Mapping with Images

Quantitative analysis of cognition on physical space with computer vision

Liu Liu

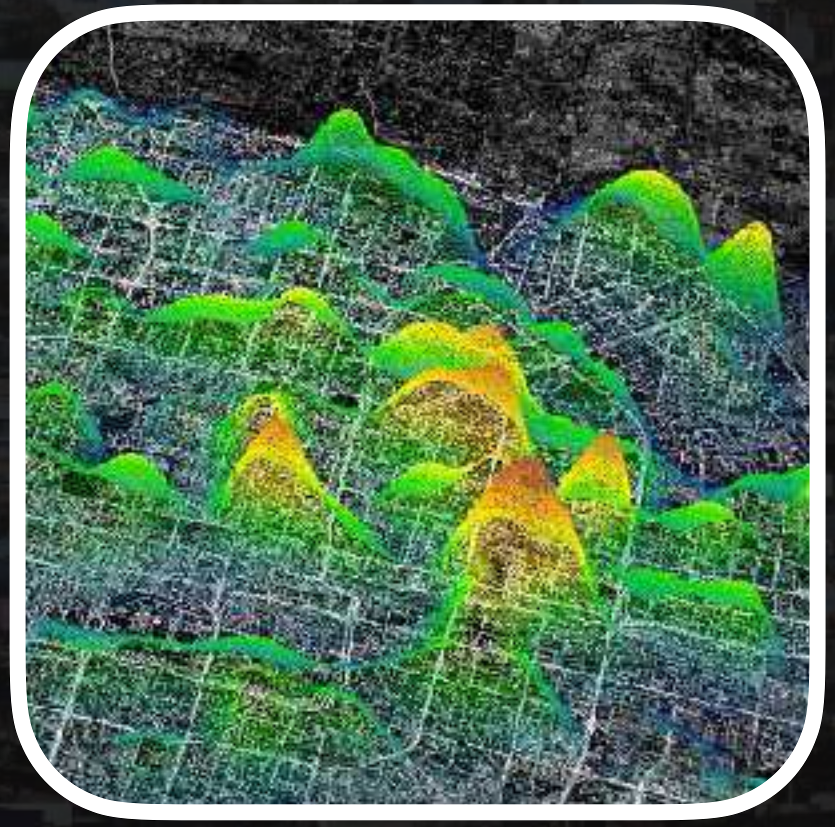
2022.10.12

C-IMAGE

StreetScore

Tools

Data



2014
thesis finished
graduated as MCP

2015

2016

2017
quit from CAUPD
founded start-up

2018

2019

2020

2021

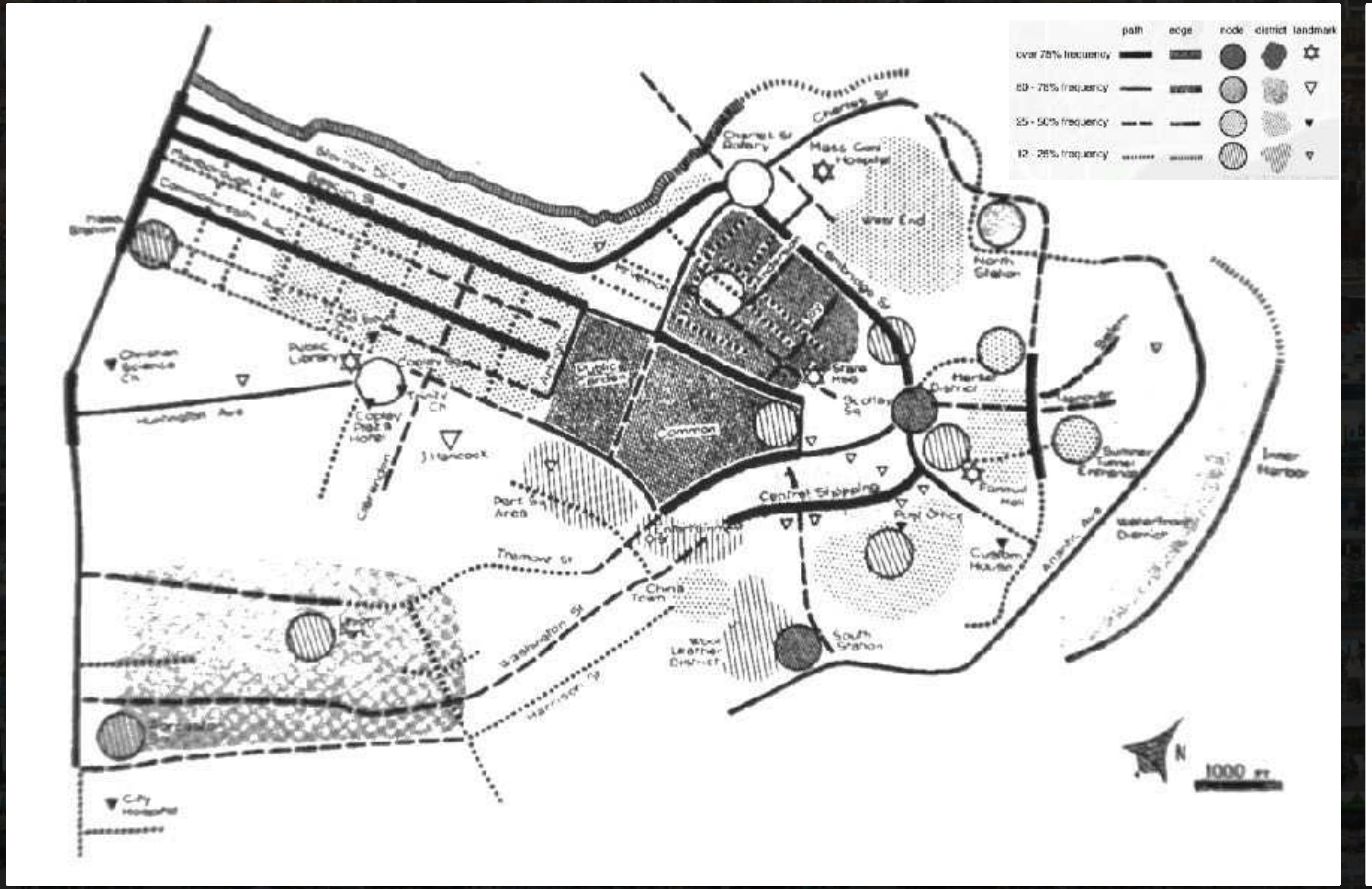
2022
back to DUSP
start from scratch

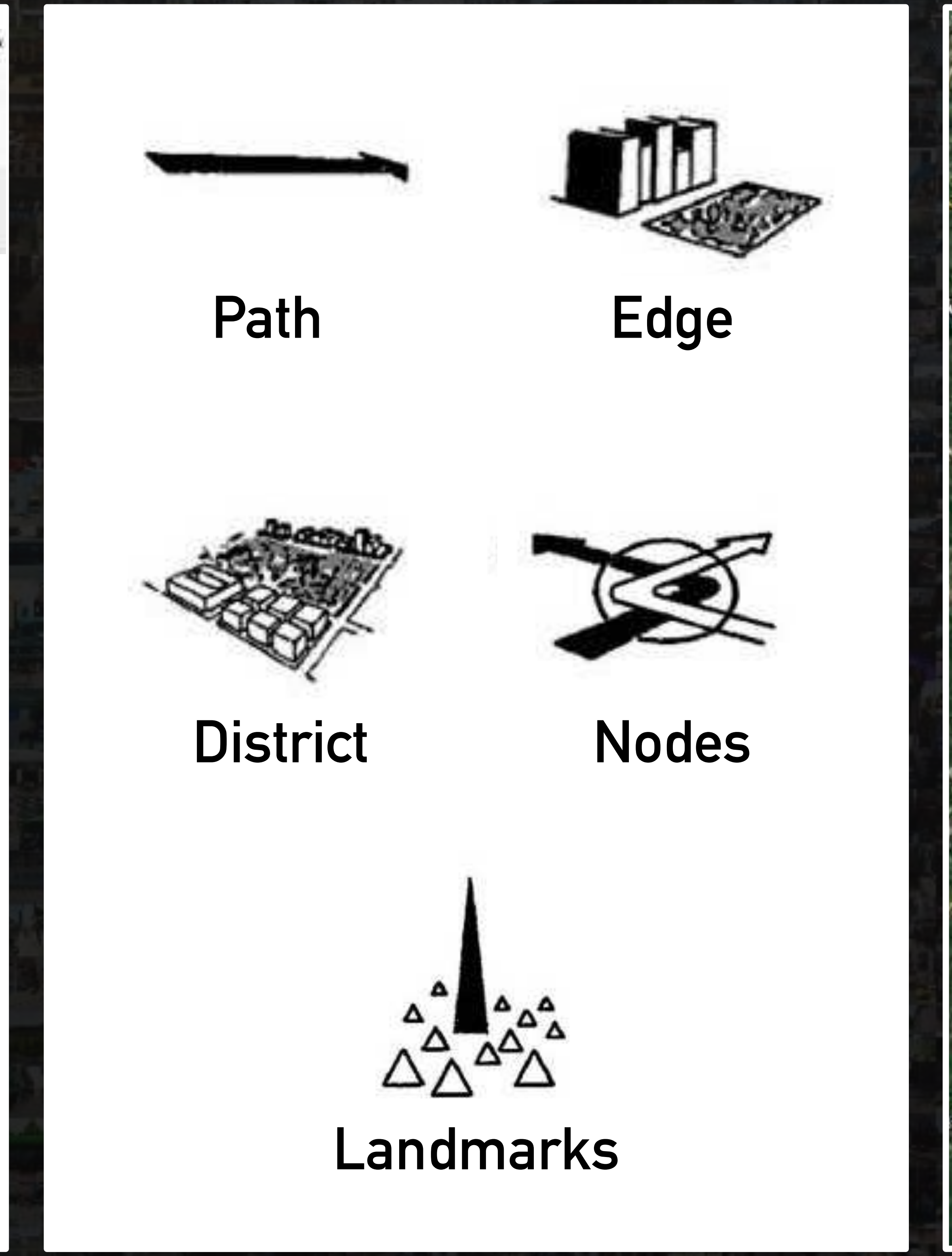

CHINA
CIMAGE
LIU LIU
ADVISOR BRENT D. RYAN
CITY
COLLAGE
CHALLENGE
CHANGE
COLLABORATION
CHANCE
COGNITION
CONCENTRATED
CITIZEN
CONCEPTUAL
CONTENT-BASED
COMPUTATION
CROWD-SOURCEING

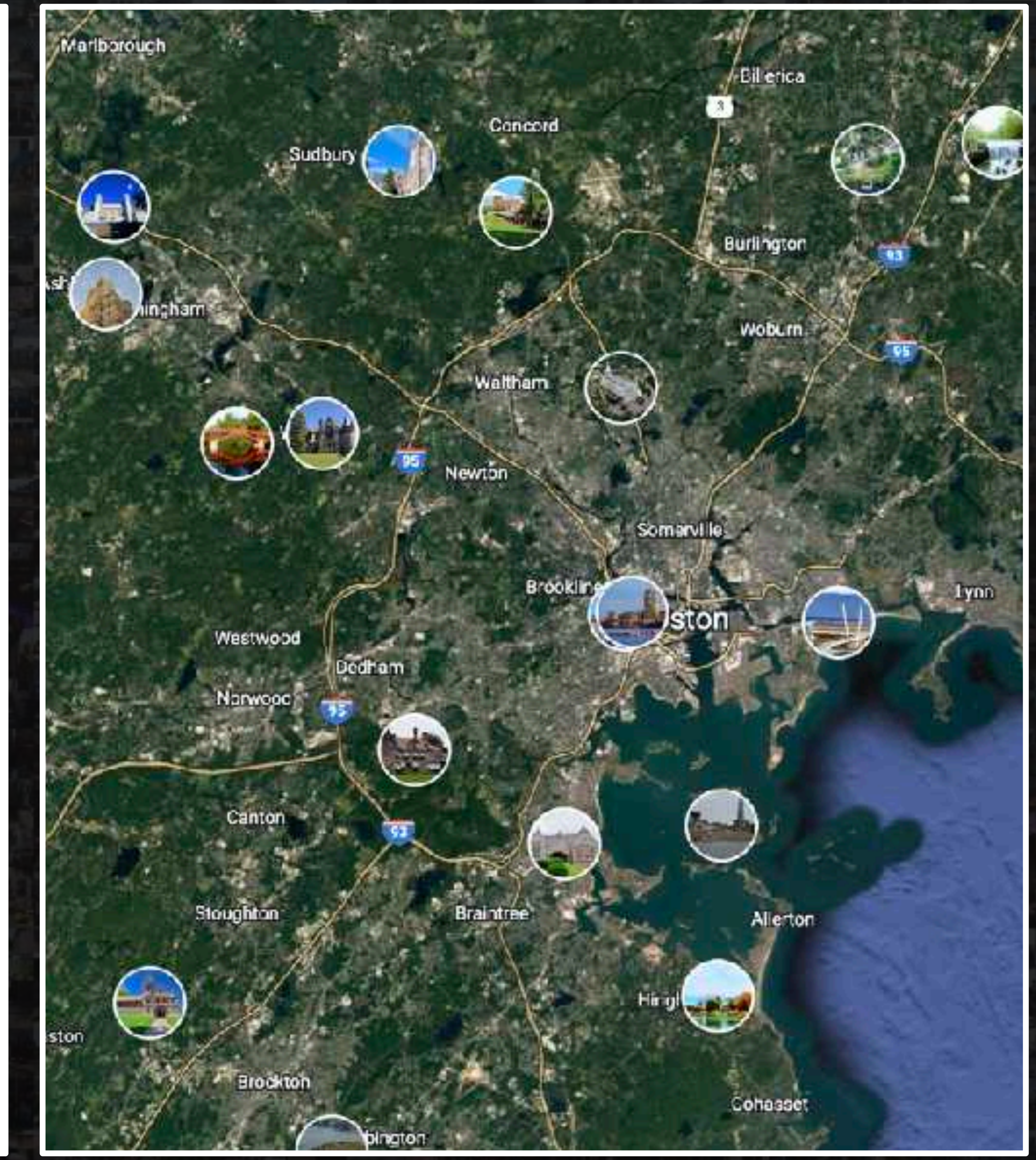
C-IMAGE Project

City Cognitive Mapping through Geo-Tagged Images

Since 1960s, Lynch did a series of research about city image by inviting people to draw their mental maps or by interviewing people in the city / after compiling all these sketches together, he generalized 5 elements — path, edge, district, node, and landmark — as the basic unit in people's perceptions.







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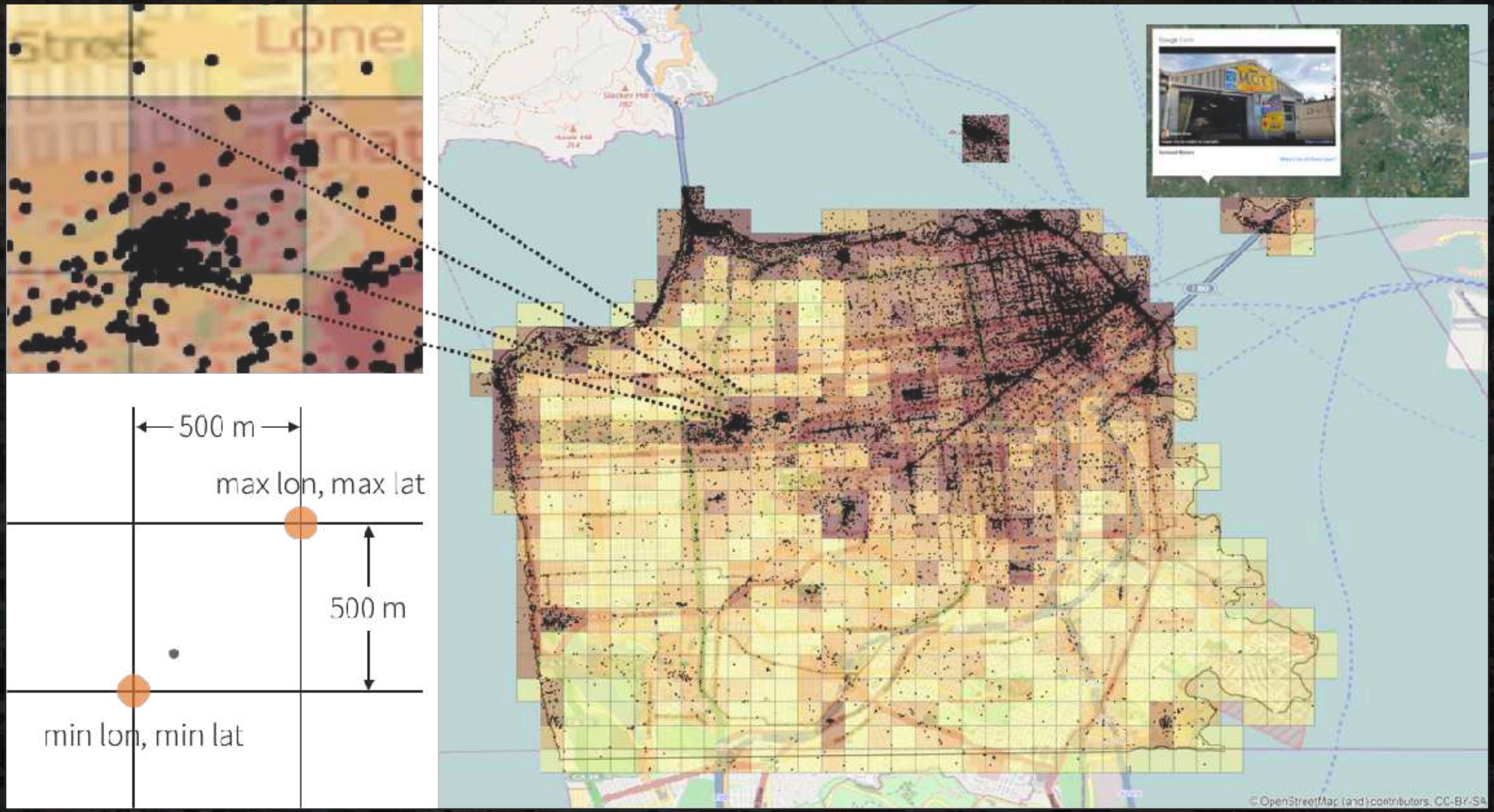
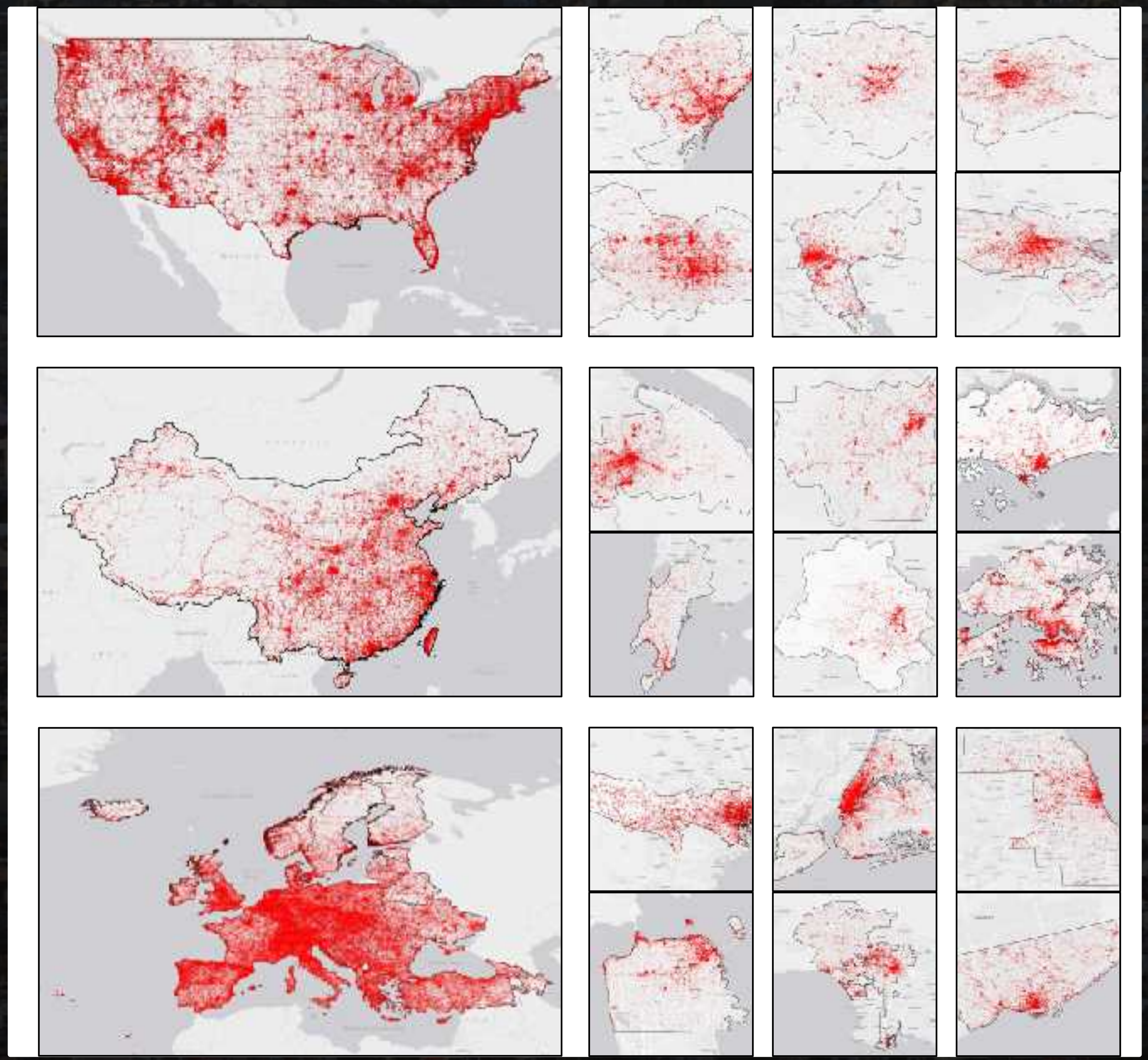
C-IMAGE Project

Data Collection

Through the data API from Panomramio, I collected millions of geo-tagged photos from 26 cities. For each city, we cut the city into 500 by 500 meter grid, then use the top right corner which has largest lat and lon and the bottom left corner to compose requests of downloading all the images.





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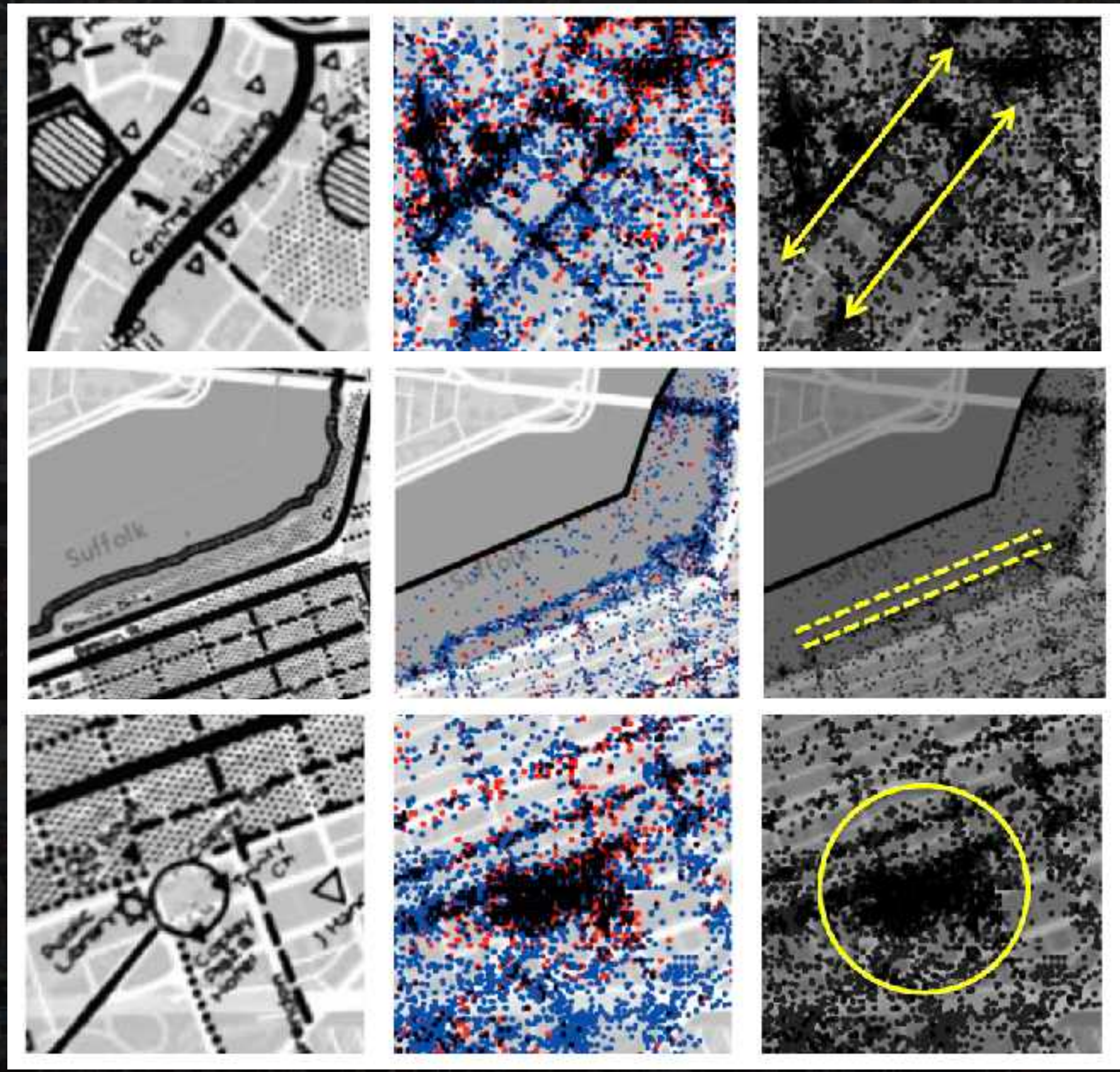
C-IMAGE Project

Comparing to the five elements

The scattered plots of geo-tagged photos from Panoramio and Flickr(later added), I roughly compared with Kevin Lynch's city image map of Boston. The Path, Node, and edge are clear to see, but district is ill-defined.

clues about paths, edges, and nodes



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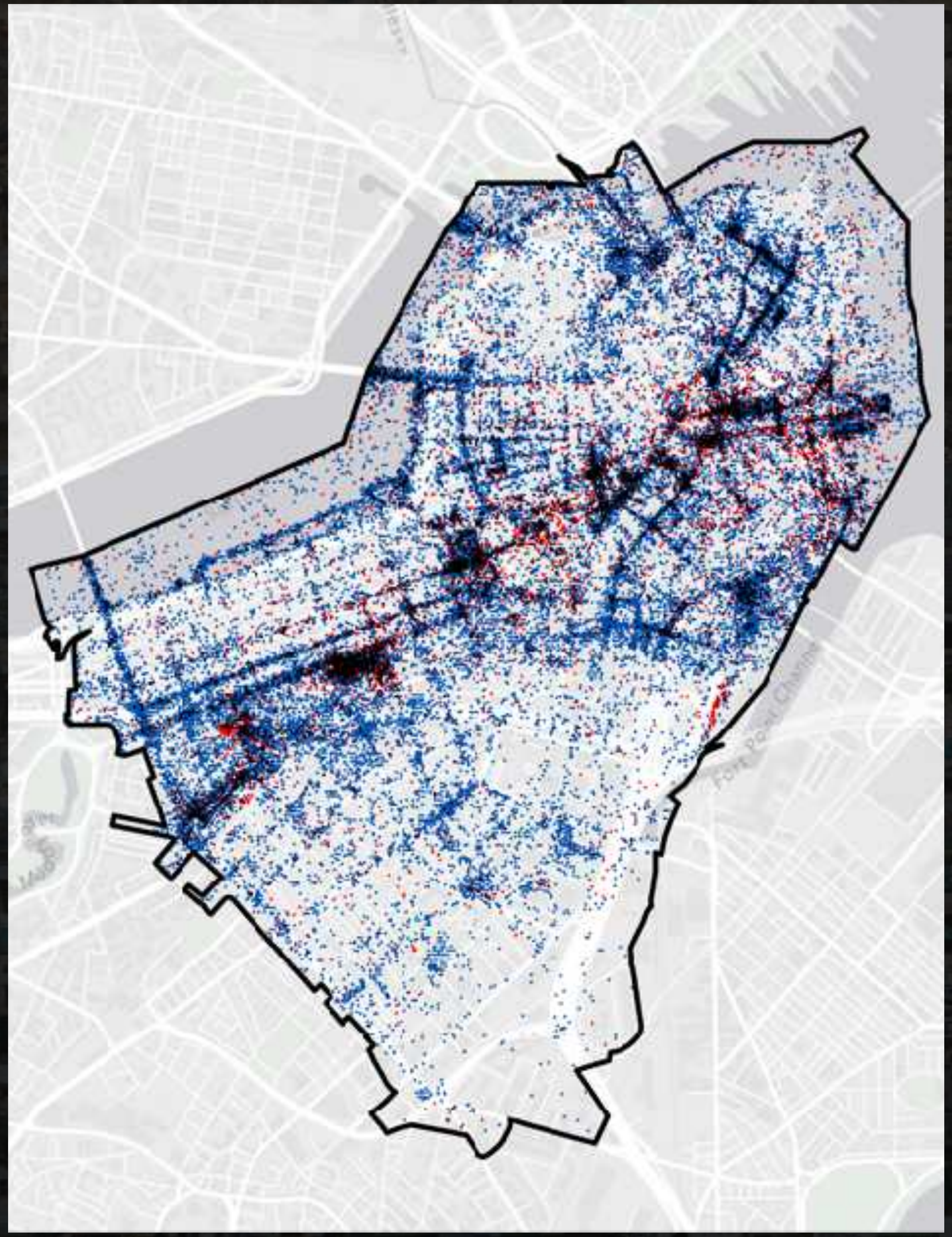
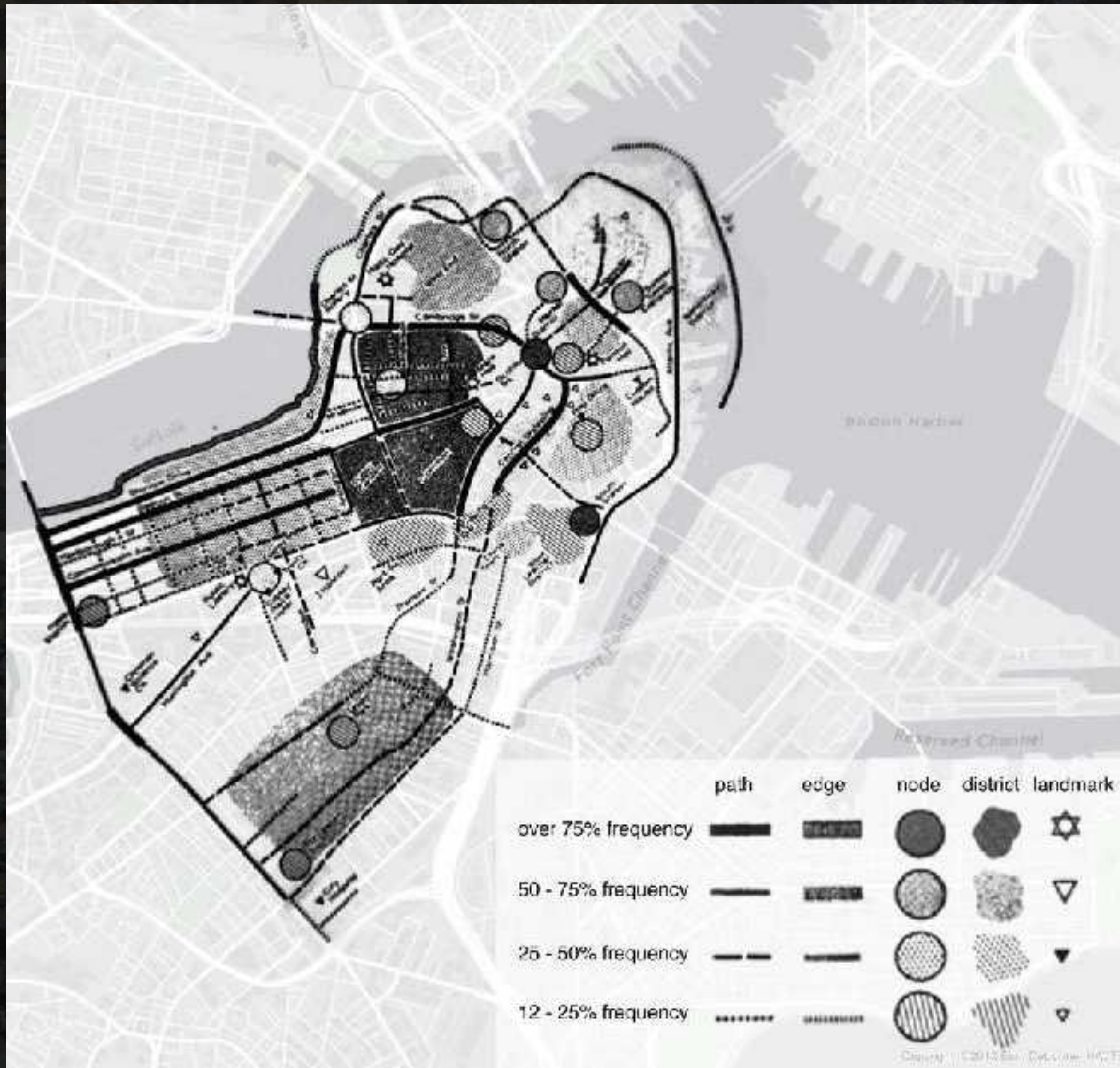
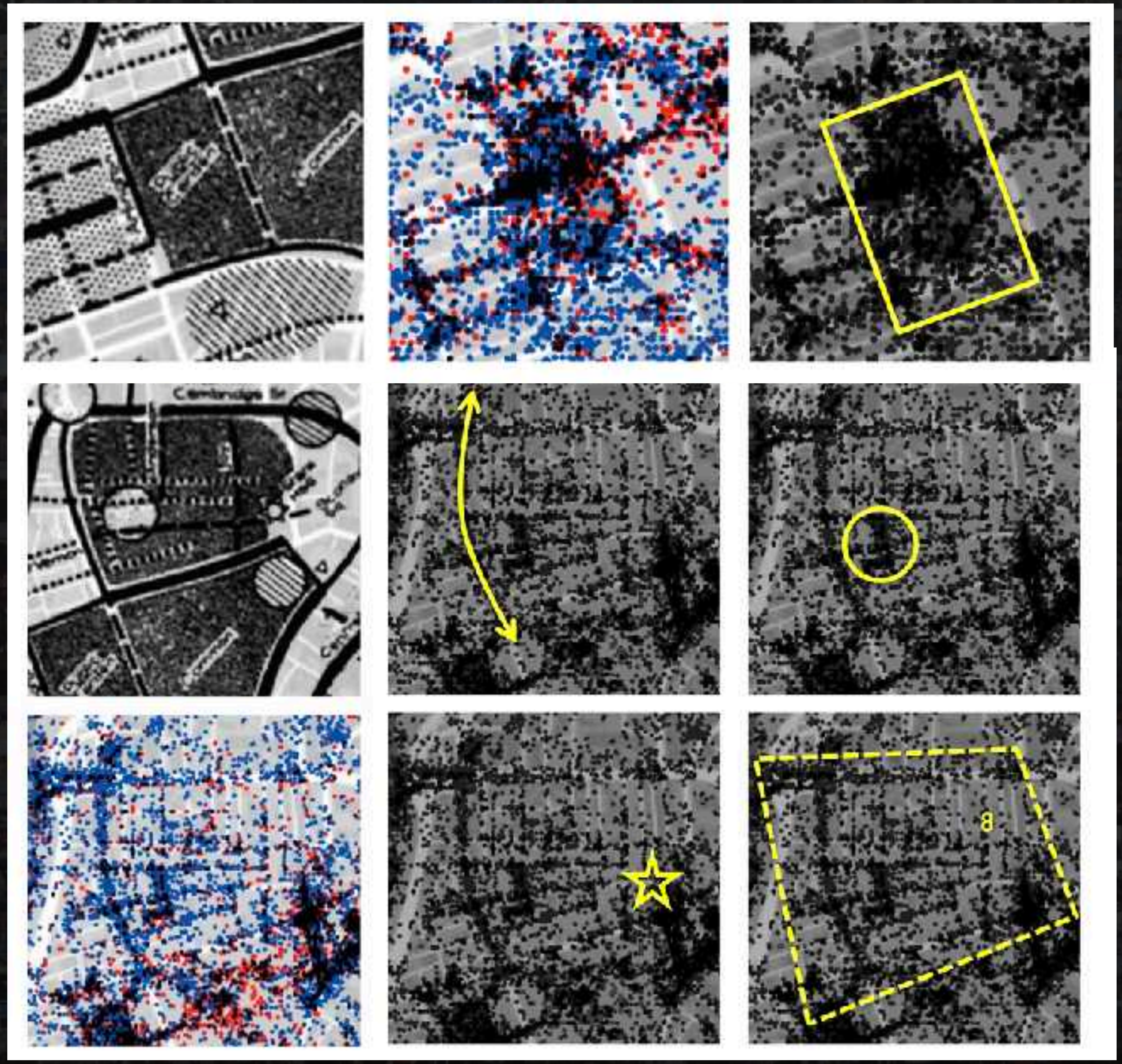




