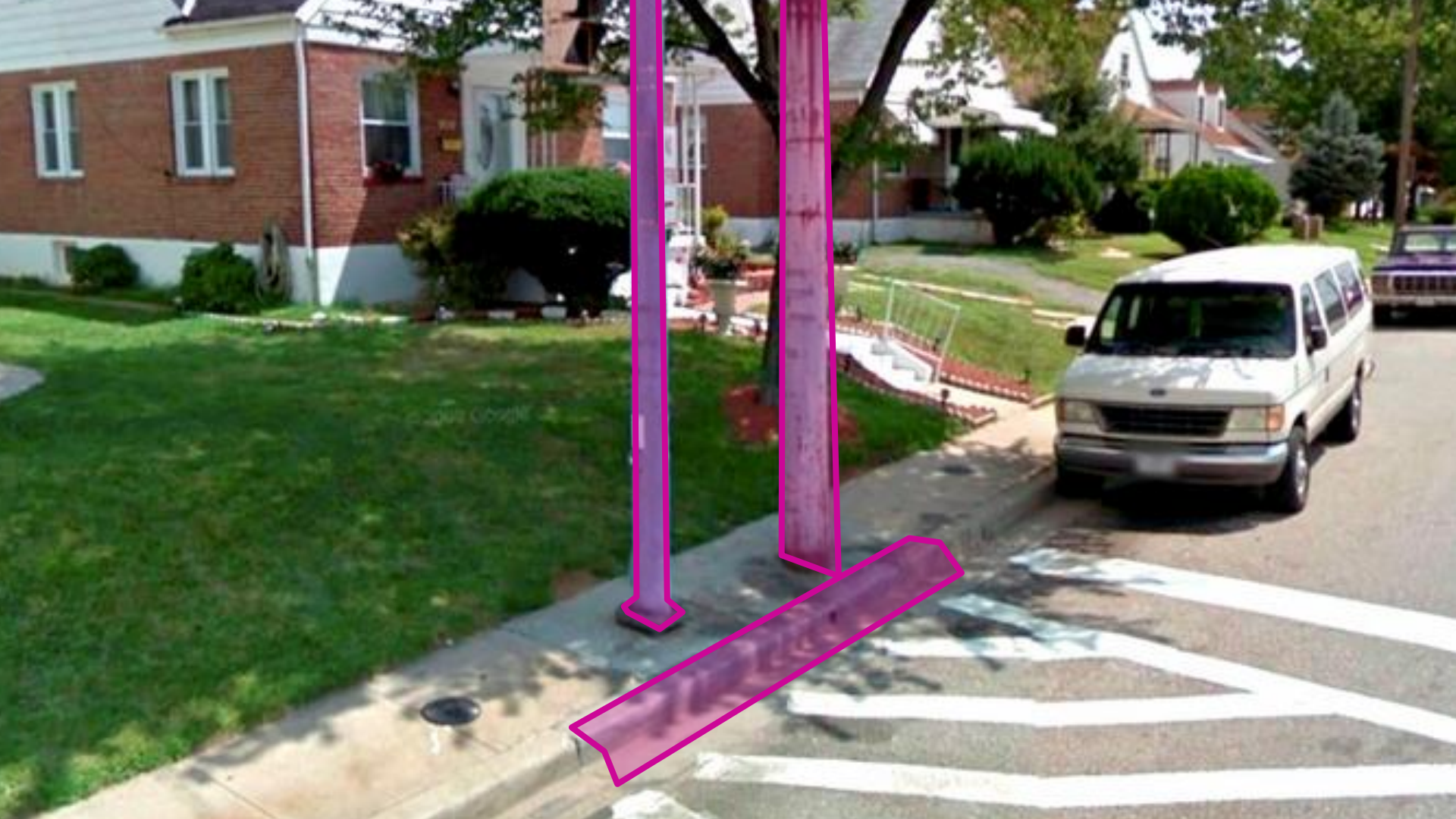
In this paper, we focus specifically on the role of landmarks in helping blind and low-vision people find and identify bus stop locations. While some transit agencies provide brief descriptions of their bus stops online (e.g., [26]), this information often lacks detail or is inaccessible to visually impaired riders—if available at all. Similar to our previous interview findings [2], if available at all, significant access barrier often because that locating bus stops is inconsistently off roadways [1]. The challenge of locating bus stops is a consistently off roadways [1]. The challenge of locating bus stops is a consistently off roadways [1]. The challenge of locating bus stops is a consistently off roadways [1].

Crowdsourcing Accessibility Data from Google Street View

Hara K., Le V., & Froehlich. J.E. 2012, 2013; Hara K., et al. 2013

What **accessibility** problems exist in this image?





Labeling Interface

Show instruction

Working on the Default task out of Default required for this HIT.




Press Esc to cancel your outline.

Problems found: Carb Ramp Missing (0) Object in Path (0) Surface Problem (0) Prematurely Ending Sidewalk (0) Other (0)

Please enter any additional comments about this street or sidewalk that may affect mobility impaired persons or feedback on the hit itself (optional)

Skip the image

There are no accessibility problems in this image



Carb Ramp Missing



Object in Path



Surface Problem



Prematurely Ending Sidewalk

Labeling Interface

Show instruction

Working on the Default task out of Default required for this HIT.




Press Esc to cancel your outline.

Problems found: Carb Ramp Missing (0) Object in Path (0) Surface Problem (0) Prematurely Ending Sidewalk (0) Other (0)

Please enter any additional comments about this street or sidewalk that may affect mobility impaired persons or feedback on the hit itself (optional)

Skip the image

There are no accessibility problems in this image



Carb Ramp Missing



Object in Path



Surface Problem



Prematurely Ending Sidewalk



Crowdsourced Data Accuracy

We could collect street-level accessibility data from static Google Street View using crowdsourcing with **81% accuracy** and this figure went up to **93% with majority voting**

Washington, D.C.



District of Columbia

Arlington

© 2016 Google

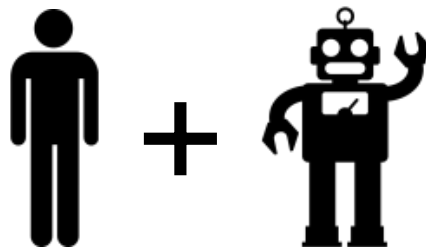


Sole reliance on paid-crowdsourcing
limits the method's **scalability**

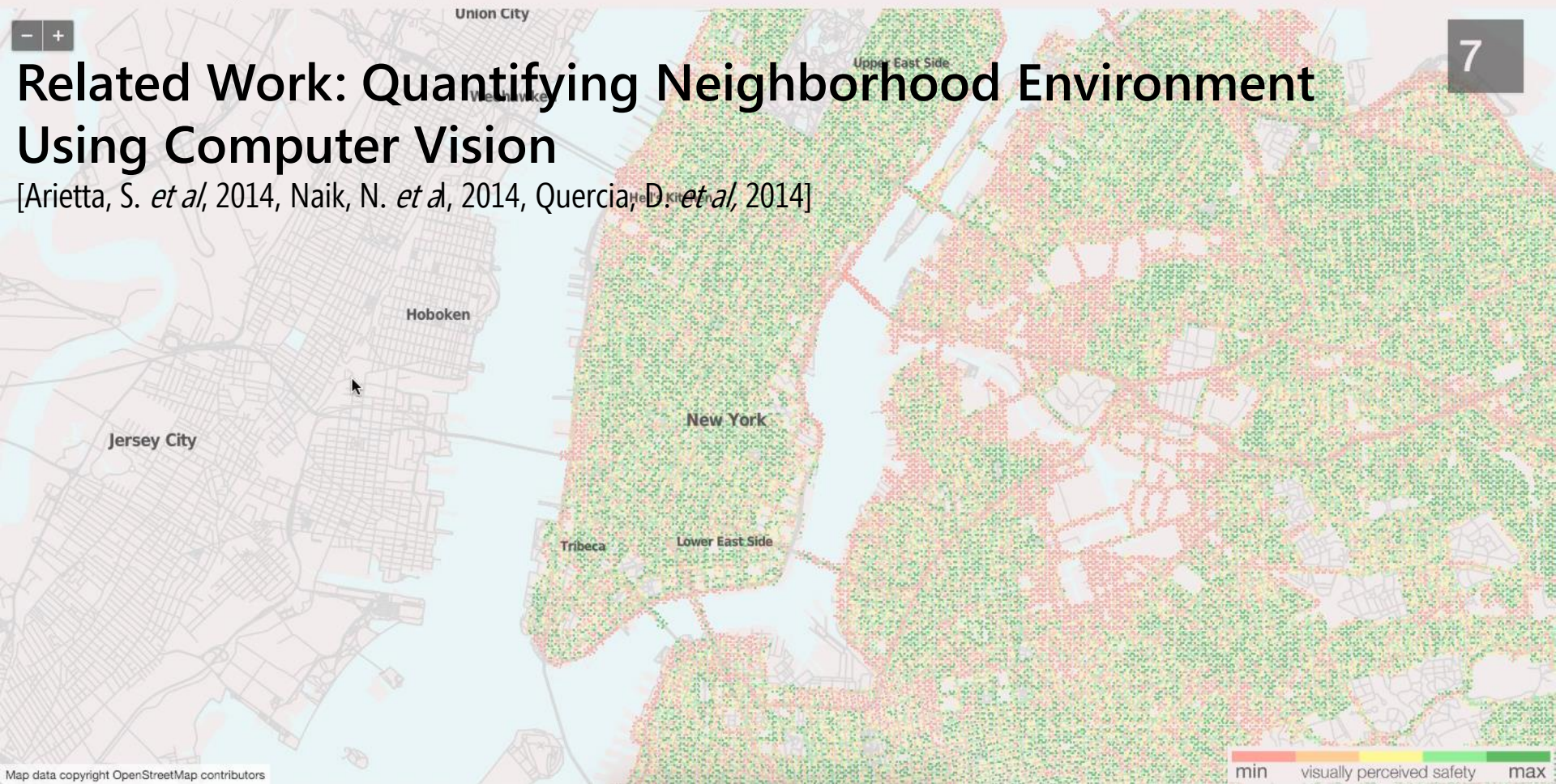
Scalable Data Collection Methods



Volunteered
Data Collection

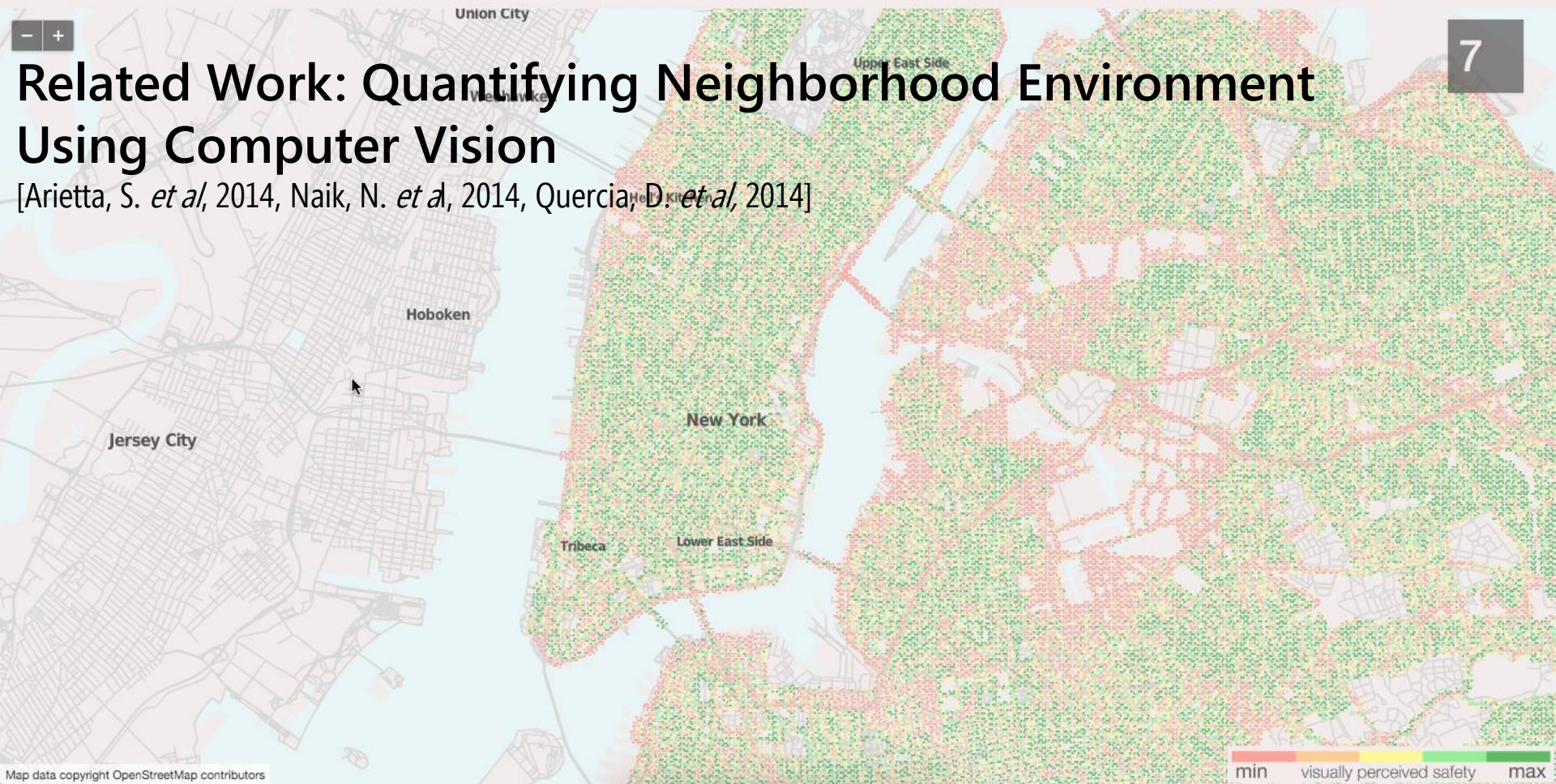


Semi-automated
Data Collection



Related Work: Quantifying Neighborhood Environment Using Computer Vision

[Arietta, S. *et al*, 2014, Naik, N. *et al*, 2014, Quercia, D. *et al*, 2014]



Related Work: Quantifying Neighborhood Environment Using Computer Vision

[Arietta, S. *et al*, 2014, Naik, N. *et al*, 2014, Quercia, D. *et al*, 2014]

Union City

7

Related Work: Quantifying Neighborhood Environment Using Computer Vision

[Arietta, S. *et al*, 2014, Naik, N. *et al*, 2014, Quercia, D. *et al*, 2014]

We need more granular information to understand **which sidewalks are accessible/inaccessible** and **why**

Jersey City

Hoboken

Tribeca

Lower East Side

Related Work: Object Detection with Human-in-the-Loop

Branson *et al.* 2010, Quinn *et al.* 2010; Su *et al.* 2012

CrowdFlow: Integrating Mechanical Turk for Speed-C

Alexander J. Quinn¹, Benjamin B. Bederson
University of Maryland
Human-Computer Interaction
Department of Computer Science
College Park, MD 20742
aq@cs.umd.edu, bederson@cs.umd.edu, tomy

Abstract

Humans and machines have competing strengths for tasks such as natural language processing and image understanding. Whereas humans do these things naturally with potentially high accuracy, machines offer greater speed and flexibility. CrowdFlow is our toolkit for a model for blending the two in order to attain tighter control over the inherent tradeoffs in speed, cost and quality. With CrowdFlow, humans and machines work together to do a set of tasks at a user-specified point in the tradeoff space. They work symbiotically, with the humans providing training data to the machine while the machine provides first cut results to the humans to save effort in cases where the machine's answer was already correct. The CrowdFlow toolkit can be considered as a generalization of our other domain-specific efforts aimed at enabling cloud computing services using a variety of computational resources to achieve various tradeoff points.

1. Introduction

There is a large set of problems that can be solved either human computation or machine learning. These include recognizing the faces of missing children in surveillance video translating documents between languages, or summarizing opinions of blogs relating to a particular topic, and many other problems of natural language processing (NLP).

Generally, humans can solve these problems with accuracy that machines alone could do, though human effort tends to be costly and time-consuming. Online labor markets such as Amazon Mechanical Turk (AMT) [13] give us a way to crowdsource human labor. However, this is slower and

Visual Recognition with Humans in the Loop

Steve Branson¹, Catherine Wah¹, Florian Schroff¹, Boris Winder², Pietro Perona², and Serge Belongie¹

¹ University of California, San Diego
{sbranson, cwah, gschroff, bbabenko, sjb}@cs.ucsd.edu

² California Institute of Technology
{winder, perona}@caltech.edu

Abstract. We present an interactive, hybrid human-machine system for object classification. The method applies to classes recognizable by people with appropriate expertise (e.g. airplane model), but not (in general) by people without. We present a visual version of the 20 questions game based on simple visual attributes are posed interactively to identify the true class while minimizing the number of questions. We introduce a new algorithm for incorporating almost any off-the-shelf multi-class algorithm into the visual 20 questions game, and provide a method to account for imperfect user responses and unreliable algorithms. We evaluate our methods on Birds-200 of 200 tightly-related bird species, and on the Anin dataset. Our results demonstrate that incorporating human interaction improves recognition accuracy to levels that are good enough for many applications, while at the same time, computer vision requirements are reduced.

Crowdsourcing Annotations for Visual Object Detection

Hao Su, Jia Deng, Li Fei-Fei
Computer Science Department, Stanford University

Abstract

A large number of images with ground truth bounding boxes are critical for learning object detectors, which is a fundamental task in computer vision. In this paper, we study strategies to crowd-source bounding box annotations. The core challenge of building such a system is to effectively control the data quality with minimal cost. Our key observation is that drawing a bounding box is significantly more difficult and time-consuming than giving answers to multiple choice questions. Thus quality control through additional verification tasks is more cost-effective than consensus based algorithms. In particular, we present a system that consists of three simple sub-tasks—a drawing task, a quality verification task and a coverage verification task. Experimental results demonstrate that our system is scalable, accurate, and cost-effective.

1 Introduction

Object detection is one of the fundamental tasks of visual recognition. Given an input image, an object detector outputs a bounding box wherever an object of interest exists. To learn a good detector, it is necessary to have a large number of training images with ground truth annotations in the form of interest, i.e. tight rectangles around the object of interest. Indeed, state of the art detection systems (Viola and Jones 2004; Felzenszwalb et al. 2010) have relied on accurate bounding box annotations. Although it is possible to use weaker supervision, e.g. binary labels of object presence, it substantially increases the difficulty of learning.

In this paper, we study strategies to crowd-source bounding box annotations. Our goal is to build a system that is fully automated, highly accurate, and cost-effective. Given a collection of images where the object of interest has been verified to exist, for each image the system collects a tight bounding box for every instance of the object. Specifically, we have the following two requirements.

- Quality. Each bounding box should be accurate and

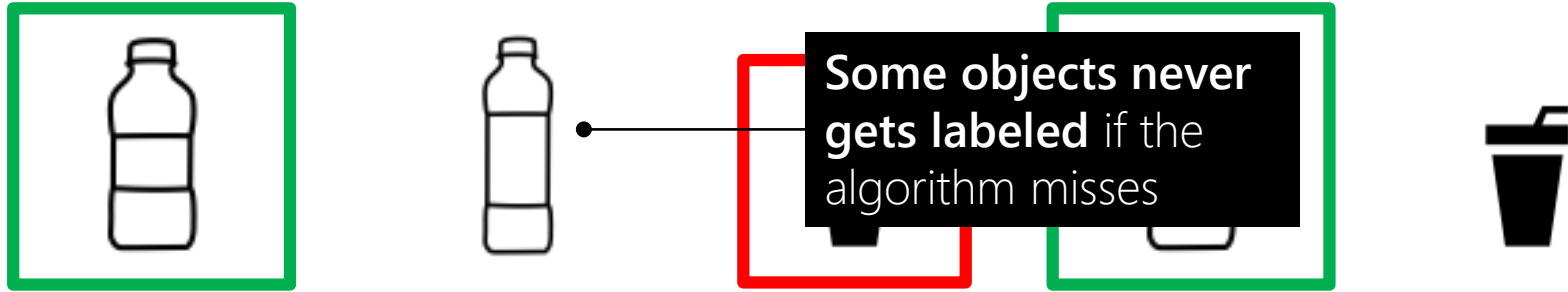


Figure 1: An example of bounding box annotations for the "bottle" category.

- Coverage. Every object instance needs to have a bounding box. This is important for detection because it tells the learning algorithms with certainty what is not the object.

Figure 1 shows examples of bounding box annotations that meet both the quality and coverage requirements. The core challenge of building such a system is how to achieve both high quality and complete coverage in a cost-effective way, i.e. minimizing cost while guaranteeing quality. A basic quality control strategy is majority voting—collecting answers from multiple human subjects and taking the consensus. This approach has been successfully applied to image annotation tasks such as verifying the presence of objects or attributes (Deng et al. 2008; Sorokin and Forsyth 2008). However, drawing bounding box is significantly more time-consuming than answering multiple choice questions.

Related Work: Object Detection with Human-in-the-Loop



Task: Detect all the bottles

Step 1: An object detection algorithm detects bottles

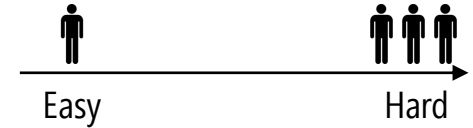
Step 2: Humans verify the object detection outputs

More accurate compared to computer vision alone and cheaper than human labeling

Adaptive Workflow for Optimizing Efficiency

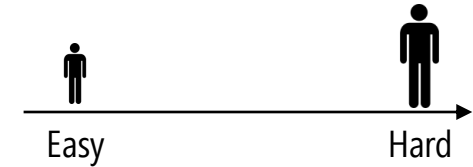
Varying the number of workers to recruit depending on task difficulty

[Kamar *et al.* 2012; Welinder and Perona 2010]



Assigning stronger workers to harder tasks

[Dai *et al.* 2011]



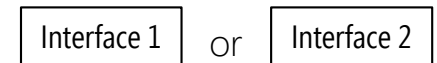
Reducing the tasks that require human work

[Deng *et al.* 2014; Jain, Grauman, and Betke 2016]

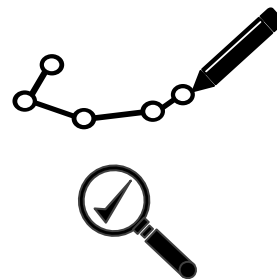
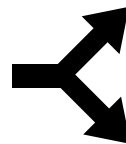
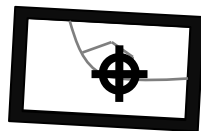


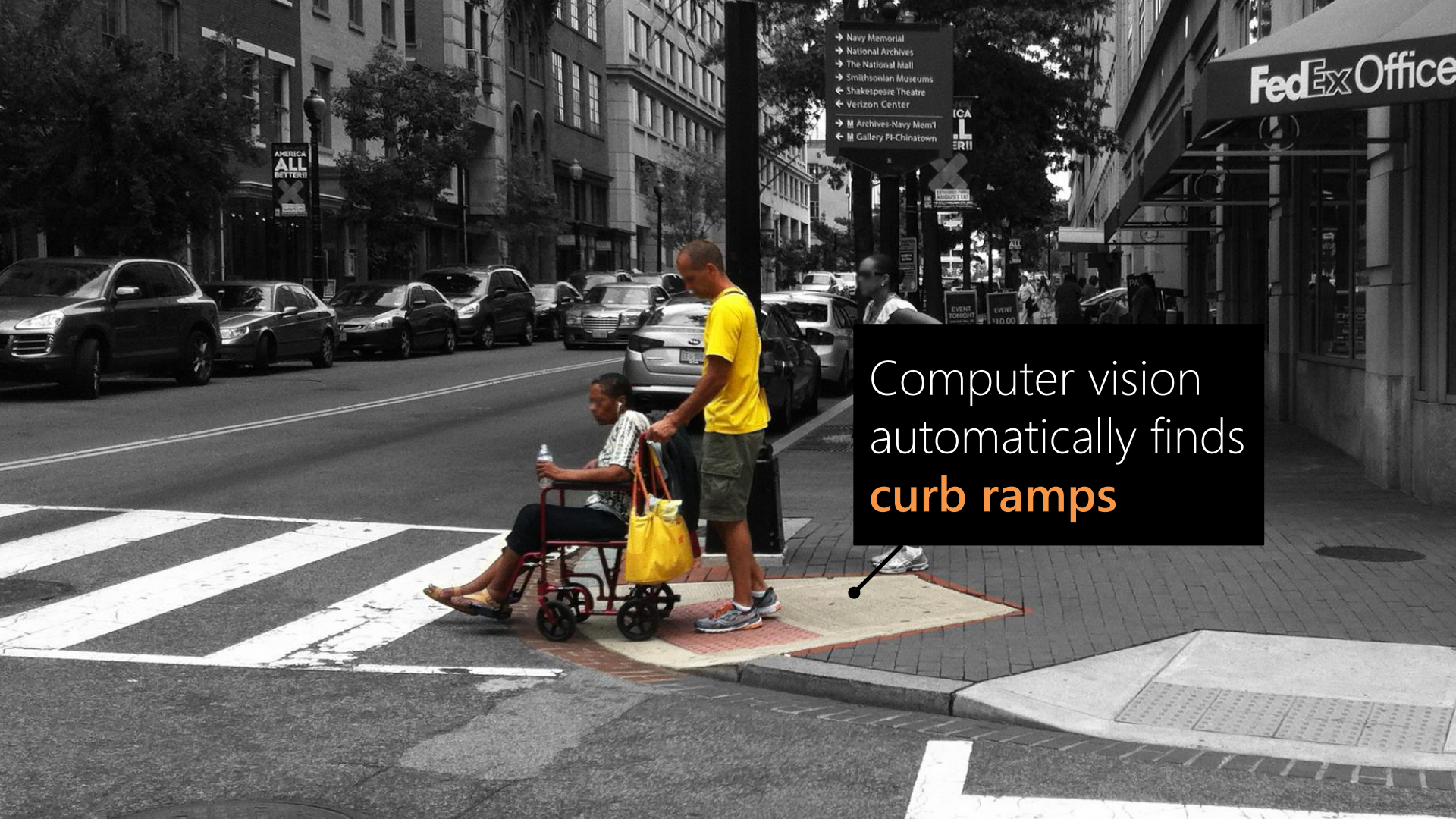
Changing task interface based on worker characteristics

