

Street View for Whom?

An Initial Examination of Google Street View's Urban Coverage and Socioeconomic Indicators in the US

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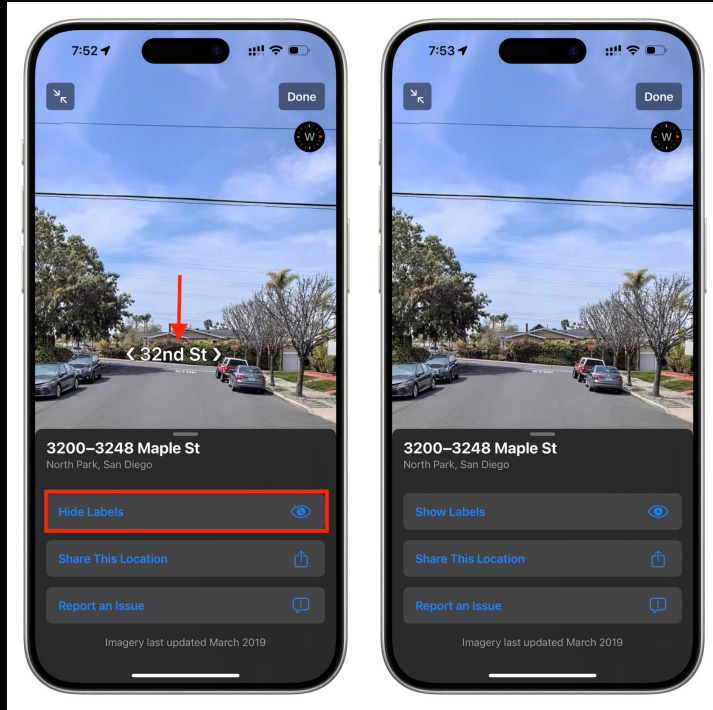
PAUL G. ALLEN SCHOOL
OF COMPUTER SCIENCE & ENGINEERING

UNIVERSITY of
WASHINGTON

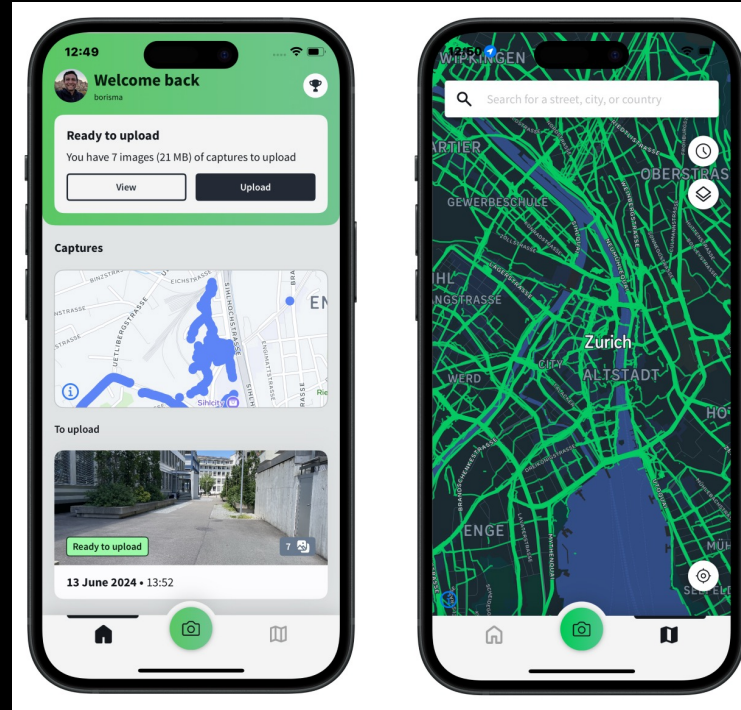
A grayscale street-level photograph of a city street. The street is lined with multi-story buildings on both sides. On the left, a large black SUV is parked. Further down the street, several other cars are visible. On the right, a silver car is parked. The buildings have various signs, including "COMES NEWSAGENCY", "coffee breakfast lunch", and "Landscape Gallery &". A large white arrow is painted on the road, pointing towards the viewer. The text "STREET-LEVEL IMAGERY HAS BECOME FUNDIMENTAL TO URBAN INFORMATICS, SUPPORTING DIVERSE RESEARCH ACROSS VARIOUS FIELDS." is overlaid in white, bold, uppercase letters across the center of the image.

**STREET-LEVEL IMAGERY HAS BECOME FUNDIMENTAL
TO URBAN INFORMATICS, SUPPORTING DIVERSE
RESEARCH ACROSS VARIOUS FIELDS.**

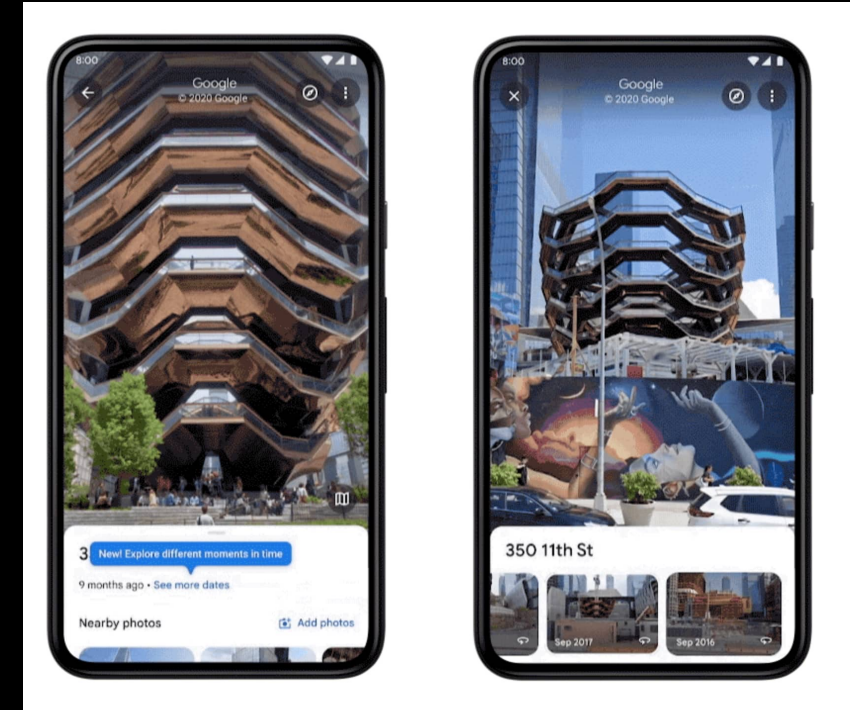
MAJOR PROVIDERS



Apple Lookaround



Mapillary (Meta)



Google Street View

Also have...

BaiduMaps, KartaView, Grabmaps, etc.



