Ma(i)cro Visions: Utilizing Social Network Service data for a transformational process of urban social spaces

by

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Bachelor of Architecture

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SUBMITTED TO THE DEPARTMENT OF ARCHITECTURE IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE IN ARCHITECTURE STUDIES
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ABSTRACT

The proliferation of data and technological evolution visualizes normally unseen dimensions of human interaction. However in urban studies, only a few embrace this new way of seeing as a practical tool to observe the public realm. This thesis recognizes the digital traces we leave on the web in our everyday life as a new resource to understand the human interaction with the city. The thesis explores reading social space with social network service data and develops a manual for a new way of reading the city that integrates this new layer of information with traditional methods. The research collects Instagram location data which is stored when people tag their post with a location. I read these data points to form a psychological geography comprised of meaningful places that people recognize, share and remember. The thesis is twofold: understanding the behavior of this data and finding ways to use it. The thesis first, maps demographic characteristics, the psychological geography, and the built form, and overlaps them to understand the relationship among people, perception and the built form in Boston. The analysis concludes that qualitative social space reading becomes more limited as the population turns vulnerable and the location density decreases, because the meaningful places for people shift towards commercial and private spaces. This calls for a new reading of social space that combines traditional quantitative city reading process with this new collective perception, which forms the second part of the thesis. The manual studies the spatial character of pathways, areas and buildings that appear pivotal or are completely invisible in the psychological geography. The thesis argues that the human perception of a neighborhood constructed through micro documentations of people's everyday experiences informs urban designers with the spatial character of places that form the local identity.

Thesis Supervisor: Michael Dennis
Title: Professor of Architecture

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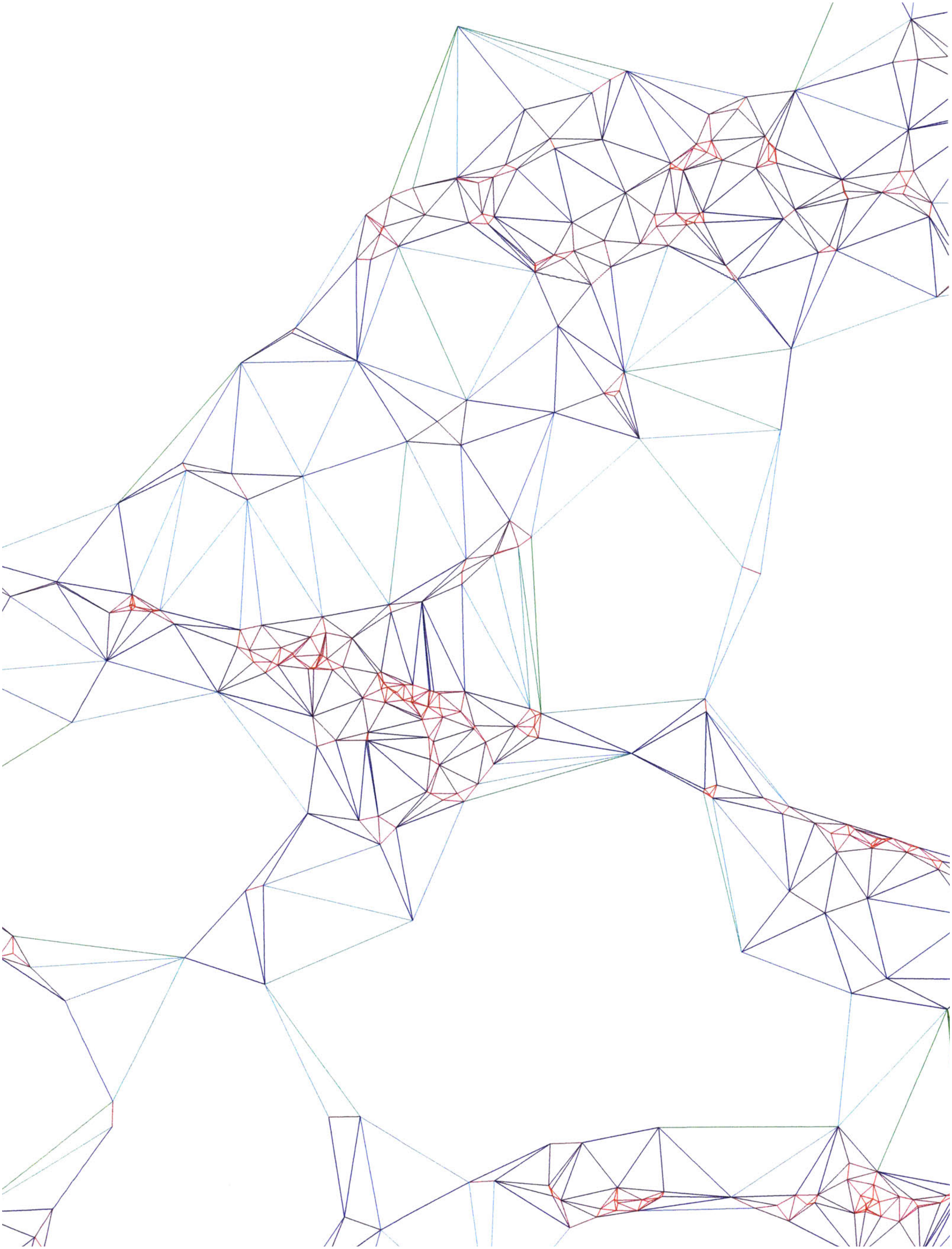

Ma(i)cro visions
Utilizing Social Network Service data for a transformational process of urban social spaces

By Chaewon Ahn
SMarchS Architecture and Urbanism

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Contents

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Thesis has been a lone process and through these pages I would express my gratitude to have shared this time and space with wonderful people around me.

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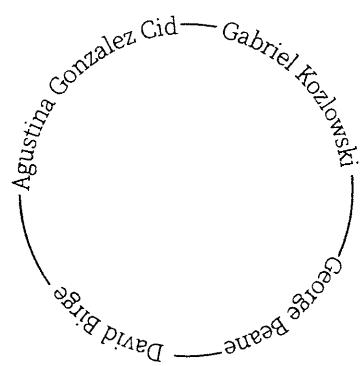

I tried to decide who wins the acknowledgment race, and I decided to put none of you first. Thank you for accompanying the process in separate paths, but side by side. You are the most intense people I have ever shared the office with. Your boundless friendship and peer pressure brought me here. Thank you.

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And finally my family. Thank you for your unconditional love and support.

CH1

Introduction: an inquiry on observing the city

1 Introduction

"...We cannot know that the world is not as it should be without knowing how it is, nor can we know that the world is as it is without knowing how it should be. We cannot know that the world is not as it should be without knowing that it can be changed, nor can we know that it can be changed without knowing how it is."

- Vilém Flusser, Gestures, University of Minnesota Press, 2014: 10.

Motivation of research

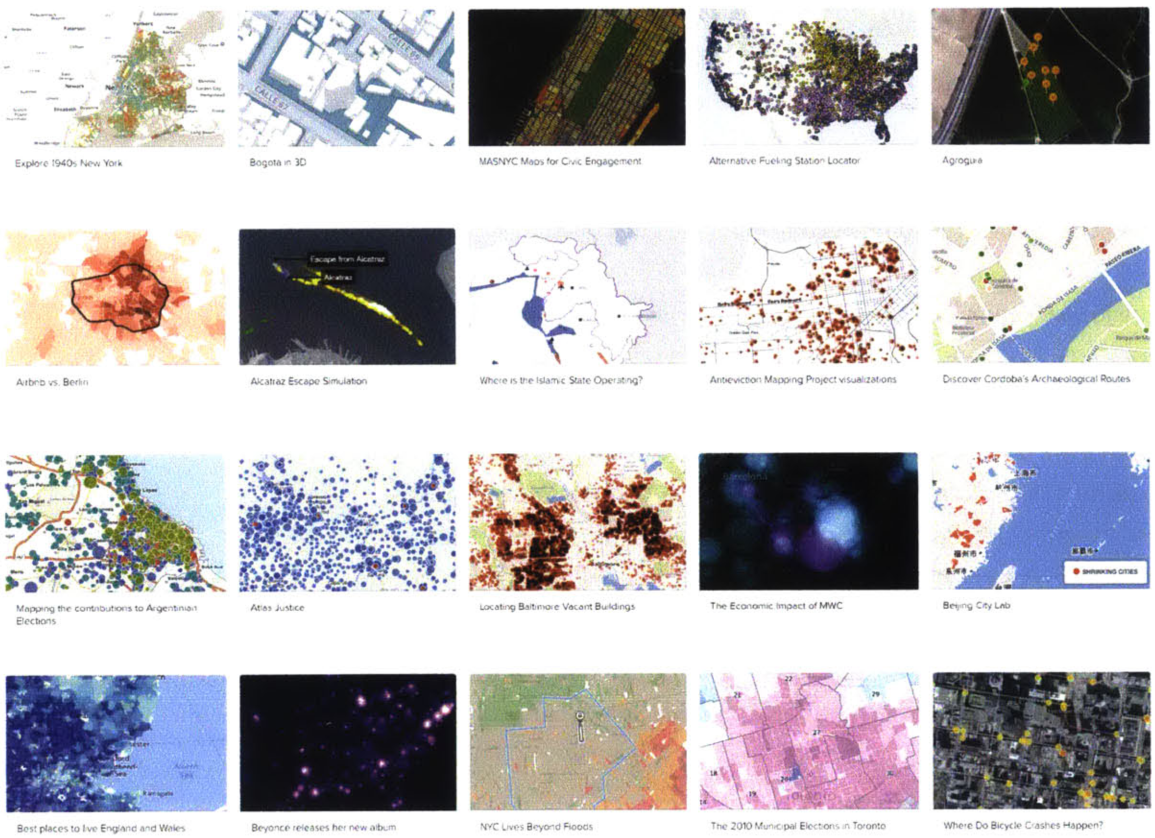
The way we read the city sets bounds to what needs to be changed because it is always intertwined with the way things ideally should be. Therefore, in urban studies, how we observe the city has always been inextricable to what action we take. In architecture and planning, this can always be observed though how the context and ideal connects to the proposal.

The modernistic planning reads the city through a vision of macro-scale. Proposals of a 'Big picture' are derived from belief about knowledge and society which is inextricably linked to the rise of capitalism, and the emergence of a scientific mode of legitimation. The concept of an orderly and spatially integrated city that meets the needs of society, and the fostering of the interventionist state.**1** On the other hand postmodernists criticized such totalizing visions and reformist tendencies, emphasizing the importance of micro-scale 'everyday' experiences: the view from below as a 'flâneur'. However, Edward Soja wrote in 'Thirdspace (1996)' that the polarized perceptions on cities, either macro or micro, are always insufficient.**2**

In the middle of these visions on the city at variance, comes information technology in the picture. Contemporary human existence leaves innumerate digital traces on the web. Information of where people go, what they do, and what they think is recorded via cell phones, credit card transactions, Social Network Services, and so on. These digital traces are becoming more and more accessible with simple programming knowledge, as the web opens API services to increase interconnectivity between web services. Between 2000 and 2010 the number of API services that open content increased from one to 2,6473,

1 Beauregard, R A. 1989. "Between Modernity and Postmodernity: The Ambiguous Position of US Planning." Environment and Planning D: Society and Space 7 (4): 381–95.