[Jain and Grauman 2013, Lin *et al.* 2012, Russakovsky *et al.* 2015]



Tohme
遠目·Remote Eye





- Navy Memorial
- National Archives
- The National Mall
- Smithsonian Museums
- ← Shakespeare Theatre
- ← Verizon Center
- M Archives-Navy Mem'l
- ← M Gallery Pt-Chinatown

Computer vision
automatically finds
curb ramps

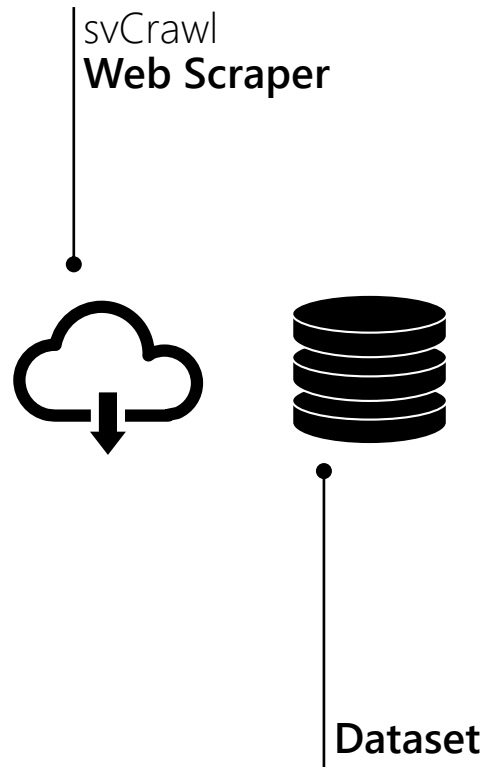


Without curb cuts, **people with ambulatory disabilities simply cannot navigate the city.**

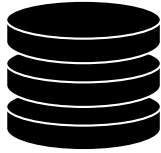
Kinney v. Yerusalim, 1993
3rd Circuit, Court of Appeals

Curb Ramps are Visually Salient





svCrawl
Web Scraper

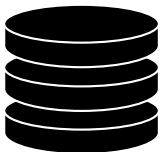
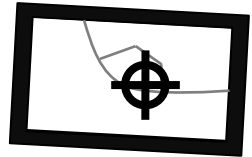


3D Depth Map
GIS Metadata (e.g., topological data)
Top down map images
Street View images
Dataset

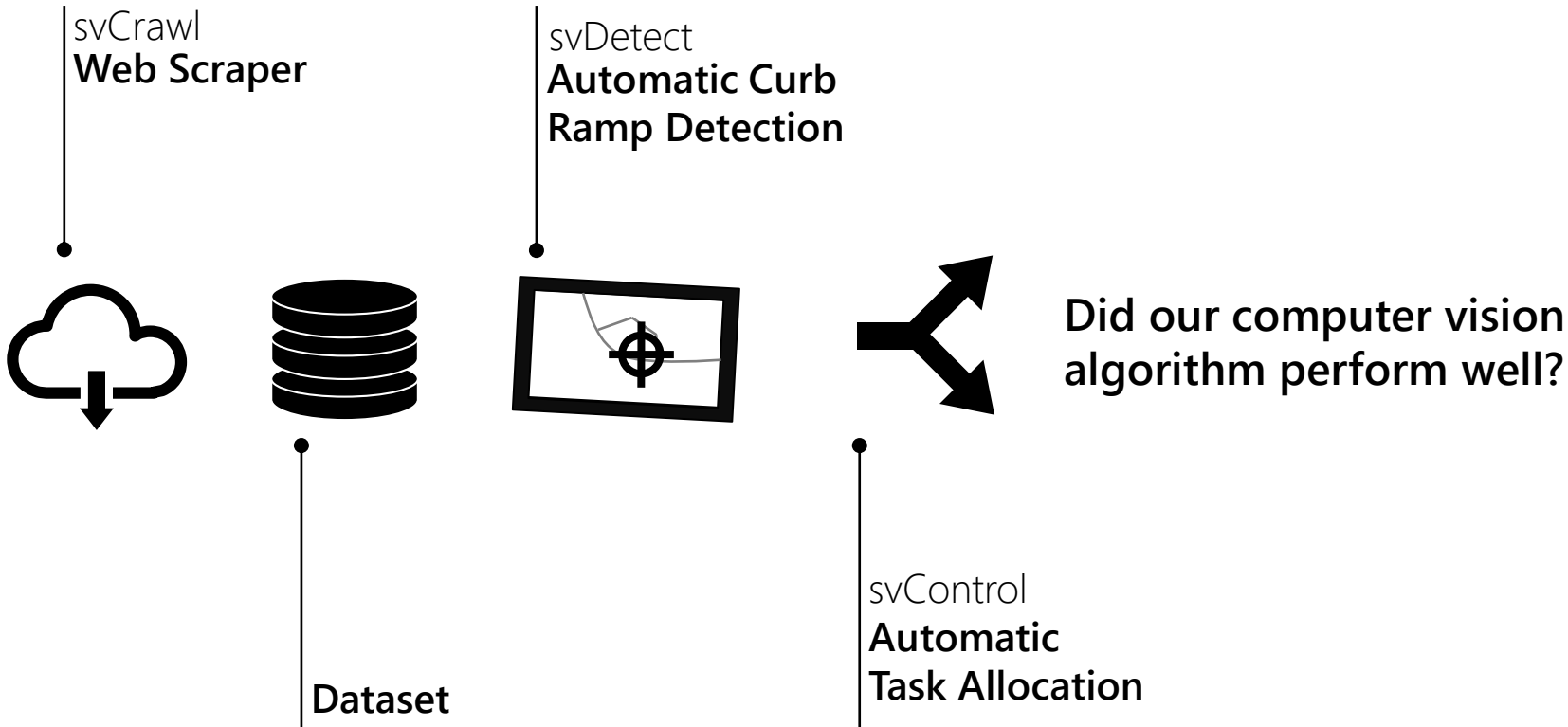
svCrawl
Web Scraper

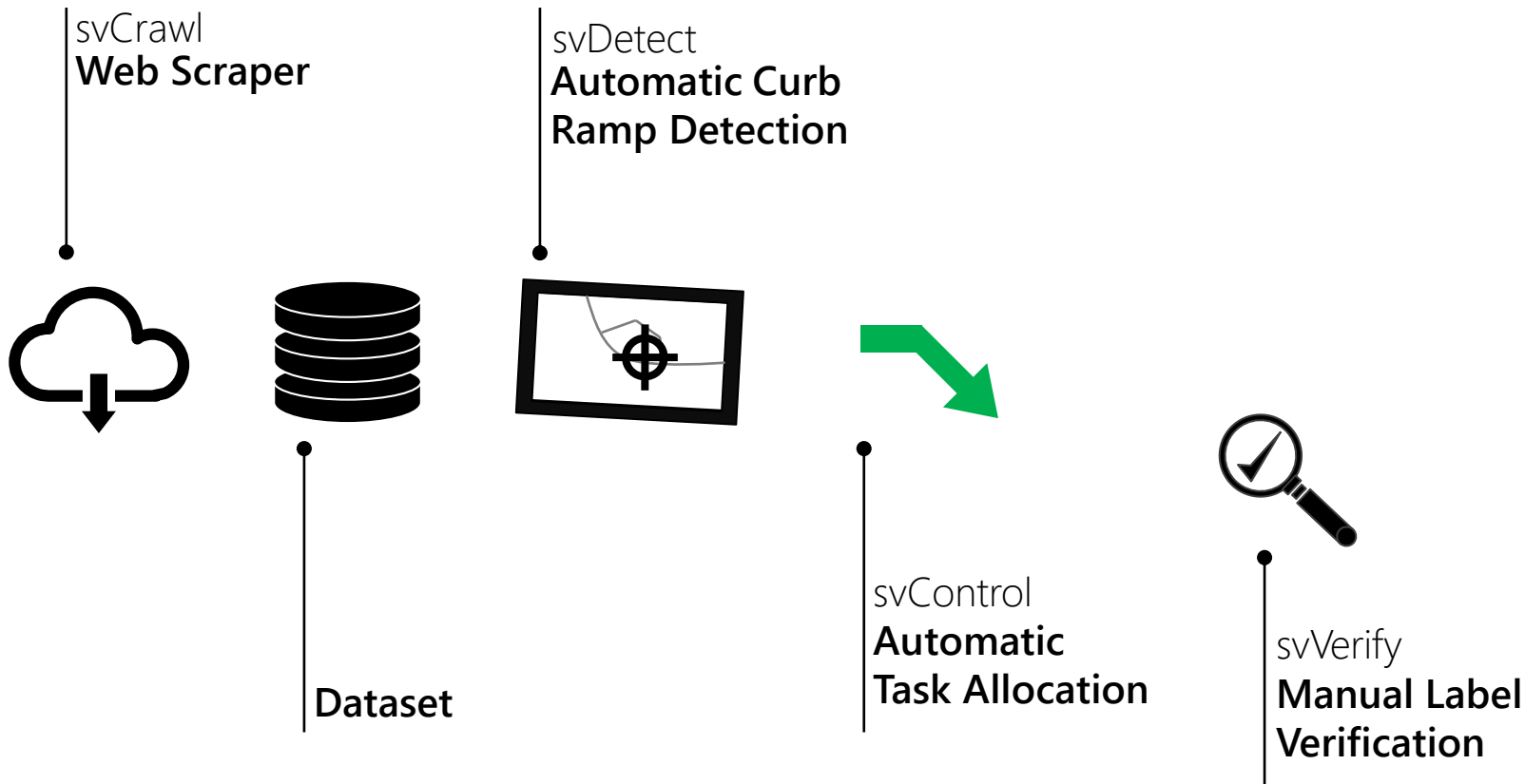


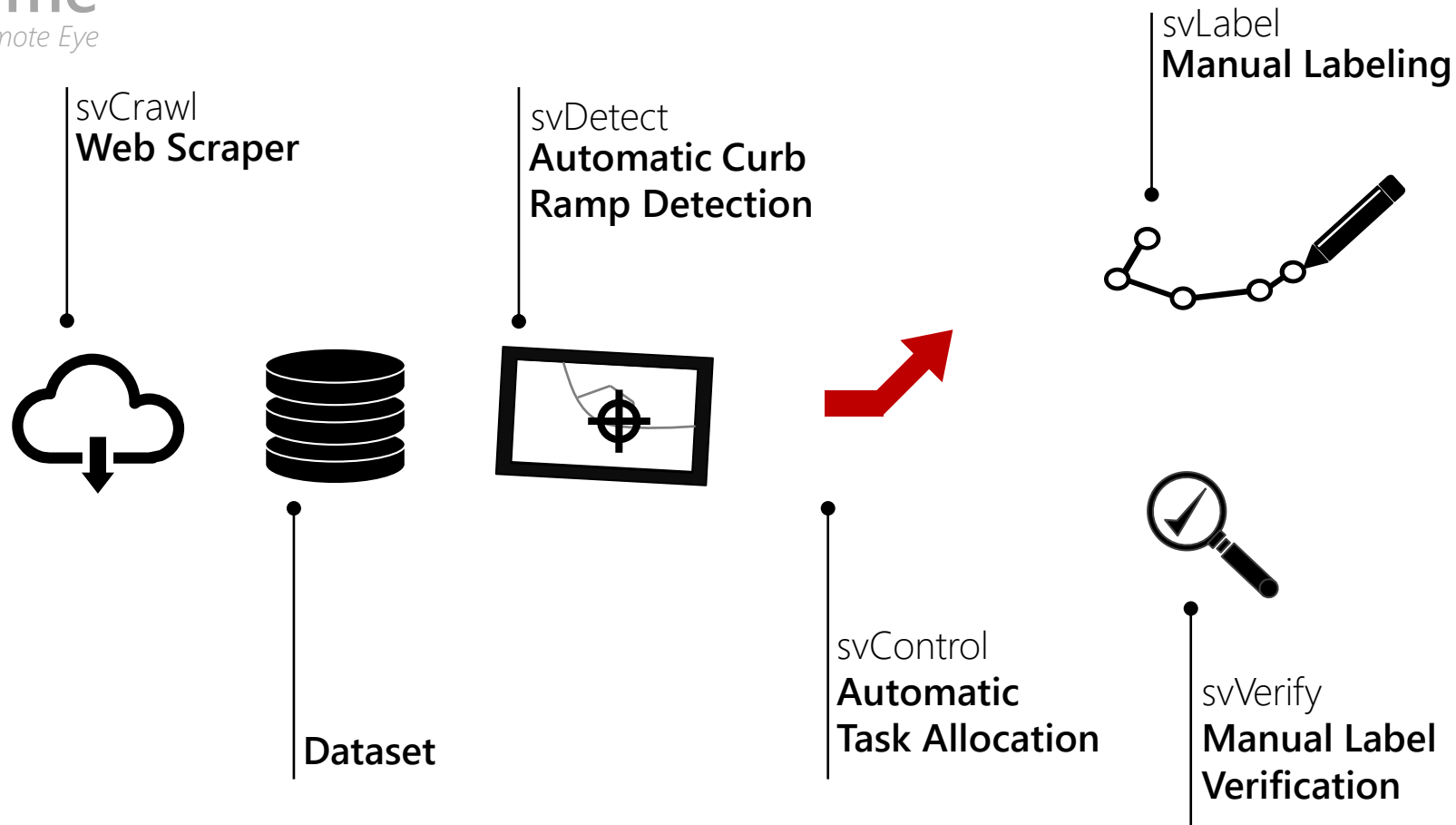
svDetect
**Automatic Curb
Ramp Detection**



Dataset

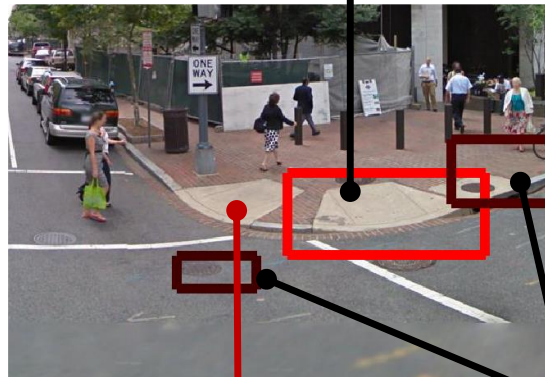




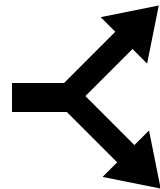
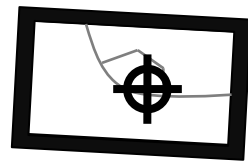


Correct
detection

How do we define
computer vision **failure**?

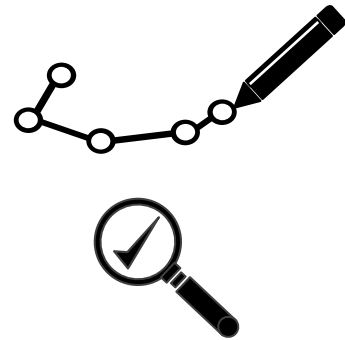
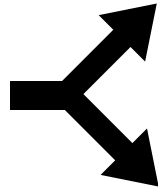
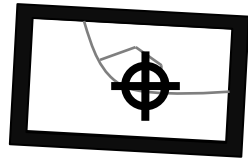
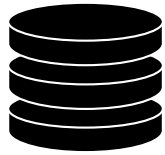


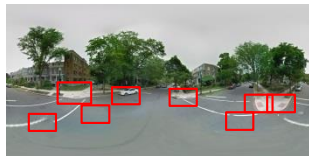
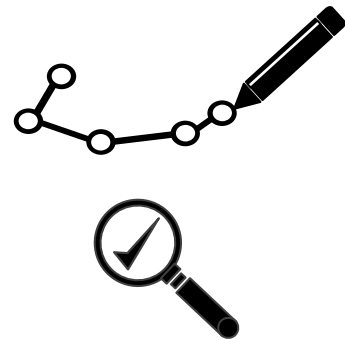
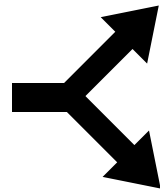
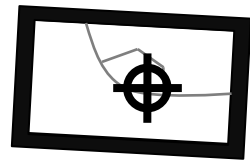
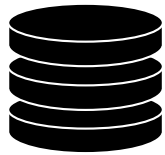
False positive detections

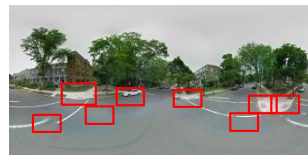
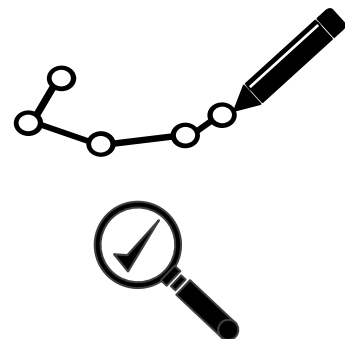
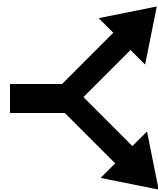
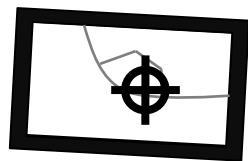


False Negative Error = Computer Vision Failure

Because asking humans to label missed curb ramps is much more expensive than asking to verify





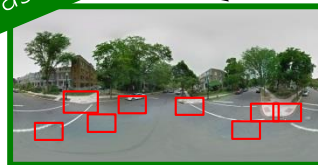


A feature vector used to in
the workflow controller

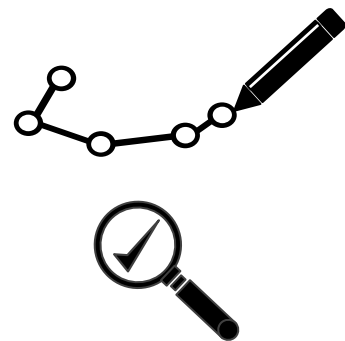
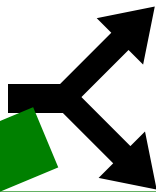
Complexity: 0.14
Cardinality: 0.33
Depth: 0.21
CV: 0.22

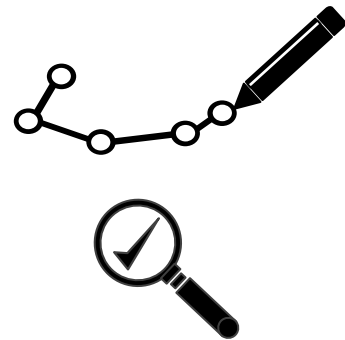
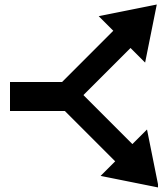
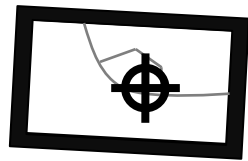
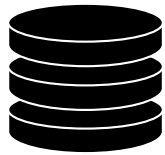


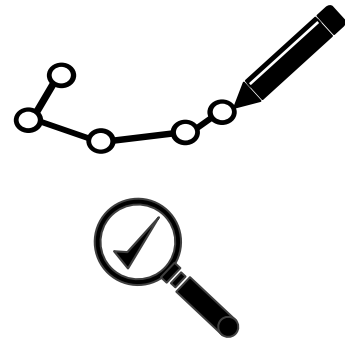
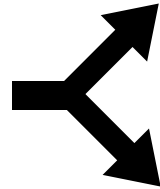
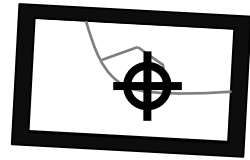
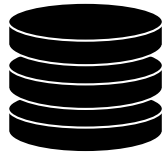
Pass!

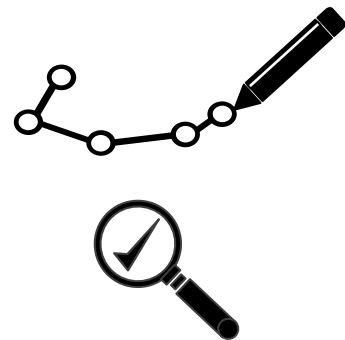
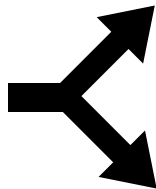
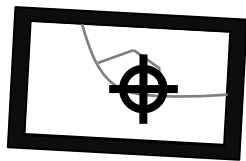
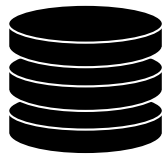


Complexity: 0.14
Cardinality: 0.33
Depth: 0.21
CV: 0.22

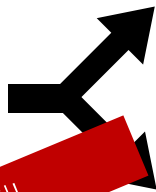
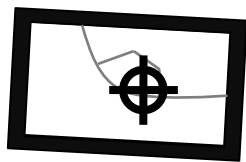