KartaView

GrabMaps

WITH

**OVER 220 BILLION IMAGES
ACROSS 100+ COUNTRIES**

**Google Street View (GSV) have become particularly
influential due to its geographic coverage.**



Assessing the equity and evolution of urban visual perceptual quality with time series street view imagery

Zeyu Wang^a, Koichi Ito^a, Filip Biljecki^{a,b,*}

Research Paper

Measuring human perceptions of a large-scale urban region using machine learning

Fan Zhang^{a,b,c}, Bolei Zhou^d, Liu Liu^e, Yu Liu^a, Helene H. Fung^f, Hui Lin^{b,g,*}, Carlo Ratti^c

ARTICLE IN PRESS

Keywords:
Urban perception
Place semantics
Street-level imagery
Deep learning
Built environment

Physical urban change and its socio-environmental impact: Insights from street view imagery

Yingjie Liu^{a,1}, Zeyu Wang^{b,1}, Siyi Ren^c, Runying Chen^c, Yixiang Shen^d, Filip Biljecki^{e,f,*}

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^b Department of Urban Engineering
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ARTICLE IN PRESS

Keywords:
Urban renewal
Gentrification
Change detection
Deep learning

Tohme: Detecting Curb Ramps in Google Street View Using Crowdsourcing, Computer Vision, and Machine Learning

Kotaro Hara^{1,2}, Jin Sun, Robert Moore^{1,2}, David Jacobs, Jon E. Froehlich^{1,2}

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Using deep learning and Google Street View to estimate the demographic makeup of neighborhoods across the United States

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Edited by Kenneth

The United States is a diverse country with a rich cultural and linguistic heritage. However, the demographic makeup of neighborhoods across the country is often overlooked. In this paper, we present a new method for estimating the demographic makeup of neighborhoods across the United States using deep learning and Google Street View (GSV) imagery. Our method, called "Deep Demographics", uses a deep convolutional neural network (CNN) to extract features from GSV images and estimate the demographic makeup of neighborhoods. We evaluate our method on a large-scale dataset of GSV images and find that it outperforms existing methods in estimating the demographic makeup of neighborhoods across the United States.

PNAS

RESEARCH ARTICLE

SOCIAL SCIENCES
SUSTAINABILITY SCIENCE

OPEN ACCESS



Urban visual intelligence: Uncovering hidden city profiles with street view images

Zhuangyuan Fan^a, Fan Zhang^{b,1}, Becky P. Y. Loo^{a,c}, and Carlo Ratti^d

Edited by Richard Shearmur, McGill University
Member Susan Hanson

A longstanding line of research has shown that the appearance of a city's built environment can be used to infer its socioeconomic status. In this paper, we address the problem of inferring the socioeconomic status of a city from street view images. We propose a deep learning-based method for inferring the socioeconomic status of a city from street view images. Our method, called "Urban Visual Intelligence", uses a deep convolutional neural network (CNN) to extract features from street view images and infer the socioeconomic status of a city. We evaluate our method on a large-scale dataset of street view images and find that it outperforms existing methods in inferring the socioeconomic status of a city from street view images.

Paper Session 4: Finding your Way (to this session)

ASSETS '19, October 28–30, 2019, Pittsburgh, PA, USA

Deep Learning for Automatically Detecting Sidewalk Accessibility Problems Using Streetscape Imagery

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ABSTRACT

Recent work has applied machine learning methods to automatically find and/or assess pedestrian infrastructure in online map imagery (e.g., satellite photos, streetscape panoramas). While promising, these methods have been limited by two interrelated issues: small training sets and the choice of machine learning model. In this paper, aided by the recently released Project Sidewalk dataset of 300,000+ image-based sidewalk accessibility labels, we present the first examination of deep learning to automatically assess sidewalks in Google Street View (GSV) panoramas. Specifically, we investigate two application areas: automatically validating crowdsourced labels and automatically predicting sidewalk accessibility from GSV imagery. We introduce a deep convolutional neural network (ResNet) modified to support both image and non-image (contextual) features (e.g., geography). We present an analysis of performance, the effect of our non-image features and training set size, and cross-city generalizability. Our results significantly improve on prior methods in sidewalk accessibility detection, and our external validation results show that our method outperforms existing methods in predicting sidewalk accessibility.

Author Keywords

Neural networks, computer vision, accessibility, sidewalks, curb ramps, Google Streetview

and infrequent. ¹ Moreover, the resulting data is in disparate formats, is not typically open (i.e., published online), and is not intended for end-user tools [23, 50]. To expand who can collect sidewalk data and to improve data granularity and freshness, researchers have introduced smartphone-based tools [15, 46, 52] as well as instrumented wheelchairs [35, 39, 51, 57], both of which capture sidewalk information *in situ* as it's experienced. However, these tools have been limited by low adoption, small geographic coverage, and high user burden (e.g., requiring users to take out their phones, load an app, take a picture, annotate it, and upload it) [20, 23].

To partially address these challenges, researchers have begun leveraging automatic methods for sidewalk assessment using machine learning and online imagery (e.g., satellite photos [10, 8], panoramic streetscape imagery [31, 32, 41]). 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 of machine learning model, both of which negatively impact performance. In this paper, we attempt to address both of these issues.

We present the first examination of deep learning methods to automatically assess sidewalk accessibility in terms of curb

GSV has been leveraged by researchers to sensing urban environment, perform virtual audits at scale.

COMMENT | 13 August 2023

Putting Africa on the map

A lack of street view imagery in many countries mean valuable data isn't available to researchers.

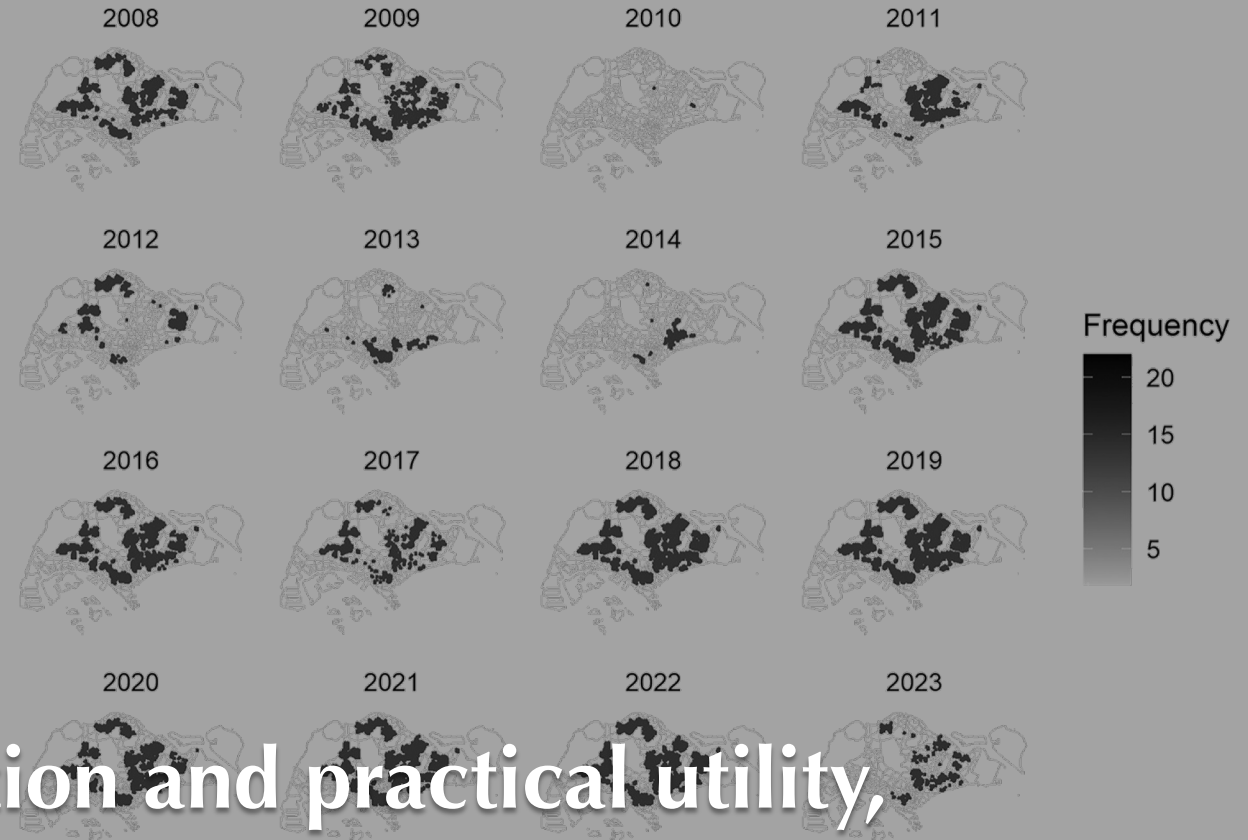
By [Mette Bendixen](#), [Tawanda Kanhema](#) & [Lars L. Iversen](#)



a

Despite GSV's widespread adoption and practical utility, disparities in how frequently or recently these images are updated across neighborhoods and cities remain largely unexamined.