difficult to find districts



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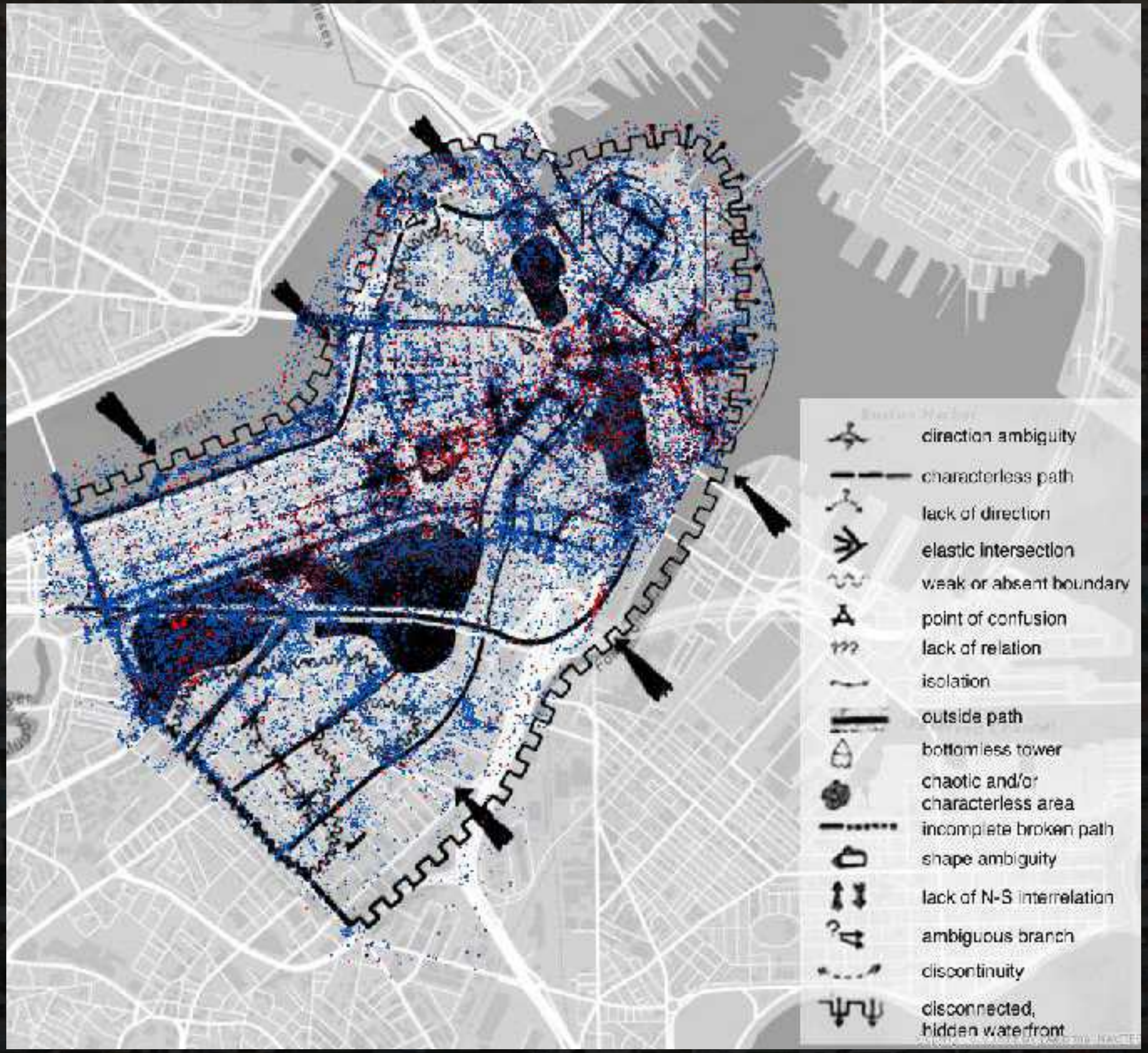
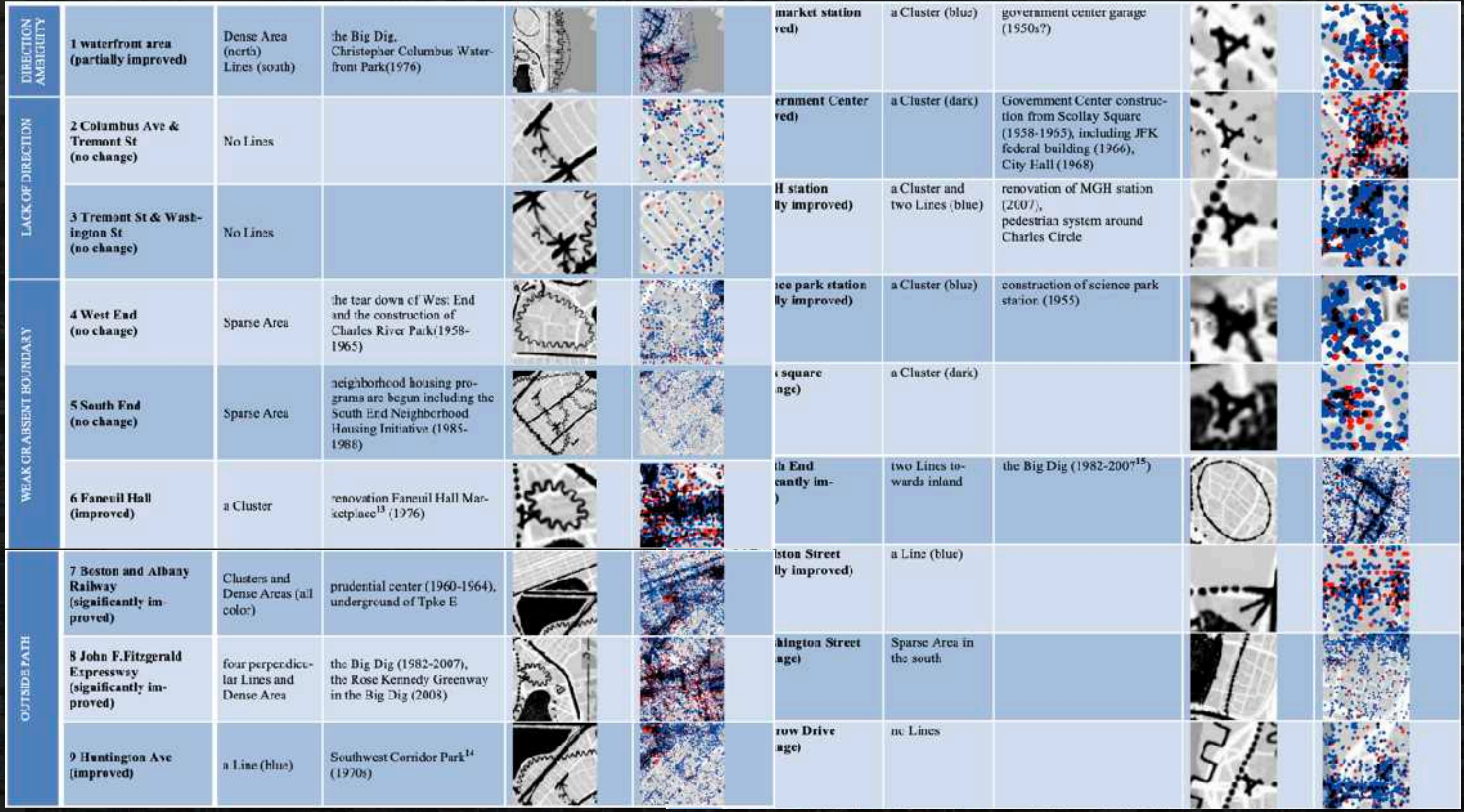
C-IMAGE Project

Comparing to the problem map (urban changes)

This is a project that originally comes from my thesis. By collecting millions of photos from 26 cities and then employing deep learning to perform scene recognition on them.





DIRECTION AMBIGUITY	1 waterfront area (partially improved)	Dense Area (north) Lines (south)	the Big Dig, Christopher Columbus Waterfront Park(1976)			market station red)	a Cluster (blue)	government center garage (1950s?)		
LACK OF DIRECTION	2 Columbus Ave & Tremont St (no change)	No Lines				ernment Center red)	a Cluster (dark)	Government Center construction from Scollay Square (1958-1965), including JFK federal building (1966), City Hall (1968)		
	3 Tremont St & Washington St (no change)	No Lines				H station lly improved)	a Cluster and two Lines (blue)	renovation of MGH station (2007), pedestrian system around Charles Circle		
WEAK OR ABSENT BOUNDARY	4 West End (no change)	Sparse Area	the tear down of West End and the construction of Charles River Park(1958-1965)			nce park station lly improved)	a Cluster (blue)	construction of science park station (1955)		
	5 South End (no change)	Sparse Area	neighborhood housing programs are begun including the South End Neighborhood Housing Initiative (1985-1988)			square nge)	a Cluster (dark)			
	6 Faneuil Hall (improved)	a Cluster	renovation Faneuil Hall Marketplace[13] (1976)			h End cantly im-)	two Lines towards inland	the Big Dig (1982-2007[15])		
OUTSIDE PATH	7 Boston and Albany Railway (significantly improved)	Clusters and Dense Areas (all color)	prudential center (1960-1964), underground of Tpke E			lston Street lly improved)	a Line (blue)			
	8 John F.Fitzgerald Expressway (significantly improved)	four perpendicular Lines and Dense Area	the Big Dig (1982-2007), the Rose Kennedy Greenway in the Big Dig (2008)			hington Street nge)	Sparse Area in the south			
	9 Huntington Ave (improved)	a Line (blue)	Southwest Corridor Park[14] (1970s)			row Drive nge)	no Lines			

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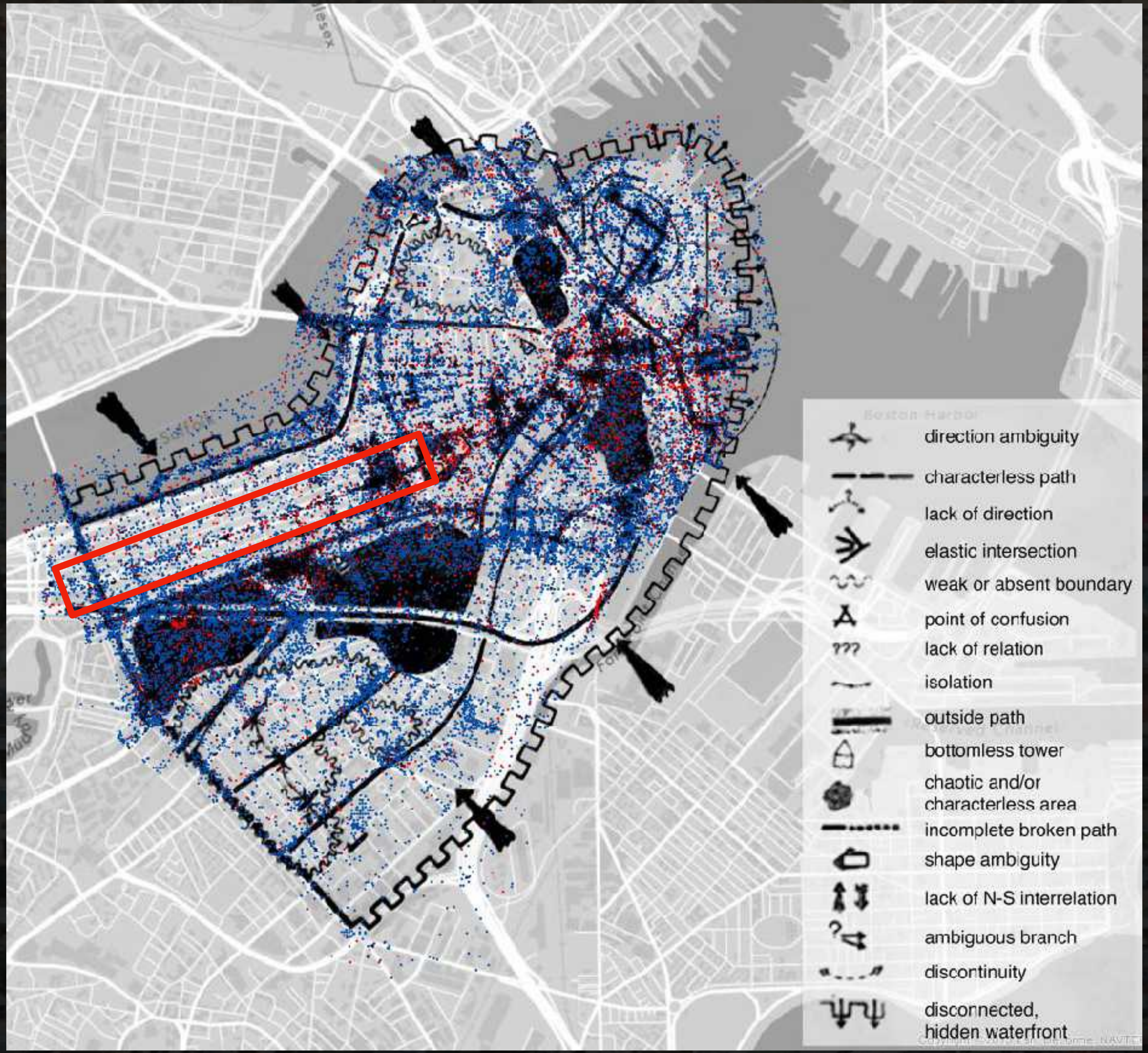

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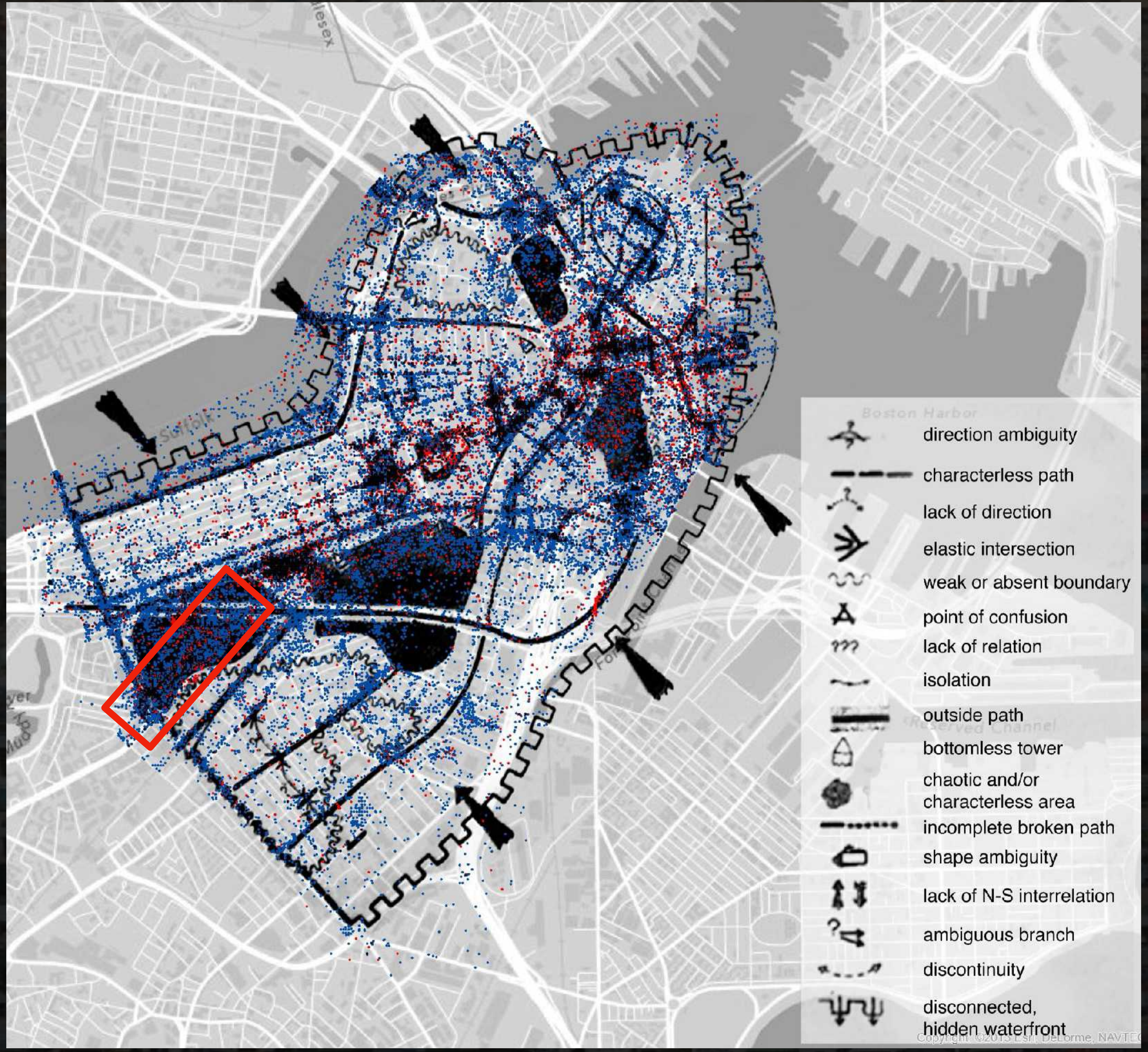

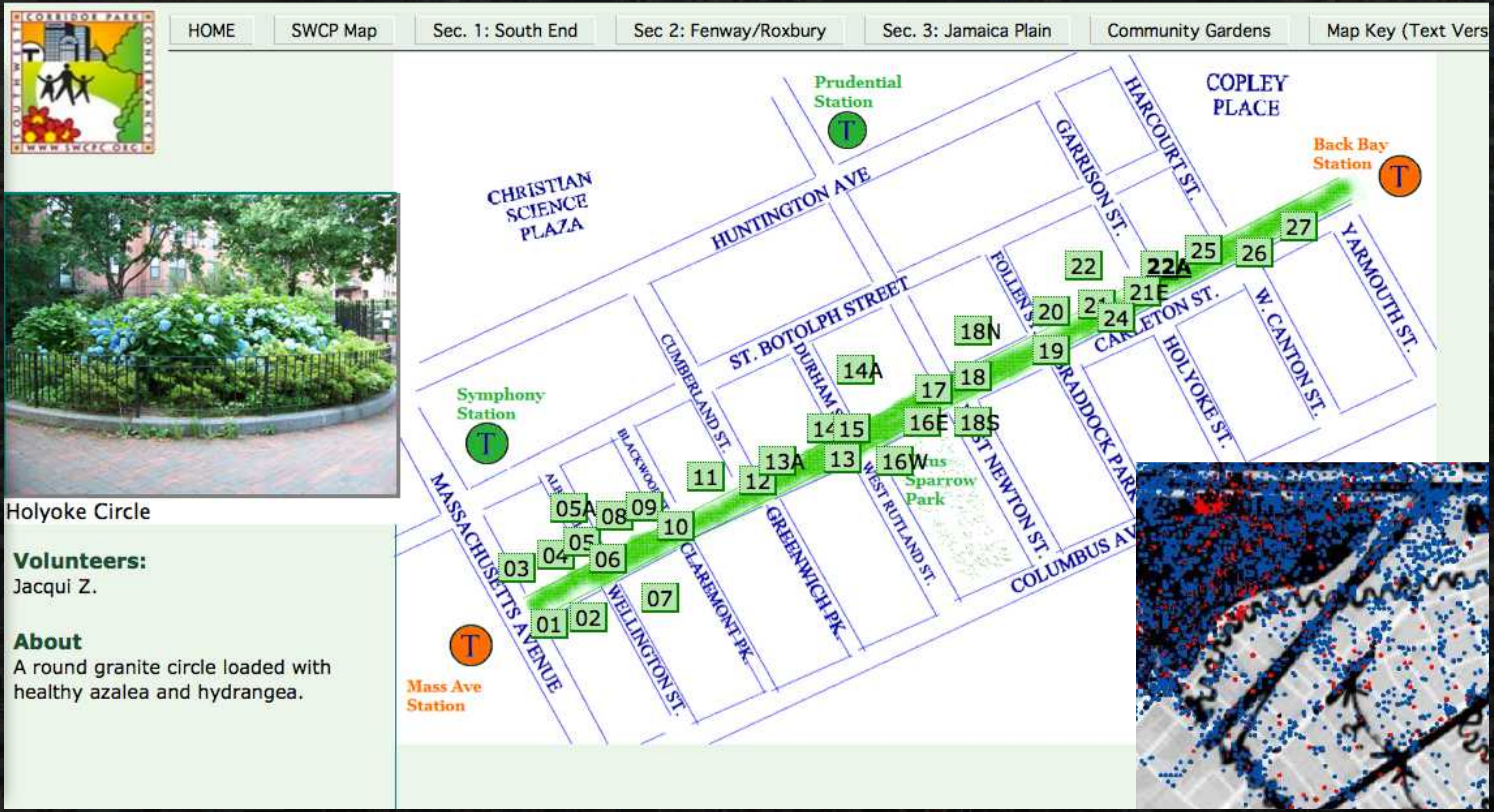

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C-IMAGE Project

Replotting through scene classification


1 Sailing / Boating


2 Driving


6 Vocationing / Touring


50 Shingles


17 Eating


19 Socializing


22 Competing


61 Sand


28 Farming


30 Shopping


32 Working


68 Running Water


40 Railroad


41 Trees


48 Asphalt


80 Matte

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C-IMAGE Project

Replotting through scene classification

1 sailing boating
2 driving
3 bilking
4 transporting things or people
5 sunbathing
6 vacationing/ touring
7 hiking
8 climbing
9 camping
10 reading
11 studying/ learning
12 teaching
13 research
14 diving
15 swimming
16 bathing
17 eating
18 cleaning
19 socilizing
20 cogregating
21 waiting in line/ queue
22 competing
23 sports
24 exercising
25 playing
26 gaming
27 spectating/ being in an audience
28 farming
29 construcing/ building
30 shopping
31 medical activity
32 working
33 using tools
34 digging
35 conducting business
36 praying
37 fencing
38 railing
39 wire
40 railroad
41 trees
42 grass
43 vegetation
44 shrubbery
45 foliage
46 leaves
47 flowers
48 asphalt
49 pavement
50 shingles
51 carpet
52 brick
53 tiles
54 concrete
55 metal
56 paper
57 wood (not part of a tree)
58 vinyl/linoleum
59 rubber/plastic
60 cloth
61 sand
62 rock/stone
63 dirt/soil
64 marble
65 glass
66 waves/surf
67 ocean
68 running water
69 still water
70 ice
71 snow
72 clouds
73 smoke
74 fire
75 natural light
76 direct sun/ sunny
77 electric/indoor lighting
78 aged/worn
79 glossy
80 matte
81 sterile
82 moist/damp
83 dry
84 dirty
85 rusty
86 warm
87 cold
88 natural
89 man-made
90 open area
91 semi-enclosed area
92 enclosed area
93 far-away horizon
94 no horizon
95 rugged scene
96 mostly vertical components
97 mostly horizontal components
98 symmetrical
99 cluttered space
100 scary
101 soothing
102 stressful

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level
800
600
400
200
47986 Vars
0.5
1.0
level
1500
1000
500
13731 Vars
0.3
0.6
0.9
1.2
29655 Vars
0.3
0.6
0.9
level
1000
500
9077 Vars
0.25
0.50
0.75
1.00
1.25
level
600
400
200

C-IMAGE Project

Replotting through scene classification

1 sailing boating	2 driving	3 bilking	4 transporting things or people	5 sunbathing	6 vacationing/ touring	7 hiking	8 climbing	9 camping	10 reading	11 studying/ learning	12 teaching	13 research	14 diving	15 swimming
16 bathing	17 eating	18 cleaning	19 socilizing	20 cogregating	21 waiting in line/ queue	22 competing	23 sports	24 exercising	25 playing	26 gaming	27 spectating/ being in an audience	28 farming	29 construcing/ building	30 shopping
31 medical activity	32 working	33 using tools	34 digging	35 conducting business	36 praying	37 fencing	38 railing	39 wire	40 railroad	41 trees	42 grass	43 vegetation	44 shrubbery	45 foliage
46 leaves	47 flowers	48 asphalt	49 pavement	50 shingles	51 carpet	52 brick	53 tiles	54 concrete	55 metal	56 paper	57 wood (not part of a tree)	58 vinyl/linoleum	59 rubber/plastic	60 cloth
61 sand	62 rock/stone	63 dirt/soil	64 marble	65 glass	66 waves/ surf	67 ocean	68 running water	69 still water	70 ice	71 snow	72 clouds	73 smoke	74 fire	75 natural light
76 direct sun/ sunny	77 electric/indoor lighting	78 aged/ worn	79 glossy	80 matte	81 sterile	82 moist/damp	83 dry	84 dirty	85 rusty	86 warm	87 cold	88 natural	89 man-made	90 open area
91 semi-enclosed area	92 enclosed area	93 far-away horizon	94 no horizon	95 rugged scene	96 mostly vertical components	97 mostly horizontal components	98 symmetrical	99 cluttered space	100 scary	101 soothing	102 stressful			

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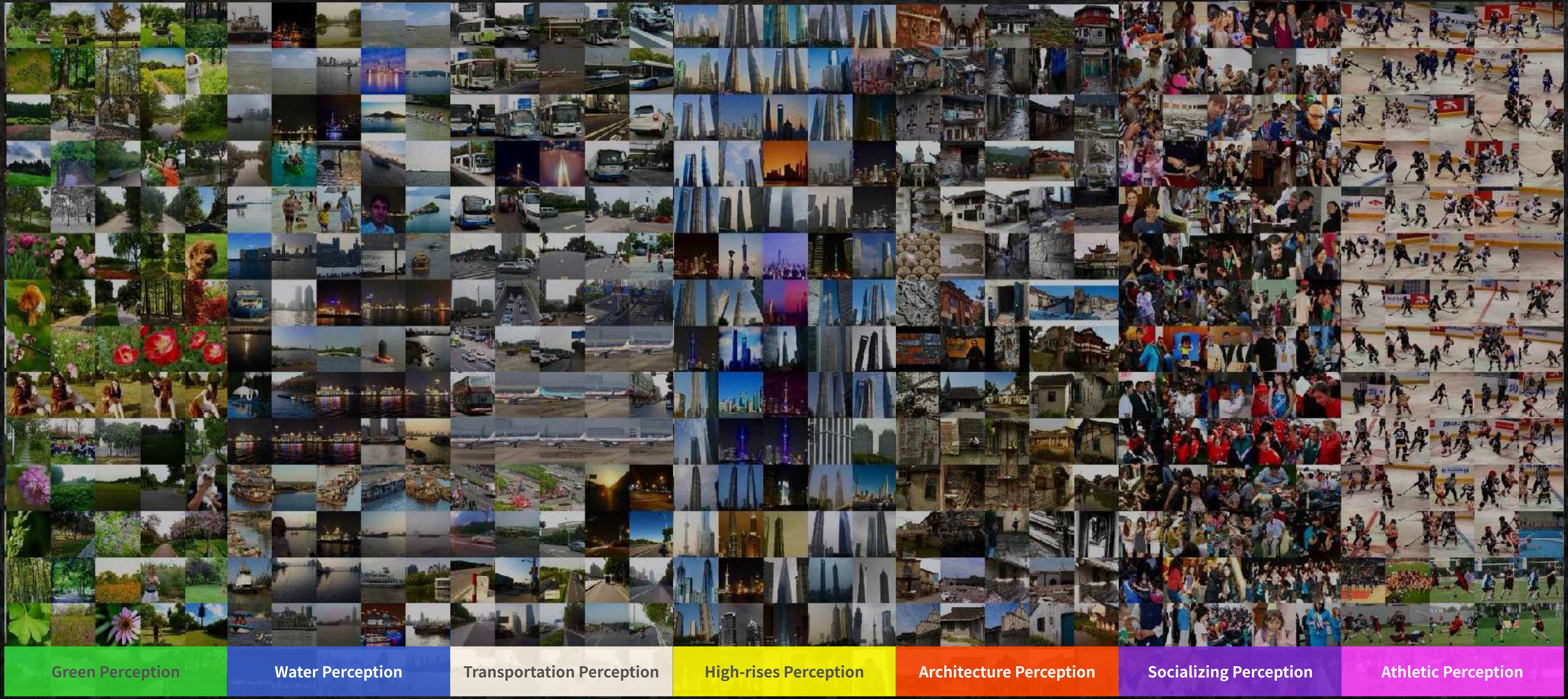
C-IMAGE Project

Replotting through scene classification



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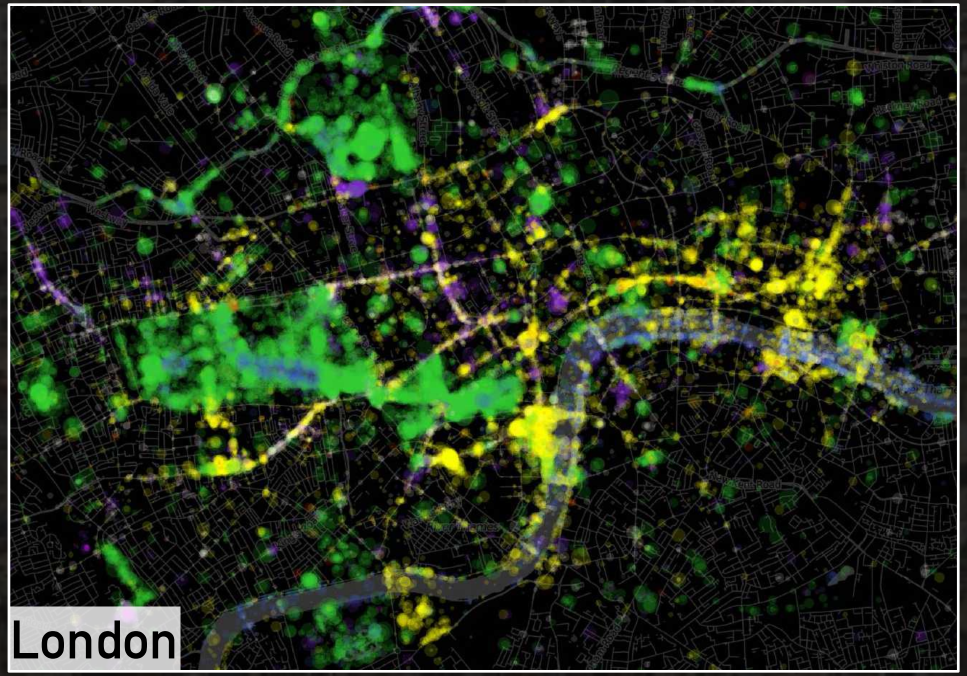
C-IMAGE Project

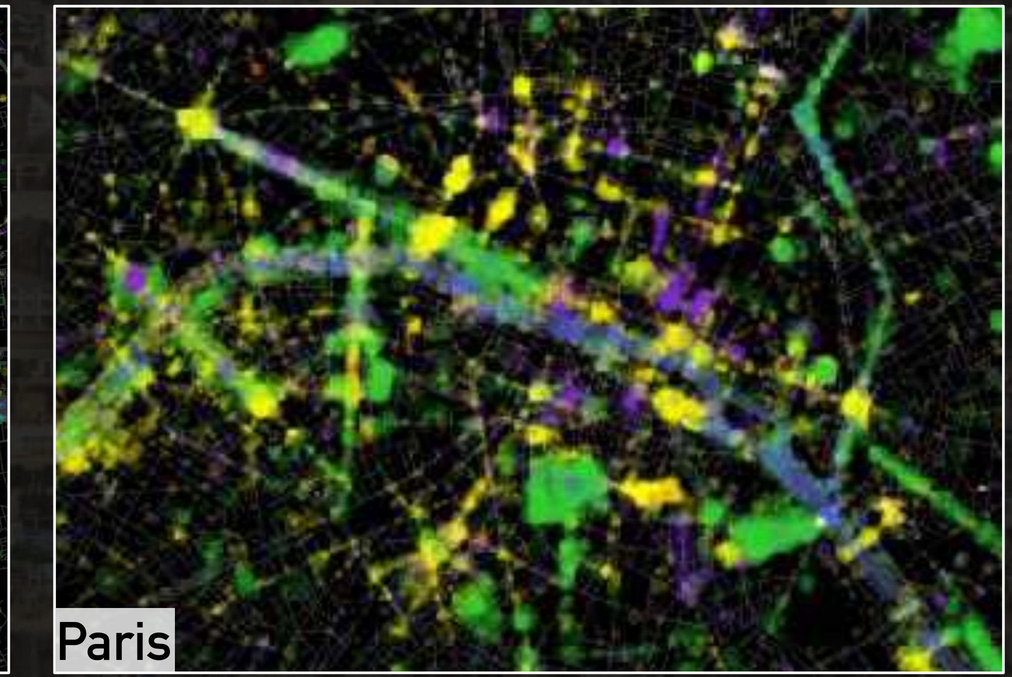
A reflection between "Real Space" and "Perceived Space"

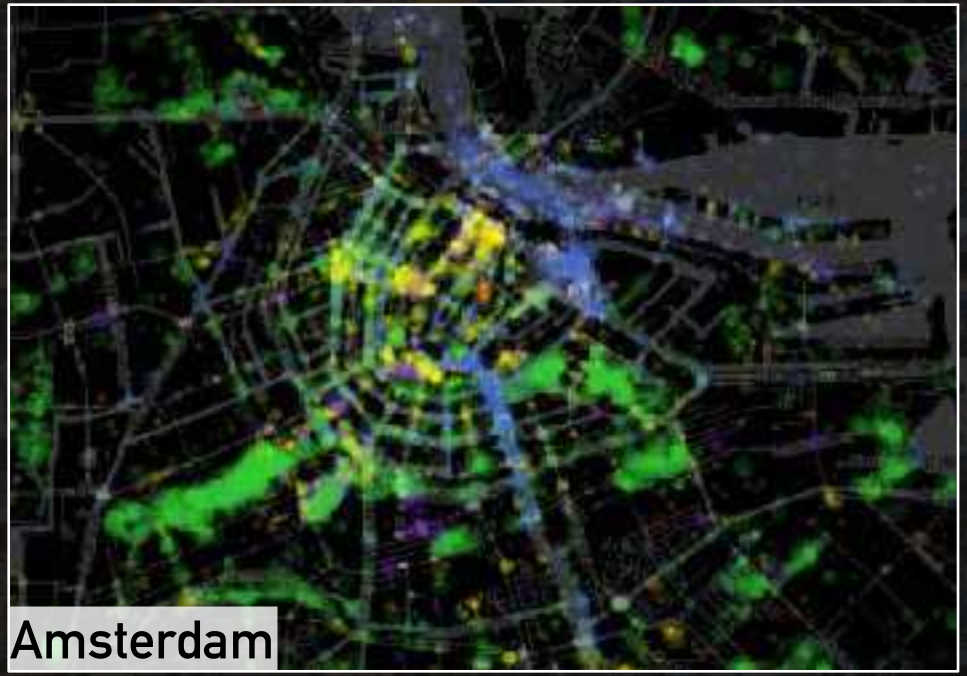
Through image analysis of hundreds of thousands of photos from Panoramio, city maps can be generalized into a perceived world which includes large amount of subjective feelings from the public. For example, this is the perceived map of London, in which green dots stand for green space, blue dots are water space, yellow dots represent high-rises, and purple dots mean crowds of people.