2 Soja, Edward W. 1996. Thirdspace: journeys to Los Angeles and other real-and-imagined places. Cambridge, Mass: Blackwell: 314.



[Fig 1] carto db library

counted by a website called 'programmable web'.3 This means that human activities are captured more than ever and that the usage of the information is also becoming rapidly commonplace. On the other hand, multiple tools are developed to facilitate easy data visualization. Cloud computing platforms like 'carto db' or 'mapbox' enable web map publishing and customization instantaneously.

3 "API Growth Doubles in 2010, Social and Mobile Are Trends." 2015. ProgrammableWeb. Accessed May 21. http://www.programmableweb.com/news/api-growth-doubles-2010-social-and-mobile-are-trends/2011/01/03.

The rich resource and large variety of tools are implemented in urban design and planning as well, but little work is done to integrate the points and lines of data with the existing ways of reading the city. This thesis resonates with this drift and explores the possibility to proliferate the contemporary existence as a data generator to better understand the complexity of human interaction with the city. Therefore, this thesis explores reading social space with social network service data and develops a manual for a new way of reading the city that integrates this new layer of information with traditional methods.

This manual situates itself somewhere between the physical reading of the city analyzing programs and spatial elements quantitatively, and the experiential reading of field trips and interviews. It reads the city that is independent from a singular perception of the architect or urban planner, yet generates a bigger picture to understand the given neighborhood. Through a newly proposed way of reading the city with crowdsourced perceptions on the city, the thesis suggests a new macro vision that is accumulated through micro documentations that evidence individuals experiences, and perceptions.

Throough this Manual, the thesis ultimately argues that mass collections of micro documentations in urban design and urban planning allows us to overcome both the totalizing modernist vision on social space, and liberates the limitations of everyday urbanism.

Research Question

'Ma(i)cro visions' explores reading social space with social network service data and develops a manual for a new way of reading the city that integrates this new layer of information with traditional methods. The thesis investigates the character of social space in peoples everyday life through spatial analysis on places captured through SNS data, and then studies the spatial configuration of the places to inform future social space design. It takes notice on the intention of geo-tagging activities, which are spontaneous acts to share and remember moments in everyday life that happened in those specific locations. Mapping geo-tagged social network service posts will enable an observation of the geography of places people relate them to, and generate a macro vision of the psychological geography of meaningful places.

The Man

The Perception

The City

To know how to use the data to inform urban design, we first need to understand the nature of the data. Therefore, the thesis is structured twofold: first, understanding the nature of the SNS data and then second, using the findings to set rules that guide future space reading processes with this new layer of information.

The first part of the thesis explores the relationship between the psychological geography constructed through social network service data, the demographic characteristic and the built form of the city. The research investigates in the following questions.

1. What is the relationship between the built form, the population characteristic and the psychological geography of digitally recorded meaningful places?

2. What consists those meaningful places and what factors have a relationship with the agglomeration and dispersal of such places?

The second part of the thesis proposes a manual to read social space utilizing Social Network Service location data, informed by the previous phase of research. It sets a methodology to identify physical spaces in neighborhoods through spatial alanysis on the psychological geography. The main questions in this section are as follows.

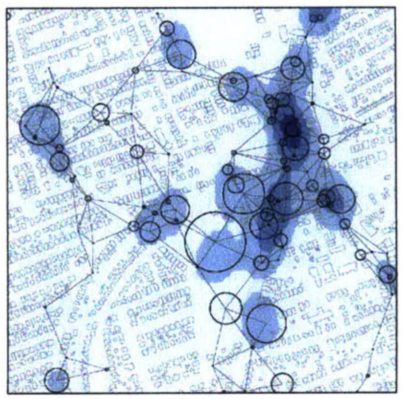
1. What physical element does the psychological geography inform us?

2. What relationship can we imagine between this perceptional reading and the traditional reading of the city?

Physical Reading

Public Institutions
Recreational open space
Landmark

Program and spatial element



Perceptional Reading

Parcels that contain locations

Psychological geography

Experiential Reading

The ambiance of the site
Interviews

Site visit

CH2

Literature review

The psychological city:
Observing the city in urban studies

Information technology:
Opportunity, Areas of application

1 The psychological city:
observing the city in urban studies

Observing the psychological geography of the city has been an improtant theme in urban studies. Kevin Lynch's 'The image of the city (1961)' and William Whyte's 'The social life of small urban spaces (1980)' are one of the representative readings that studied human perception and behavior in public space. They are similar in that both attempted to incorporate the invisible reading of citizen's mental image of the movement of people, to understand what spatial or functional element influenced the perception or behavior.

'The image of the city (1961)' analyzes the visual quality of the city by studying the mental image of the city, which is held by its citizens.**1** Since the environmental image is a product made by the observer and the environment,**2** his analysis sets the physical environment as independent variables that are relates to identity and structure. The physical environment to be analyzed is narrowed down into perceptible objects that can be classified into five categories: paths, edges, districts, nodes, and landmarks. Then, he conducts interviews of a small sample of citizens and second, extracts systematic examination of the environmental image evoked in trained observers in the field.**3** They interviewed thirty people in Boston and sixteen of them went for the second session in which subjects are supposed to classify photography's randomly given to the subject for an identification. Then a trained observer was sent to the site to draw a map. The result was overlapped for comparison, and reconfirmed the five element types (node, district, landmark, edge, path) being discovered with some exceptions in LA.

1 Lynch, Kevin. The image of the city. Vol. 11. MIT press, 1960: 2.
2 bid., 8

3 Lynch, Kevin. The image of the city. Vol. 11. MIT press, 1960: 140.

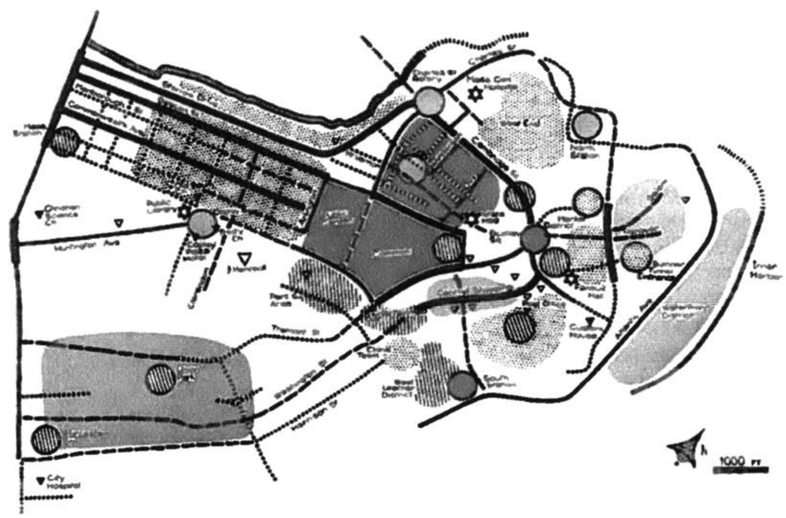


FIG. 35. *The Boston image as derived from verbal interviews*

[Fig 2] The image of the city

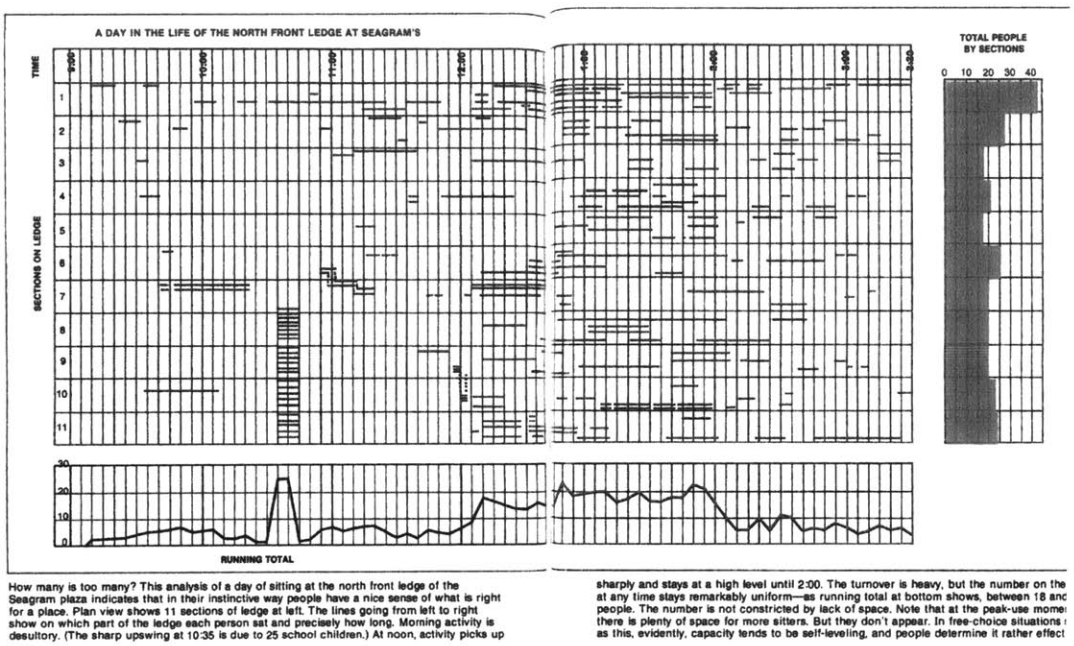
The research in 'The social life of small urban spaces (1980)' relies on scientific observation of the people's movement and then, through identifying the physical or formless factors that generated different patterns, understands why some places work and others do not. The factors Wythe identifies are sitting space, natural conditions (sun, wind, trees, water), the undesirables, effective capacity, indoor spaces, and activities. The research uses time-laps filming that takes pictures in a specific interval, and analyzes the density and duration of a small gathering of people.

Both studies share similarities in the approach that collects or observes individual's actual perception and mobility in cities. However, while 'The image of the city' predefines the physical environment as an independent variable and attempts to extract meaning through human input of information, and the latter starts with the raw data and then discovers the physical elements through emergent patterns from the data. Ma(i)cro vision succeeds the concept of collecting individual perceptions from 'The image of the city', but in terms of data and analytics rather assimilates itself with 'The social life of small urban spaces'.

Coming back to the contemporary context, raises questions on how data and information technology is percieved and utilized in urban studies.

The proliferation of data and technological evolution impacts planning, design and management of cities in complex and multi-dimensional ways. This trend was featured on the very recent issue (autumn 2014) of the 'Urban Design' magazine. Turton polly describes that data and technology has highlights areas such as, crowd funded place making actions, real time city planning, risk analysis to inform urban design, user centered designs utilizing internet platforms and visual analytics to inform design.**4**

4 Turton, Polly. "Data, technology and urban design", Urban Design: Data, technology and urban design, 132, Autumn 2014: 20–36.