The spatio-temporal distribution of images retrieved from Google Street View in Singapore

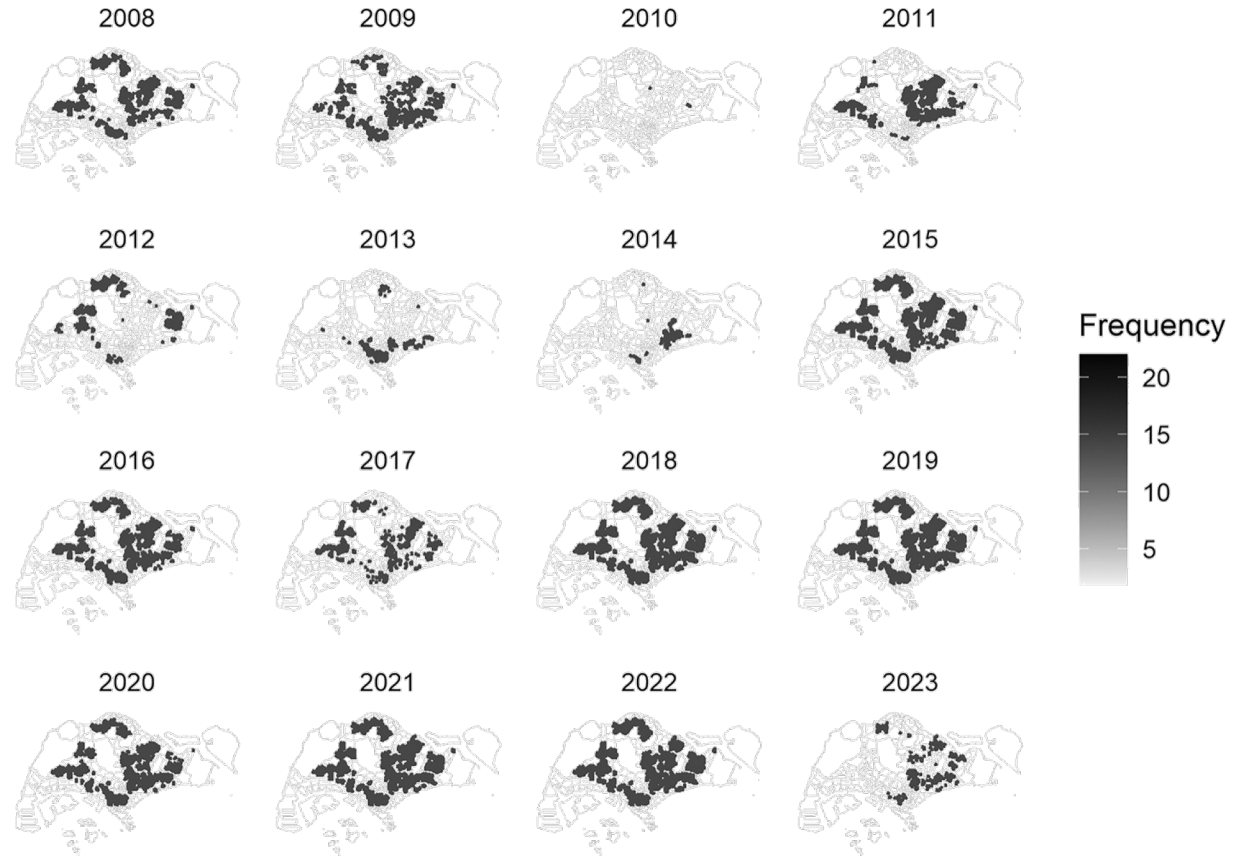


Source: Wang, Z., Ito, K., & Biljecki, F. (2024). Assessing the equity and evolution of urban visual perceptual quality with time series street view imagery. *Cities*, 145, 104704.

Such disparities may reflect deeper inequalities in the digital representation of urban spaces, potentially biasing downstream analyses and influencing policy decisions.



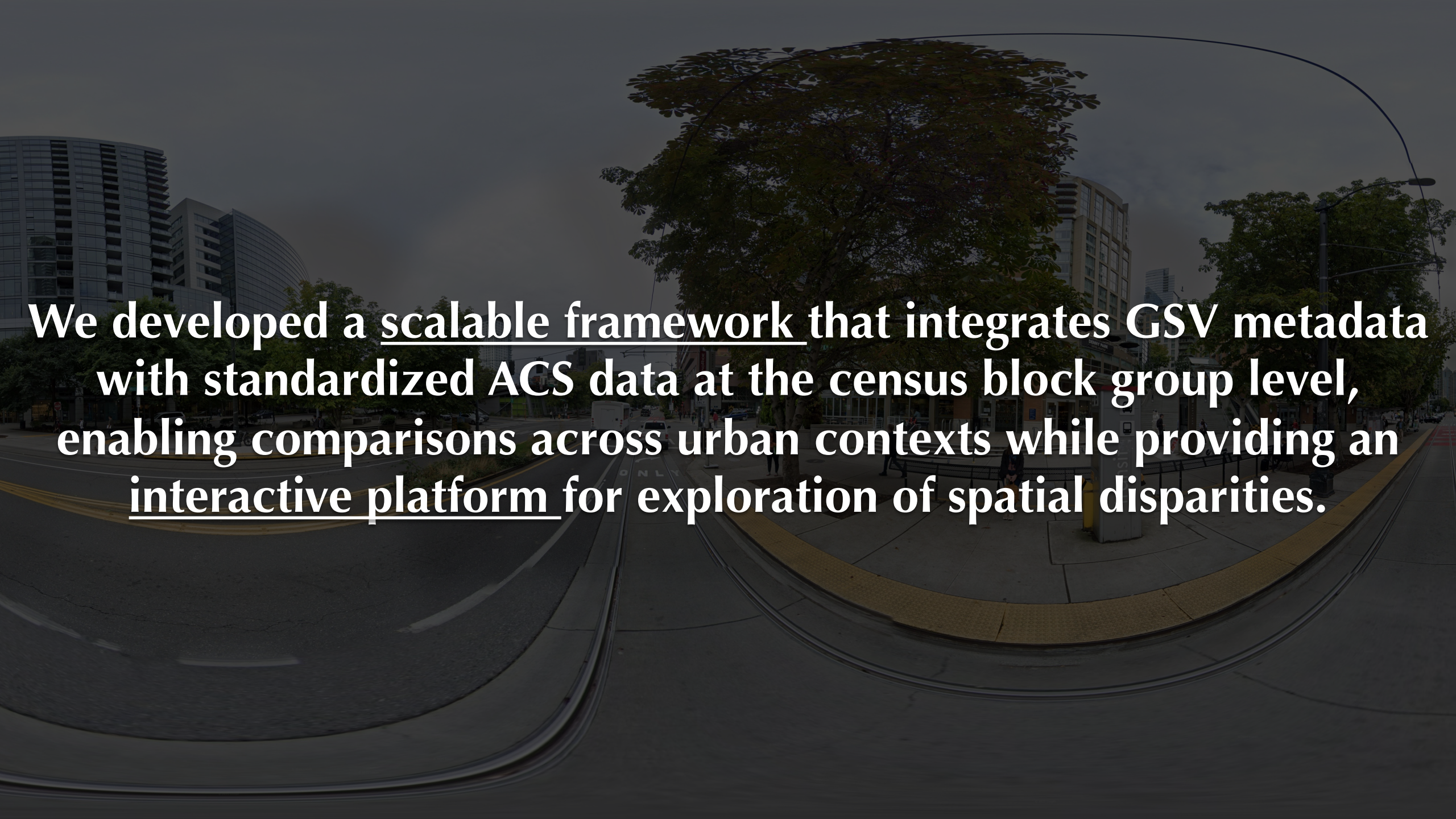
The spatio-temporal distribution of images retrieved from Google Street View in Singapore



Source: Wang, Z., Ito, K., & Biljecki, F. (2024). Assessing the equity and evolution of urban visual perceptual quality with time series street view imagery. *Cities*, 145, 104704.

