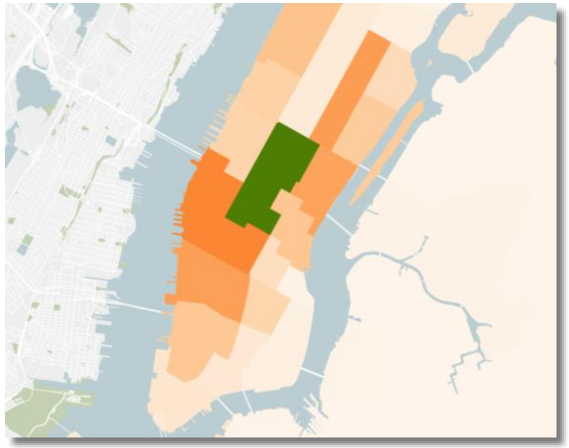
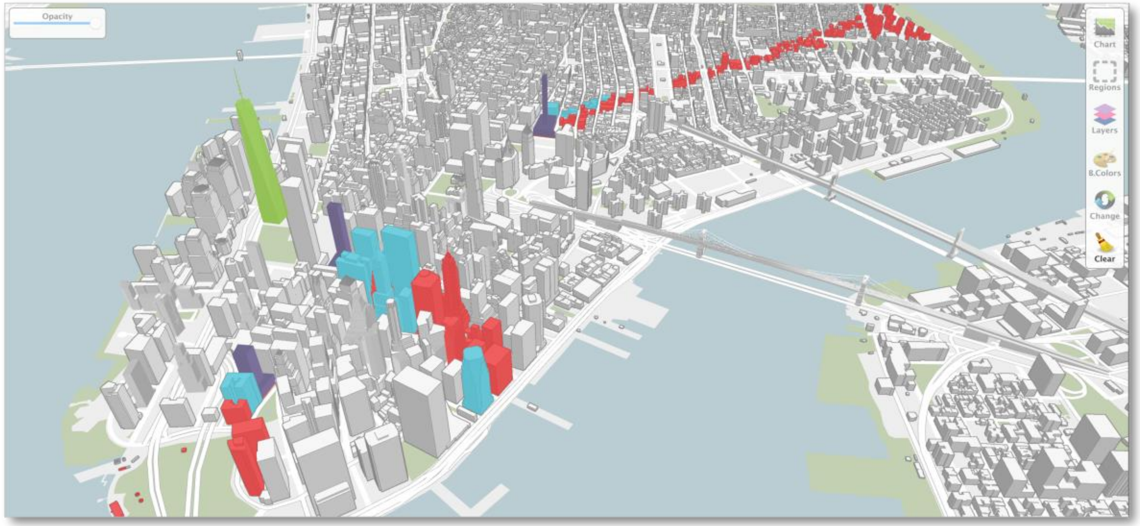
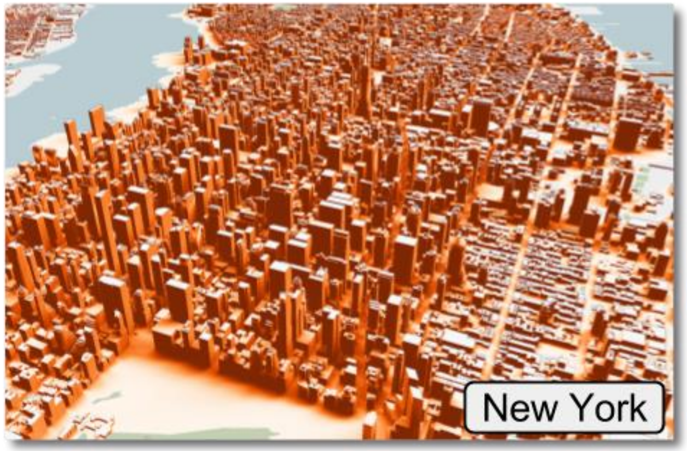






Interactive Visual Analysis of Large Urban Data

Harish Doraiswamy

New York University

NYU

VIDA
VISUALIZATION IMAGING AND DATA ANALYSIS CENTER

Data Exhaust from Cities

Infrastructure

Environment

Photo by *MTA*

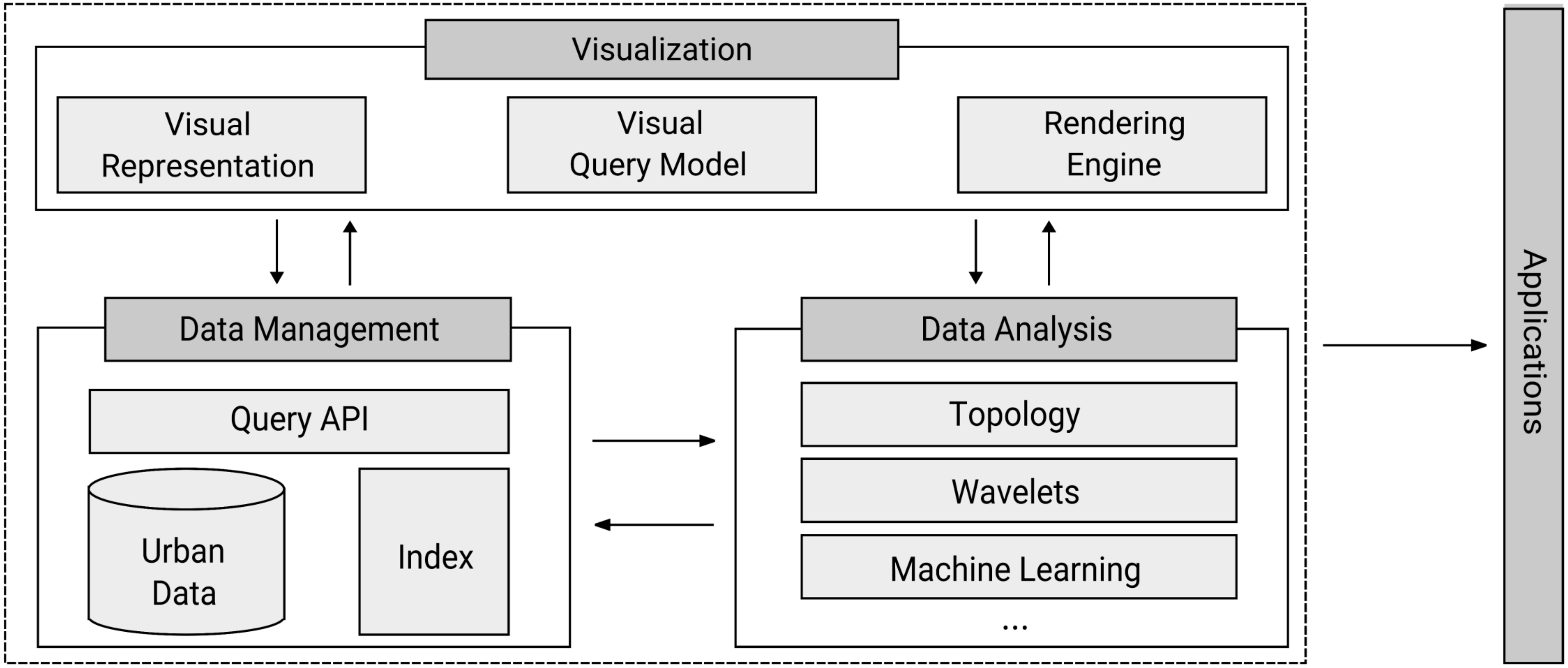
Photo by *Yinka Oyesiku*

People

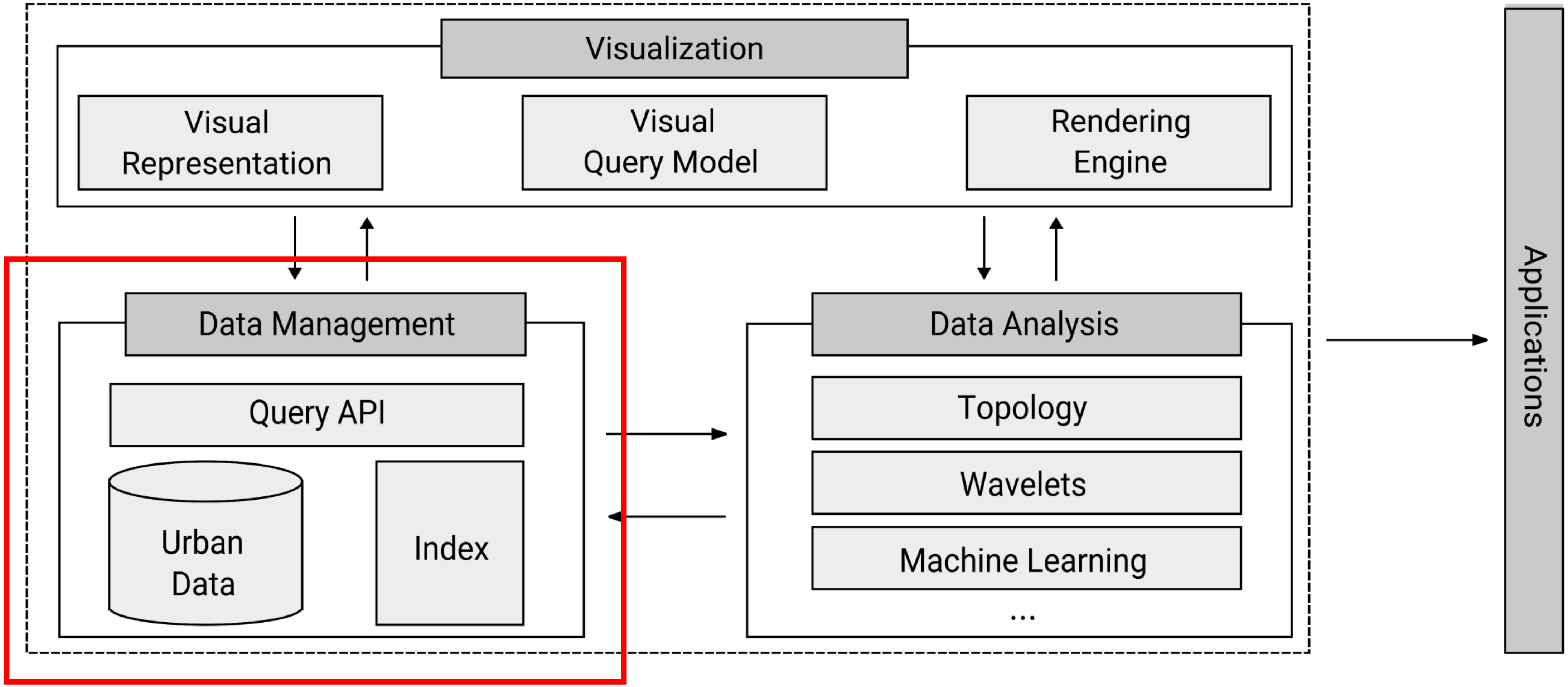
flickr

twitter

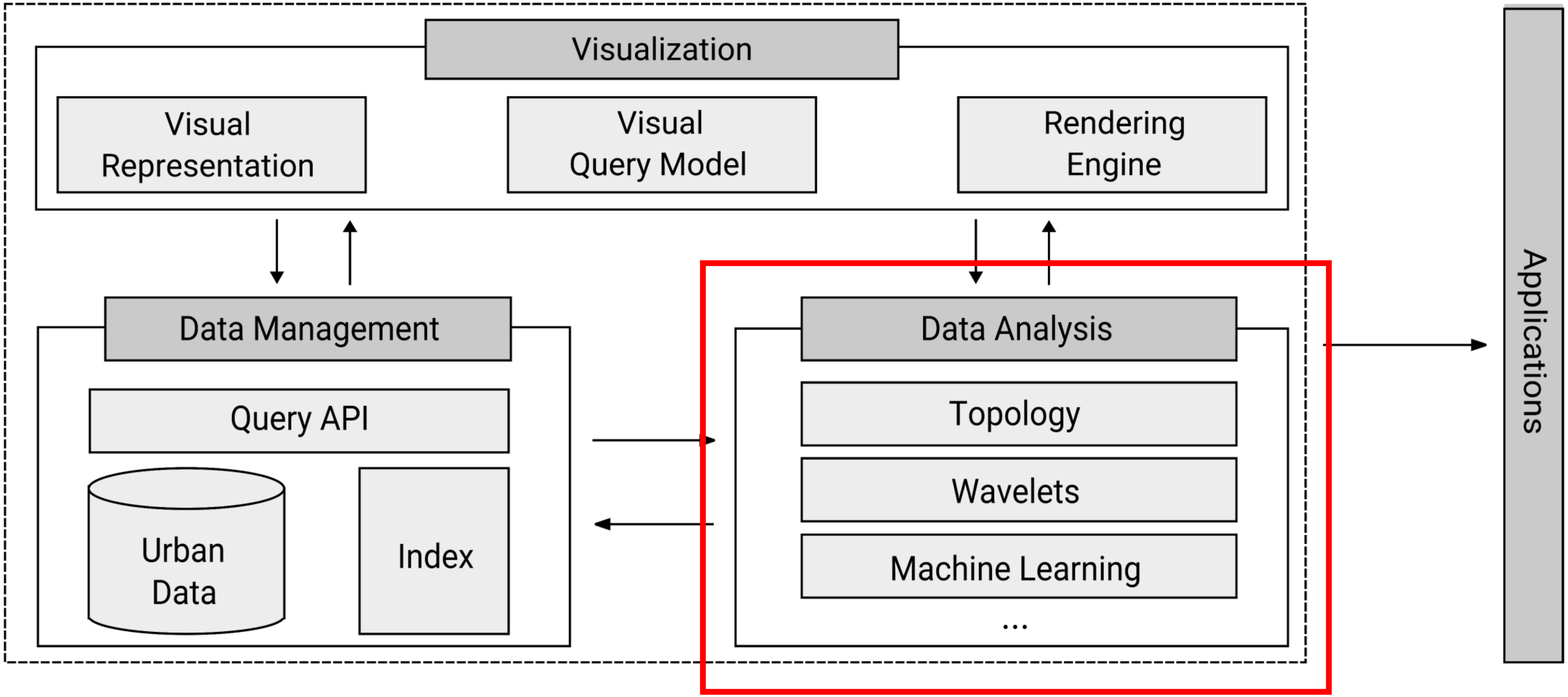
Visual Analytics

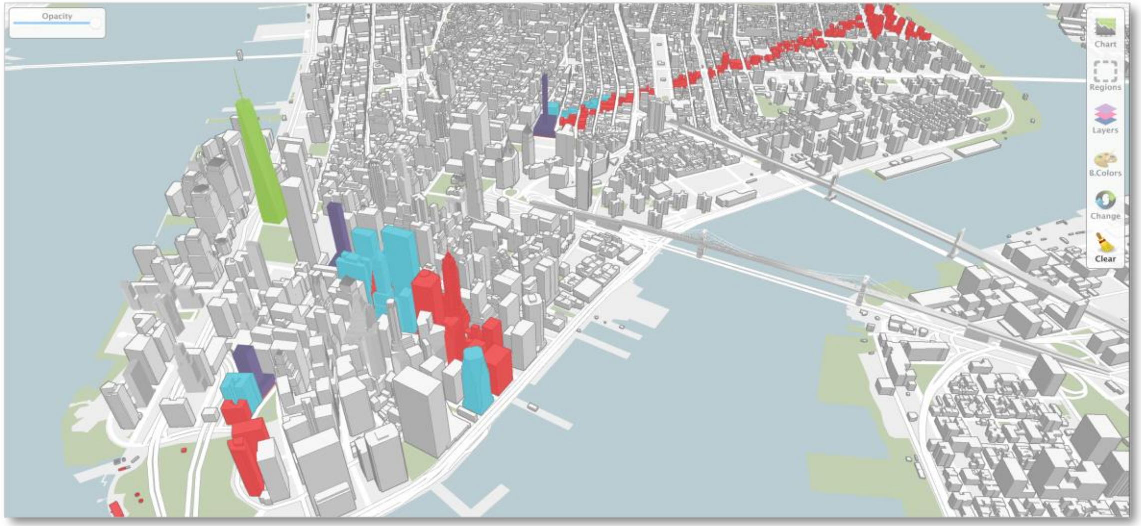


Visual Analytics



Visual Analytics





Urbane

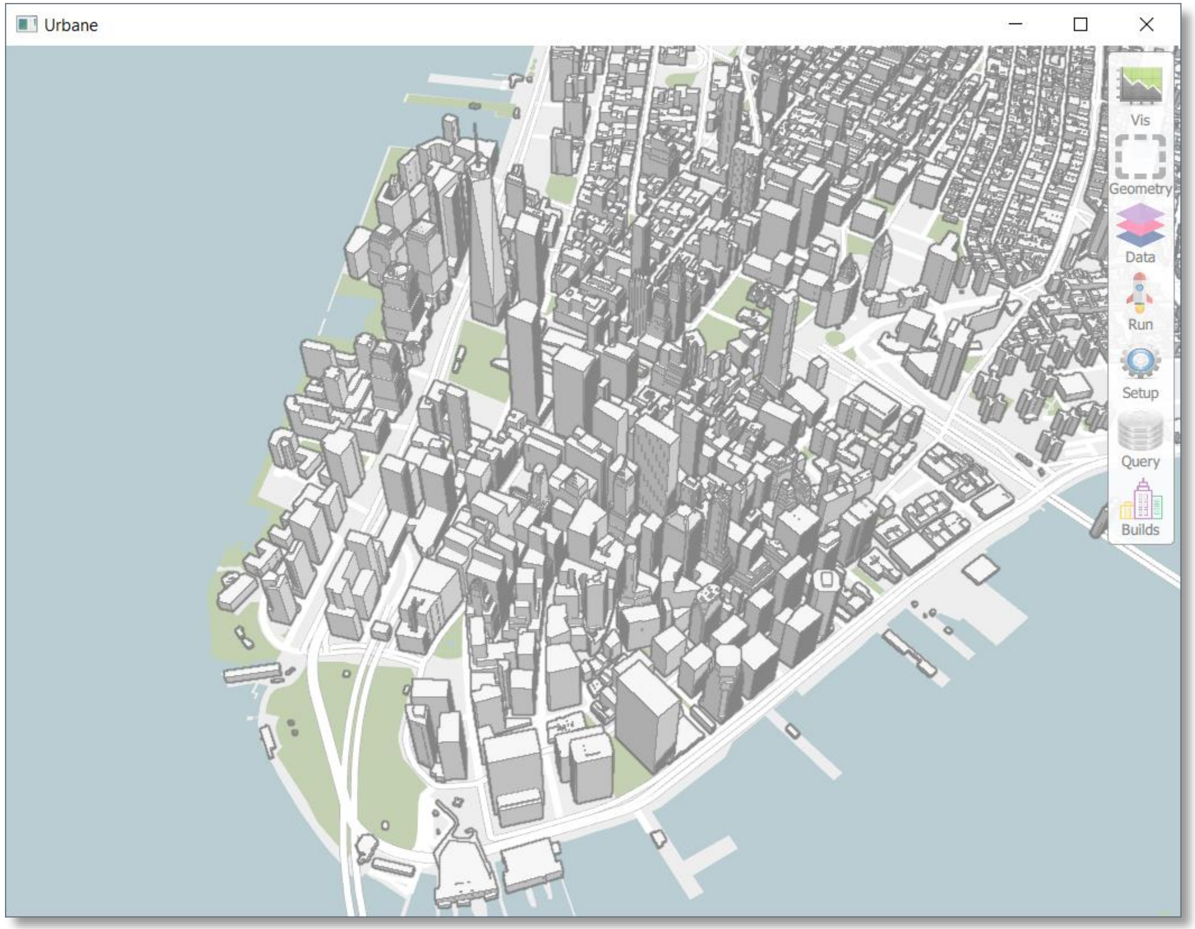
Urbane: A 3D Framework to Support Data Driven Decision Making in Urban Development
Nivan Ferreira, Marcos Lage, Harish Doraiswamy, Huy T. Vo, Luc Wilson, Heidi Werner, Muchan Park, Claudio Silva
IEEE VAST 2015

Interactive Visual Exploration of Spatio-Temporal Urban Data Sets using Urbane
Harish Doraiswamy, Eleni Tzirita Zacharatou, Fabio Miranda, Marcos Lage, Anastasia Ailamaki, Claudio Silva, Juliana Freire
SIGMOD Demo 2018 (Best Demonstration Award)

Urbane

- In collaboration with architects from Kohn Pedersen Fox (KPF)
- Two Questions
  - How does a new construction impact the city

Demo

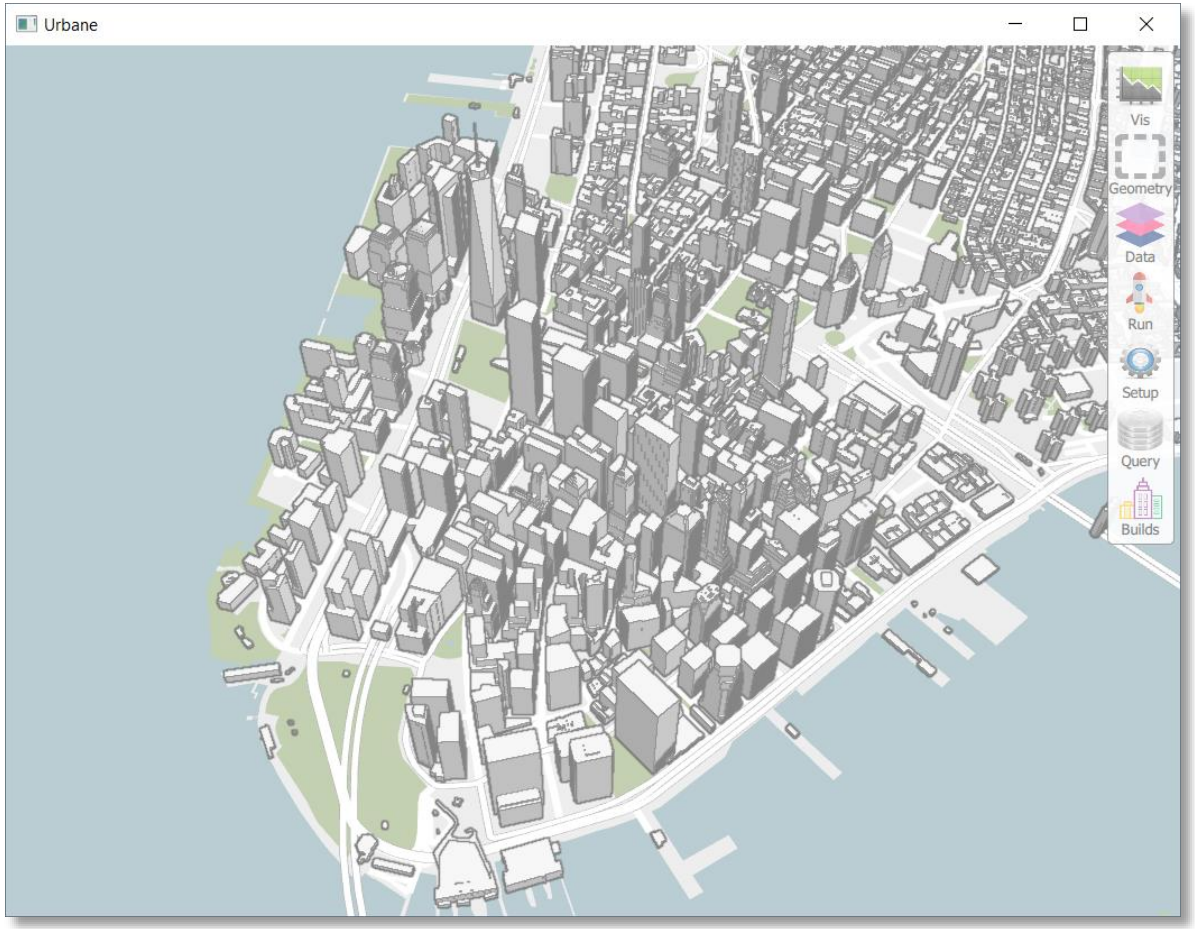


Urbane

IEEE VAST 2015

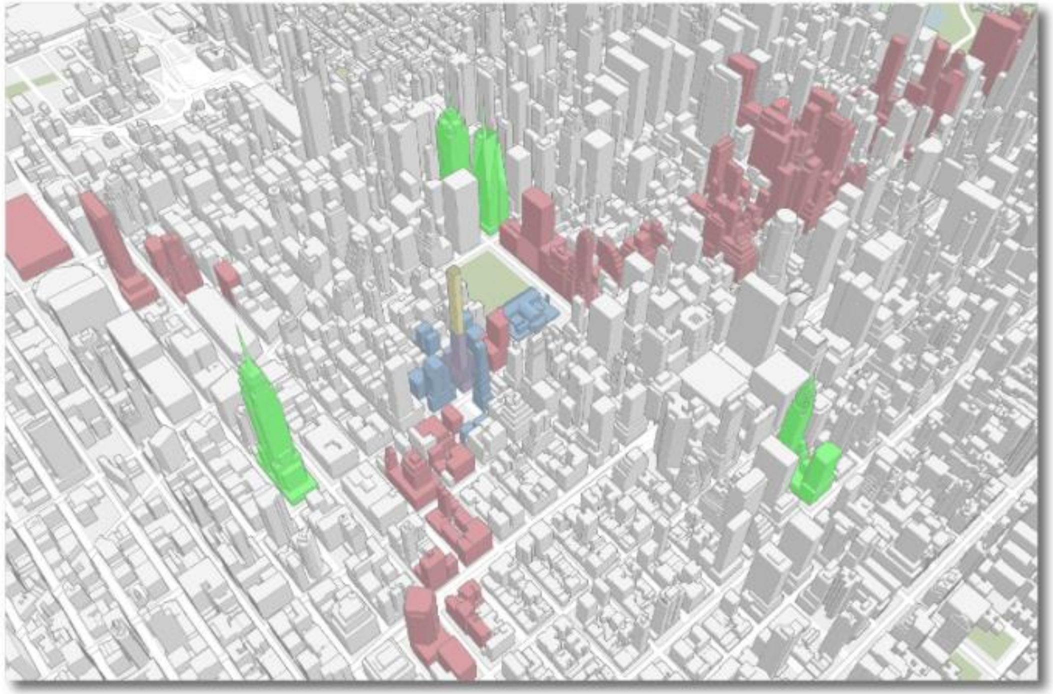
- In collaboration with architects from Kohn Pedersen Fox (KPF)
- Two Questions
  - How does a new construction impact the city
  - How to identify locations for new development