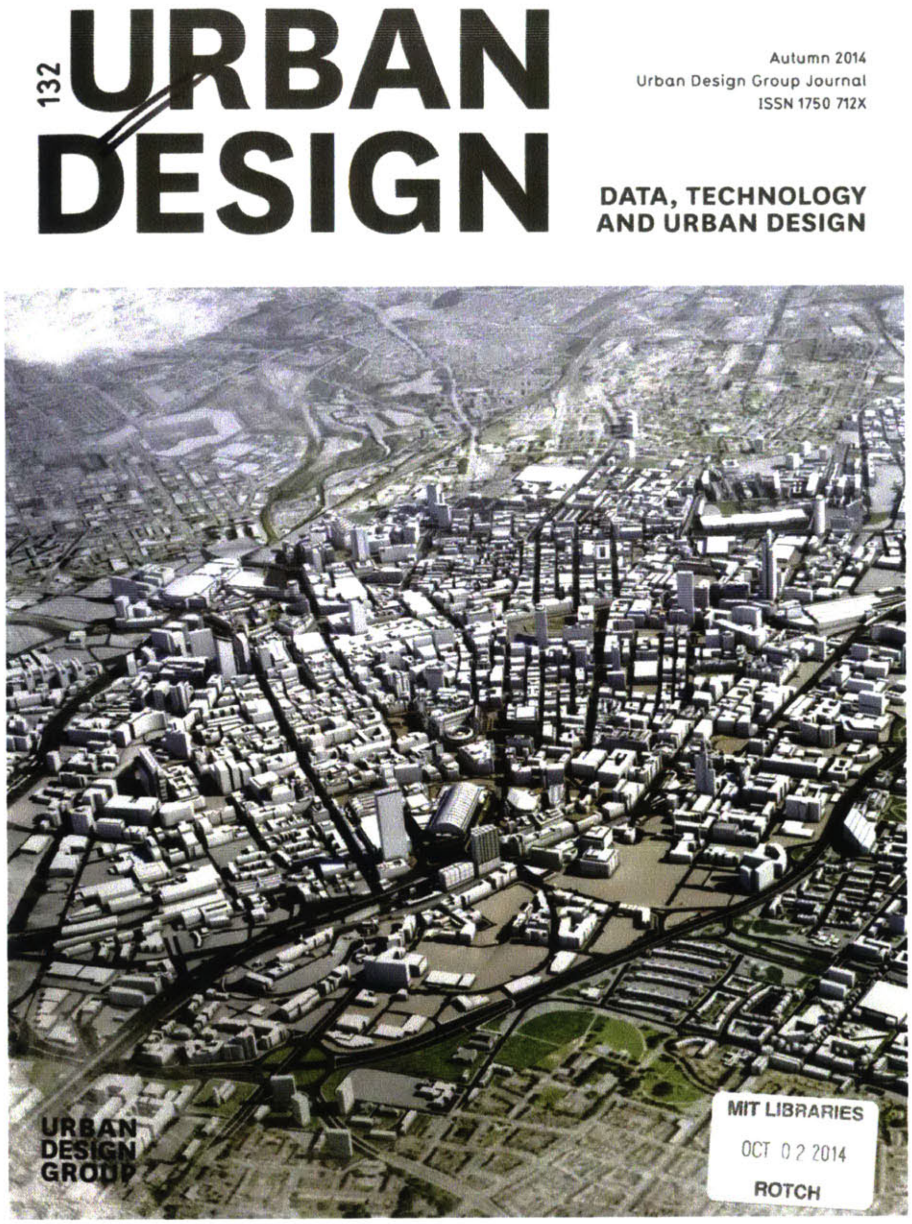


[Fig 3] The social life of small urban spaces

In fact, several precedents have already started analyzing the city through data that is generated in our everyday life.

In 2012, Vanessa Frias-Martinez published 'Characterizing Urban Landscapes using Geolocated Tweets' analyzed geo-located tweets to determine land uses through the tweet patterns and mapped the urban points of interest through a density analysis of the tweets. Following, 'Exploiting Foursquare and Cellular Data to Infer User Activity in Urban Environments' by Anastasios Noulas, was published in 2013 that combined a dataset collected from a telecom provider in Spain with geo-tagged foursquare venues to analyze the possibility to infer activity types of geographical areas. Both studies test the credibility of social network data as a tool to extract knowledge about human activities in the city. The studies remain an objective stance by refusing to hastily deduct the hidden intension of the data creation, which did not allow the data to be further informative in design.

There has been a lot of work in urban computing that is coming from computer science studies, however, there has been little work that percieves this opportunity as a way to inform design. The literature guides the research towards an apporach that links the analytics through data with the filed of urban planning and architecture.



[Fig 4] Urban Design Group Journal

CH3

Research process

Material
Instagram location data
Census demographic data
Land use data

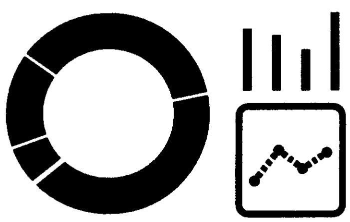
Sites
Central, South Dorchester, Mattapan in Boston

1 Research process

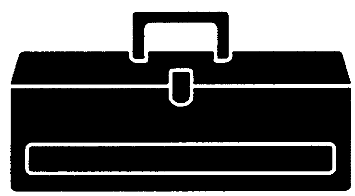
The goal of the research is to understand how the data looks like, what the places actually are, and what spatial elements generate these places of different characteristics. The research undergoes three steps in order to achieve the goal: 1) a distance based analysis to understand the nature of the place distribution, 2) a spatial join between the location data and different types of data (land use data and demographic data) to understand the relationship between the location, the program, and the people constituting each neighborhood, and finally 3) an empirical observation on the spatial configuration of sampled locations of the found geography of meaningful places.

The research utilizes various quantitative spatial analysis methods to understand the composed geography of places in depth.

In the first part of the analysis focuses on the location data itself, in three different planning districts in Boston to compare the location distribution pattern: Central Boston, South Dorchester, and Mattapan. The location density, average distance between locations, and the distribution of posts with other users tagged are compared. The intention is to map the different patterns of physiological geography of places, formed in different parts of the city. As a final product, a map with locations inter connected to each other within a 10 minutes walk (800 meters) is presented to visualize the different structure of the net of digitally highlighted places, demonstrating the difference in density, distance and connectivity.



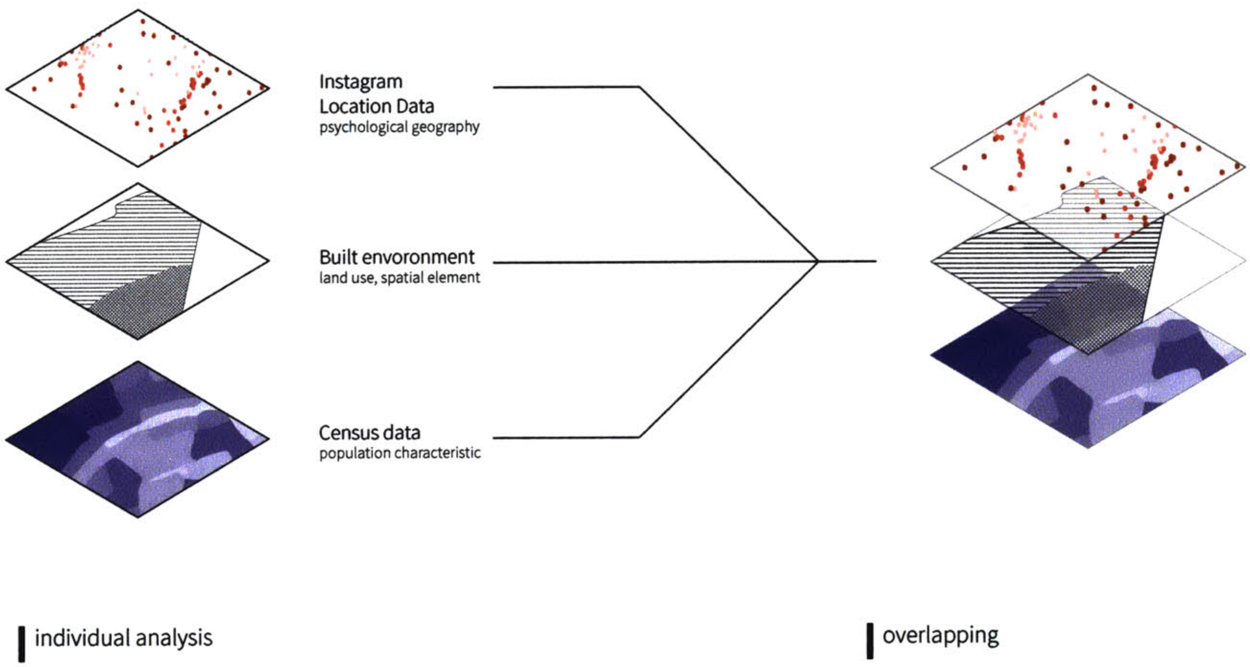
Knowing



Using

The second analysis conducts spatial joins of the location distribution data and the land use map. The intention is to see the relationship between the spatial distribution patterns of digitally recorded places and the land use structure of the area. The land use categories of the three planning districts are simplified into public, commercial and residential. Overlapping the simplified land use with the psychological geography will identify the type of social interaction expected in each place. Then, the psychological geography renders this additional layer of information, showing what social interaction actually happens in the city. It primarily reclassifies the places to observe concentrations of specific types of places. And ultimately, tests whether the assumption that people's activity is determined by the composition of programs holds valid or not.

Third, the demographic data is spatially joined with the location data to understand the relationship between the post density and the population characteristics. The planning districts are indexed with census data to show the characteristic of the resident population in terms of crime, income, population density, travel to work, poverty, and unemployment. The weighted overlay of such information generates a population characteristic index that displays a range of different types of populations. Simultaneously, a user analysis grouping identical user-ids that posted in multiple locations within the timeframe of 2010 to 2014, will provide a normalization criteria that determines how much of the data is generated by residents and by visitors. The intention of the analysis is to map the characteristic of the population that is directly exposed to each distinct location pattern and to draw a relationship between the population characteristic and the location patterns.



Finally, the research samples specific areas of the city that consist of parcels with different characteristics assigned through the previous researches on the geotagged places and the population. By analyzing the spatial configuration of those areas, the research finally attempts to understand the program, and physical elements of the spaces. The areas are abstracted into nodes of locations and paths that connect the locations. Each node and path will be analyzed to understand what program of each place and what physical form consist it. Each area generates a different constellation of such elements. The goals is to generate a catalogue of different constellations for each type of area, with which will enable designers to understand what compositions attract social activities more or less.