Gaps

- Lack scalable and reproducible frameworks for integrating standardized demographic data with SVI metadata.
- Most analyses are limited to specific cities or regions, preventing broader geographic comparisons.
- Lacks accessible, interactive tools for transparent exploration of spatial representation patterns.

The background image is a wide-angle, fisheye photograph of a city street intersection. In the foreground, a large, leafy tree stands on the right side of the road. The street curves to the left, with a yellow curb and a white line marking. In the background, modern high-rise buildings with glass facades are visible under a cloudy sky. The overall scene is urban and contemporary.

We developed a scalable framework that integrates GSV metadata with standardized ACS data at the census block group level, enabling comparisons across urban contexts while providing an interactive platform for exploration of spatial disparities.

Pipeline



```
{bbox| min lat,  
max lat, min lon,  
max lon}
```

City Bounding
Box (OSM)

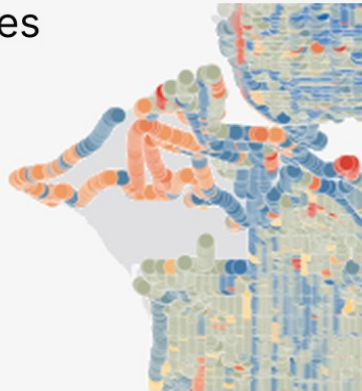


Queries



Google Maps

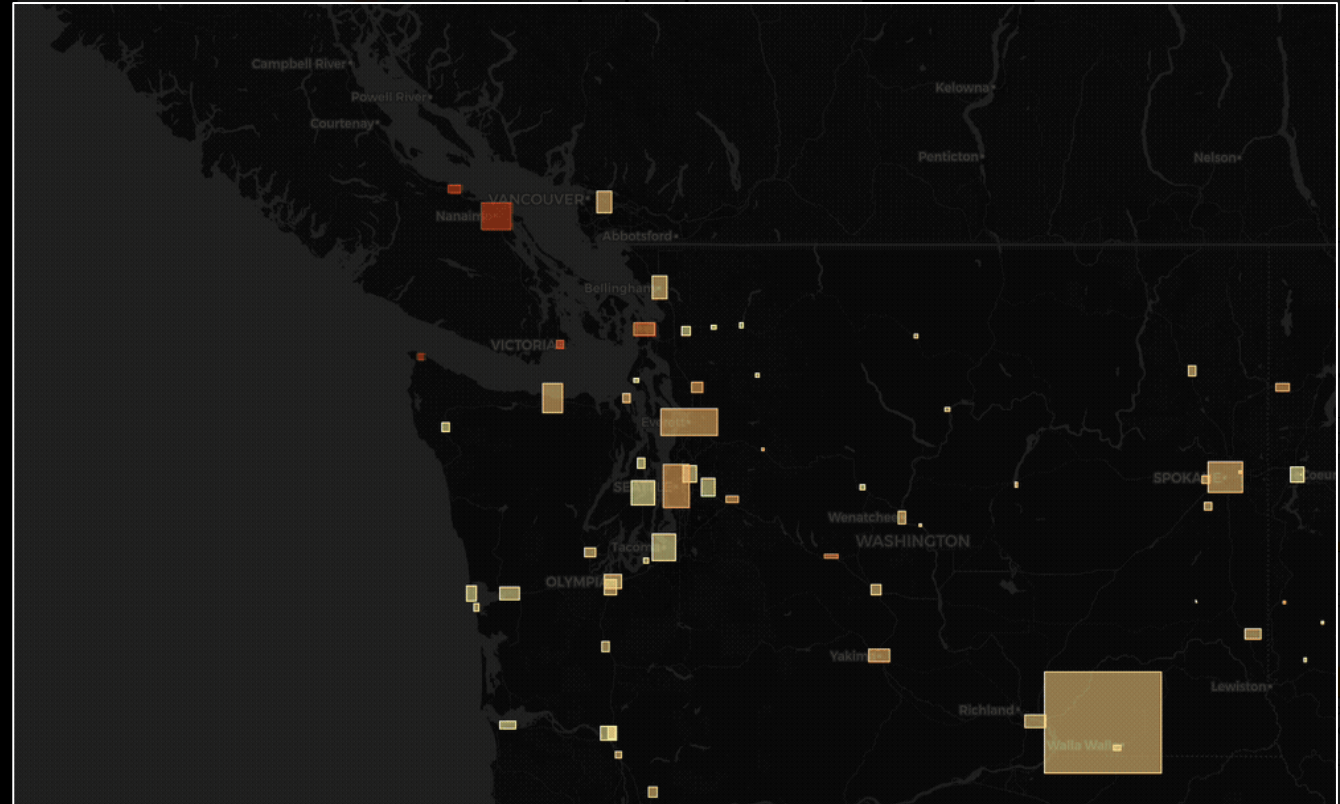
Street View
Static API



Latest available
GSV metadata

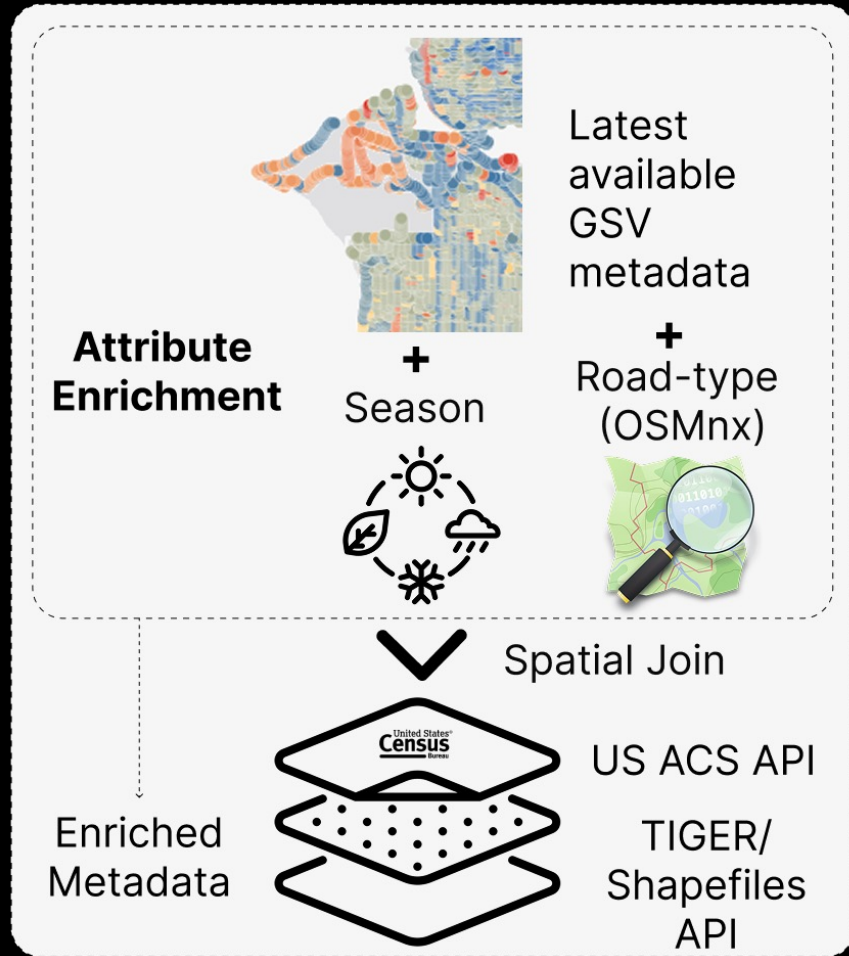
**GSVTracker &
Downloader**

Bounding Boxes

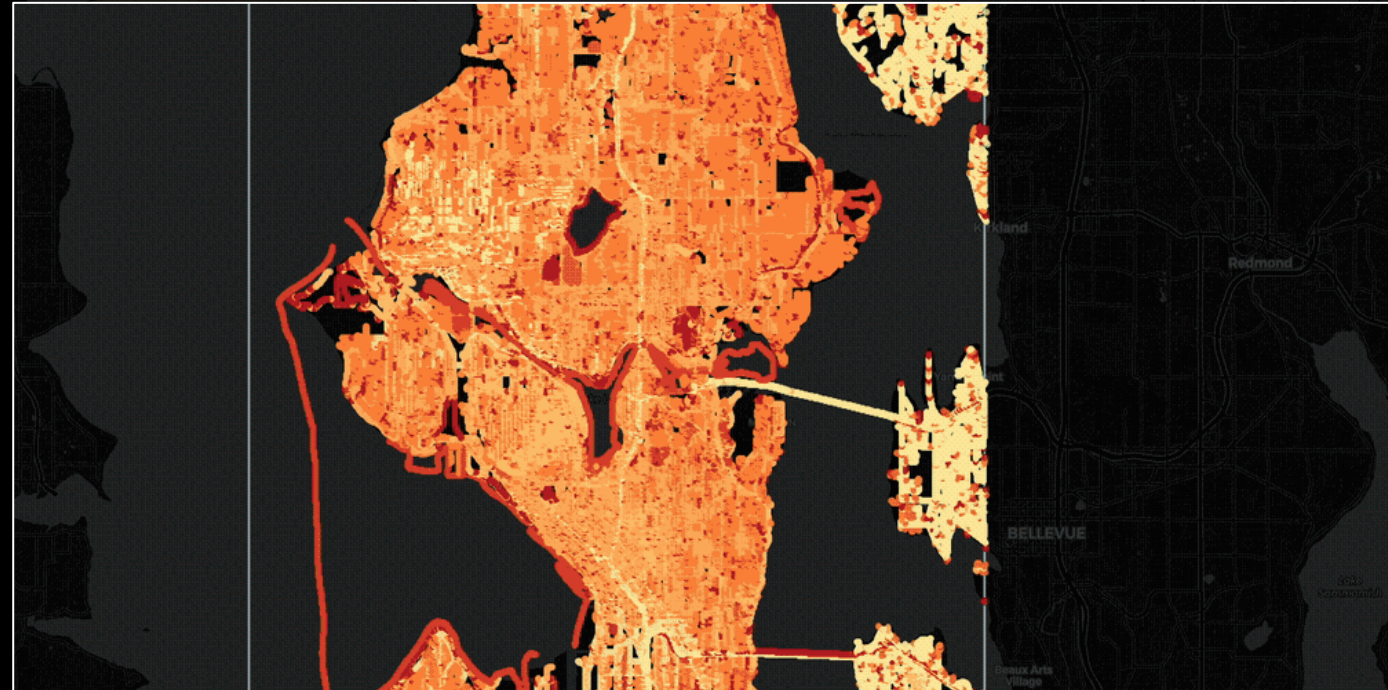


GSVantage
Interactive Tool

Pipeline



GSV Metadata

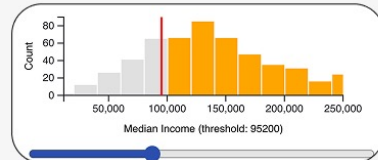
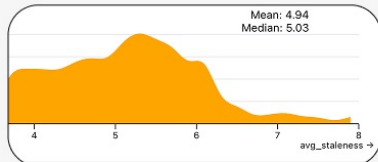
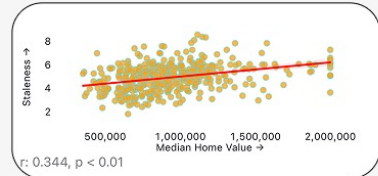
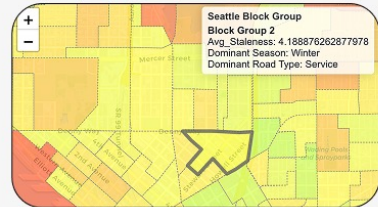