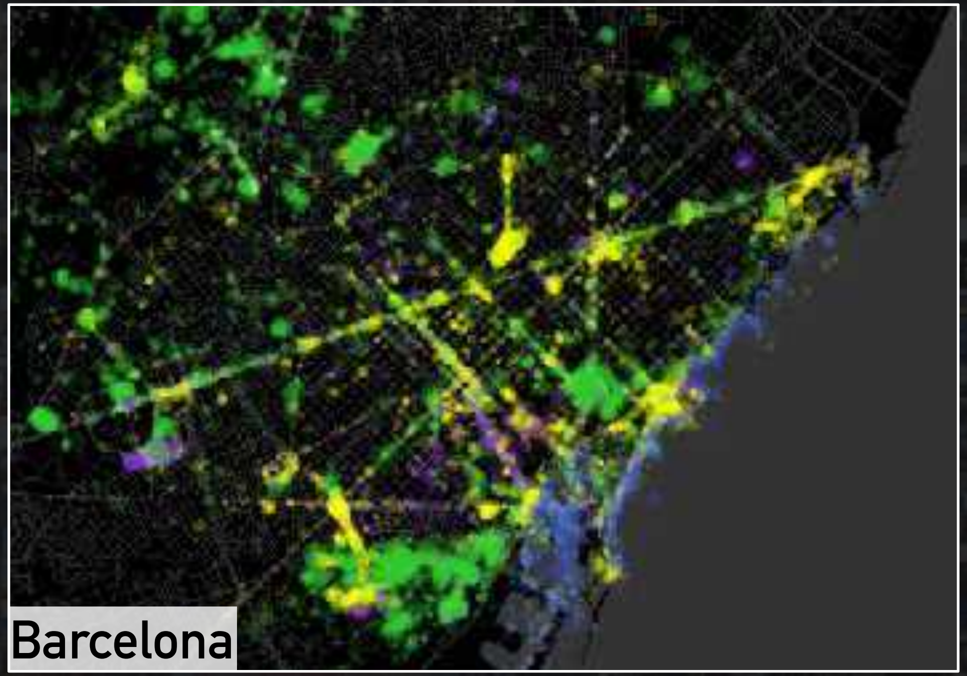
C-IMAGE Project

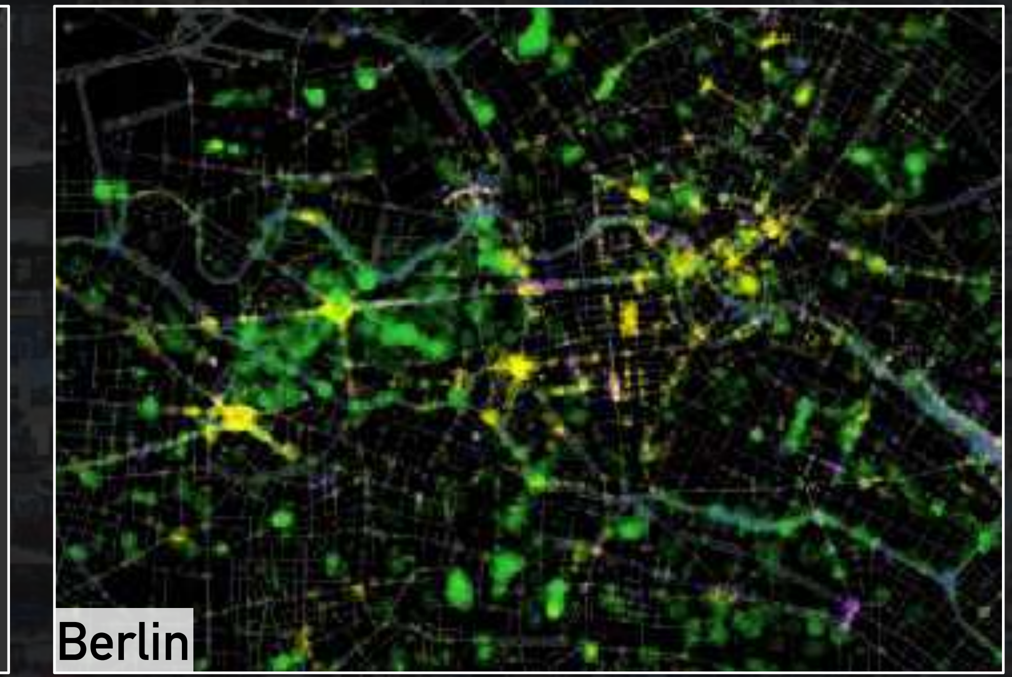
A reflection between "Real Space" and "Perceived Space"

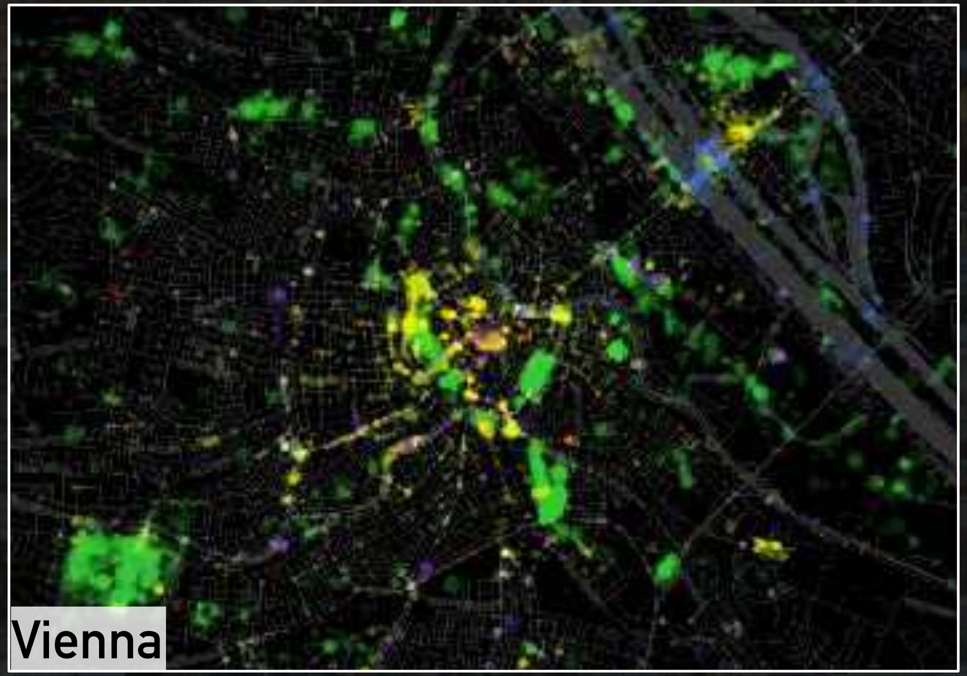


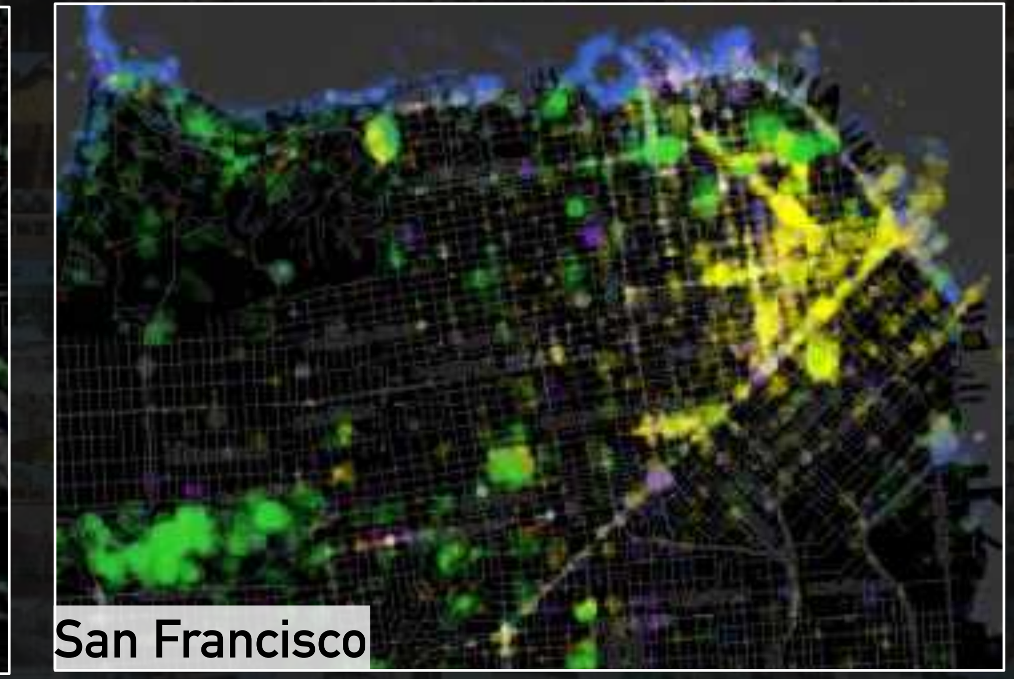


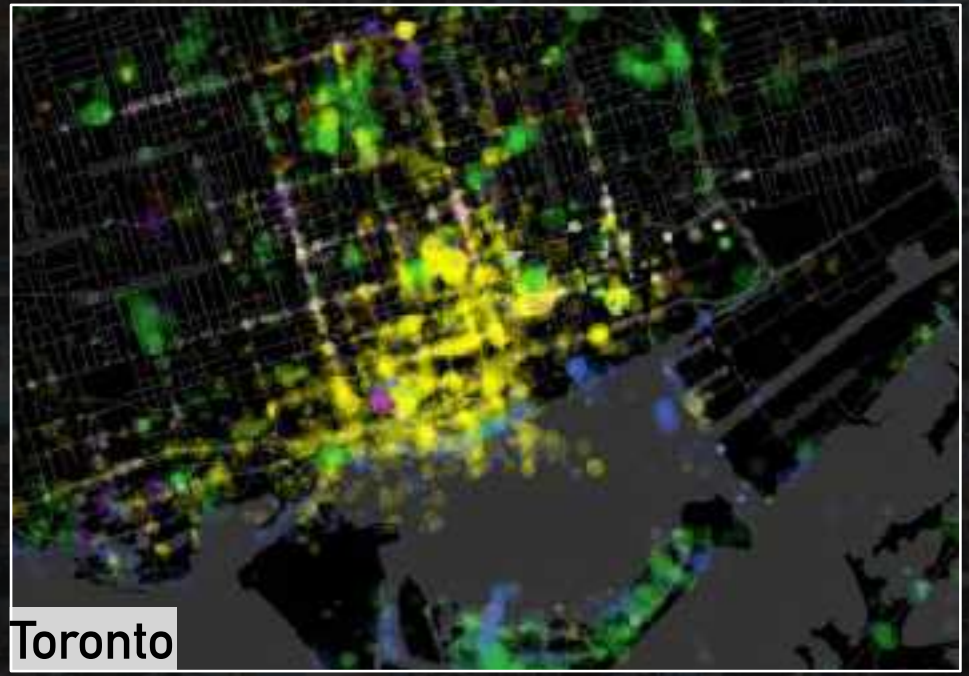


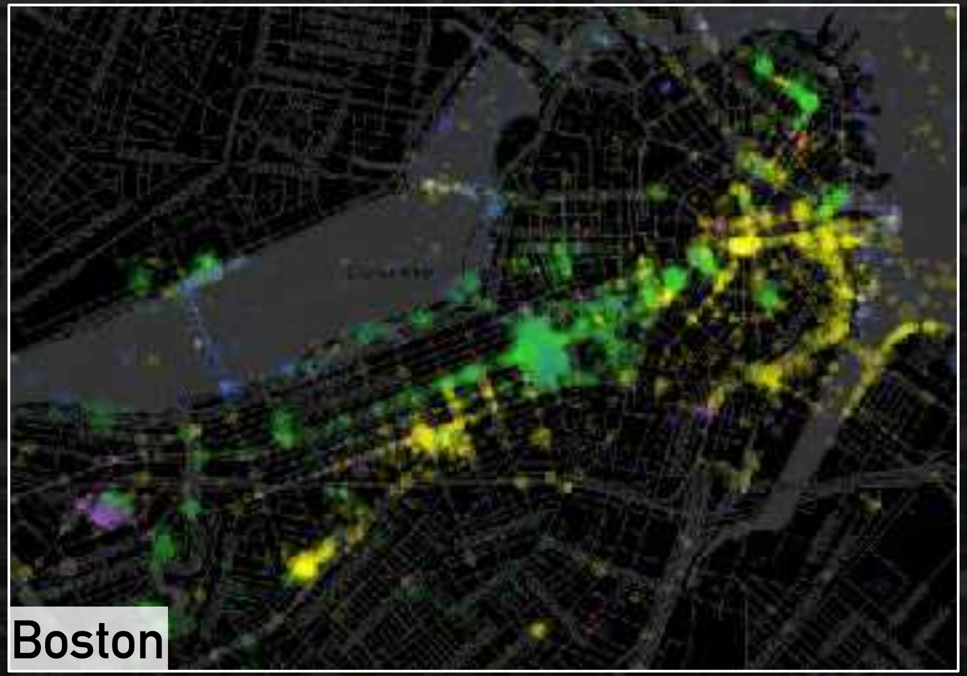


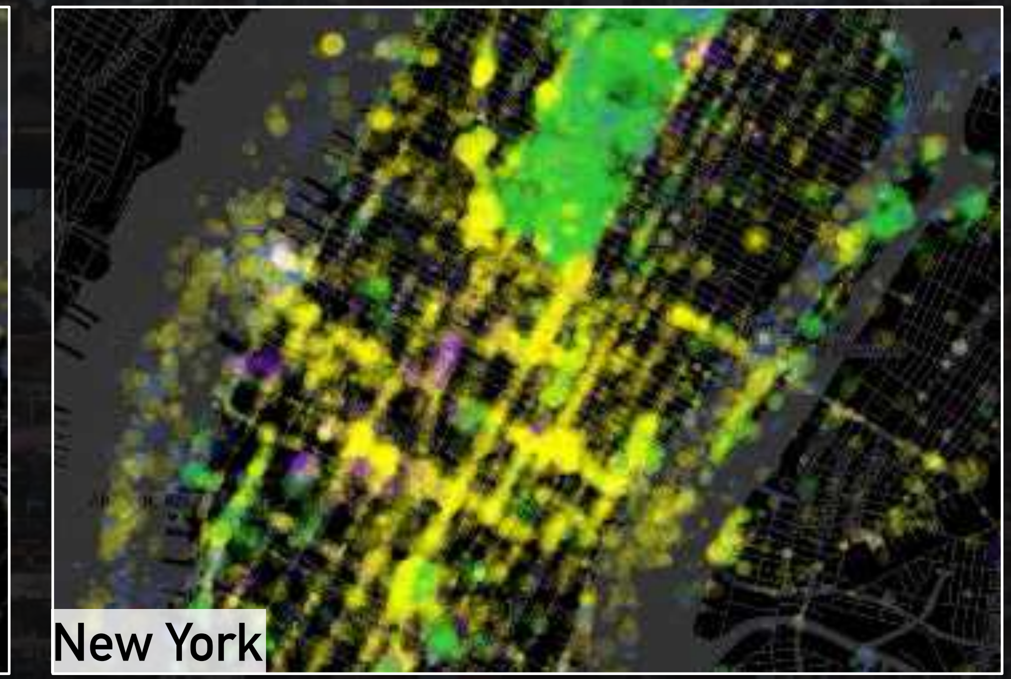


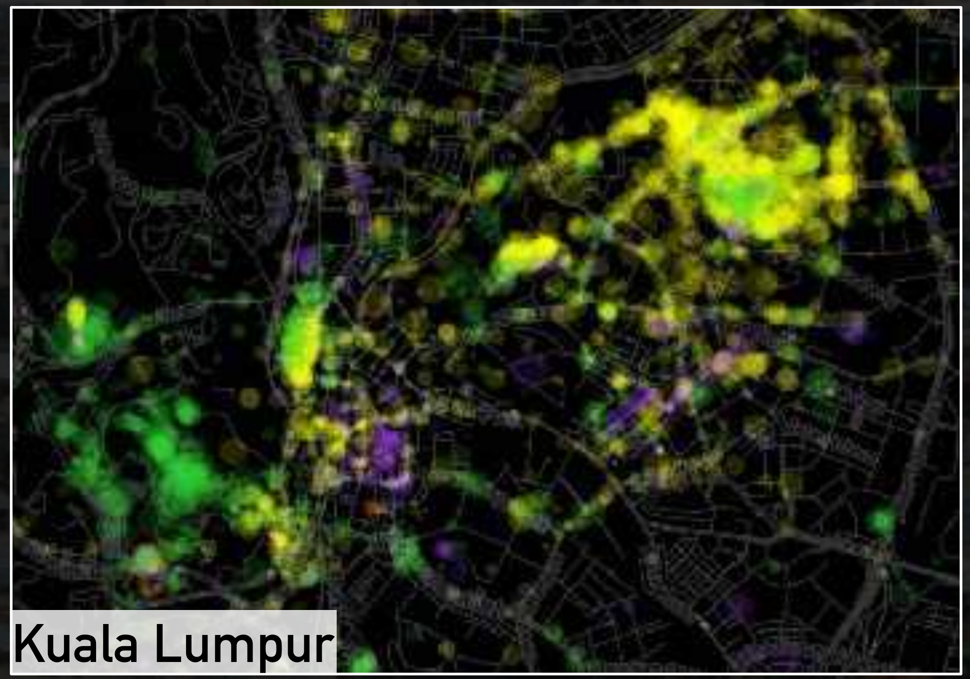


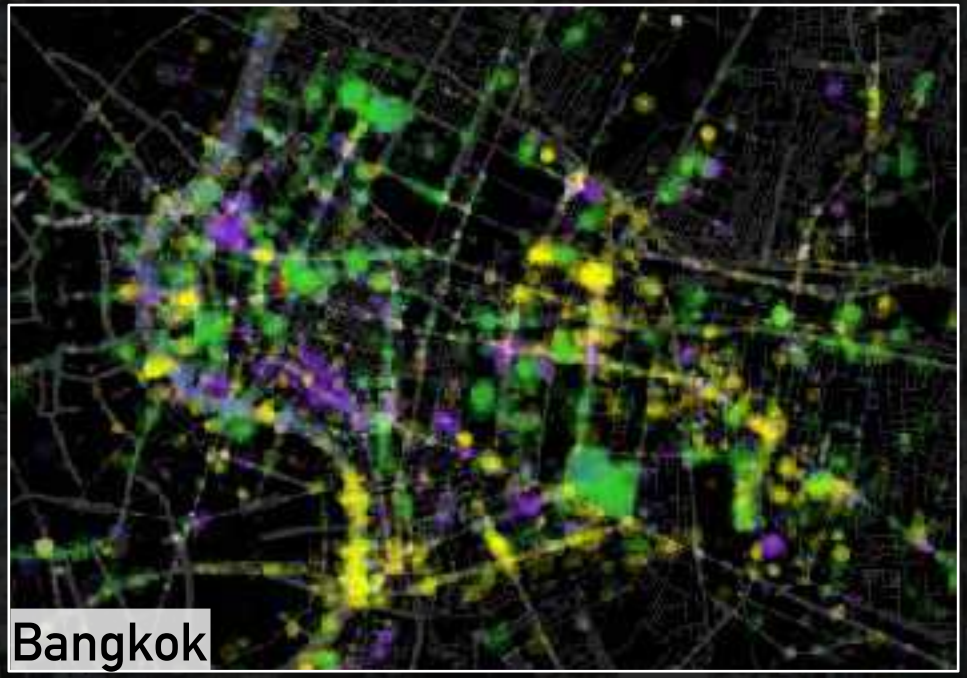


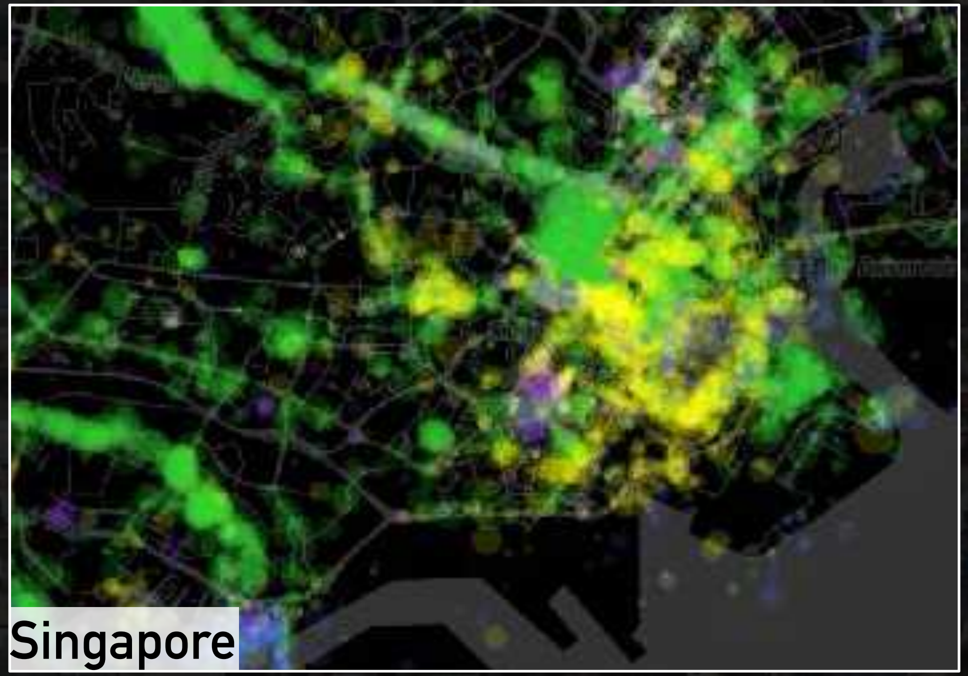


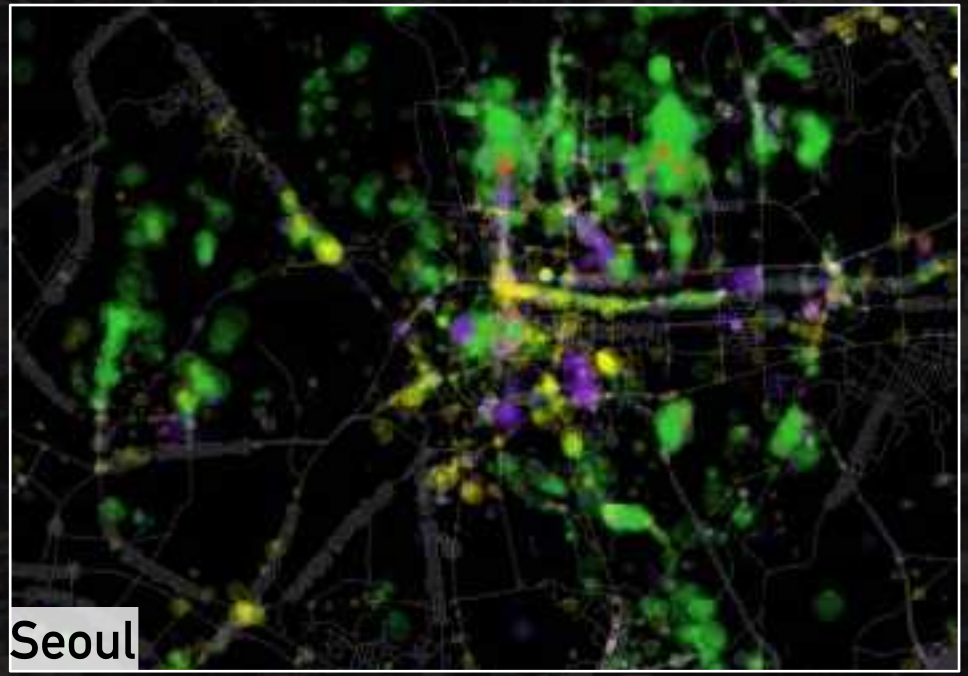


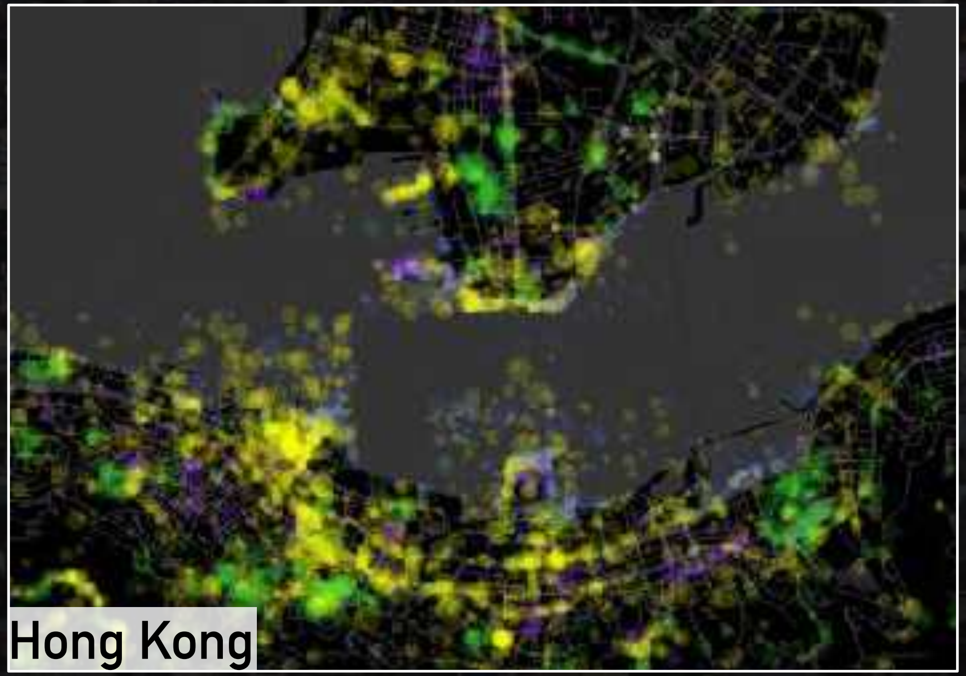












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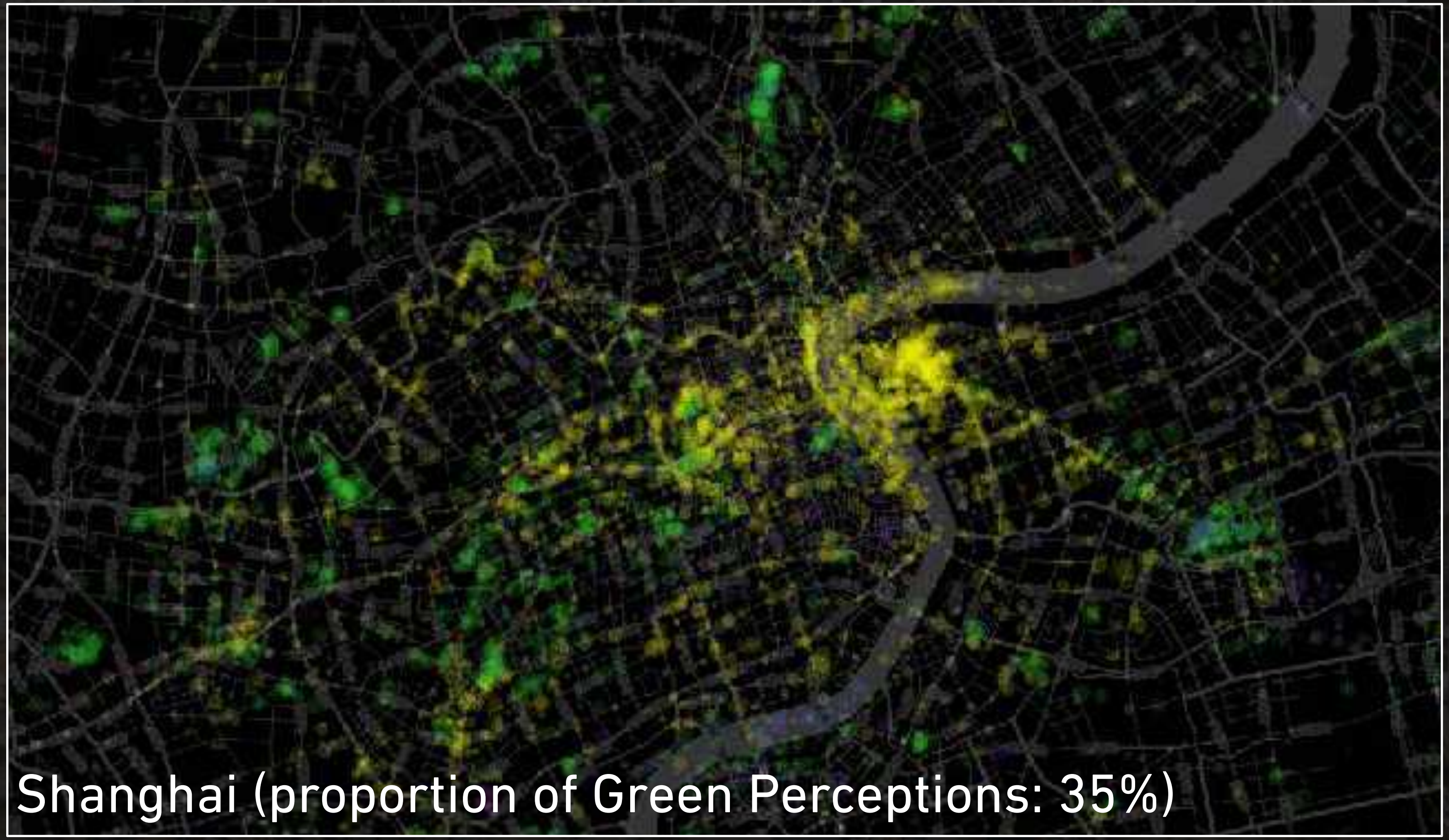
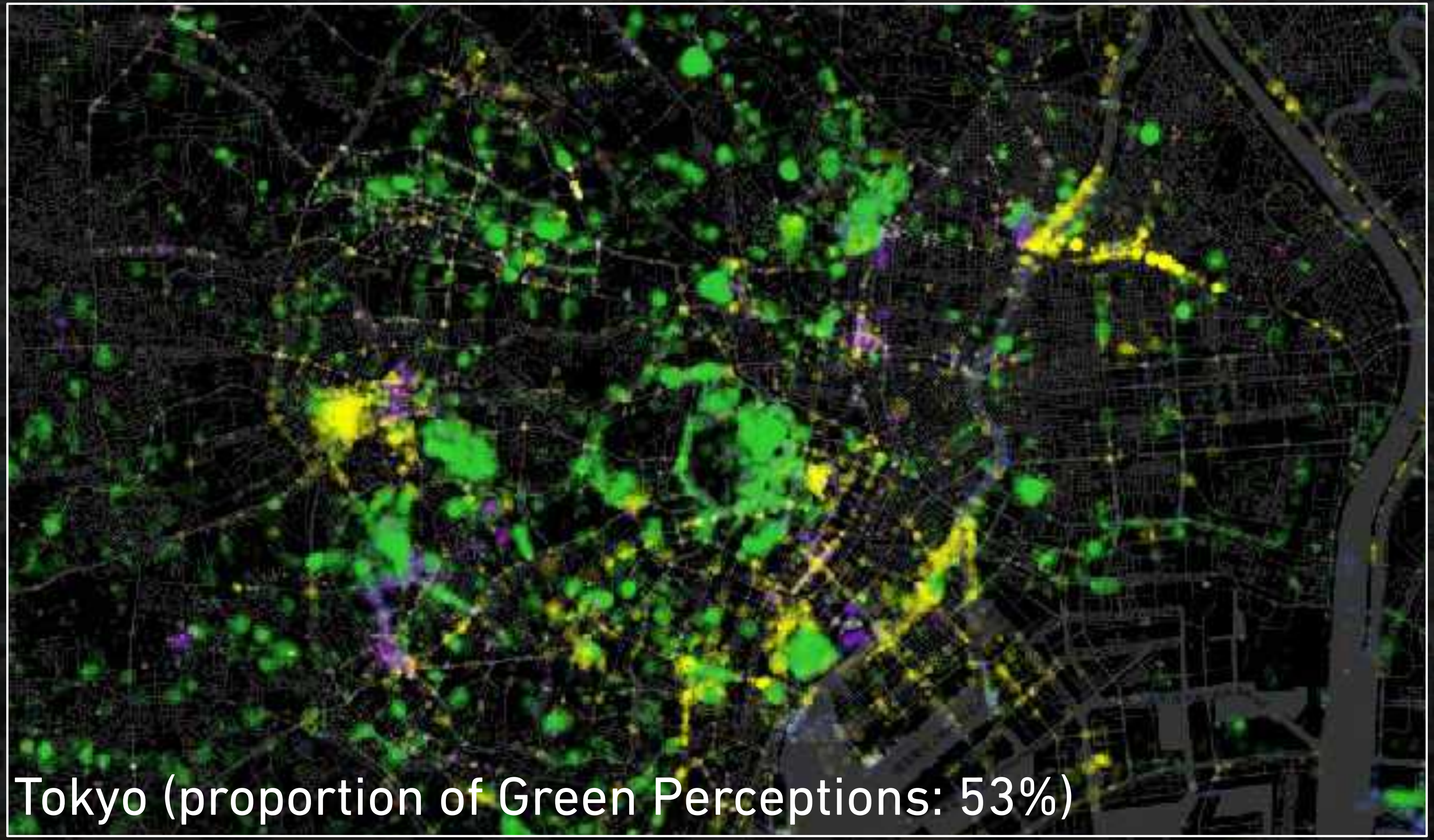
C-IMAGE Project

