Project Sidewalk: A Web-based Crowdsourcing Tool for Collecting Sidewalk Accessibility Data at Scale

Manaswi Saha
PhD Student | Computer Science | University of Washington
30.6 million U.S. adults have a mobility impairment

Source: US Census, 2010
15.2 million use an assistive aid

Source: US Census, 2010
No Curb Ramps
SURFACE PROBLEMS
Incomplete Sidewalks
Physical Obstacles

No Curb Ramp

Surface Degradation
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
KEY STAKEHOLDERS

People with Mobility Impairments
KEY STAKEHOLDERS

Caregivers

Government Officials
e.g., *DOTs
Why is Accessibility Data Collection Hard?

Motivation:

- Slow, Manual, and Laborious
- Huge Cost
- Localized
PAST WORK SINCE 2012

Studying the state of street-level accessibility using Google Street View
A Feasibility Study of Crowdsourced View to Determine Sidewalk Accessibility

Kotaro Hara, Victoria Lee, Jun Il Humes Computer Interaction Lab Computer Science Department University of Michigan, Ann Arbor, MI, USA kharu@umich.edu

ABSTRACT

We explore the feasibility of using crowd workers from Amazon Mechanical Turk (MTurk) to evaluate sidewalk accessibility by using a manually created dataset of 100 Google Street View images. We examine the effect of three different accessibility labeling sub-tasks: visibility, checkable, and checkable on sidewalk and render the paper to be a guide for future research on crowdsourcing in transportation accessibility.

Index Terms: Crowdsourcing, accessibility, urban navigation, Google Street View, Mechanical Turk, image labeling.

ACM Classification Keywords: H.5.1. Information interfaces and presentation (e.g., HTL, PDF); I.2.9. Security and Protection; I.5.4. Human-centered computing (e.g., accessibility, usability, HCI, e.g., building a usable system); D.2.2. Algorithms (e.g., heuristics, problem solving)


Combining Crowdsourcing and C-Identify Street-level Accessibility

Kotaro Hara, Victoria Lee, Jun Il Humes Computer Interaction Lab Computer Science Department University of Michigan, Ann Arbor, MI, USA kharu@umich.edu

ABSTRACT

Many motivated individuals, missing curb ramps, and other obstacles pose considerable accessibility challenges; however, there are currently few, if any, mechanisms to determine accessibility to sidewalks. In this paper, we examine the feasibility of using crowd sourced workers from Amazon Mechanical Turk (MTurk) to determine curb accessibility on sidewalk segments in Google Street View imagery. We propose and analyze a new mechanism to identify and evaluate curb accessibility on sidewalks in Google Street View images. We perform an experiment to study the feasibility of crowd workers from MTurk to determine curb accessibility on sidewalk segments in Google Street View imagery. We recruit and test 100 crowd workers from MTurk, who are asked to identify and evaluate curb accessibility on sidewalk segments in Google Street View images. We performed a series of experiments to evaluate the feasibility and effectiveness of the mechanism. Our findings confirm the feasibility of using MTurk workers to determine curb accessibility on sidewalk segments in Google Street View imagery. Our findings show that the MTurk workers could effectively evaluate curb accessibility on sidewalk segments in Google Street View imagery.

Index Terms: Curb accessibility, curb ramp, sidewalk, crowd source, MTurk, human computer interaction


Improving Public Transit Accessibility

Crowdsourcing Bus Stop Landmark Locality

Kotaro Hara, Bhiwani Ahmadi, Mogul Campbell Sara Pfeimm, Robert Moore, Kelly Moshkalev

ABSTRACT

Local transit and bus stop design relies on human physical knowledge of the environments. The current practice for finding bus stop location is to search for dwell points on bus routes. However, there are currently few, if any, mechanisms to determine where bus stops can be found. In this paper, we describe the feasibility of using crowd sourced workers from Amazon Mechanical Turk (MTurk) to determine bus stop locations on Google Street View imagery. We recruit and test 100 crowd workers from MTurk, who are asked to identify and evaluate bus stop locations on sidewalk segments in Google Street View images. Our findings confirm the feasibility of using MTurk workers to determine bus stop locations on sidewalk segments in Google Street View imagery. We performed a series of experiments to evaluate the feasibility and effectiveness of the mechanism. Our findings show that the MTurk workers could effectively evaluate bus stop locations on sidewalk segments in Google Street View imagery.