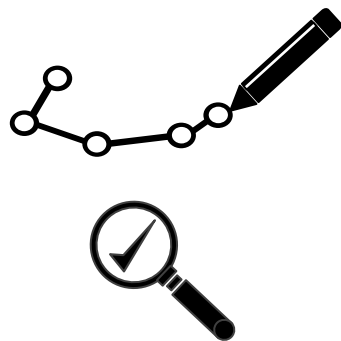


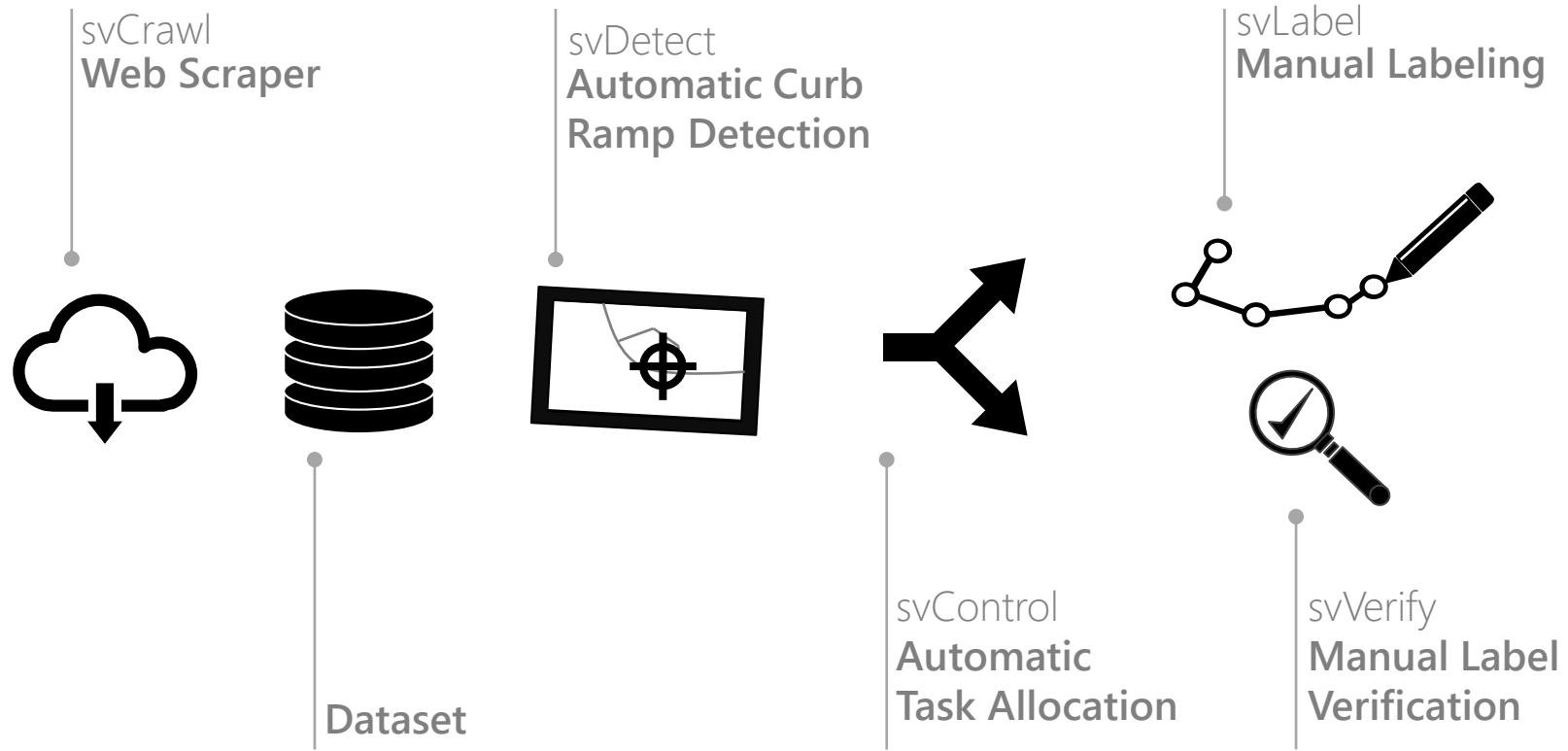


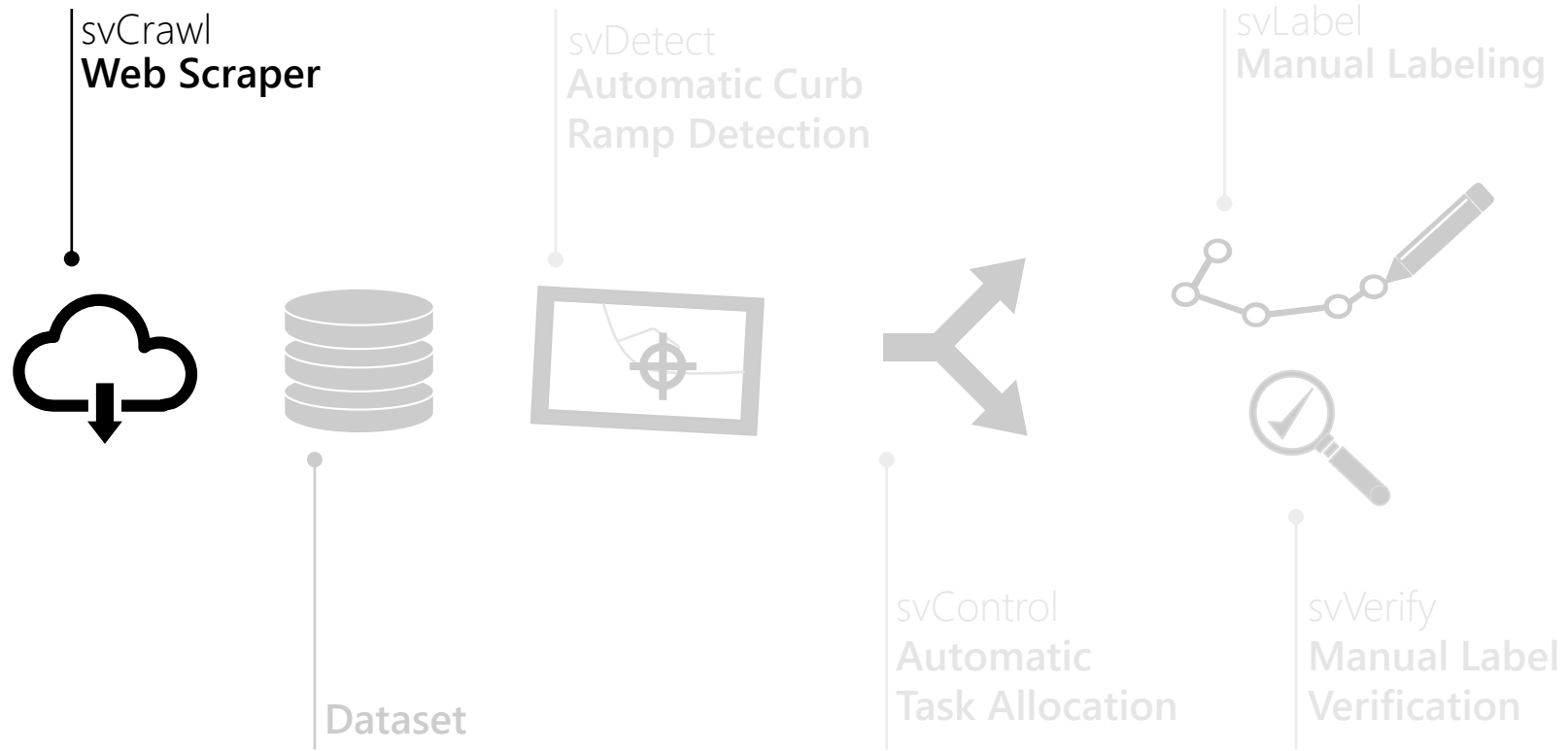
Complexity: 0.82
Cardinality: 0.25
Depth: 0.96
CV: 0.54



Complexity: 0.82
Cardinality: 0.25
Depth: 0.96
CV: 0.54







Street View Images

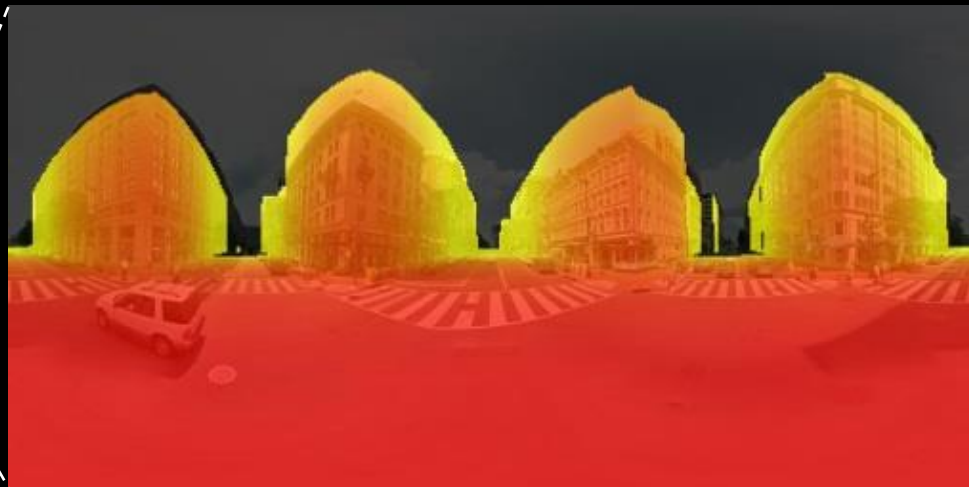
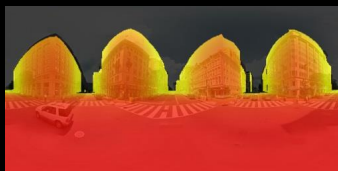


We collected images from intersections because that's where we find curb ramps

Street View Images



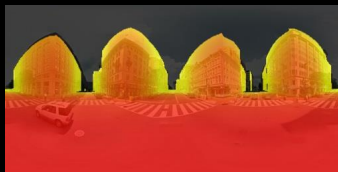
Point-cloud Data



Street View Images



Point-cloud Data



Metadata
(*e.g.*, street topology)

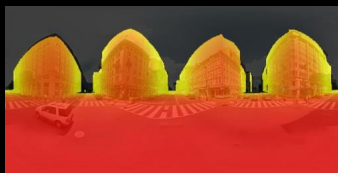
```
{  
  - Data: {  
    image_width: "13312",  
    image_height: "6656",  
    tile_width: "512",  
    tile_height: "512",  
    image_date: "2014-07",  
    imagery_type: 1,  
    copyright: "© 2015 Google"  
  },  
  - Projection: {  
    projection_type: "spherical",  
  }  
}
```

```
- Links: [  
  - {  
    yawDeg: "118.97",  
    panoId: "WDH0V_F6s9QEAXFMMwktOg",  
    road_argb: "0x80fdf872",  
    description: "Morse St NE"  
  },  
  - {  
    yawDeg: "299.71",  
    panoId: "UCZmw_4Q1SrGAiJoEa9fng",  
    road_argb: "0x80fdf872",  
    description: "Morse St NE"  
  }  
]
```

Street View Images



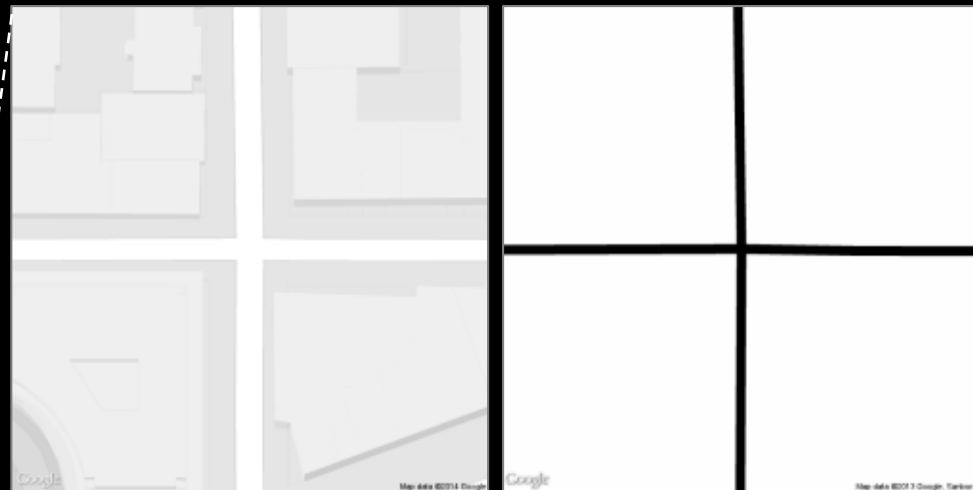
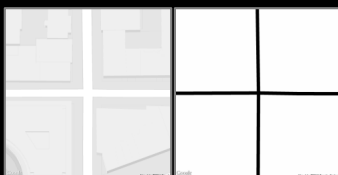
Point-cloud Data



Metadata
(*e.g.*, street topology)

```
{  
  - Data: {  
    image_width: "13312",  
    image_height: "6656",  
    tile_width: "512",  
    tile_height: "512",  
    image_date: "2014-07",  
    imagery_type: 1,  
    copyright: "© 2015 Google"  
  },  
  - Projection: {  
    projection_type: "spherical",  
  }  
}
```

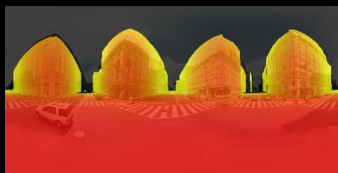
Top-down Google
Maps Imagery



Street View Images



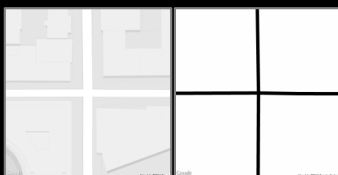
Point-cloud Data



Metadata
(*e.g.*, street topology)

```
{  
  - Data: {  
    image_width: "13312",  
    image_height: "6656",  
    tile_width: "512",  
    tile_height: "512",  
    image_date: "2014-07",  
    imagery_type: 1,  
    copyright: "© 2015 Google"  
  },  
  - Projection: {  
    projection_type: "spherical",  
  }  
}
```

Top-down Google
Maps Imagery

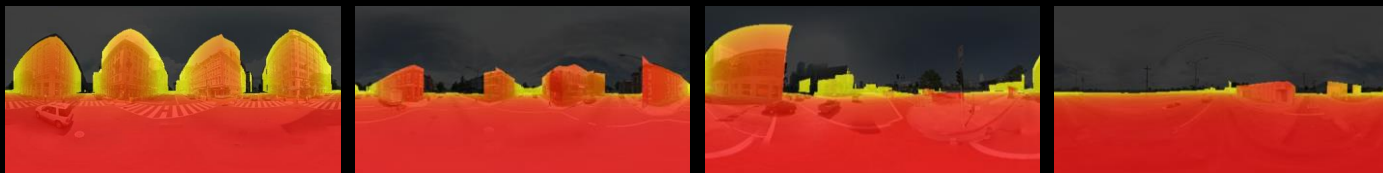


Used to train curb ramp detector
and workflow controller

Street View Images



Point-cloud Data

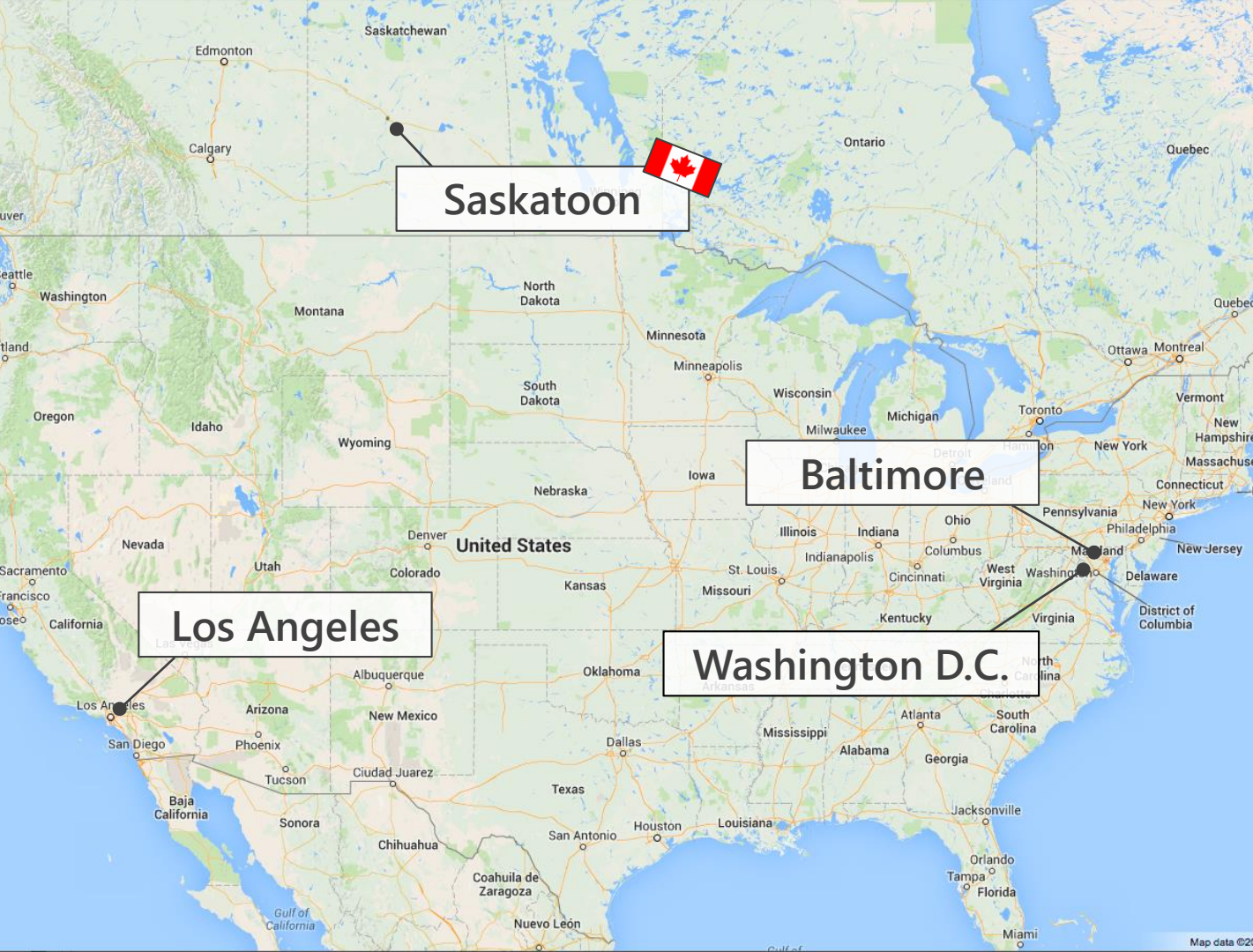


Metadata (e.g., street topology)



Top-down Google Maps Imagery





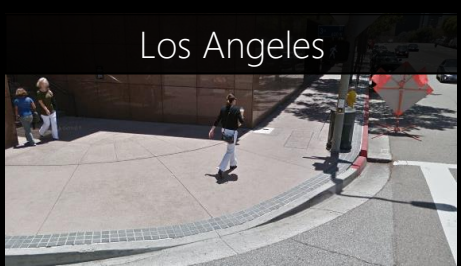
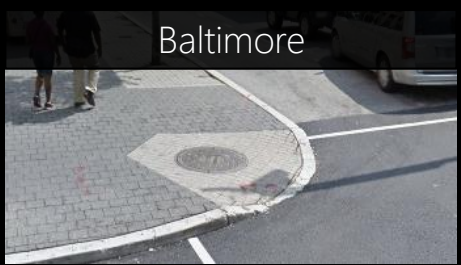
Saskatoon



Baltimore

Los Angeles

Washington D.C.



Washington D.C.

Baltimore

Los Angeles

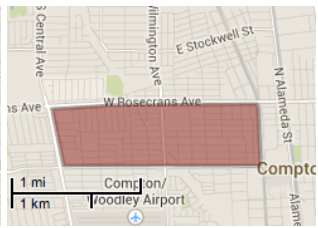
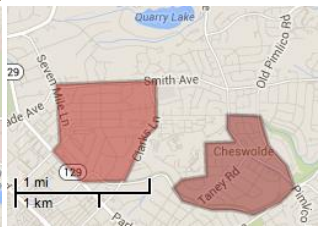
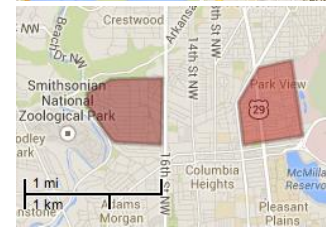
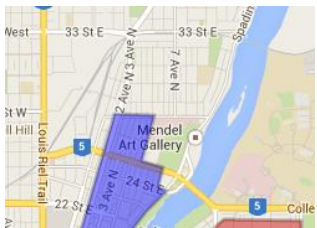
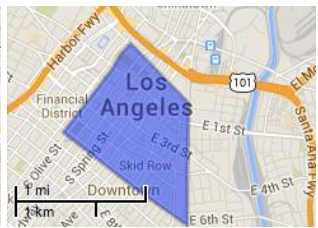
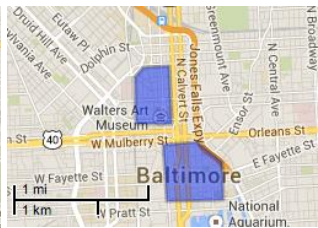
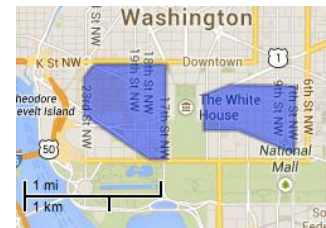
Saskatoon

D.C. | Downtown



D.C. | Residential





Total Area: 11.3 km²

Intersections: 1,086

Curb Ramps: 2,877

Missing Curb Ramps: 647

Avg. GSV Data Age: 2.2 yr*

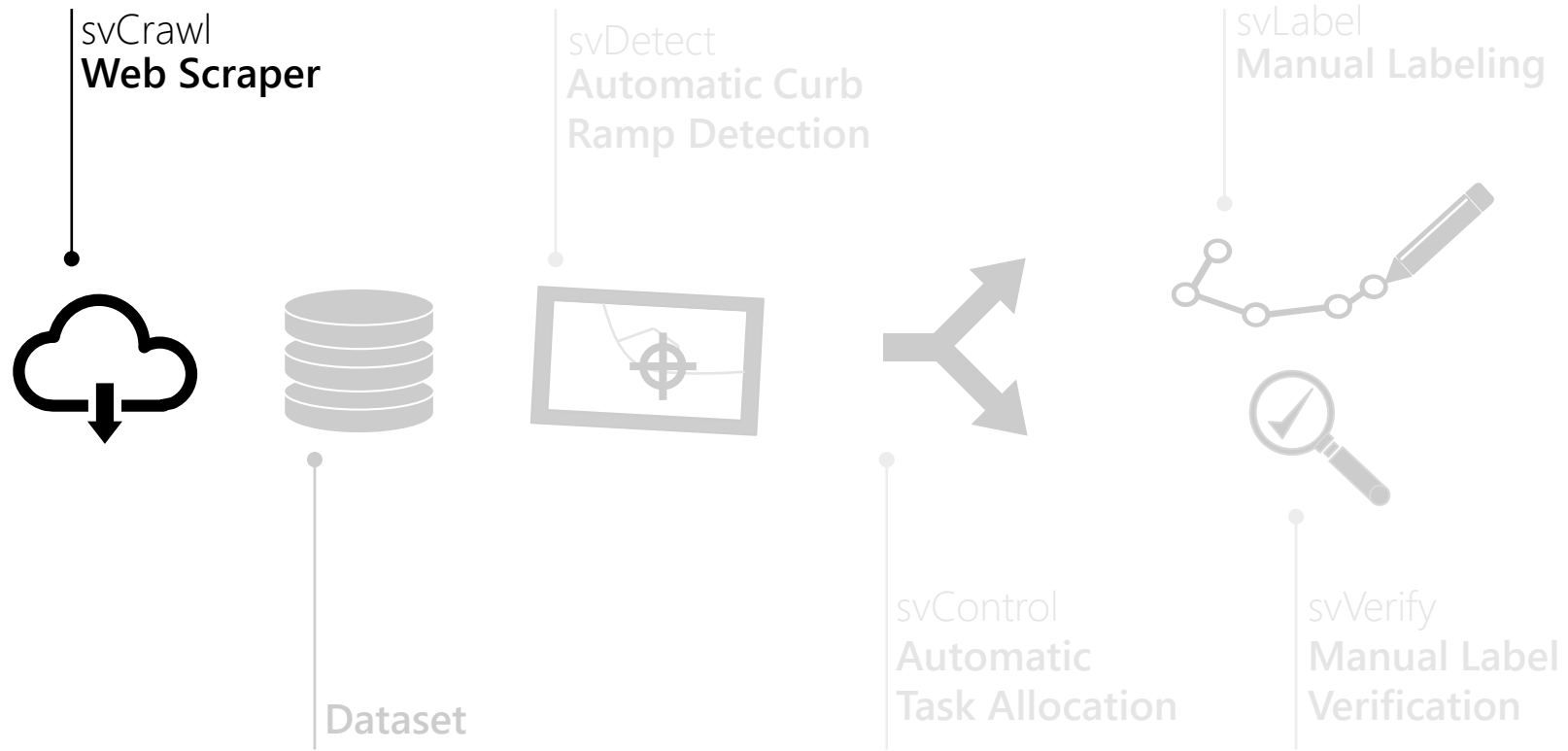
Washington D.C.