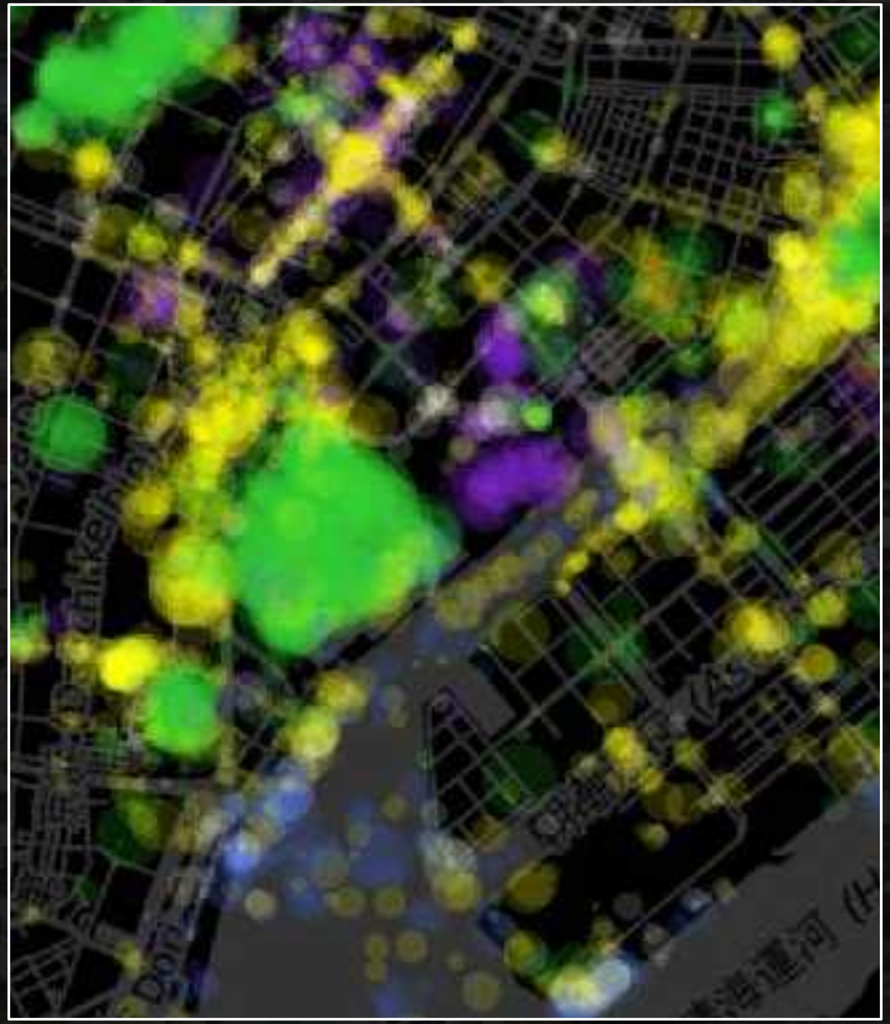
A reflection between "Real Space" and "Perceived Space"



Shanghai (proportion of Green Perceptions: 35%)



Tokyo (proportion of Green Perceptions: 53%)



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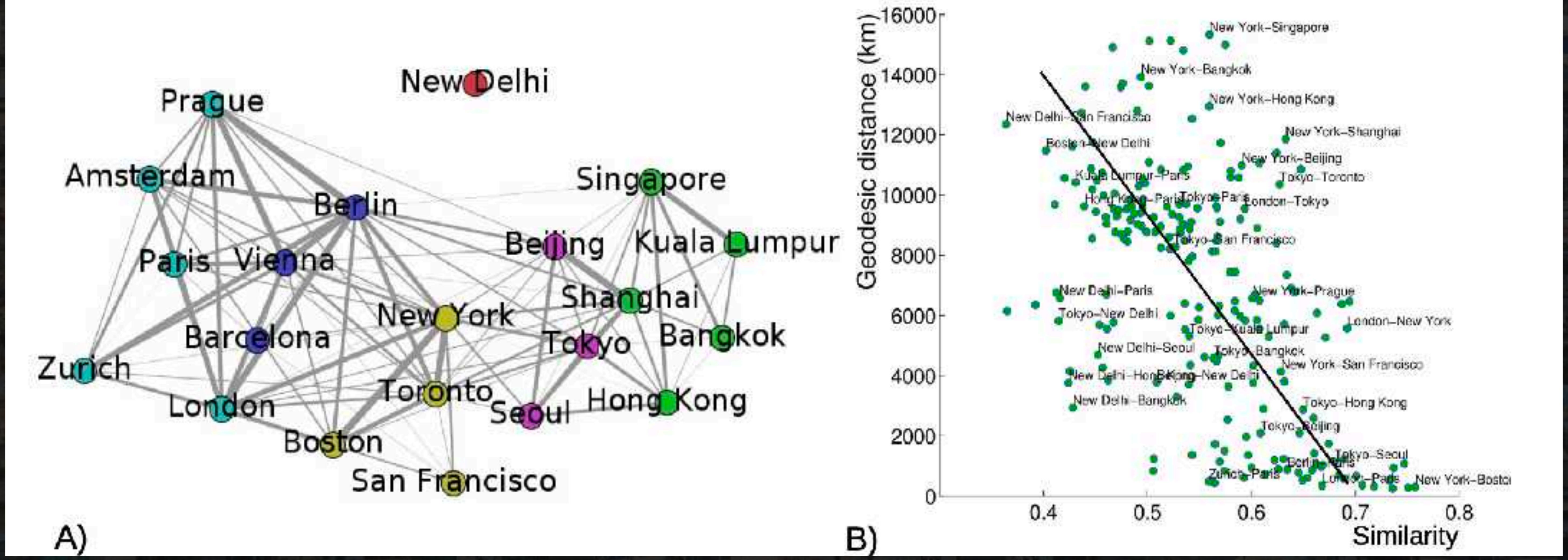
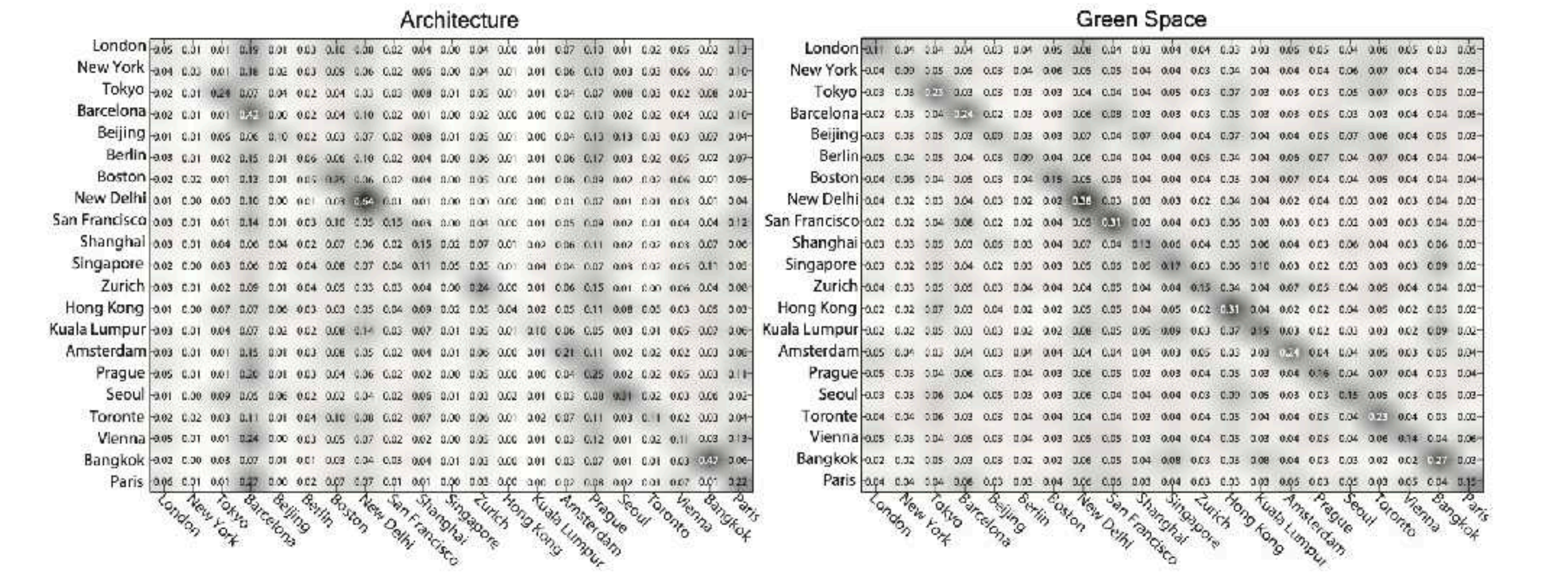
C-IMAGE Project

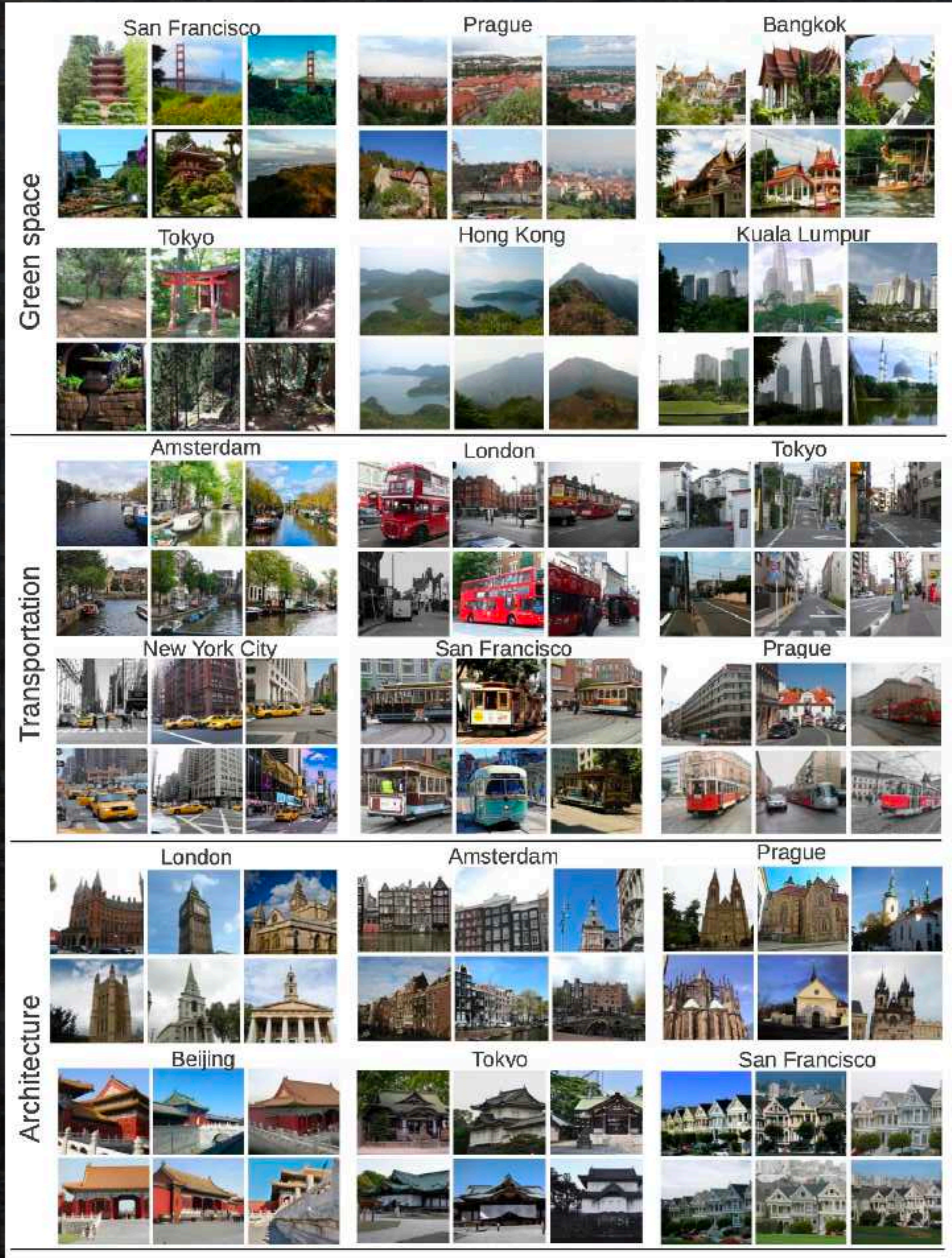
further exploration 1: sub category in comparison

C-IMAGE Project

further exploration 2: finding city identity through deep features







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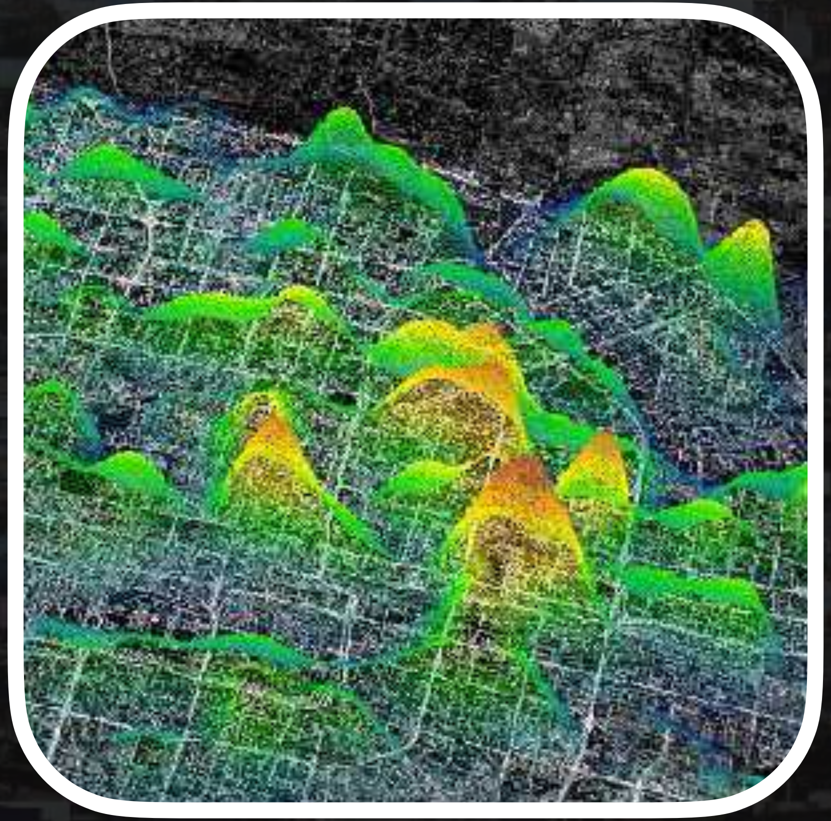
C-IMAGE

StreetScore

Tools

Data



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thesis finished
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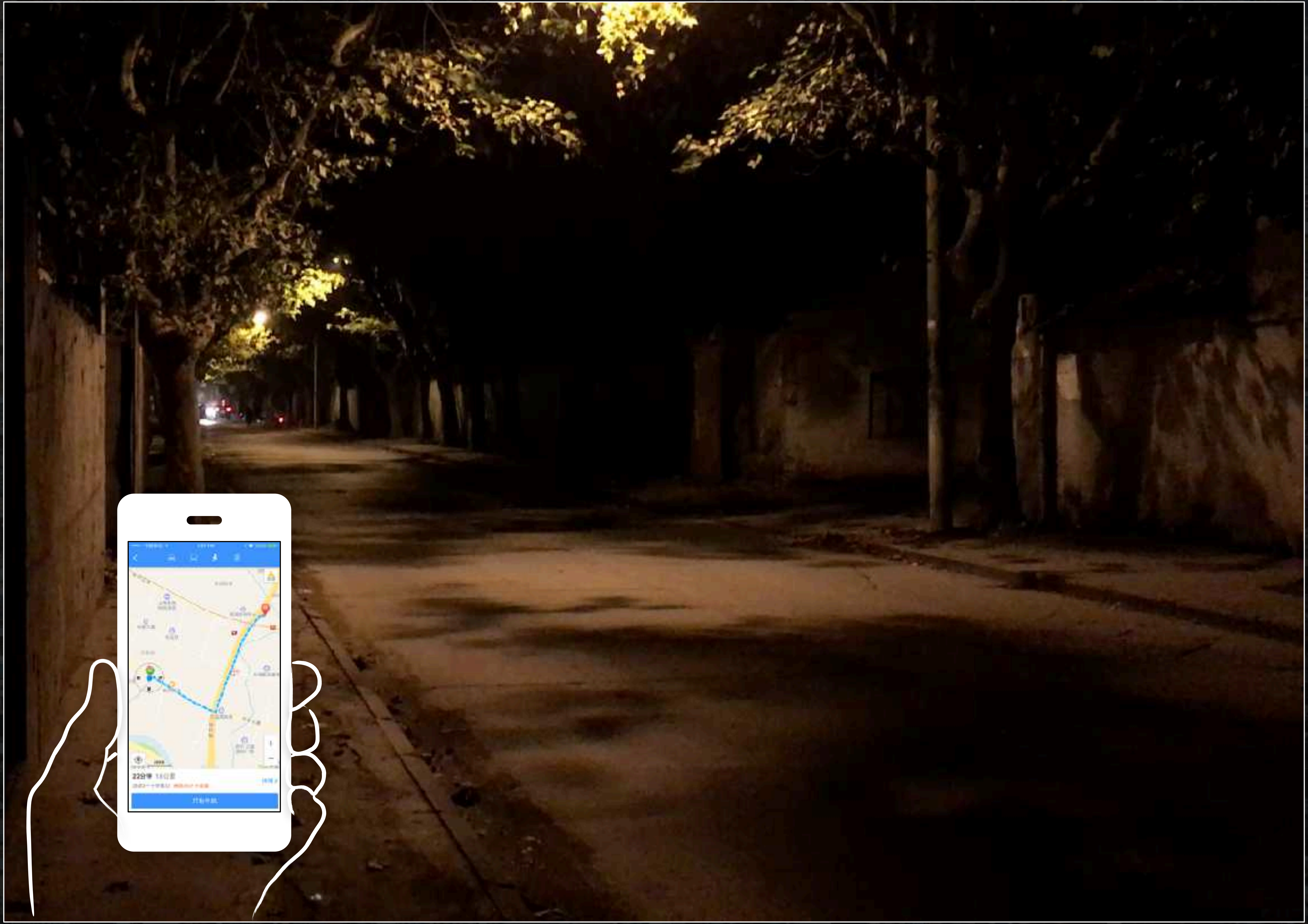
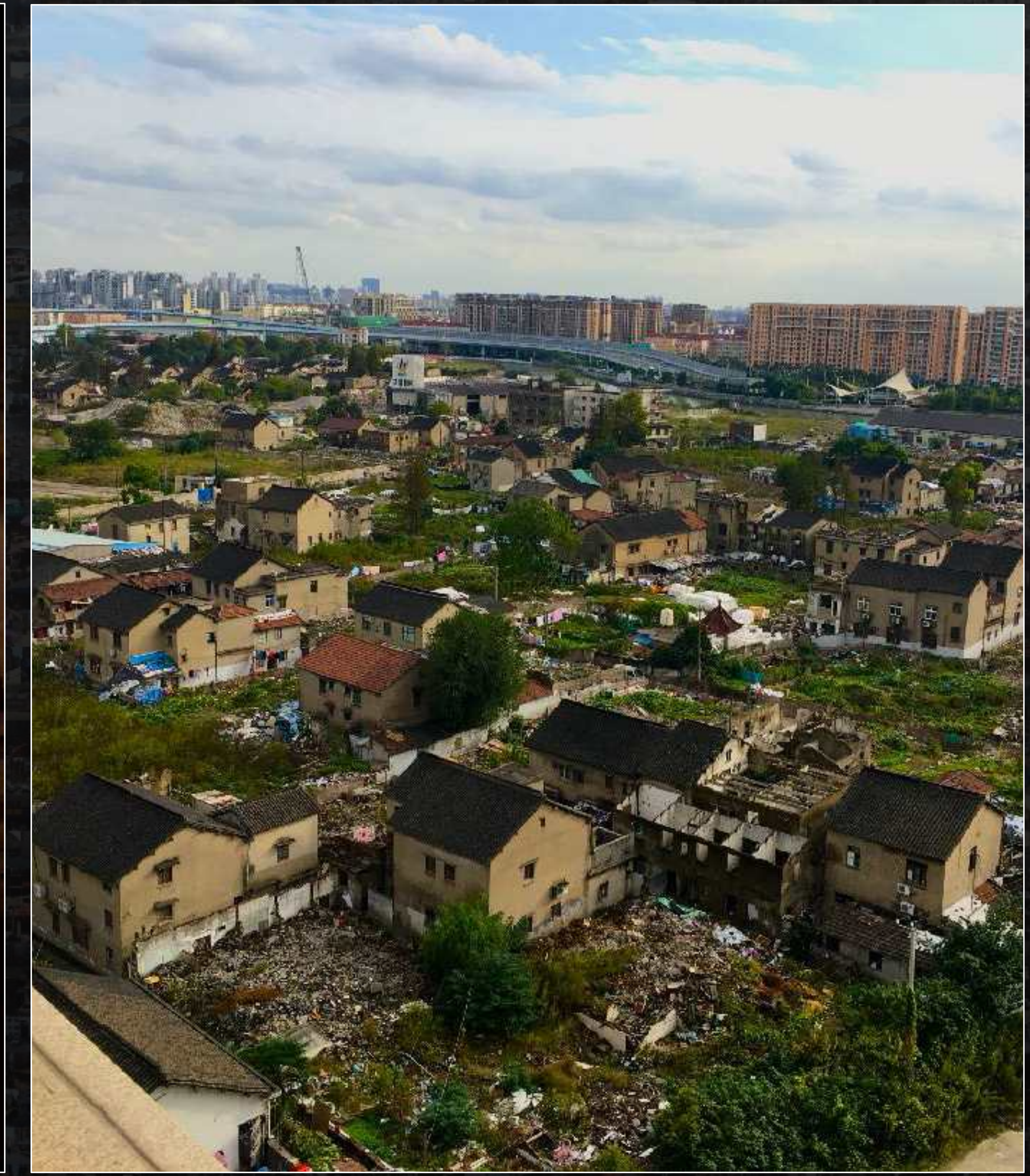
back to DUSP
start from scratch

StreeTalk Project

Evaluating street quality based on deep features and pairwise labeling method





- Liu, Liu, Fan Zhang, Bolei Zhou, Zhoutong Wang, and Yingxin Li. "STREETALK: A NAVIGATION SYSTEM FOR PEDESTRIANS AND CYCLISTS." Landscape Architecture Frontiers 6, no. 2 (2018): 94-101.

StreeTalk Project

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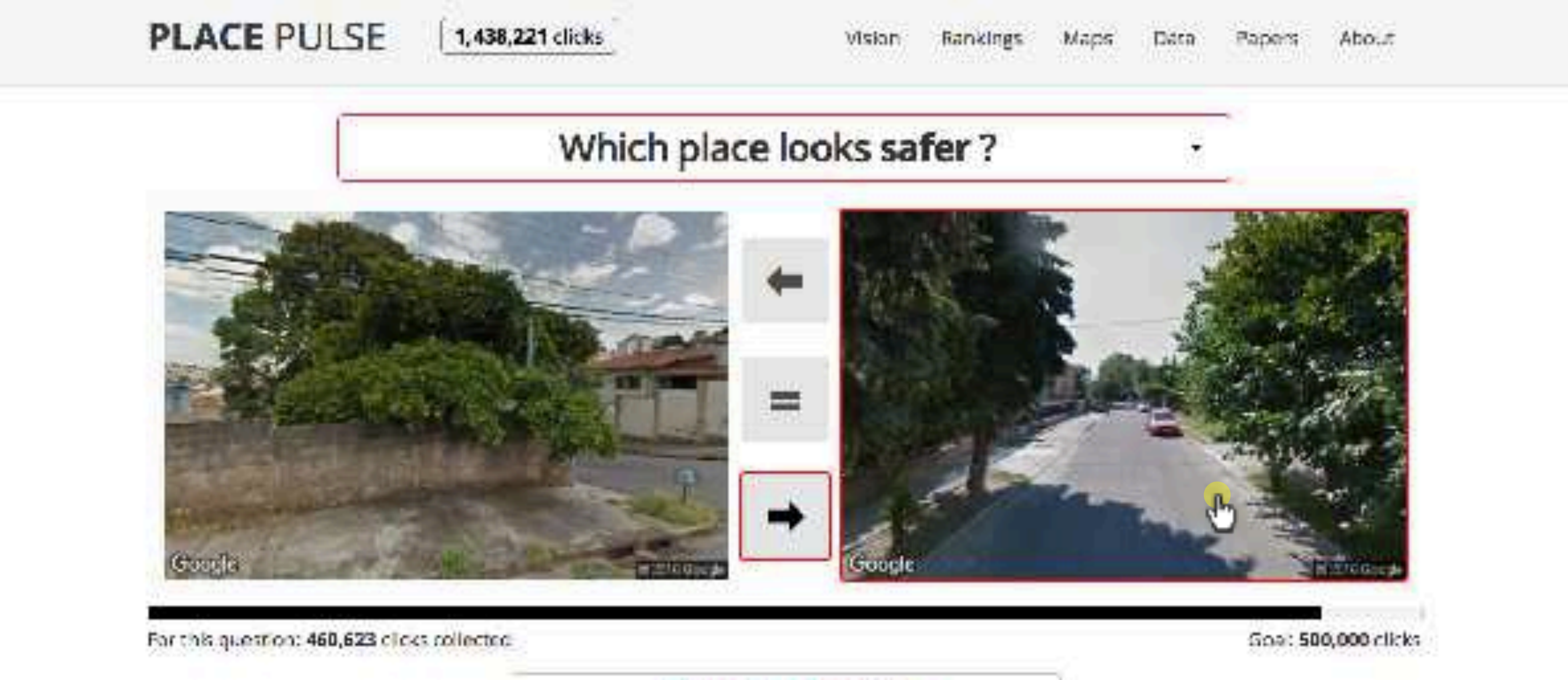
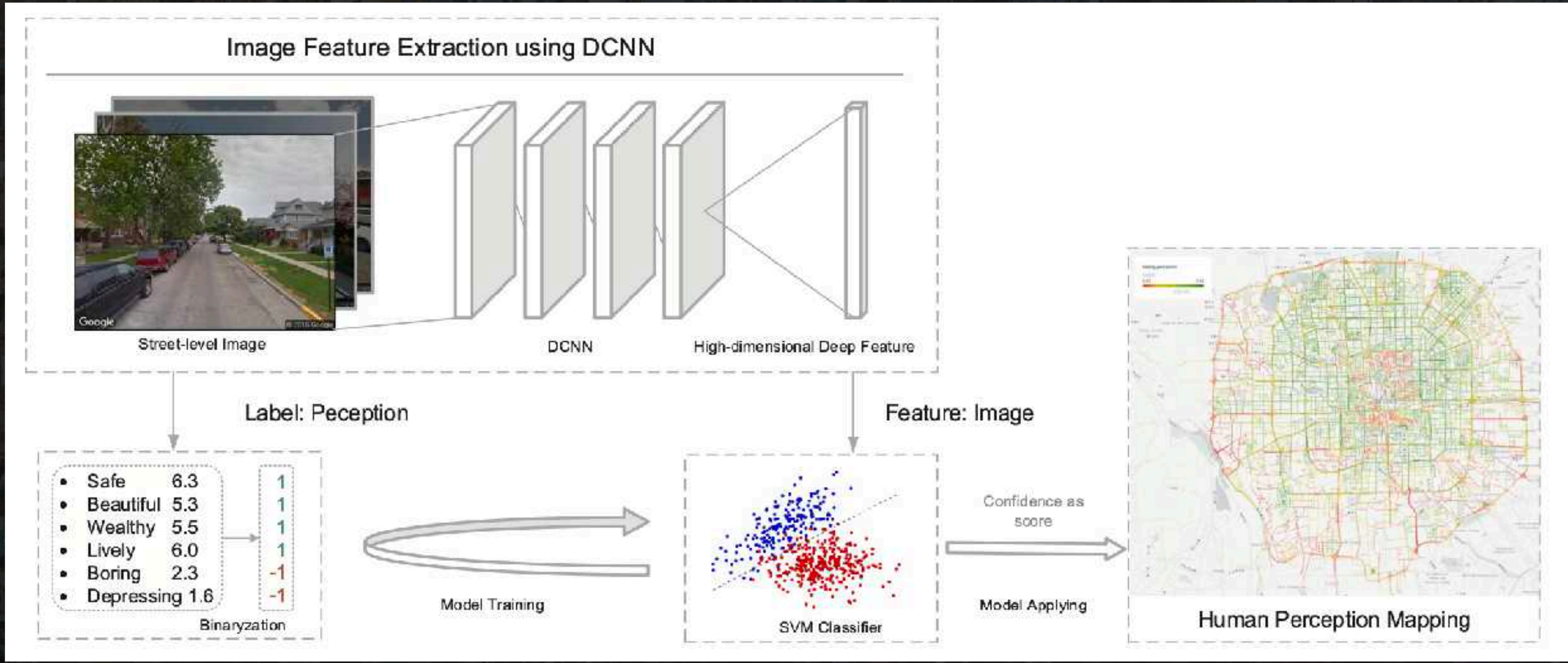



Fig. 3. Image samples from the MIT Place Pulse dataset with their perceptual score of the 6 dimensions.



- *Zhang, F., Zhou, B., Liu, L., Liu, Y., Fung, H. H., Lin, H., & Ratti, C. (2018). Measuring human perceptions of a large-scale urban region using machine learning. Landscape and Urban Planning, 180, 148-160.*

StreeTalk Project

Evaluating street quality based on deep features and pairwise labeling method

We found that the data quality of the safety scoring model after a series of data processing exceeded expectations.