Index Terms: Bus stop, landmark, MTurk, human computer interaction


Tohme: Detecting Curb Ramps in Crowdsourcing, Computer Vision

Kotaro Hara, Yu Xun, Robert Moore, Jun Il Humes

ABSTRACT

As a part of our prior work that combines Google Street View imagery and computational analysis to identify curb ramp, we present a feasible and practical method to detect curb ramps at the curb. We collected 2,000 curb ramp images from Google Street View dataset, and we trained two machine learning classifiers for curb ramp detection, one for object detection and another for object classification. We show that the method is effective in detecting curb ramp images, which is useful for future research on curb ramp detection.

Index Terms: Curb ramp, object detection, computer vision


Low vision and blind individuals rely on knowing physical landmarks to help locate and verify bus stop locations. We propose a framework for crowdsourcing bus stop landmark locations using Google Street View imagery. Our framework is designed to be used in a variety of scenarios, such as for visually impaired urban dwellers, low vision individuals, and visually impaired individuals who use public transportation. Our findings are significant in that they demonstrate the feasibility of using human computation to identify and verify bus stop landmarks, which can be useful for low vision and blind individuals who use public transportation.

Index Terms: Bus stop, landmark, Google Street View, human computation


See: Hara et al., 2012; Hara et al., 2013; Hara et al., 2014; Hara et al., 2015
**A Feasibility Study of Crowdsourcing View to Determine Side**

**Katara Hara, Victoria Lo, Jei Hara**

Computer Science Department, University of Maryland, College Park, MD, USA

**Jie Li**

Computer Science and Electrical Engineering, University of Maryland, College Park

**Abstract**

**ABSTRACT**

This paper presents a feasibility study of using crowdsourcing to determine side view for street-level imagery. We recruit an online labor of 1000 crowd workers to evaluate the accuracy of 10 randomly selected images from 10 different urban areas. We present the results for two main images and the overall image quality. The overall accuracy of 1000 crowd workers is 99.8% with a standard deviation of 2.5%. The accuracy of 1000 crowd workers is 99.8% with a standard deviation of 2.5%. The results suggest that crowdsourcing is a viable tool for determining side view for street-level imagery. The study provides insights into the effectiveness and reliability of using crowdsourcing for such tasks.

**Keywords**

Crowdsourcing, side view determination, urban areas, street-level imagery

**How to cite this paper**


---

**Our Past Work**

**Katara Hara, Victoria Lo, Jei Hara**

Computer Science Department, University of Maryland, College Park, MD, USA

**Jie Li**

Computer Science and Electrical Engineering, University of Maryland, College Park

**Abstract**

**ABSTRACT**

This paper presents a feasibility study of using crowdsourcing to determine side view for street-level imagery. We recruit an online labor of 1000 crowd workers to evaluate the accuracy of 10 randomly selected images from 10 different urban areas. We present the results for two main images and the overall image quality. The overall accuracy of 1000 crowd workers is 99.8% with a standard deviation of 2.5%. The accuracy of 1000 crowd workers is 99.8% with a standard deviation of 2.5%. The results suggest that crowdsourcing is a viable tool for determining side view for street-level imagery. The study provides insights into the effectiveness and reliability of using crowdsourcing for such tasks.

**Keywords**

Crowdsourcing, side view determination, urban areas, street-level imagery

**How to cite this paper**


---

**Small Geographic Regions**

**Katara Hara, Victoria Lo, Jei Hara**

Computer Science Department, University of Maryland, College Park, MD, USA

**Jie Li**

Computer Science and Electrical Engineering, University of Maryland, College Park

**Abstract**

**ABSTRACT**

This paper presents a feasibility study of using crowdsourcing to determine side view for street-level imagery. We recruit an online labor of 1000 crowd workers to evaluate the accuracy of 10 randomly selected images from 10 different urban areas. We present the results for two main images and the overall image quality. The overall accuracy of 1000 crowd workers is 99.8% with a standard deviation of 2.5%. The accuracy of 1000 crowd workers is 99.8% with a standard deviation of 2.5%. The results suggest that crowdsourcing is a viable tool for determining side view for street-level imagery. The study provides insights into the effectiveness and reliability of using crowdsourcing for such tasks.

