Scalable Techniques to Study the **Equitable**
Distribution and Condition of US Sidewalks

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**ITS Washington**
Dec 14th, 2022, Tacoma
INDEPENDENCE, QUALITY OF LIFE, PHYSICAL ACTIVITY

Thapar et al., 2004; Nuernberger, 2008
PHYSICAL OBSTACLES
Sidewalk that unexpectedly ends

Incomplete Sidewalks
Highly degraded sidewalk

SURFACE PROBLEMS
Worst-case sidewalk

Physical Obstacles
- No Curb Ramp

Surface Degradation
The problem is not just a lack of accessible sidewalks. It's a lack of data.
The National Council on Disability notes 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
BACKGROUND

STUDY OF OPEN DATA ON SIDEWALKS

178 US CITIES

54% OPEN STREET DATA
20% SIDEWALKS
10% CURB RAMPS
<5% BASIC ACCESSIBILITY INFO

We are pursuing a two-fold solution
To develop new data collection methods that combine machine learning, crowdsourcing, and online map imagery
To enable new urban accessibility analyses and create accessibility-aware mapping tools not previously possible
PROJECT SIDEWALK
http://projectsidewalk.org
Online map imagery + Remote crowdsourcing interfaces → Human labels → Machine learning

Labeling missions → Validation missions
Outcomes

Machine Learning

- Improved urban planning
- Interactive visualization tools
- New Urban Analytics
- Improved government transparency
ABSTRACT

Recent work has applied machine learning methods to automatically detect sidewalks on accurate digital representations of urban infrastructure in online map imagery (e.g., satellite photos, streetview panoramas). While promising, these methods have been limited to a small number of cities (e.g., San Francisco) and have not been broadly applied to images from other online map providers. We present the first large-scale evaluation of sidewalk detection methods on images from Google Street View (GSV) panoramas. Specifically, we investigate two application areas: automatically generating street-level labels and automatically labeling sidewalk accessibility issues. For both tasks, we introduce and use a residual neural network (ResNet) model to support both image and non-image (traditional) features. For all tasks, we present an analysis of the performance of our non-image features and training strategies, and the effect non-image features have on the models. Our results significantly improve on prior automated methods and in some cases, meet or exceed human labeling performance.

Author Keywords
Crowdsource accessibility, computer vision, Google Street View, Amazon Mechanical Turk

INTRODUCTION

Sidewalks should benefit all of us. They provide a safe, environmentally-friendly conduit for moving about a city. For people with disabilities, sidewalks can have a significant impact on their independence [45], quality of life [28], and physical activity [17]. While mapping tools like Google and Apple Maps have begun offering pedestrian-focused features, they do not incorporate sidewalk routes or information on sidewalk accessibility [15, 13], which limits their usability and disproportionately affects people with disabilities. A key challenge is where does it come from? How is it collected?

Traditional streetwise audio—which gather data on the presence and quality of sidewalks—are performed via in-person inspections by city transit departments or community volunteers. However, these audits are expensive, labor intensive, and infrequent. Moreover, the resulting data is in separate formats, is not typically open (i.e., published online), and is not integrated for end-user tools [23, 50]. To expand who can collect sidewalk data and improve the usability and accessibility of this information, researchers have introduced smartphone-based tools [13, 46, 52] as well as instrumented wheelchairs [15, 36, 51, 57]. These research efforts have focused on collecting data for a single city or a very small sample of cities. While promising, these tools have been limited by low data adoption, small geographic coverage, and high user burden (e.g., requiring users to take notes or to take pictures on an app, take a picture, annotate it, and upload it) [20, 23].

To partially address these scalability issues, researchers have begun developing automated methods for sidewalk assessment using machine learning and online imagery (e.g., satellite photos [10, 8], panoramic streetview imagery [31, 32, 90]). While still early, these complementary approaches promise to dramatically decrease manual labor and cost. However, they have been limited by two interrelated issues: small training sets and the choice in machine learning models—both of which negatively impact performance. In this paper, we attempt to address both of these issues.

We present the first evaluation of deep learning methods to automatically assess sidewalk accessibility in terms of curb ramps, missing curb ramps, surface problems, and sidewalk obstructions from widely available streetview imagery. Our work is enabled by the recently released Project Sidewalk open dataset, which contains a corpus of 300,000+ image-based sidewalk accessibility labels collected via remote crowdourcing in Google Street View (GSV) [50] (Figure 1). Specifically, we investigate two application tasks using GSV panoramas: automatically generating crowd-derived labels and automatically labeling sidewalk accessibility issues.