Demo



Urbane: Queries

- 3D Geometry-based Queries

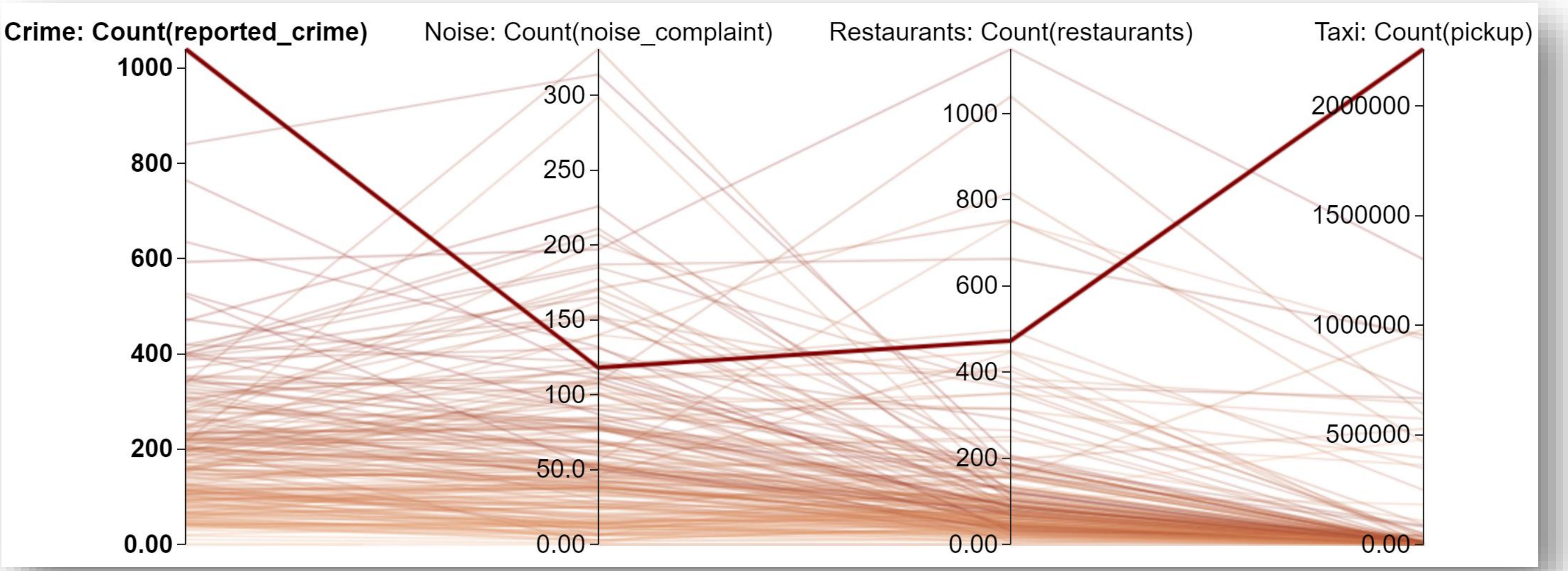


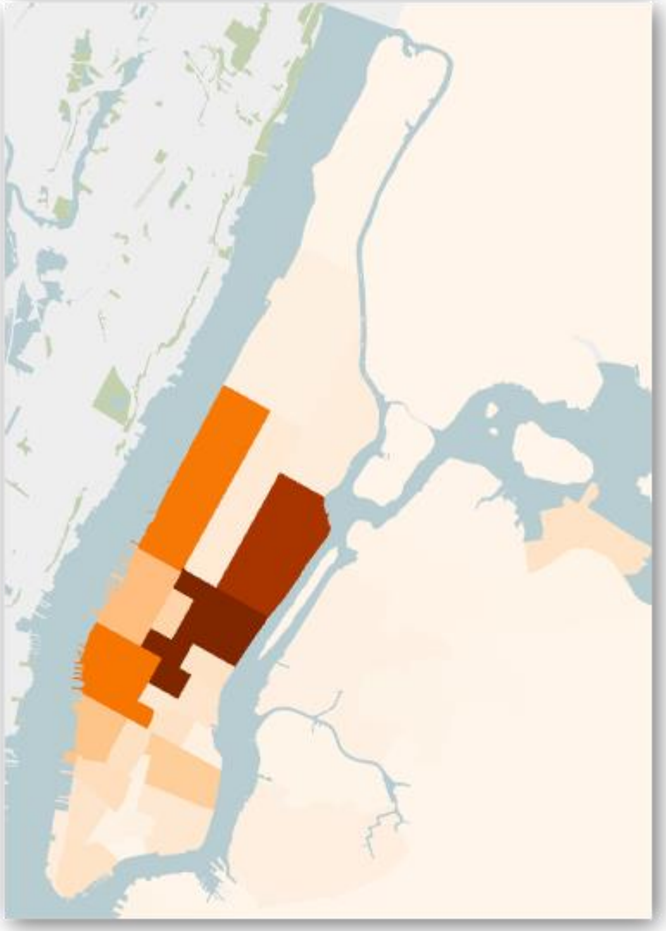
View Impact Queries

Sky Exposure Queries

Urbane: Queries

- 2D Spatial Queries

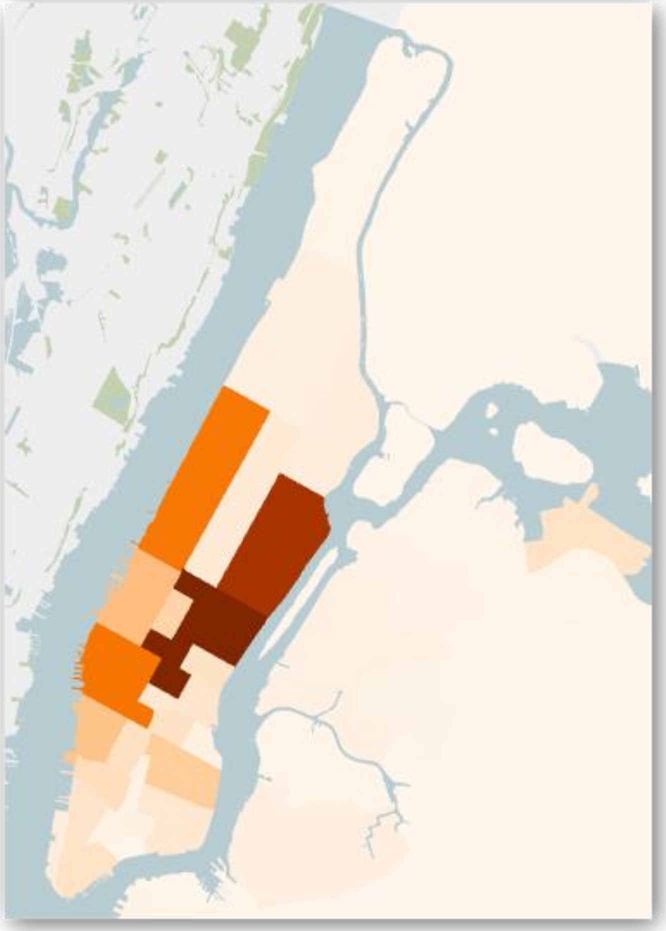


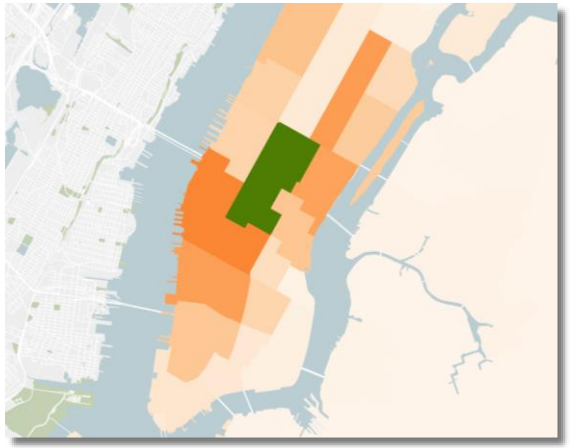


Spatial Aggregation Queries

Desiderata

Interactive response times





Spatial Aggregation Queries

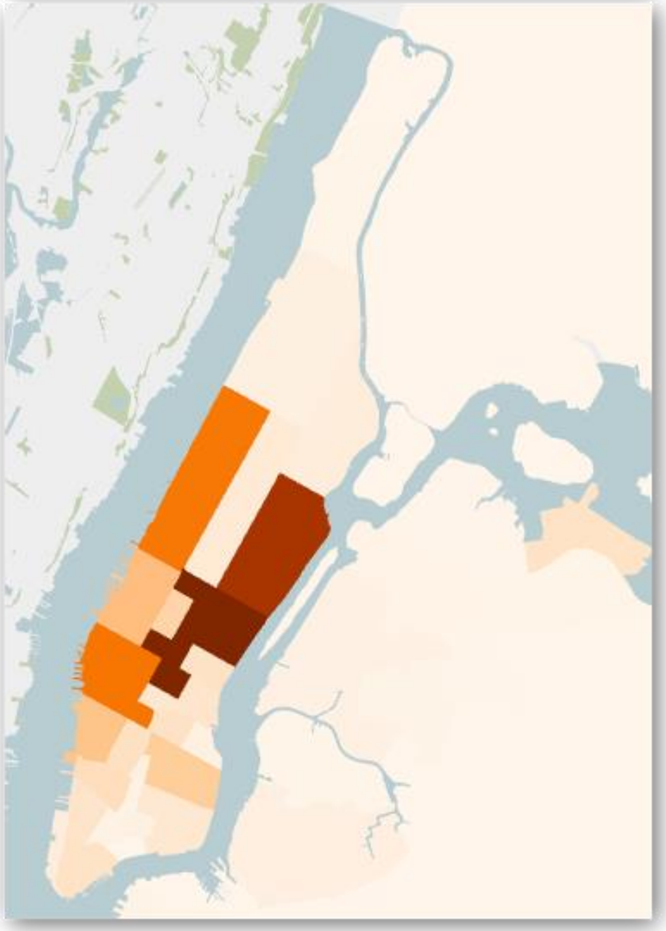
GPU Rasterization for Real-Time Spatial Aggregation over Arbitrary Polygons
Eleni Tzirita Zacharatou, Harish Doraiswamy, Anastasia Ailamaki, Claudio Silva, Juliana Freire
Proceedings of the VLDB Endowment (PVLDB), 11(3), 2017, 352-365

NYC Taxi Data

- Yellow cab trips
- ~175 million trips / year
- Spatial-Temporal
  - 2 spatial attributes
  - 2 temporal attributes
- Other attributes
  - Fare, tip
  - Distance
  - Duration
  - …

Spatial Aggregation Queries

SELECT COUNT(*)
FROM taxi *T*, neighborhoods *N*
WHERE *T*.pickup INSIDE *N*.geometry
GROUP BY *N*.id



Spatial Aggregation Queries

SELECT COUNT(*)
FROM taxi *T*, neighborhoods *N*
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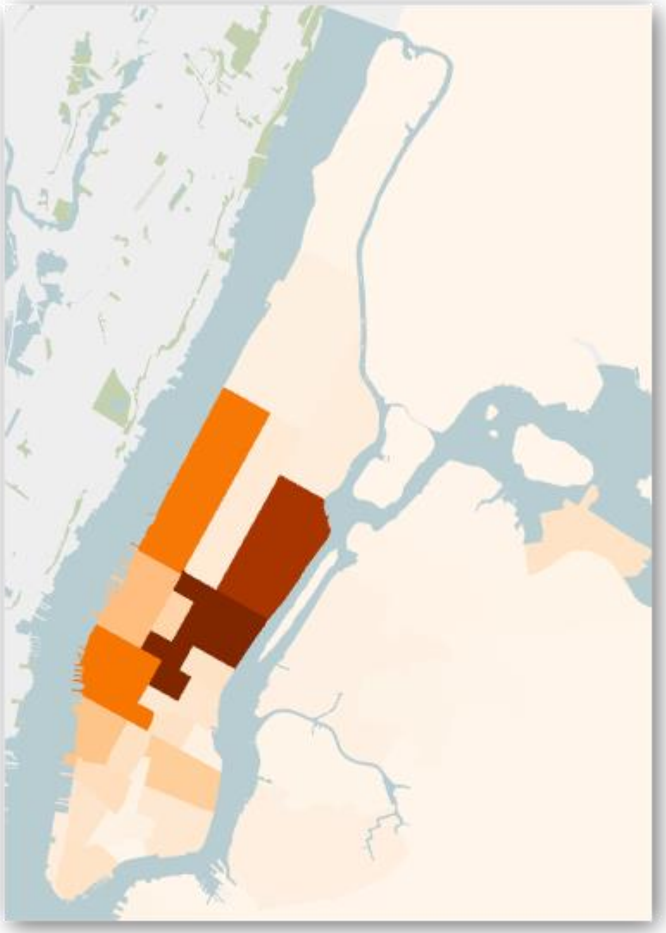
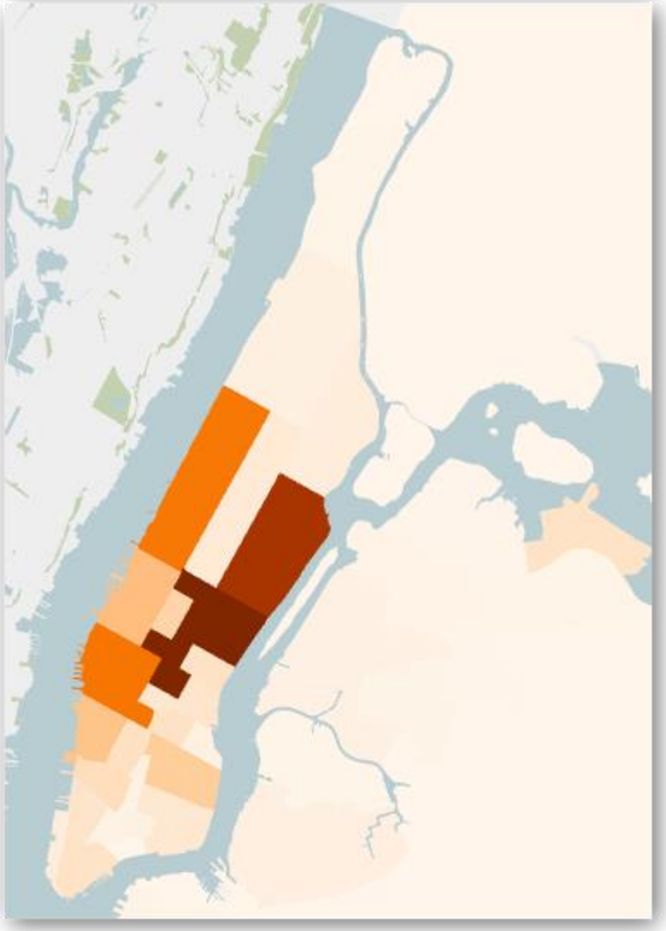


- Pre-compute the aggregation

Spatial Aggregation Queries

SELECT COUNT(*)
FROM taxi *T*, neighborhoods *N*
WHERE *T*.pickup INSIDE *N*.geometry
AND *T*.picktime in March 2011
GROUP BY *N*.id

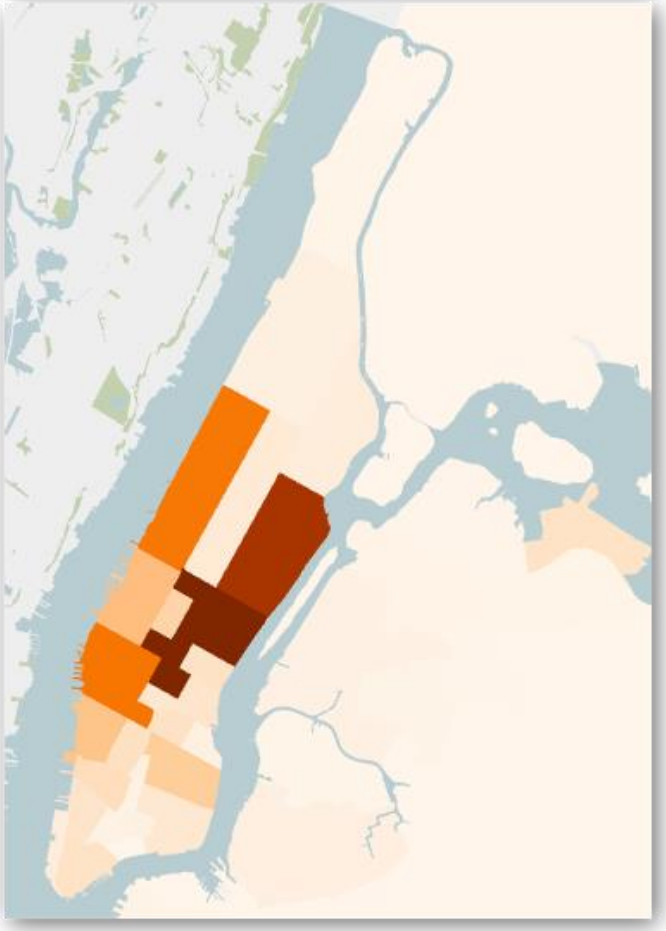


- Use CUBE-base structures
  - Nanocubes, Hashed cubes etc.
- Rectangular regions
  - multiple queries per polygon
  - No control over accuracy

Spatial Aggregation Queries

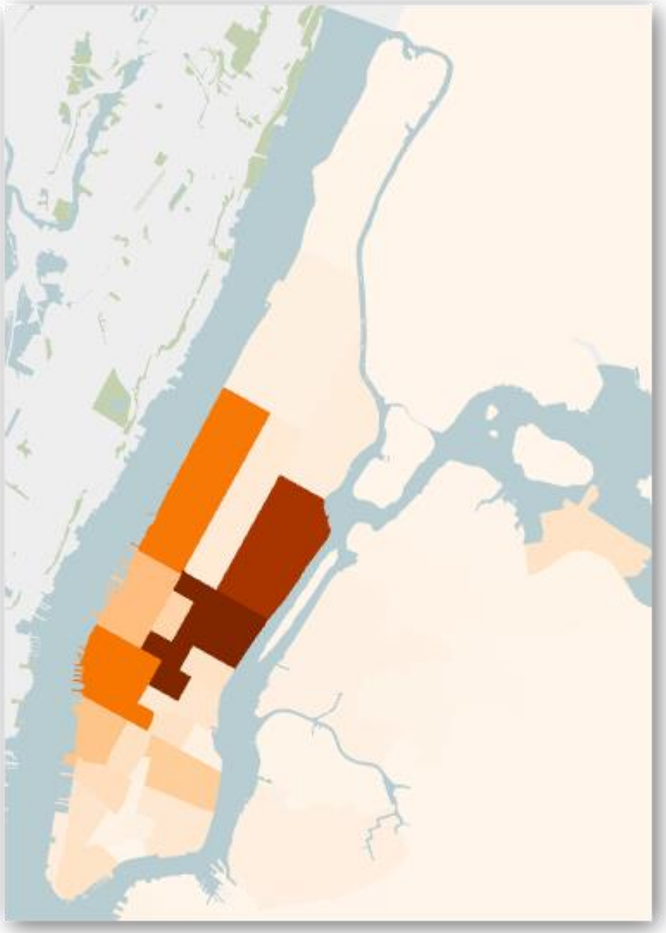
SELECT COUNT(*)
FROM taxi *T*, neighborhoods *N*
WHERE *T*.pickup INSIDE *N*.geometry
AND *T*.picktime in March 2011
AND *T*.duration > 10 minutes
GROUP BY *N*.id

- Use CUBE-base structures
  - Nanocubes, Hashed cubes etc.



Spatial Aggregation Queries

SELECT AVG(*T*.fare)
FROM taxi *T*, neighborhoods *N*
WHERE *T*.pickup INSIDE *N*.geometry
AND *T*.picktime in March 2011
AND *T*.duration > 10 minutes
GROUP BY *N*.id

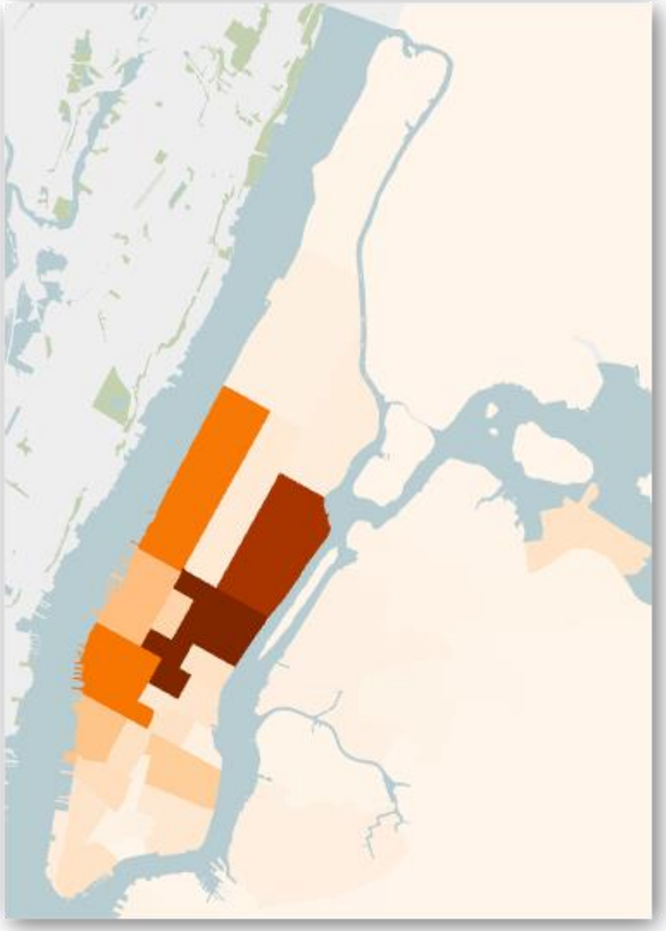


- Use CUBE-base structures
  - Nanocubes, Hashed cubes etc.
- Space explosion

Spatial Aggregation Queries

SELECT AVG(*T*.fare)
FROM taxi *T*, neighborhoods *N*
WHERE *T*.pickup INSIDE *N*.geometry
AND T.picktime in March 2011
AND T.duration > 10 minutes
GROUP BY *N*.id

- Existing spatial databases

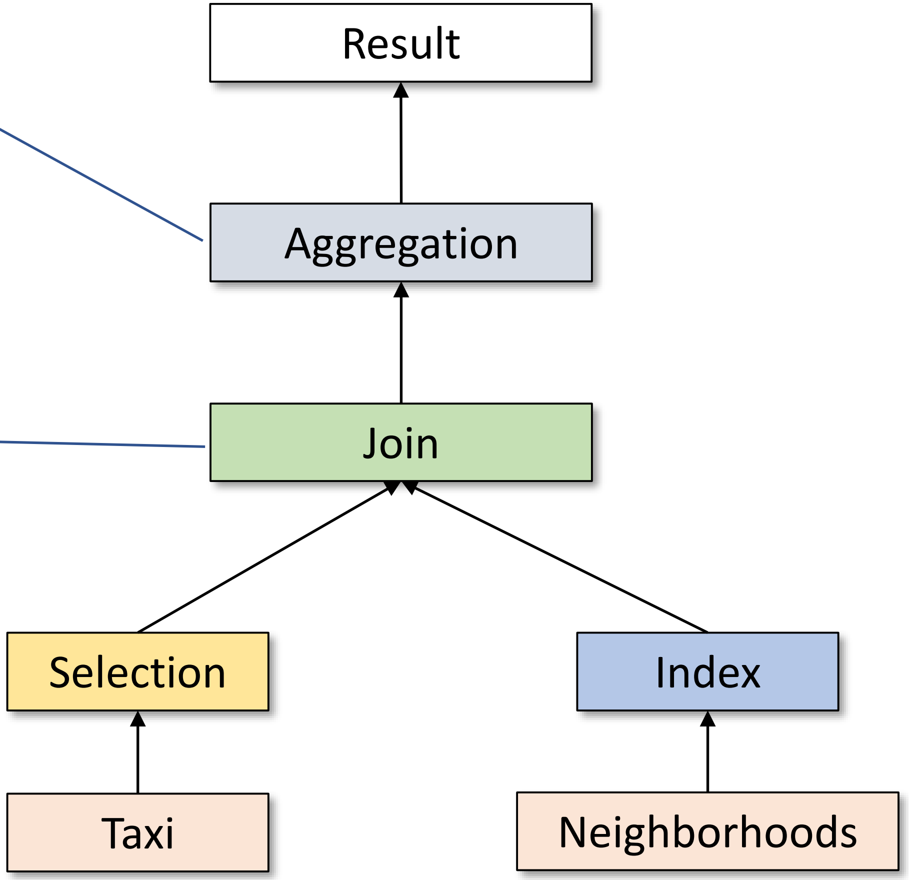


Spatial Aggregation Queries

SELECT AV
FROM taxi
WHERE *T*.pickup INSIDE *N*.geometry
AND T.picktime in March 2011
AND T.dura
GROUP BY