**Keywords**

Crowdsourcing, side view determination, urban areas, street-level imagery

**How to cite this paper**


---

**Specialized populations**

**Katara Hara, Victoria Lo, Jei Hara**

Computer Science Department, University of Maryland, College Park, MD, USA

**Jie Li**

Computer Science and Electrical Engineering, University of Maryland, College Park

**Abstract**

**ABSTRACT**

This paper presents a feasibility study of using crowdsourcing to determine side view for street-level imagery. We recruit an online labor of 1000 crowd workers to evaluate the accuracy of 10 randomly selected images from 10 different urban areas. We present the results for two main images and the overall image quality. The overall accuracy of 1000 crowd workers is 99.8% with a standard deviation of 2.5%. The accuracy of 1000 crowd workers is 99.8% with a standard deviation of 2.5%. The results suggest that crowdsourcing is a viable tool for determining side view for street-level imagery. The study provides insights into the effectiveness and reliability of using crowdsourcing for such tasks.

**Keywords**

Crowdsourcing, side view determination, urban areas, street-level imagery

**How to cite this paper**


---
OUR PAST WORK

A Feasibility Study of Crowdsourced View to Determine Side

Katara Hara, Victoria Lo, Jeou-Ki Hong

Computer Science Department

Ewha Womans University

Seoul, Korea (jma@ewha.ac.kr, vlo@ewha.ac.kr)

Combining Crowdsourcing and C-Identify Street-level Access

Katara Hara, Victoria Lo, Jeou-Ki Hong

Computer Science Department

Ewha Womans University

Seoul, Korea (jma@ewha.ac.kr, vlo@ewha.ac.kr)

Improving Public Transit Accessibility

Crowdsourcing Bus Stop Landmark Loc

Katara Hara, Wonkook Kim, Robert Moore, Jelena Grabic

University of Maryland, College Park

USA (kwk@umd.edu, kmr@umd.edu, jg2374@umd.edu)

Tomeh: Detecting Curb Ramps in Crowdsourcing, Computer Vision

Katara Hara, Robert Moore

University of Maryland, College Park

USA (kmr@umd.edu, kmo@umd.edu)

COMBINING CROWDSOURCING AND C-IDENTIFY STREET-LEVEL ACCESS

Katara Hara, Victoria Lo, Jeou-Ki Hong

Computer Science Department

Ewha Womans University

Seoul, Korea (jma@ewha.ac.kr, vlo@ewha.ac.kr)

ABSTRACT

Our past work on the feasibility of using crowd-sourced data to create an accurate map of public transit stops was the driving force behind the project. This paper describes our approach, the challenges we encountered, and the results we achieved.

1. INTRODUCTION

Several methods have been developed to create crowd-sourced maps. Many of these methods are based on social networking platforms and rely on users to contribute data. One of the most widely used approaches is the “map the gap” method, which involves the use of volunteers to fill in gaps in existing maps.

In this paper, we will review our previous work on the feasibility of using crowd-sourced data to create an accurate map of public transit stops. We will discuss the limitations of current methods and propose a new approach that takes advantage of the strengths of both methods.

1.1 Limitations of Existing Methods

Existing methods for creating crowd-sourced maps are limited in several ways. First, they are often too slow and require a large amount of user effort. Second, they are often too inaccurate and can lead to errors in the final map. Finally, they often lack the ability to handle large amounts of data.

2. Our Approach

In this section, we will describe our approach for creating an accurate map of public transit stops. We will outline the steps involved in our approach, including data collection, data processing, and map generation.

2.1 Data Collection

We collected data from several sources, including social networking platforms, online forums, and public transit agencies. We used a web crawler to automatically collect data from these sources.

2.2 Data Processing

We then processed the collected data using a combination of natural language processing and statistical methods. We used a combination of machine learning algorithms and manual review to identify and correct errors in the data.

2.3 Map Generation

Finally, we used the processed data to generate a map of public transit stops. We used a combination of geographic information systems and visualization tools to create the final map.

3. Results

Our approach was successful in generating an accurate map of public transit stops. We were able to identify and correct errors in the data and generate a high-quality map.

4. Conclusion

In this paper, we have described our approach for creating an accurate map of public transit stops. We have shown that our approach is effective and can be used to create high-quality maps.

ACKNOWLEDGMENTS

This work was supported in part by the National Institute of Standards and Technology (NIST) under Award No. 70NANB18H150 and in part by the National Science Foundation (NSF) under Award No. 1727158.

REFERENCES


NO public deployments
How do we enable and sustain large-scale data collection of sidewalk accessibility across diverse users?
KEY RESEARCH QUESTIONS

User Behavior

Data Accuracy

Data Utility
User Behavior

RQ1 What are the *behavioral differences* between paid crowd workers and volunteers?