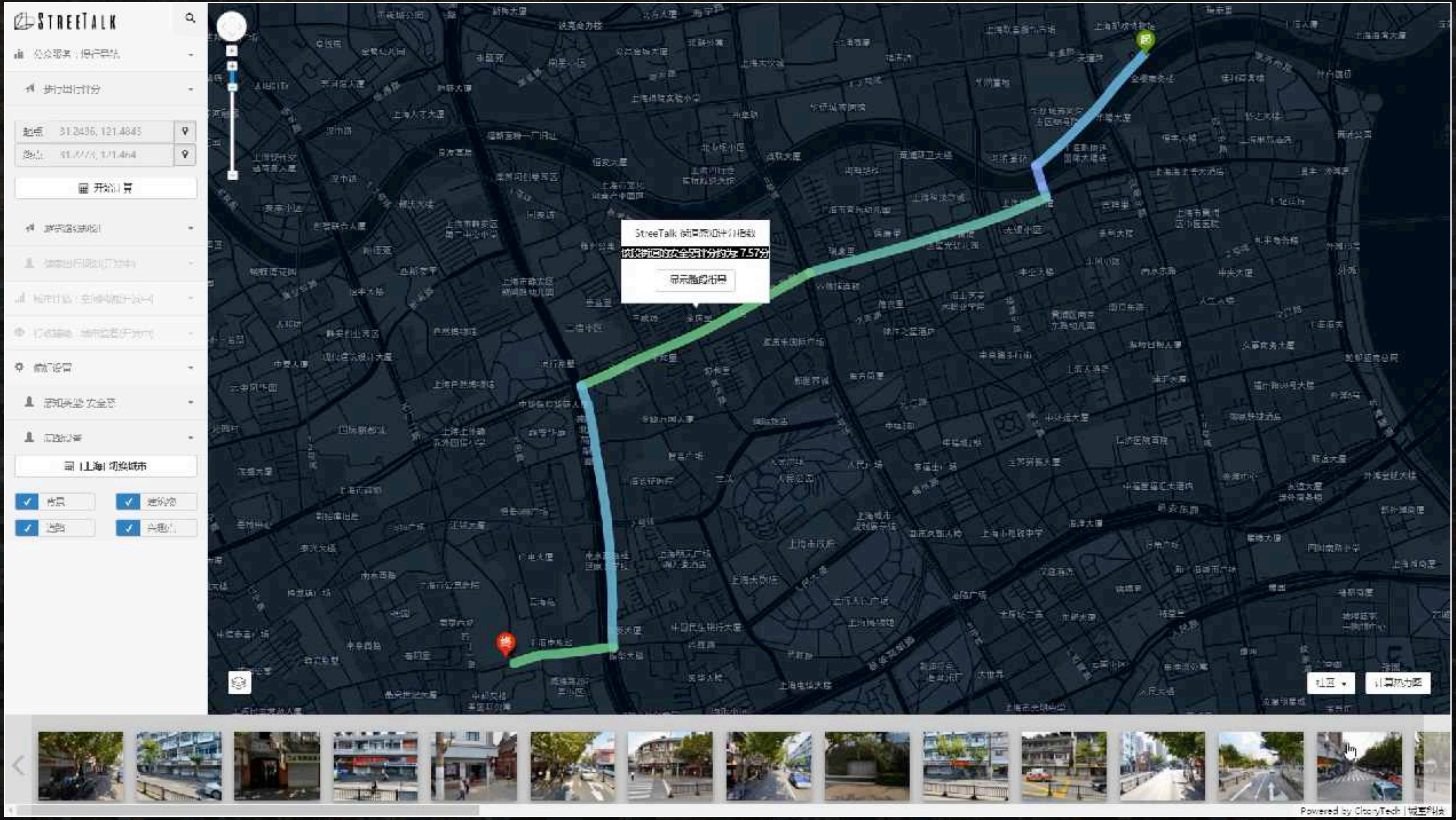
Fig. 9. Image samples from Shanghai that were predicted with high safe scores (left) and low safe scores (right).

- *Zhang, F., Zhou, B., Liu, L., Liu, Y., Fung, H. H., Lin, H., & Ratti, C. (2018). Measuring human perceptions of a large-scale urban region using machine learning. Landscape and Urban Planning, 180, 148-160.*

StreeTalk Project

Evaluating street quality based on deep features and pairwise labeling method

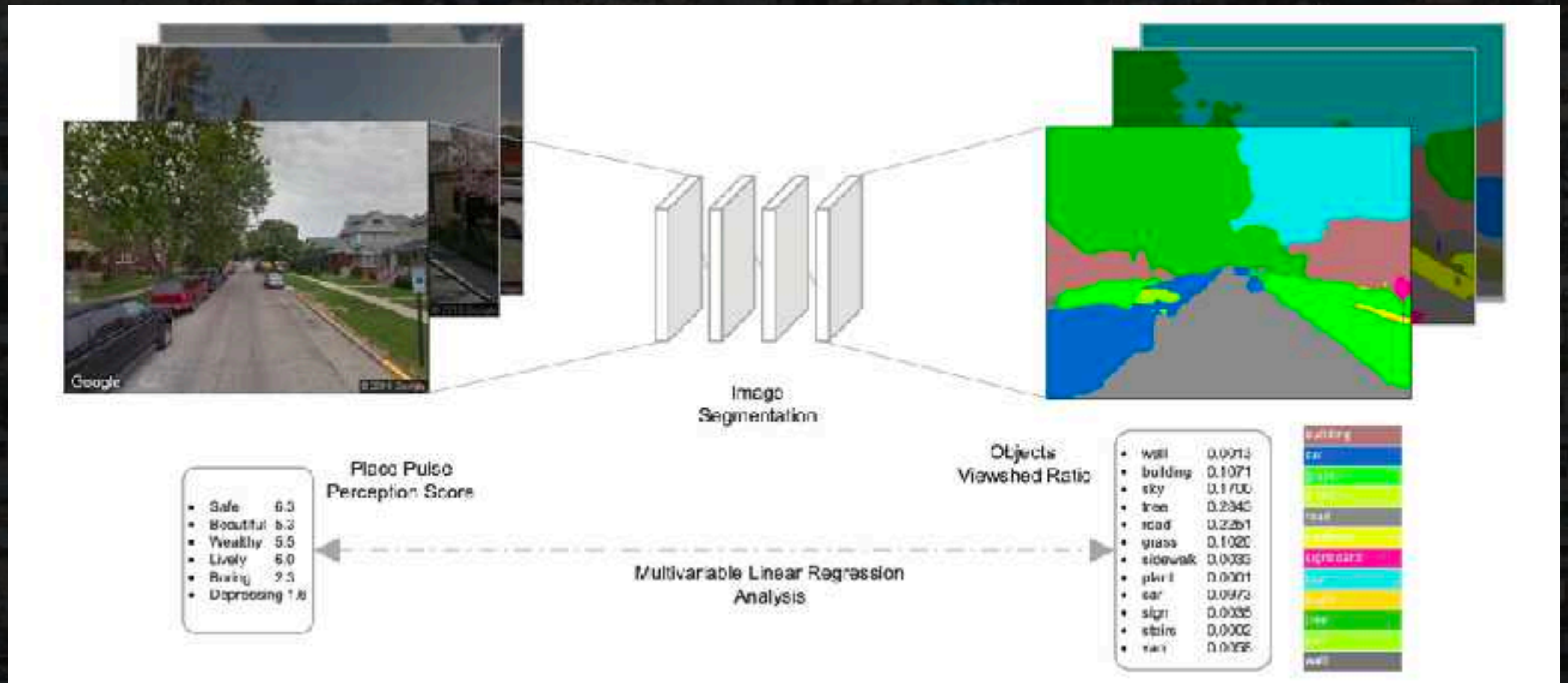
We developed an algorithm of calculating safety scores from visual context of street views, thus established a pedestrian routing web app based on average score along each road.

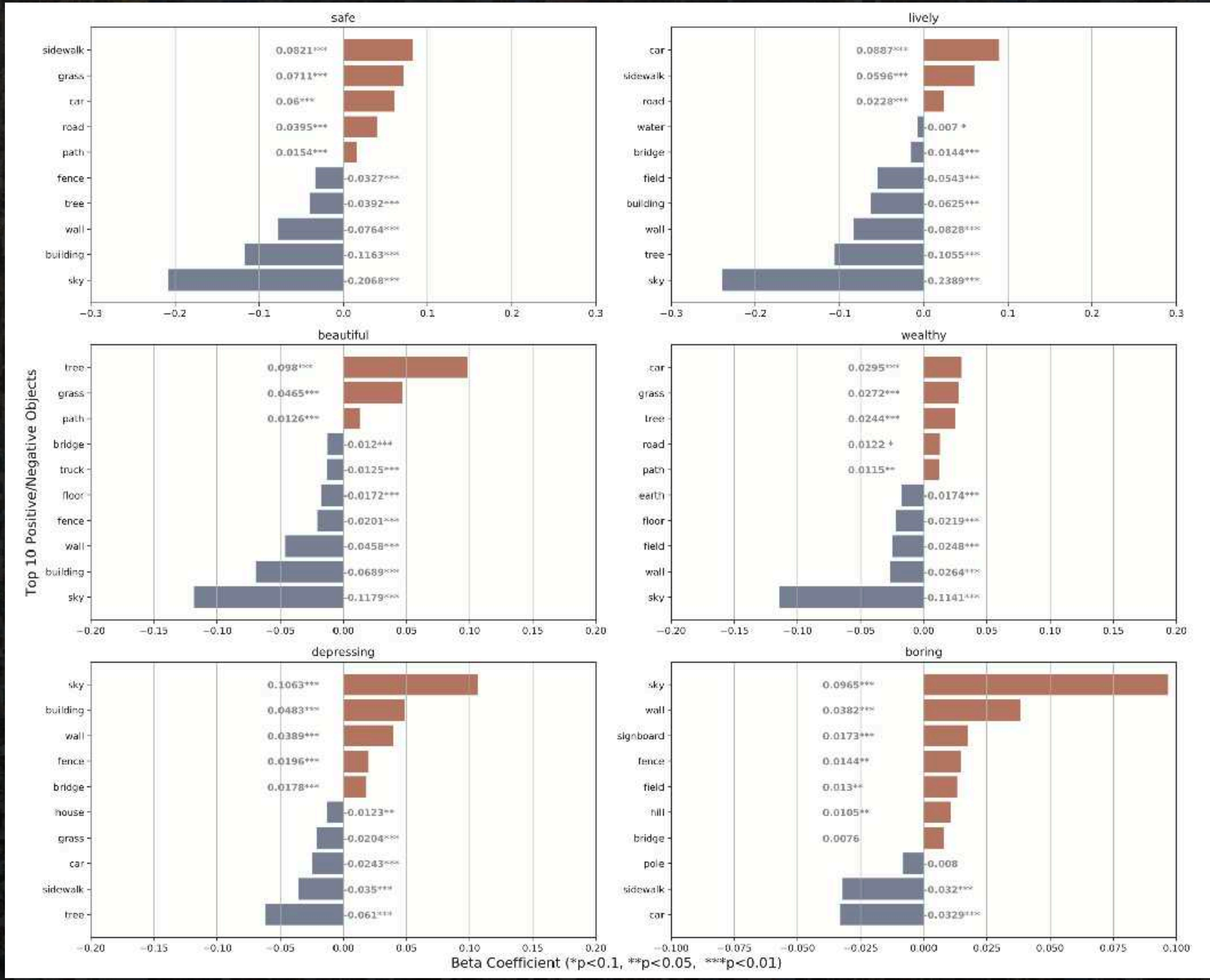


the pedestrian routing tool based on better score of safety scores

StreeTalk Project

correlation between perceptional scores and street objects





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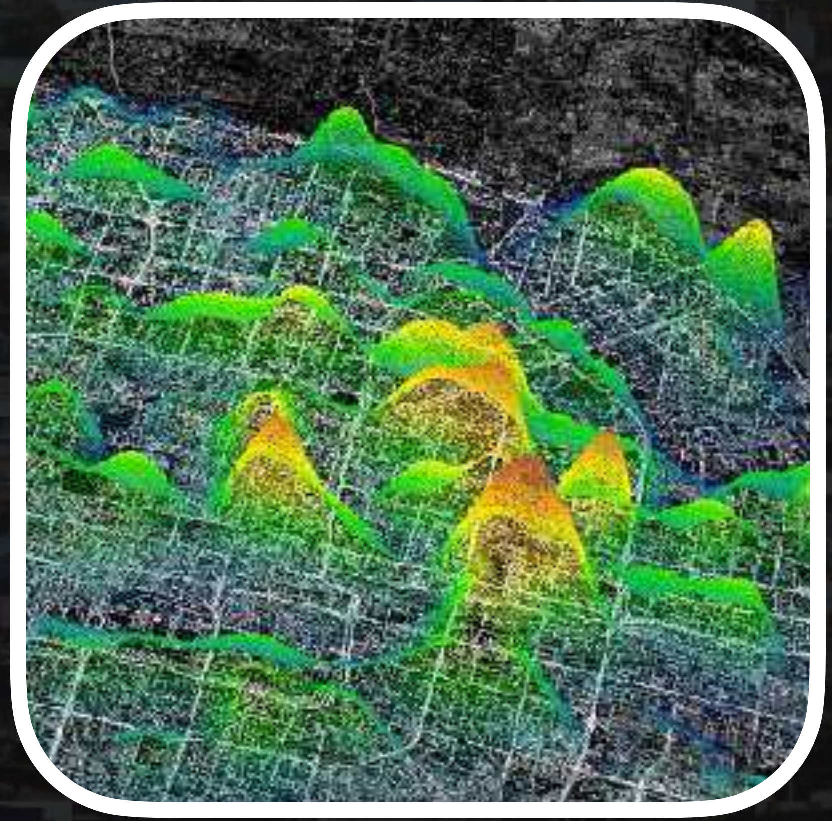
C-IMAGE

StreetScore

Tools

Data



2014
thesis finished
graduated as MCP

2015

2016

2017
quit from CAUPD
founded start-up

2018

2019

2020

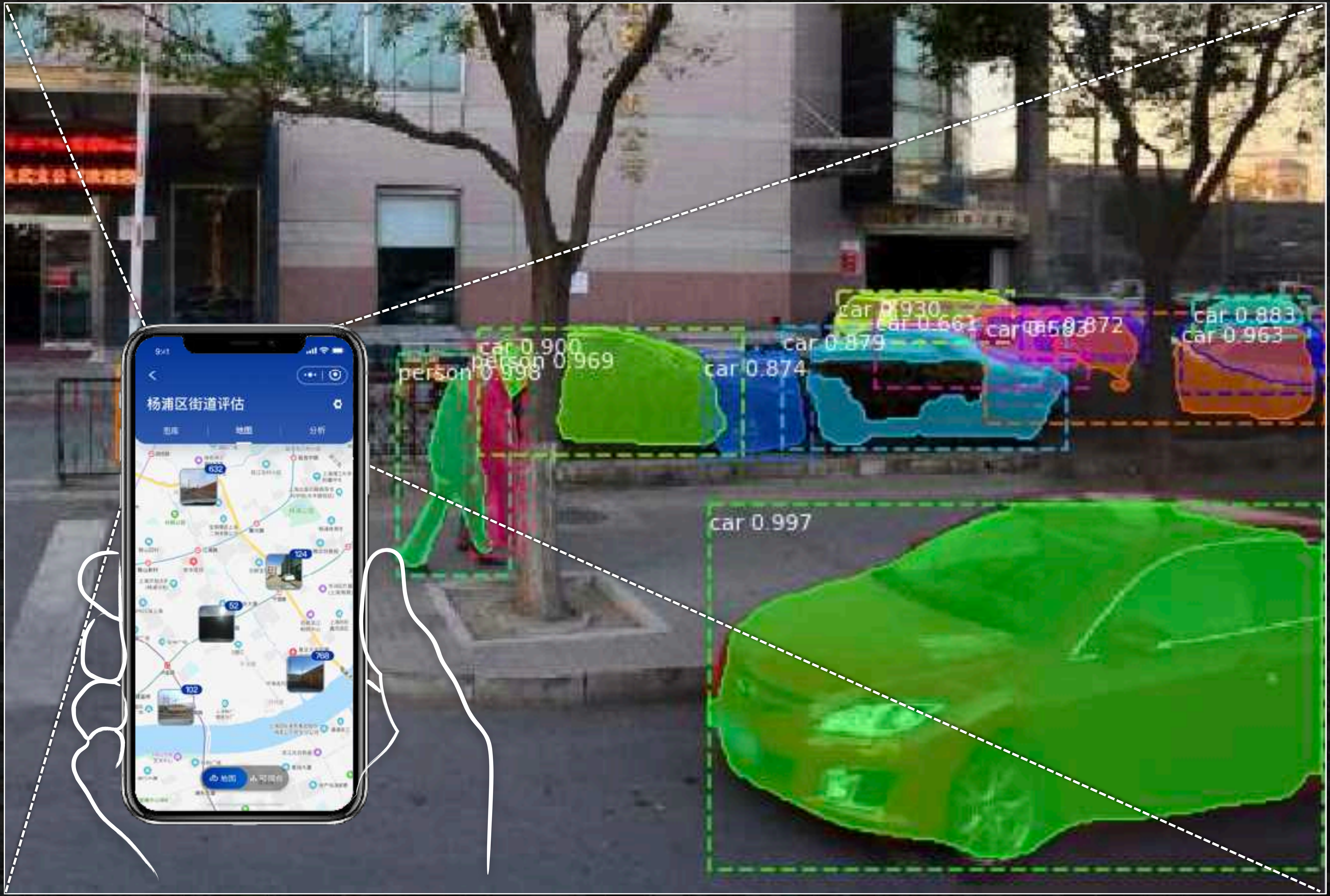
2021

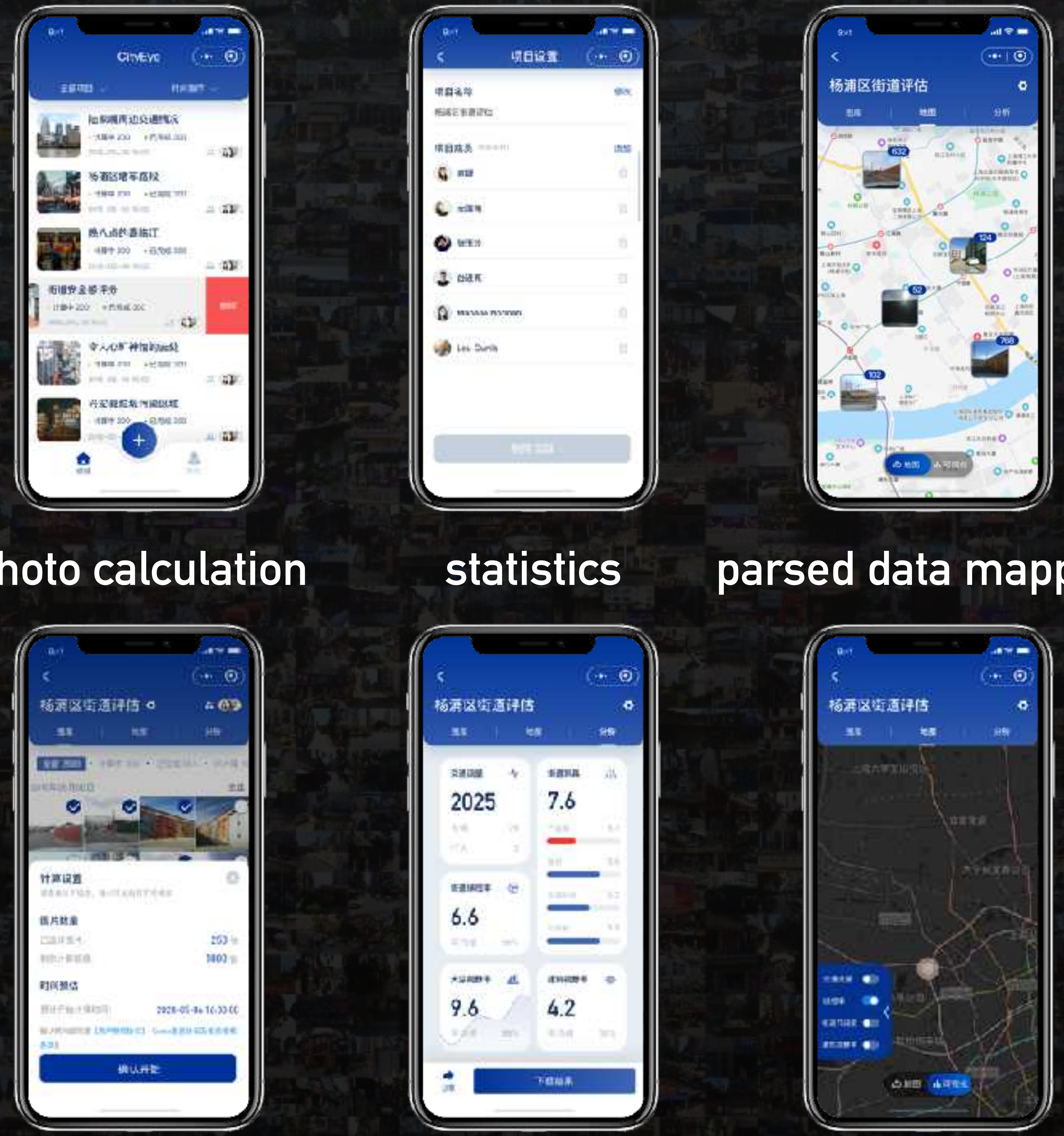
2022
back to DUSP
start from scratch

Data Collection

CityEye project (WeChat Miniapp)

CityEye is a WeChat mini for grouping photos. One of the reasons why I would like to develop this tool, is just because it suffers for group photo management after organizing a field trip, when thousands of photos will be taken.





project list

member management

mapping

photo calculation

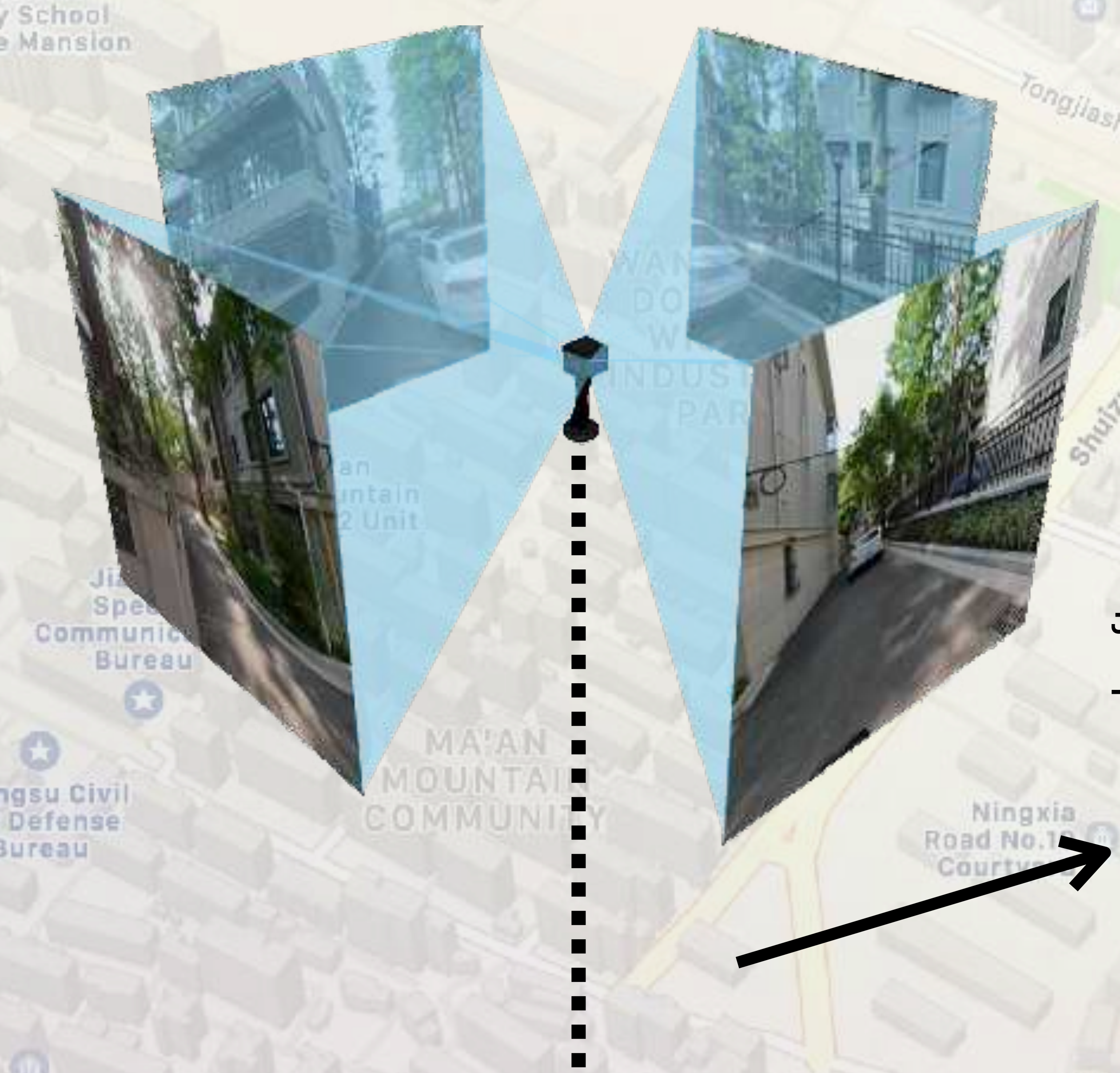
statistics

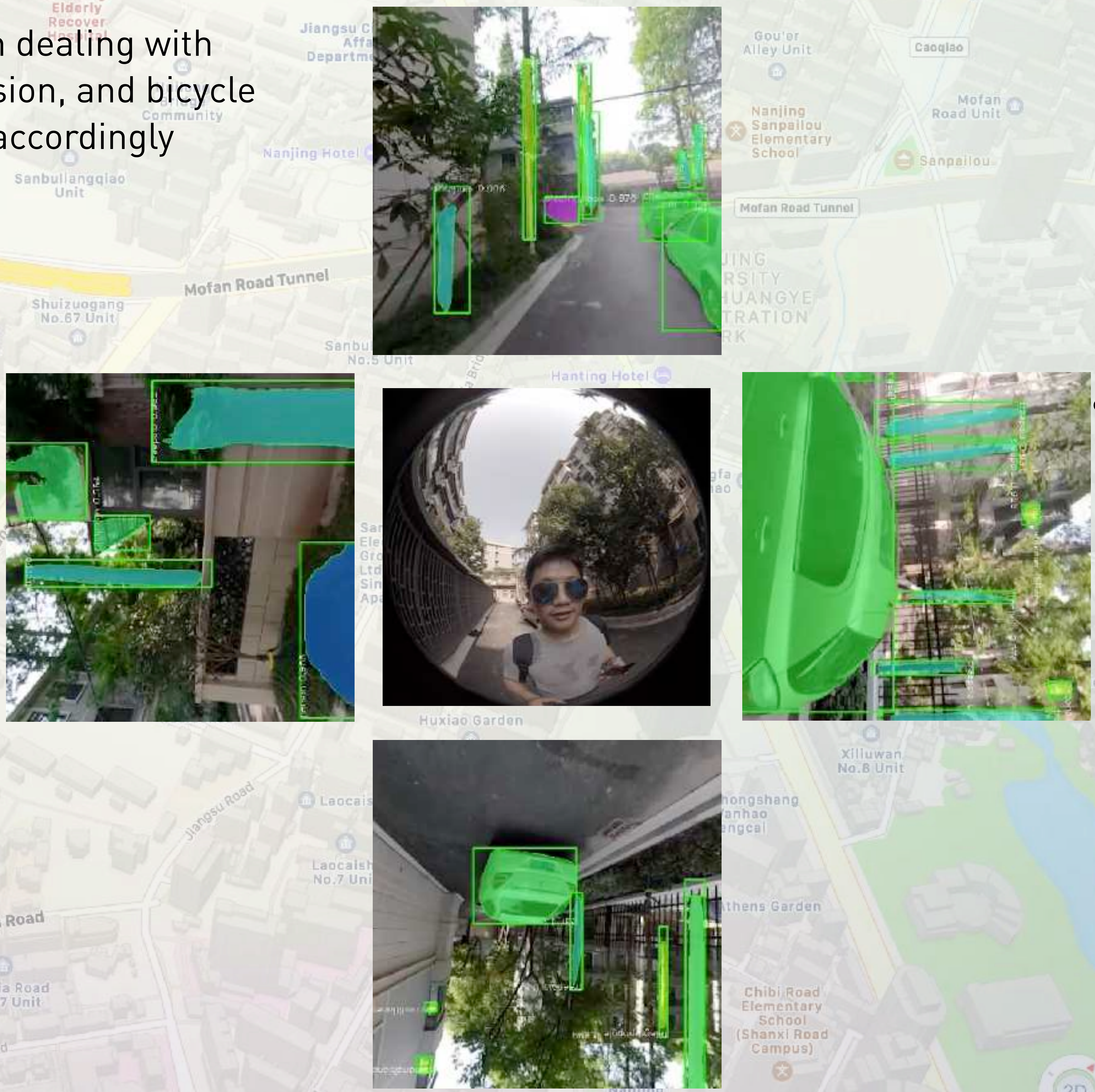
parsed data mapping

Data Collection

Other way of data collections

To get more first-hand dataset, we developed an independent solution in dealing with image data collection and processing. As to pedestrian vision, vehicle vision, and bicycle vision we deliver specific approaches of data collaboration and develop accordingly image processing APIs.