Materialize the Join

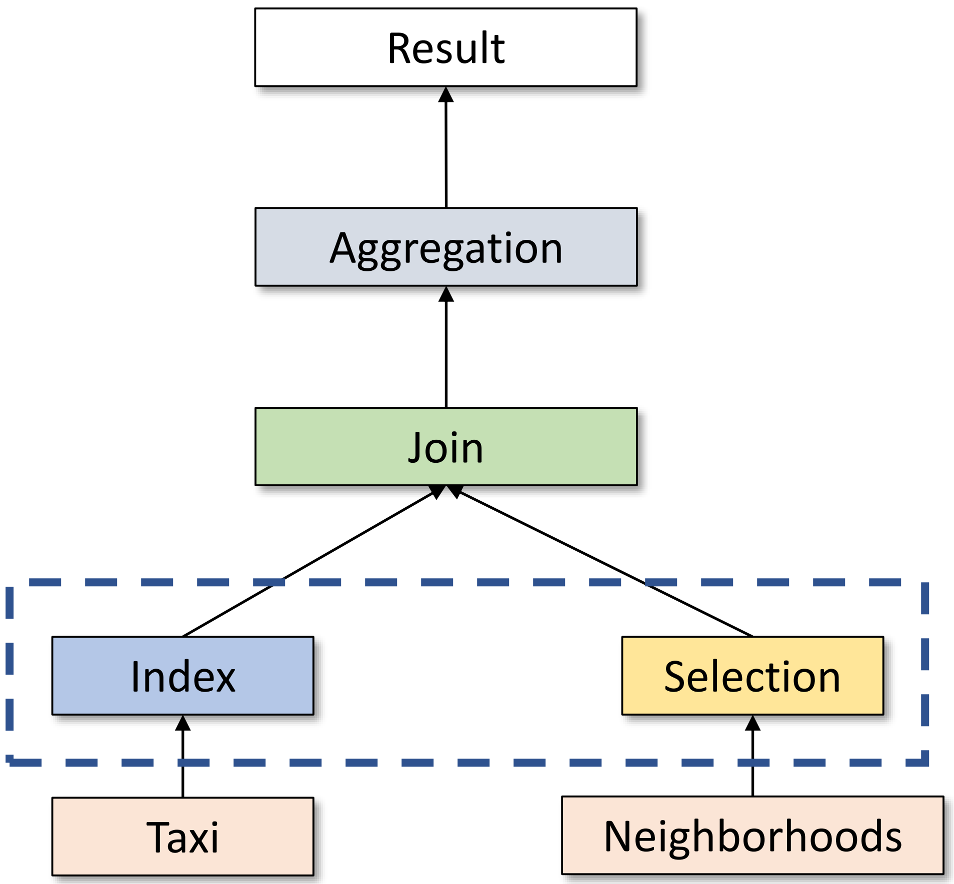
Point in Polygon Tests



- Existing spatial databases
- Several minutes

Spatial Aggregation Queries

SELECT AVG(*T*.fare)
FROM taxi *T*, neighborhoods *N*
WHERE *T*.pickup INSIDE *N*.geometry
AND T.picktime in March 2011
AND T.duration > 10 minutes
GROUP BY *N*.id



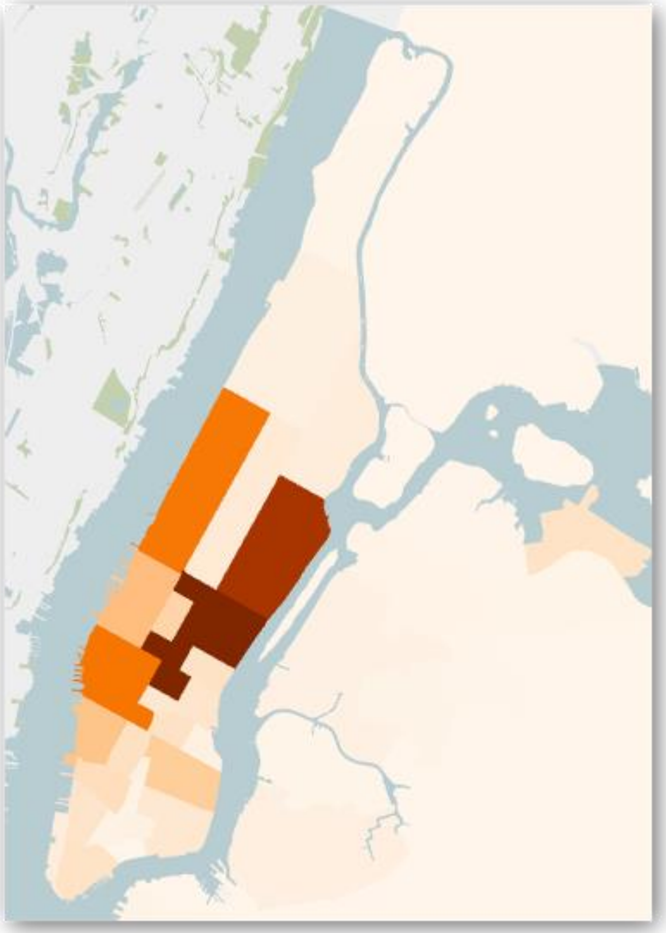
- Existing spatial databases
- Several minutes

Desiderata

Interactive response times

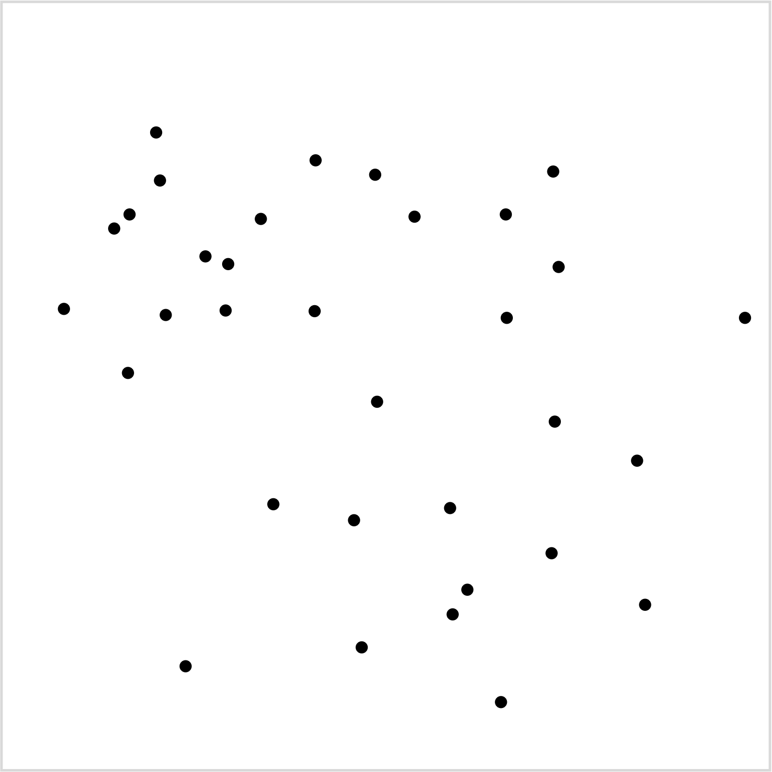
Avoid costly preprocessing

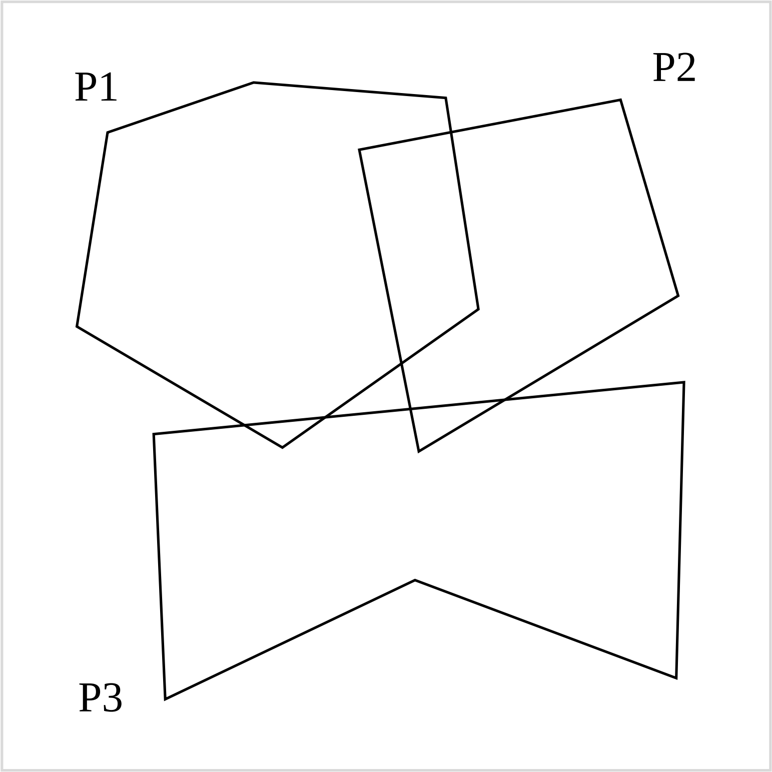
Approximations are Tolerable



Running Example

SELECT COUNT(*)
FROM taxi *T*, neighborhoods *N*
WHERE *T*.pickup INSIDE *N*.geometry
GROUP BY *N*.id





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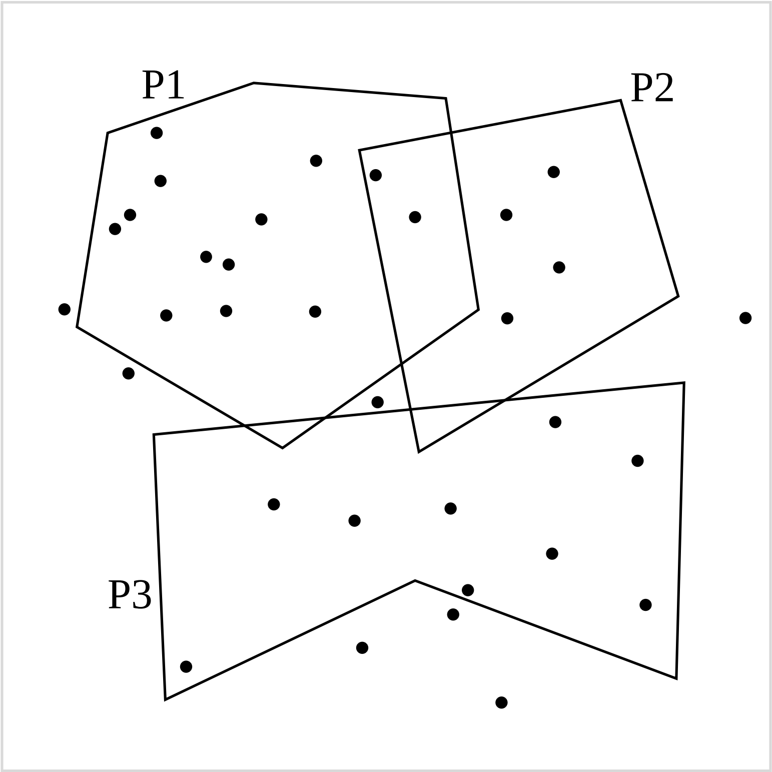

Idea

SELECT COUNT(*)
FROM taxi *T*, neighborhoods *N*
WHERE *T*.pickup INSIDE *N*.geometry
GROUP BY *N*.id

Drawing Points

Idea

SELECT COUNT(*)
FROM taxi *T*, neighborhoods *N*
WHERE *T*.pickup INSIDE *N*.geometry
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SELECT COUNT(*)
FROM taxi *T*, neighborhoods *N*
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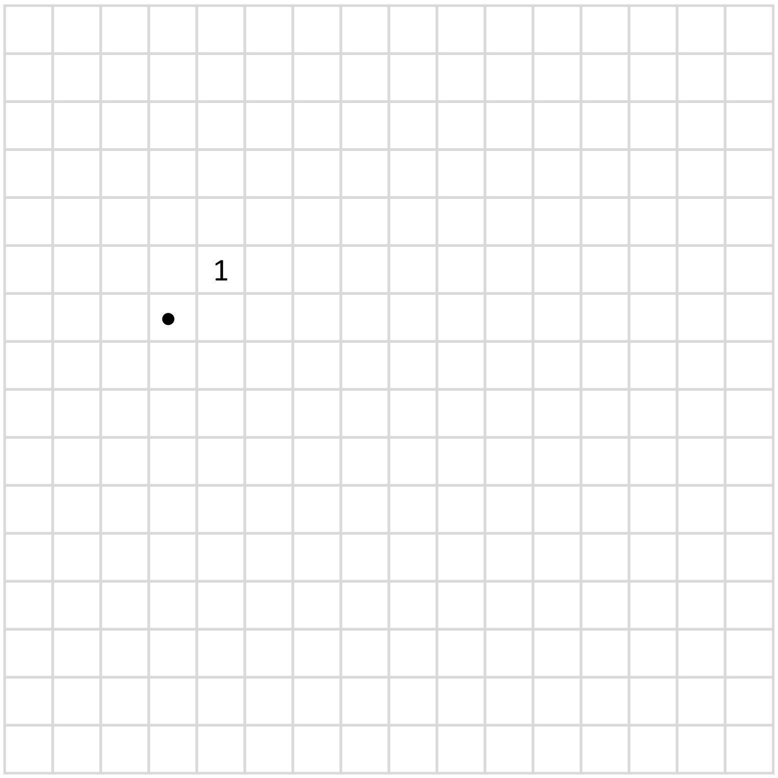

Idea

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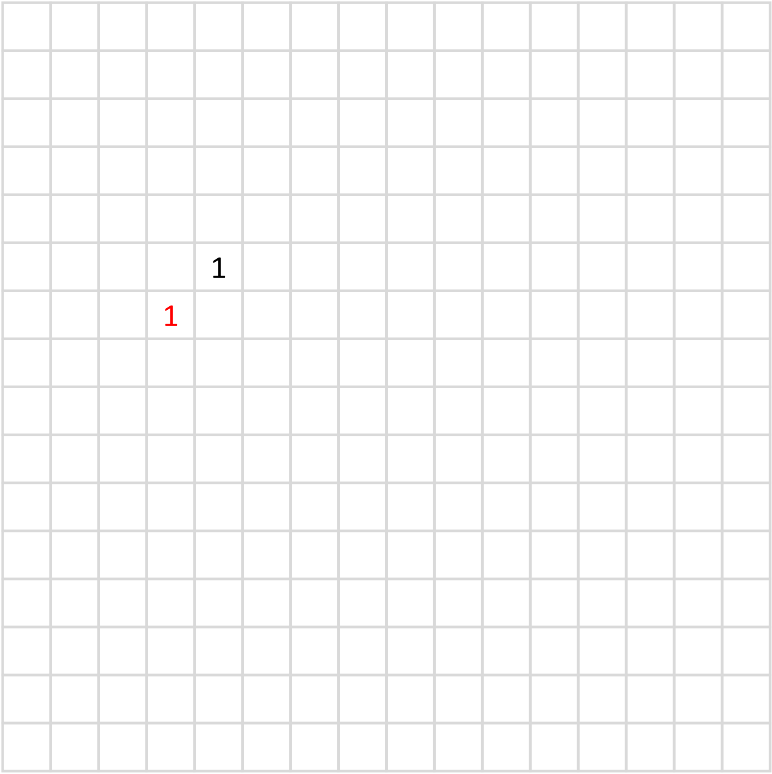
GROUP BY *N*.id

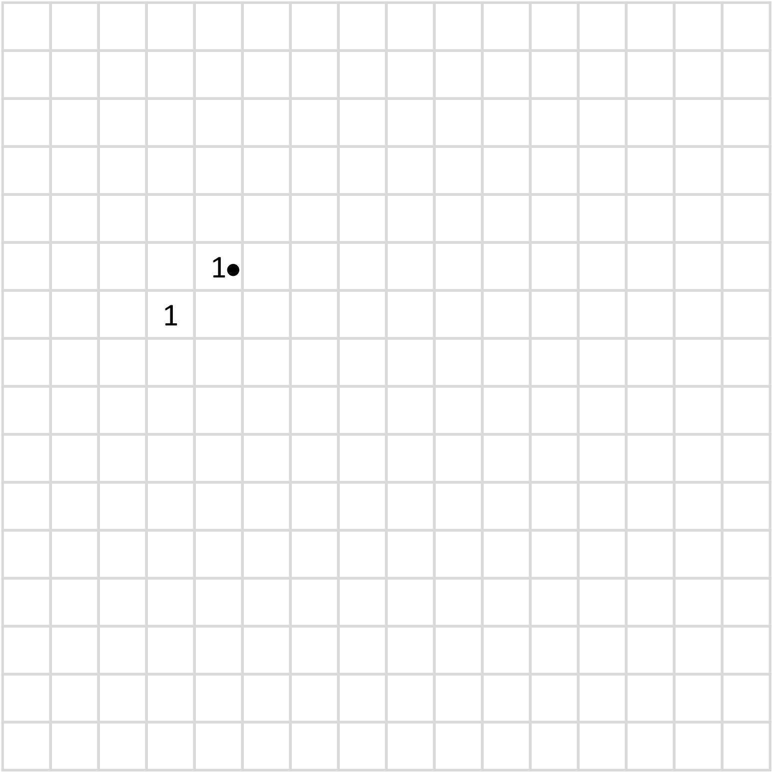
Drawing Points



Idea

SELECT COUNT(*)
FROM taxi *T*, neighborhoods *N*
WHERE *T*.pickup INSIDE *N*.geometry
GROUP BY *N*.id

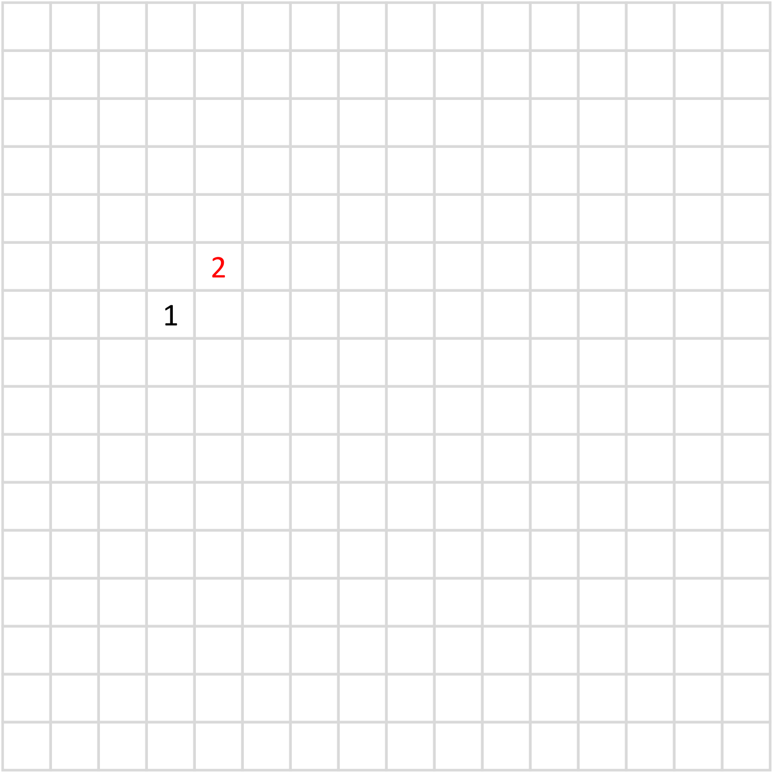
Drawing Points



Idea

```
SELECT COUNT(*)
FROM taxi T, neighborhoods N
WHERE T.pickup INSIDE N.geometry
GROUP BY N.id
```

Drawing Points

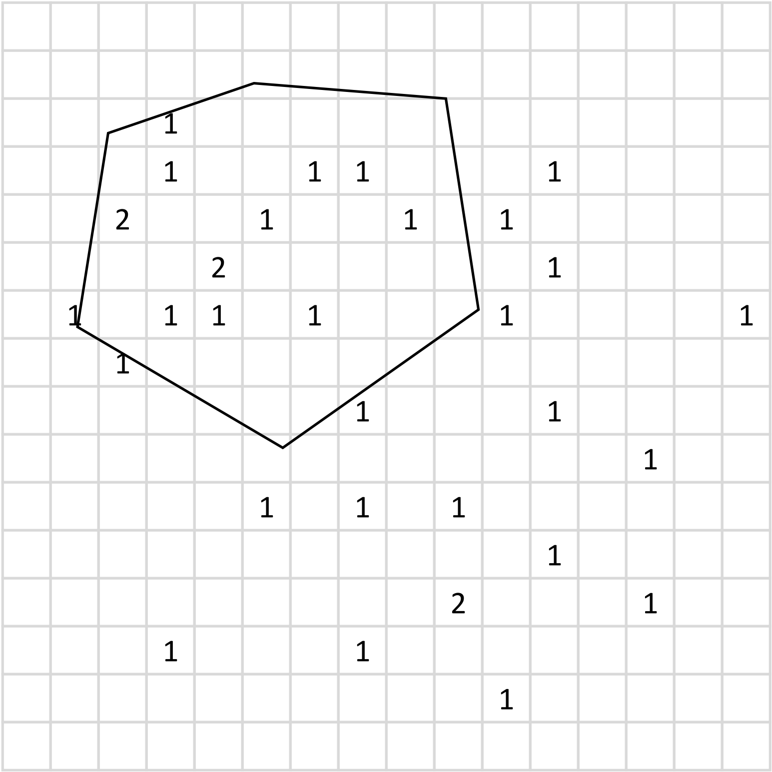


Idea

SELECT COUNT(*)
FROM taxi *T*, neighborhoods *N*
WHERE *T*.pickup INSIDE *N*.geometry
GROUP BY *N*.id

Drawing Points

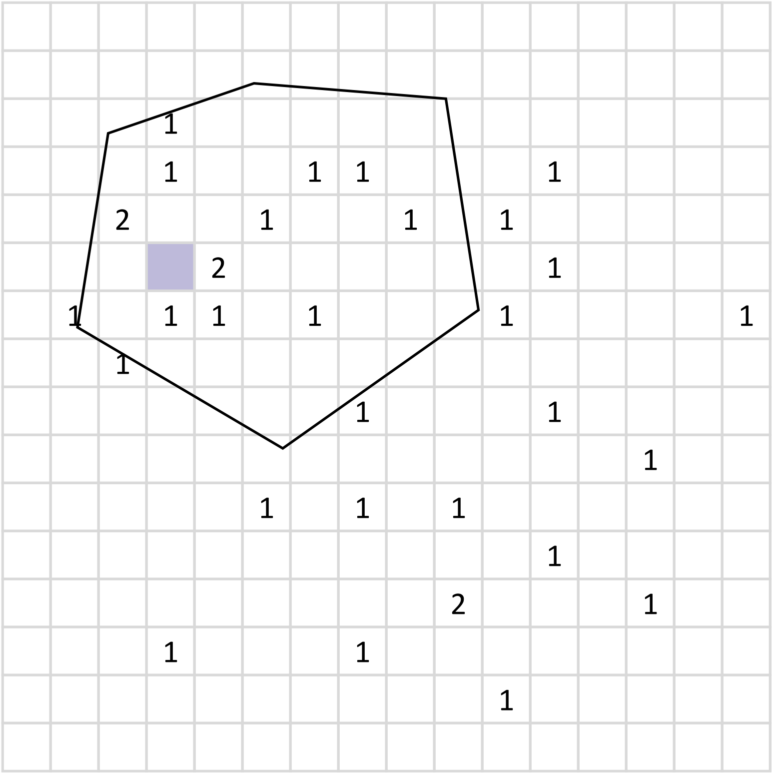
Drawing Polygons



Idea

```
SELECT COUNT(*)
FROM taxi T, neighborhoods N
WHERE T.pickup INSIDE N.geometry
GROUP BY N.id
```