Stick to image digital data or hard copies of all past work for this paper or online supplementary materials. Do not include references to work not cited in the text. Please use references only if they are necessary to clarify an important point. All other content should be detailed in the manuscript. Acknowledge any work not otherwise cited.

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Virtually explore city streets
PROJECT SIDEWALK

TWO DATA COLLECTION MISSIONS

1. FIND, LABEL, & ASSESS SIDEWALKS

2. VALIDATING & CORRECTING LABELS

Current Neighborhood
New York, N.Y. - Amsterdam
0.2 miles - 10 labels

Is this an Obstacle?

Correct Examples

Incorrect Examples
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.
PROJECT SIDEWALK
EXPLORATION MISSION

Explore 250 ft in Central Oradell

Your mission is to explore 250 ft in Central Oradell and find all the accessibility features that affect mobility impaired travelers!

OK
Explore the streets and find all the accessibility attributes.

Current Neighborhood
Central Oradell, Oradell
0.0 miles
33 labels

Current Mission
Explore 250 ft of this neighborhood
0% complete

Follow the red line

Do you see any unlabeled problems? If not,

Turn right
Explore the streets and find all the accessibility attributes.
EXAMPLE OBSTACLE TAGS

- Tree
- Fire hydrant
- Parked car
- Pole
- Garbage/recycling can
- Stairs
- Vegetation
- Height difference
PROJECT SIDEWALK
TWO DATA COLLECTION MISSIONS

1. FIND, LABEL, & ASSESS SIDEWALKS

2. VALIDATING & CORRECTING LABELS
Is this a **Surface Problem**?

NOT ON THE PEDESTRIAN PATHWAY
Sidewalks often have buffer zones.
Only mark barriers in the pedestrian path.
We also try to make Project Sidewalk **fun** and **educational**
Screenshot of user dashboard showing badges and achievements.

**Your missions**
140

**Distance**
2.03 mi

**Labels**
568

**Validations**
1249

**Accuracy**
90.7%

**Achievements**

**Missions**
Congratulations, you've earned all mission badges!

**Labels**
Great job! 432 more labels until your next achievement.

**Distance**
Thanks for helping! 2.97 more miles until your next achievement.

**Validations**
Amazing work! 3751 more validations until your next achievement.
## Overall Leaderboard

Leaders are calculated based on their labels, distance, and accuracy.

<table>
<thead>
<tr>
<th>#</th>
<th>Username</th>
<th>Labels</th>
<th>Missions</th>
<th>Distance</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>mariana.velasco</td>
<td>2894</td>
<td>150</td>
<td>9.6 miles</td>
<td>85.3%</td>
</tr>
<tr>
<td>2</td>
<td>maria</td>
<td>1918</td>
<td>51</td>
<td>9.0 miles</td>
<td>89.1%</td>
</tr>
<tr>
<td>3</td>
<td>abarragan99</td>
<td>1895</td>
<td>81</td>
<td>2.7 miles</td>
<td>86.5%</td>
</tr>
<tr>
<td>4</td>
<td>marian.trevino</td>
<td>1543</td>
<td>66</td>
<td>9.4 miles</td>
<td>82.2%</td>
</tr>
<tr>
<td>5</td>
<td>dordaz</td>
<td>1483</td>
<td>46</td>
<td>3.5 miles</td>
<td>84.2%</td>
</tr>
<tr>
<td>6</td>
<td>Gerardo R</td>
<td>1274</td>
<td>86</td>
<td>5.4 miles</td>
<td>87.6%</td>
</tr>
<tr>
<td>7</td>
<td>mariagarza</td>
<td>1205</td>
<td>62</td>
<td>9.4 miles</td>
<td>87.2%</td>
</tr>
<tr>
<td>8</td>
<td>ana.alvarezc</td>
<td>1053</td>
<td>63</td>
<td>9.8 miles</td>
<td>84.8%</td>
</tr>
<tr>
<td>9</td>
<td>Gari01234</td>
<td>848</td>
<td>62</td>
<td>4.6 miles</td>
<td>89.1%</td>
</tr>
<tr>
<td>10</td>
<td>Luis Gonzalez</td>
<td>812</td>
<td>59</td>
<td>9.7 miles</td>
<td>94.1%</td>
</tr>
</tbody>
</table>

Want to make it into the Top 10? [Start exploring!](/leaderboard)
TEN CITIES IN NORTH AMERICA