Baltimore

Los Angeles

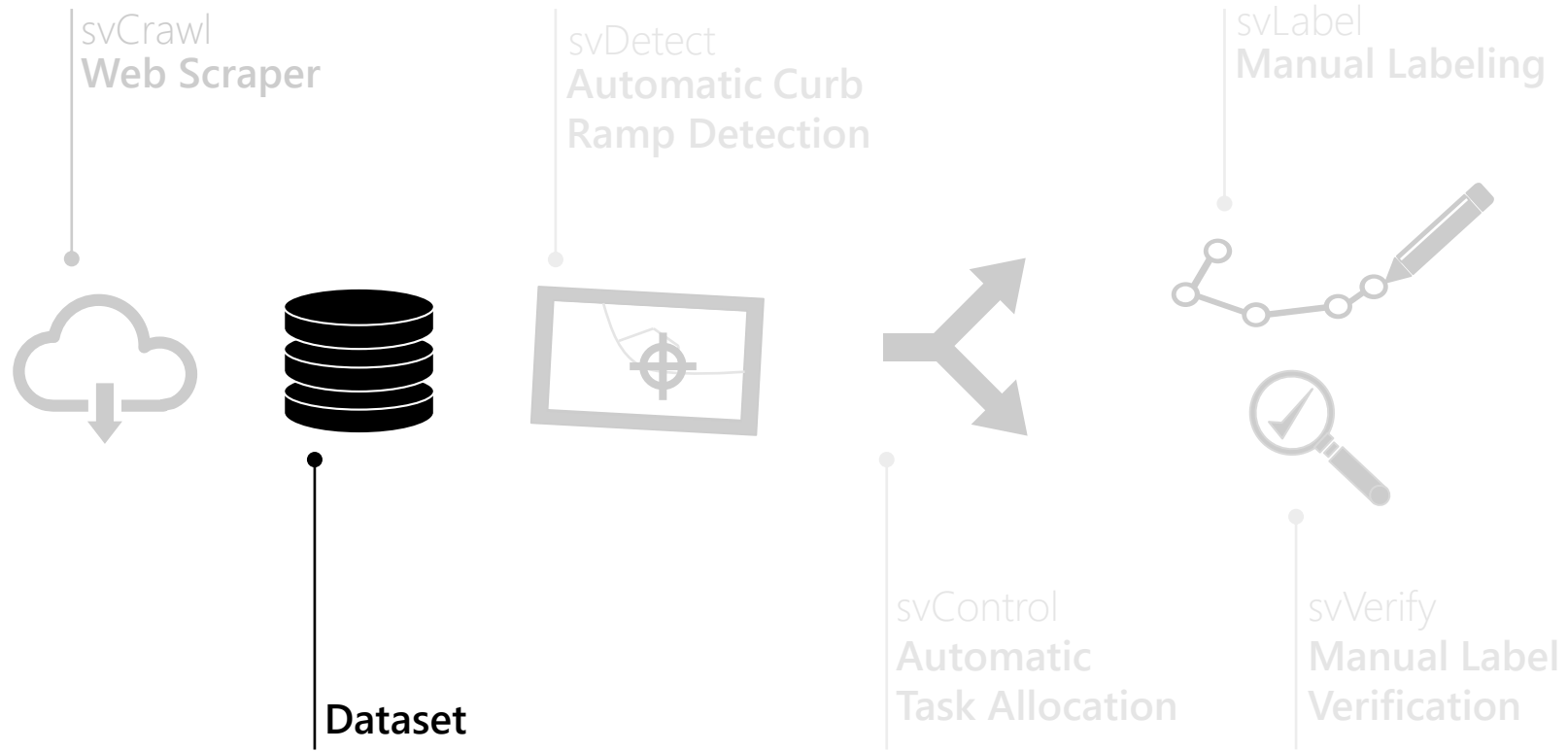
Saskatoon

* At the time of downloading data in summer 2013



Tohme

遠目·Remote Eye



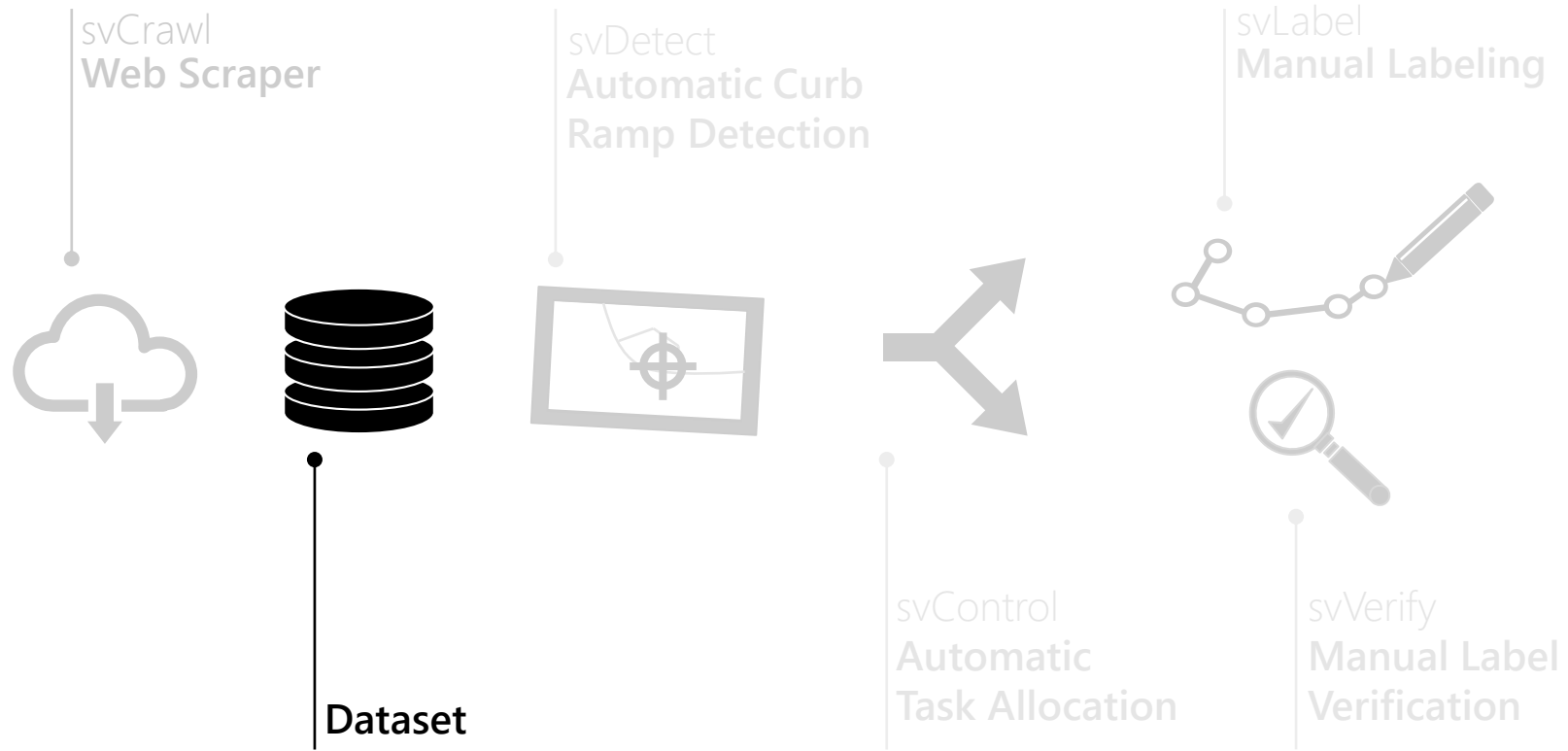
Ground Truth Curb Ramp Dataset

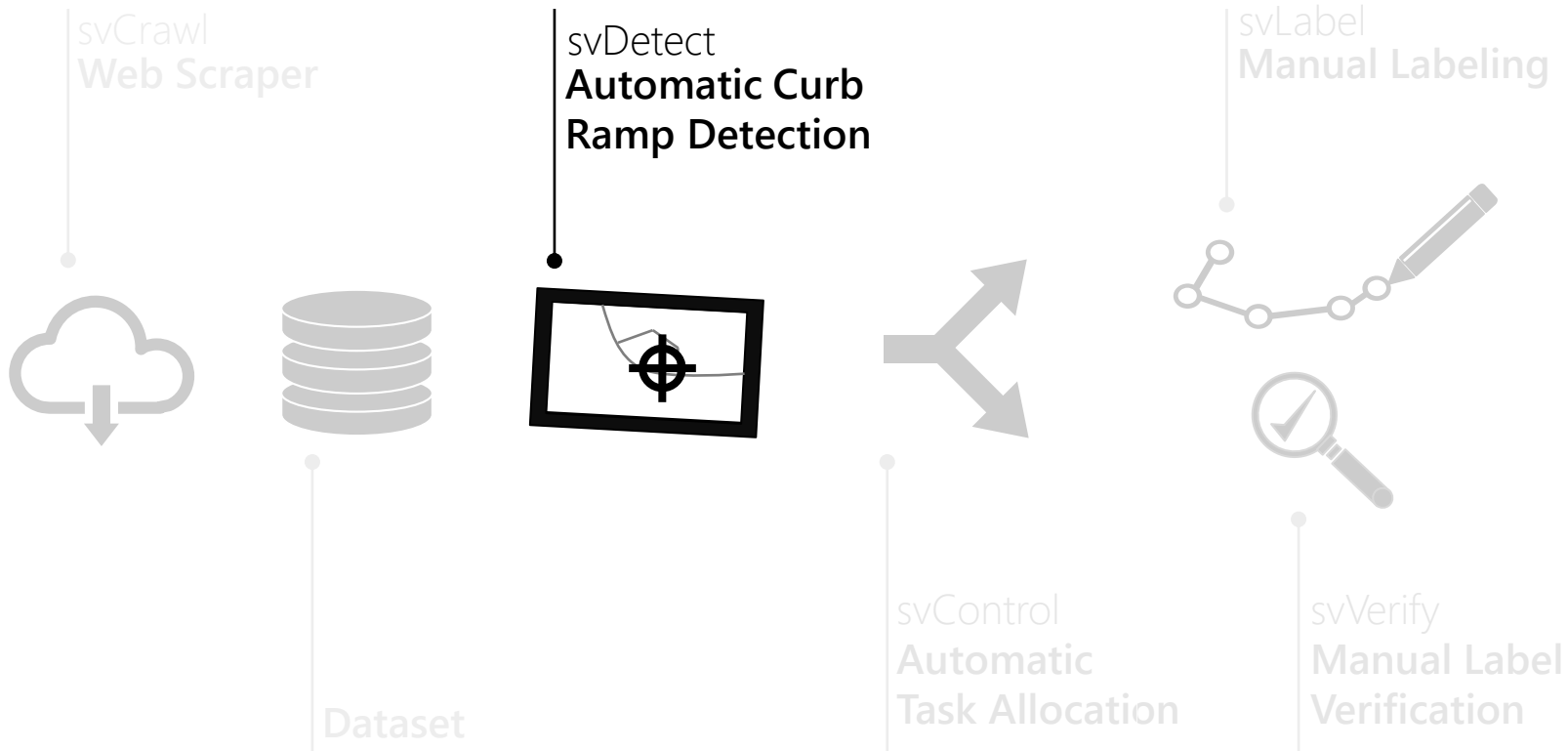
2 researchers labeled curb ramps in our dataset

2,877 curb ramp labels (*Avg.* = 2.6 per intersection)

Tohme

遠目·Remote Eye





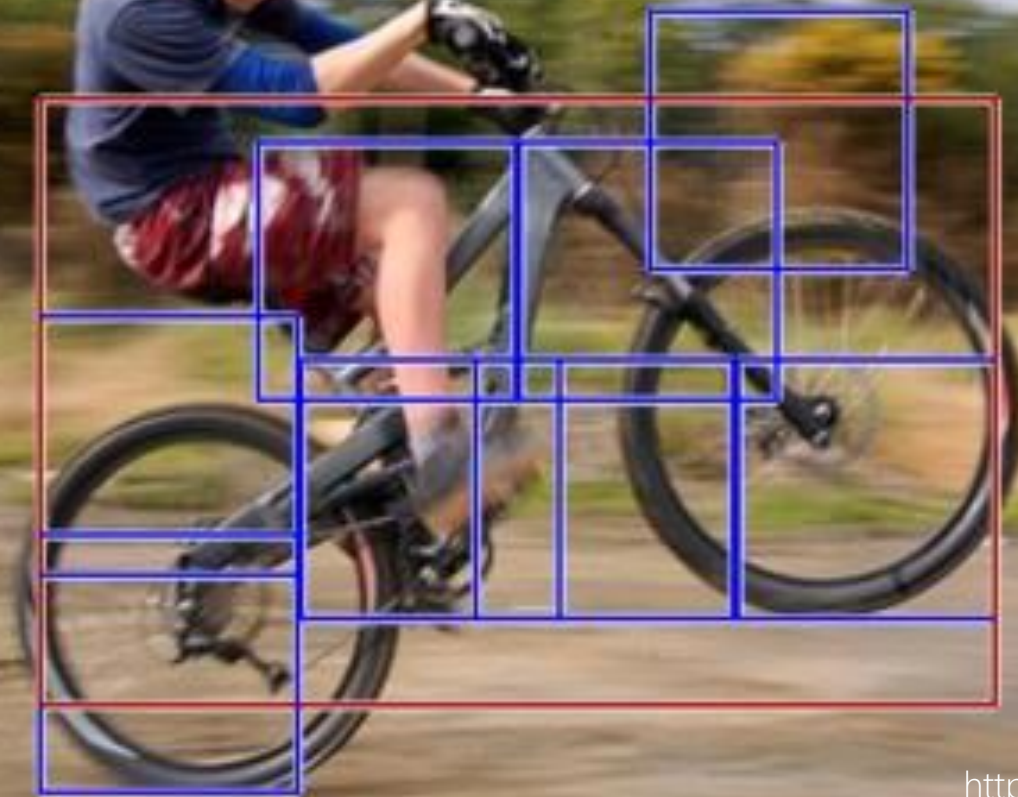
Automatic Curb Ramp Detection

1. Curb ramp detection with Deformable Part Model
2. Post-processing to filter out errors
3. SVM-based classification for output refinement