Drawing Polygons

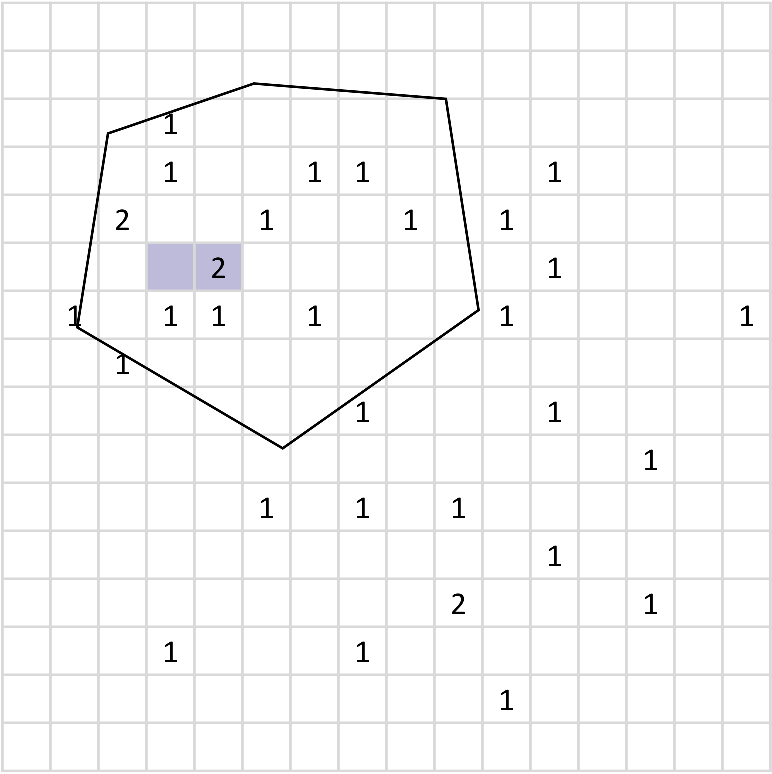


0

Idea

SELECT COUNT(*)
FROM taxi *T*, neighborhoods *N*
WHERE *T*.pickup INSIDE *N*.geometry
GROUP BY *N*.id

Drawing Polygons

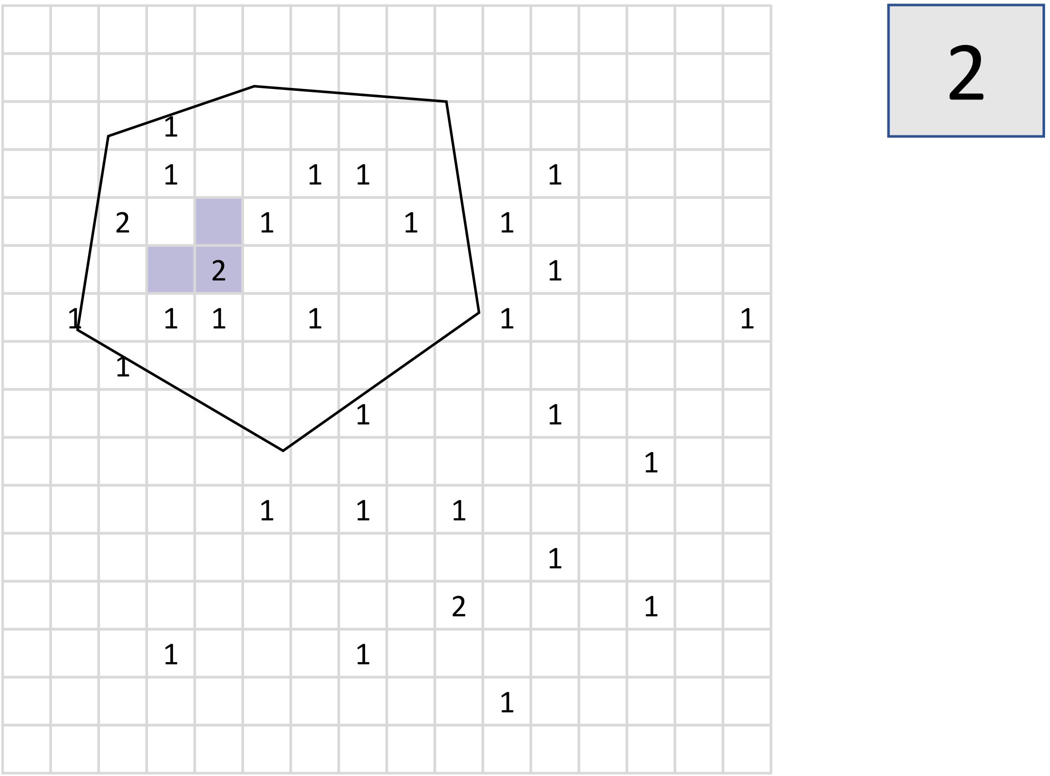


2

Idea

SELECT COUNT(*)
FROM taxi *T*, neighborhoods *N*
WHERE *T*.pickup INSIDE *N*.geometry
GROUP BY *N*.id

Drawing Polygons



Idea

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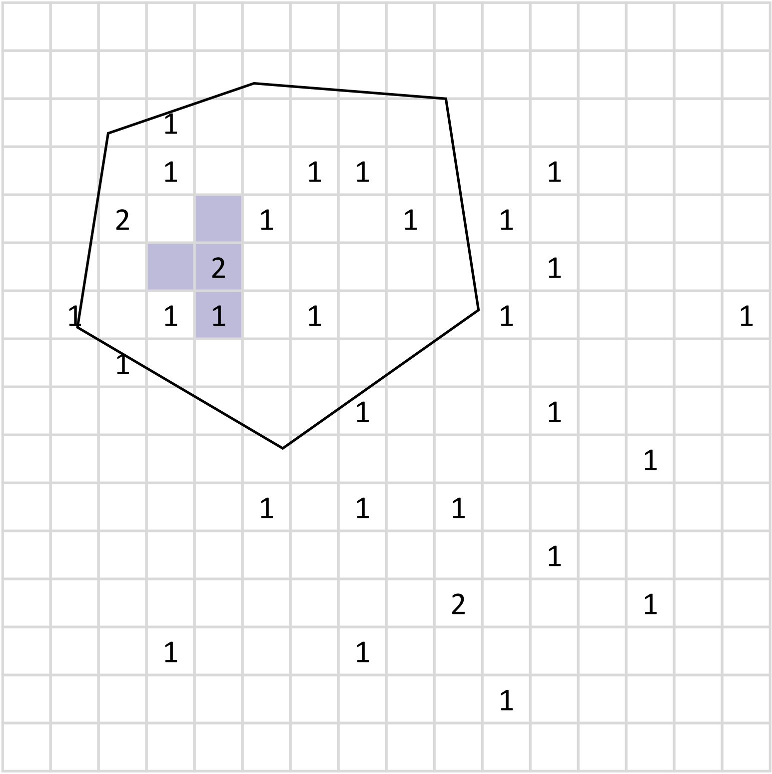
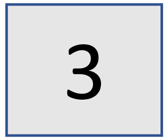
WHERE *T*.pickup INSIDE *N*.geometry
GROUP BY *N*.id

Drawing Polygons

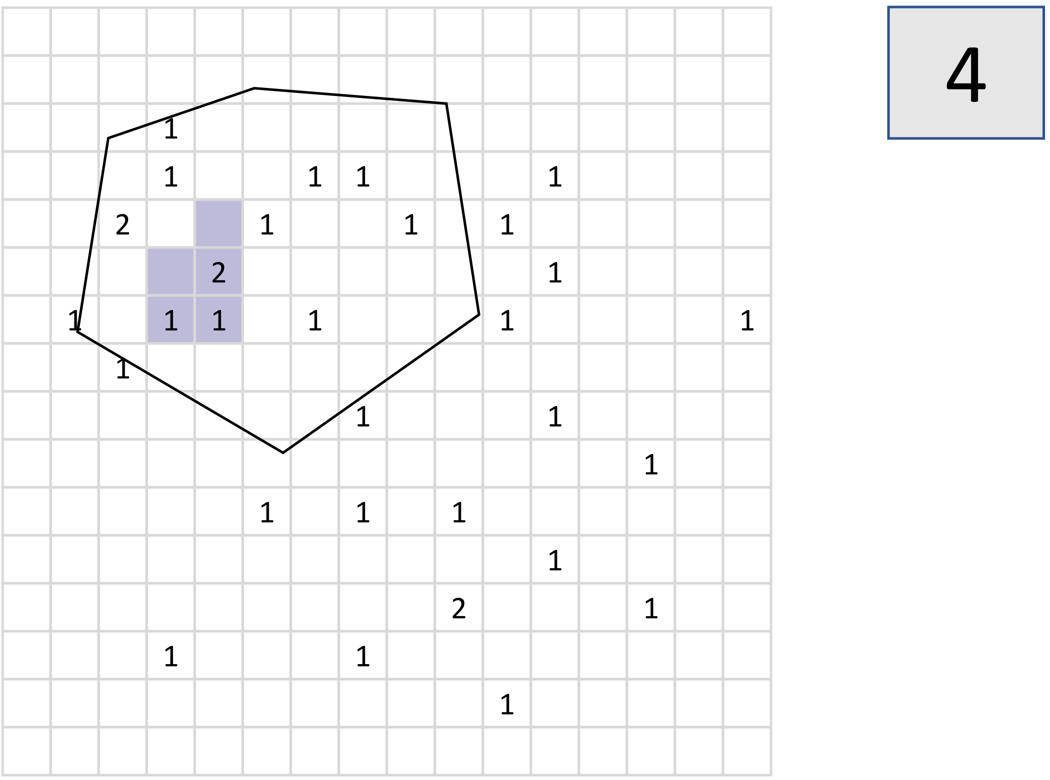




Idea

SELECT COUNT(*)
FROM taxi *T*, neighborhoods *N*
WHERE *T*.pickup INSIDE *N*.geometry
GROUP BY *N*.id

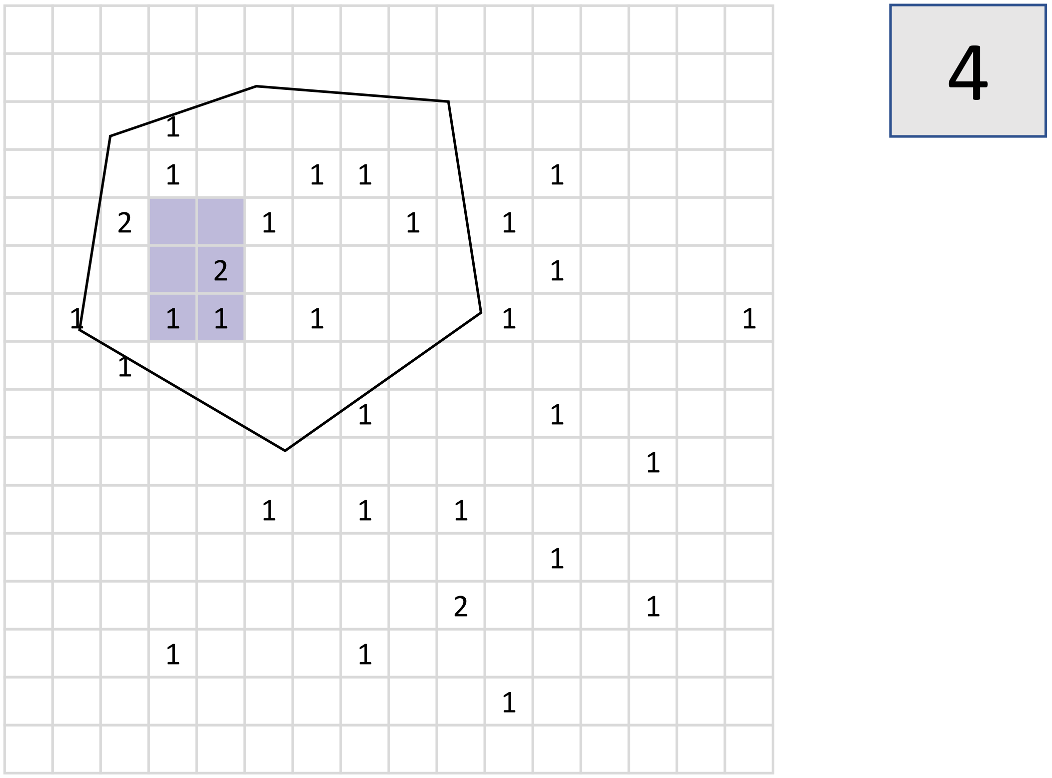
Drawing Polygons



Idea

```
SELECT COUNT(*)
FROM taxi T, neighborhoods N
WHERE T.pickup INSIDE N.geometry
GROUP BY N.id
```

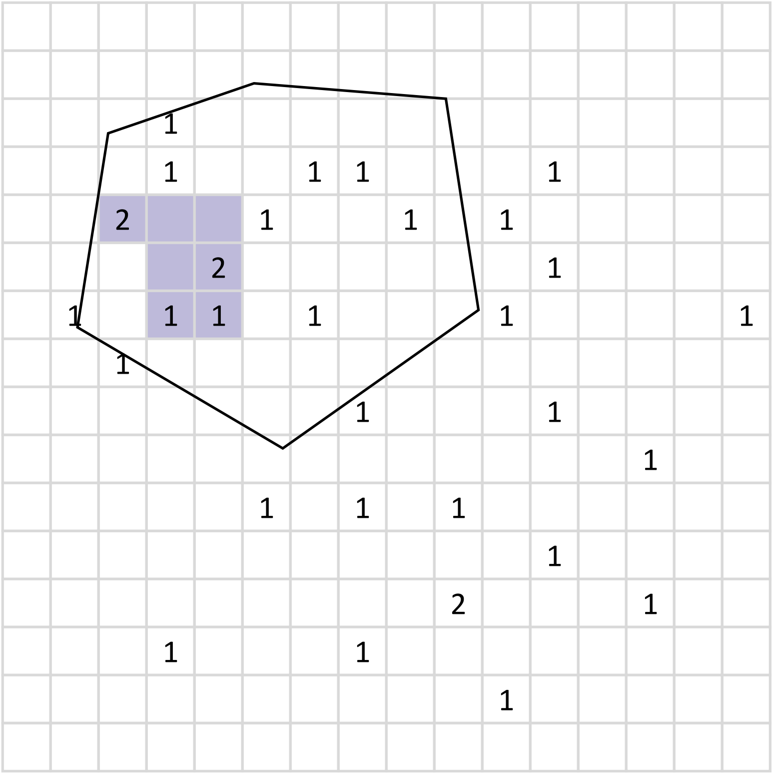
Drawing Polygons



Idea

SELECT COUNT(*)
FROM taxi *T*, neighborhoods *N*
WHERE *T*.pickup INSIDE *N*.geometry
GROUP BY *N*.id

Drawing Polygons

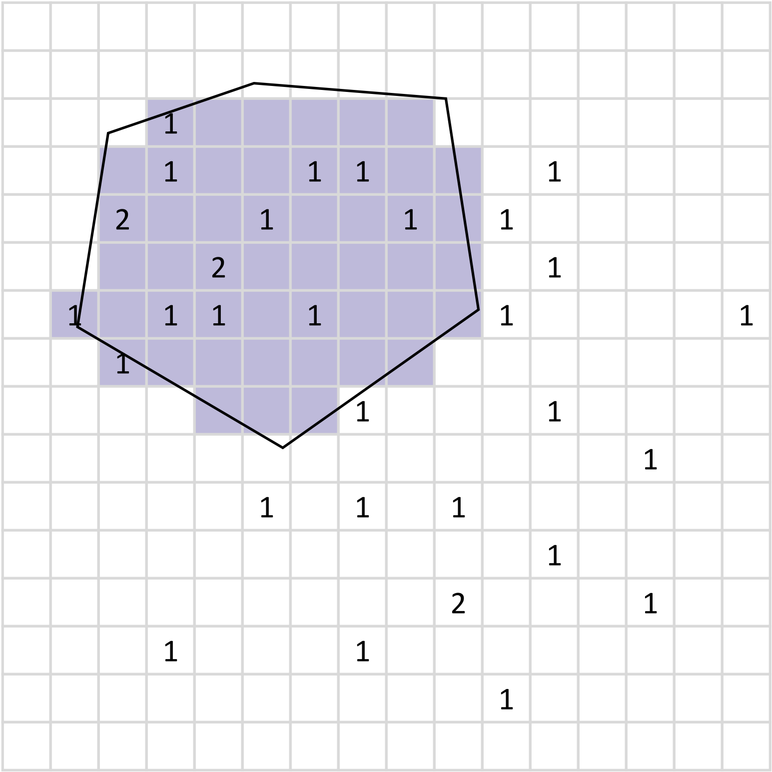


6

Idea

```
SELECT COUNT(*)
FROM taxi T, neighborhoods N
WHERE T.pickup INSIDE N.geometry
GROUP BY N.id
```

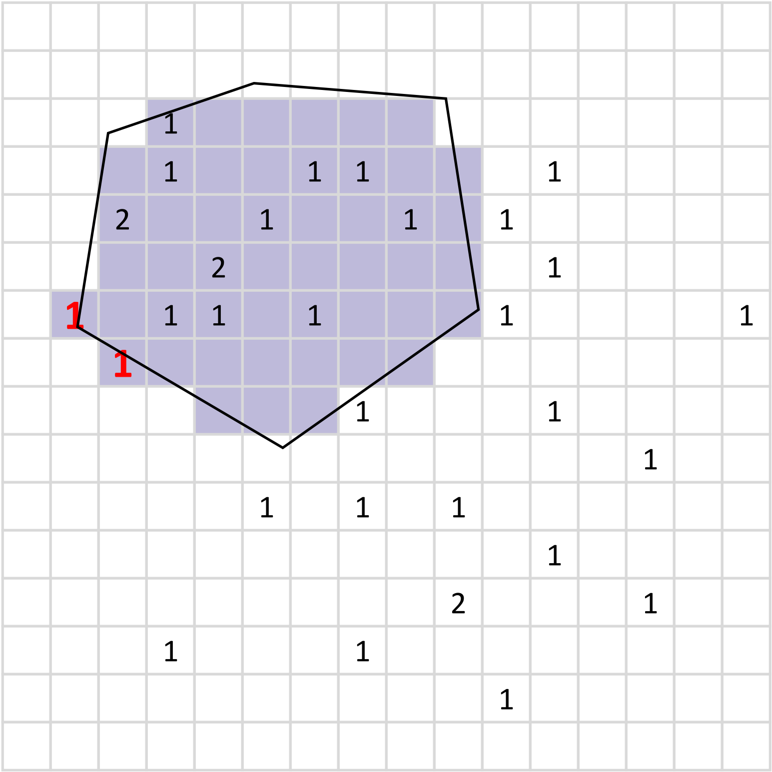
Drawing Polygons



15

Idea

SELECT COUNT(*)
FROM taxi *T*, neighborhoods *N*
WHERE *T*.pickup INSIDE *N*.geometry
GROUP BY *N*.id

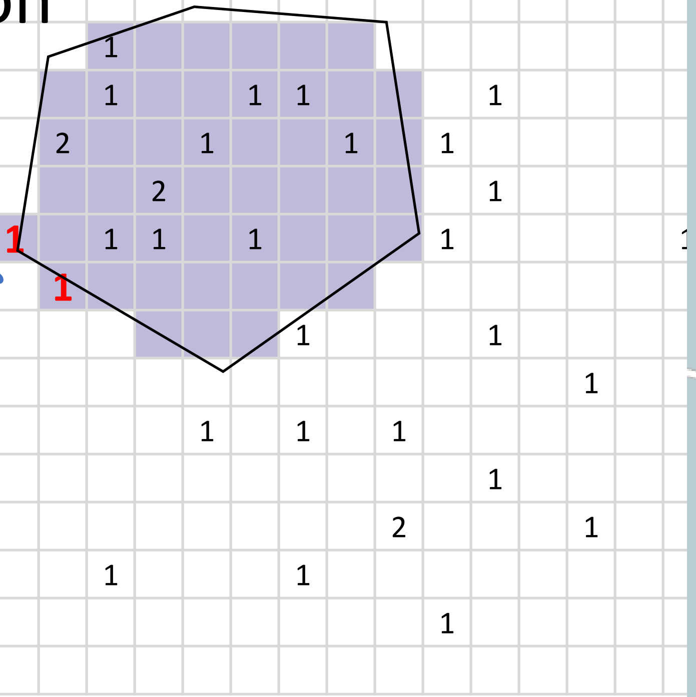


Idea

```
SELECT COUNT(*)
FROM taxi T, neighborhoods N
WHERE T.pickup INSIDE N.geometry
GROUP BY N.id
```

- How to bound the approximation?
- Approximate the Polygon
  - Hausdorff distance

$$H(P_a, P) \leq \varepsilon$$



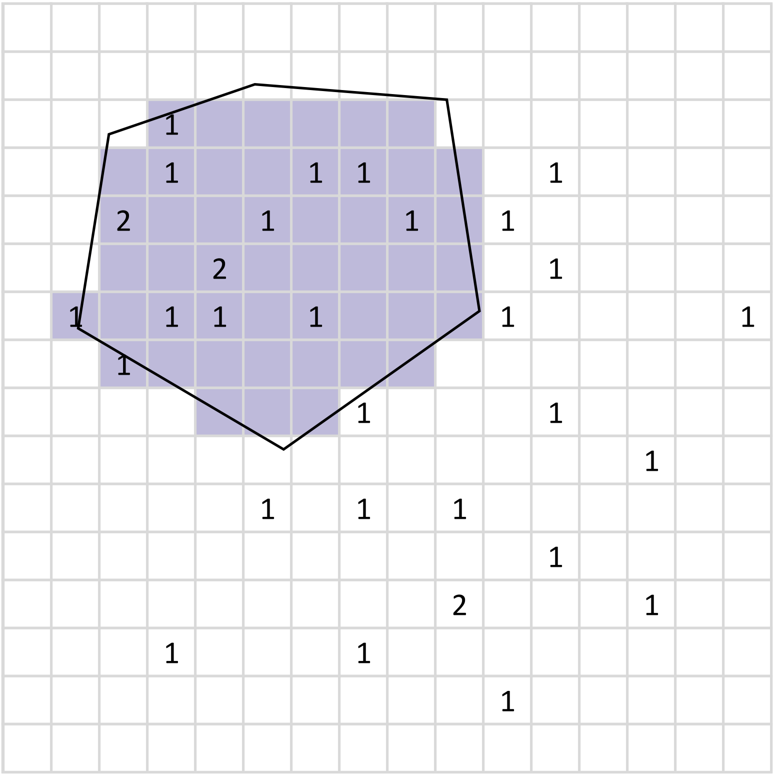
Raster Join

SELECT COUNT(*)
FROM taxi *T*, neighborhoods *N*
WHERE *T*.pickup INSIDE *N*.geometry
GROUP BY *N*.id

- Drawing Points
- Drawing Polygons

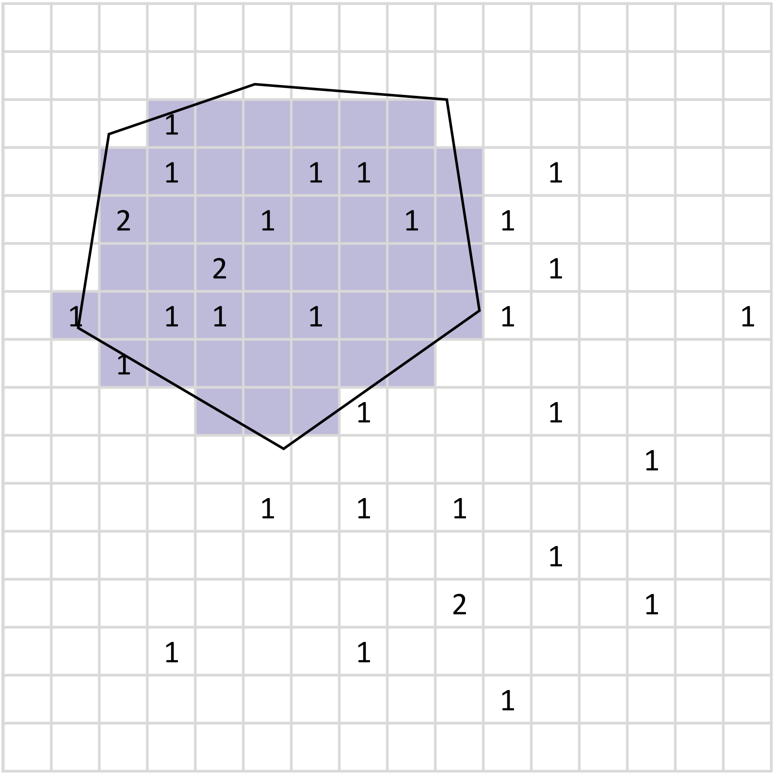
Graphics Pipeline

Rasterization



Accurate Raster Join

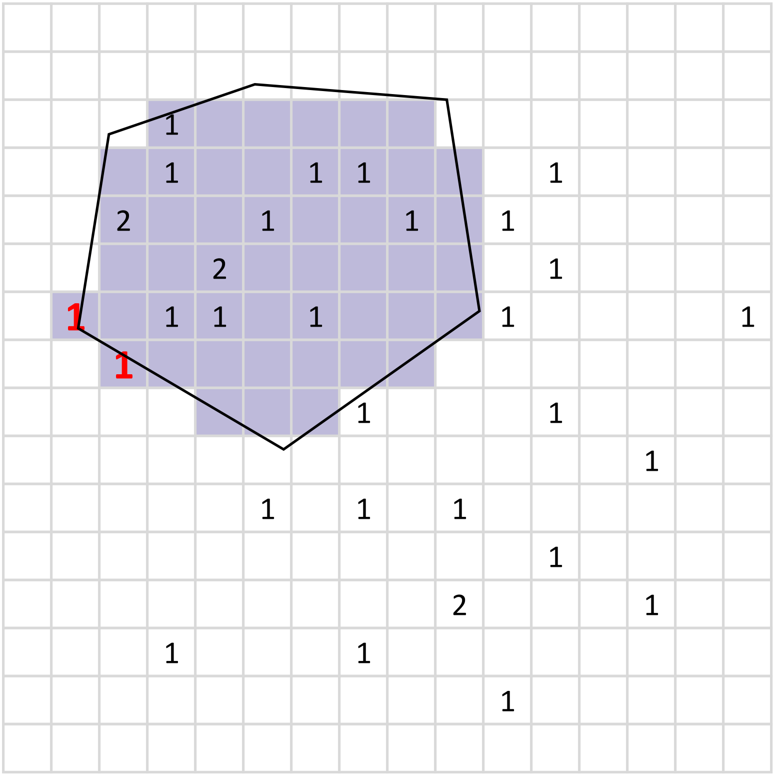
```
SELECT COUNT(*)
FROM taxi T, neighborhoods N
WHERE T.pickup INSIDE N.geometry
GROUP BY N.id
```