Functions

Spatial Distribution of Image Staleness: Sea

Pipeline

GSVantage Interactive Tool



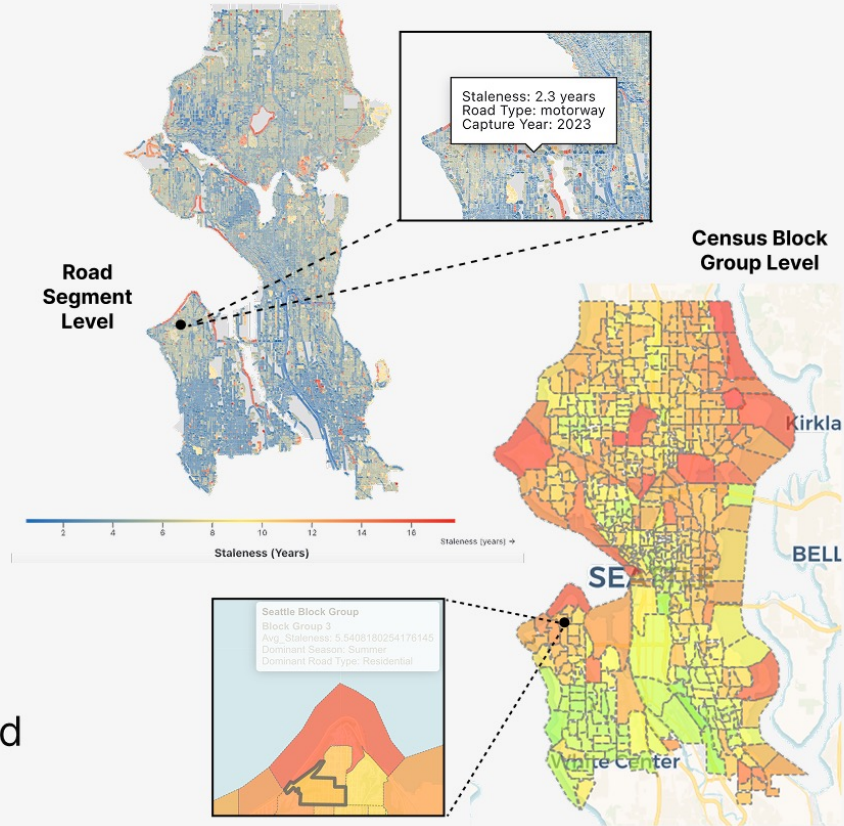
Functions

Interactive Mapping

Correlation Analysis

Staleness Distribution

Neighborhood Filtering



Spatial Distribution of Image Staleness: Seattle Case

Correlation Analysis & Visual Analytics Dashboard

Demo



Home



Atlanta

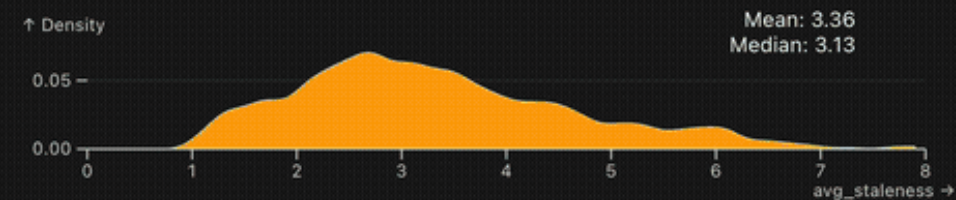
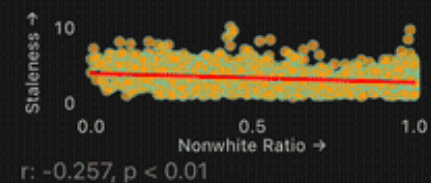
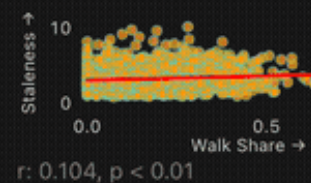
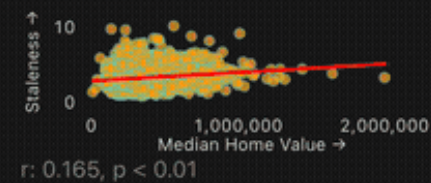
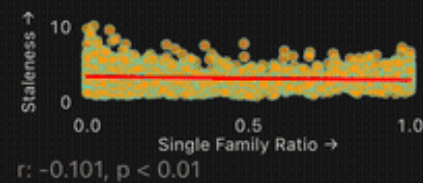
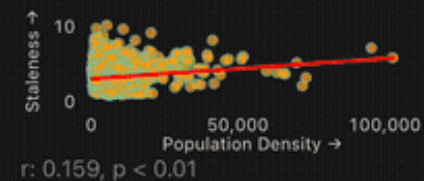
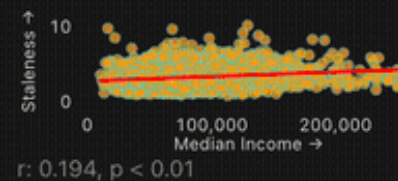
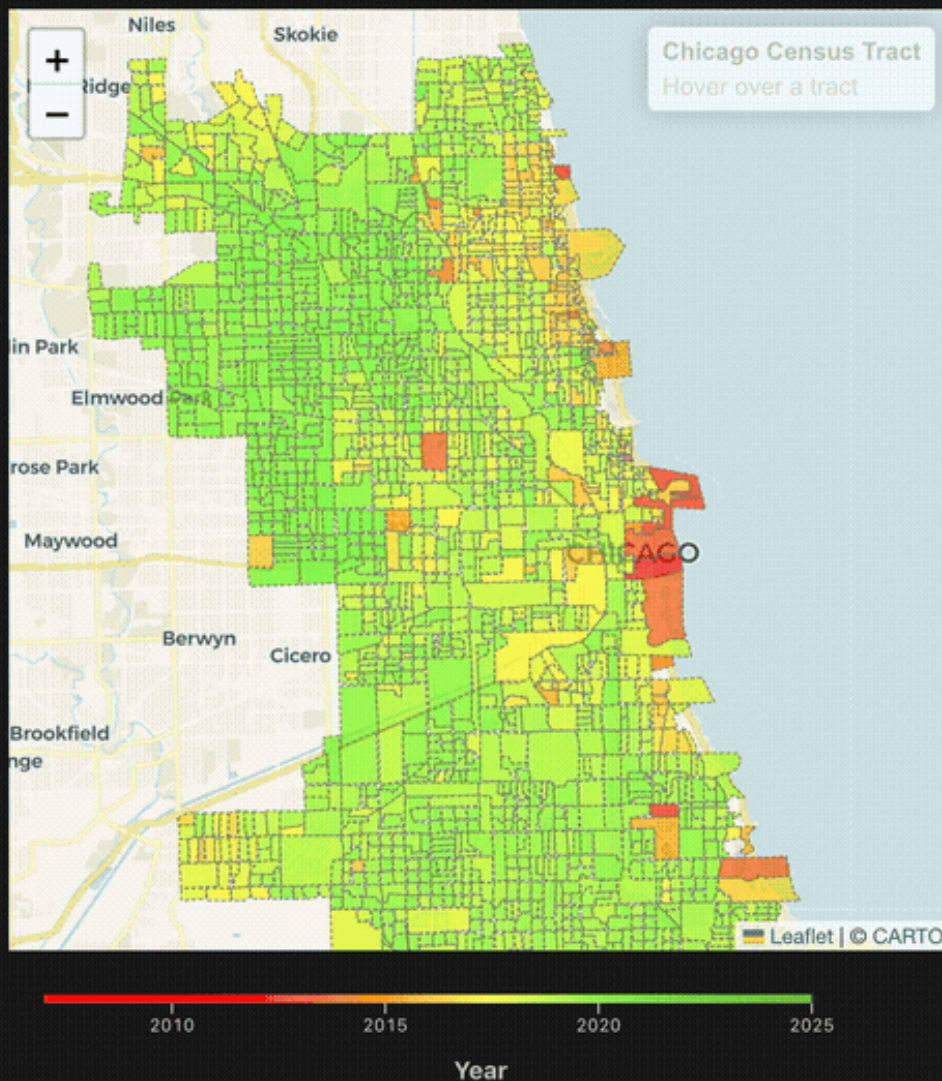
Chicago

Detroit

Seattle

Demo

Chicago

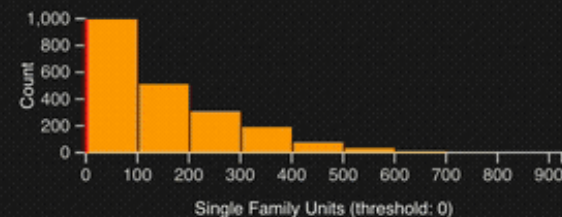
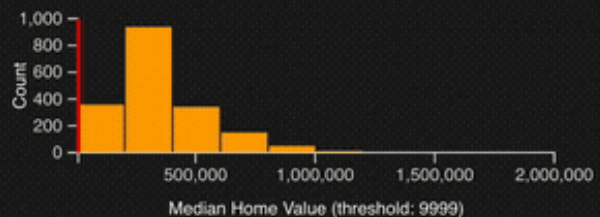
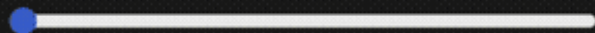
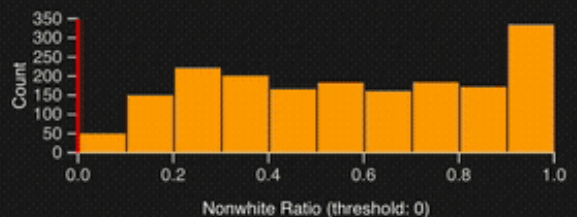
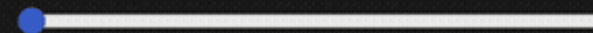
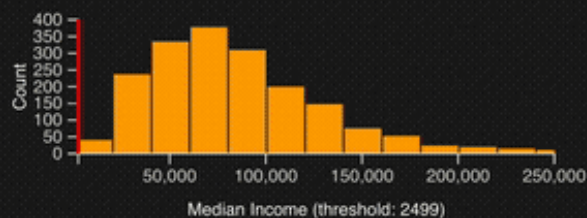
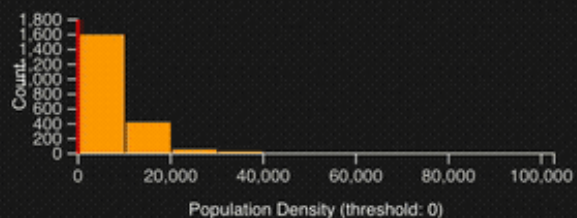