Data Accuracy

Data Utility
KEY RESEARCH QUESTIONS

User Behavior

RQ1 What are the **behavioral differences** between paid crowd workers and volunteers?

Data Accuracy

RQ2 What are the **labeling quality differences** between paid crowd workers and volunteers and the **common mistakes** made?

Data Utility
PROJECT SIDEWALK DEPLOYMENT STUDY

KEY RESEARCH QUESTIONS

User Behavior

**RQ1** What are the behavioral differences between paid crowd workers and volunteers?

Data Accuracy

**RQ2** What are the labeling quality differences between paid crowd workers and volunteers and the common mistakes made?

Data Utility

**RQ3** What are the perceptions of utility of crowdsourced accessibility data and concerns of key stakeholder groups?
Let's create a path for everyone

Interactive tool that empowers anyone to virtually walk city streets and remotely label accessibility problems

http://projectsidewalk.io
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!
Tool Walkthrough

Audit the streets and find all the accessibility attributes

Current Neighborhood
Fort McNair, D.C.

Current Mission
Audit 1000ft of this neighborhood
15% complete

- 2 curb ramps
- 0 missing curb ramp
- 0 surface problem

Follow the red line

Do you see any unlabeled problems? If not, turn slightly towards right.
Audit the streets and find all the accessibility attributes

GSV exploration and labeling pane

Current Neighborhood
Fort McNair, D.C.
0.0 miles 0 labels

Current Mission
Audit 1000ft of this neighborhood
15% Complete

- 2 curb ramps
- 0 missing curb ramp
- 0 surface problem

Follow the red line

Do you see any unlabeled problems? If not,

Turn slightly towards right

© 2017 Google  Terms of Use  Report a problem
Audit the streets and find all the accessibility attributes.

Labeling button menu bar:
- Curb Ramp
- Missing Curb Ramp
- Obstacle in Path
- Surface Problem
- Other

Current Neighborhood:
Fort McNair, D.C.
- 0.0 miles
- 0 labels

Current Mission:
Audit 1000ft of this neighborhood
- 15% complete

- 2 curb ramps
- 0 missing curb ramp
- 0 surface problem

Follow the red line

Do you see any unlabeled problems? If not;
Turn slightly towards right
Audit the streets and find all the accessibility attributes.

- **Passable**: 1 2 3 4 5
- **Not Passable**: 6

Description (e.g., light pole blocking sidewalk)

Temporary (e.g., construction, trash)

Label icon
TOOL WALKTHROUGH

Audit the streets and find all the accessibility attributes

Context Menu

Severity Rating

Description

Passable: 1 2 3 4 5 Not Passable

Description (e.g., light pole blocking sidewalk)

Current Neighborhood
Fort McNair, D.C.

Current Mission
Audit 1000ft of this neighborhood
15% complete

2 curb ramps

0 missing curb ramp 2 obstacles

0 surface problem 0 other
Mission Progress Pane

Tool Walkthrough

Current Neighborhood
Fort McNair, D.C.

Current Mission
Audit 1000ft of this neighborhood

Progress bar

Contributions

Audit the streets and find all the accessibility attributes

- 2 curb ramps
- 0 missing curb ramp
- 0 surface problem

Follow the red line

Do you see any unlabeled problems? If not,

Turn slightly towards right

© 2017 Google Terms of Use Report a problem
In this Street View image, we have drawn an arrow to a curb ramp. Let's label it. Click the flashing "Curb Ramp" button above.
Now, you can rate the quality of the curb ramp where 1 is passable and 5 is not passable for a wheelchair user. **Let's rate it as 1, passable.**
Great! Let’s adjust the view to look at another corner of the intersection. **Grab and drag the Street View image to look left.**
Ordinarily, you would label the areas under the flashing arrows with a Missing Curb Ramp. However, we want to get you started on actual missions, so let's finish this tutorial!
Project Sidewalk System Deployment Study

18-month deployment ~ Fall 2016 - Spring 2018

Washington DC
Deployment Study

Data Collected

Fall 2016 - Spring 2018

797 Users
2941 Miles
205,385 Labels

Volunteers
Turkers
DEPLOYMENT STUDY

LABEL EXAMPLES

142,835 Curb Ramps
18,719 Missing Curb Ramps
21,736 Obstacles
8309 Surface Problems
HOW ACCURATELY DID USERS PERFORM?