- Seattle, WA
- Newberg, OR
- Chicago, IL
- Columbus, OH
- Pittsburgh, PA
- Washington DC
- San Pedro Garza García, MX
- Mexico City, MX
- La Piedad, MX
- Newberg, NJ

Project Sidewalk
TWIN CITIES

9,029+ users
716,982+ labels
317,701+ validations
San Pedro Garza García, MX
http://spgg.projectsidewalk.org

La Piedad, MX
http://la-piedad.projectsidewalk.org

Mexico City, MX
http://cdmx.projectsidewalk.org
Creemos un camino para todas las personas

Cómo puedes ayudar

Explora virtualmente las calles de la ciudad para mejorar la accesibilidad.
Project Sidewalk provides us with data that is essential to improving San Pedro’s urban accessibility. With Project Sidewalk, we know the main problems to be solved, how many problems there are, and their location... The results will be used to inform a new Pedestrian Master Plan for our municipality.
CURB RAMPS
SEVERITY RATING 5
http://sidewalkgallery.io/

Narrow + obstacle
Not enough landing space
Points into traffic

Narrow
No friction/tactile strip
Not level with street

Steep + obstacle
Steep
Poor design
NEW CURB RAMP IS NOT ACCESSIBLE. CAN ONLY BE ENTERED FROM ONE DIRECTION.
# Average Severity Ratings

<table>
<thead>
<tr>
<th>City</th>
<th>Curb Ramp</th>
<th>Missing Ramp</th>
<th>Missing Sidewalk</th>
<th>Sidewalk Obstacle</th>
<th>Surface Problem</th>
</tr>
</thead>
<tbody>
<tr>
<td>Seattle, WA</td>
<td>1.5 (0.7)</td>
<td>3.8 (1.0)</td>
<td>4 (0.8)</td>
<td>3.2 (1.1)</td>
<td>2.9 (0.9)</td>
</tr>
<tr>
<td>Columbus, OH</td>
<td>1.4 (0.7)</td>
<td>3.8 (1.2)</td>
<td>4.1 (1.1)</td>
<td>2.2 (1.4)</td>
<td>2.1 (1.0)</td>
</tr>
<tr>
<td>Newberg, OR</td>
<td>1.5 (0.7)</td>
<td>3.9 (1.0)</td>
<td>3.9 (0.9)</td>
<td>3.1 (1.1)</td>
<td>2.7 (1.0)</td>
</tr>
<tr>
<td>Mexico City, MX</td>
<td>2.8 (1.4)</td>
<td>4.7 (0.6)</td>
<td>4.6 (0.8)</td>
<td>4.1 (1.0)</td>
<td>3.6 (1.2)</td>
</tr>
<tr>
<td>San Pedro, MX</td>
<td>2.8 (1.4)</td>
<td>4.4 (0.9)</td>
<td>4.5 (0.9)</td>
<td>4 (0.9)</td>
<td>3.6 (1.1)</td>
</tr>
</tbody>
</table>

Cell format: Avg Severity (Stdev). Scale: 1 (best) to 5 (worst)
We did not find a relationship with areas where there are accidents involving pedestrians. A pattern was found, where there are more points with a severity of 3+ in the west of the city.
EvaluANDO: del activismo peatonal a la colaboración comunitaria para el registro de obstáculos en las banquetas

El caso de EvaluANDO MPO, destaca no solo por haber compuesto un mapa del municipio con sujeto a evaluación de calidad vehicular, sino por el acompañamiento a la comunidad y la participación en la mejora. En este sentido, la propuesta de EvaluANDO MPO es fundamental. Además, se ha mostrado como una herramienta de aprendizaje para la mejora continua de las condiciones de movilidad. La participación de las comunidades y la ciudadanía en el proceso de evaluación de las infraestructuras peatonales es crucial para brindar una movilidad más segura y accesible.

En el proceso de movilidad urbana, la participación ciudadana es esencial. El mapa de EvaluANDO MPO, que representa los obstáculos en las banquetas, es una herramienta útil para identificar áreas de mejora. Este proceso no solo implica la creación de un mapa, sino también la implementación de soluciones. El mapa es una herramienta que permite a las autoridades y a la comunidad identificar y priorizar las áreas que requieren intervenciones. Además, este tipo de iniciativas contribuyen al desarrollo de una movilidad más segura y accesible para todos.