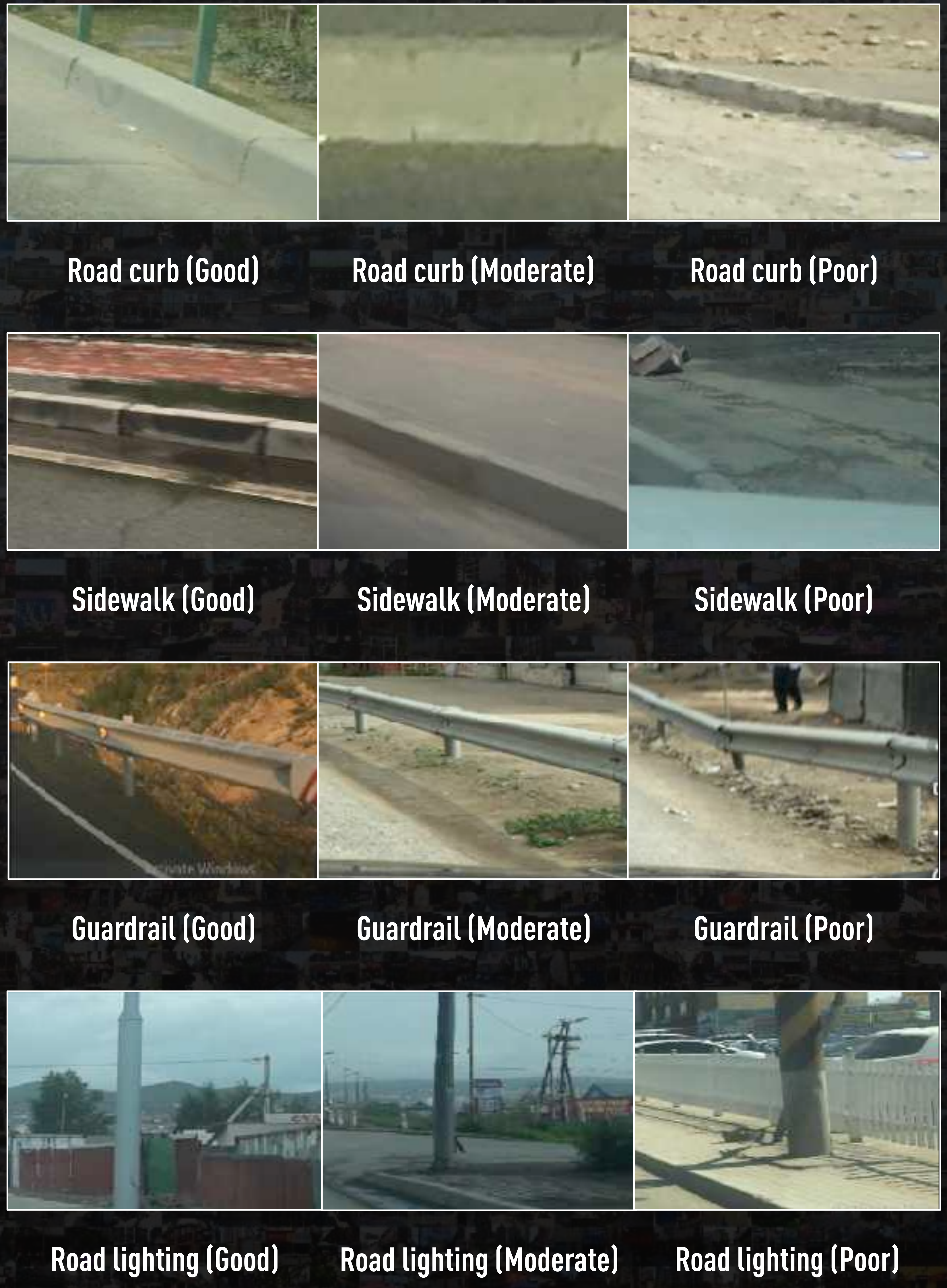




Data Labeling

Pairwise Labeling Pipeline Tool

The road assets condition assessment based on UGC streetview images



- *Zhang, D., Yi, H., Chen, Y., Jiang, N., Shao, J., & Liu, L. (2022). An urban infrastructure assessment system built on geo-tagged images and machine learning. Computational Urban Science, 2(1), 1-21.*

Data Labeling

Pairwise Labeling Pipeline Tool

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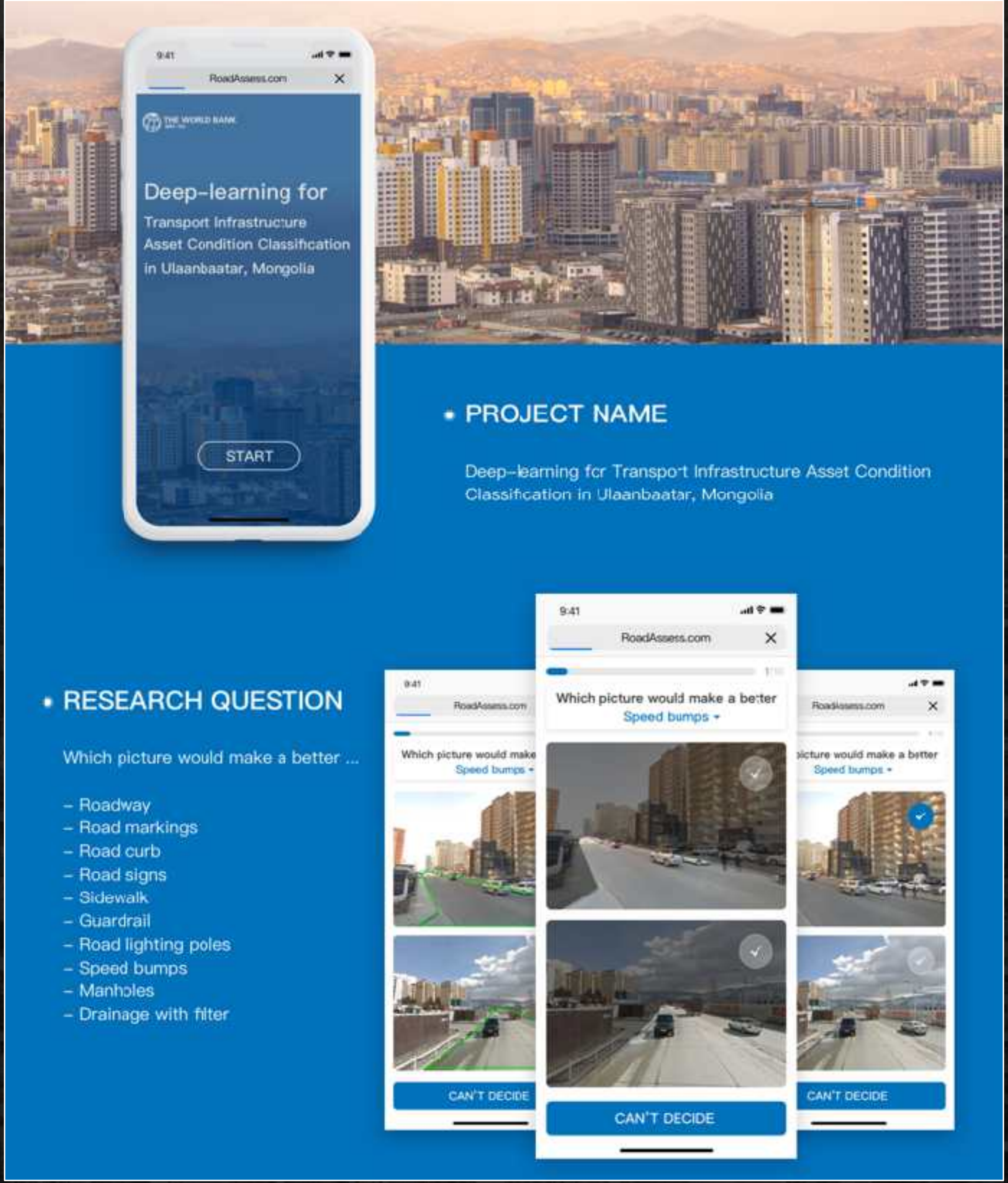
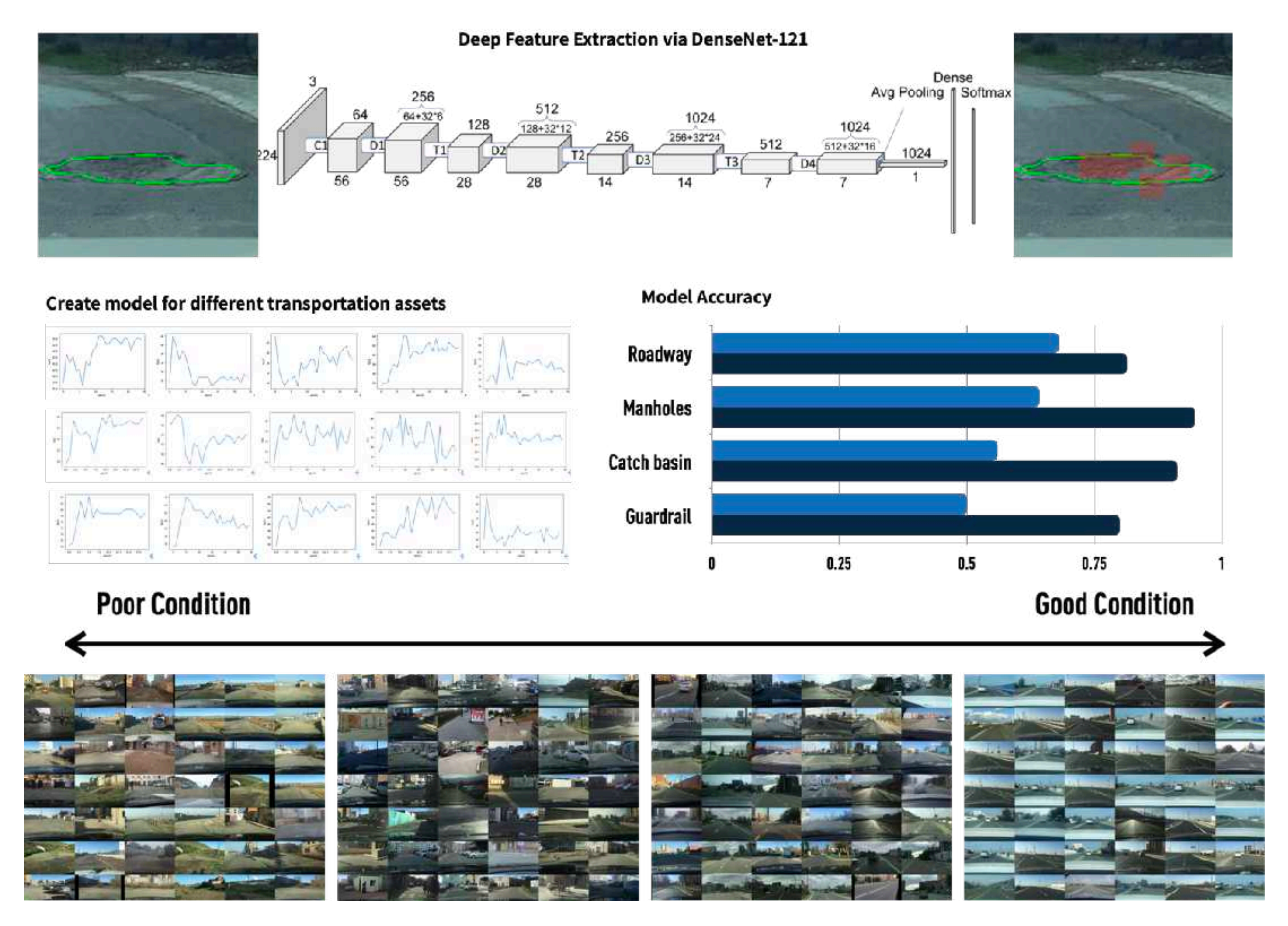




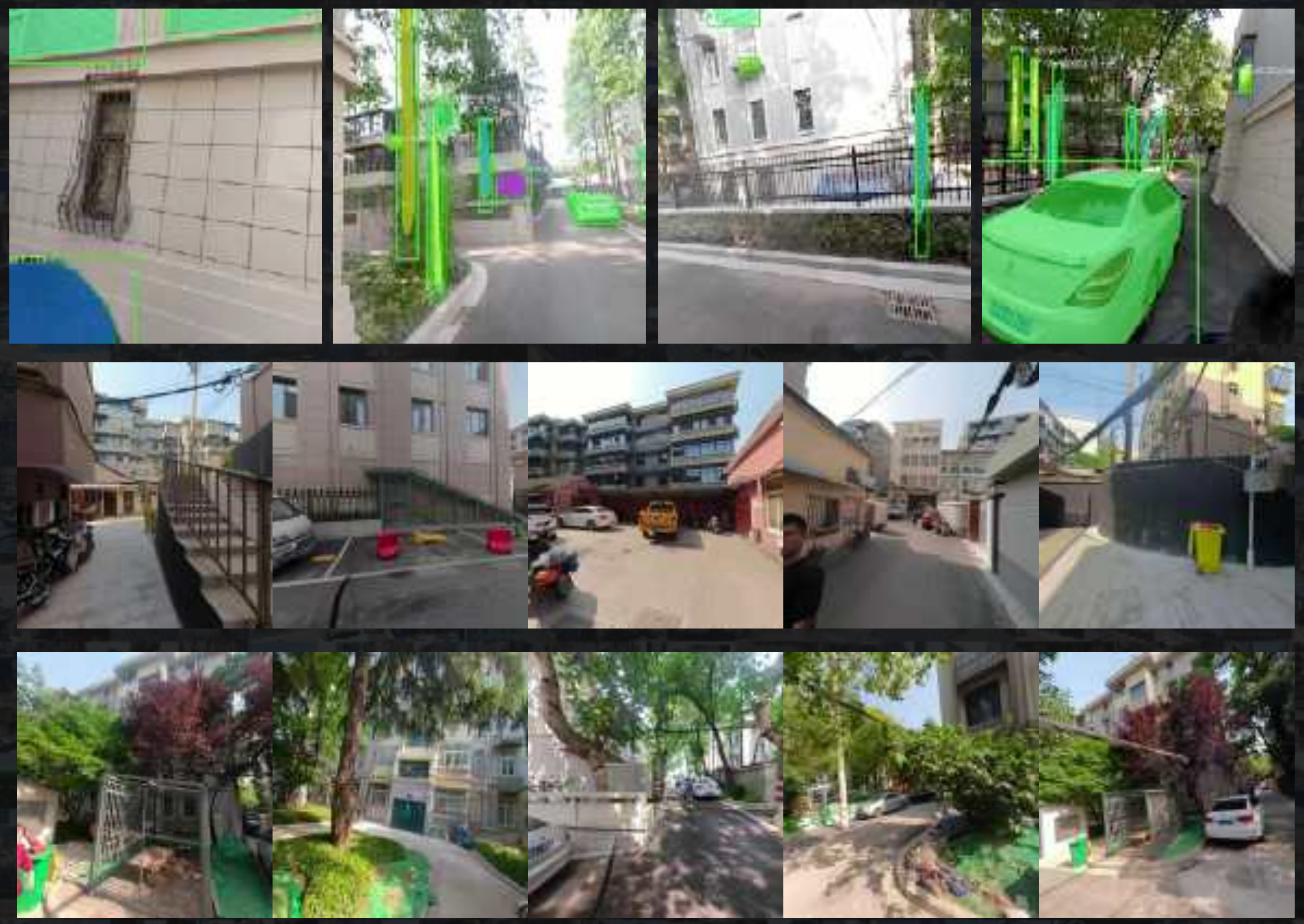
- *Zhang, D., Yi, H., Chen, Y., Jiang, N., Shao, J., & Liu, L. (2022). An urban infrastructure assessment system built on geo-tagged images and machine learning. Computational Urban Science, 2(1), 1-21.*

Data Labeling

Pairwise Labeling Pipeline Tool

Visual comfort around subway stations in Beijing

Visual comfort evaluation in Nanjing

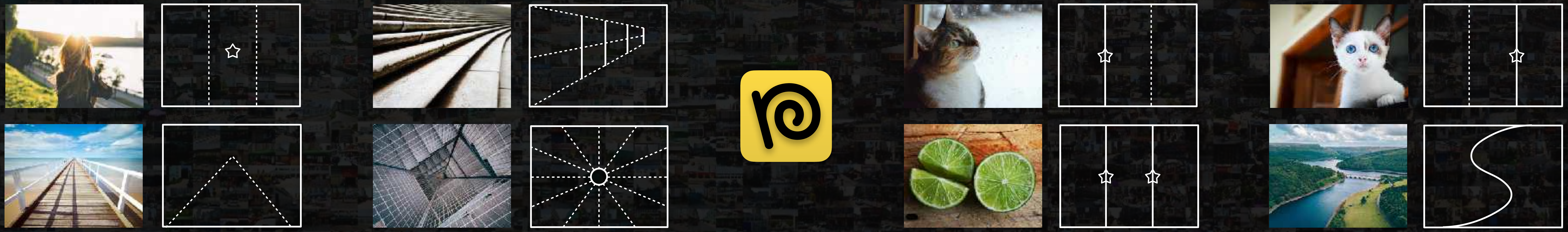


Skyline preferences survey in Shanghai

Aesthetic preference of store signs in Shanghai

Data Collaboration

How to inspire individual curiosity of taking photos?

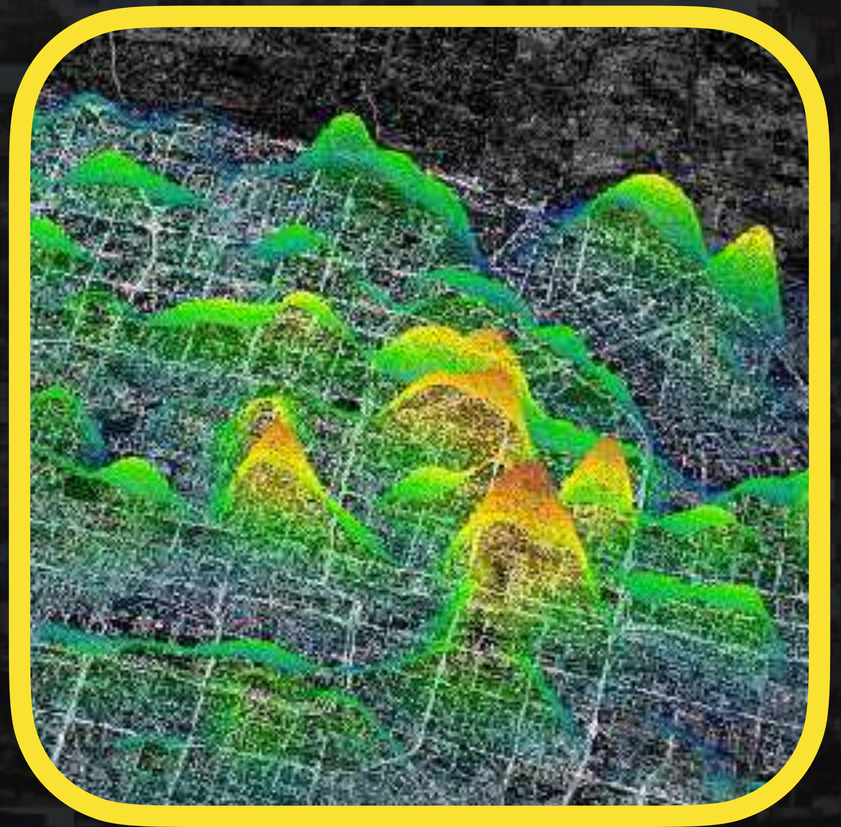


C-IMAGE

StreetScore

Tools

Data



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Streetview Data

Baidu SV Tencent SV | Google SV

During past years, we have collected over 100 million street views from Baidu, covering the all 324 cities/towns in China. We are also collecting street views from Google covering the top cities world wide.

Data Type	cities	photos
Baidu SV	324	111,697,328
Tencent SV	281	6,868,552
Google SV	10	4,242,844

Milan

Tokyo

Paris

Frankfurt

Moscow

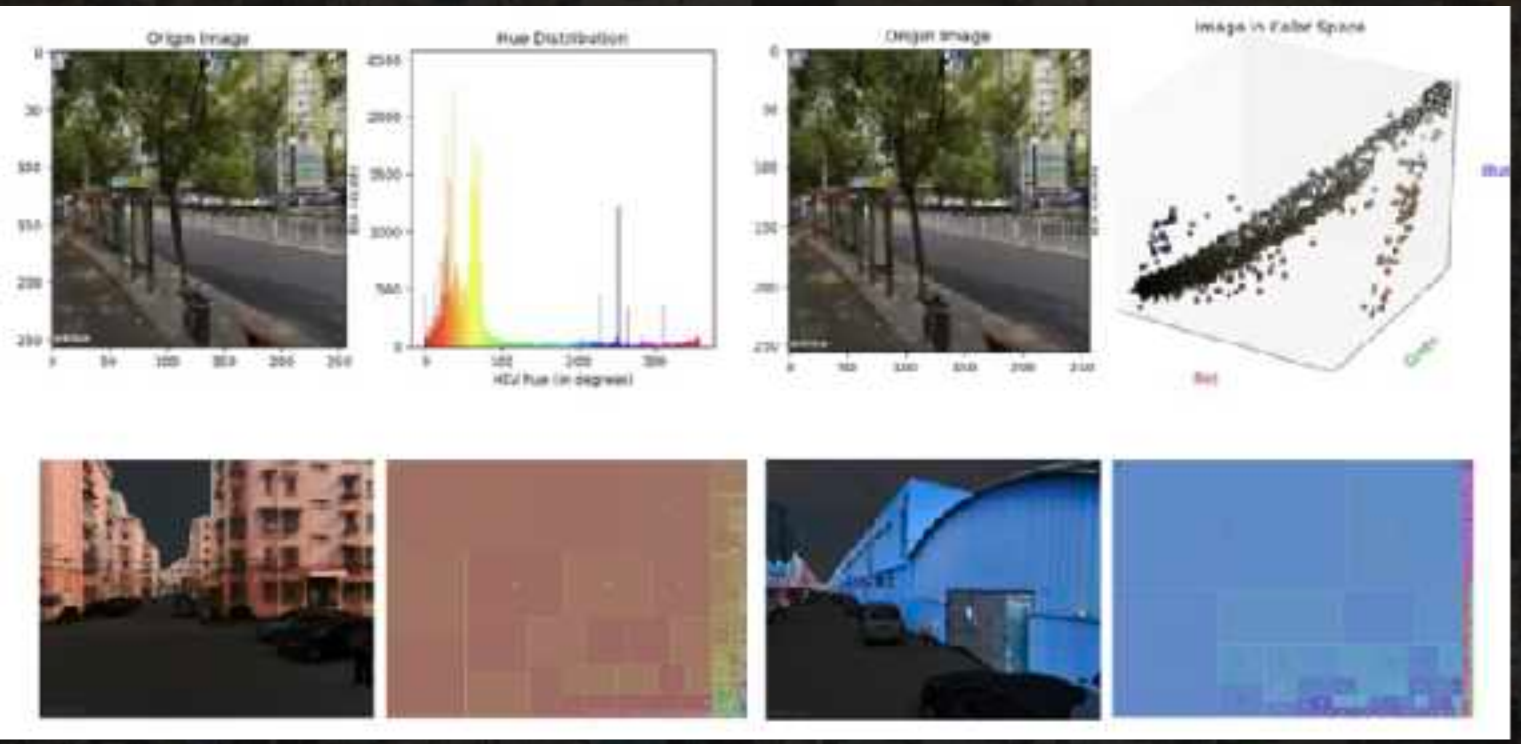
Toronto

Streetview Data

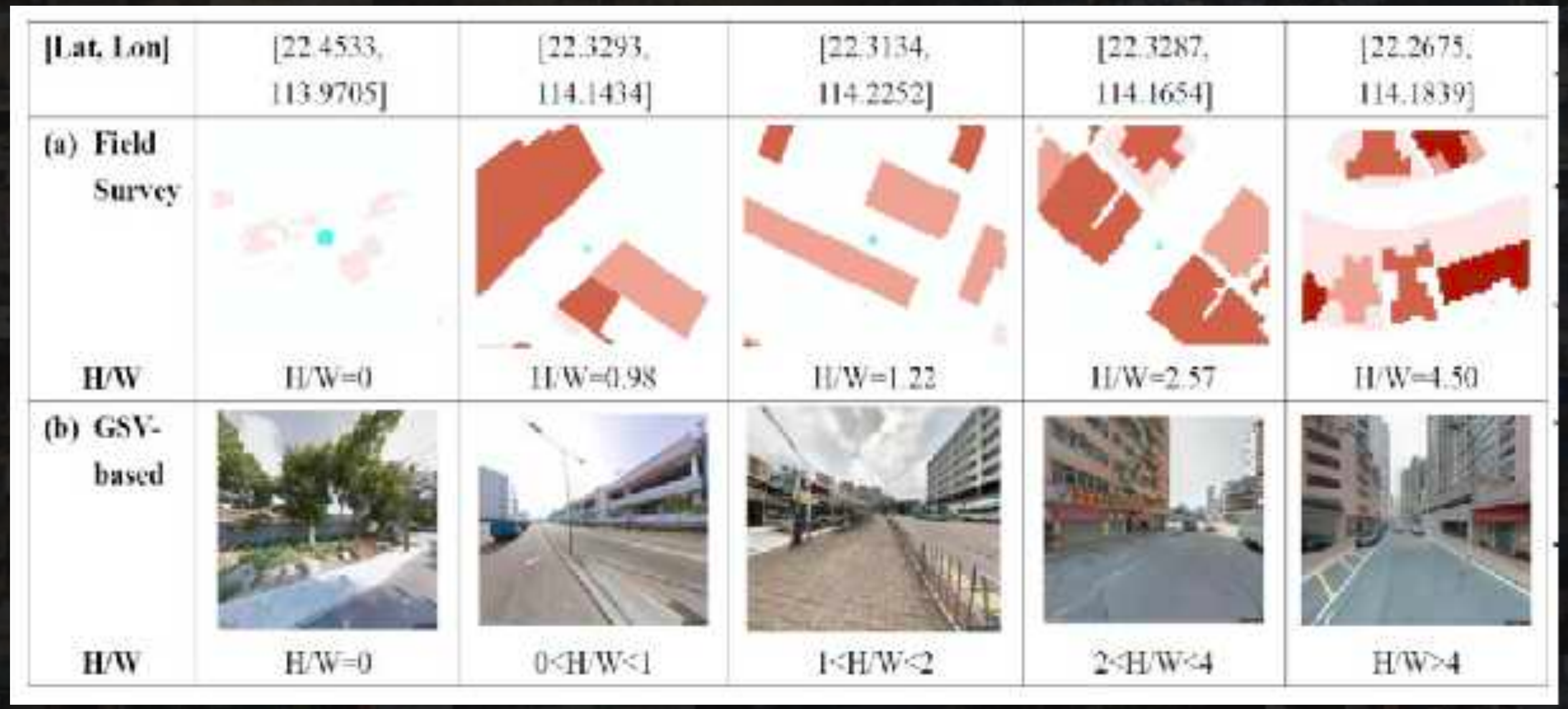
Recognizing image contents using computer vision

We have pipelined over 20 algorithm on to geo-tagged photos, including object detection, segmentation, and scene recognition.

Building Color Decomposition



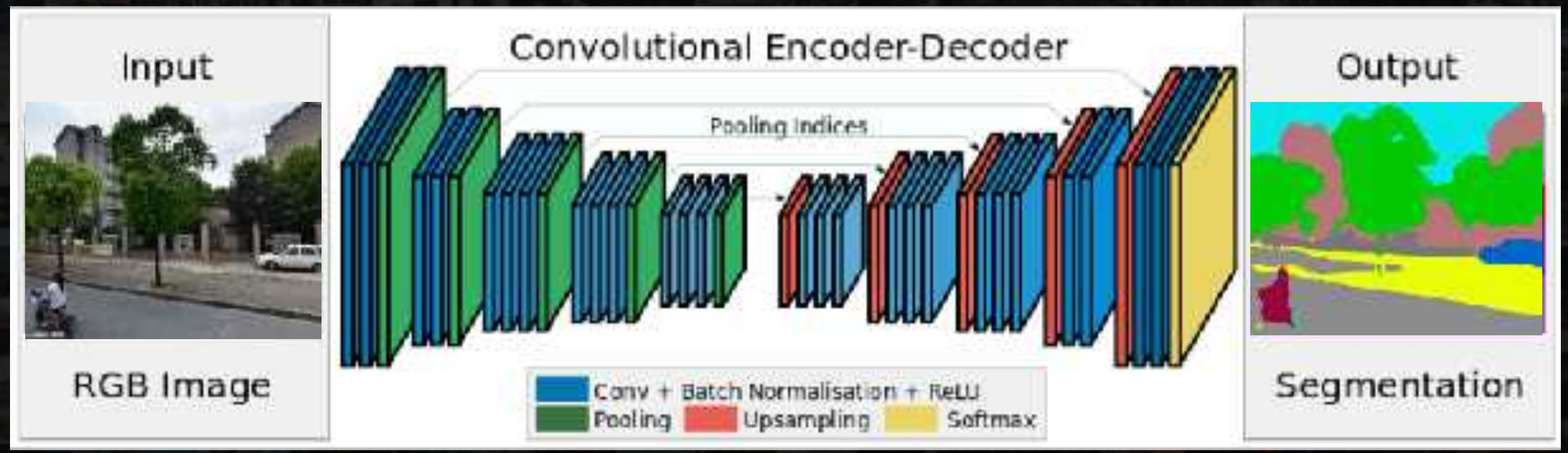
W/H ratio Estimation



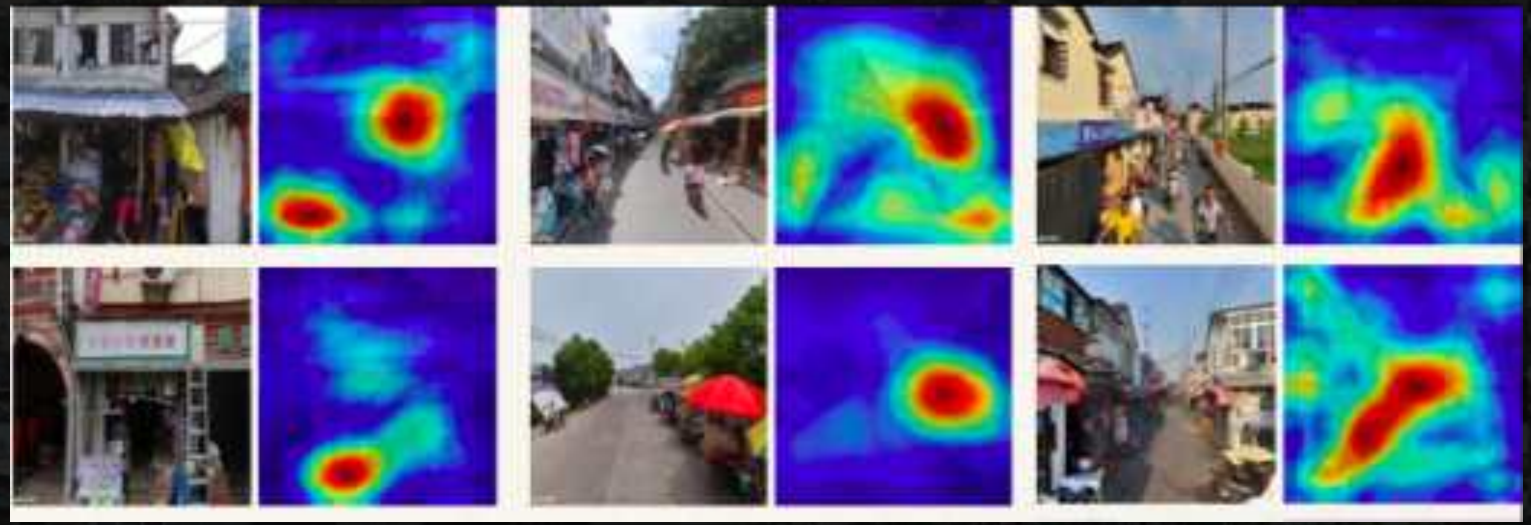
[Lat, Lon]	[22.4533, 113.9705]	[22.3293, 114.1434]	[22.3134, 114.2252]	[22.3287, 114.1654]	[22.2675, 114.1839]
(a) Field Survey					
H/W	H/W=0	H/W=0.98	H/W=1.22	H/W=2.57	H/W=4.50
(b) GSV-based					
H/W	H/W=0	0<H/W<1	1<H/W<2	2<H/W<4	H/W>4

Transparency of street facade

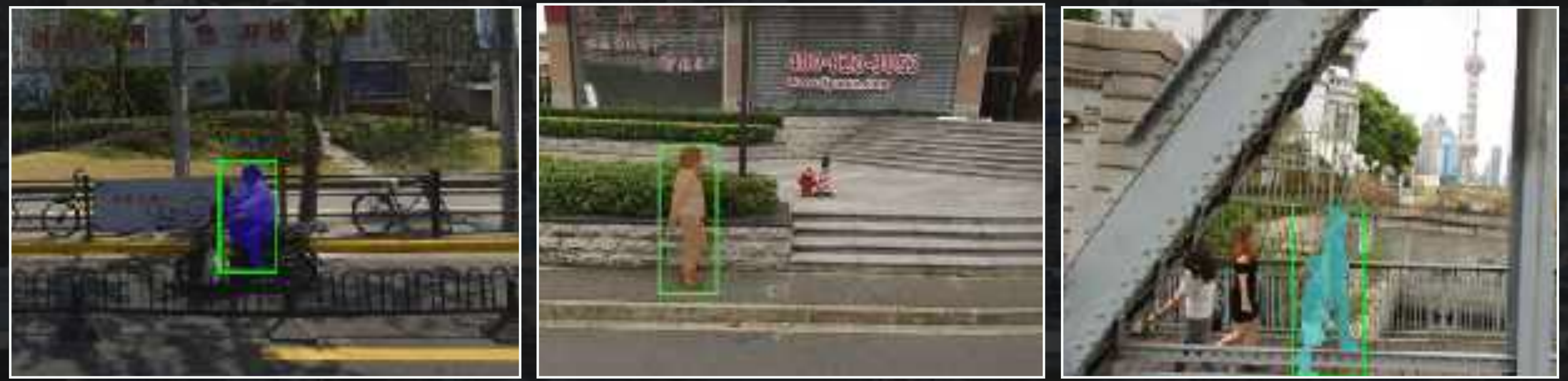
Road segmentation (greenery, sky ratio)



Informal venders



Pedestrians



Public Facilities

Vehicles

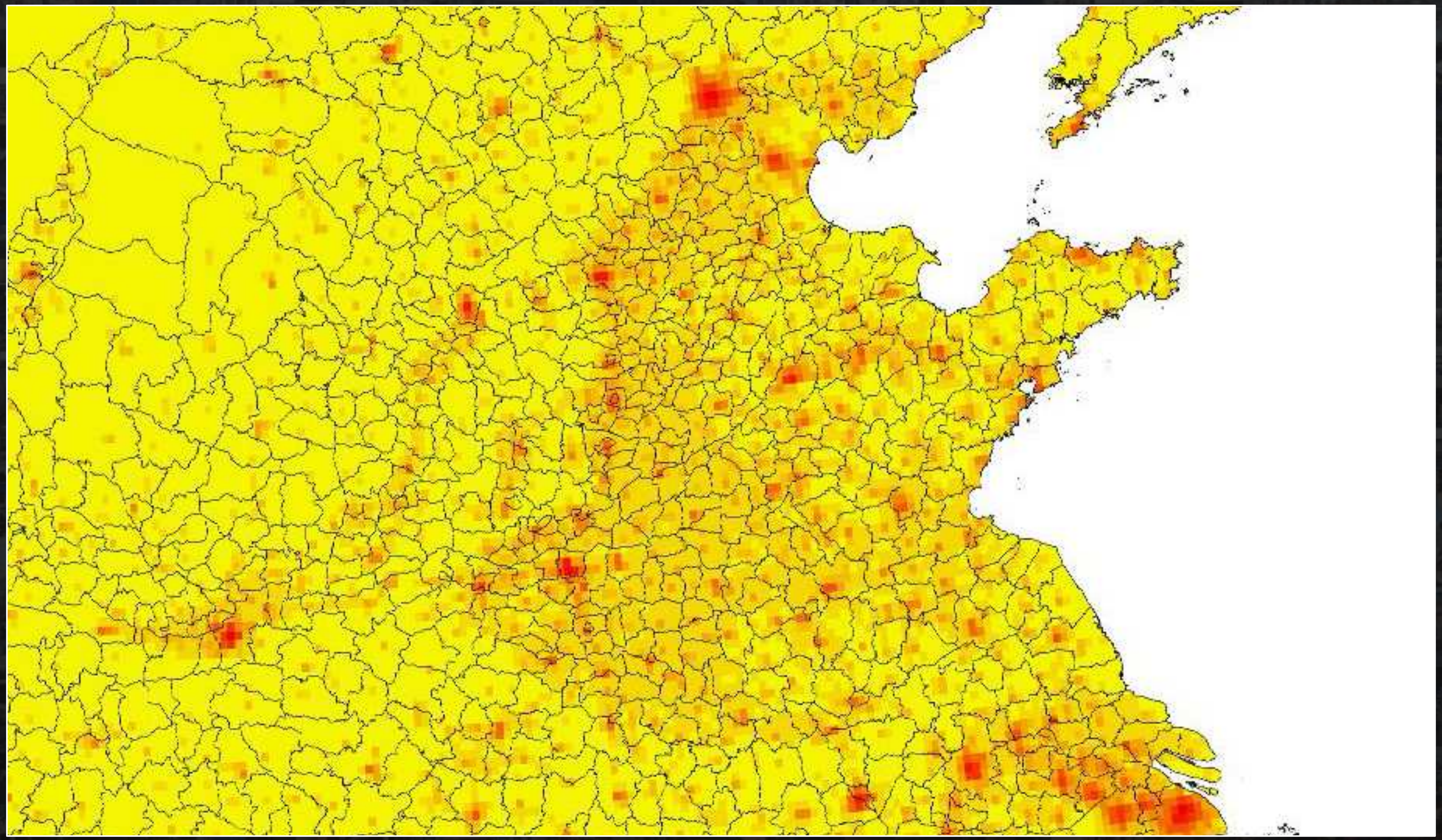
Street Furniture

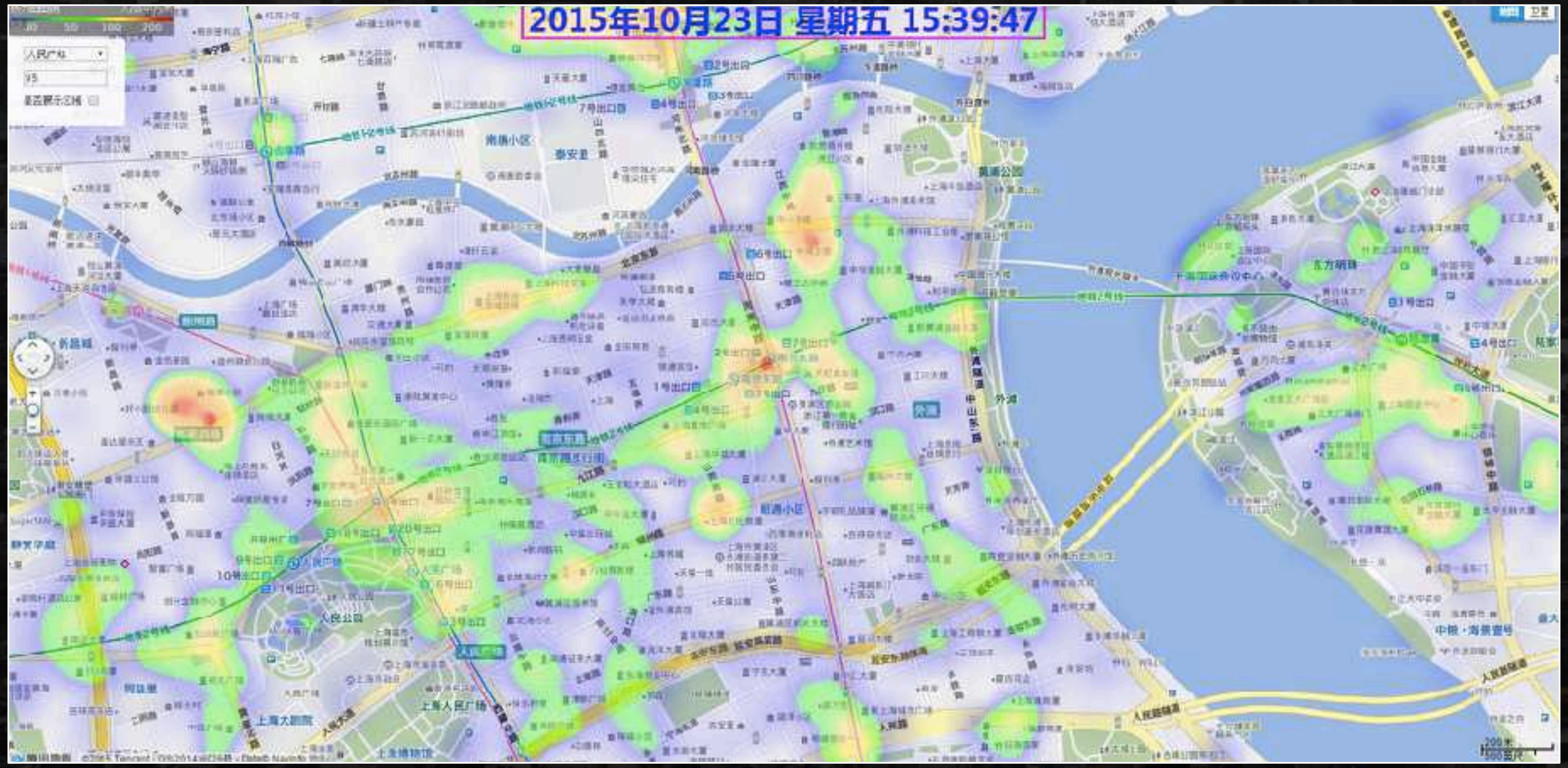
Street Signs

LBS Data

National level LBS data from Tencent 2015

Over 843 million users's check-in and OD data across China mainland from Tencent. The check in data is collected based on 10km x 10km grids and the OD pairs are based on a 2300 x 2300 matrix which is based on a county level unit.