~70%

*raw accuracy across all user groups

*Calculated on a subset of the dataset
Only 51% of users finished tutorial (avg. time: ~5 mins)

Only 30% finished their first mission

Most people who complete at least one mission, complete at least one more.
Key Research Questions

**RQ1**
What are the behavioral differences between paid crowd workers and volunteers?

**RQ2**
What are the labeling quality differences between paid crowd workers and volunteers and the common mistakes made?

**RQ3**
What are the perceptions of utility of crowdsourced accessibility data and concerns of key stakeholder groups?
PROJECT SIDEWALK DEPLOYMENT STUDY

USER GROUPS

Anonymous Users  Registered Users  Paid crowdworkers (Turkers)

Volunteers
DID ALL USER GROUPS BEHAVE THE SAME WAY?

Registered users

- completed more missions
- contributed more labels
- audited faster
- spent most time on Project Sidewalk

Turkers did more work and were more persistent than both
PROJECT SIDEWALK DEPLOYMENT STUDY

KEY RESEARCH QUESTIONS

**RQ1** What are the **behavioral differences** between paid crowd workers and volunteers?

**RQ2** What are the **labeling quality differences** between paid crowd workers and volunteers and the **common mistakes** made?

**RQ3** What are the **perceptions of utility** of crowdsourced accessibility data and concerns of **key stakeholder groups**?
Key Research Questions

RQ1: What are the behavioral differences between paid crowd workers and volunteers?

RQ2: What are the labeling quality differences between paid crowd workers and volunteers and the common mistakes made?

RQ3: What are the perceptions of utility of crowdsourced accessibility data and concerns of key stakeholder groups?
Did all user groups label the same way?

44 miles of ground truth data by 3 researchers

From mix of 50 registered and 16 anonymous user routes

Across four quadrants and different land-use zones of DC

62 of 172 DC neighborhoods

Clustered labels from single user then across users
RQ2: DATA VALIDATION STUDY

DATA VALIDATION STUDY: DATASET

4617 label clusters

3212 Curb Ramps
87 Missing Curb Ramps
295 obstacles
1023 Surface Problems
RQ2: DATA VALIDATION STUDY

DATA VALIDATION STUDY: METRICS

Precision  Measures correctness of an applied label

Recall  Measures %age of correctly identified issues

False Positive

False Negative
How accurately did users perform?

RQ2: Data validation study

How accurately did users perform?

Multiple labelers

- Precision
- Recall

- All
- Anon
- Reg
- Turk
- Turk 3
- Turk 5
- Turk 3 maj
- Turk 5 maj
RQ2: Data Validation Study

**How accurately did users perform?**

Turkers found significantly more issues with similar precision.
RQ2: DATA VALIDATION STUDY

WHAT ARE THE HARDEST LABEL TYPES?

Confusion with what justifies as a missing curb ramp

Missing Curb Ramps

20.5% precision | 69.3% recall
RQ2: DATA VALIDATION STUDY

WHAT ARE THE HARDEST LABEL TYPES?

Hard to find
Requires diligent exploration
Often confused with each other

Surface problems | Obstacles in Path

72.6% precision | 47.5% precision
27.1% recall | 39.9% recall
RQ2: QUALITATIVE ANALYSIS OF ERRORS

WHAT ARE THE COMMON LABELING MISTAKES?
WHAT ARE THE COMMON LABELING MISTAKES?

RQ2: QUALITATIVE ANALYSIS OF ERRORS

54 False positives

54 False negatives

432 total error samples analyzed
WHAT ARE THE COMMON LABELING MISTAKES?

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

Curb Ramps

- 44.4% driveway transition
- 22.2% driveways
- 14.8% random

66.7% - driveways
WHAT ARE THE COMMON LABELING MISTAKES?

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

Curb Ramps

- 44.4% driveway transition
- 22.2% driveways
- 14.8% random

Missing Curb Ramps

- 29.6% house-to-curb
- 25.9% no pedestrian route
- 24.1% curb ramp exists

\(\sim 30\%\) extended residential walkways
RQ2: Qualitative Analysis of Errors

What are the common labeling mistakes?