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PARTNERSHIP OF THREE ORGANIZATIONS

Oradell Girl Scouts

National Multiple Sclerosis Society
Bergen Multiple Sclerosis Community Council

Hackensack Meridian School of Medicine
Initial Presentation to Oradell City Council
Mar 2022

First Mapathon (Hybrid)
Apr 2022

Second Mapathon (Hybrid)
Aug 2022

Girl Scout Data Analysis
Oct 2022

Planned Presentation to City Council
Jan 2023
## Oradell Deployment

### Collected Data

<table>
<thead>
<tr>
<th>Users</th>
<th>Miles Audited</th>
<th>Labels</th>
<th>Validations</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>81</td>
<td>48.6 miles</td>
<td>11,135</td>
<td>14,919</td>
<td>93.1%</td>
</tr>
</tbody>
</table>

~35% of streets have been audited more than once

As calculated by user validations of labels
SIDEWALK DATA

ORADELL DEPLOYMENT

Legend:
- Curb Ramps
- Missing Curb Ramps
- Obstacle
- Surface Problems
- Missing Sidewalk
- Occlusion
- Crosswalk
- Signal
- Other

Map showing sidewalk data with various data points and a bar chart indicating the number of occurrences for different categories.
Trellis plots of Sidewalk data

Oradell Deployment

Curb Ramps: 733 labels
Missing Curb Ramps: 381 labels
Obstacles: 161 labels
Surface Problems: 1,542 labels
Missing Sidewalks: 2,456 labels
Surface Problems
1,542 labels

Missing Sidewalks
2,456 labels
HIGH SEVERITY (≥ 4)

- Curb Ramps: 733 labels
  - 1.8% (13 labels) of curb ramps

- Missing Curb Ramps: 381 labels
  - 85.0% (323 labels) of missing curb ramps

- Obstacles: 161 labels
  - 43.5% (70 labels) of obstacles

- Surface Problems: 1,542 labels
  - 7.3% (112 labels) of surface problems
Surface Problems

Oradell Deployment

Surface Problems

All Labels
1,542 labels

High Severity
7.3%
(112 labels)
of surface problems
ORADELL DEPLOYMENT

HIGH SEVERITY (≥ 4) SURFACE PROBLEMS
<table>
<thead>
<tr>
<th>Surface Problem Tags</th>
<th>Count</th>
<th>% of Surface Tags</th>
<th>Avg Severity (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>height difference</td>
<td>1455</td>
<td>29.0%</td>
<td>1.96 (0.99)</td>
</tr>
<tr>
<td>cracks</td>
<td>1256</td>
<td>25.0%</td>
<td>1.71 (0.79)</td>
</tr>
<tr>
<td>uneven/slanted</td>
<td>1031</td>
<td>21.0%</td>
<td>2.34 (1.02)</td>
</tr>
<tr>
<td>grass</td>
<td>547</td>
<td>11.0%</td>
<td>1.46 (0.63)</td>
</tr>
<tr>
<td>very broken</td>
<td>235</td>
<td>5.0%</td>
<td>2.44 (1.04)</td>
</tr>
<tr>
<td>bumpy</td>
<td>177</td>
<td>4.0%</td>
<td>2.25 (0.92)</td>
</tr>
<tr>
<td>n/a</td>
<td>90</td>
<td>2.0%</td>
<td>2.00 (1.02)</td>
</tr>
<tr>
<td>narrow sidewalk</td>
<td>88</td>
<td>2.0%</td>
<td>2.59 (0.93)</td>
</tr>
<tr>
<td>brick/cobblestone</td>
<td>74</td>
<td>1.0%</td>
<td>1.95 (0.72)</td>
</tr>
<tr>
<td>sand/gravel</td>
<td>47</td>
<td>1.0%</td>
<td>2.26 (0.94)</td>
</tr>
<tr>
<td>construction</td>
<td>2</td>
<td>0.0%</td>
<td>4.00 (n/a)</td>
</tr>
<tr>
<td>street has no sidewalks</td>
<td>1</td>
<td>0.0%</td>
<td>3.00 (n/a)</td>
</tr>
</tbody>
</table>
What can we do with **Project Sidewalk data?**
Sidewalk Disparities

Motivation

WHERE
sidewalks are

HOW
they are connected

WHAT
their conditions are

RELATIONSHIP
to socio-economic factors

Hosseini et al.
How can we use crowdsourced sidewalk assessment data to examine sidewalk condition patterns in a city?
And how do sidewalk quality patterns map to socioeconomic factors like wealth, race, density and education?
TRADITIONAL ACCESSIBILITY AUDITS

SIDEWALK DATA COLLECTION

Walkability Audit
Wake County, North Carolina

Walkability Audit
Wake County, North Carolina

Safe Routes to School Walkability Audit
Rock Hill, South Carolina
Your work is making a difference

Users like you have already mapped 1,199 miles of Seattle, WA—that's 93.6% of the target area in the city!