2 Material

Instagram

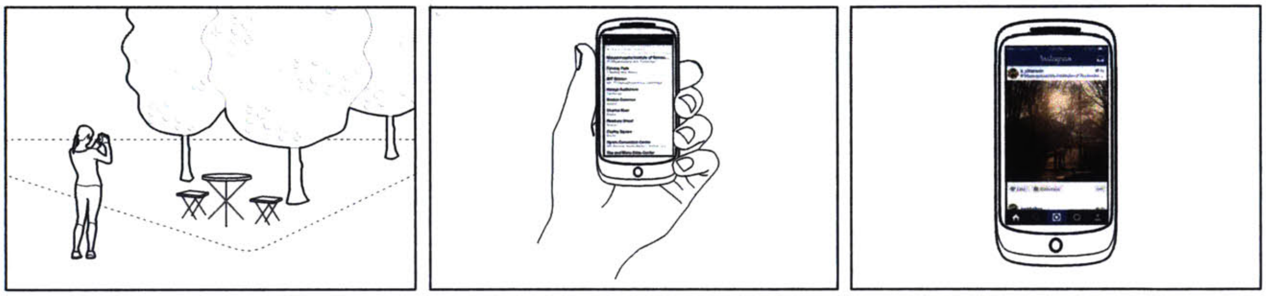
The research takes Instagram as the source of Social Network Service data collection to capture the actual social activities happening in the city. The aggregated information will generate a macro image of the city of 'places' people recognize subconsciously. Instagram is one of the most fast growing social network services, which allows users to edit and share photos with their friends. During 2013, Instagram reached 150 million monthly active users in half the time it took Twitter and in two years less than Facebook.[1] However, all Social Network Service data inherently have a limited user group and content shared this specific user group. This research takes this limitation not as a reason to exclude this specific dataset, but as a logical basis to articulate the type of data to be collected and the way it should be read.

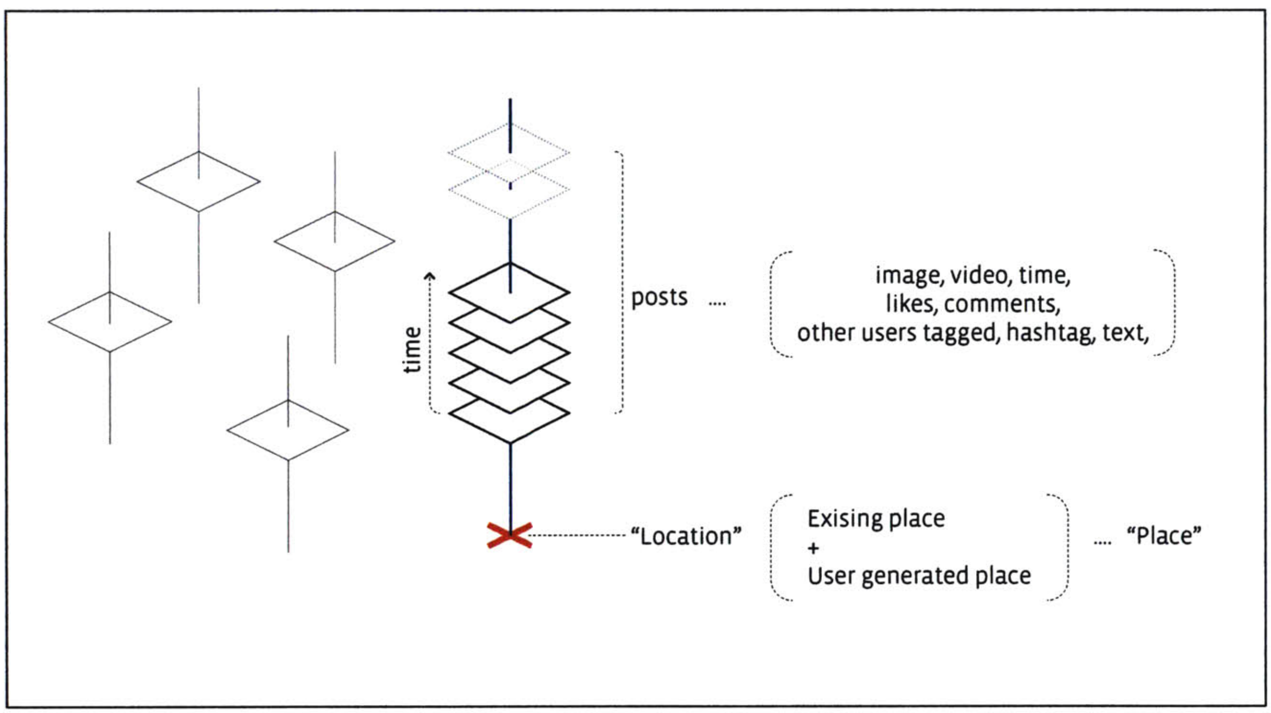
The user demographic shows that women, people under 50 years, African-Americans and Hispanics, urban residents are more likely to use it than men, whites or people over 50 years old, or rural residents.[2] According to a recent image analysis research, the content of posts comprises of largely 8 different types of categories (friends, food, gadget, captioned photo, pet, activity, seflie and fashion), with 46.6% of photos of selifies and friends, followed with 16% of posts on activities.[3] Even though there is a specific user group more dominant over others, the types of posts inform us that the posts are not limited to private experiences and in fact, and allow us to see the personal experiences related to people and activities in the city.

1 "This Chart Shows How Instagram Reached 150 Million Users In Half The Time Of Twitter", accessed December 9, 2014, http://www.businessinsider.com/instagram-growth-chart-2014-2

2 Duggan, Maeve, and Joanna Brenner. The demographics of social media users, 2012. Vol. 14. Washington, DC: Pew Research Center's Internet & American Life Project, 2013: 6.

3 Hu, Yuheng, Lydia Manikonda, and Subbarao Kambhampati. "What We Instagram: A First Analysis of Instagram Photo Content and User Types.", 2014: 4.





1. Geo-tagged SNS data traces human activity in the city.
2. Instagram locations are places that people recognize, share and remember.
3. So it is possible to understand the human perception and experience in relation to the built form, and the social configuration of each social space.

The research analyzes Instagram locations and the posts tagged on those locations. Instagram locations exist as a list of places detected nearby your device. When a person wants to geotag their post by adding the location, the location can be selected from the cumulated list or newly added. This act involves a motivation of the user to record the place the photo is taken. Therefore, I am reading these points of data as meaningful places that people recognize, share and remember. Through this action, anonymous space becomes a part of moments recorded and shared. It becomes a place that embeds meaning.

Locations have names and a time when they are created. They may embed multiple posts that are generated in different times by different users. Each post contains information of the time, user, tagged user, text, hash tag, likes and comments. This research confines its boundary of analysis to the location data and the number of posts, and interprets the location data distribution as the distribution of meaningful places in the city.

DATA COLLECTION

The data is acquired through **API** (application programming interface), which is a platform provided by websites for software developers to build an application that utilizes information or functionalities from the provider's web service. The information is structured into building blocks, which can be reconstructed by software developers suited for the purpose of the program they desire to build. I utilized this API platform to request information posted through Instagram publicly by anonymous users.

To query information through API, the developer needs to build an URL that contains the developers credential information and the information that will be queried through the URL. In order to build a URL, the developer needs to know what information needs to be provided to obtain the target information. It is general that each platform provides information in their own way, therefore, the code to construct the desirable URL needed to be divided into several steps.

SEARCH 1

```
https://api.instagram.com/v1/locations/search?lat=48.858844&lng=2.294351&access_token=ACCESS-TOKEN
```

Fixed URL to query 'location' endpoints

Search Parameter

Personal access token

list of locations with location id

SEARCH 2

```
https://api.instagram.com/v1/locations/{location-id}/media/recent?access_token=ACCESS-TOKEN
```

Fixed URL to query 'location' endpoints

Search Parameter

Fixed URL to query 'recent media'

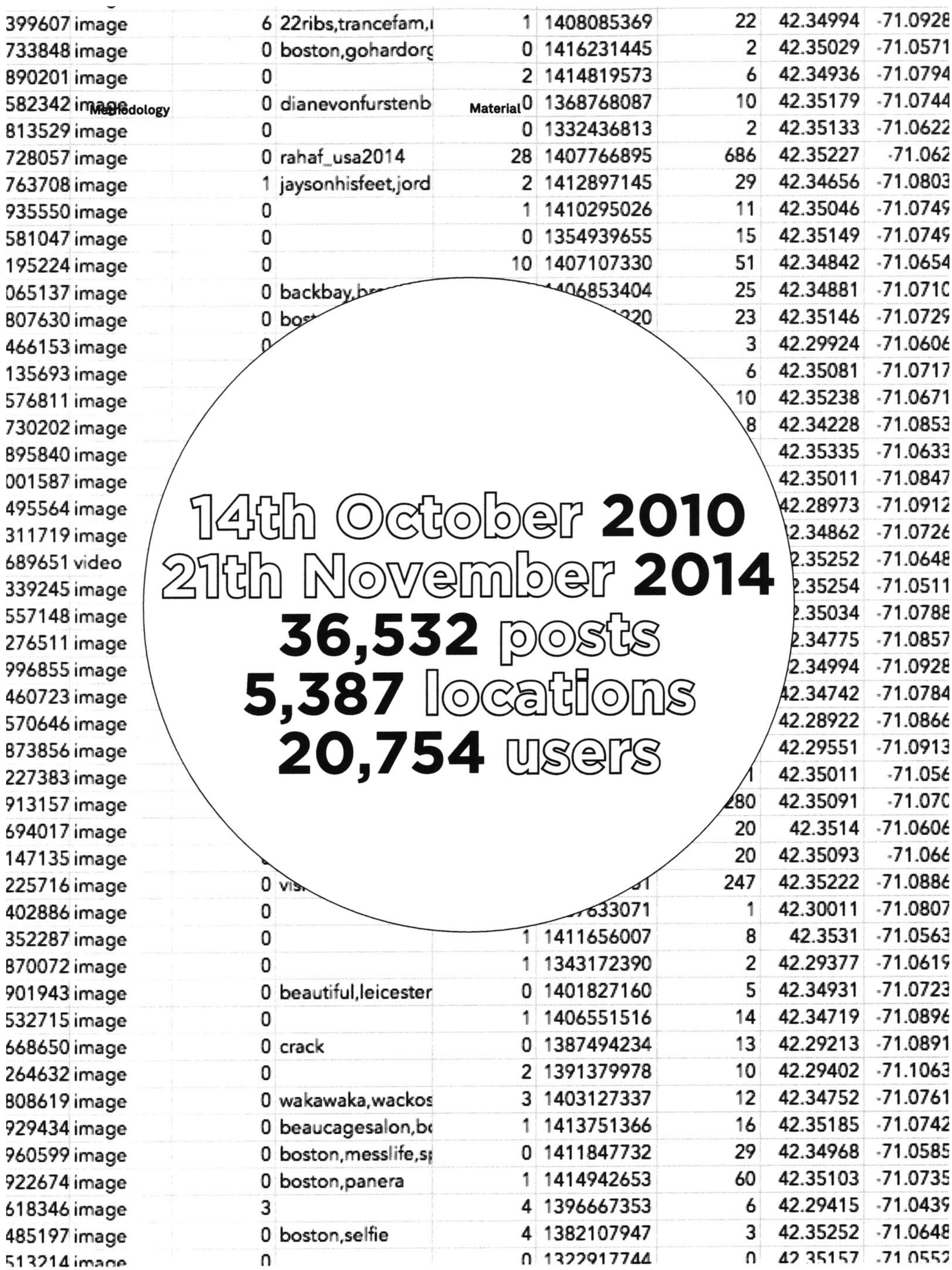
Personal access token

The final target information is the location, and posts tagged to the location in the certain area being analyzed. Since Instagram demands for the 'location id' to access all that information, the first target was to obtain the 'location id's. This allows to search recent posts created near the location that has the specific 'location id' obtained in the previous process.