Demo

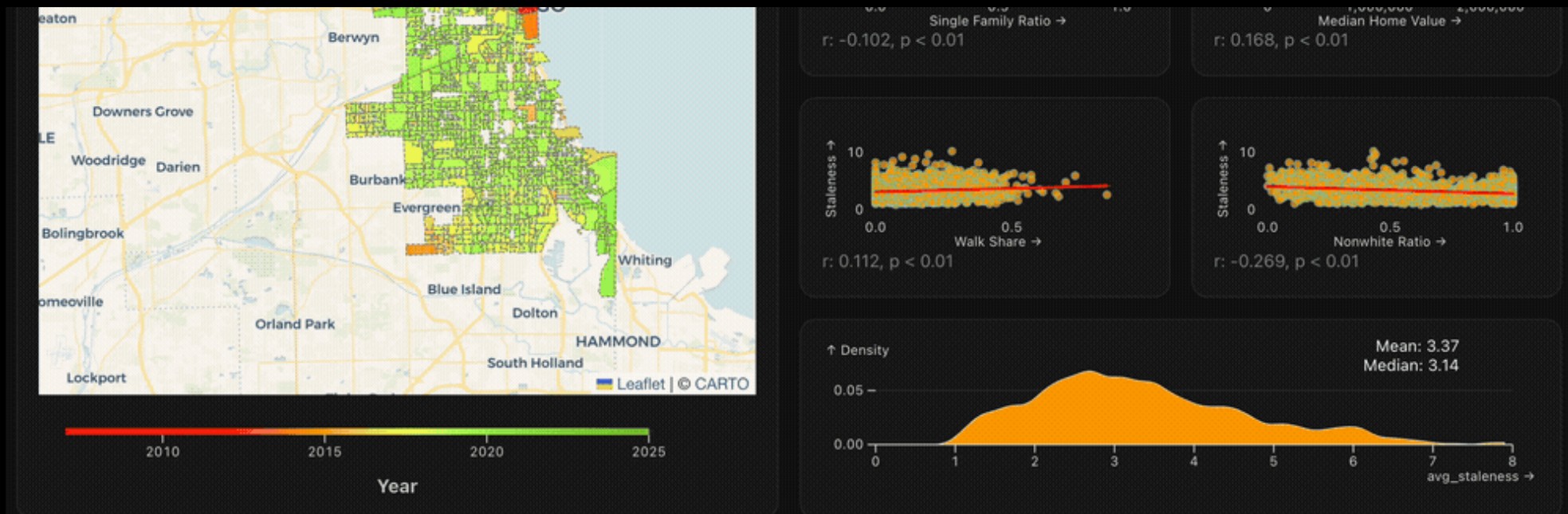
Select your targeted neighbourhood

Use the filters below to explore how Google Street View image freshness varies by neighborhood characteristics.

Example: I want to see the distribution of image staleness in high-income neighbourhood.



Demo

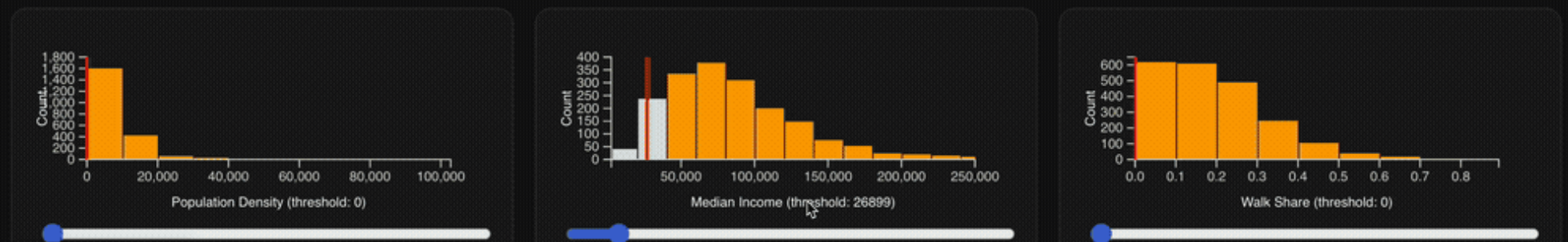


Reset All Filters

Select your targeted neighbourhood

Use the filters below to explore how Google Street View image freshness varies by neighborhood characteristics.

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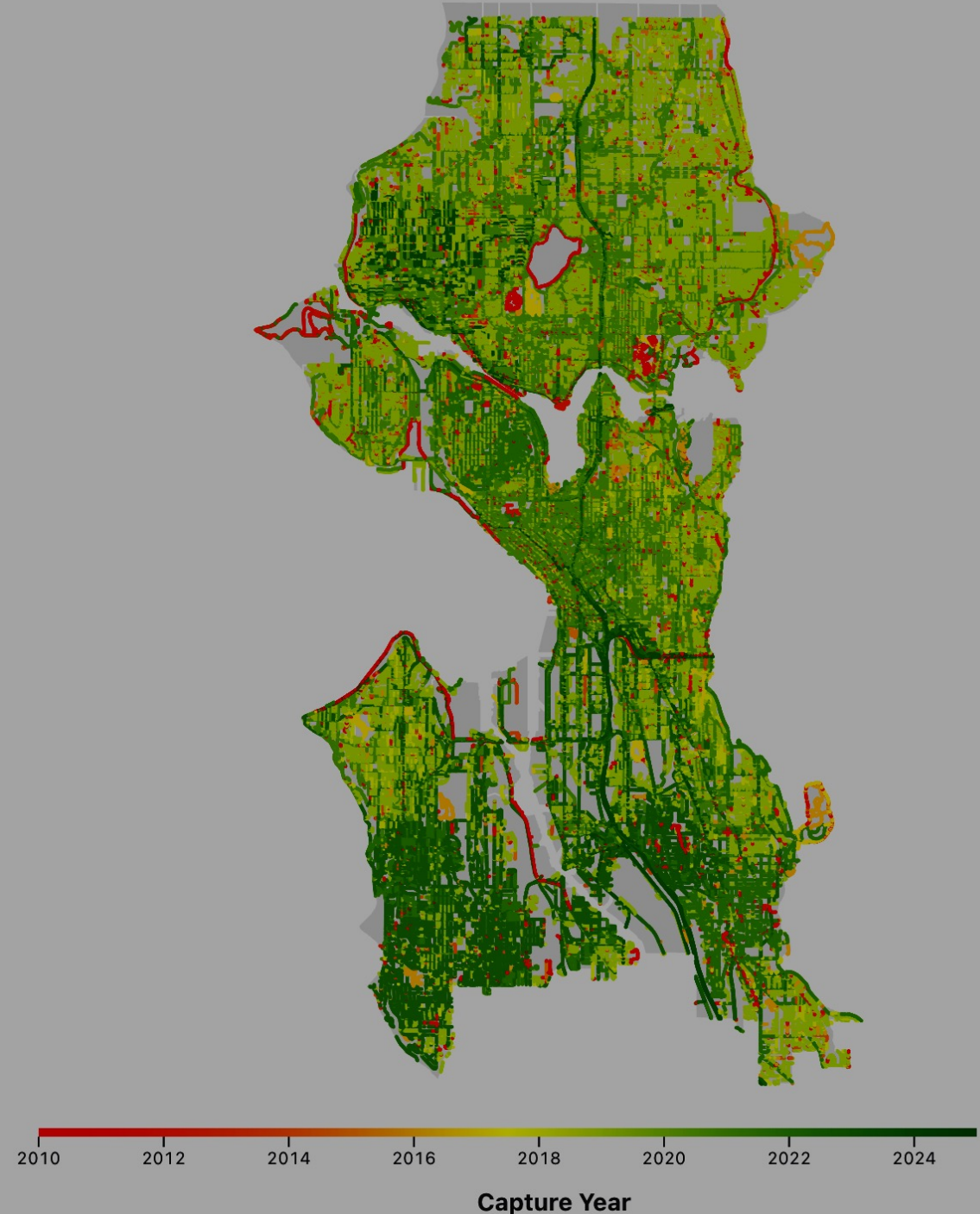


Initial Results

We observed a generally consistent “Digital Redlining” pattern in Google’s SVI update frequency.