93.6% target area mapped
1,198.9 miles covered
209,351 labels
187,220 validations
PROJECT SIDEWALK IN SEATTLE

- Curb Ramps: 71,457
- Missing Curbs: 35,043
- Obstacles: 14,278
- Surface Problems: 28,473
- Missing Sidewalks: 32,775
ACCESS SCORE MODEL

LABEL TYPES

- Curb Ramps
- Missing Curb Ramps
- Obstacles
- Surface Problem
- Missing Sidewalk
ACCESS SCORE MODEL

SEVERITY RATING

😊 Severity 1
😊 Severity 2
😊 Severity 3
🙁 Severity 4
🙁 Severity 5
Access Score Model

Significance Vector
\[ x_a = (1.0, -1.0, -0.6, -0.8) \]

Accessibility Feature Vector
\[ w_s = (1, 1, 2, 1) \]

AccessScore: Sidewalk Segment
\[ A_{S_{sidewalk}} = \frac{1}{1 + e^{-(w_s \cdot x_a)}} = 0.12 \]
METHOD

HIGH ACCESS SCORE STREET
METHOD

LOW ACCESS SCORE STREET
METHOD

ACCESS SCORE

Labels

Sidewalk Access Score

Neighborhood Access Score
METHOD

LIMITATIONS OF CROWDSOURCING
FINDINGS

SPATIAL DISTRIBUTION PER SIDEWALK SEGMENT
FINDINGS

SPATIAL DISTRIBUTION PER NEIGHBORHOOD

ACCESS SCORE

COUNT

ACCESS SCORE

COUNT

Seattle

22nd Avenue

23rd Avenue

Southwest

Beacon A

Alaska Avenue

Rainier Avenue
## SOCIO-ECONOMIC CORRELATIONS

- Population
- Race & Citizenship
- Education
- Income
- Housing
- Modes of travel