Accurate Raster Join

SELECT COUNT(*)
FROM taxi *T*, neighborhoods *N*
WHERE *T*.pickup INSIDE *N*.geometry
GROUP BY *N*.id

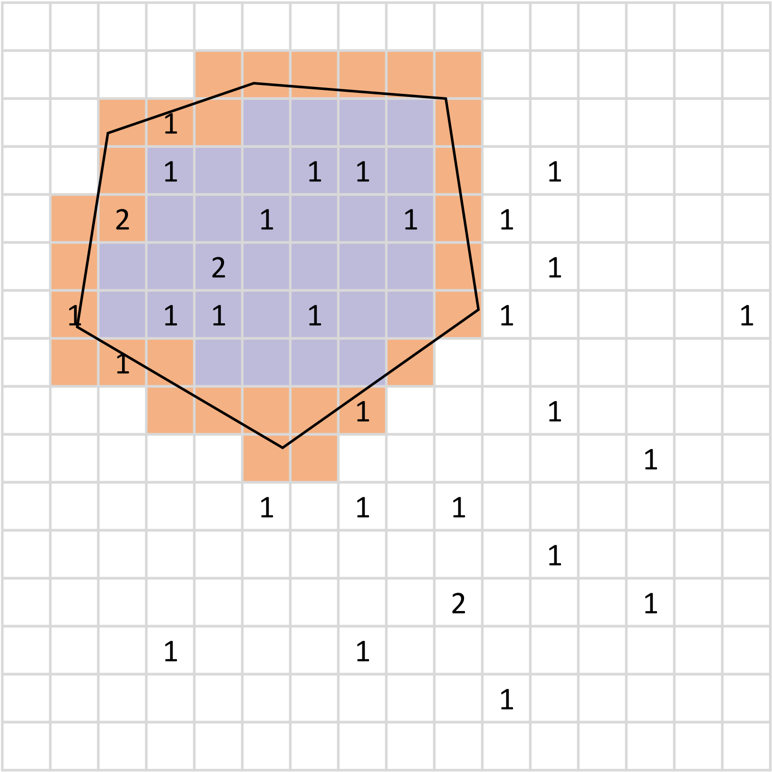
- Error only at boundaries



Accurate Raster Join

SELECT COUNT(*)
FROM taxi *T*, neighborhoods *N*
WHERE *T*.pickup INSIDE *N*.geometry
GROUP BY *N*.id

- Error only at boundaries
- Identify boundaries
- Point-in-polygon test only on points falling on the boundary



Accurate Raster Join

SELECT COUNT(*)
FROM taxi *T*, neighborhoods *N*
WHERE *T*.pickup INSIDE *N*.geometry
GROUP BY *N*.id

- Error only at boundaries
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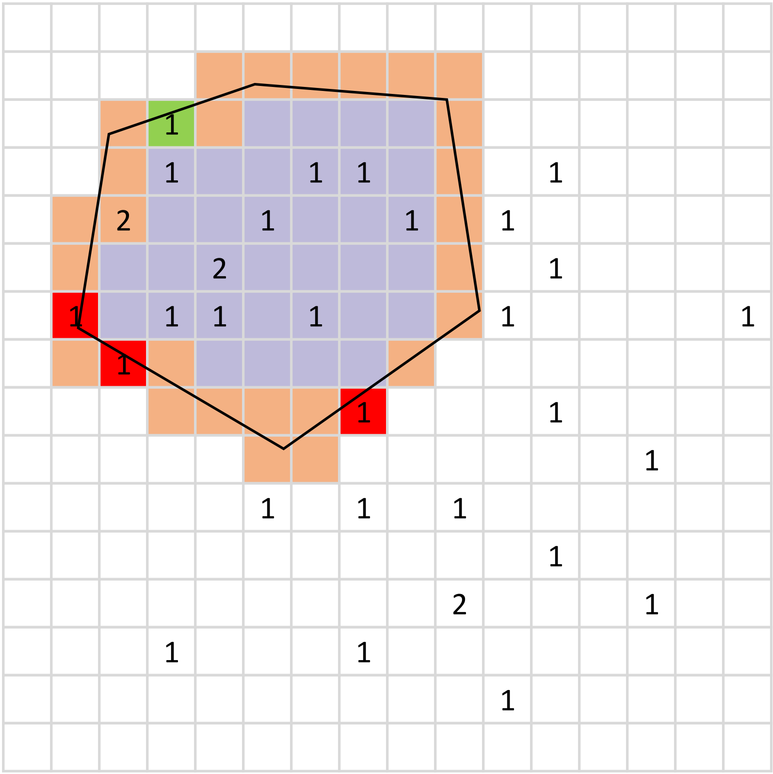
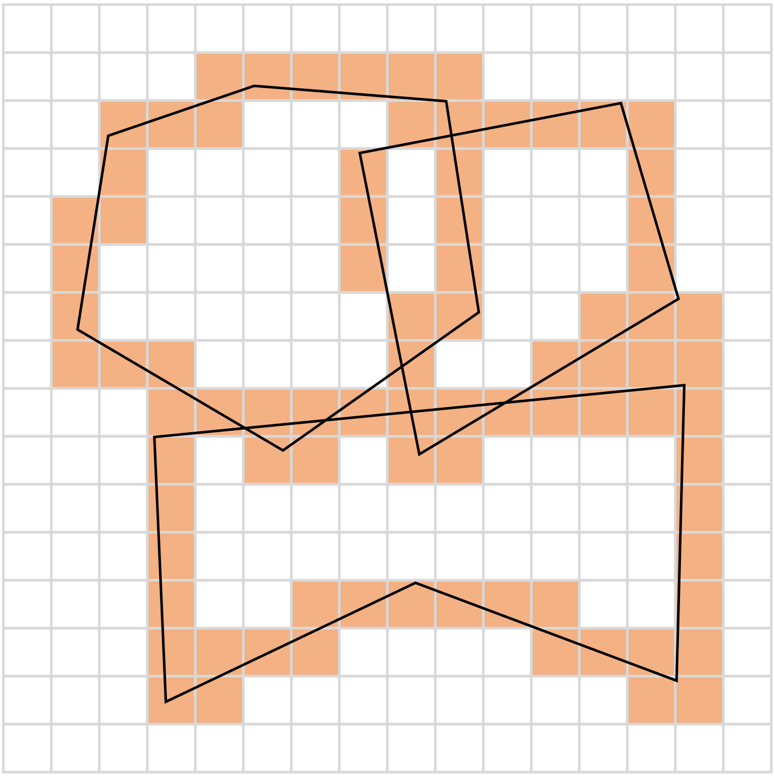


Accurate Raster Join

SELECT COUNT(*)
FROM taxi *T*, neighborhoods *N*
WHERE *T*.pickup INSIDE *N*.geometry
GROUP BY *N*.id

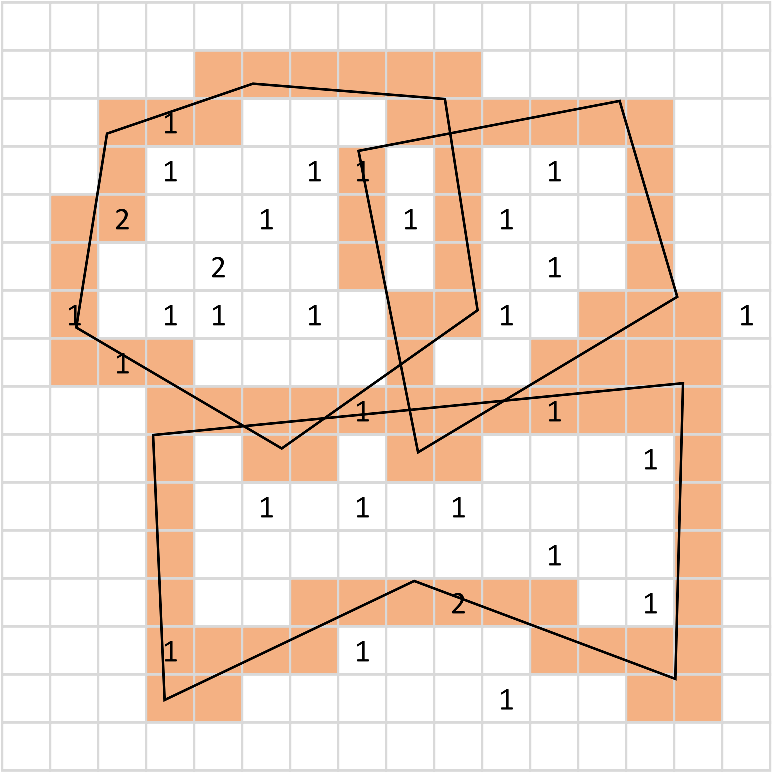
- Draw Polygon Boundaries



SELECT COUNT(*)
FROM taxi *T*, neighborhoods *N*
WHERE *T*.pickup INSIDE *N*.geometry
GROUP BY *N*.id

Accurate Raster Join

- Draw Polygon Boundaries
- Drawing Points
    - Accumulate points not on boundary
    - Point-in-polygon tests for points on boundary

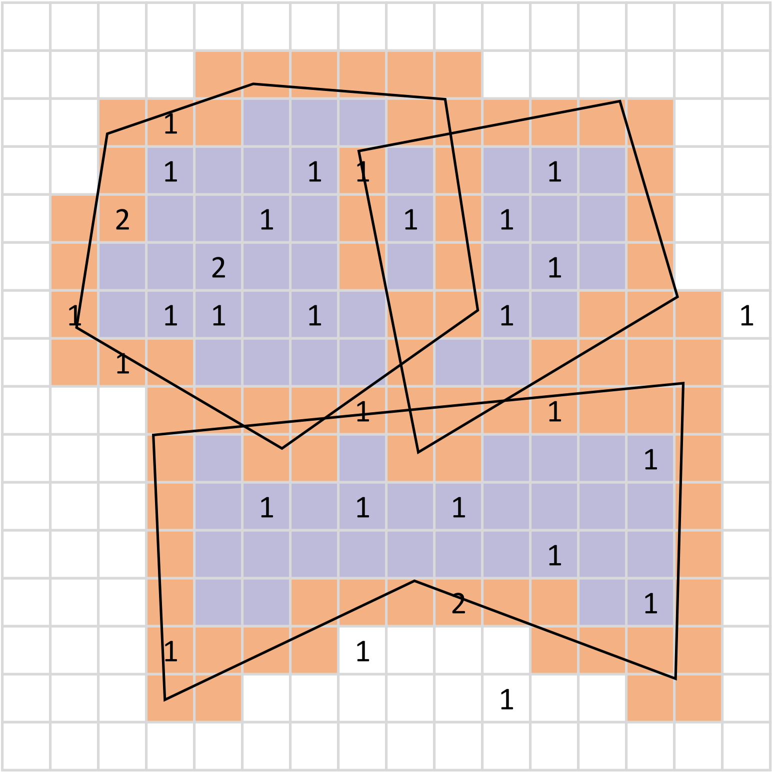


Polygon Index

Accurate Raster Join

```
SELECT COUNT(*)
FROM taxi T, neighborhoods N
WHERE T.pickup INSIDE N.geometry
GROUP BY N.id
```

- Draw Polygon Boundaries
- Drawing Points
  - Accumulate points not on boundary
  - Point-in-polygon tests for points on boundary
- Drawing Polygons



Raster Join: Experiments

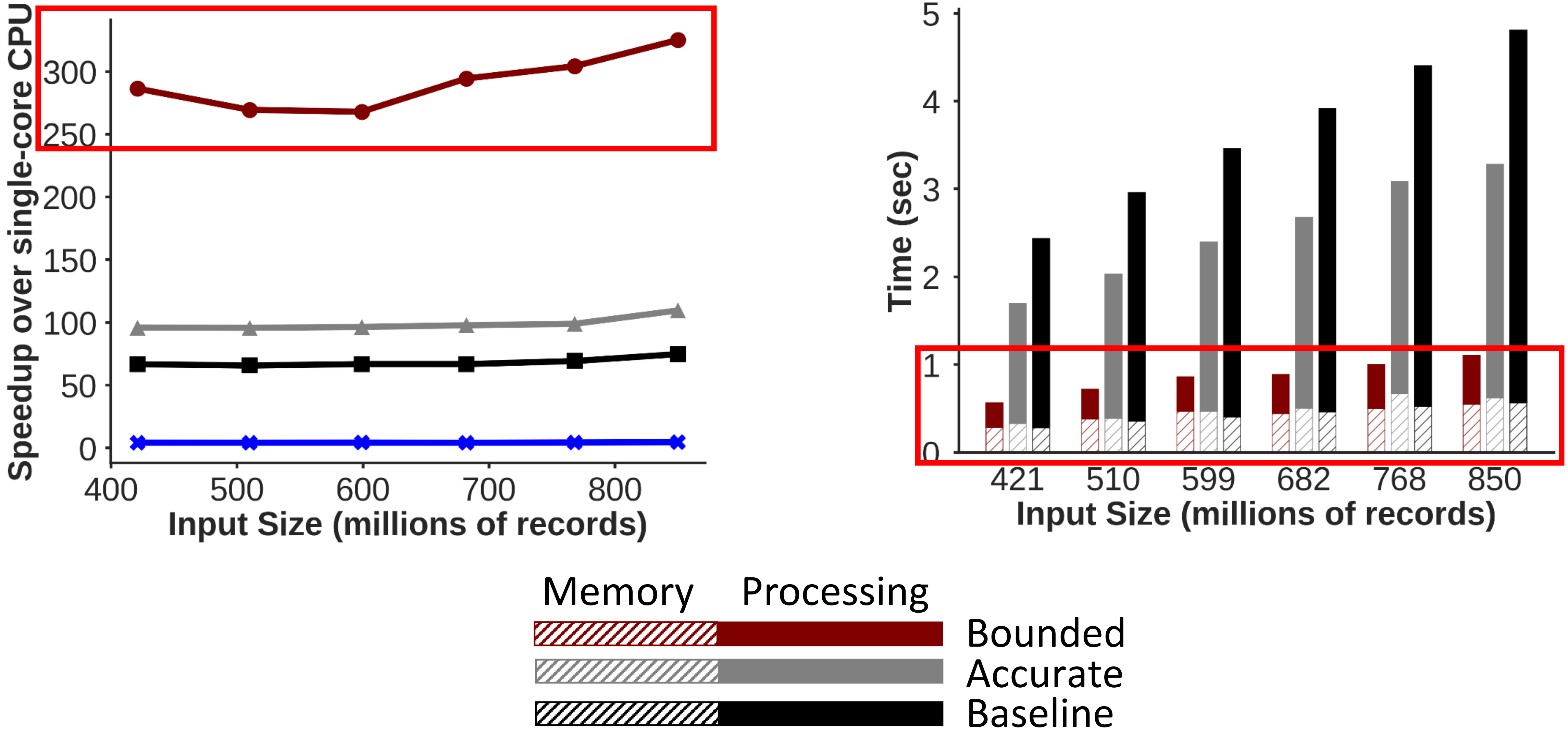
SELECT COUNT(*)
FROM taxi *T*, neighborhoods *N*
WHERE *T*.pickup INSIDE *N*.geometry
GROUP BY *N*.id

- OpenGL implementation
- NYC Taxi Data
  - > 800 million trips
- NYC Neighborhoods
  - 260 Polygons
- This laptop
  - Intel Core i7 @ 2.60 GHz
  - 16 GB RAM
  - NVIDIA GTX 1060 (Mobile)

https://github.com/ViDA-NYU/raster-join

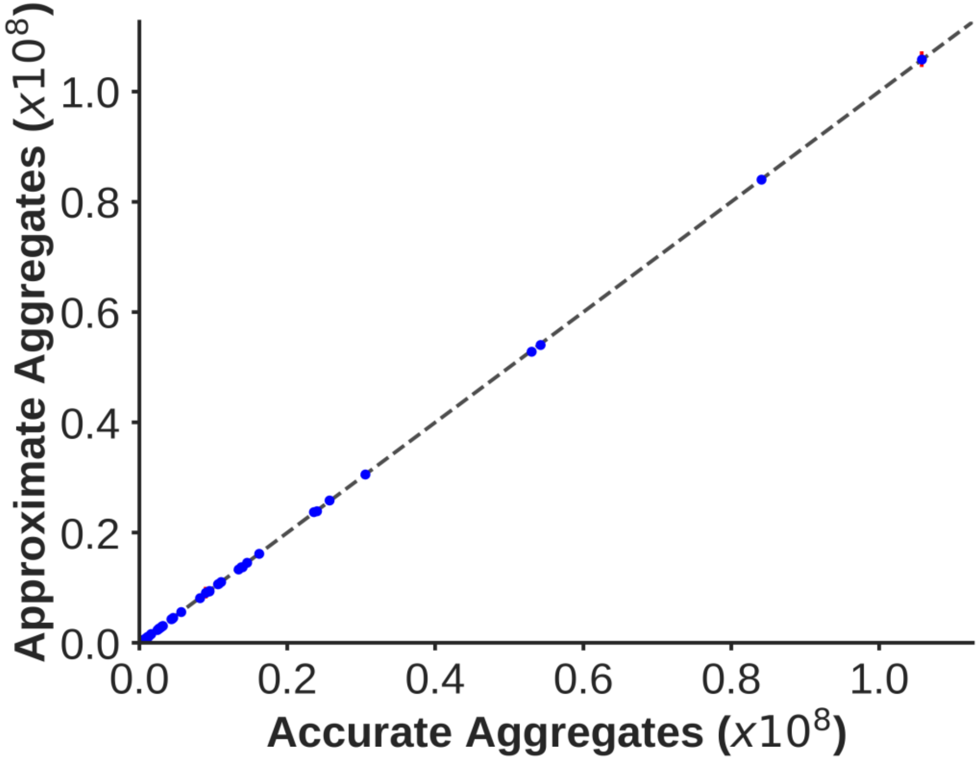
Raster Join: Performance

```
SELECT COUNT(*)
FROM taxi T, neighborhoods N
WHERE T.pickup INSIDE N.geometry
GROUP BY N.id
```

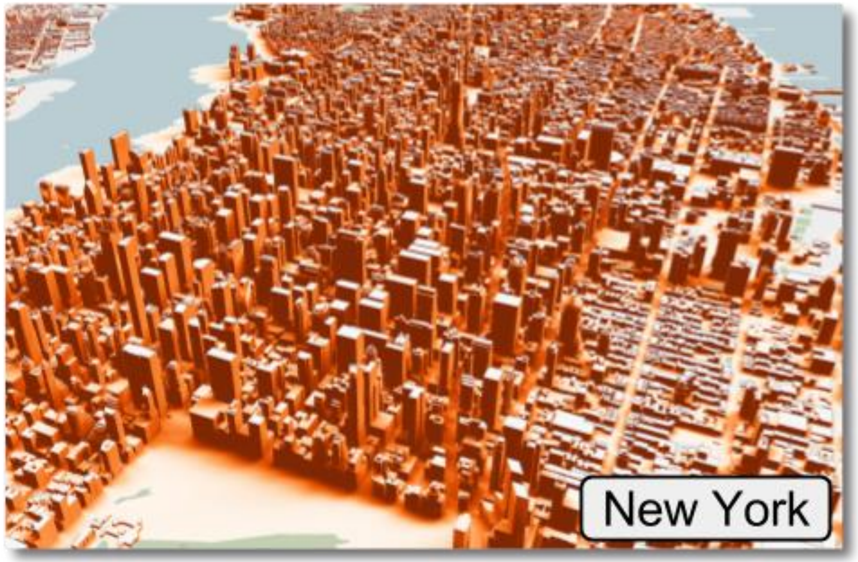


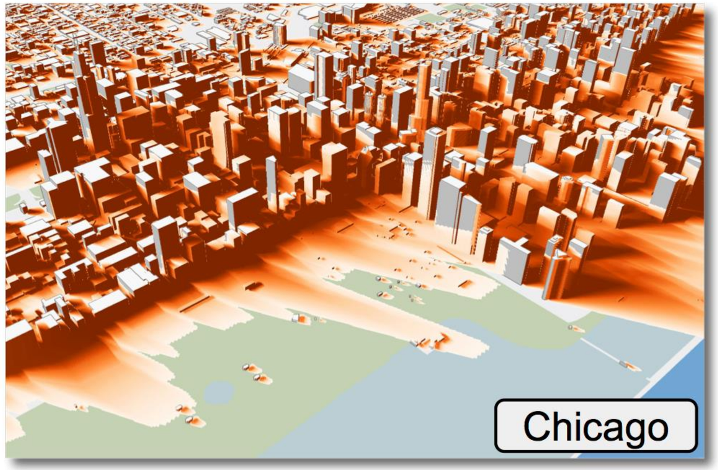
Raster Join: Accuracy

```
SELECT COUNT(*)
FROM taxi T, neighborhoods N
WHERE T.pickup INSIDE N.geometry
GROUP BY N.id
```



Mapping the Shadows of a City





Shadow Accrual Maps: Efficient Accumulation of City-Scale Shadows over Time
Fabio Miranda, Harish Doraiswamy, Marcos Lage, Luc Wilson, Mondrian Hsieh, Claudio Silva
IEEE Transactions on Visualization and Computer Graphics, 25(3), 2019, 1559-1574

Direct Sunlight and Shadows

Plant Physiol Biochem. 2012 Dec;61:187-96. doi: 10.1016/j.plaphy.2012.10.005. Epub 2012 Oc

Effects of s
Pall.).

Zhao D[1], Hao Z, T

Author infor

Abstract

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PMID: 2314

Light Exposure and Shade Effects on Growth, Flowering, and Leaf Morpholog of *Spiraea alba* Du Roi and *Spiraea tomentosa* L

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Nature **31**, 324-326 (05 February 1885) | doi:10.1038/031324b0

The Influence of Direct Sunlight on Vegetatic

M. BUYSMAN

THE influence of direct sunlight on vegetation is generally but surely deserves to be a subject of special study. In the paper we shall only endeavour to describe some facts with influence. In the first place, the effect of the sun's rays in regions will be traced, and afterwards in the temperate ar The constant high temperature within the tropics is the ca plants being less dependent on the direct solar heat than the greater part of the temperate and cold zones, but, not this, there are plants even in the tropical regions requiring growth the direct rays of the sun.

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Amazon rainforests green-up with sunlight in dry season

Alfredo R. Huete, Kamel Didan, Yosio E. Shimabukuro, Piyachat Ratana, Scott R. Saleska, Lucy R. Hutyra, Wenze Yang, Ramakrishna R. Nemani, Ranga Myneni

First published: 22 March 2006 Full publication history

DOI: 10.1029/2005GL025583 View/save citation

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Am score 3

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Volume 33, Issue 6
March 2006

Abstract

[1] Metabolism and phenology of Amazon rainforests significantly influence global dynamics of climate, carbon and water, but remain poorly understood. We analyzed Amazon vegetation phenology at multiple scales with Moderate Resolution Imaging Spectroradiometer (MODIS) satellite measurements from 2000 to 2005. MODIS Enhanced Vegetation Index (EVI, an index of canopy photosynthetic capacity) increased by 25% with sunlight during the dry season across Amazon forests, opposite to ecosystem model predictions that water limitation should cause dry season declines in forest canopy photosynthesis. In contrast to intact forests, areas converted to pasture showed dry-season declines in EVI-derived photosynthetic capacity, presumably because removal of deep-rooted forest trees reduced access to deep soil water. Local canopy photosynthesis measured from eddy flux towers in both a rainforest and forest conversion site

Direct Sunlight and Shadows

[Source: New York Times]

Direct Sunlight and Shadows

Shadows

Chapter 8

Within urban environments, the structures constituting the city's built fabric constantly c
ate vicinity. As the city develops and redevelops, the extent and duration of the shadows
cess continues, direct sunlight exposure becomes an increasingly scarce resource for peo
focuses on the interaction between proposed new and altered structures and the shad
space, historic and cultural resources, and natural areas.