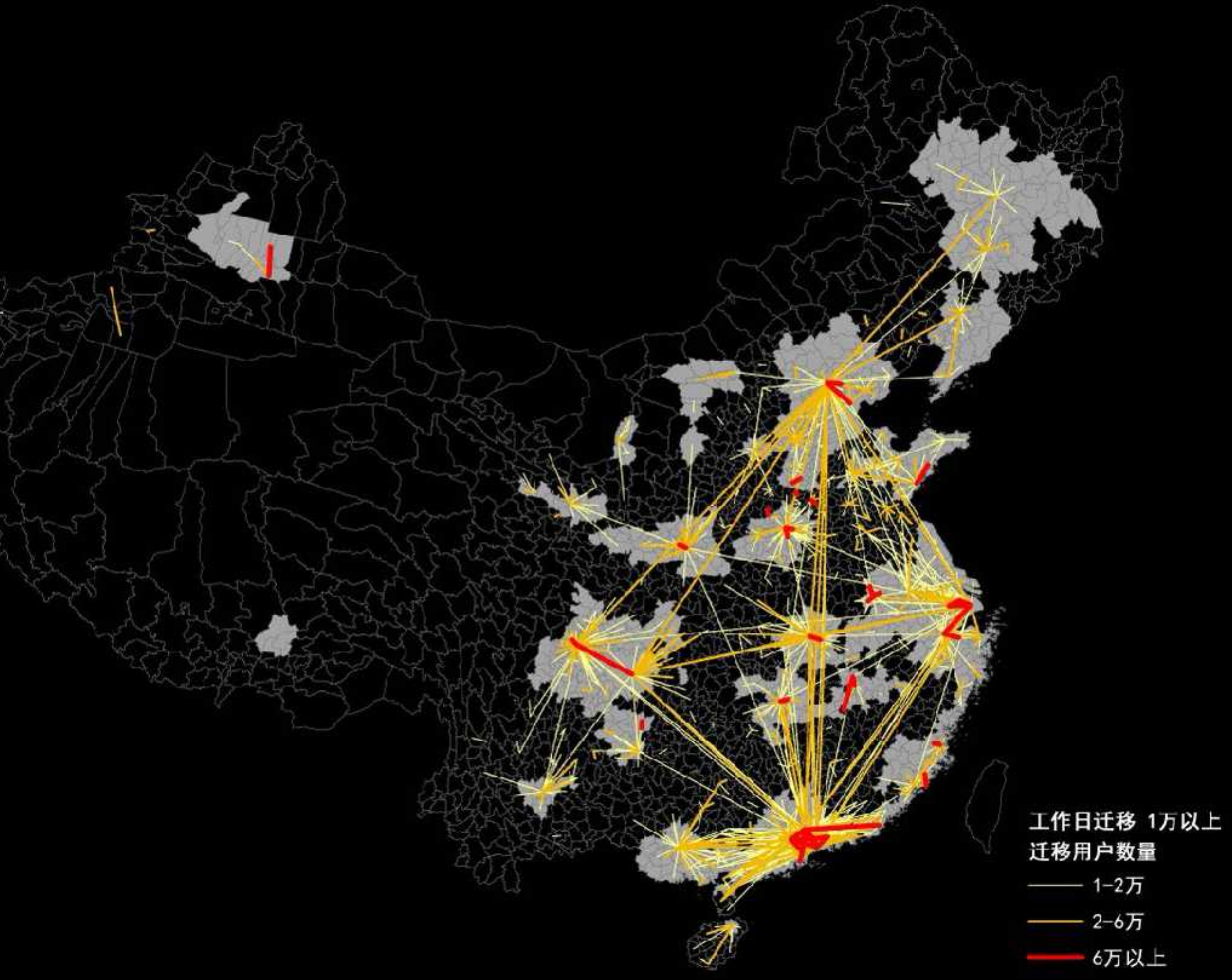


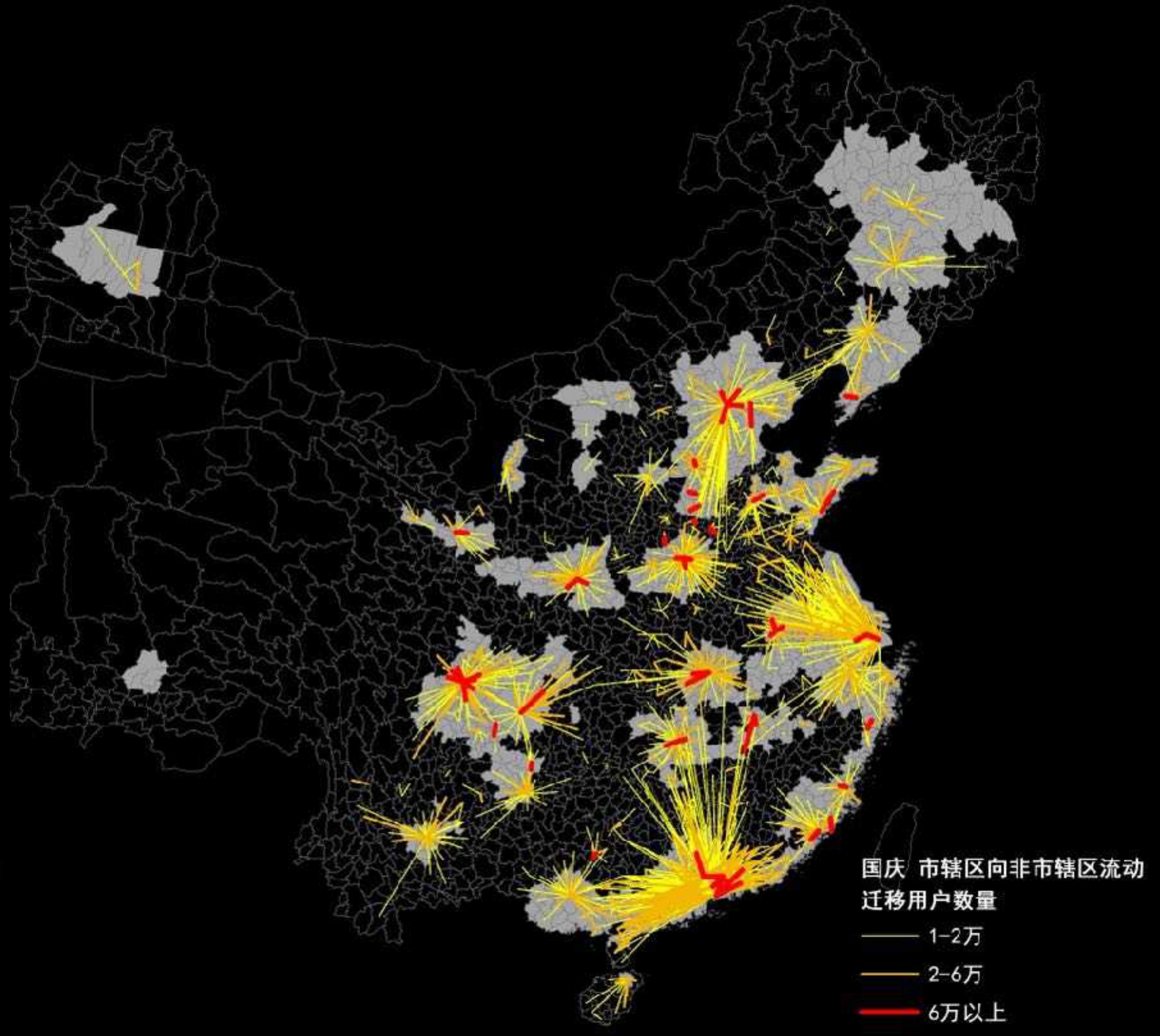


LBS Data

National level LBS data from Tencent 2015

Based on the dataset, I conducted the project of validating different city clusters plans as a chapter in the project of National urban system planning.

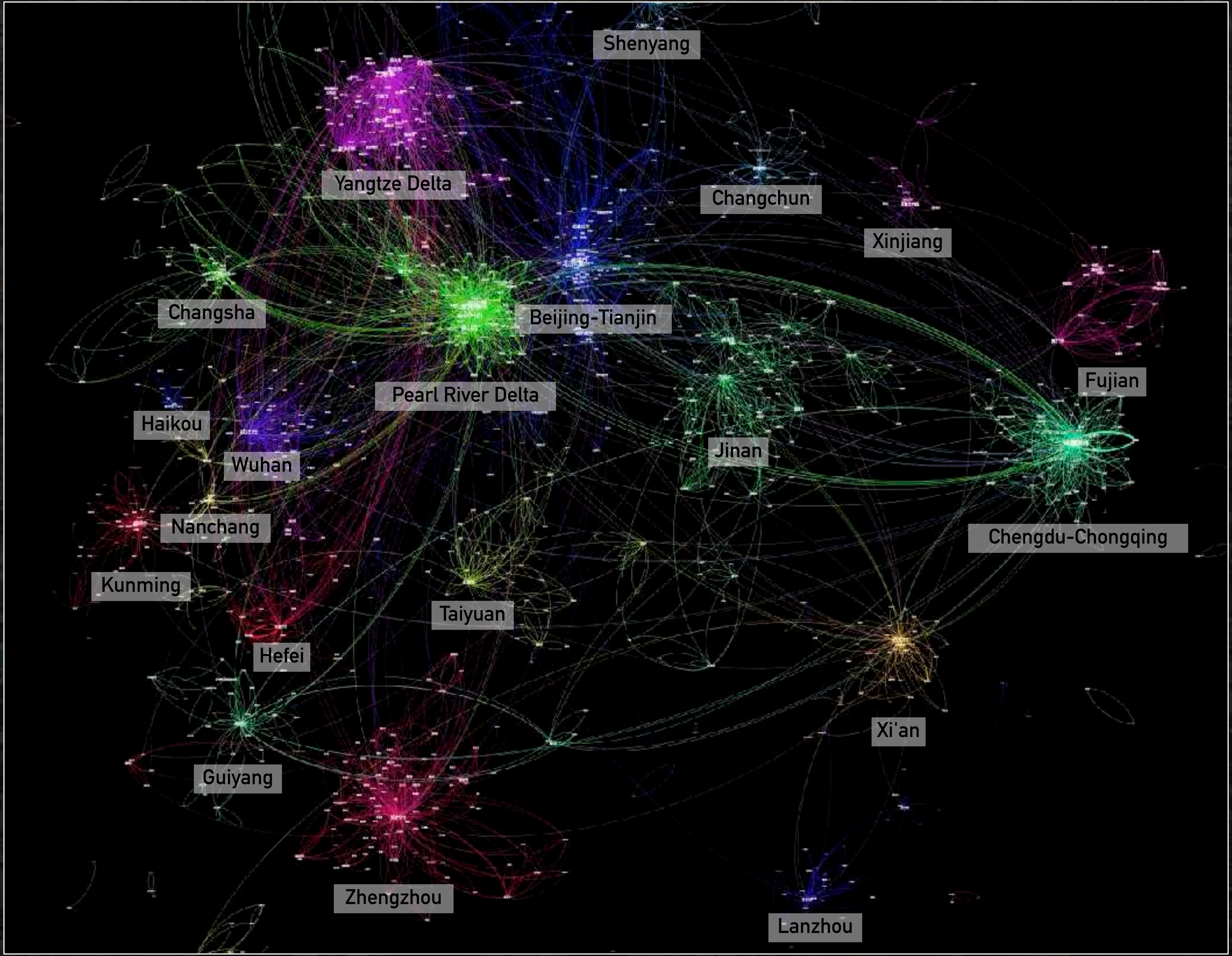


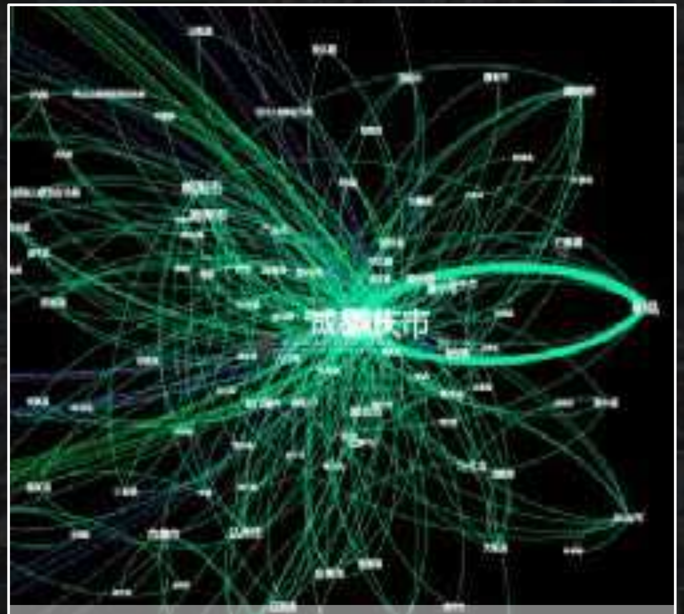


LBS Data

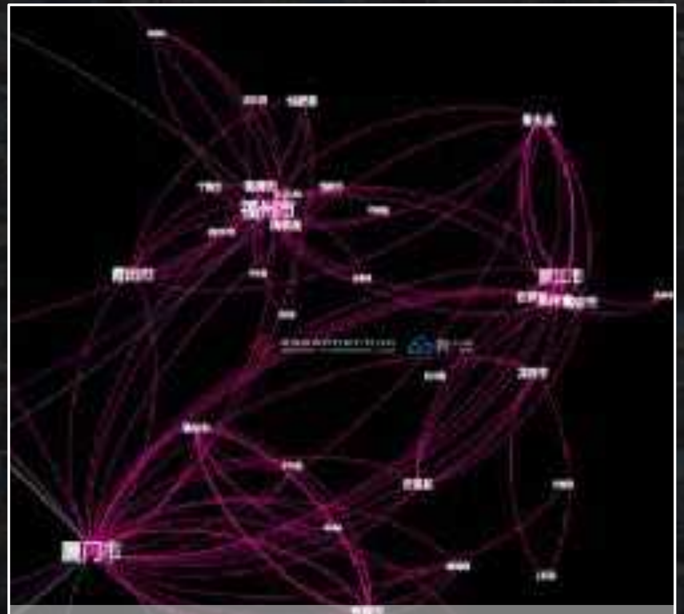
National level LBS data from Tencent 2015

Part city clustering results based on community detection and hierarchical K-cores.



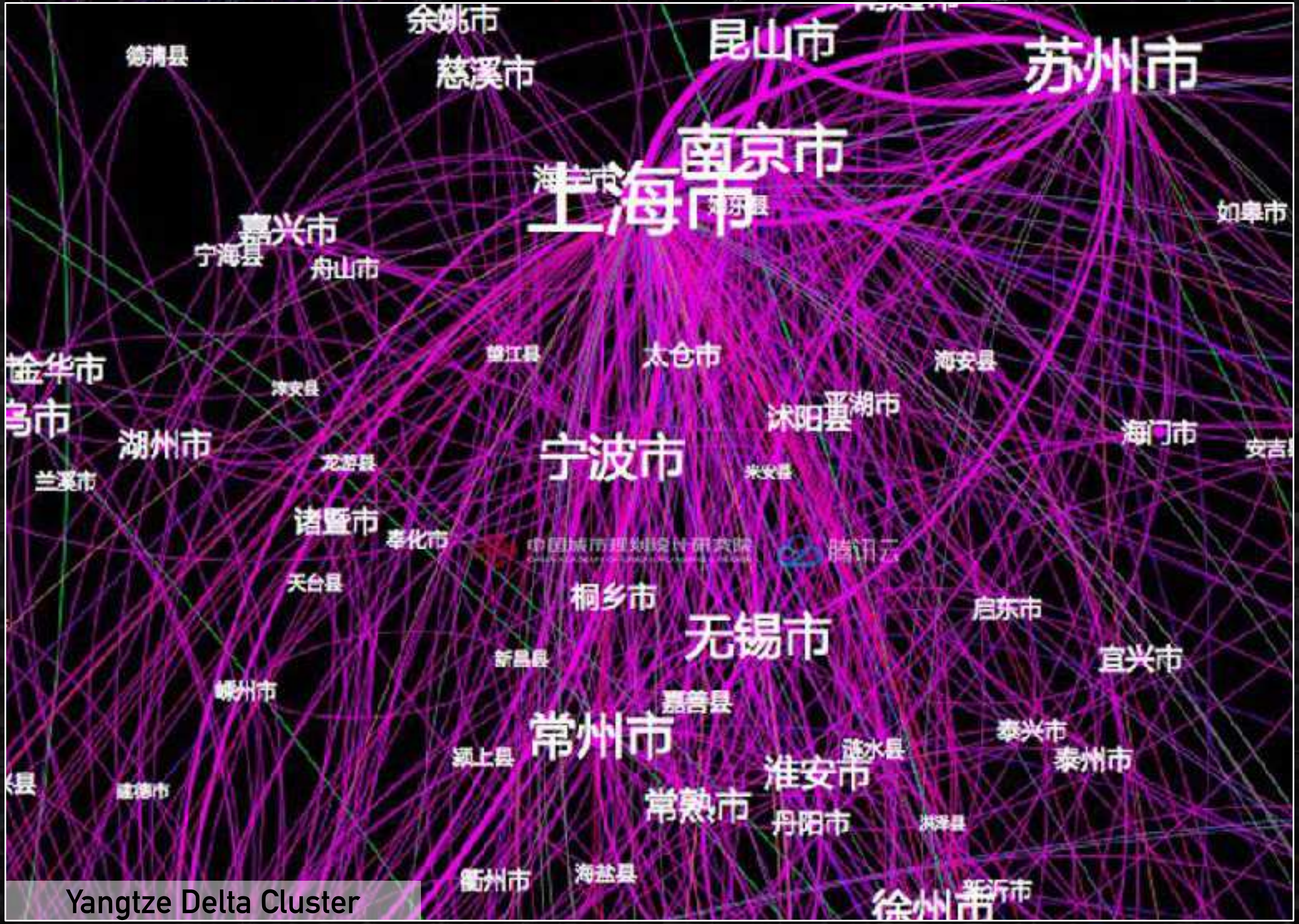


Chengdu-Chongqing Cluster



Fujian Cluster

Beijing-Tianjin Cluster



Yangtze Delta Cluster

LBS Data

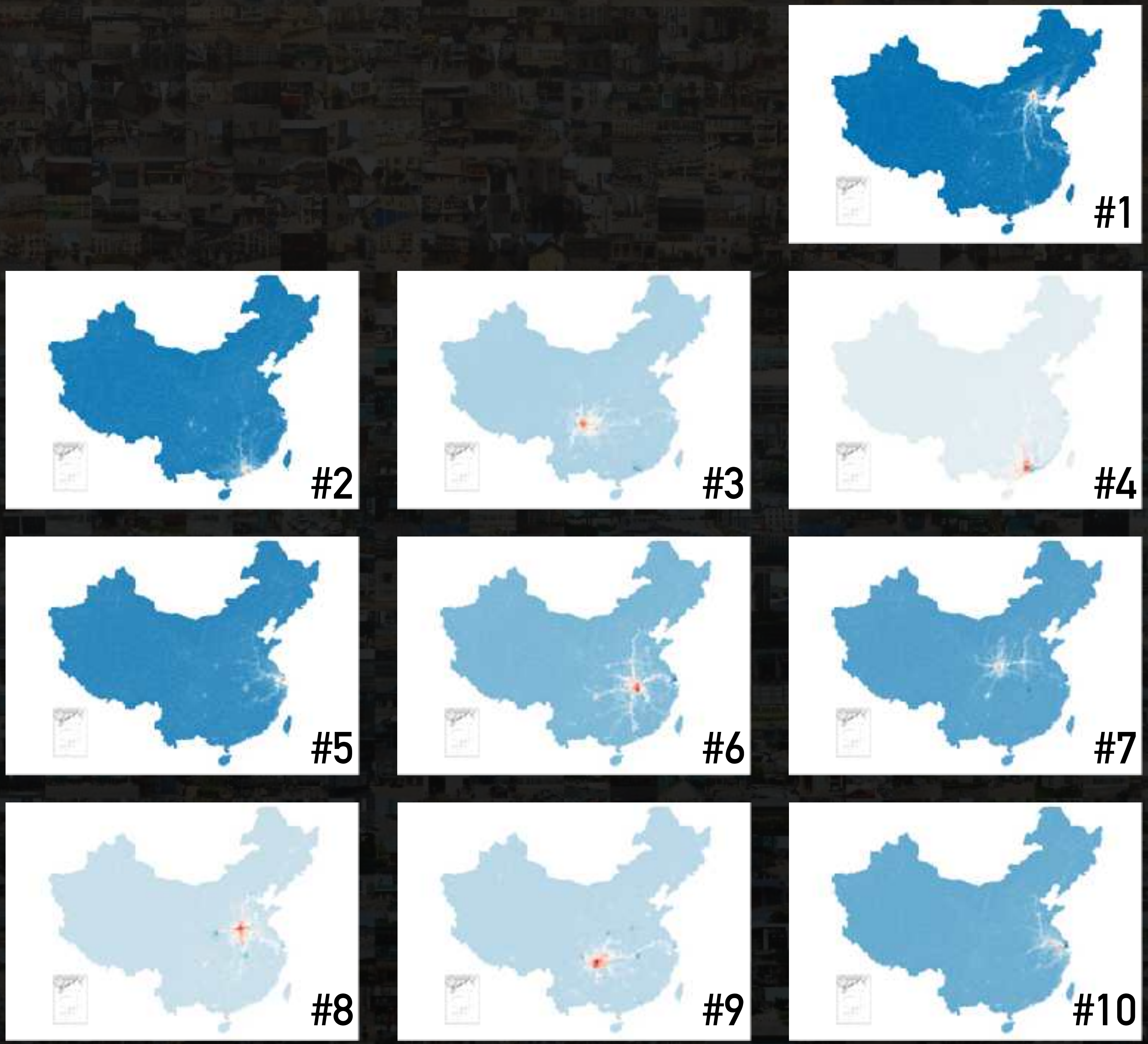
National level LBS data from Tencent 2015

Part city clustering results based on community detection and hierarchical K-cores.

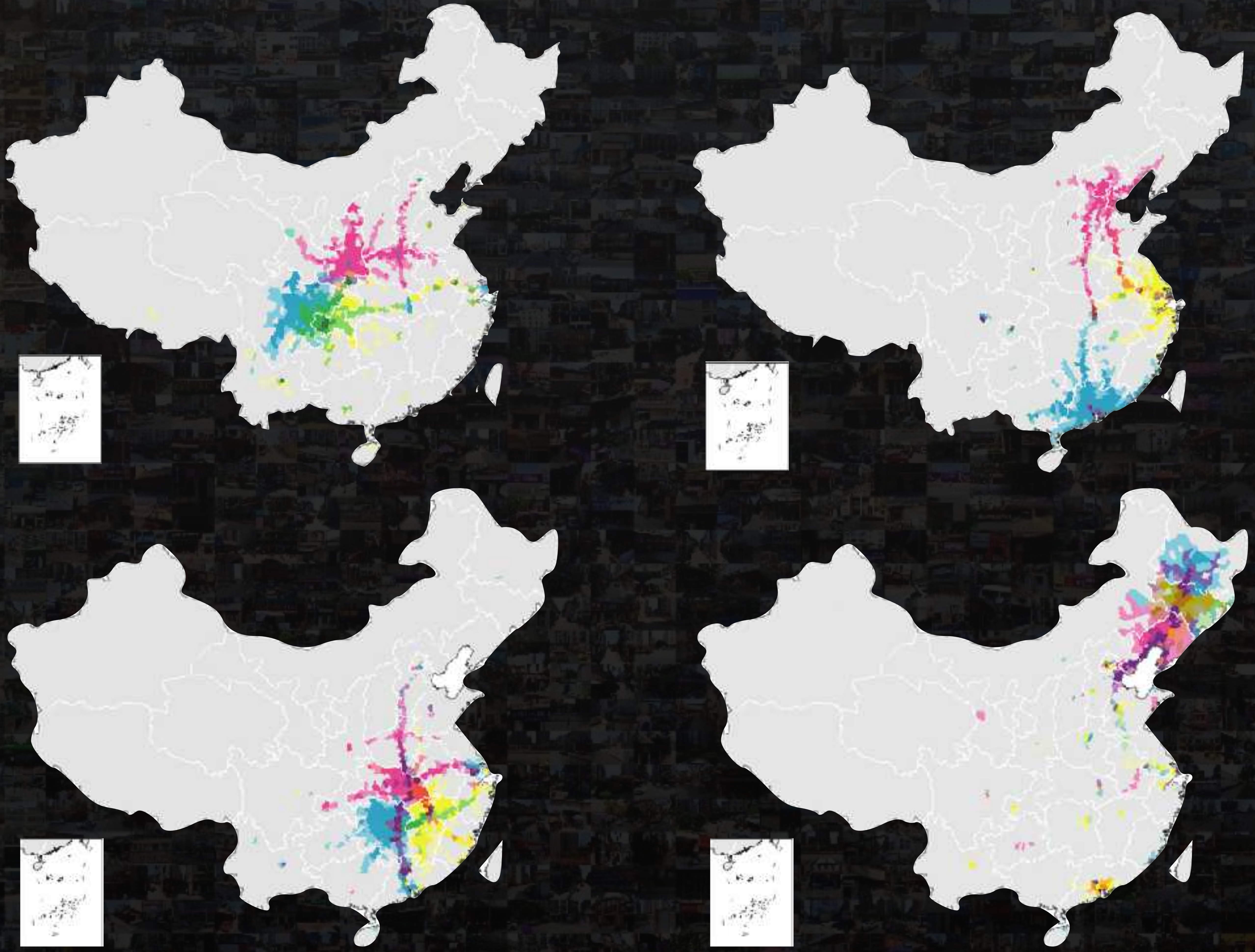
LBS Data

National level LBS data (trajectory) from Tencent 2017

[Depicting the Blurred Regional Boundaries in China Using Individual Mobility Data]
We propose a Singular Value Decomposition (SVD)-based method to depict the impact areas of regions in China using individual connections among cities.



Top ten eigen-mobility-patterns



Overlays of eigen-mobility-patterns

LBS Data

Shanghai LBS Data (Baidu)

The entire city ($5070\ km^2$) is divided into 2699 units.

There are over 60 different labels within each unit, and each label is represented by that category as a percentage of the unit's total population.

A total of 3,386,800 pieces of data represent the direction and number of people flow between LBS units, with a maximum value of 131,768.