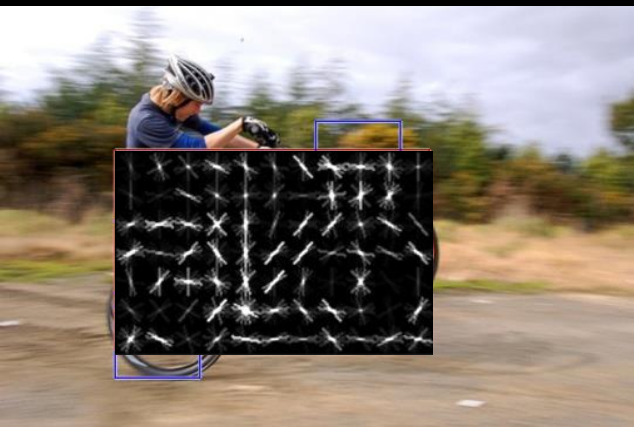
Deformable Part Models

Felzenszwalb *et al.* 2008

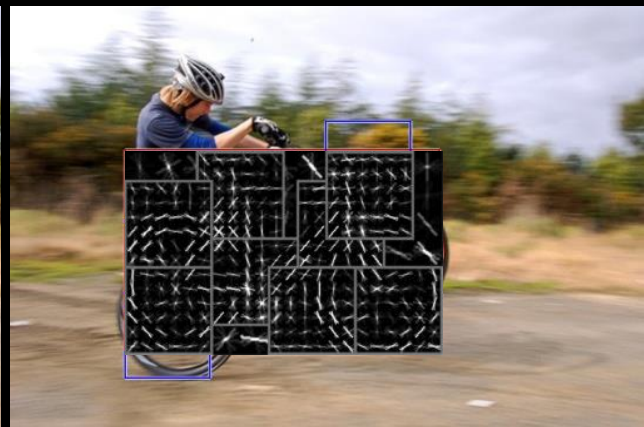


Deformable Part Models

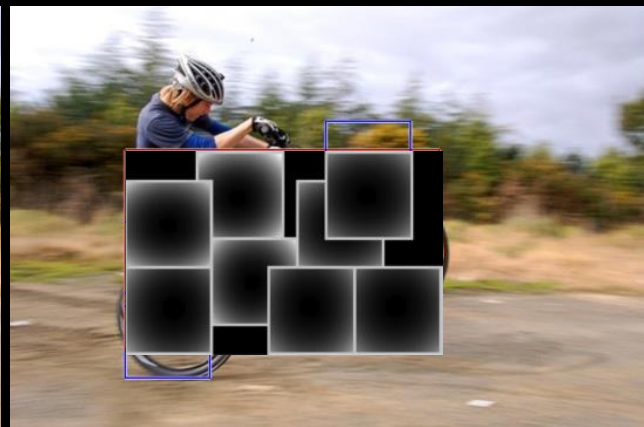
Felzenszwalb *et al.* 2008



Root filter



Parts filter



Displacement cost



Automatic Curb Ramp Detection

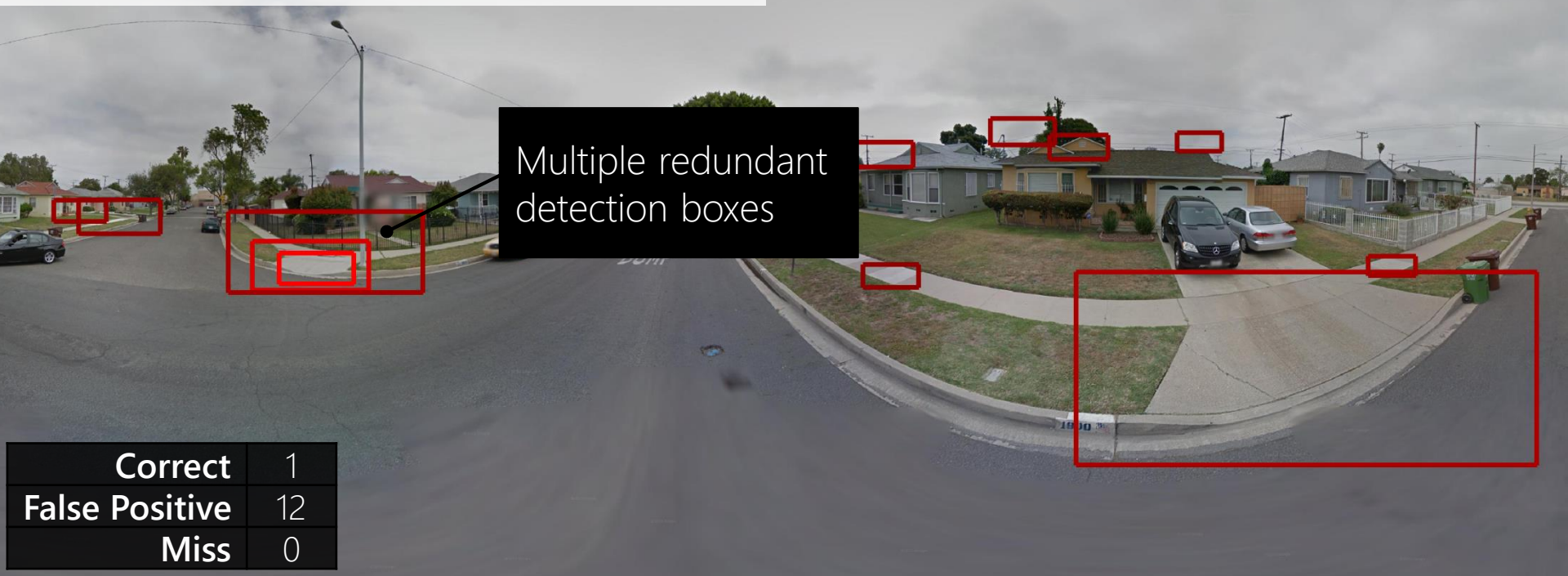




Detected Labels

Stage 1: Deformable Part Model

Sliding window detection with deformable part model



Multiple redundant
detection boxes

Correct	1
False Positive	12
Miss	0



Detected Labels

Stage 1: Deformable Part Model

Sliding window detection with deformable part model

Curb ramps shouldn't be in the sky or on roofs



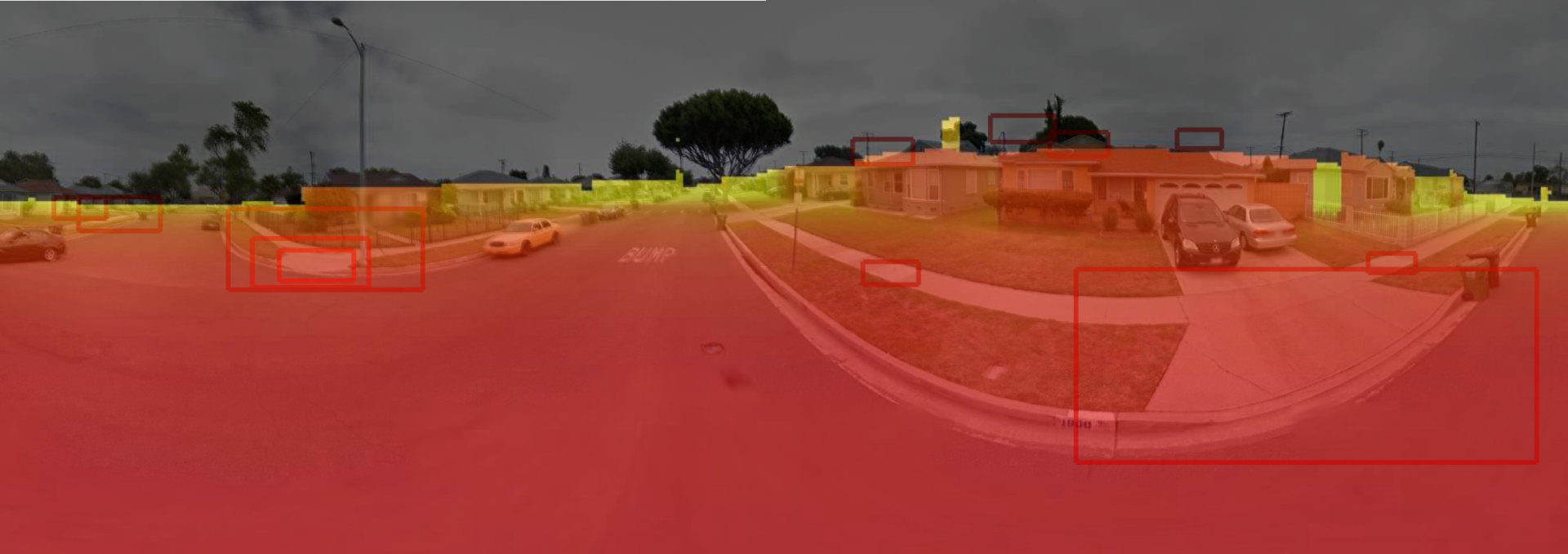
Correct	1
False Positive	12
Miss	0



Detected Labels

Stage 2: Post-processing

Rejects errors using 3D data and applies non-maxima suppression





Detected Labels

Stage 2: Post-processing

Rejects errors using 3D data and applies non-maxima suppression



Correct	1
False Positive	5
Miss	0



Detected Labels

Stage 3: SVM-based Refinement

Takes size, color, and position and further filters out false detections



Correct	1
False Positive	5
Miss	0



Detected Labels

Stage 3: SVM-based Refinement

Takes size, color, and position and further filters out false detections



Correct	1
False Positive	3
Miss	0



Automatic Curb Ramp Detection

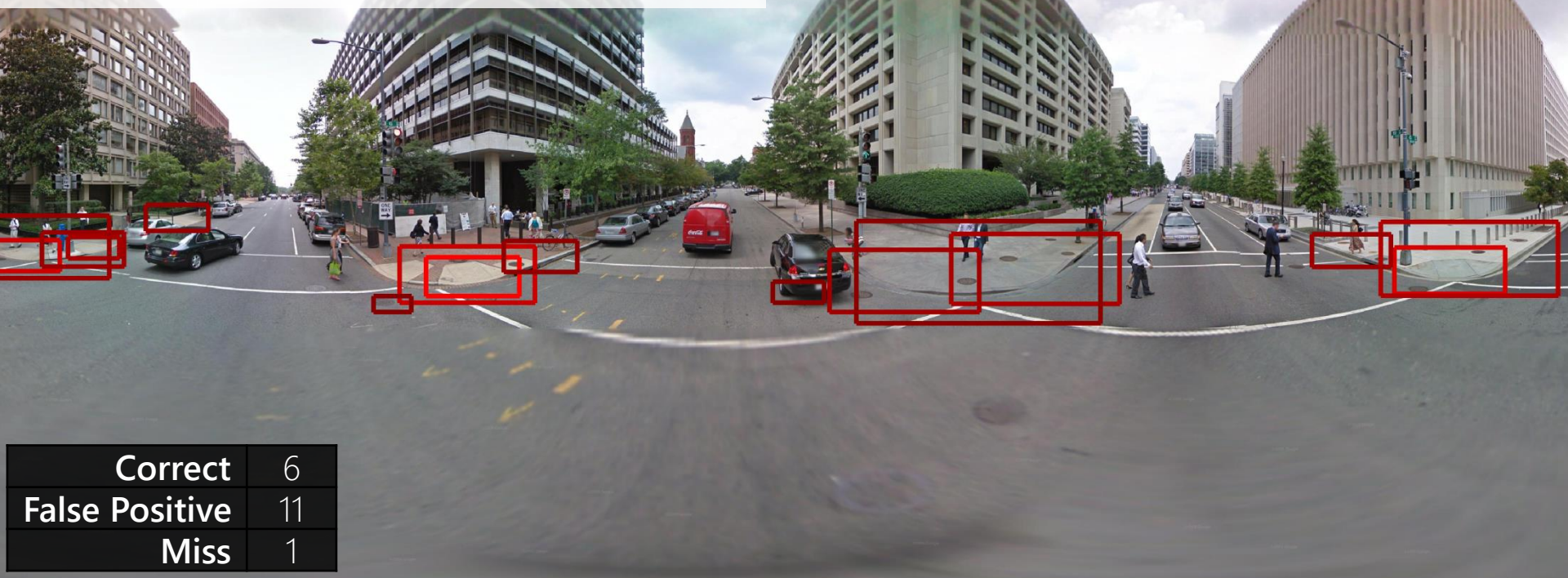




Detected Labels

Stage 1: Deformable Part Model

Sliding window detection with deformable part model



Correct 6

False Positive 11

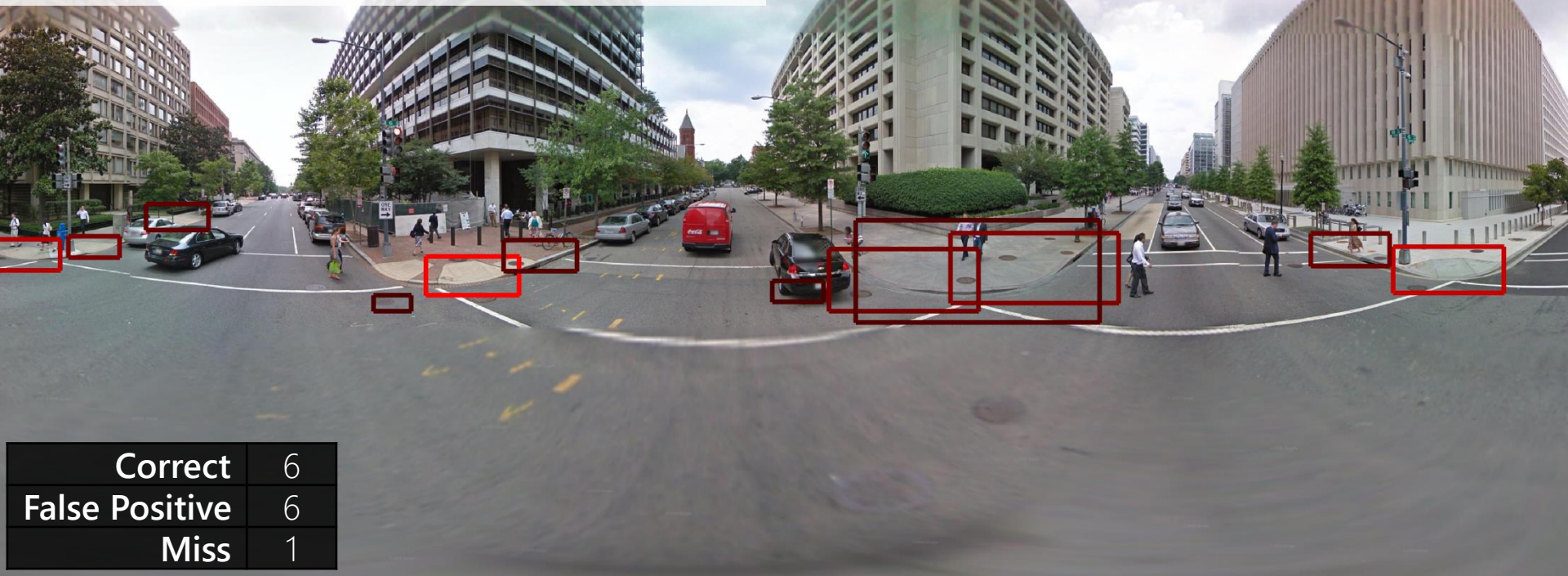
Miss 1



Detected Labels

Stage 2: Post-processing

Rejects errors using 3D data and applies non-maxima suppression



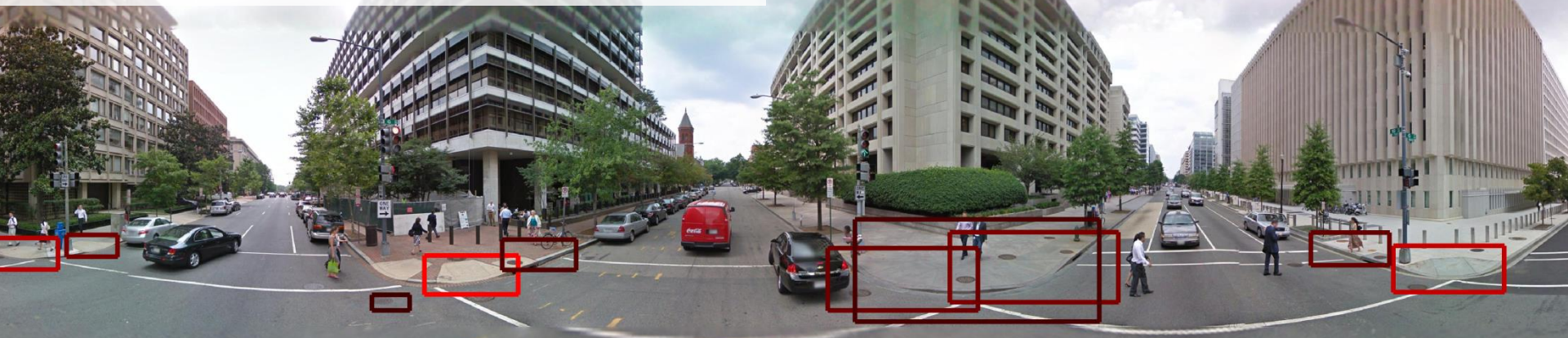
Correct	6
False Positive	6
Miss	1



Detected Labels

Stage 3: SVM-based Refinement

Takes size, color, and position and further filters out false detections



Correct 6

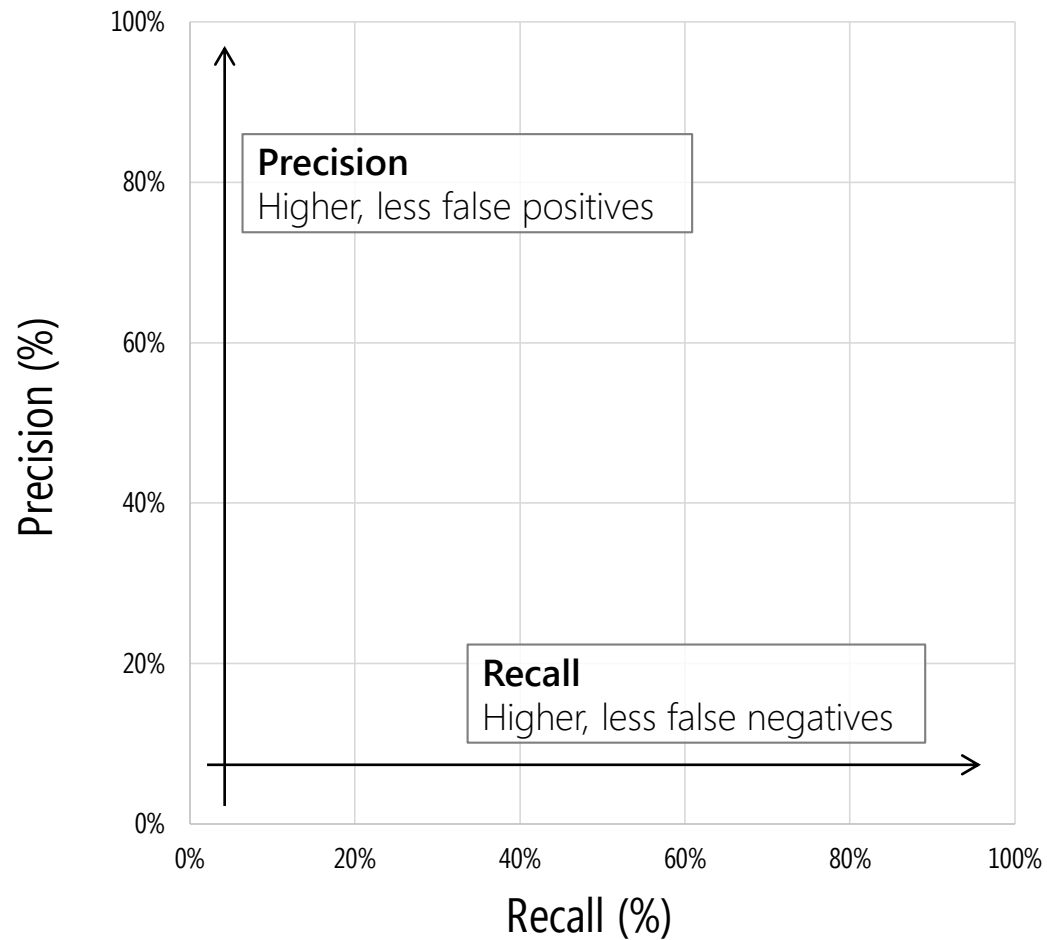
False Positive 4

Miss 1

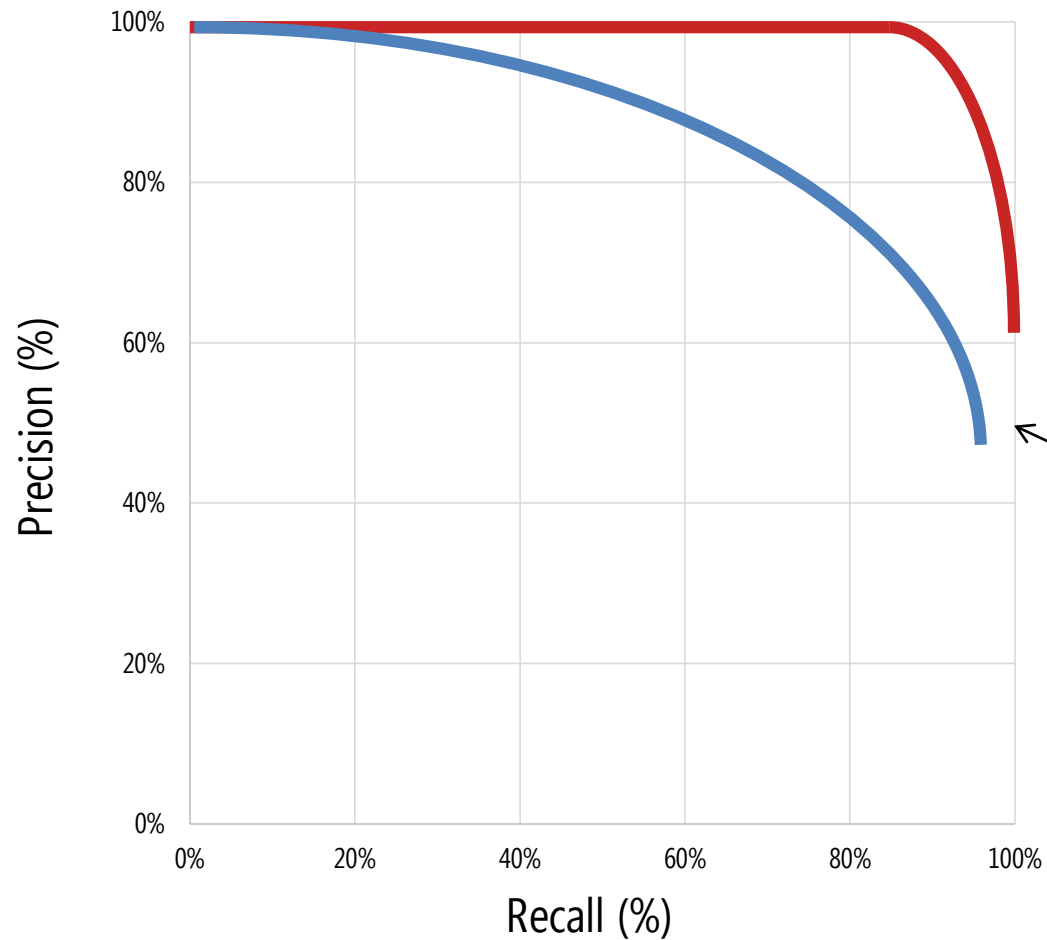
Automatic Curb Ramp Detection Accuracy

Used two-fold cross validation to evaluate CV sub-system

COMPUTER VISION SUB-SYSTEM RESULTS

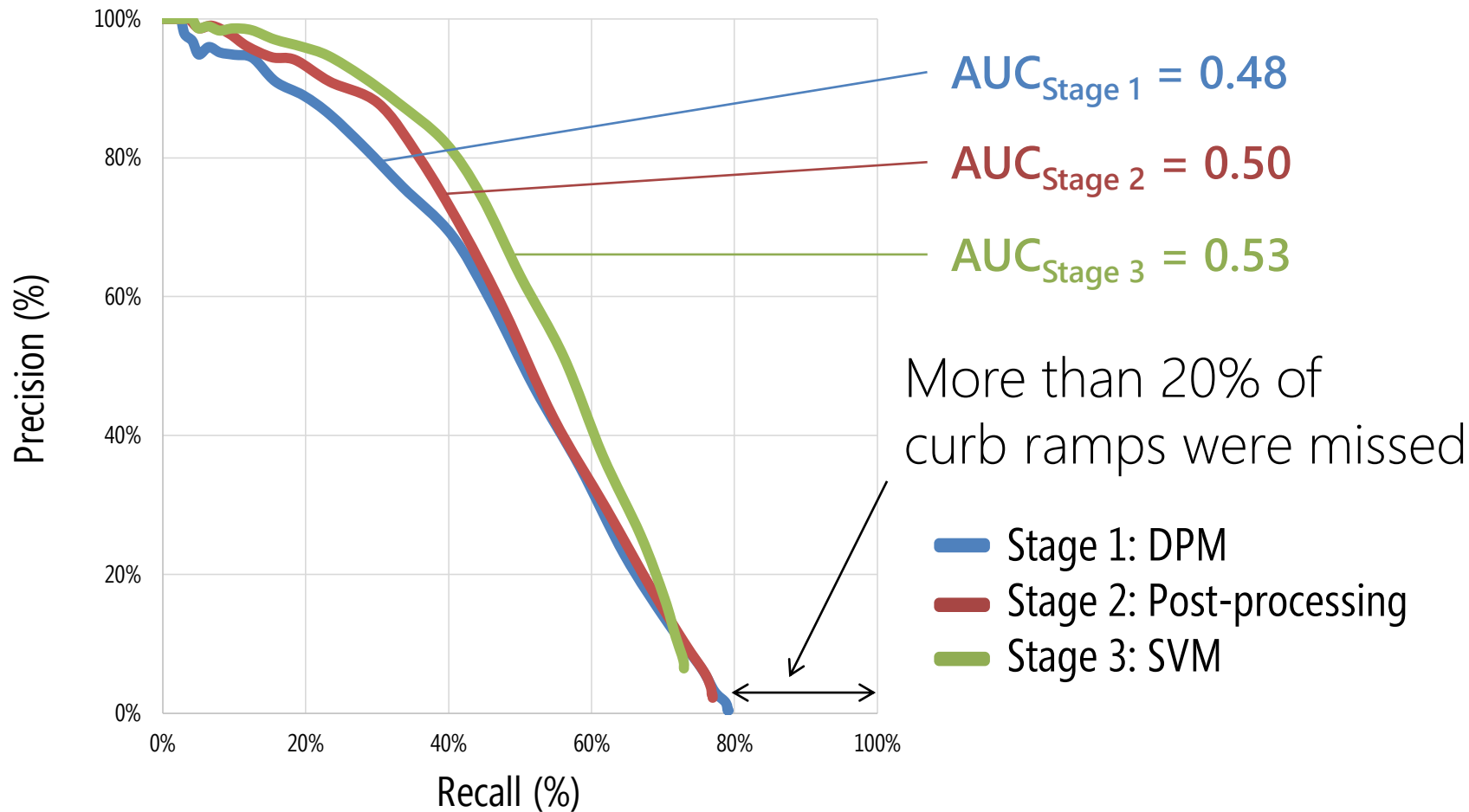


COMPUTER VISION SUB-SYSTEM RESULTS

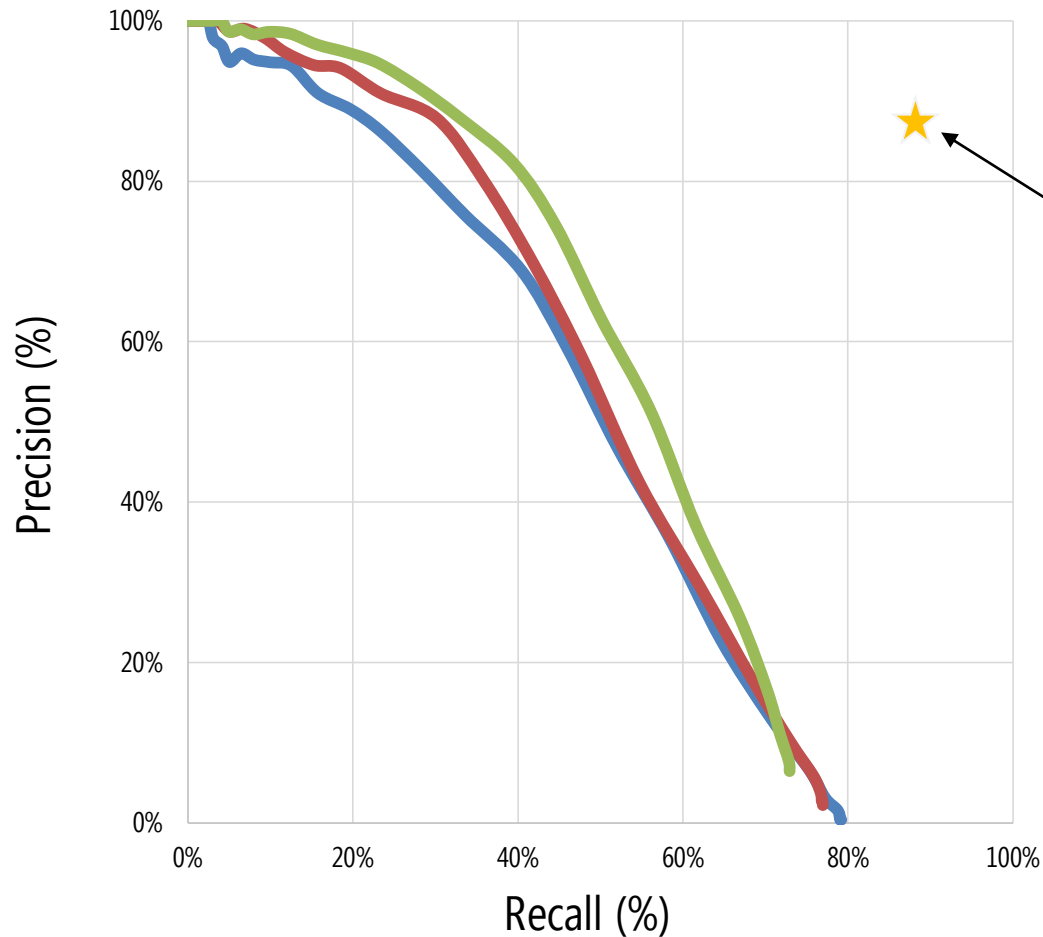


Goal: maximize
area under curve

COMPUTER VISION SUB-SYSTEM RESULTS



COMPUTER VISION SUB-SYSTEM RESULTS



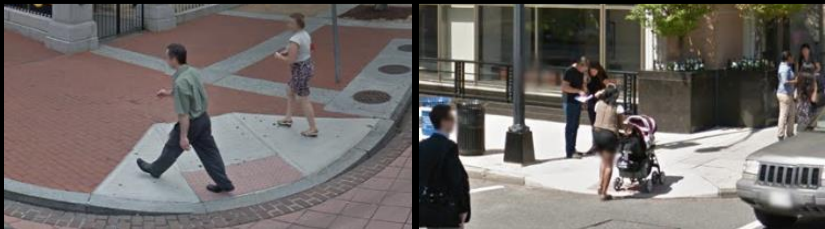
Pr, Re = 84%, 88%
1 turker

Computer vision alone is not sufficient to accurately find curb ramps

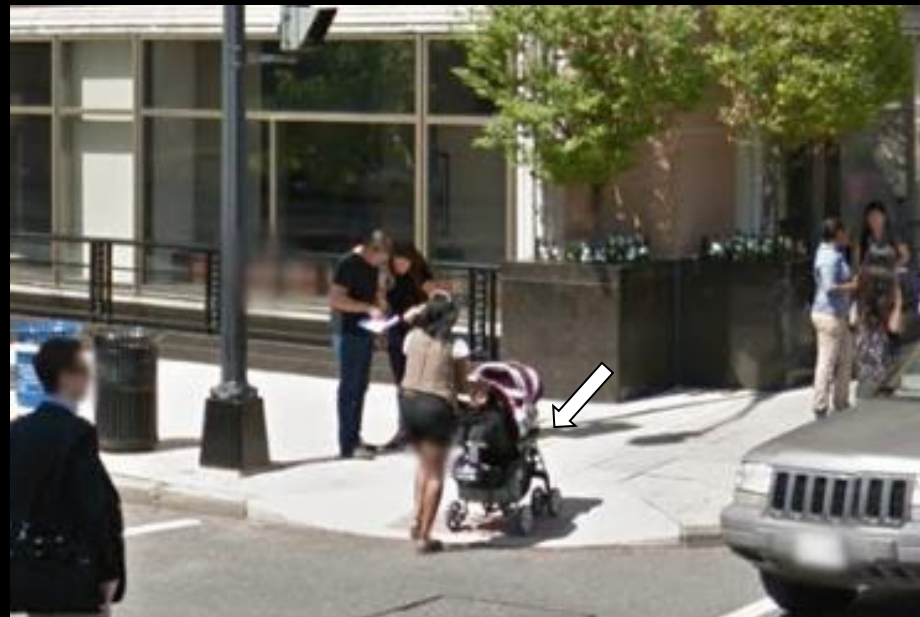
- Stage 1: DPM
- Stage 2: Post-processing
- Stage 3: SVM