Sunlight and shadows affect people and their use of open space all day long and througho
fects vary by season. Sunlight can entice outdoor activities, support vegetation, and enl
such as stained glass windows and carved detail on historic structures. Conversely, shadow
and sustainability of natural features and the architectural significance of built features.

The purpose of this chapter is to assess whether new structures may cast shadows o
accessible resources or other resources of concern such as natural resources, and to asses
pact. Potential mitigation strategies and alternatives are also presented and should be ex
verse shadow impacts are identified. Because of the sunlight-sensitive nature of many ope
al resources, and natural resources, this chapter is closely linked to the data and anal
Space," Chapter 9, "Historic and Cultural Resources," and Chapter 11, "Natural Resources."

The majority of projects subject to CEQR do not require a detailed shadow analysis. Sectio
of analysis to screen most projects for the purpose of assessing shadow impacts. As with
under CEQR, it is important for an applicant to work closely with the lead agency during
view process. The lead agency may determine that it is appropriate to consult or coor
technical agencies for a particular project. The New York City Department of City Plannir
for information, technical review, and recommendations relating to shadows. With regar
City Landmarks Preservation Commission (LPC), the New York City Department of Environ

City Environmental Quality Review Technical Ma

Ancient lights

LAW

WRITTEN BY: The Editors of Encyclopædia Britannica
LAST UPDATED: 9-12-2008 See Article History

Ancient lights, in English property law, the right of a building or house owner to the light received from and through his windows. Windows used for light by an owner for 20 years or more could not be obstructed by the erection of an edifice or by any other act by an adjacent landowner. This rule of law originated in England in 1663, based on the theory that a landowner acquired an easement to the light by virtue of his use of the windows for that purpose for the statutory length of time. The doctrine did not acquire wide acceptance by courts in the United States.

Ancient lights signs below windows in Clerkenwell, London.
Mike Newman

Boston developer wants exception to shadow law

Tall order is sought for tower pr

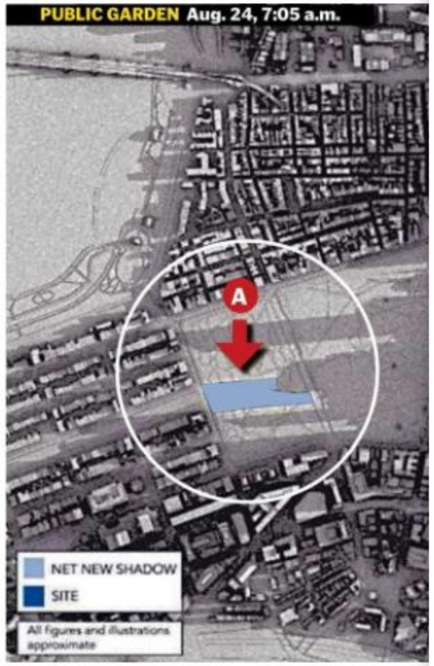
Donna Goodison Monday, April 10, 2017

Credit: COURTESY RENDERING

TOWER OF POTENTIAL: City officials say an exemption from two
new development is necessary to bring in $153 million. (ARTIST

SHIRLEY LEUNG

Shadow debate shows how d



This simulation released by developer Millennium Partners shows the shadows that its proposed tower w on the Public Garden (arrow A) during one portion of the year.

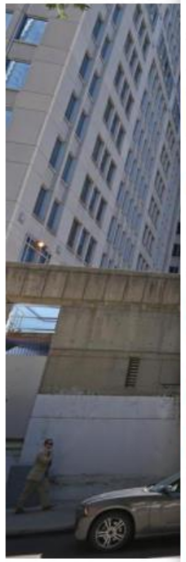
By Shirley Leung | GLOBE STAFF APRIL 25, 2017

It was as close as we would get to a mea culpa from city planning and development czar Bri Golden on Shadowgate.

"Look, this isn't the way we wanted it," Golden told me after being grilled by the Boston City Council Monday about changing two-decade-old laws that limit shadows on the Public Garden and Boston Common.

DANTE RAMOS

The absurdity of the Boston Common shadow debate



The Winthrop Square Ga

By Dante Ramos | A

I DON'T KNOW HOV
Common is ridiculous

At earlier points in ou

Boston City Council votes in favor of changing 'shadow' law

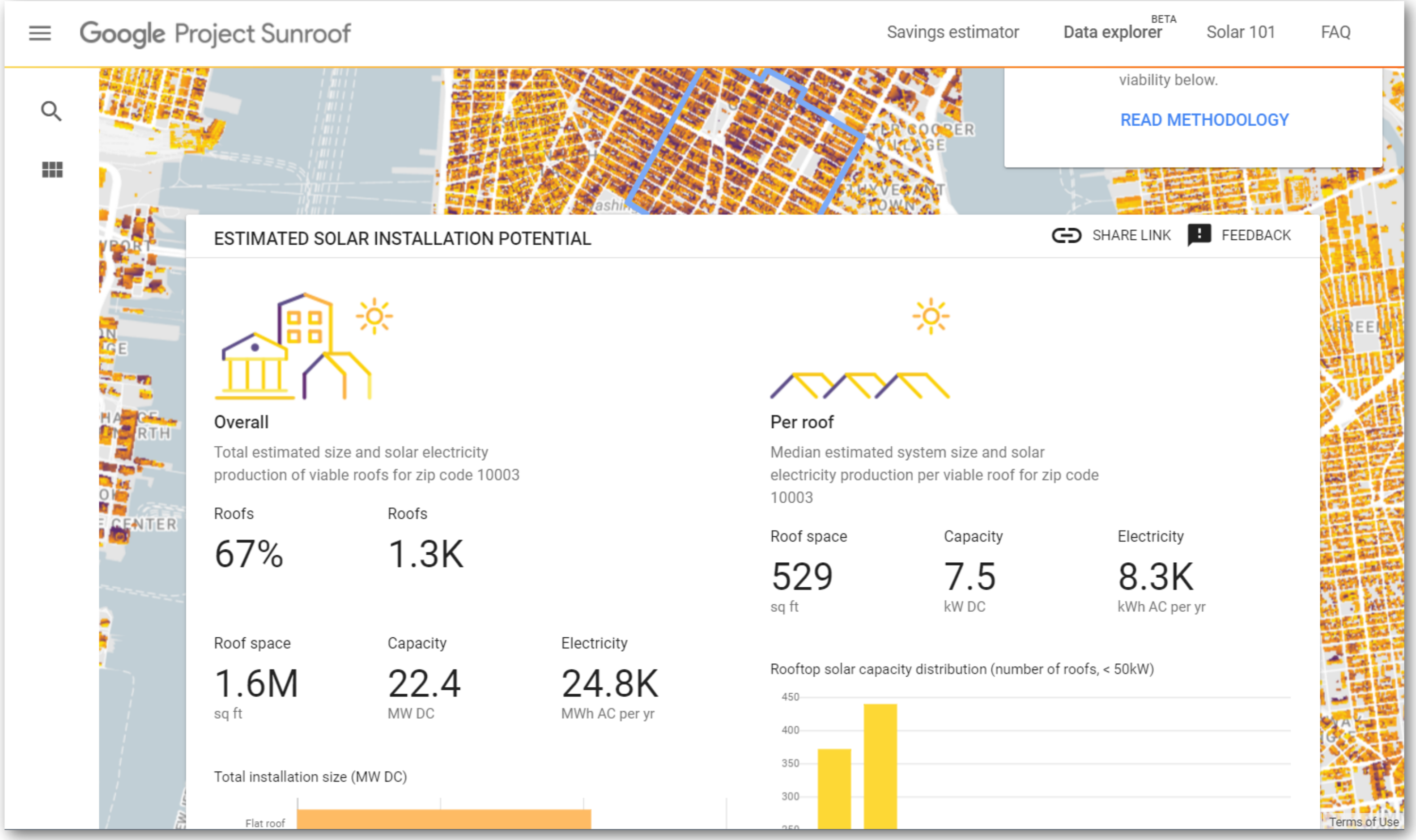
Council backs shade

Dan Atkinson Thursday, April 27, 2017

Credit: Stuart Cahill

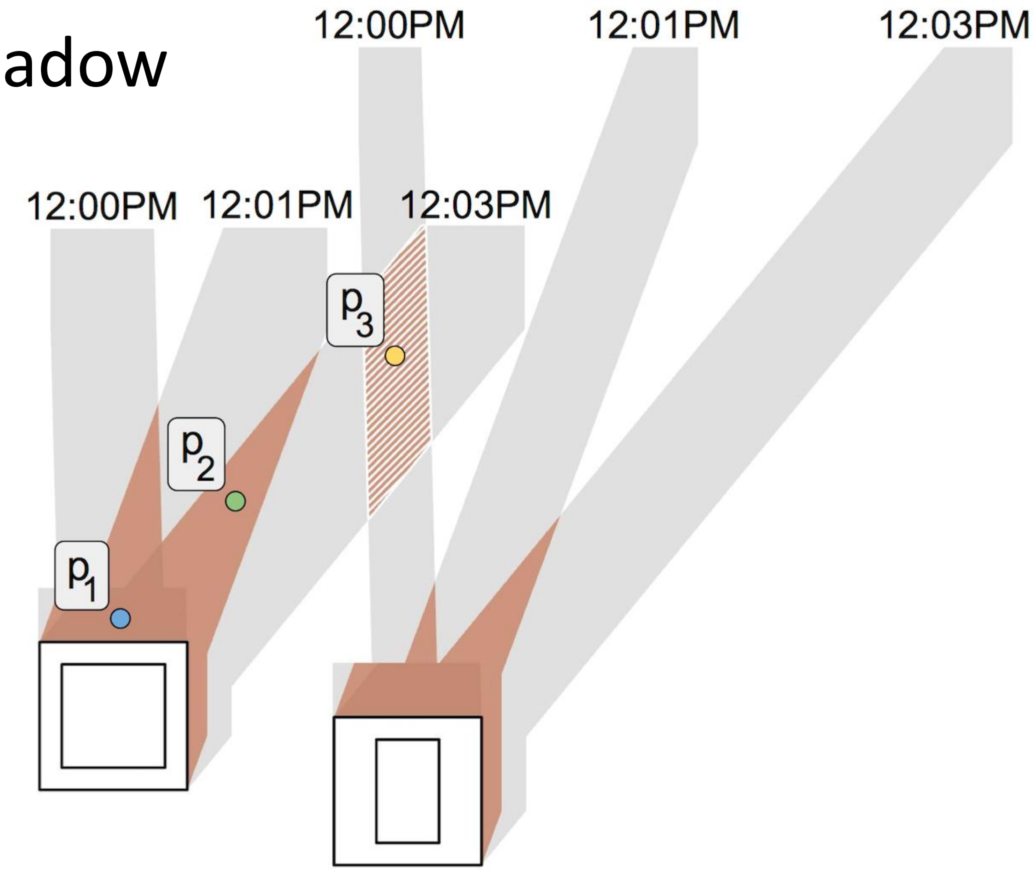
The Winthrop Square parking garage at 240 Devonshire St. Wednesday, April 26, 2017. (Staff photo by Stuart Cahill)

Direct Sunlight and Shadows



Shadow Accumulation

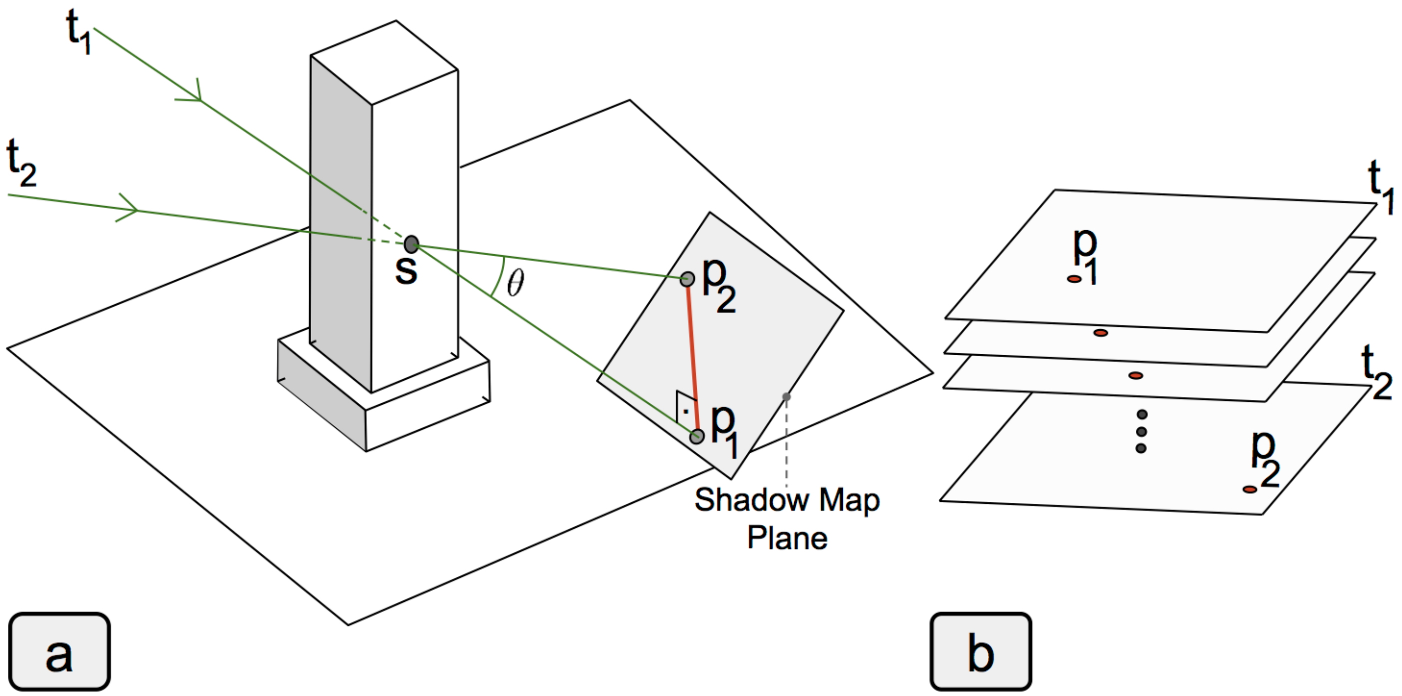
- Amount of time a given point is in shadow
- Depends on the sun position (day of the year)
- Existing techniques
  - Compute shadow for every time step
  - Expensive



Shadow Accumulation

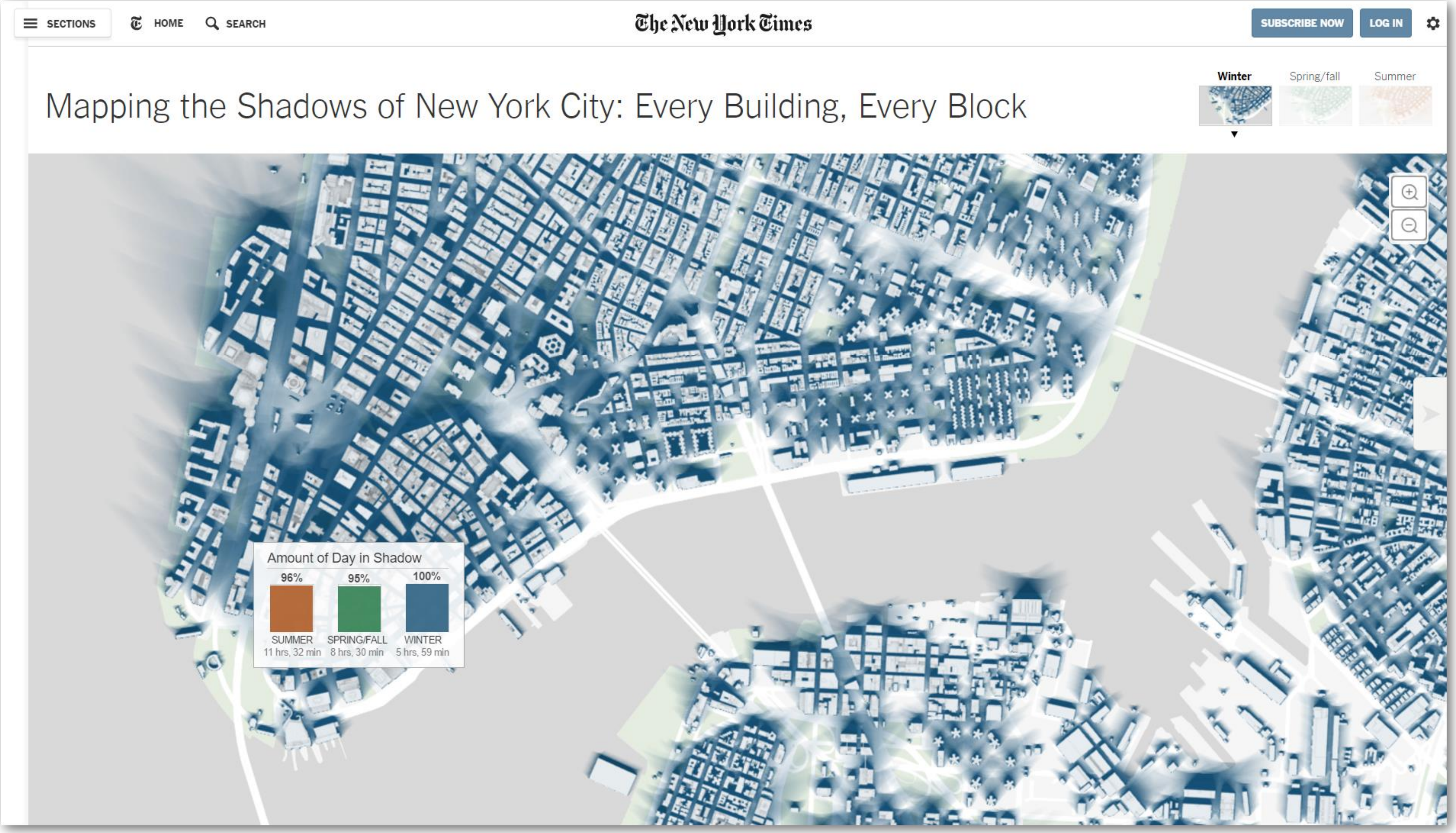
Efficient

70X Speedup



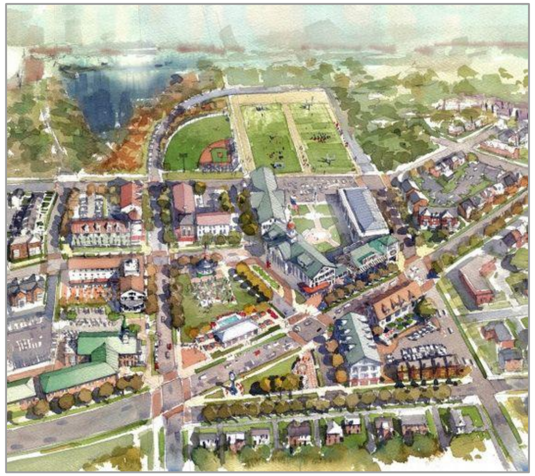
Shadow Accrual Maps

Shadows profiler



https://www.nytimes.com/interactive/2016/12/21/upshot/Mapping-the-Shadows-of-New-York-City.html

Scales of the city



macro

Suburbanization
Transport infrastructure
Population density

meso

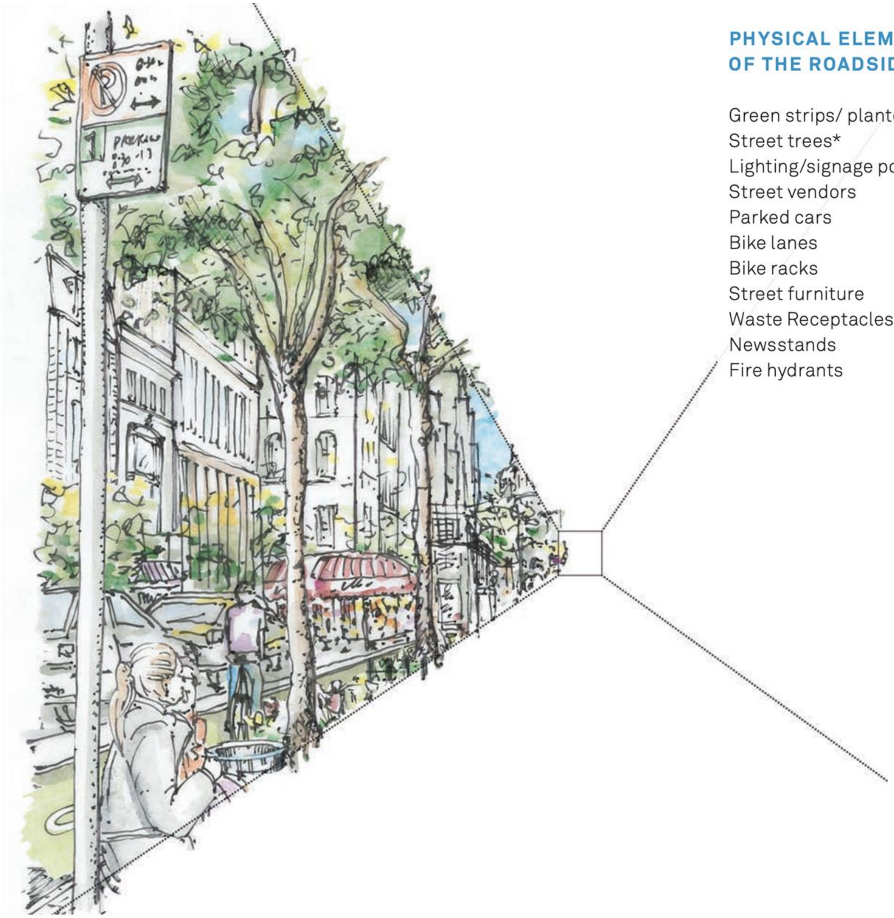
Access to amenities
Green space
Street width