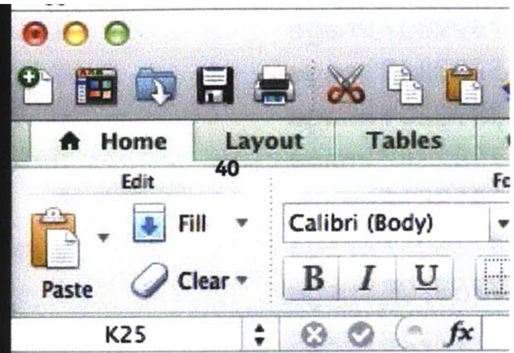
First step was getting a point grid to query 'location id's. It is possible to search up to 100 locations, within the 1000 meters radius around one point that has latitude and longitude though Instagram API. Therefore, we needed to generate a point grid above the site with a 100 meters distance between each other. After creating the points in GIS we got the latitude and longitude, by geo-referencing the points. Once we got the points, we parsed a URL that directs the API service to do the 'location search' which is getting 'location-id's around the point we created in a radius of 1000 meters.**4** Once the 'location-id' was saved, we could move on to do the second query called 'recent media search' to obtain the recent posts that happened around the location by providing the 'location-id'.

4 "Location Endpoints". Accessed May 21. http://instagram.com/developer/endpoints/locations/

The python script that allowed all the steps above mentioned, at the end, wrote a CSV file that can be imported to ArcMAP and further be geo-referenced to the X-Y coordinates. Once the data is expressed as points that contain all the meta data embedded in GIS programs, it is ready to be spatially analyzed through statistically rigorous analytic tools.


Methodology
Material
14th October 2010
21th November 2014
36,532 posts
5,387 locations
20,754 users

```
read_csv(path):
if os.path.isfile(path):
    with open(path, 'rU') as f:
        reader = DictReader(f, encoding='utf-8')
        data = [row for row in reader]
else:
    data = []
return data

write_csv(path, data, fields):
with open(path, 'wb') as f:
    w = DictWriter(f, fieldnames=fields, encoding='utf-8', q
            quoting=csv.QUOTE_NONNUMERIC)
    w.writeheader()
    for row in data:
        w.writerow(row)

get_media(location):
distance = DEFAULT_DISTANCE
path = '/v1/locations/' + str(location['id']) + '/media/rece
media = request(path)
return media

get_locations(point):
distance = DEFAULT_DISTANCE
path = '/v1/locations/search'
locations = request(path, {
    'distance': distance,
    'lat': point['lat'],
    'lng': point['lon'],
    })
return locations['data']

read_points():
return read_csv(point_csv)

write_points():
write_csv(point_csv, DATA['points'], POINT_FIELDS)
print "saved", len(DATA['points']), "points"

read_csv_to_dictionary(filename, id_key='id'):
data = {}
rows = read_csv(filename)
for row in rows:
    key = row[id_key]
    data[key] = row
return data

write_media():
data = DATA['posts'].values()
write_csv(post_csv, data, POST_FIELDS)
print "saved", len(DATA['posts']), "posts"

write_locations():
write_csv(locations_csv, DATA['locations'].values(), LOCATIO
print "saved", len(DATA['locations']), "locations"
```



	A	B	C	D
1	id	type	users_	tags
2	8238534805	image	2	
3	8501595819	image	0	shelbygoestobo
4	8383243112	image	2	newshoes,friday
5	4173167738	image	0	
6	4125339898	image	0	pcp,tcb,fbf,rlc,nl
7	4683436131	image	0	
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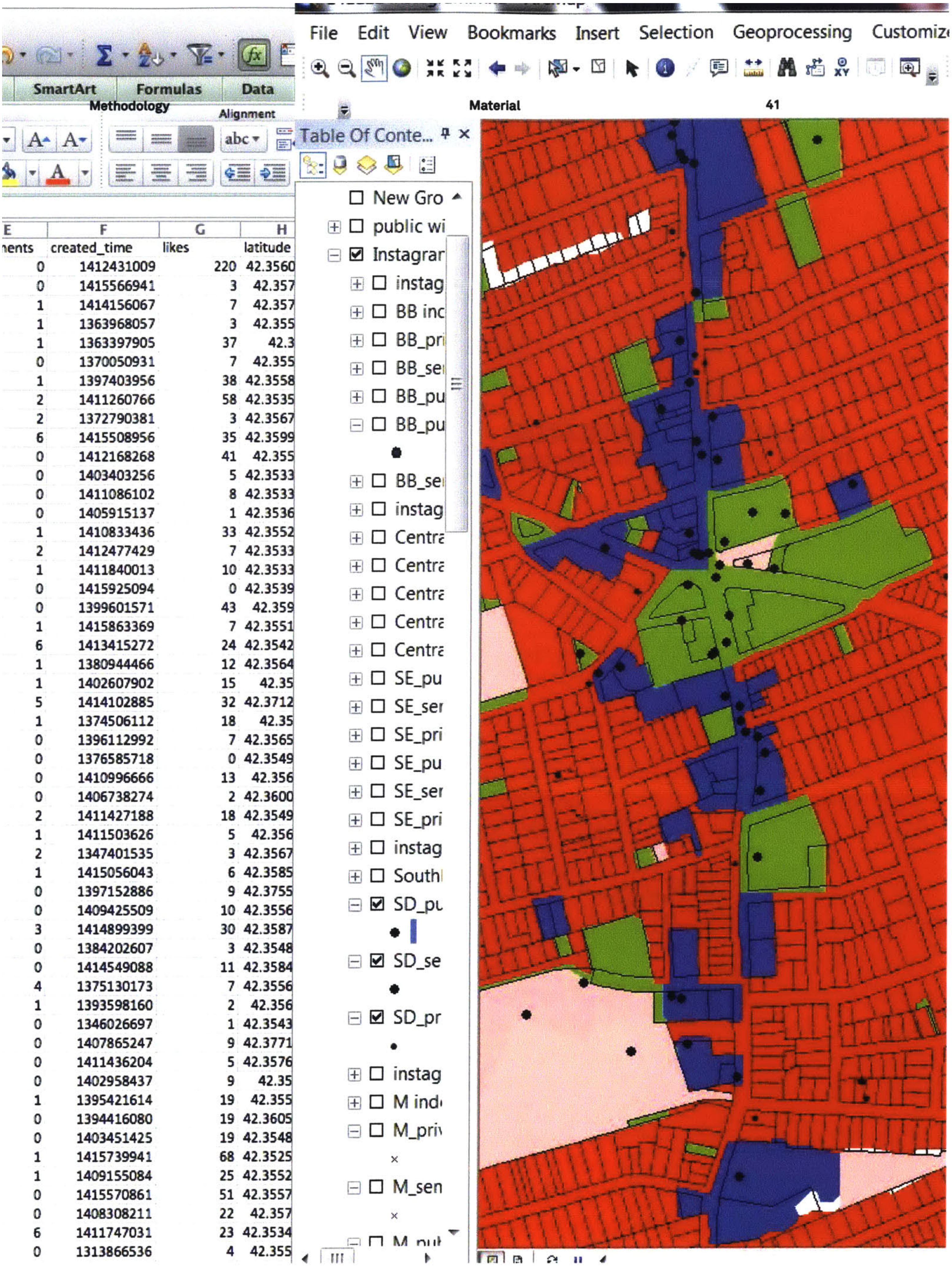

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2	1372790381	3	42.3567
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0	1405915137	1	42.3536
1	1410833436	33	42.3552
2	1412477429	7	42.3533
1	1411840013	10	42.3533
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0	1411436204	5	42.3576
0	1402958437	9	42.35
1	1395421614	19	42.355
0	1394416080	19	42.3605
0	1403451425	19	42.3548
1	1415739941	68	42.3525
1	1409155084	25	42.3552
0	1415570861	51	42.3557
0	1408308211	22	42.357
6	1411747031	23	42.3534
0	1313866536	4	42.355

Instagram Locations
In Back Bay and Central Boston


× Posts

Factors to define the Socio-economic index

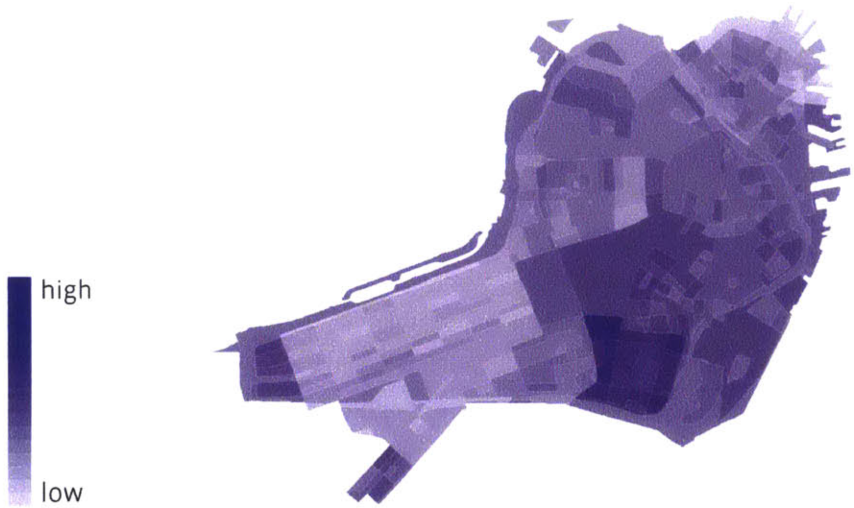
Census data

The socio-economic index shows the population character of the studied area. The data is collected through social explorer from the ACS US Census data of 2010 and later geoprocessed in GIS. Six different datasets are equally weighed and overlapped. Out of the extensive dataset, I selected the population density, crime, unemployment, average income, percentage below poverty line, and the travel time to work to be used as factors to define the socio-economic index. I selected these factors relying on Sarah Botterman's study[5] on indicators that define social cohesion in urban social studies. The intension was to select demographic factors that are proven from previous studies to form a specific type of neighborhood.