Curb Ramp Detection is a Hard Problem

Occlusion

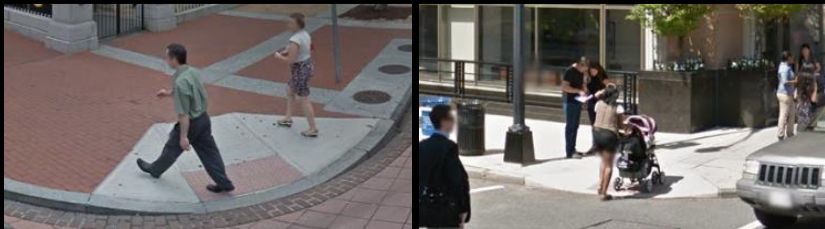


Occlusion



Curb Ramp Detection is a Hard Problem

Occlusion



Illumination

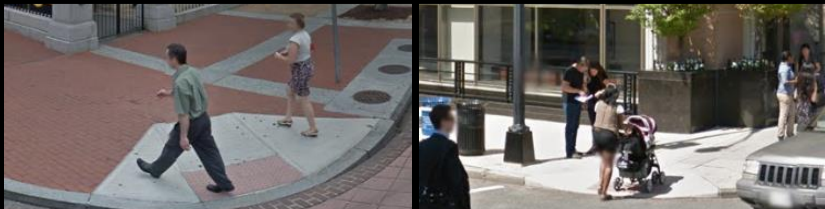


Illumination



Curb Ramp Detection is a Hard Problem

Occlusion



Illumination



Scale

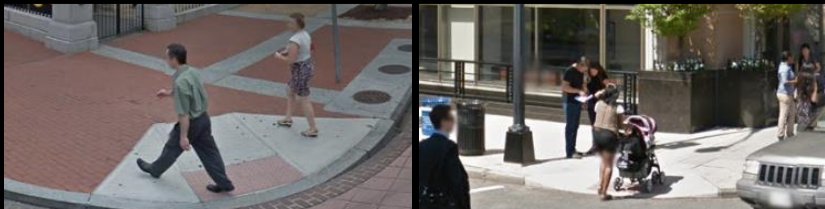


Scale



Curb Ramp Detection is a Hard Problem

Occlusion



Illumination



Scale



Viewpoint Variation

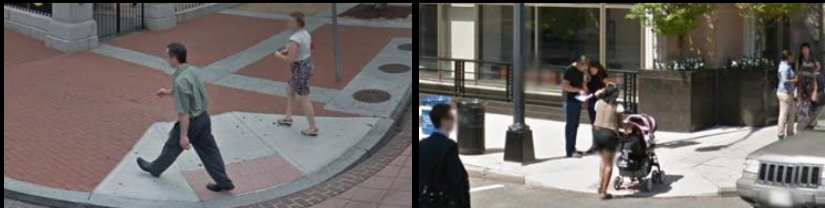


View Point Variation



Curb Ramp Detection is a Hard Problem

Occlusion



Illumination



Scale



Viewpoint Variation



Structures Similar to Curb Ramps

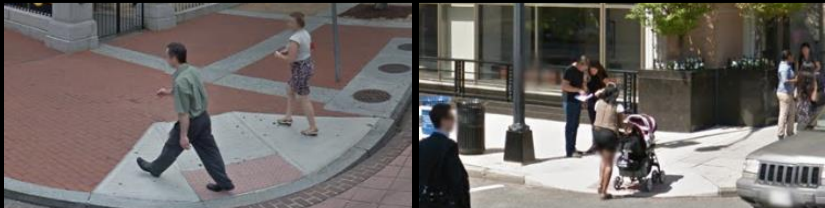


Structures Similar to Curb Ramps



Curb Ramp Detection is a Hard Problem

Occlusion



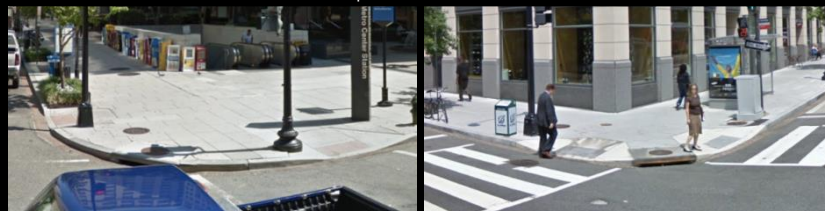
Illumination



Scale



Viewpoint Variation



Structures Similar to Curb Ramps



Curb Ramp Design Variation

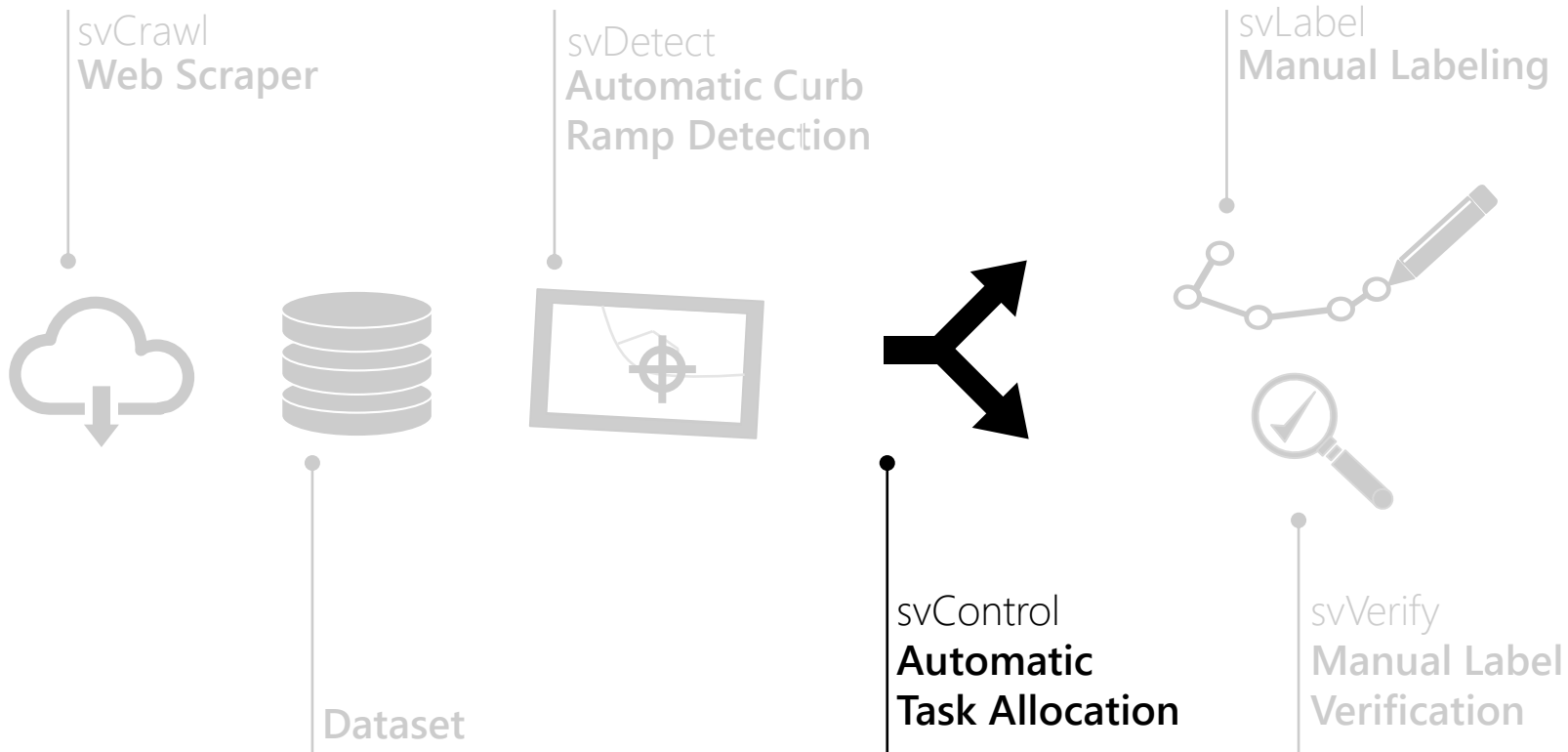


Curb Ramp Design Variation



Tohme

遠目·Remote Eye



A number of streets from metadata



Depth information for a road width and variance in distance



Top-down images to assess complexity of an intersection



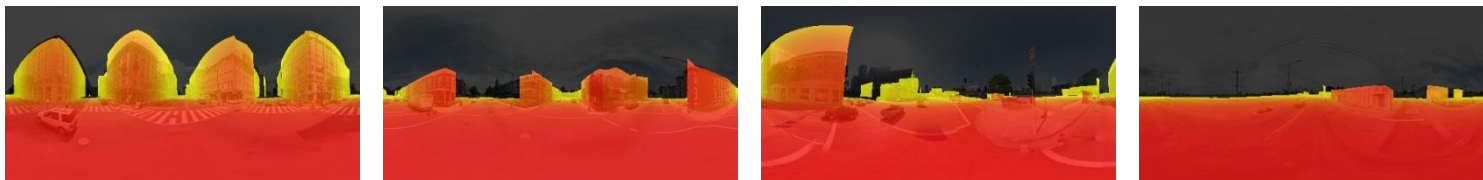
A number of detections and confidence values



A number of street from metadata



Depth information for a road width and variance in distance



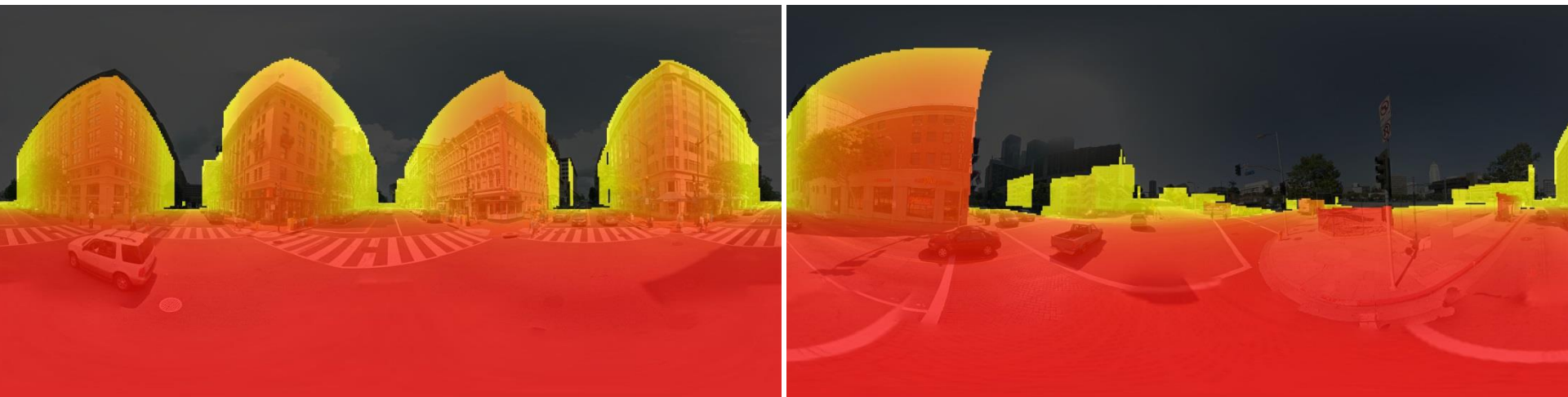
Top-down images to assess complexity of an intersection



A number of detections and confidence values



Depth information for a road width and variance in distance



Finding curbs on distant sidewalks is difficult; they look smaller (i.e., scaling issue)

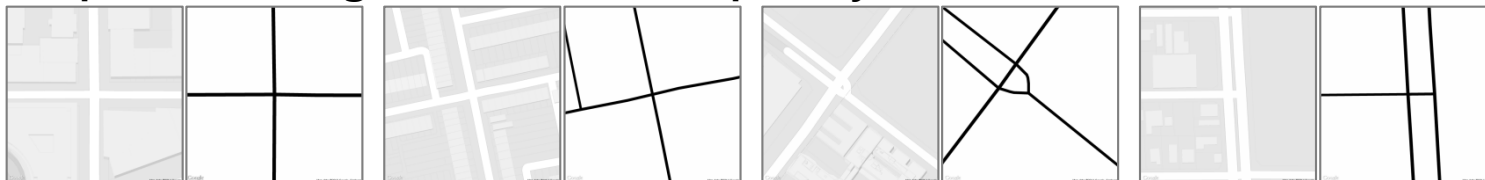
A number of streets from metadata



Depth information for a road width and variance in distance

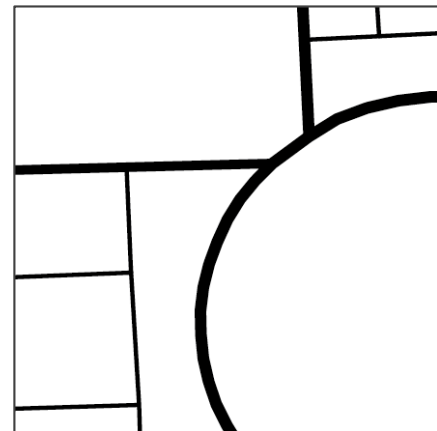
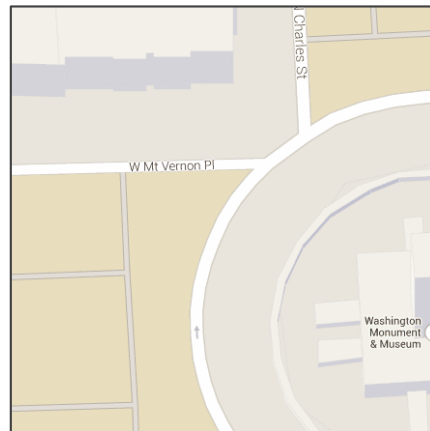
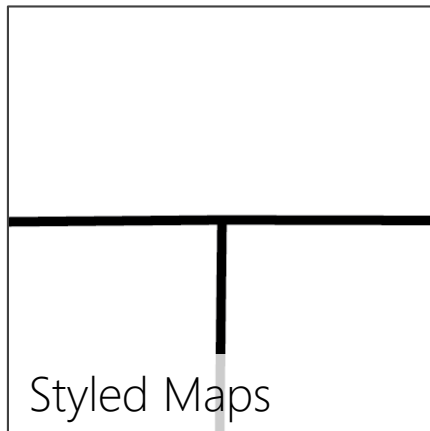
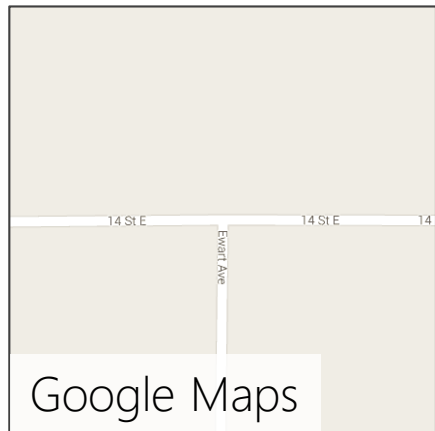


Top-down images to assess complexity of an intersection



A number of detections and confidence values





As a proxy for intersection complexity, we count the number of black :
more black pixels = more complex intersection
(*i.e.*, more viewpoint variation)

A number of streets from metadata



Depth information for a road width and variance in distance



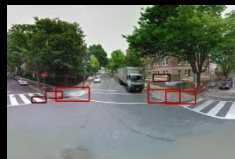
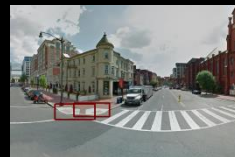
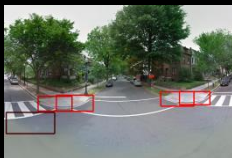
Top-down images to assess complexity of an intersection



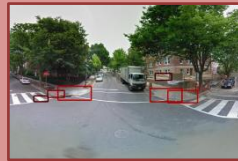
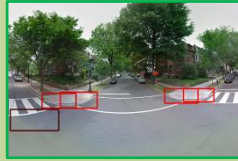
CV Output: A number of detections and confidence values



↔ Binary Classification

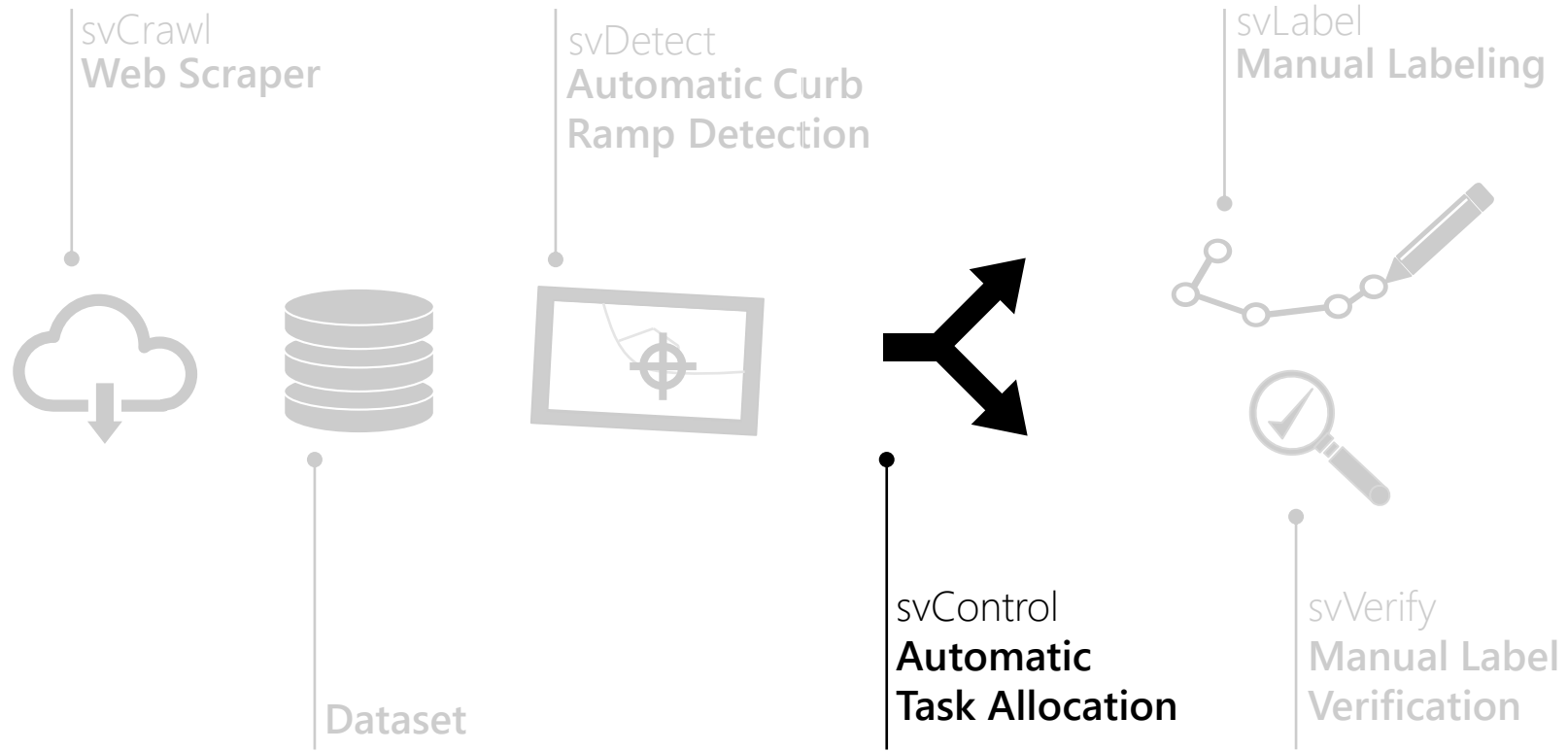


↔ Binary classifier to detect false-negatives



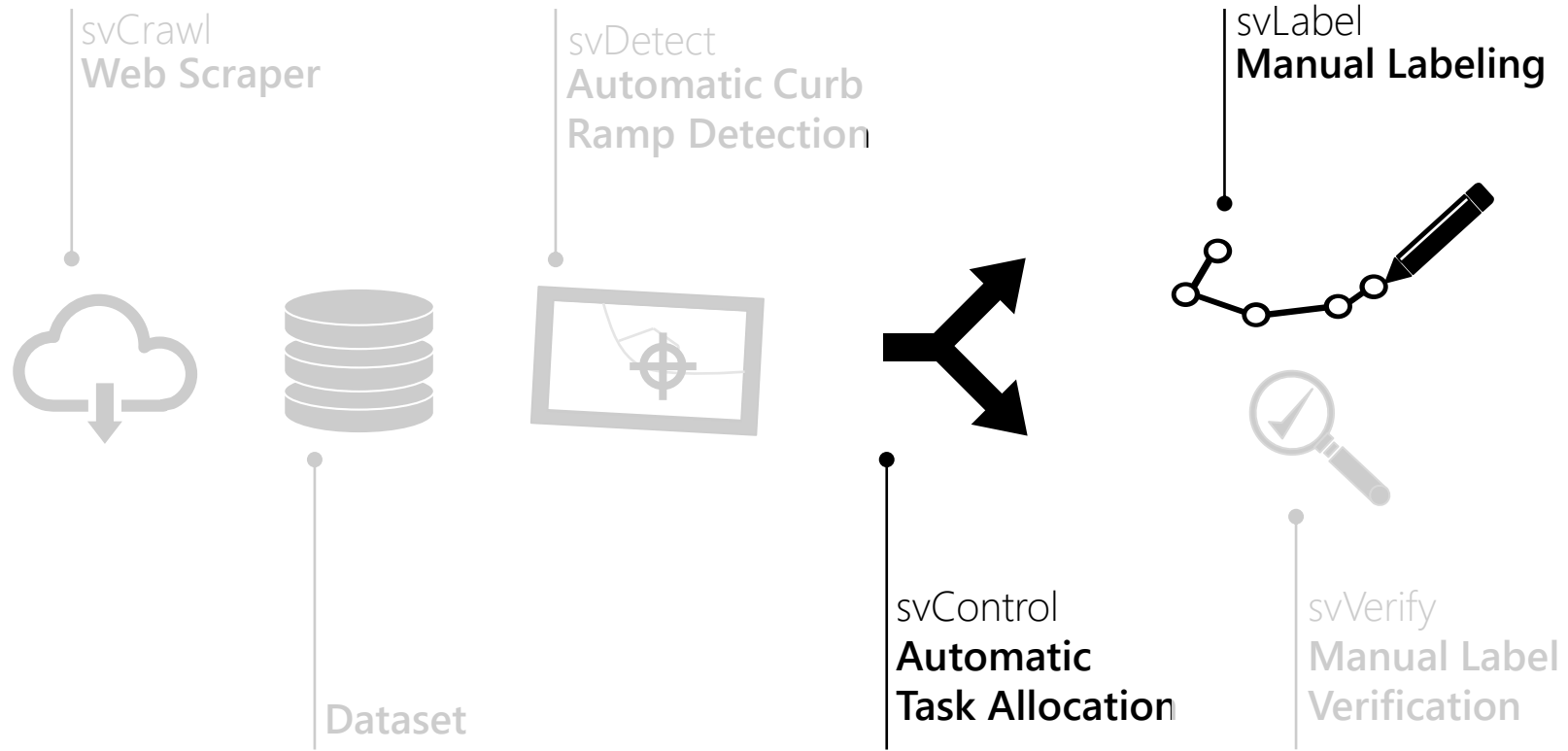
Pass

Fail





Tohme


遠目·Remote Eye





Find and label the following


 Explore


 Curb Ramp

 Missing Curb Ramp

 Zoom In

 Zoom Out

 Undo


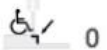
 Redo

Status

Mission:
Your mission is to **find and label** the presence and absence of curb ramps at intersections.

Progress:
You have finished 0 out of 5.

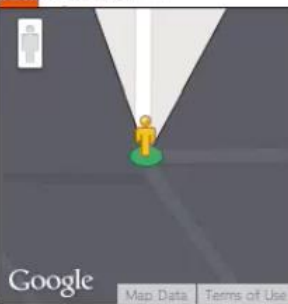
Labeled Landmarks:

 0  0

You've submitted 0 curb ramp labels and 0 missing curb ramp labels.

Keyboard Shortcuts:
ESC: Cancel drawing
Z / Shift+Z: Zoom in / Zoom out

Observed area: 14%



Google

© 2014 Google | Terms of Use | Report a problem

Google

Map Data | Terms of Use

Please enter any comments about this intersection that may affect people with mobility impairment (optional)

Skip Submit

Help Us Improve Street Accessibility

Hi, we're exploring new ways to find accessibility problems in cities, and we need your help! In this task, **your mission is to label curb ramps** and **missing curb ramps** in Google Street View. Curb ramps are very important--without them, people in wheelchairs cannot move about the city.



An image of curb ramps at an intersection.



A lack of a curb ramp at this corner obstruct wheelchair users from getting on and off the sidewalk.

We'll **begin with a short, interactive tutorial** to get you started! Thanks for your help in improving the accessibility of cities.

Next

Find and label the following

Explore

Curb Ramp

Missing Curb Ramp

Zoom In

Zoom Out

Undo



Redo

Status

Mission:
Your mission is to **find and label** the presence and absence of curb ramps at intersections.

Progress:
You have finished 0 out of 5.

Labeled Landmarks:

 3  0

You've submitted 0 curb ramp labels and 0 missing curb ramp labels.

Keyboard Shortcuts:
ESC: Cancel drawing
Z / Shift+Z: Zoom in / Zoom out

Observed area: 75%

Google


© 2014 Google | Terms of Use | Report a problem

Google | Map Data | Terms of Use

Please enter any comments about this intersection that may affect people with mobility impairment (optional)

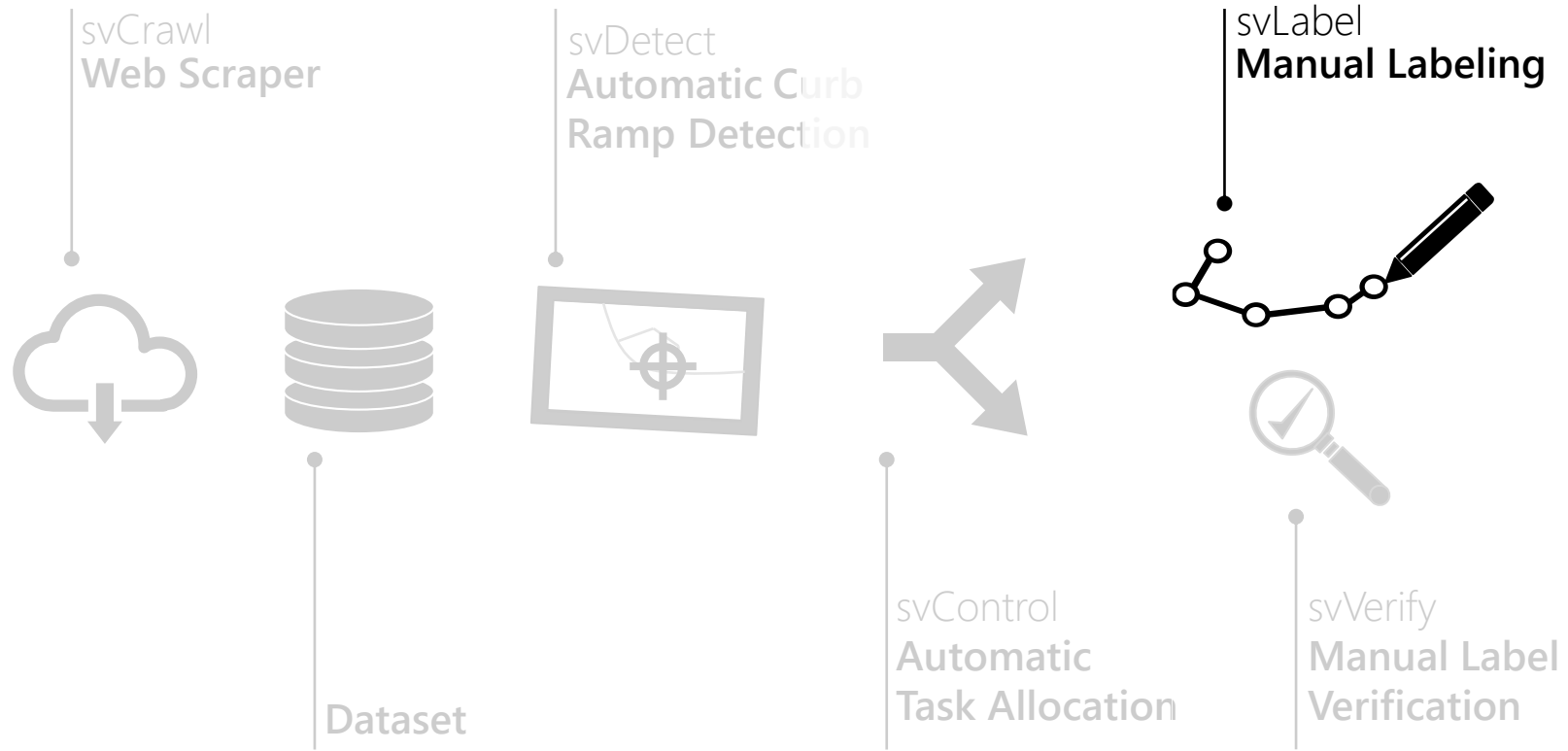
Skip

Submit



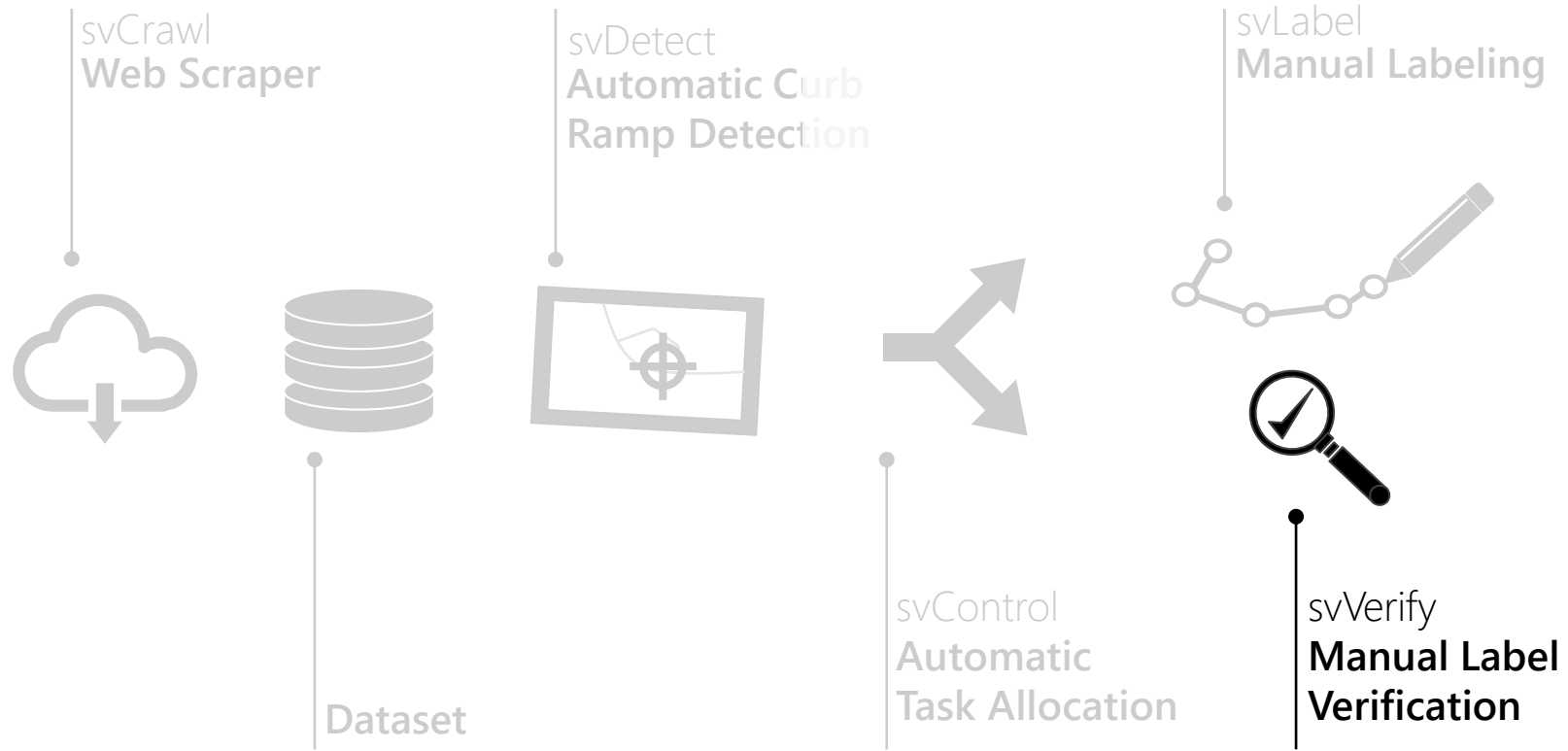
Tohme

遠目·Remote Eye




Tohme

遠目·Remote Eye



Manual Label Verification

Zoom In Zoom Out Undo Redo



Google © 2014 Google Terms of Use Report a problem

Please enter any comments about this bus stop that may affect people with visual impairment (optional)



Submit

Status

Mission:
Your mission is to **verify** the presence of curb ramps at intersections.