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

**Curb Ramps**
- 44.4% driveway transition
- 22.2% driveways
- 14.8% random

**Missing Curb Ramps**
- 29.6% house-to-curb
- 25.9% no pedestrian route
- 24.1% curb ramp exists

**Obstacles**
- 42.6% not on pedestrian route
- 37.0% space to avoid obstacle
- 9.3% wrong label type

**Surface Problems**
- 46.2% not on pedestrian route
- 32.7% incorrect label type
- 11% normal sidewalk tiling

~50% not on pedestrian route
~33% wrong label type
~9% wrong label type
## RQ2: Qualitative Analysis of Errors

### What Are the Common Labeling Mistakes?

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

<table>
<thead>
<tr>
<th>Curb Ramps</th>
<th>Missing Curb Ramps</th>
<th>Obstacles</th>
<th>Surface Problems</th>
</tr>
</thead>
<tbody>
<tr>
<td>44.4% driveway transition</td>
<td>29.6% house-to-curb</td>
<td>42.6% not on pedestrian route</td>
<td>46.2% not on pedestrian route</td>
</tr>
<tr>
<td>22.2% driveways</td>
<td>25.9% no pedestrian route</td>
<td>37.0% space to avoid obstacle</td>
<td>32.7% incorrect label type</td>
</tr>
<tr>
<td>14.8% random</td>
<td>24.1% curb ramp exists</td>
<td>9.3% wrong label type</td>
<td>11% normal sidewalk tiling</td>
</tr>
</tbody>
</table>

**Easy to correct**
KEY RESEARCH QUESTIONS

**RQ1** What are the **behavioral differences** between paid crowd workers and volunteers?

**RQ2** What are the **labeling quality differences** between paid crowd workers and volunteers and the **common mistakes** made?

**RQ3** What are the **perceptions of utility** of crowdsourced accessibility data and concerns of **key stakeholder groups**?
PROJECT SIDEWALK DEPLOYMENT STUDY

KEY RESEARCH QUESTIONS

**RQ1** Are there **behavioral and labeling quality differences** between paid crowd workers and volunteers?

**RQ2** What are the **common labeling mistakes**?

**RQ3** What are the **perceptions of utility** of crowdsourced accessibility data and concerns of **key stakeholder groups**?
WHAT ARE THE STAKEHOLDERS’ PERCEPTIONS AND CONCERNS?

RQ3: INTERVIEW STUDY

N=14 across 3 stakeholder groups: MI, CVG, GOV

Perceived Value
Usability
Design Suggestions
Concerns
RQ3: INTERVIEW STUDY
WHAT ARE THE STAKEHOLDERS’ PERCEPTIONS AND CONCERNS?

N=14 across 3 stakeholder groups

Perceived Value

Usability

Design Suggestions

Concerns
WHAT ARE THE STAKEHOLDERS’ PERCEPTIONS AND CONCERNS?

Perceived Value

Enabled rapid data collection

Gathered diverse perspectives about accessibility

Helped engage citizens in thinking about urban design
What are the stakeholders’ perceptions and concerns?

RQ3: Interview Study

Perceived Value

"It's really good for a starting point. This is a first observation, and when you send somebody out in the field, they can see those observations and pick up more information. It's just neat!"

-G4
WHAT ARE THE STAKEHOLDERS’ PERCEPTIONS AND CONCERNS?

Concerns

Data age i.e., outdated GSV imagery or labels

Data reliability

Conflicted data
Concerns

“I would have more confidence if different people did it, did the same street.”

-G4
Concerns

““My concern as a user [is that] someone said this was accessible and I got there and it wasn’t accessible, because everyone has different opinions on accessibility.”

-MI1"
What next?
More cities!

Ongoing and future work

Newberg, OR

40% Newberg mapped
43 miles covered
5,167 labels
How do we compare accessibility across cities?
What are the correlates to accessibility?
What are the (in)accessible areas of the city?
Automating data collection using computer vision

Ongoing and future work
Is this a **Curb Ramp**?
Is this an **Obstacle in Path?**
Validation Interfaces

Ongoing and Future Work

Is this an Obstacle in Path?

Agree
Disagree
Not sure
ACKNOWLEDGEMENTS

PROJECT SIDEWALK TEAM

Manaswi Saha  Michael Saugstad  Hanuma Teja Maddali  Aileen Zeng  Ryan Holland  Steven Bower

Aditya Dash  Sage Chen  Anthony Li  Kotaro Hara  Jon Froehlich
ACKNOWLEDGEMENTS

FUNDING SOURCES
NSF #1302338, Google, IBM
PI Froehlich, Co-PI David Jacobs
Help make the world more accessible for everyone!
Join us. Contact 📧 manaswi@cs.uw.edu  🔄 manaswisaha
🔗 https://github.com/ProjectSidewalk  🌐 http://projectsidewalk.io/api

Any Questions?