<table>
<thead>
<tr>
<th>Property</th>
<th>rho</th>
<th>Property</th>
<th>rho</th>
<th>Property</th>
<th>rho</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population Density (Per Sq. Mile)</td>
<td>0.52</td>
<td>Car, Truck, or Van%</td>
<td>-0.50</td>
<td>Average Gross Rent</td>
<td>-0.13</td>
</tr>
<tr>
<td>White Alone%</td>
<td>-0.23</td>
<td>Drove Alone%</td>
<td>-0.49</td>
<td>Owner Occupied%</td>
<td>-0.57</td>
</tr>
<tr>
<td>Black or African American Alone%</td>
<td>0.12</td>
<td>Carpoole%</td>
<td>-0.24</td>
<td>Renter Occupied%</td>
<td>0.57</td>
</tr>
<tr>
<td>American Indian &amp; Alaska Native Alone%</td>
<td>0.16</td>
<td>Public Transportation%</td>
<td>0.23</td>
<td>1, Detached%</td>
<td>-0.60</td>
</tr>
<tr>
<td>Asian Alone%</td>
<td>0.23</td>
<td>Motorcycle%</td>
<td>-0.07</td>
<td>1, Attached%</td>
<td>-0.04</td>
</tr>
<tr>
<td>Pacific Islander Alone%</td>
<td>0.07</td>
<td>Bicycle%</td>
<td>-0.07</td>
<td>2%</td>
<td>-0.07</td>
</tr>
<tr>
<td>Some Other Race Alone%</td>
<td>0.14</td>
<td>Walked%</td>
<td>0.50</td>
<td>3 or 4%</td>
<td>0.03</td>
</tr>
<tr>
<td>Two or More Race%</td>
<td>-0.01</td>
<td>Other Means%</td>
<td>0.04</td>
<td>5 to 9%</td>
<td>0.07</td>
</tr>
<tr>
<td>Racial Diversity</td>
<td>-0.23</td>
<td>Less than 10 Minutes%</td>
<td>0.13</td>
<td>10 to 19%</td>
<td>0.20</td>
</tr>
<tr>
<td>Citizenship - Native%</td>
<td>-0.08</td>
<td>10 to 19 Minutes%</td>
<td>0.21</td>
<td>20 to 49%</td>
<td>0.43</td>
</tr>
<tr>
<td>Foreign Born - Naturalized%</td>
<td>-0.17</td>
<td>20 to 29 Minutes%</td>
<td>0.07</td>
<td>50 or More%</td>
<td>0.51</td>
</tr>
<tr>
<td>Foreign Born - Not a Citizen%</td>
<td>0.23</td>
<td>30 to 39 Minutes%</td>
<td>-0.14</td>
<td>Housing Units Built 2014 or Later%</td>
<td>0.35</td>
</tr>
<tr>
<td>Family Households%</td>
<td>-0.49</td>
<td>40 to 59 Minutes%</td>
<td>-0.20</td>
<td>Housing Units Built 2010 to 2013%</td>
<td>0.27</td>
</tr>
<tr>
<td>Average Household Size</td>
<td>-0.42</td>
<td>60 to 89 Minutes%</td>
<td>-0.13</td>
<td>Housing Units Built 2000 to 2009%</td>
<td>0.28</td>
</tr>
<tr>
<td>Less than High School%</td>
<td>0.12</td>
<td>Median Household Income</td>
<td>-0.31</td>
<td>Housing Units Built 1990 to 1999%</td>
<td>0.22</td>
</tr>
<tr>
<td>High School Graduate%</td>
<td>0.00</td>
<td>Average Household Income</td>
<td>-0.32</td>
<td>Housing Units Built 1980 to 1989%</td>
<td>0.07</td>
</tr>
<tr>
<td>Some College%</td>
<td>0.04</td>
<td>Median Family Income</td>
<td>-0.15</td>
<td>Housing Units Built 1970 to 1979%</td>
<td>-0.02</td>
</tr>
<tr>
<td>Bachelors Degree%</td>
<td>-0.02</td>
<td>Average Family Income</td>
<td>-0.13</td>
<td>Housing Units Built 1960 to 1969%</td>
<td>-0.10</td>
</tr>
<tr>
<td>Masters Degree%</td>
<td>-0.01</td>
<td>Per Capita Income</td>
<td>-0.06</td>
<td>Housing Units Built 1950 to 1959%</td>
<td>-0.33</td>
</tr>
<tr>
<td>Professional School Degree%</td>
<td>-0.09</td>
<td>Median Housing Value</td>
<td>-0.21</td>
<td>Housing Units Built 1940 to 1949%</td>
<td>-0.42</td>
</tr>
<tr>
<td>Doctorate Degree%</td>
<td>-0.13</td>
<td>Median Gross Rent</td>
<td>-0.13</td>
<td>Housing Units Built 1939 or Earlier%</td>
<td>-0.12</td>
</tr>
<tr>
<td>Unemployed%</td>
<td>0.07</td>
<td>Median Gross Rent as a % of Income</td>
<td>0.16</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
FINDINGS
SOCIO-ECONOMIC CORRELATIONS

Lower sidewalk quality neighborhoods:

- More affluent
- Predominantly white
- Lower housing and population density
- Driving is the primary mode of transportation
FINDINGS
SOCIO-ECONOMIC CORRELATIONS

Higher sidewalk quality neighborhoods:

- Higher population and housing density
- Higher racially diversity
- Higher proportion of immigrants
- Commute primarily by walking or public transportation
FUTURE WORK

- Large-scale, cross-regional studies on sidewalk equity
- Improve the accessibility of existing infrastructure
- Influence urban design guidelines and policies
CALLING FOR PARTNERS!

Together let’s transform sidewalk accessibility in WA state!

sidewalk@cs.uw.edu
CALLING FOR PARTNERS!

Together let’s transform sidewalk accessibility in WA state!

sidewalk@cs.uw.edu

- Government initiatives
- Local communities
- Universities
- Prioritize sidewalk renovation
- Facilitate ADA transitions
- Inform urban planning policies
ACKNOWLEDGEMENTS

PROJECT SIDEWALK FUNDING SOURCES

NSF #1302338, #2125087

Google

IBM

PACIFIC NW TRANSPORTATION CONSORTIUM

Alfred P. Sloan FOUNDATION

CREATE
Center for Research and Education on Accessible Technology and Experiences
UNIVERSITY of WASHINGTON
Project Sidewalk
@projsidewalk  Follows you

Our mission: map the world's sidewalks and their accessibility using remote crowdsourcing, artificial intelligence, and online satellite & streetscape imagery

📍 Seattle, WA  🏷️ projectsidewalk.org  📅 Joined June 2016