Education
- high school or below
- college degree
- undergraduate and above

Stage
- Junior high school students
- high school student
- family with elem school students
- family with middle school students
- family with pregnant woman
- family with 0-1 yr child
- family with 1-3 yr child
- family with 3-6 yr child
- family with high school students
- graduates
- pregnancy
- undergraduates
- parenting stage

Job
- managers and business owners
- production operator
- Professional skill worker
- civilian staff
- self-employed
- service personnel

Consume
- low
- median
- high

Income
- below 2499
- 2500 to 3999
- 4000 to 7999
- 8000 to 19999
- above 20000

Gender
- Male
- Female

PrivateCar
- have a car
- have no car

Age
- under 18
- 18-24
- 25-34
- 35-44
- 45-54
- 55-64
- above 65

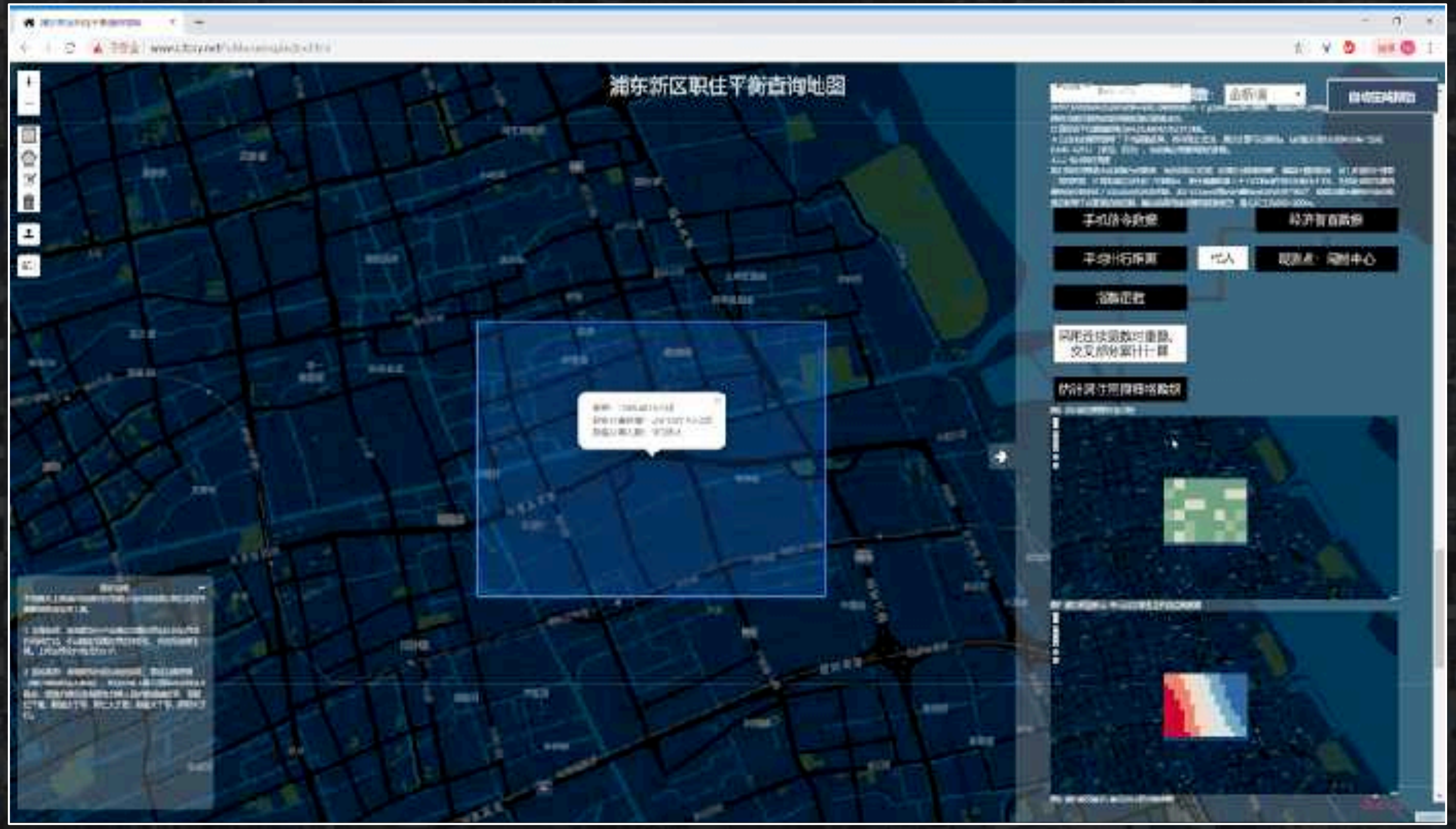
Trade
- culture and entertainment
- Daily chemical department store
- Automobile
- IT communication
- financial insurance
- education
- food industry
- appliance industry
- energy mining and chemical
- accommodation travel
- food processing
- Textile and apparel
- ad &marketing
- machinery and manufacturing
- Transportation and Postal Storage
- real estate
- medicine &health
- building materials
- social public management
- manpower &foreign trade
- Agriculture, forestry, animal husbandry and fisheries
- life service

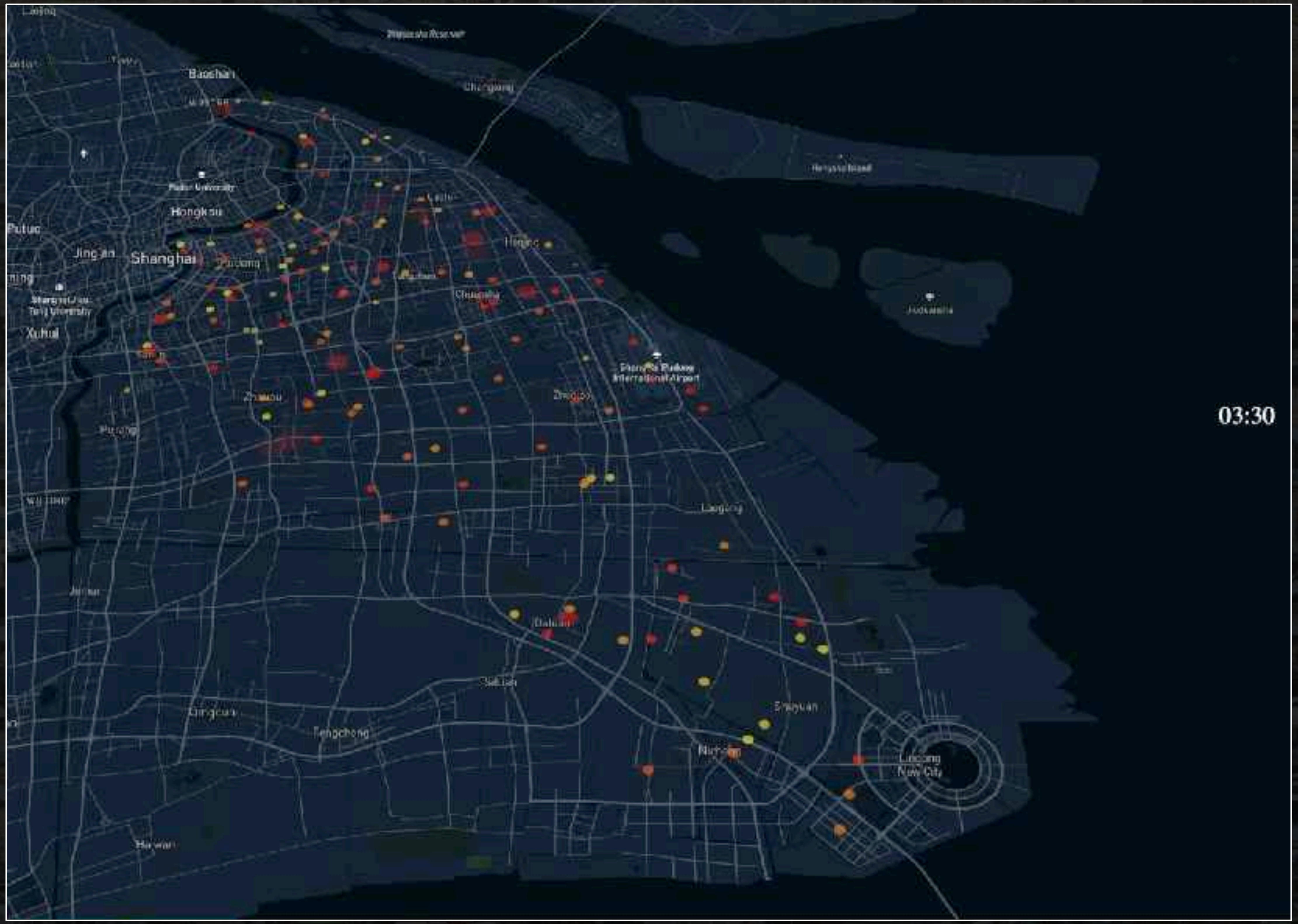
Mobile Signal Data

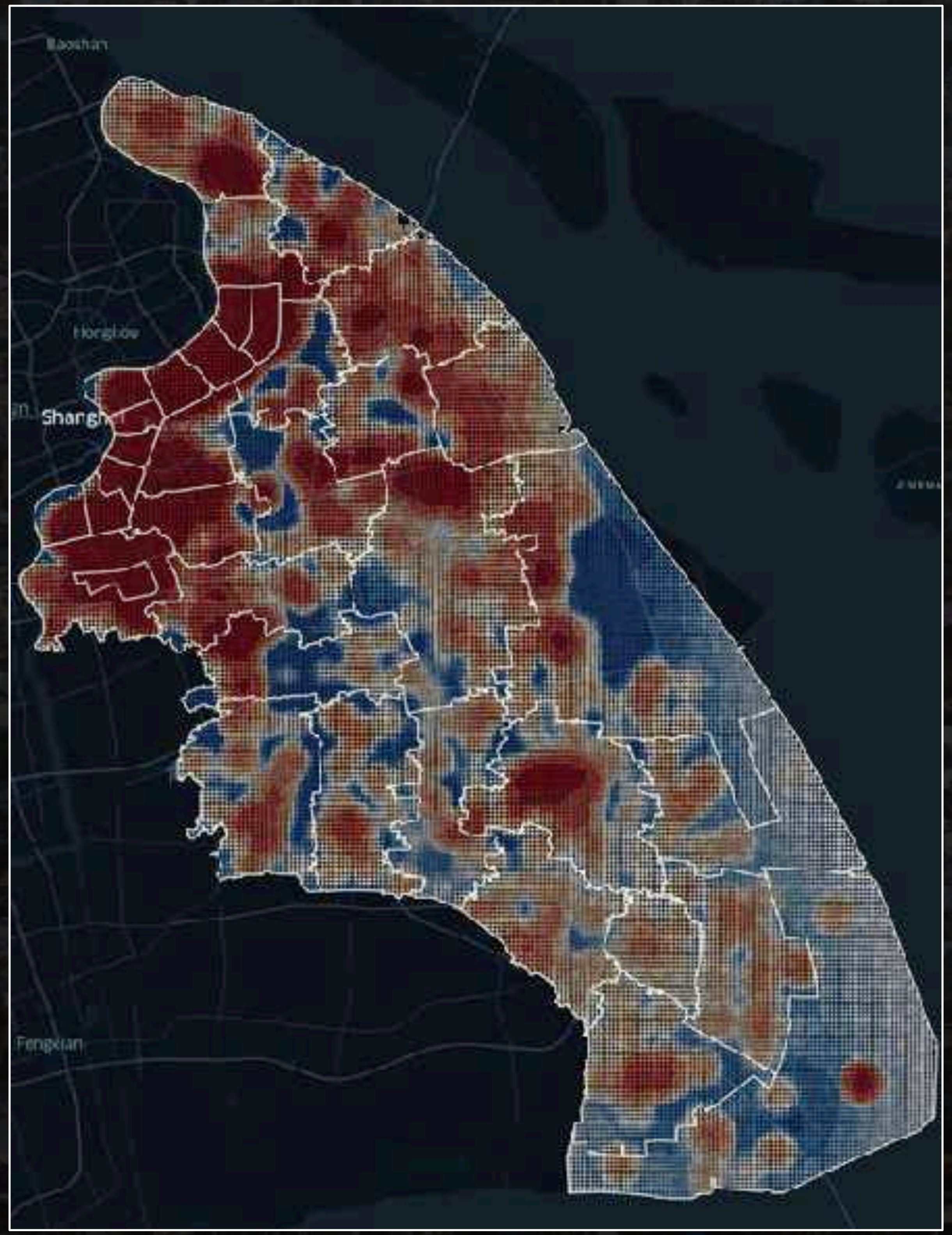
Job-Housing Balance Indicators

Typically quite a lot of planning are focusing or the balance between housing and job within a municipal district.

grid cell of 400-800m, like check-in records, but more continuous
data from mobile device carrier providers (Unicom, China Mobile, and Telecom)





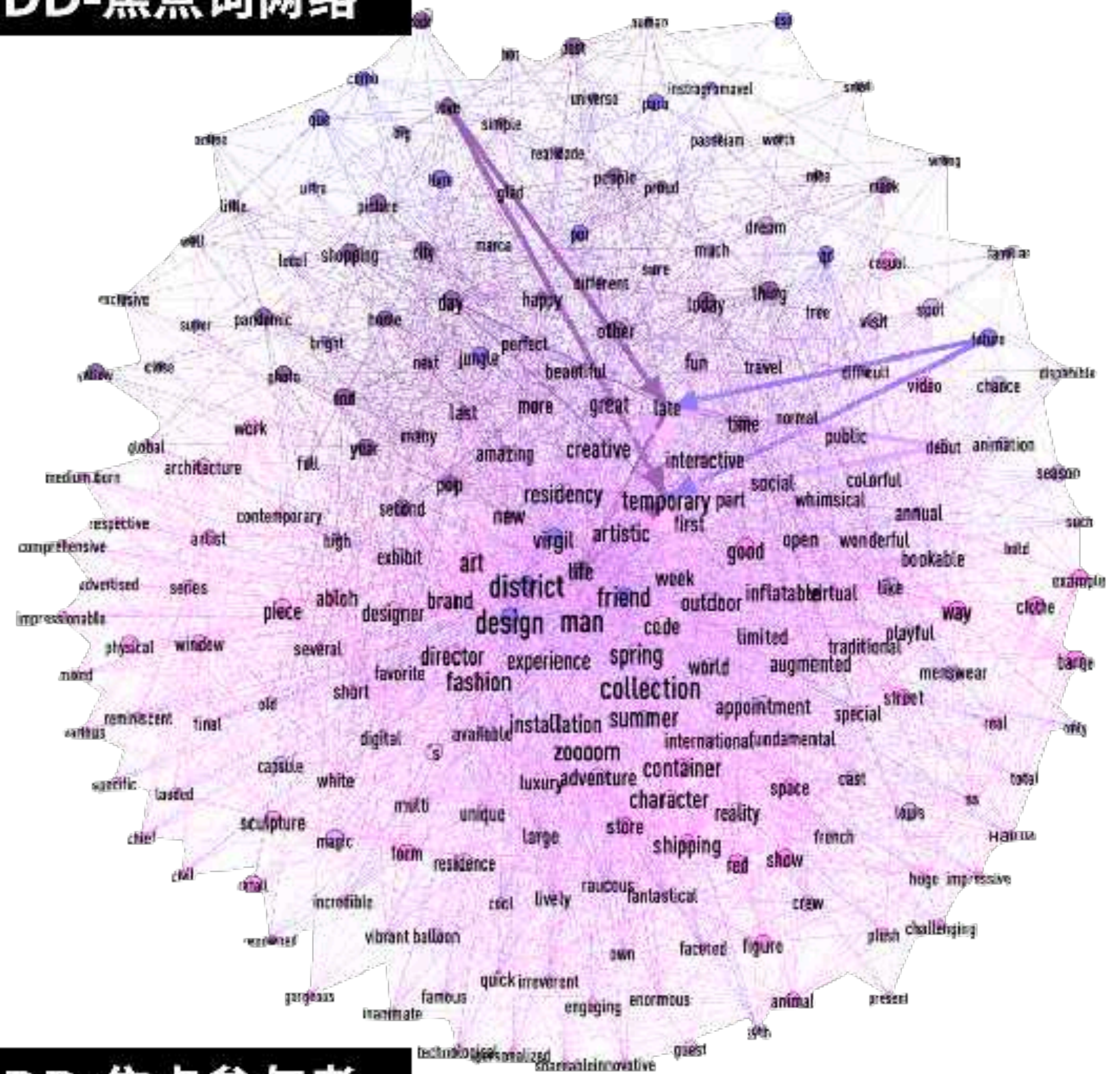


Social Media (Twitter / Instagram)

Data digestion for comercial areas

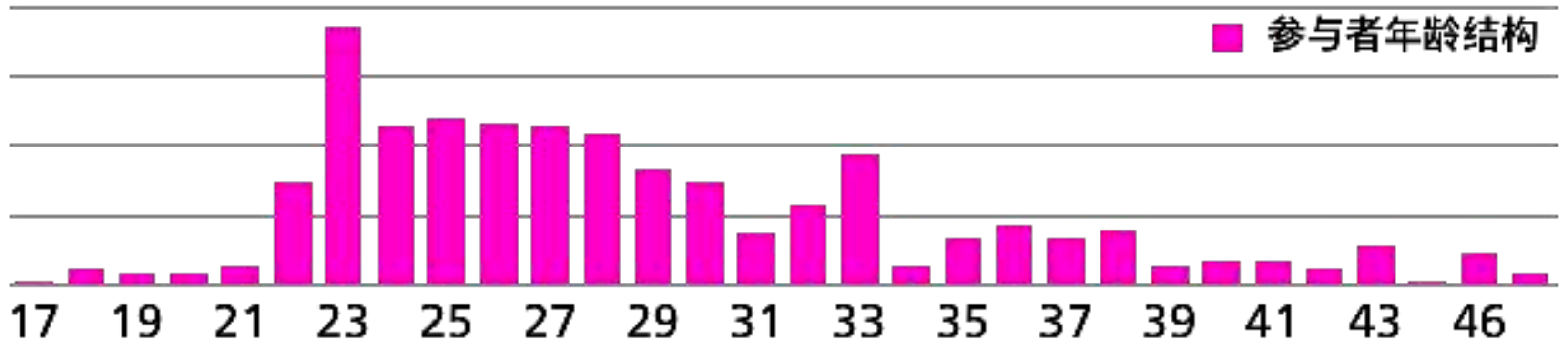
Obtain user evaluation data of certain business districts through web crawlers

MDD-焦点词网络

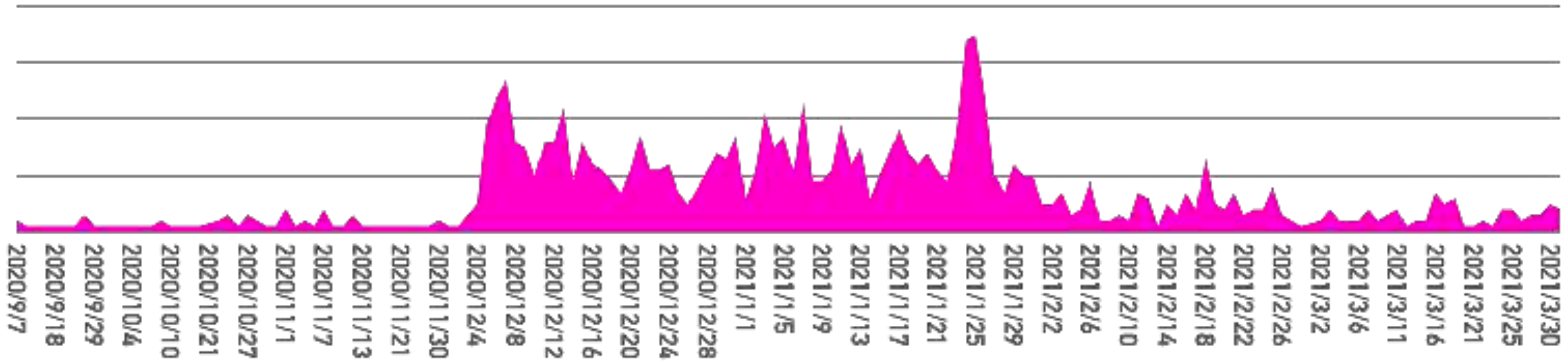


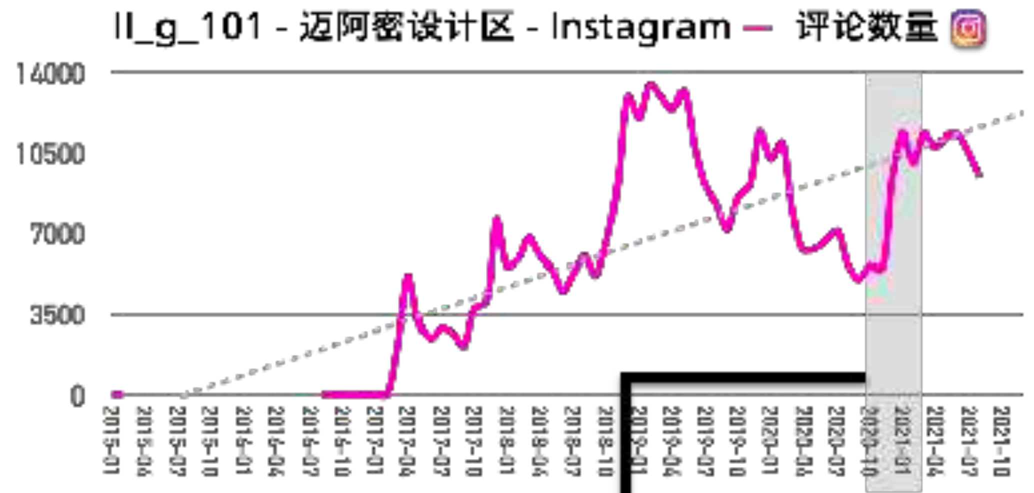
MDD-焦点图像墙

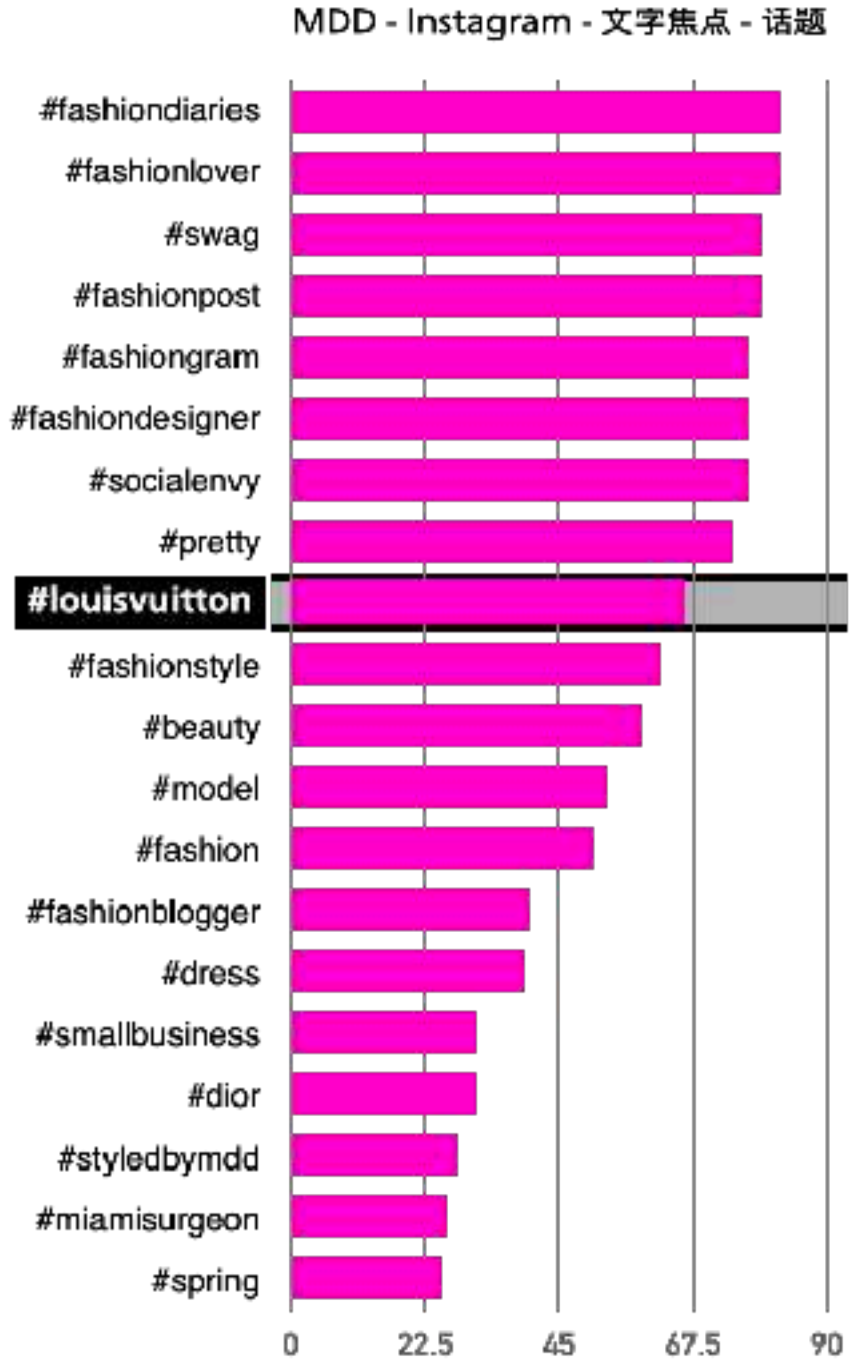
MDD-焦点参与者



MDD-焦点时间线







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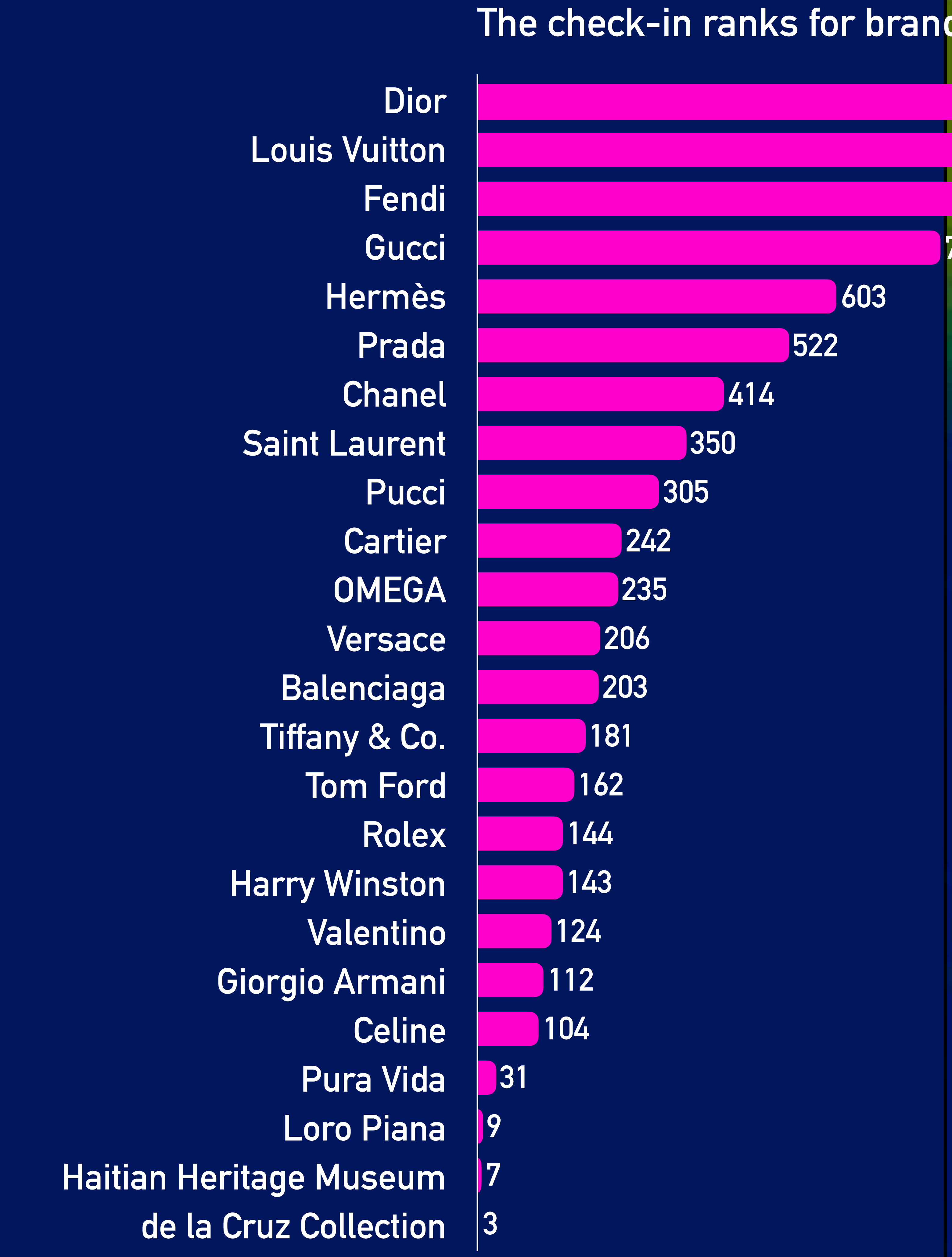
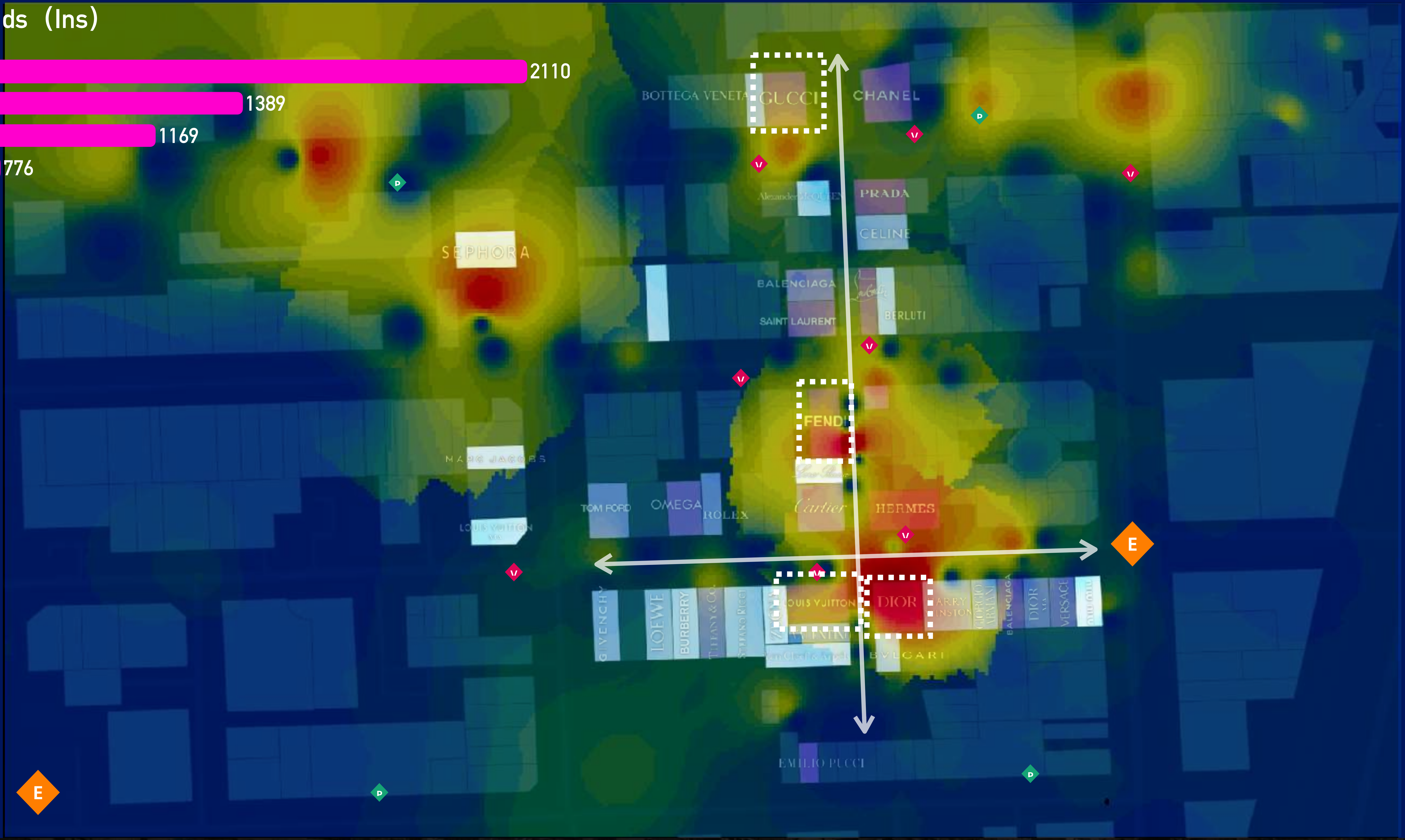




LBS Data (tentative)

Food Delivery Trajectory Data (Alibaba)

The Platform (ELE)

2nd largest food delivery in China

1.3 billion registered users

3.4 million restaurants

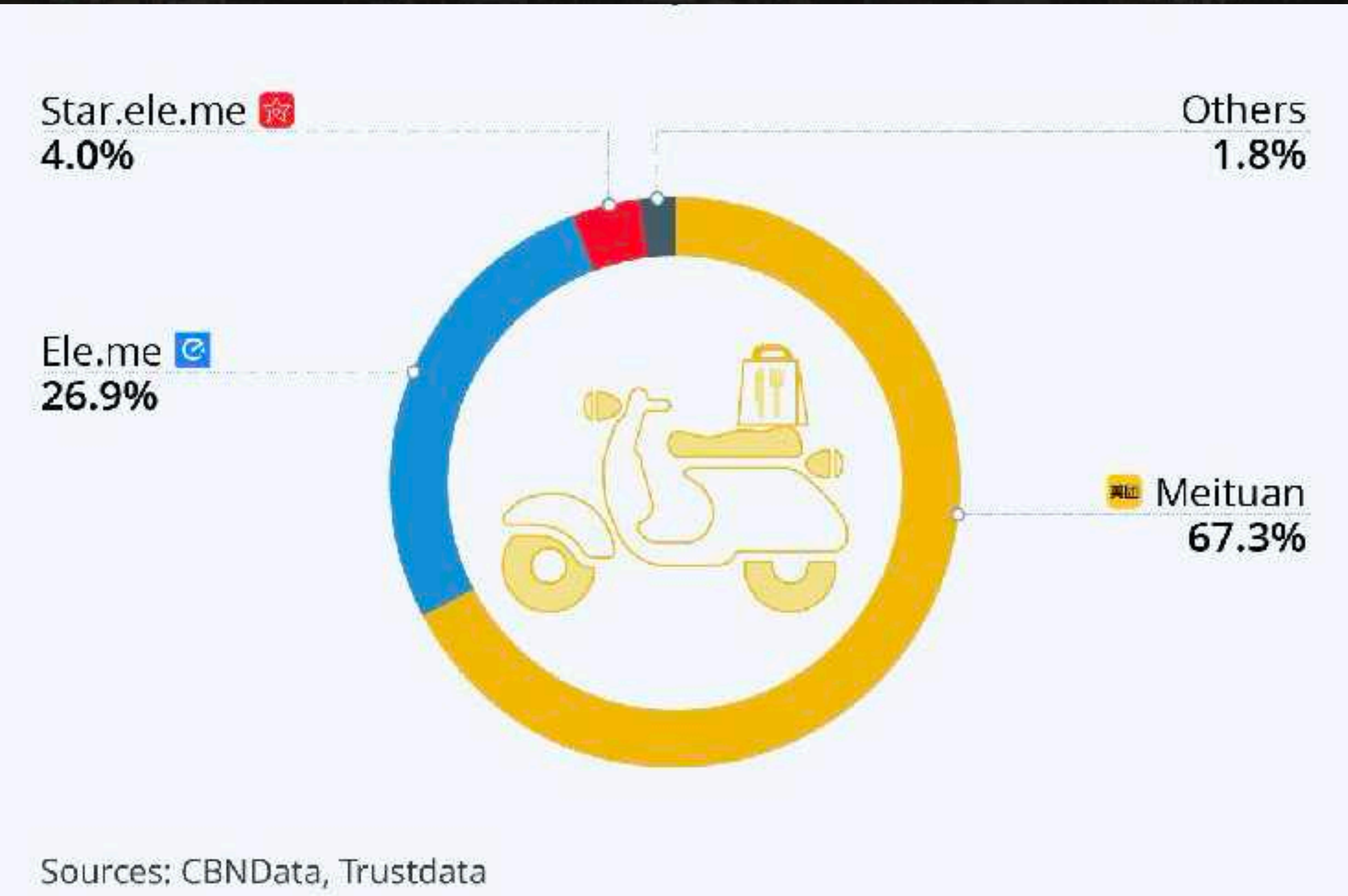
Data Facts:

362 cities in China

18 million online order per day

12 billion GPS check-ins per day

550,000 riders coverage per day




Cycling Trips of Chongqing
23:59:54
C-IMAGE
street scores
AR bullet screen
20180722
24h OD in Chongqing
Informal venders in Shanghai
City grid match
AR dianping
Projects to Tools
24h in Shanghai Pudong
Waterfront View Analysis
兴萌便利店
Shopsign labeling
AI aided photograph
82
PULSE OF BOSTON TAXI
07:19:00
Boston Taxi Trips
Streetalk maps
VGE in Lujiazui
看看新闻
Bookstore recommendation