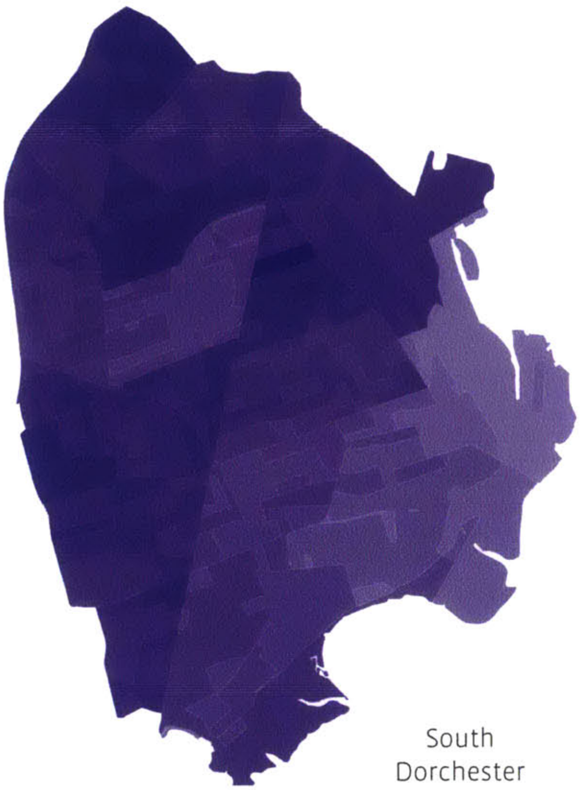
Each dataset was collected as excel files that has values assigned per parcel, census block or census tract. The first step to process the data was to geocode each dataset to the target unit. Once each dataset was geocoded, I rasterized each map utilizing standard deviation for the values. This step was necessary because each dataset recorded different types of data: percentage, dollars, minutes and so on. Therefore, to give each dataset a unified value, the rasterization process remaped all values into 16 classes that are relational to each dataset's mean value. Once the rasterized map was ready, I evenly overlapped each map to arrive to the finalized map that contains 16 classes of socio-economic index.

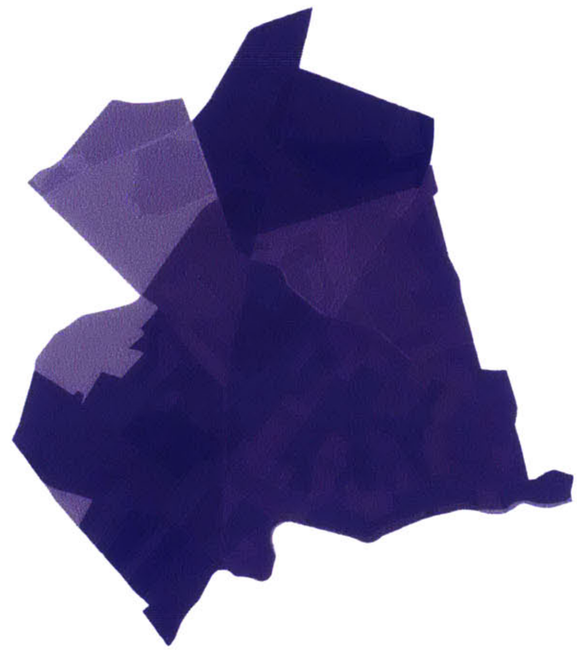
5 Botterman, Sarah, Marc Hooghe, and Tim Reeskens. 2012. "'One Size Fits All'? An Empirical Study into the Multidimensionality of Social Cohesion Indicators in Belgian Local Communities." Urban Studies 49 (1): 185–202.

Socio-economic index



Central / Back Bay

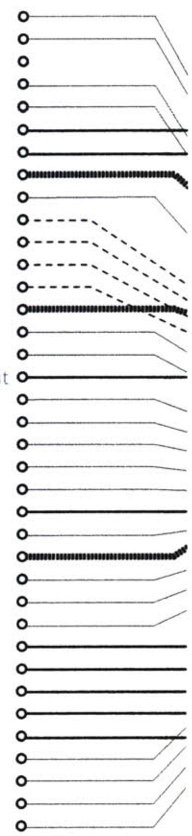




The socio-economic index displays the socio-economic character of the population geographically among the selected planning districts in Boston. The darker color indicates the population with lower social status, and implies neighborhoods with less social cohesion. The distribution of socio economic classes shows that the population character has a distinctive patterns in Central Boston, South Dorchester, and Mattapan. In general, the socio-economic index becomes lower as we move from Central Boston to South Dorchster and reach Mattapan.

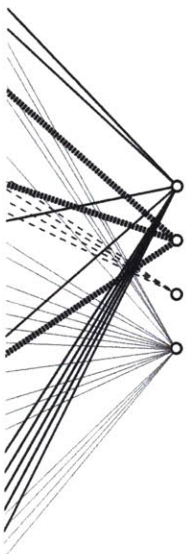
This index is used as an indicator to measure the relationship between the location density and the demographic characteristics.

CODE	CATEGORY	DEFINITION
1	Cropland	Intensive agriculture
2	Pasture	Extensive agriculture
3	Forest	Forest
4	Wetland	Nonforested freshwater wetland
5	Mining	Sand, gravel & rock
6	Open Land	Abandoned agriculture; power lines; areas of no vegetation
7	Participation Recreation	Golf; tennis; Playgrounds; skiing
8	Spectator Recreation	Stadiums; racetracks; Fairgrounds; drive-ins
9	Water Based Recreation	Beaches; marinas; Swimming pools
10	Residential	Multi-family
11	Residential	Smaller than 1/4 acre lots
12	Residential	1/4 - 1/2 acre lots
13	Residential	Larger than 1/2 acre lots
14	Salt Wetland	Salt marsh
15	Commercial	General urban; shopping center
16	ndustrial	Light & heavy industry
17	Urban Open	Parks; cemeteries; public & institutional greenspace; also vacant
18	Transportation	Airports; docks; divided highway; freight; storage; railroads
19	Waste Disposal	Landfills; sewage lagoons
20	Water	Fresh water; coastal embayment
21	Woody Perennial	Orchard; nursery; cranberry bog
22	No Change	Code used by MassGIS only during quality checking
23	Cranberry bog	
24	Powerlines	
25	Salwater sandy beach	
26	Golf	
27	Tidal salt marshes	
28	rregulary flooded salt marshes	
29	Marina	
30	New ocean	
31	Urban public	
32	Transportation facilities	
33	Heath	
34	Cemeteries	
35	Orchard	
36	Nursery	
37	Forested wetland	



Land use data

The land use data is collected through Boston's government open data as a shapefile format. The current land use is divided into 37 categories. Since the research intends to understand the role of different kinds of social space and its relationship with geo-tagging activities, the land use codes needed to be simplified through a re-categorization in terms of its function as social space. For instance public space is made of parks, forests and sports fields. But if there would be five categories that all represent it would be misleading and confusing. The research therefore, chose

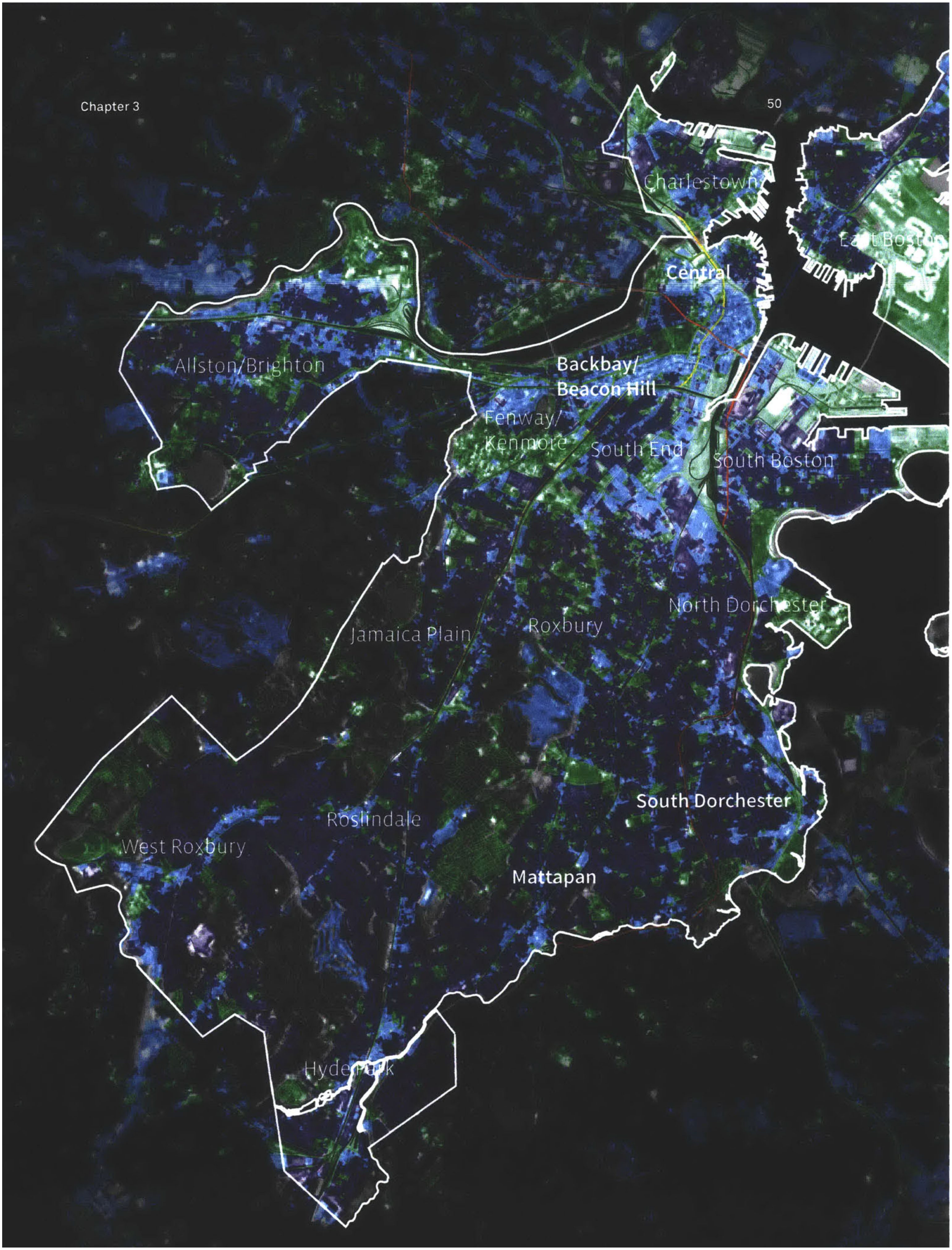


CATEGORY	DEFINITION
Public space	open, free public space
Semi public space	conditional social space: privatized public space, commercial space
Private social space	Private space where social life happens
Non social space	Industiral, office