micro

Open-front buildings
Building facades
Sidewalk

City at the micro scale

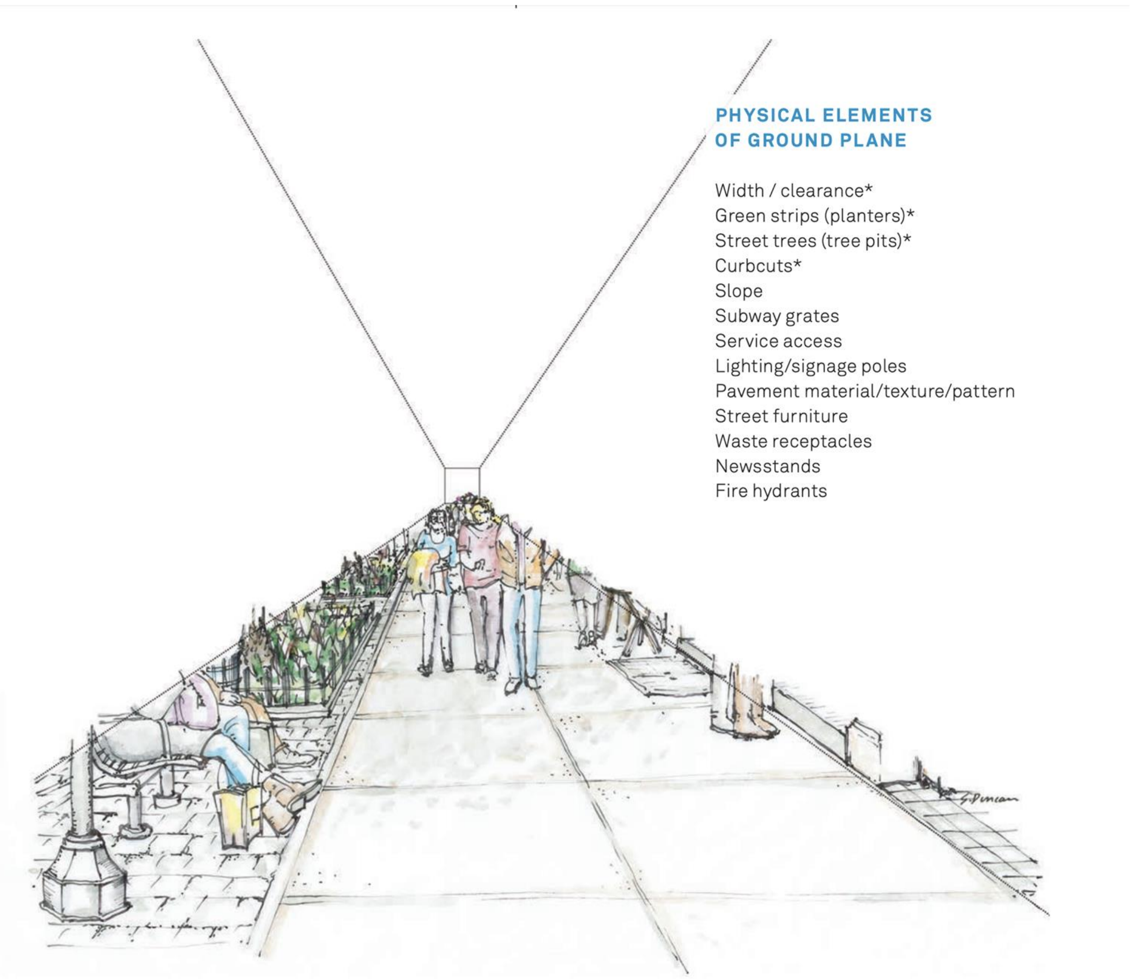
City at the micro scale



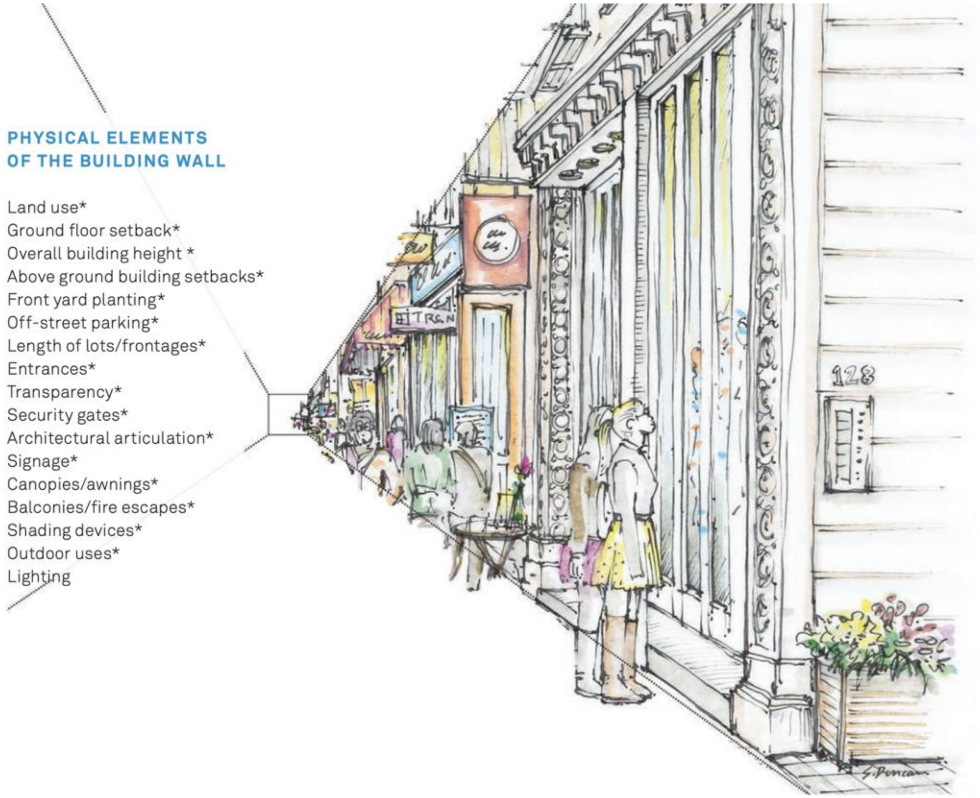
PHYSICAL ELEMENTS OF THE ROADSIDE PLANE

Green strips/ planters/ tree pits*
Street trees*
Lighting/signage poles
Street vendors
Parked cars
Bike lanes
Bike racks
Street furniture
Waste Receptacles
Newsstands
Fire hydrants

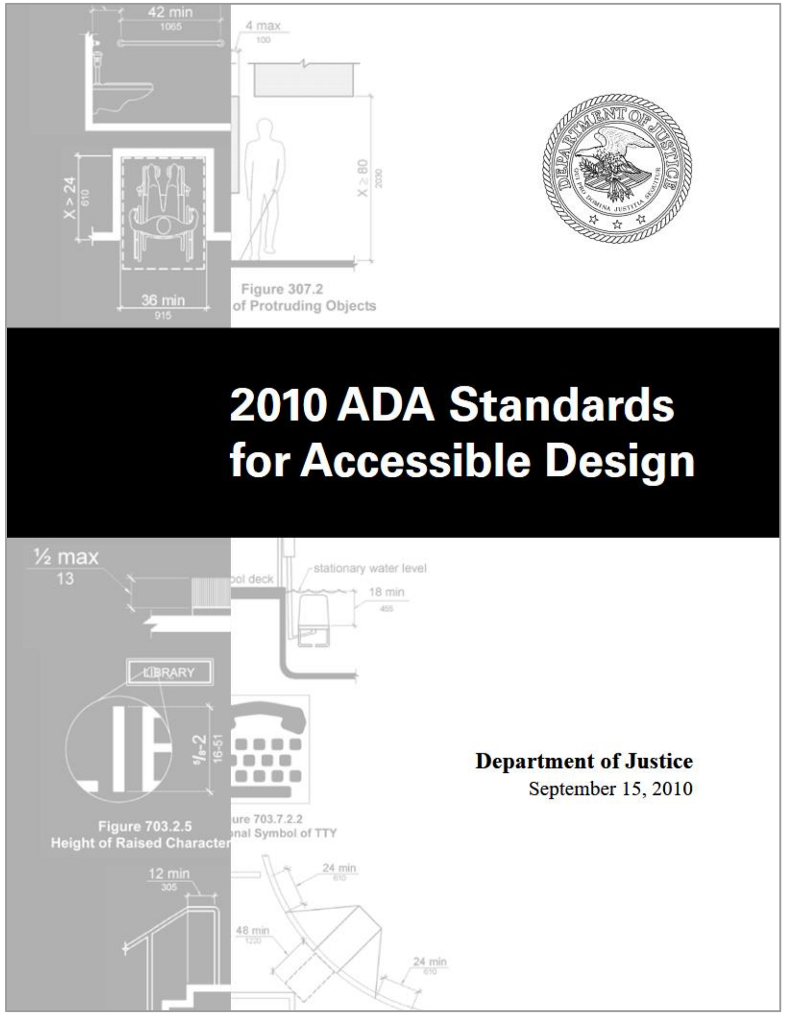
City at the micro scale



City at the micro scale



City at the micro scale

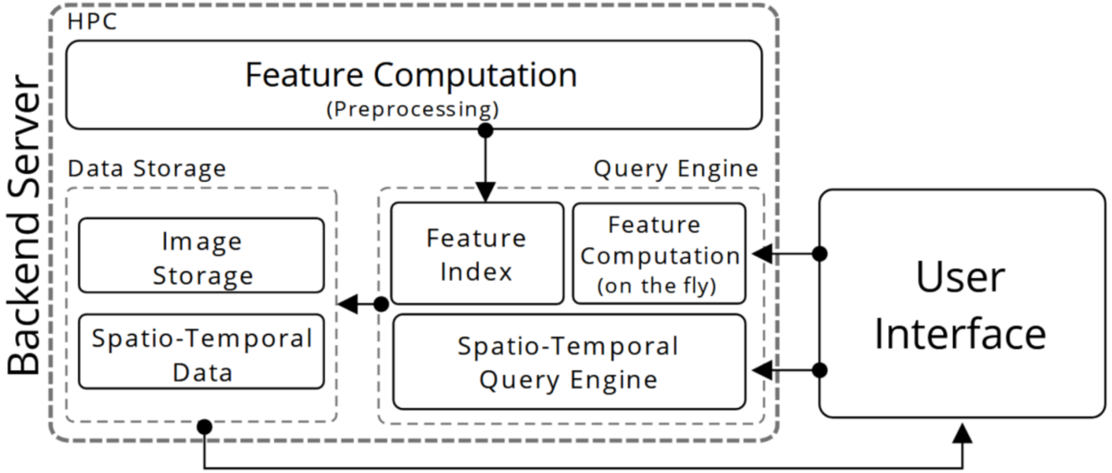


“Newly constructed or altered streets, roads, and highways must contains curb ramps or other sloped areas at intersections to streets, roads, or highways.”

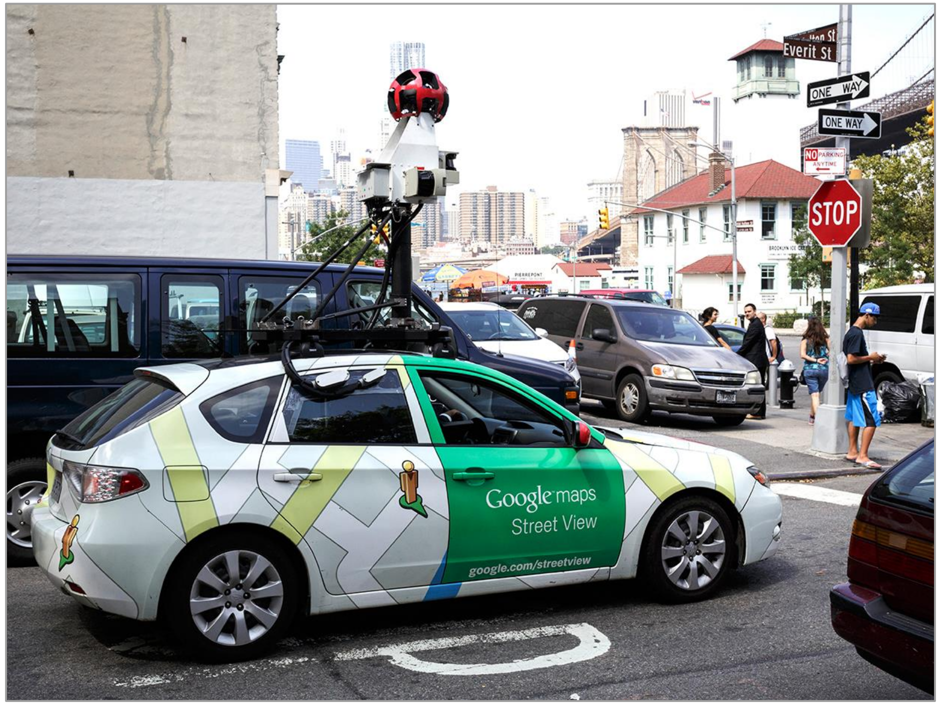
Urban Mosaic: Visual Exploration of Streetscapes Using Large-Scale Image Data
Fabio Miranda, Maryam Hosseini, Marcos Lage, Harish Doraiswamy, Graham Dove, Claudio Silva
CHI'20: Proc. SIGCHI Conf. on Human Factors in Computing, 2020, to appear

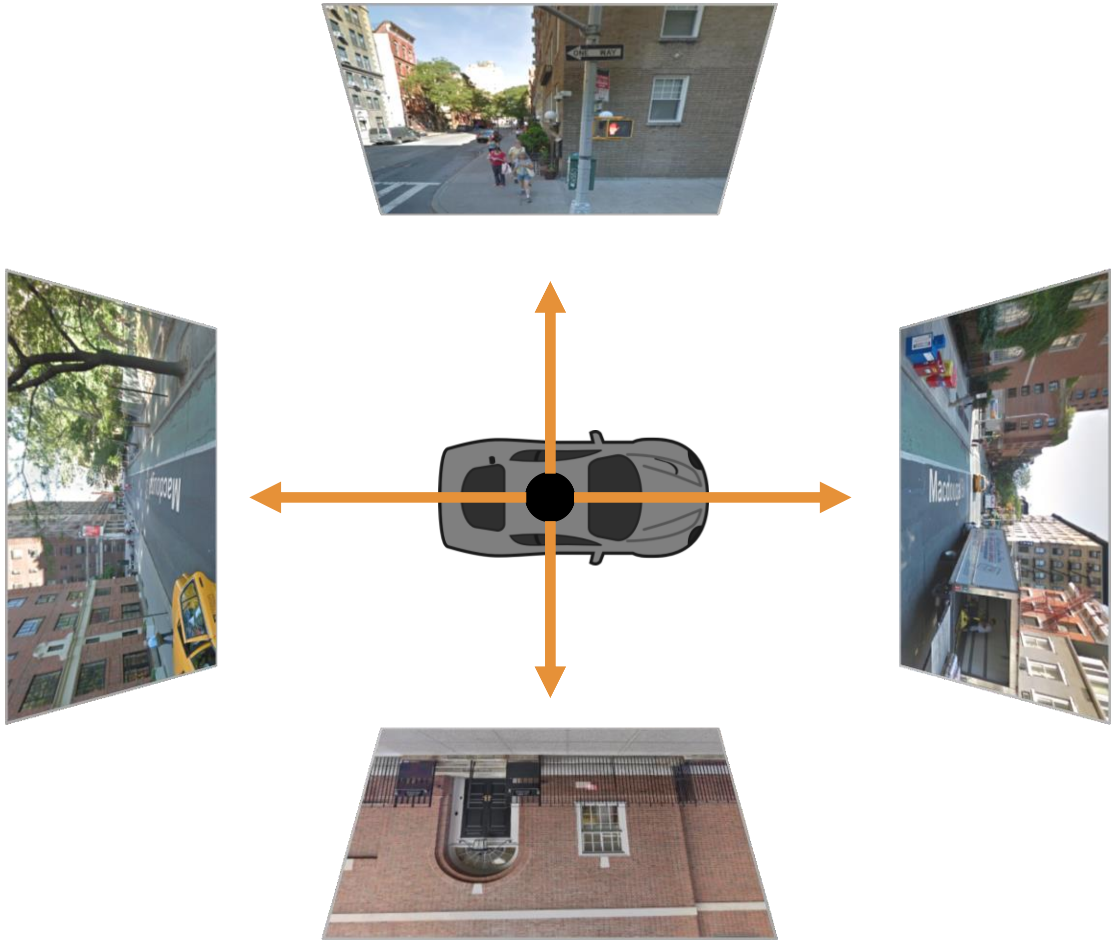
Urban Mosaic

- A tool for the exploration of the urban fabric
- Visual comparison of geographically distant areas
- Temporal analysis of unfolding urban developments

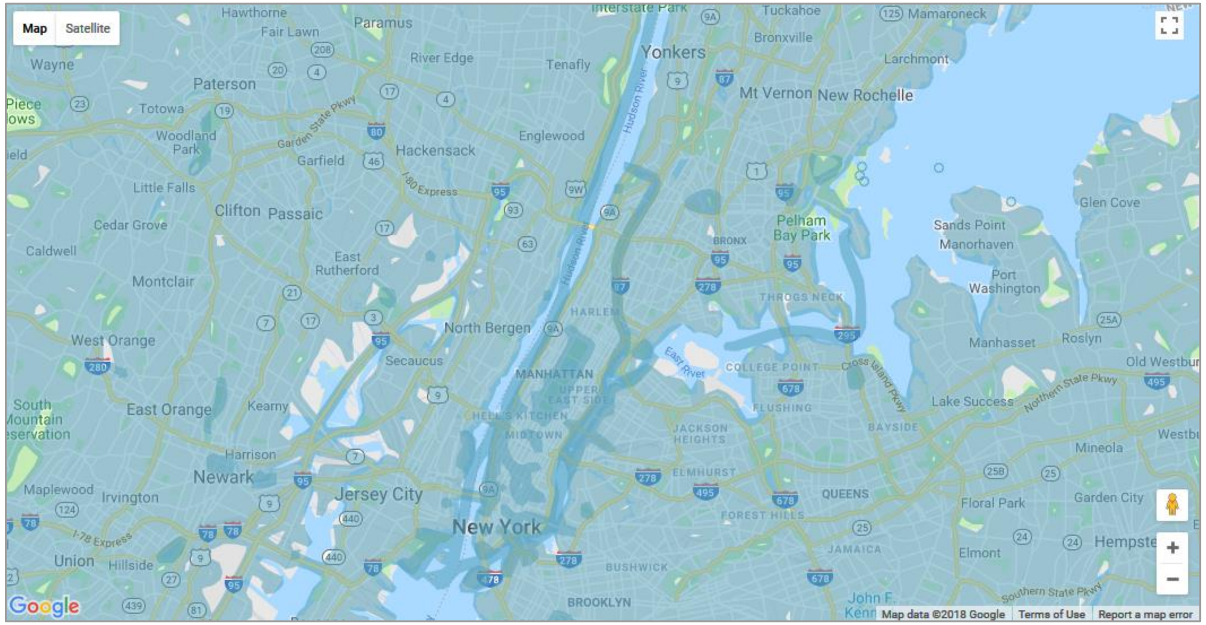


Street-level Images





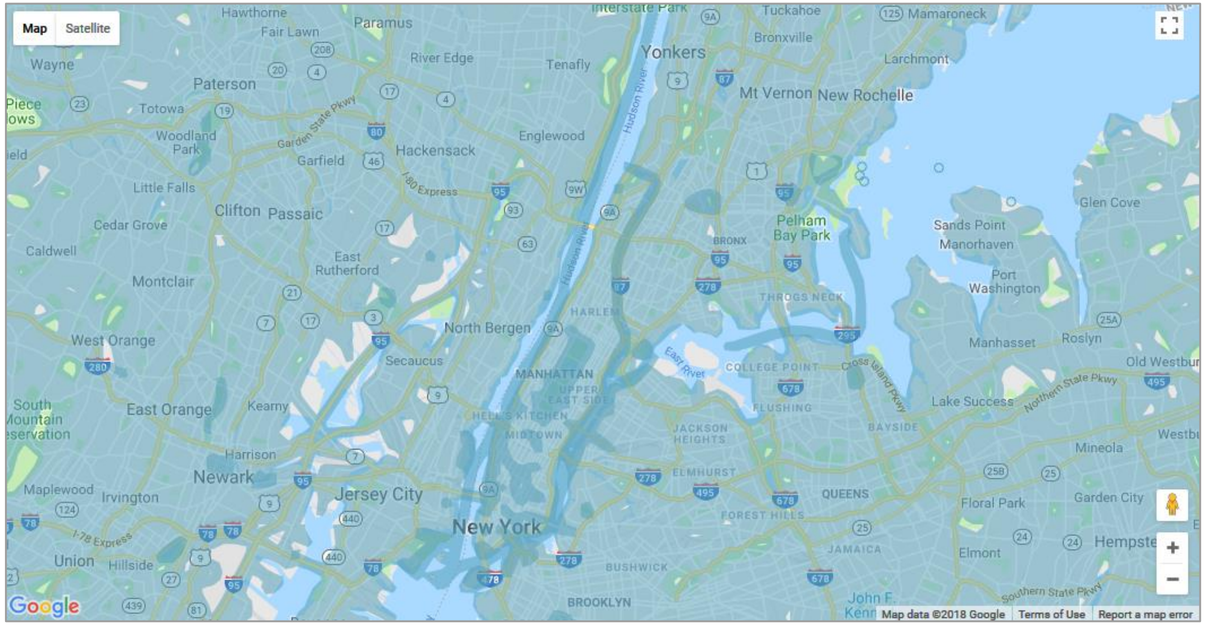
Google Street View



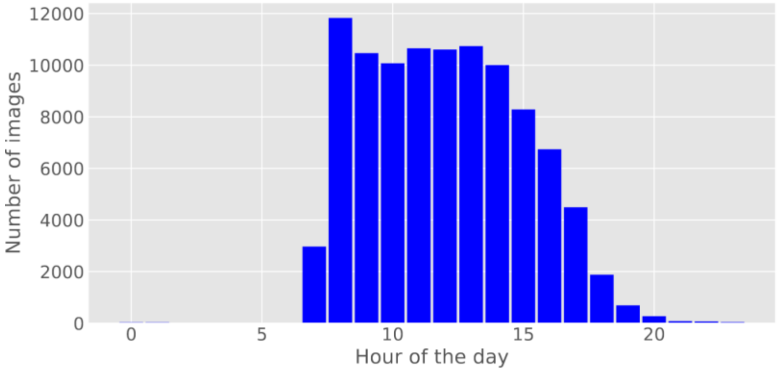
Spatially dense

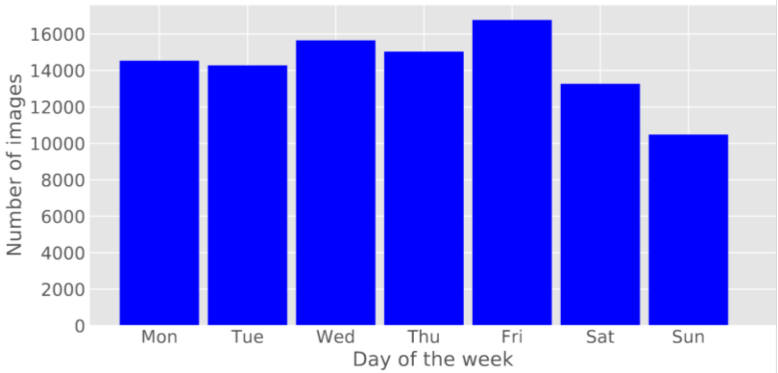
Temporally sparse

Temporally-dense street-level images



Spatially dense





More than 7.7 million images

4 TB worth of image data

Temporally-dense street-level images

Objectives

Support the interactive analysis of the city at the micro scale, over geographically distant regions.