Progress:
You have finished 0 out of 1.


Labeled Curb Ramps:

  11

Keyboard Shortcuts:

Arrow Keys	Navigate
Z	Zoom in
Shift+Z	Zoom out

The area of the scene you have observed: 14%




Google Map Data Terms of Use

This study is being conducted by the University of Maryland.

2x

Manual Label Verification

Zoom In Zoom Out Undo Redo



Google © 2014 Google Terms of Use Report a problem

Please enter any comments about this bus stop that may affect people with visual impairment (optional)



Submit

Status

Mission:
Your mission is to **verify** the presence of curb ramps at intersections.

Progress:
You have finished 0 out of 1.


Labeled Curb Ramps:

  11

Keyboard Shortcuts:

Arrow Keys	Navigate
Z	Zoom in
Shift+Z	Zoom out

The area of the scene you have observed: 14%

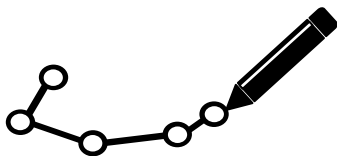


Google Map Data Terms of Use

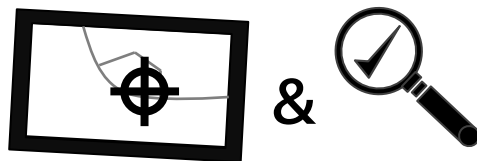
This study is being conducted by the University of Maryland.

2x

Study Method: Conditions



VS.



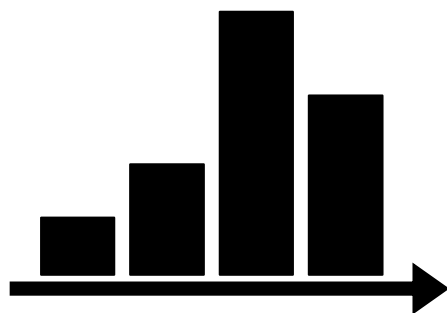
VS.

Tohme
遠目 · *Remote Eye*

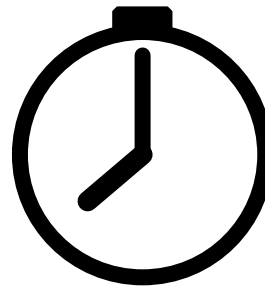
Manual labeling without
smart task allocation

CV + Verification without
smart task allocation

Study Method: Measures



Accuracy



Task Completion Time

Study Method: Approach

We recruited workers from Amazon Mechanical Turk to work on labeling tasks and verification tasks

We used 1,046 GSV images



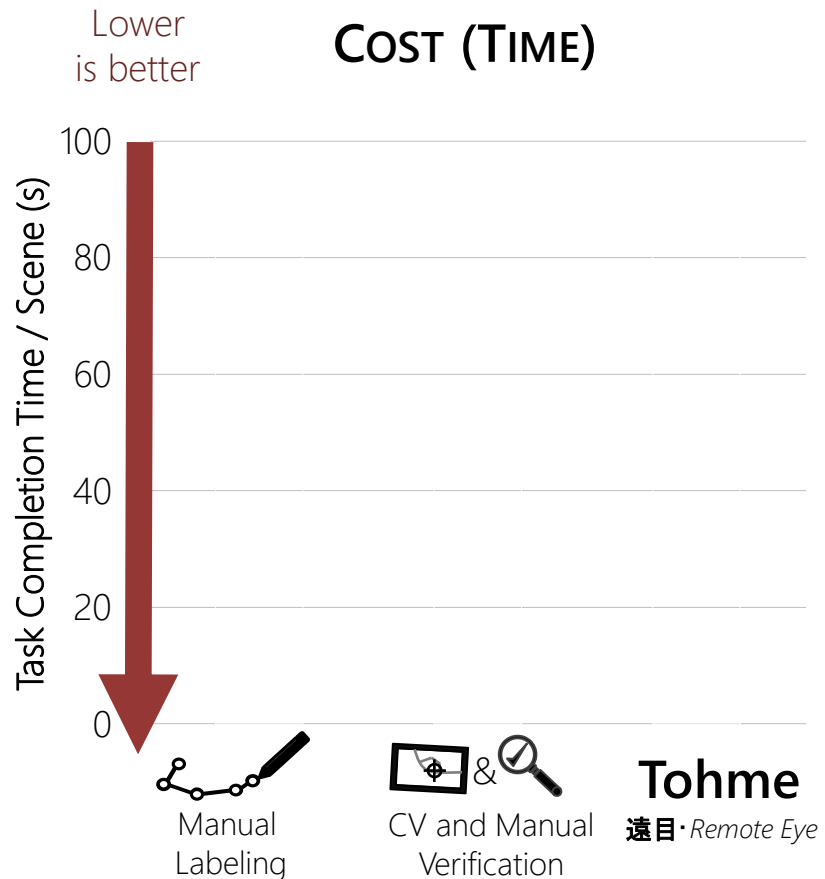
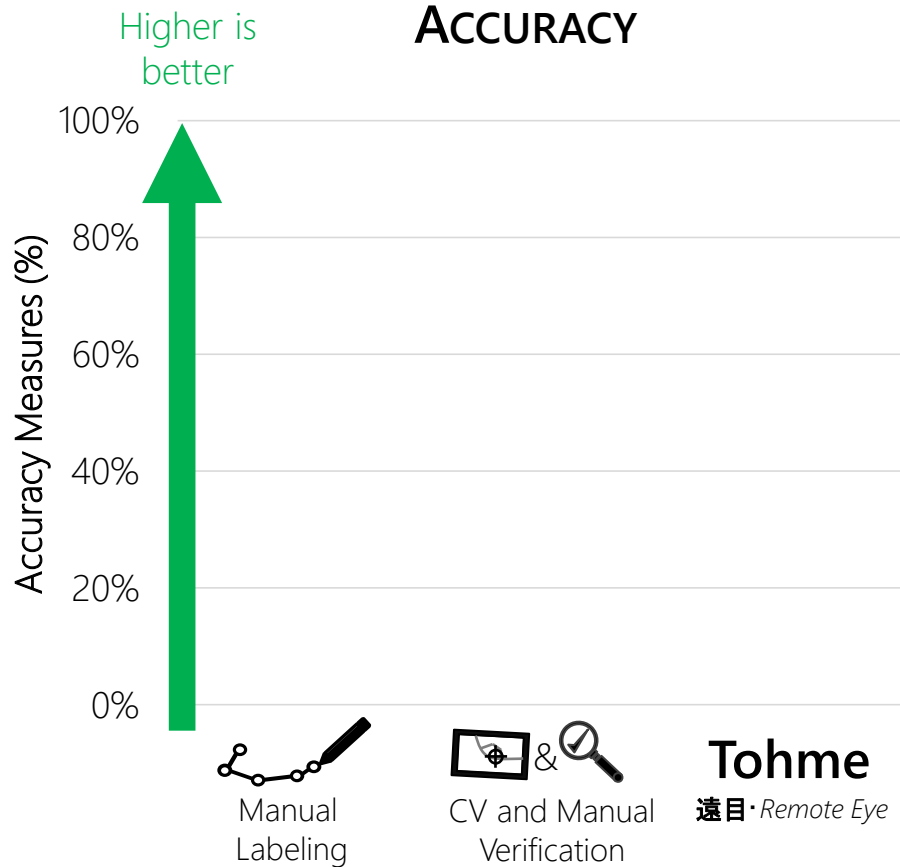
Labeling Tasks

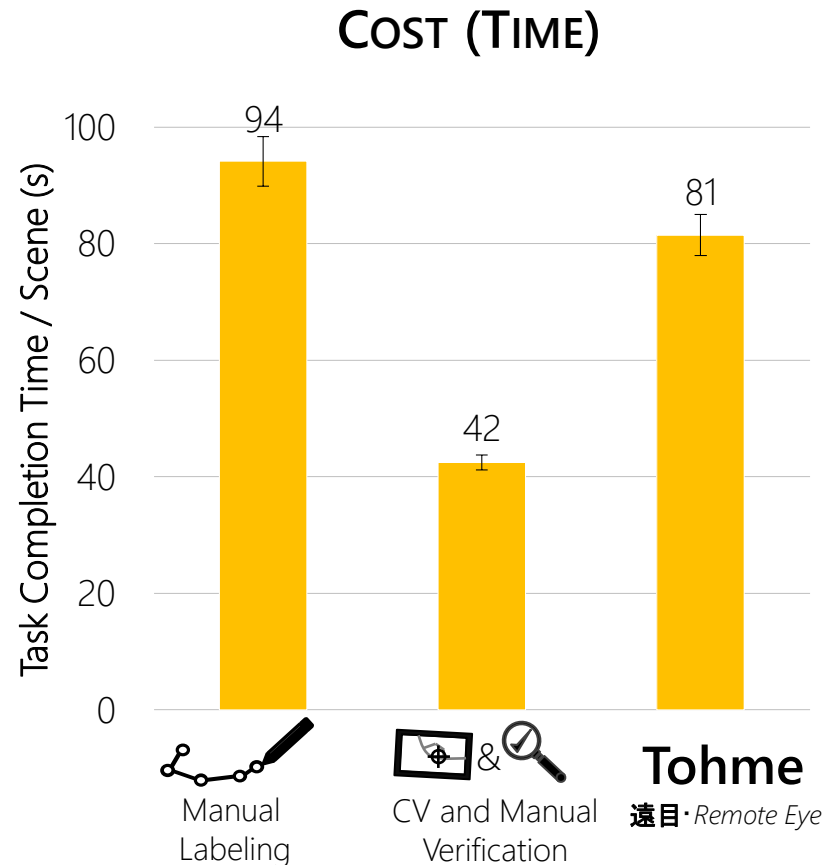
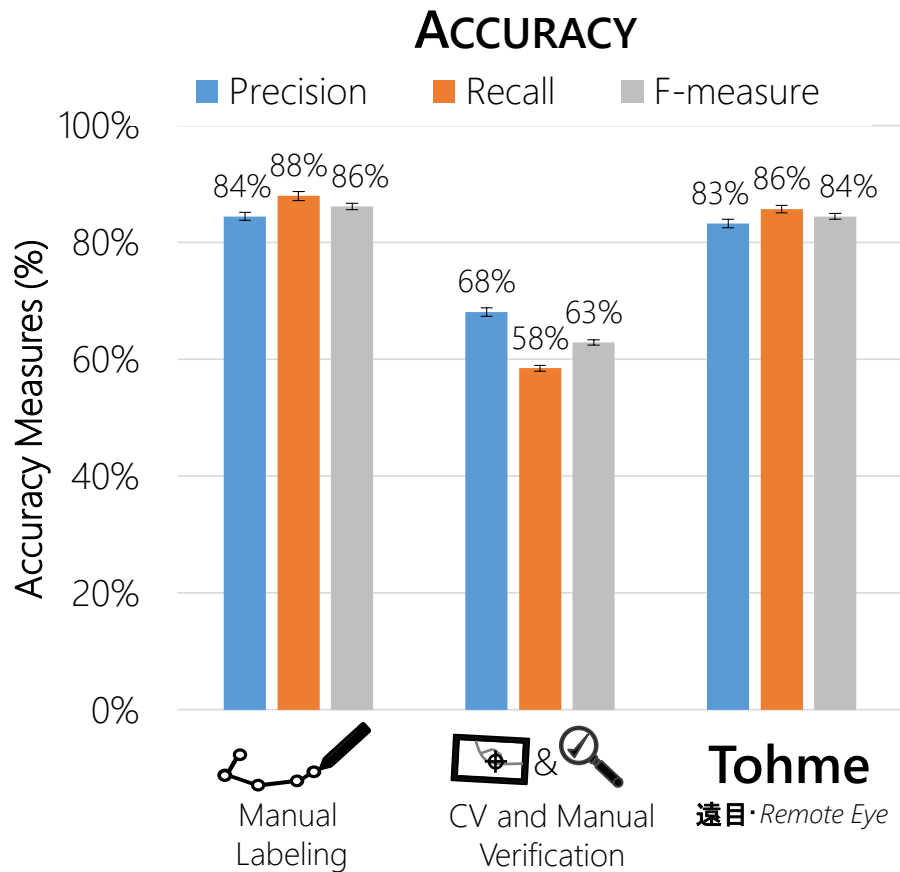


Verification Tasks

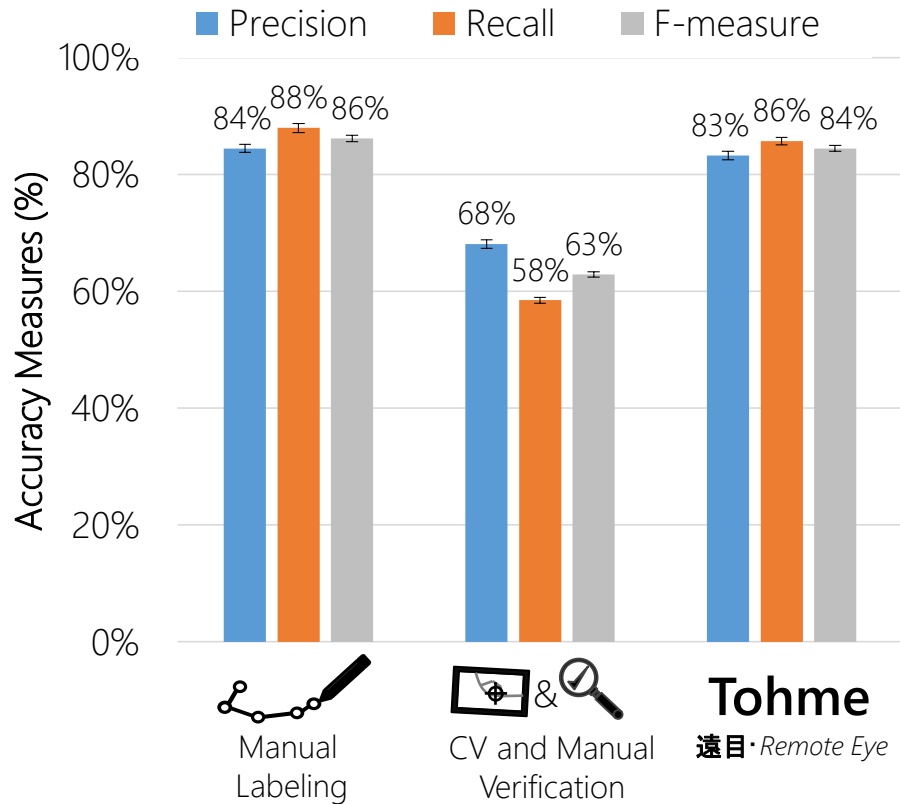
# of distinct turkers:	242	161
# of tasks completed:	6,350	4,820

We evaluated the result with Monte Carlo simulation

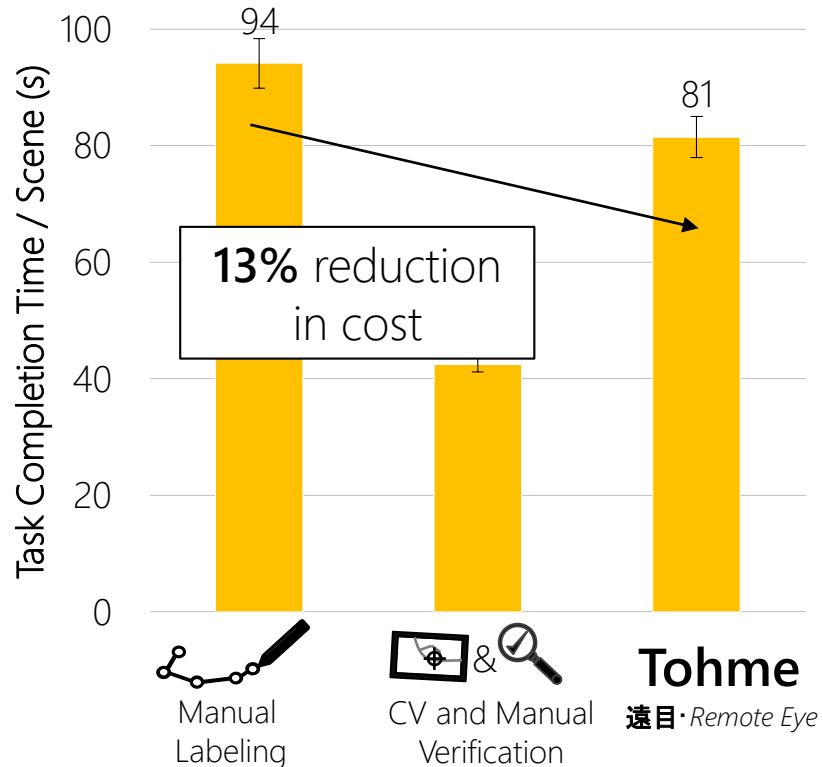




ACCURACY



COST (TIME)