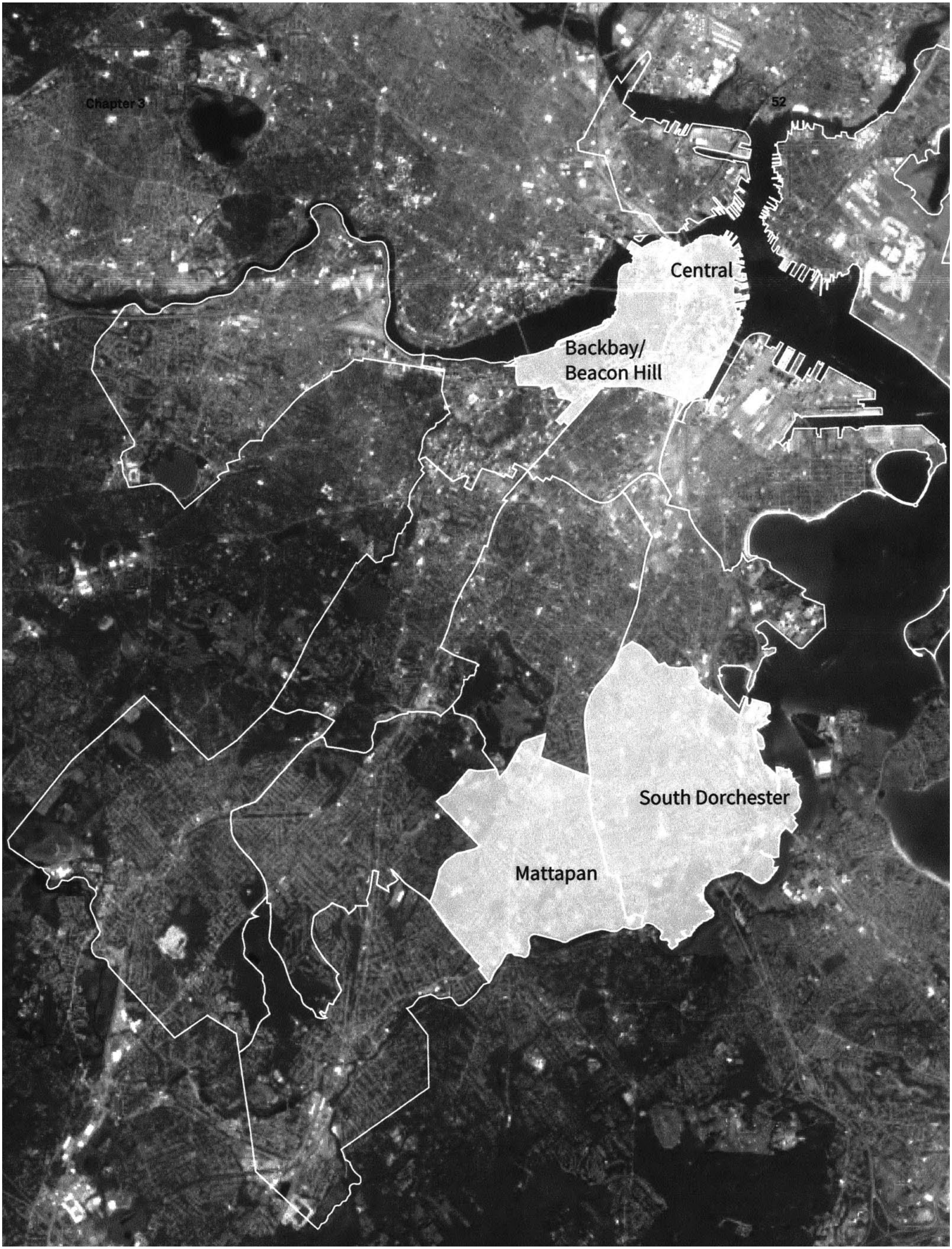
to classify the land uses into four categories that are public space, semi public space, private social space and non-social space.

This classification aims to generate a more extended classification of places for social interaction, that includes commercial space and even private space as a basis for the further analysis. The classification logic relies on readings of Ray Oldenburg's 'The great good place' and Tridib Banerjee's article on 'The Future of Public Space: Beyond Invented Streets and Reinvented Places', which argue for an inclusive vision of places for social interaction.

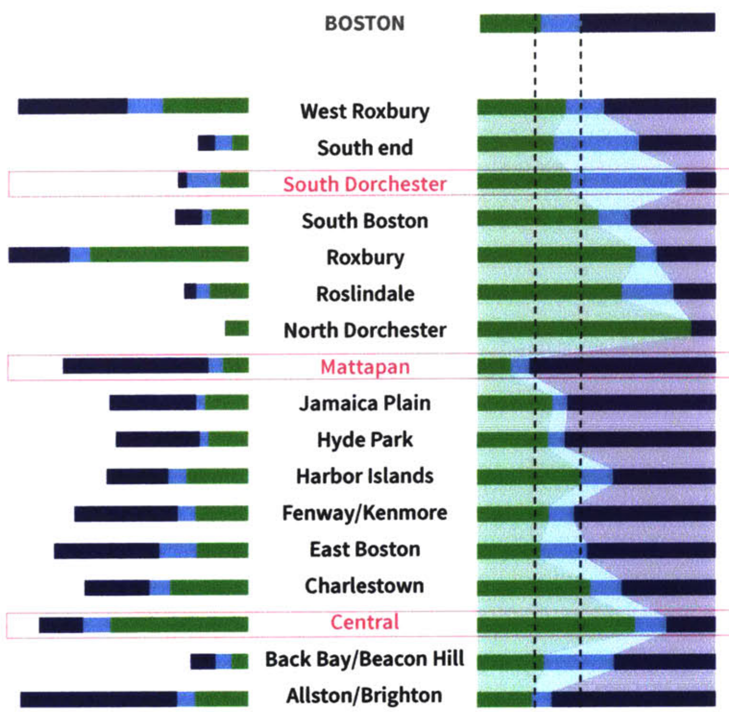
The land use data was collected from 1971 to 2005 within the administrative border of Boston.


Charlestown
Central
Allston/Brighton
Backbay/
Beacon Hill
Fenway/
Kenmore
South End
South Boston
North Dorchester
Jamaica Plain
Roxbury
South Dorchester
Roslindale
West Roxbury
Mattapan
Hyde Park


Public space
Semi public space
Private social space
Non social space


Central
Backbay/
Beacon Hill
South Dorchester
Mattapan

3 Site



Central, South Dorchester and Mattapan are chosen as a case study because of their different structure of social space. The coverage ratio of public space, privatized public space, publicly owned private space and private space differs dramatically among the sites. Central exemplifies the most public district with a high ratio of privatized public space and little private space, South Dorchester has the most evenly balanced social space ratio, and Mattapan is mainly a residential area with the lowest ratio of public space. Comparing different patterns that emerge through Instagram locations will bring insight to the relationship between the built environment and social activities.

CH4

Psychological geography

Three questions

[Psychological geography]
x [Built environment]

[Psychological geography] x [People]
25 categories

Synthesis

1 The psychological geography

This analysis aims to analyze the density and interconnection of Instagram locations. It does not go into the meta data, nor extracts the number of posts related to each location, but measures the distance between location points and compares the distribution of instagram in Central, South Dorchester and Mattapan. It is an initial analysis to understand the general structure of the Instagram location distribution.

Central is the least private district of the cases with 26% of public space, 32% of semi public (privatized public space) and 8% of private. This district is highly populated by tourists visiting government plaza, Quincy market, North end and China town. It also has a large population of workers commuting to the financial district. 3,969 locations are found and 29,206 posts are made within the research timeframe. It means that 47.6 posts in semi public space and 13% in private space. The locations generate a dense net of places of which the average distance between adjacent public spaces is 20.96 m. The average distance between all locations that are public and semi public is 8.99m.

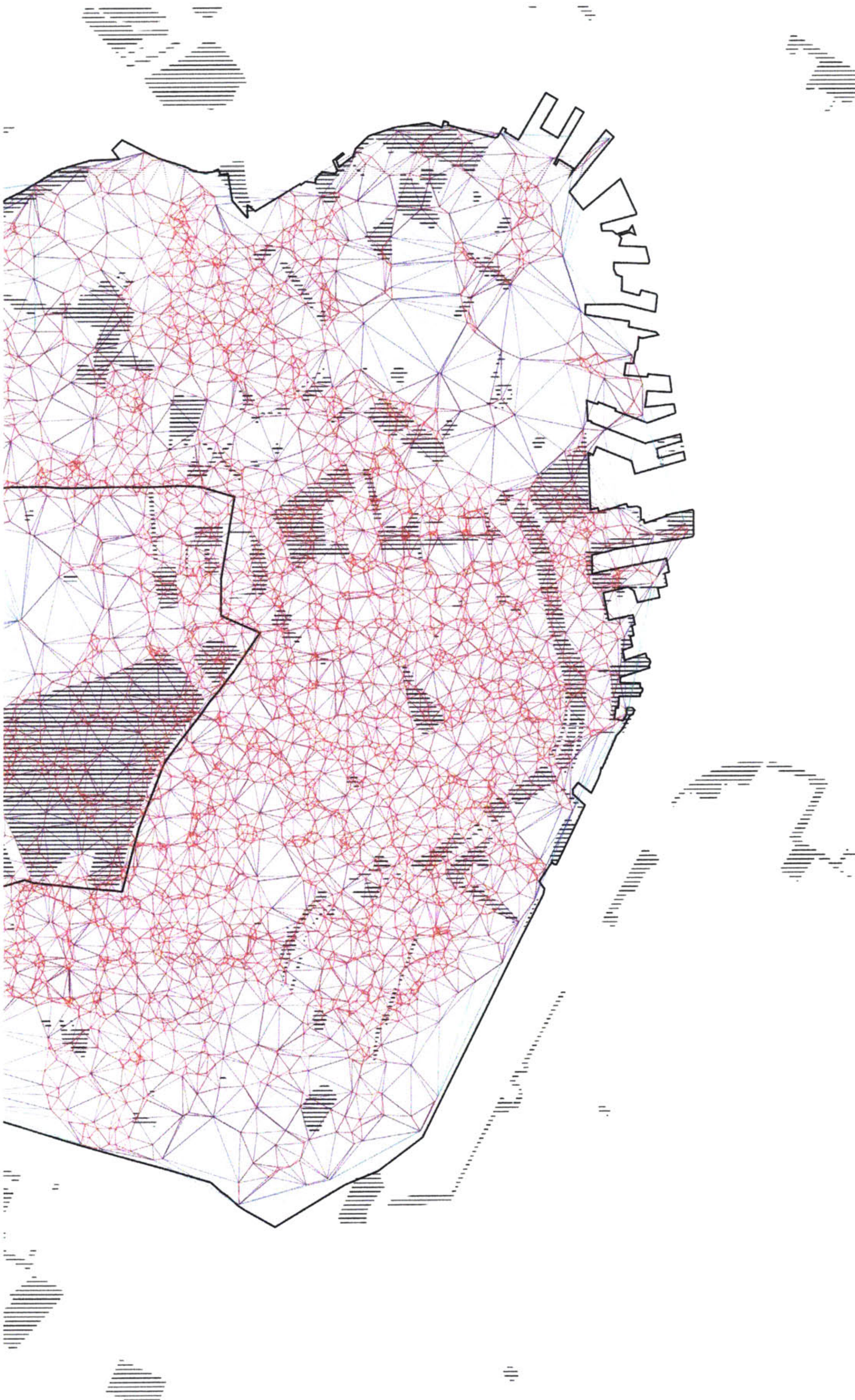
South Dorchester is selected because it is one of the most highly commercialized districts with a large residential population. Dorchester offers a variety of landscapes including 9.46 miles of waterfront, residential neighborhoods, commercial corridors, and a university campus.[1] The social space is made up of 33% public space, 7% semi public space and 10% private space. 1,069 locations are mapped with 5,746 posts, 3 posts per square centimeters. The locations form the least dense net of places with the average distance of 57.29m between adjacent public spaces. The average distance between public and semi public all locations is 33.82m.