Comparison of the urban fabric in different regions

Assessment of features in the built environment

Assessment of walkability and accessibility

Image query composition

Image embeddings

0.14	0.97	…	0.01	0.69

Image embeddings

Image embeddings

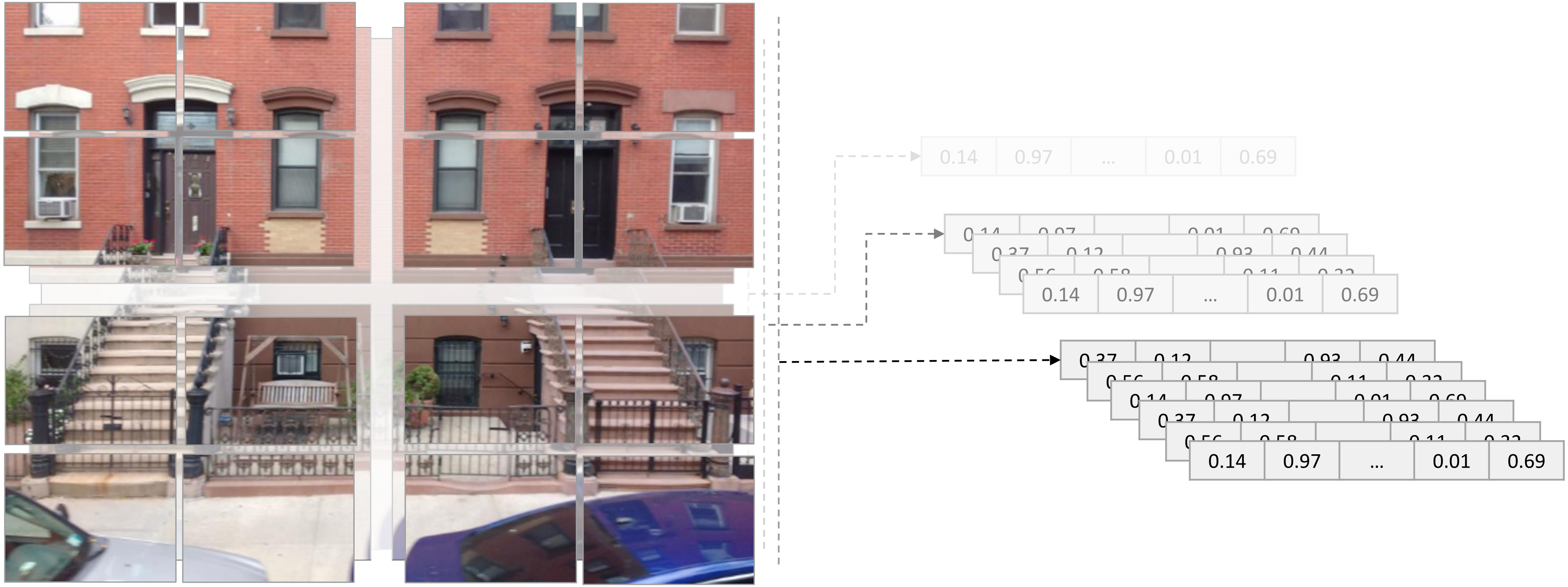
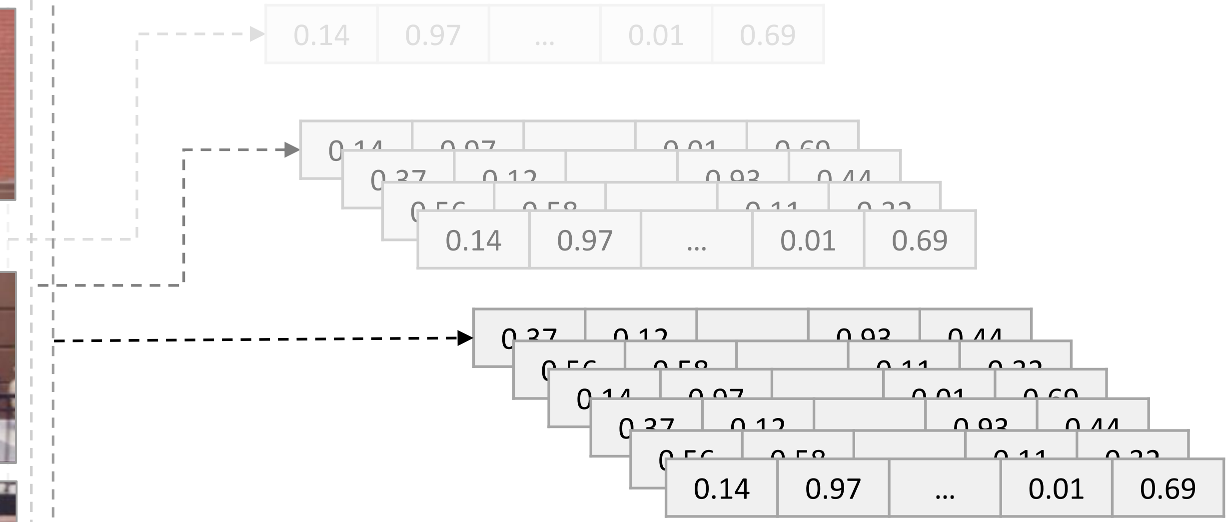


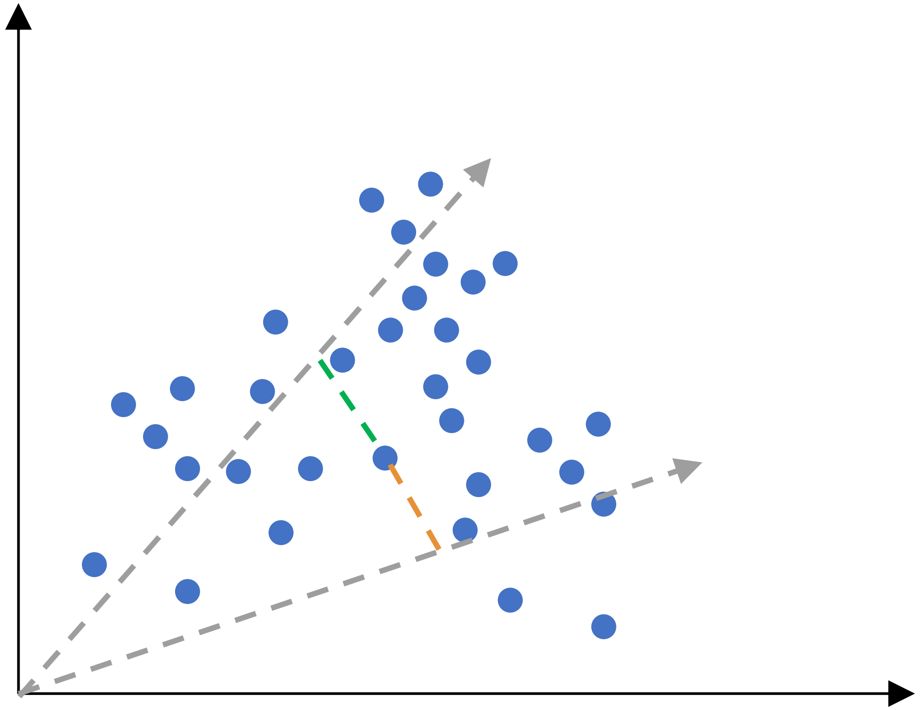
Image embeddings



21 embeddings per image

2.5 TB worth of embeddings data

Locality sensitive hashing



0.37	**0.12**	**…**	**0.93**	**0.44**

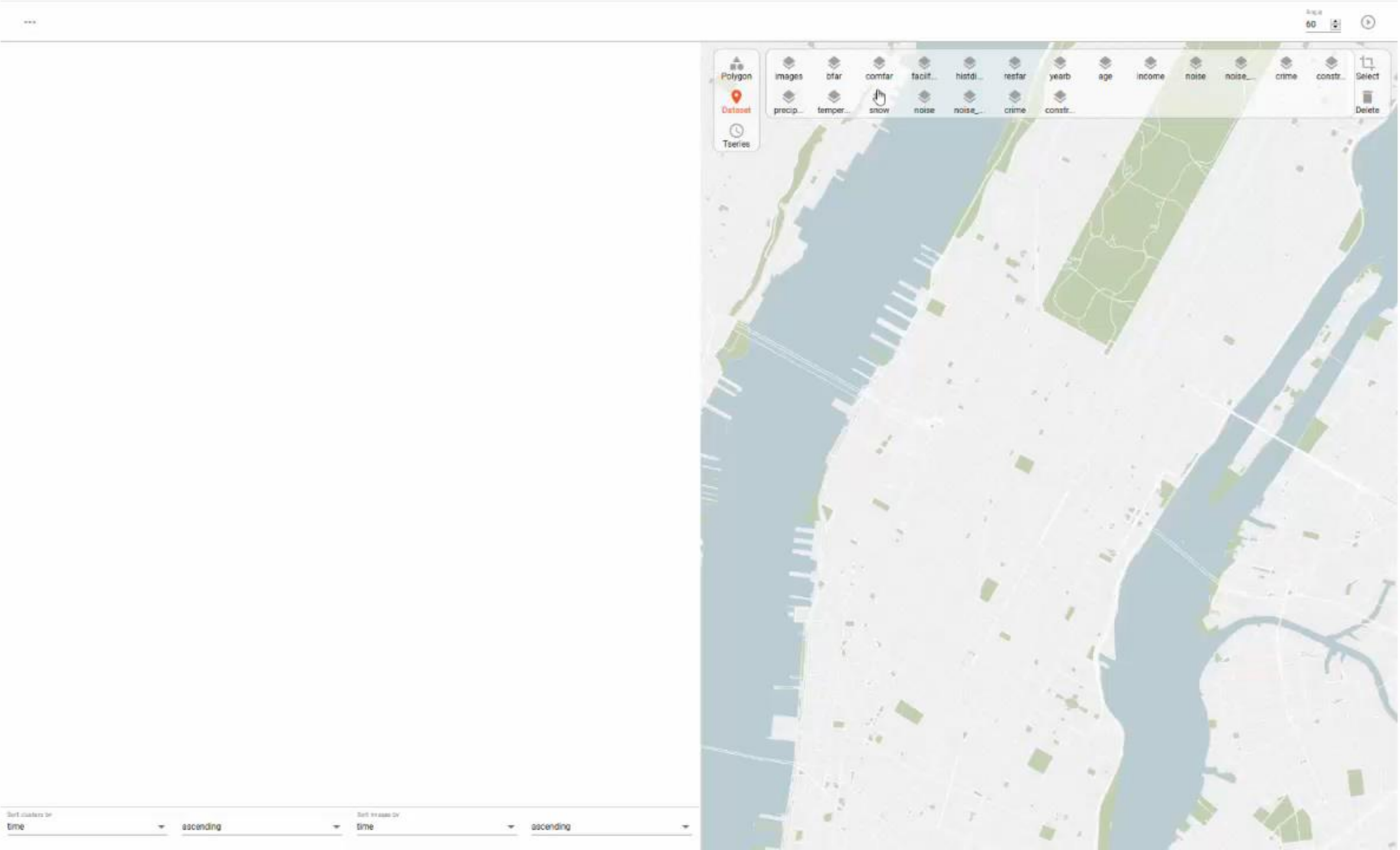
4 kbytes per embedding

0	**0**	**…**	**1**	**0**

64 bytes per embedding

$$\alpha_{1,2} = \cos^{-1}\left(\frac{\overrightarrow{v_1}\,.\,\overrightarrow{v_2}}{|\overrightarrow{v_1}||\overrightarrow{v_2}|}\right)$$

21 GB worth of
embeddings data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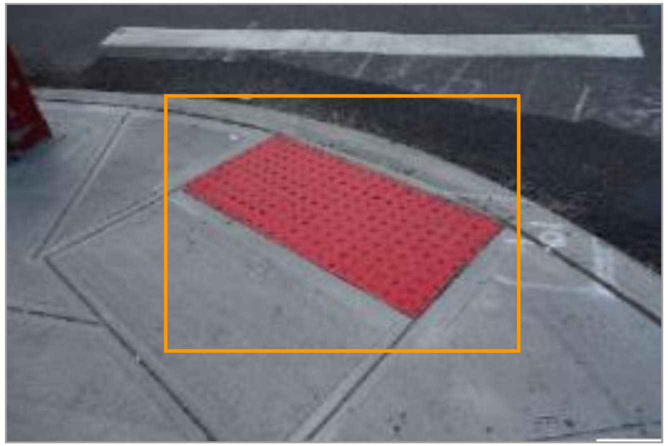
noise_...
crime
constr...
Delete
Sort clusters by
time
ascending
Sort images by
time
ascending

Use Cases

- Provided the interface to domain experts
- Urban Planners from Draw Brooklyn
  - Urban planning
  - Preservation
- Occupational therapist
  - Accessibility and walkability older adults

Accessibility: installation of tactile pavings

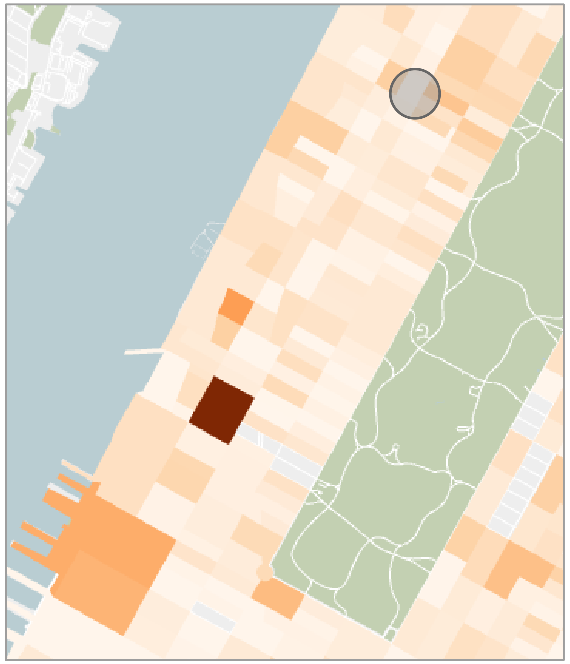


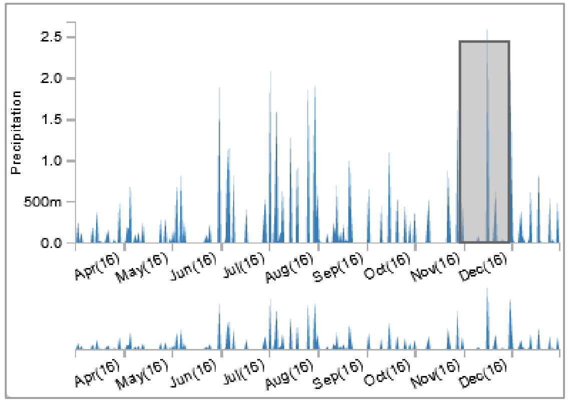
June

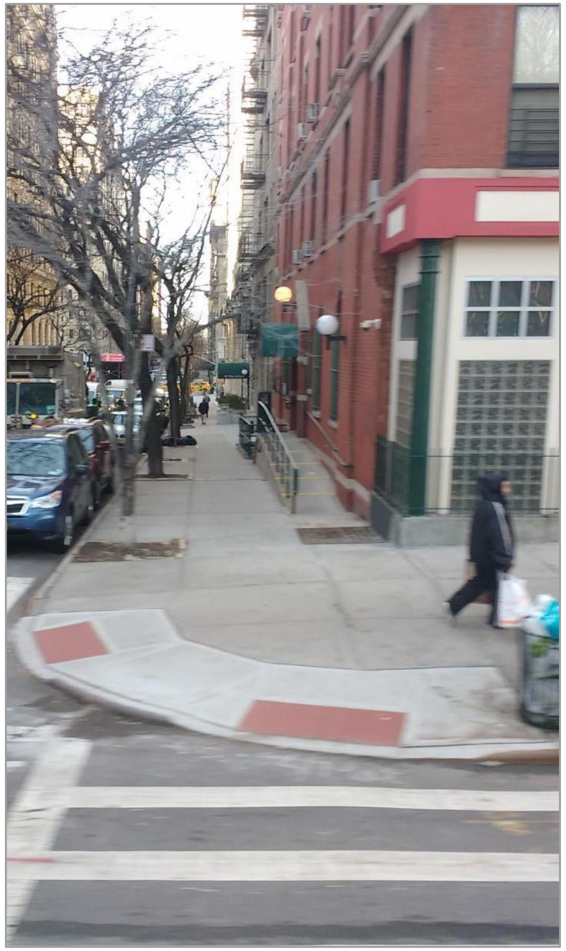
August

October

Accessibility: assessing hazards for older adults







Practitioners perspective

“What I like about the tool is that you can define what the main problem is, e.g. inclement weather or obstruction, and these are the conditions we’re are going to help the seniors identify and be safe around”.

Tracy Chippendale, Occupational Therapist at NYU

“Approaches like this can dramatically transform the way cities are planned and operated”.

Alexandros Washburn, former Chief Urban Designer of NYC

Urban Data Analysis

Other Examples

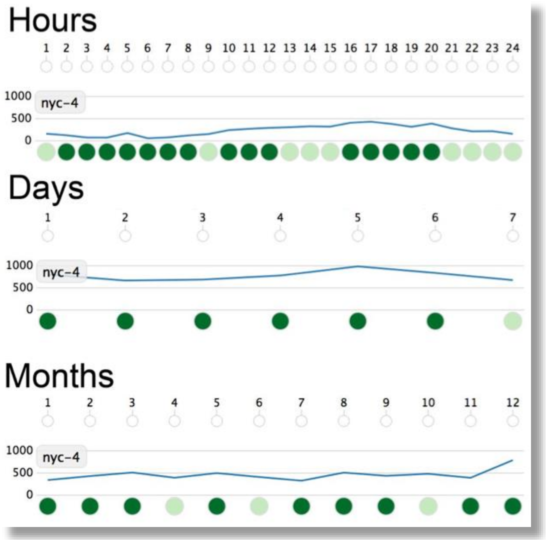
Topology-based Analysis: Understand Cities

[IEEE TVCG 2017]

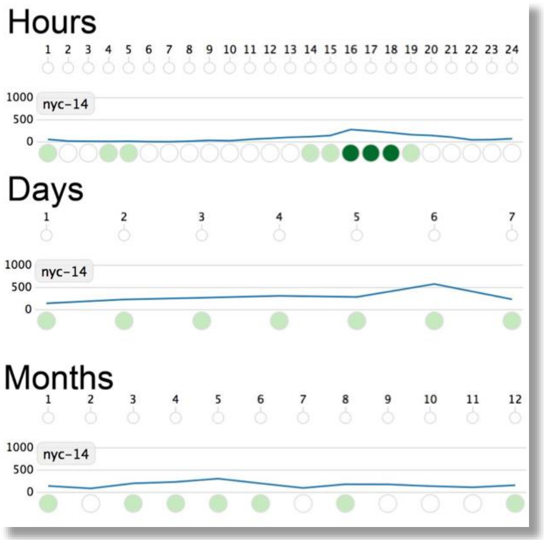
- Urban Pulse
  - Signature for different locations
  - Data oblivious
  - Rank and compare locations
  - Query similar locations

https://github.com/ViDA-NYU/urban-pulse

Rockefeller Center

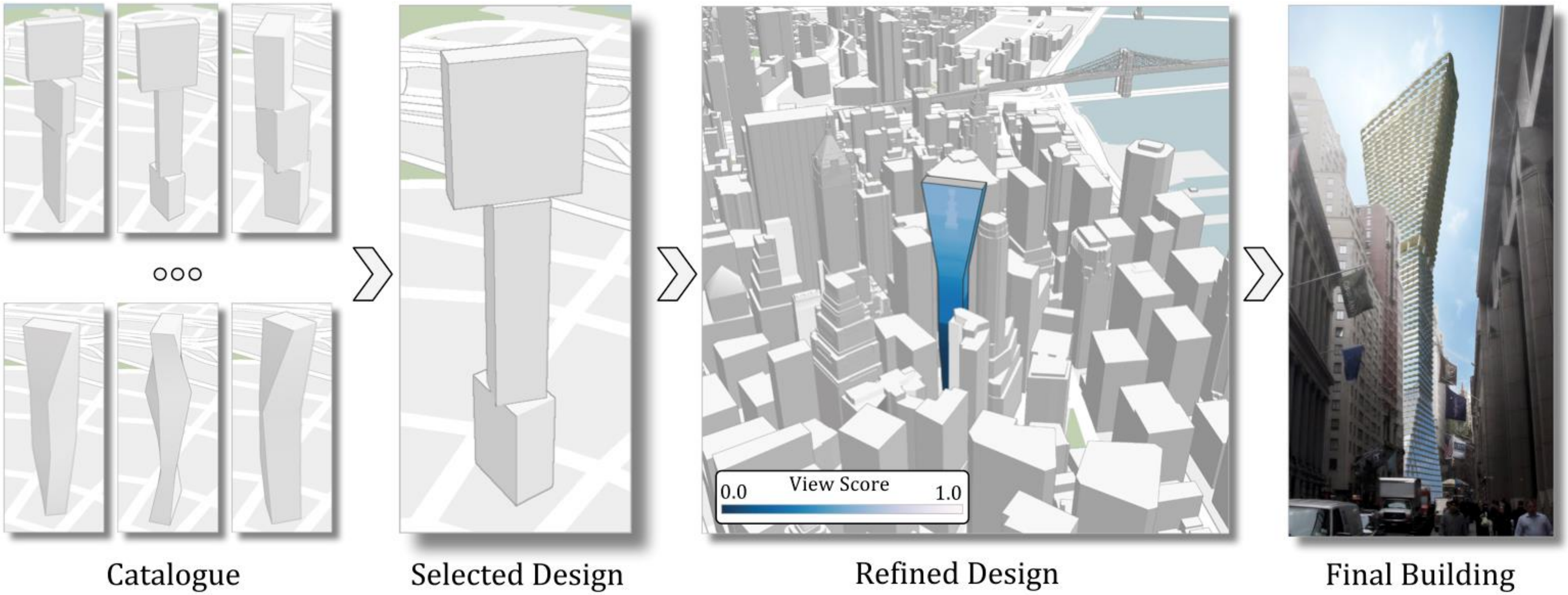


Union Square



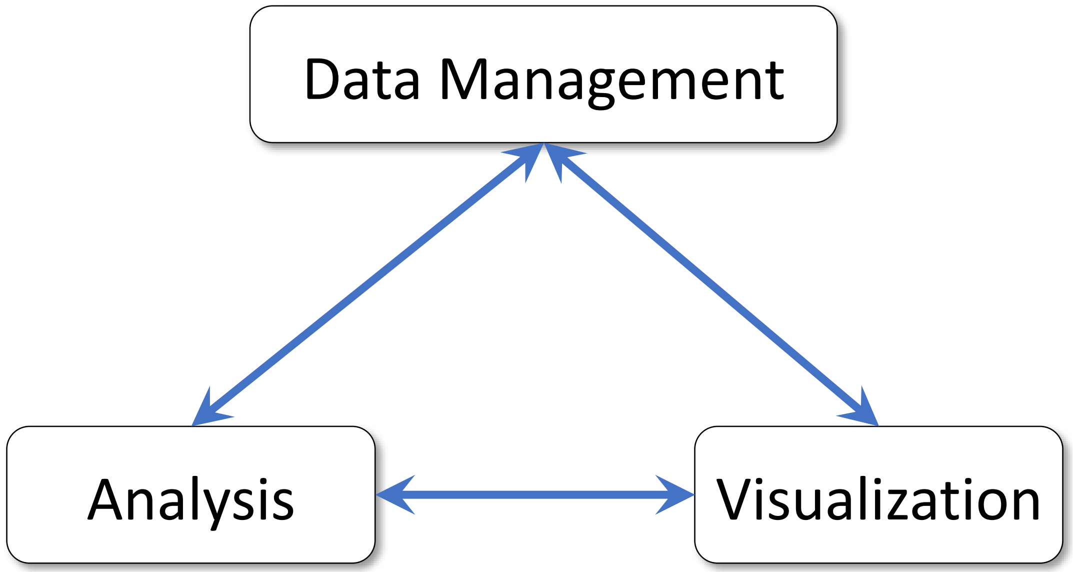
Topology-based Analysis: View-enhanced Tower Designs

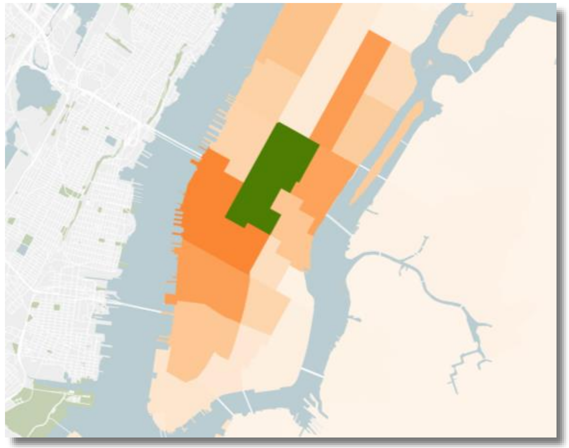
[ACM TOG 2015]

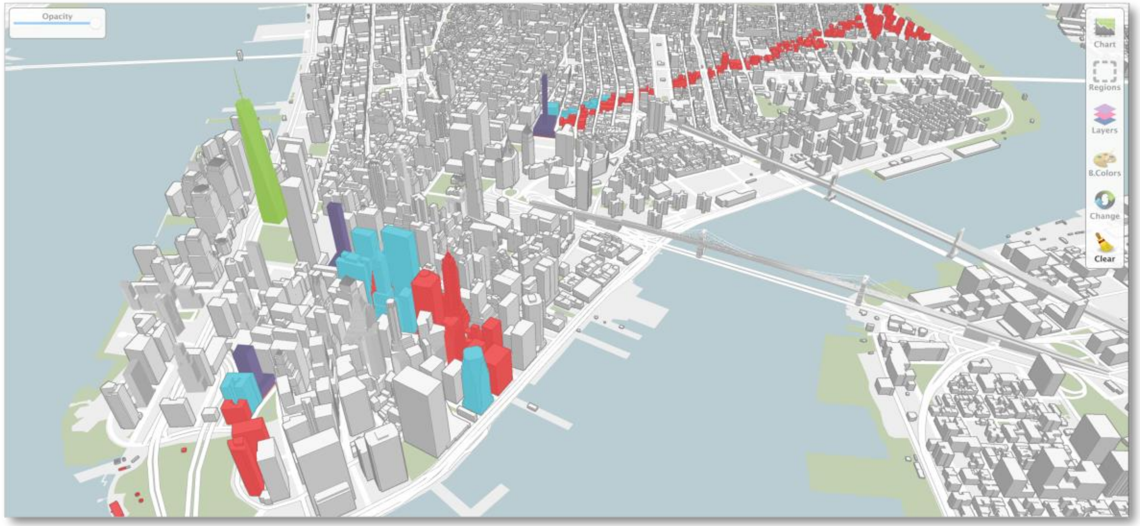


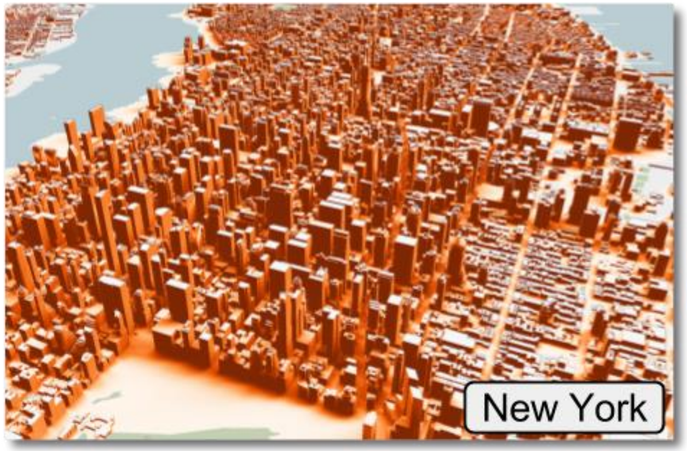
Urban Data: Plenty of Challenges

- Data Management
  - Spatio-temporal query processing
    - Trajectories
  - Images
- Visualization
  - Visual metaphors catered towards city planning, novel query interfaces, …
- Analysis
  - Finding relationships, explaining features, …









Interactive Visual Analysis of Large Urban Data

Thanks: Moore Sloan Data Science Environment at NYU, NSF, DARPA, NVIDIA, NASA, CNPq, FAPERJ, KPF, Carmera, Draw Brooklyn

NYU

harishd@nyu.edu

VIDA VISUALIZATION IMAGING AND DATA ANALYSIS CENTER