Neighborhoods that are higher-income, higher-value, pre-dominantly single-family, or suburban tend to exhibit higher image staleness;

while denser, pedestrian-oriented, and higher-minority communities receive more regular updates.

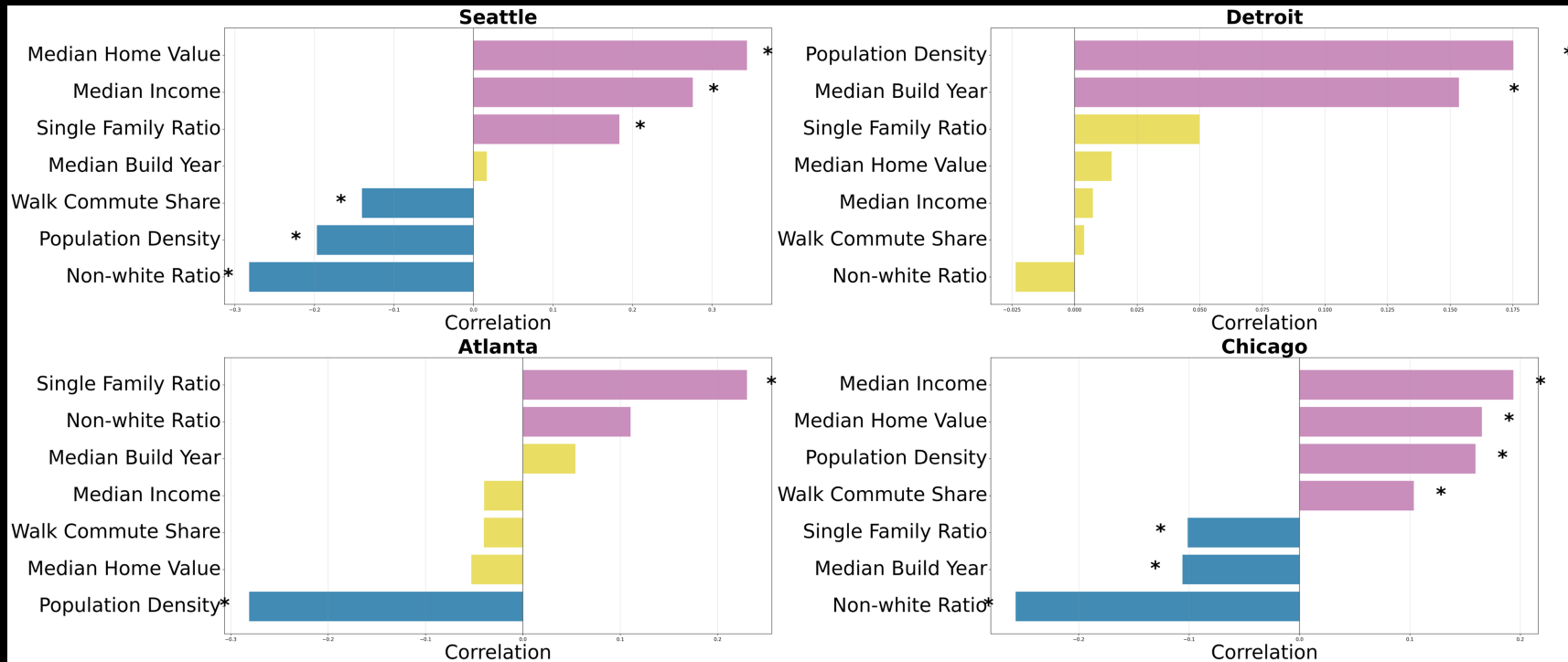


Initial Results: Are GSV updates spatially equitable?

Sufficient observations (N) | $N_{\text{Atlanta}} = 425$, $N_{\text{Chicago}} = 2142$, $N_{\text{Detroit}} = 622$, $N_{\text{Seattle}} = 537$

Consistent trends (Seattle, Chicago, Atlanta):

- $\uparrow$ Median Income / Home Value / Single-Family Ratio $\rightarrow$ **Older imagery**
- $\uparrow$ Population Density / Walk Commute Share / Non-white Ratio $\rightarrow$ **Fresher imagery**
- **Walk Commute Share** = most consistent predictor ($r \approx -0.2$ to -0.3)
- Detroit = weaker / mixed results



Contributions

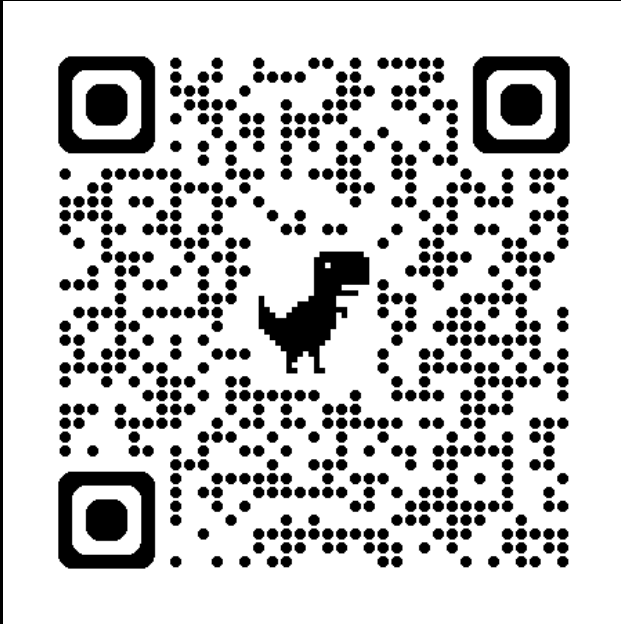
- Empirical evidence of spatial inequalities in widely used street-level imagery.
- An open-source extensible framework for integrating imagery, metadata with social economic data across diverse contexts.
- An interactive visualization tool that promotes transparency and supports audits of digital equity.

Limitations

- Spatial dependencies need further modeling.
- There may be selection bias in the choice of cities; including more cities would improve generalizability.
- Correlation $\neq$ causation.

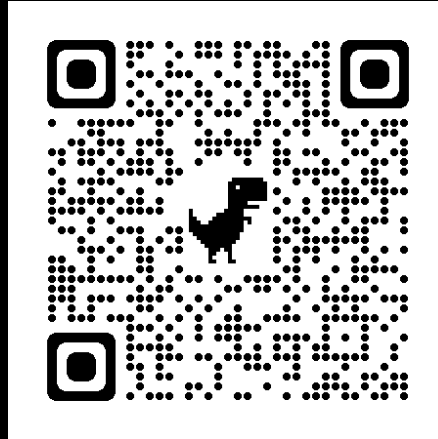
Thank you

Project Repo



github.com/makeabilitylab/GSVantage

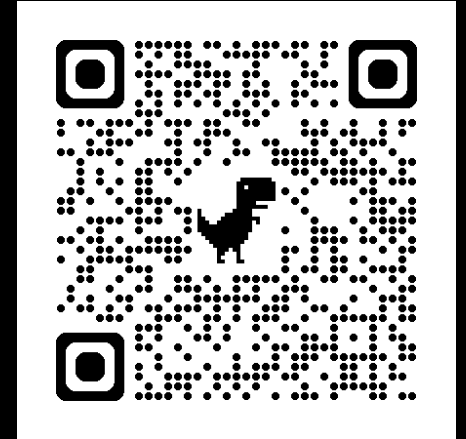
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