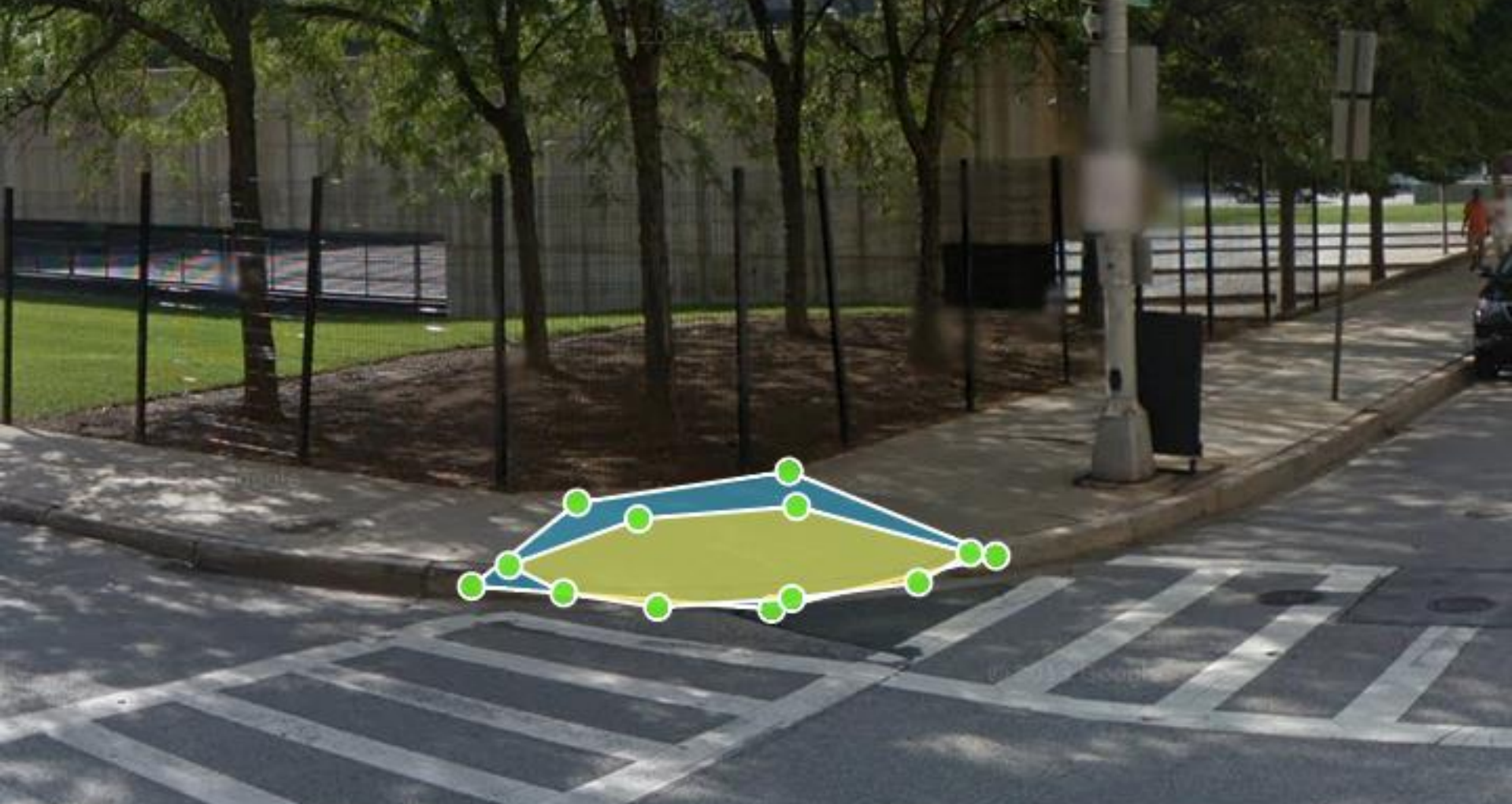


Example Labels from Manual Labeling

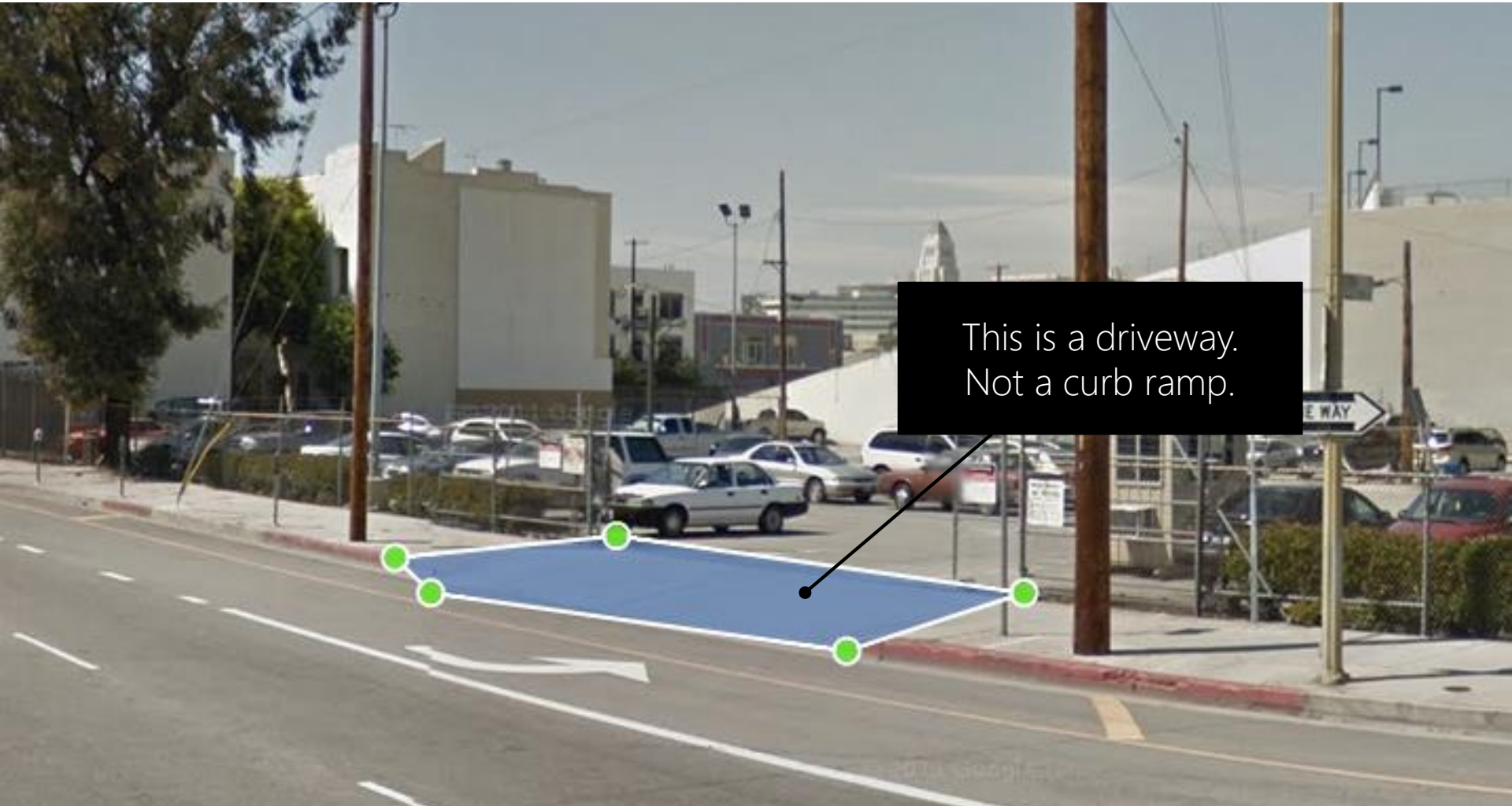






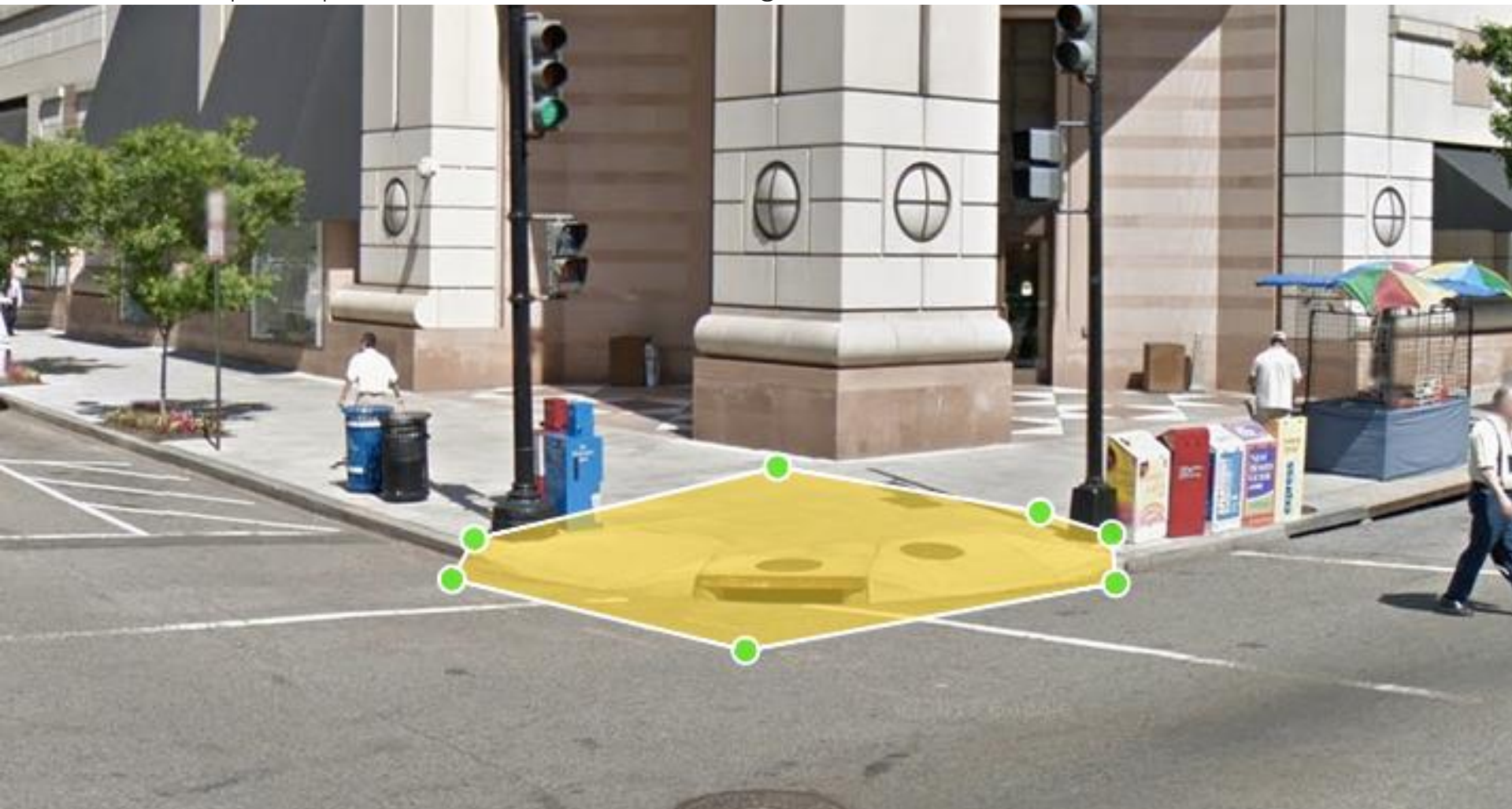






This is a driveway.
Not a curb ramp.







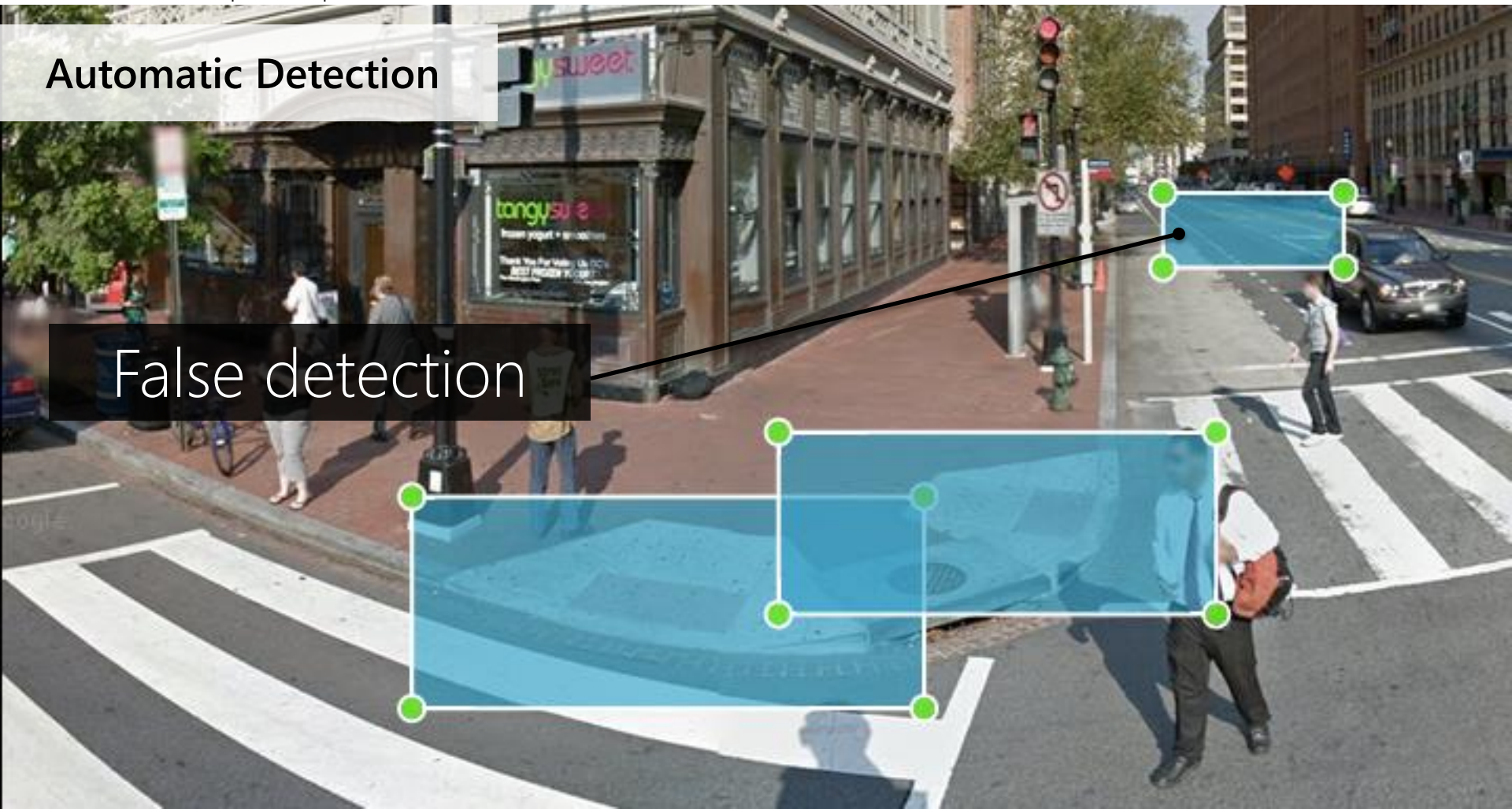
Examples Labels from CV + Verification

Raw Street View Image

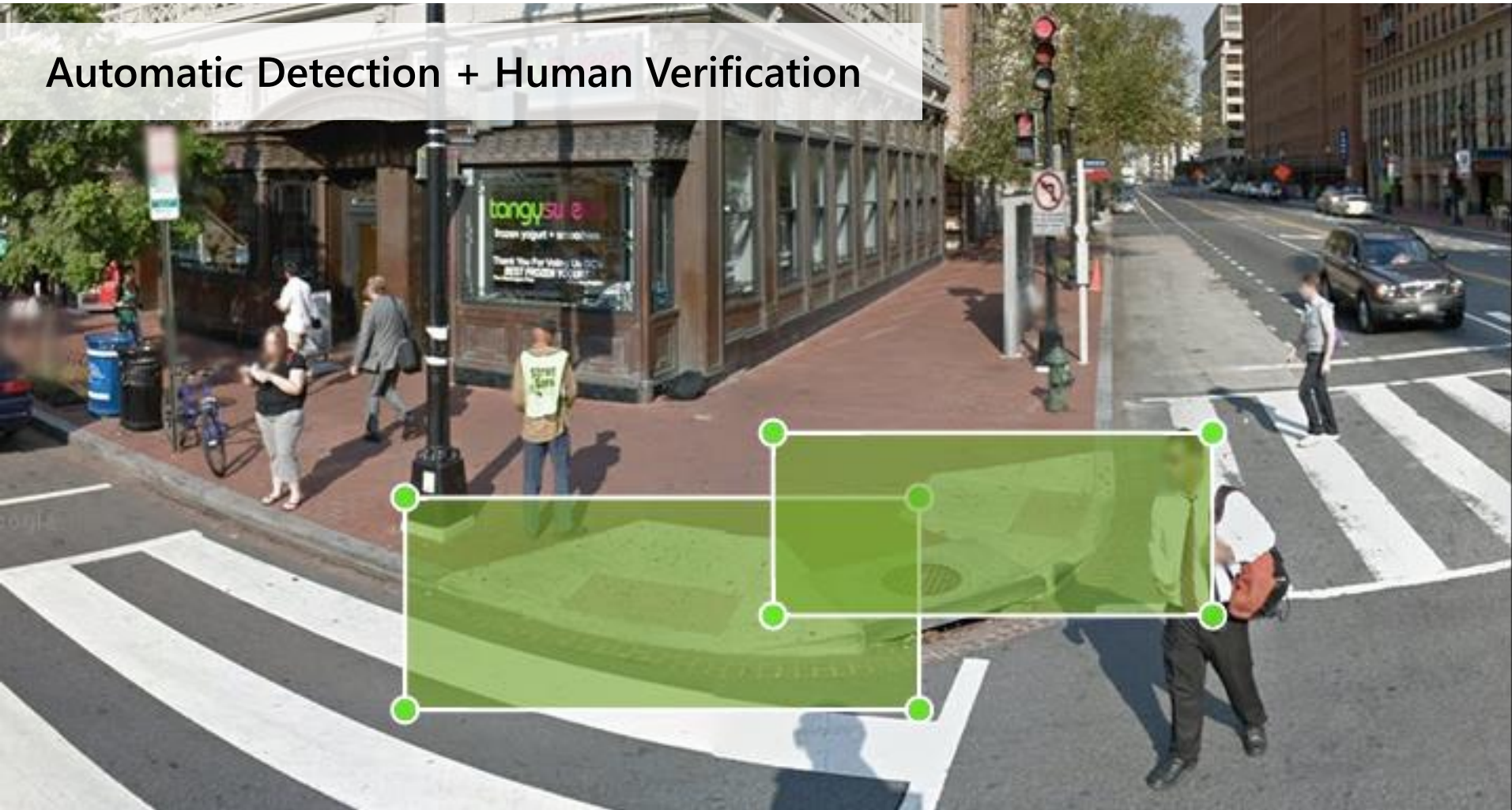


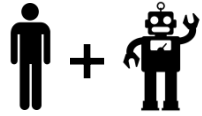
Automatic Detection

False detection



Automatic Detection + Human Verification





Summary

We developed a method that combines crowdsourcing and computation that **increased accessibility data collection efficiency without losing accuracy**

Back of Envelope Calculation

How long would it take to audit a city?

DC Total Street Distance: **1,238 mi**

Audit Speed: **7.9 mi / hour**

Estimated Total Time-cost: **157 hour (\$1.1k)**

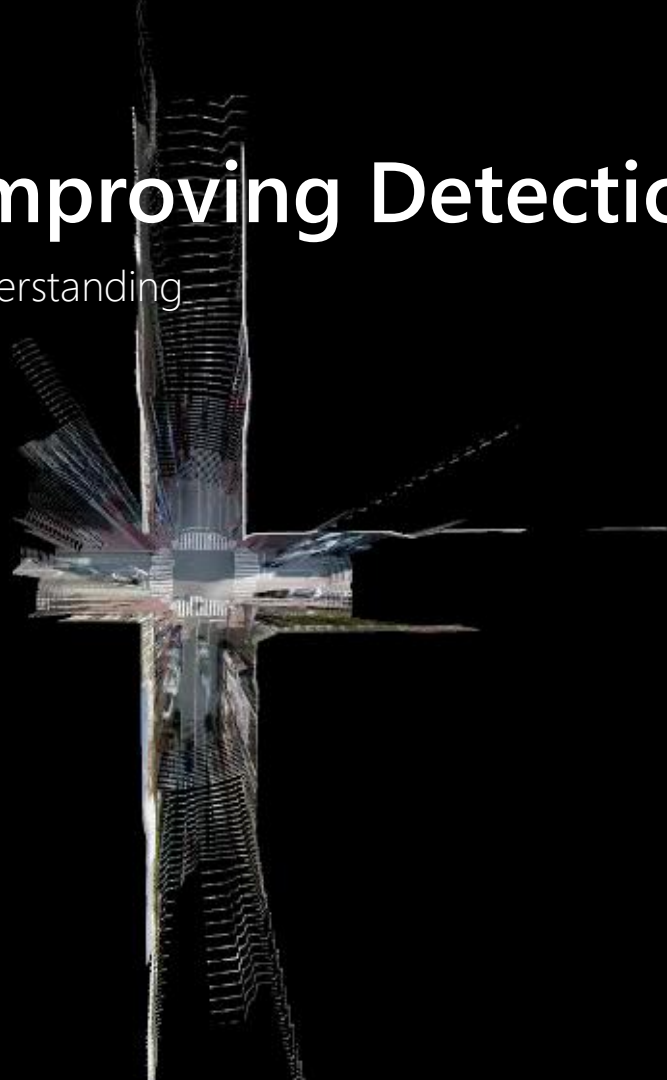
Estimated Total Time-cost with automation: **137 hour**

I think we can do better than this 😊

Future Work: Improving Detection Accuracy

Context integration & scene understanding

Using 3D-data for mensuration



An aerial satellite view of a coastal region. The top part of the image shows a blue bay or inlet. Below it, a river delta flows into the water, with various channels and sediment patterns visible. The land is a mix of green (vegetation) and brown/tan (bare earth or urban areas). A black rectangular box is overlaid on the top left, containing white text.

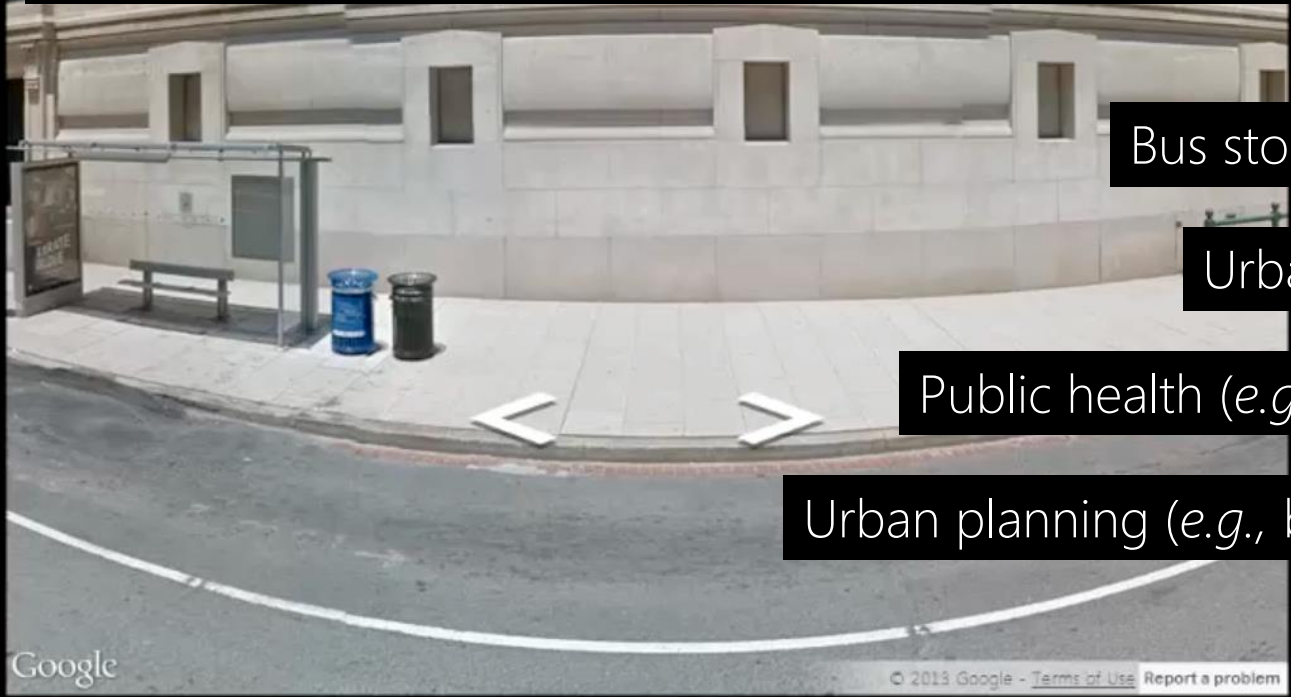
Future Work: Reacting to Changes

Using image dataset that is updated frequently, can we identify dynamic accessibility features like constructions?



Explore mode: Find the closest bus stop and label surrounding landmarks

Future Work: Research Beyond Sidewalk Accessibility



Bus stop accessibility

Urban vegetation

Public health (e.g., cleanliness)

Urban planning (e.g., bicycle roads)



Access Score_{beta} in Action

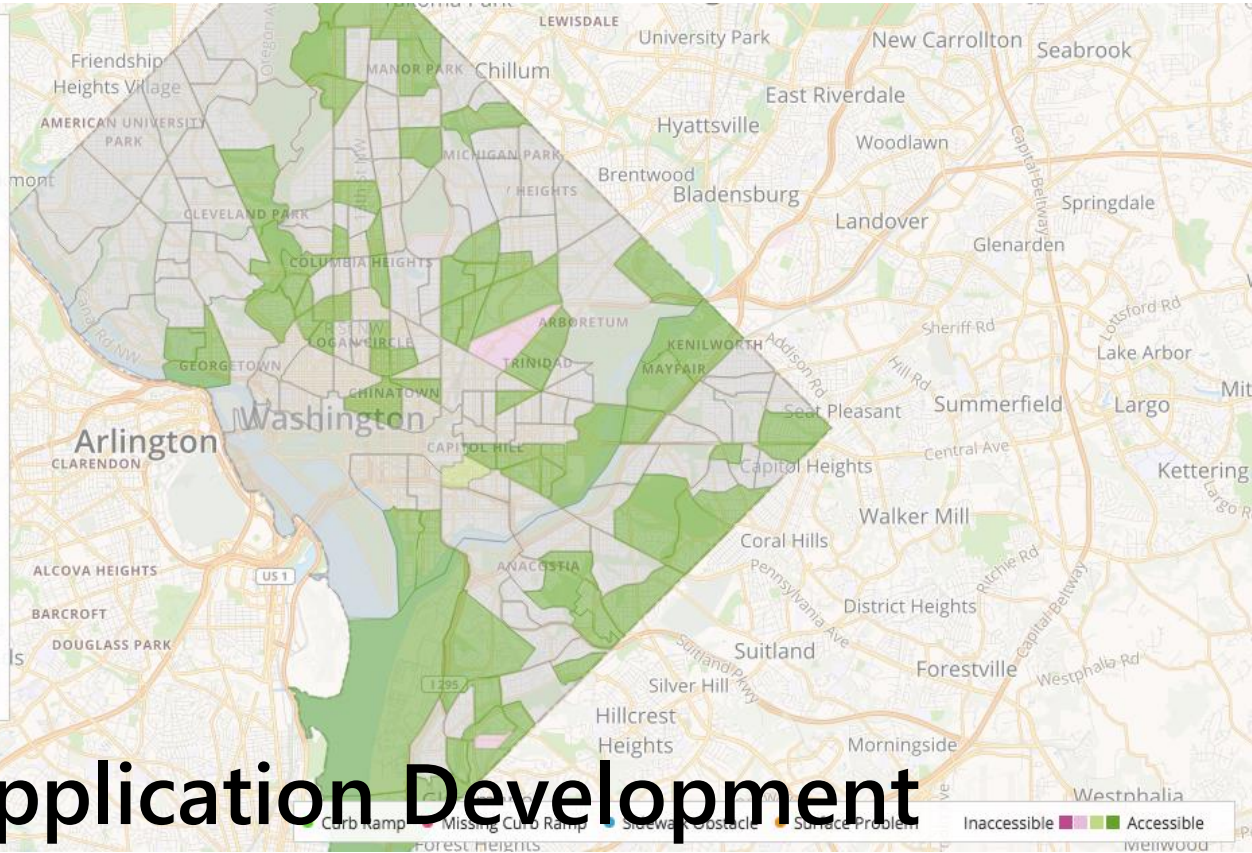
Find out about neighborhood accessibility of DC! Here, accessible neighborhoods are colored in **green** and inaccessible neighborhoods are colored in **red**.

If some accessibility features affect your mobility more than the others, use the slider below to adjust the significance of each accessibility feature!

Note, we don't have enough data to reliably calculate Access Score for some neighborhoods (yet). Wanna help us improve it? [Participate in accessibility audit!](#)

Significance

Curb Ramp	<input type="range" value="100"/>	100
No Curb Ramp	<input type="range" value="100"/>	100
Obstacle	<input type="range" value="100"/>	100
Surface Problem	<input type="range" value="100"/>	100



Future Work: Application Development

sidewalk.umiacs.umd.edu/demo

Collaborators

Advisor

Jon E. Froehlich

Professors | Researchers

Shiri Azencot and David Jacobs

Students

Cynthia L. Bennett, Megan Campbell, Christine Chan, Jonah Chazan, Vicki Le, Anthony Li, Kelly Minckler, Zachary Lawrence, Robert Moore, Rochelle H. Ng, Sean Pannella, Niles Rogoff, Manaswi Saha, Soheil Sehnezhad, Jin Sun, and Alex Zhang,



sidewalk.umiacs.umd.edu

Thank you!

Kotaro Hara | @kotarohara_en