1 "Neighborhoods at a glance", accessed December 9, 2014, http://www.bostonredevelopmentauthority.org/neighborhoods/dorchester/at-a-glance

Mattapan is a residential area with growing commercial centers. The housing mix includes small apartment buildings, single-family homes, public housing, and Boston's traditional "triple-deckers".[2] The structure of Social space of Mattapan consists of 11% public space, 3% semi public space and 23% private space. There are 339 locations with 1,580 posts, which means 1.1 posts per square centimeters. The locations form a fragmented net of places that have an average distance of 73.06m between public spaces. The average distance including public and semi public locations is 59.69m.

2 "Neighborhoods at a glance", accessed December 9, 2014, http://www.bostonredevelopmentauthority.org/neighborhoods/dorchester/at-a-glance

Even without going into specific meta data, three planning districts demonstrate a different pattern of location distribution. As seen in the following drawings, Central Boston forms the most dense net of geo-tagged places whereas the net of places becomes more and more fragmented in South Dorchester and Mattapan. It is difficult to say why this happens, but one thing that can be derived from this analysis is that compared to Mattapan or South Dorchester, Central Boston is clearly a planning district that contains more places that people wanted to share and remember along with their Instagram post.



20.96m

distance between public locations

9.3m

distance between public and commercial locations

≡ Public space

0 m

500 m

South Dorchester

57.29m

distance between public locations

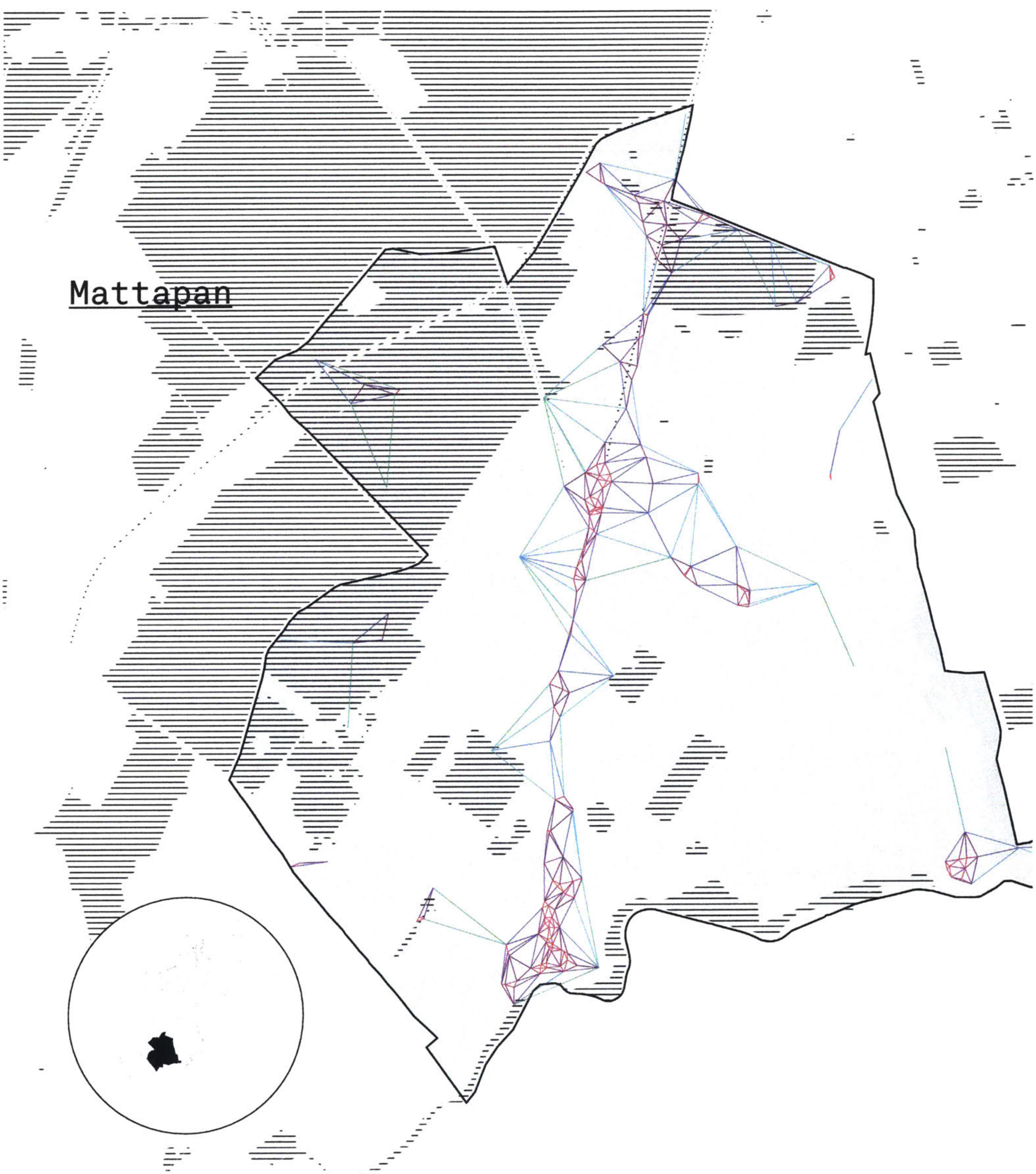
33.82m

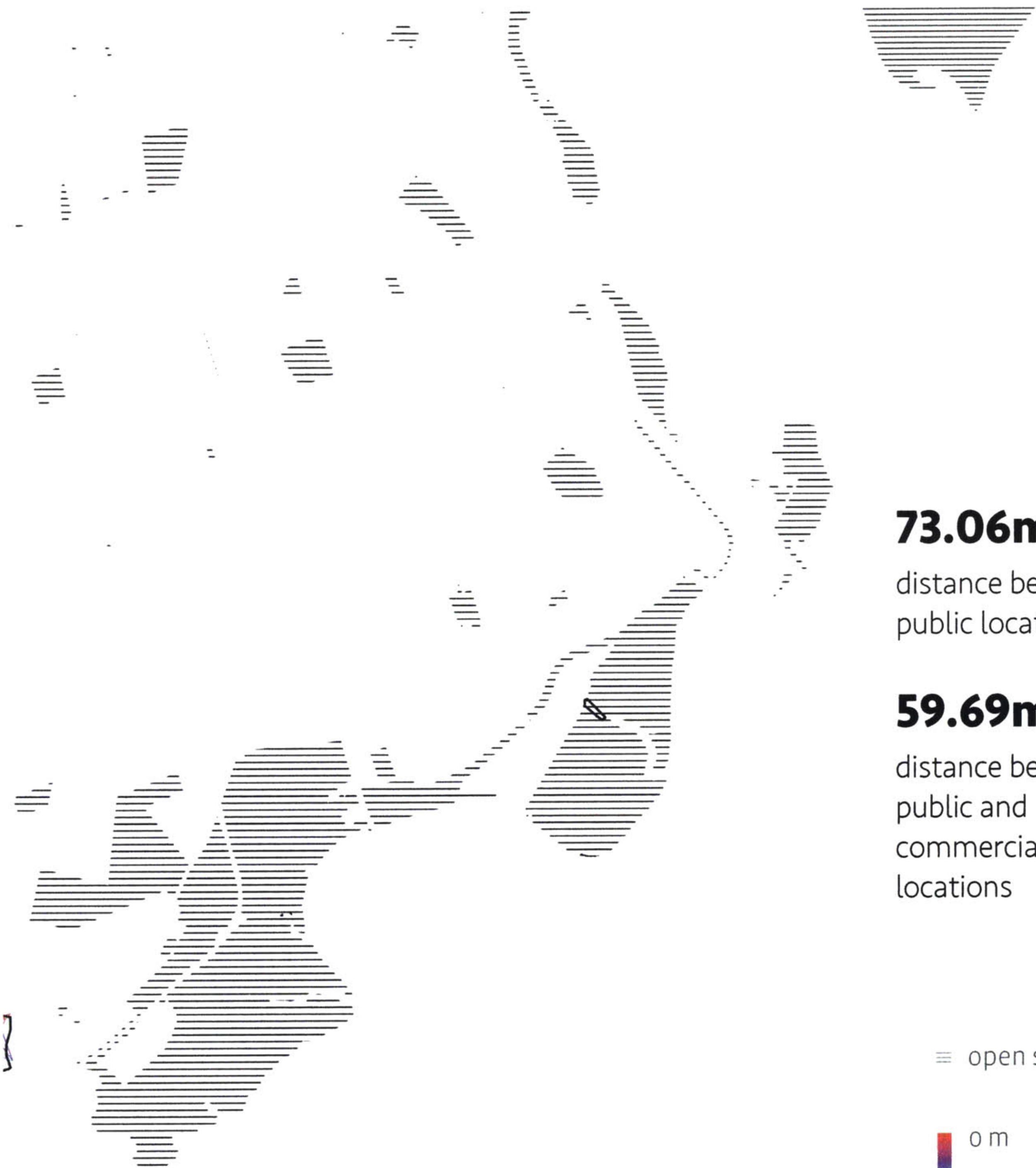
distance between public and commercial locations

≡ open space

0 m

500 m


Mattapan



73.06m

distance between public locations

59.69m

distance between public and commercial locations

open space

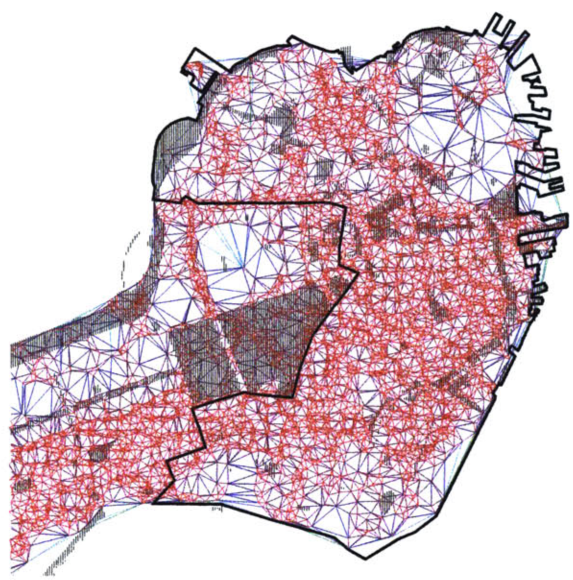
0 m

500 m

20.96 m
Distance between public locations

9.3 m
Distance between public and semi public locations

3,969
number of 'locations'



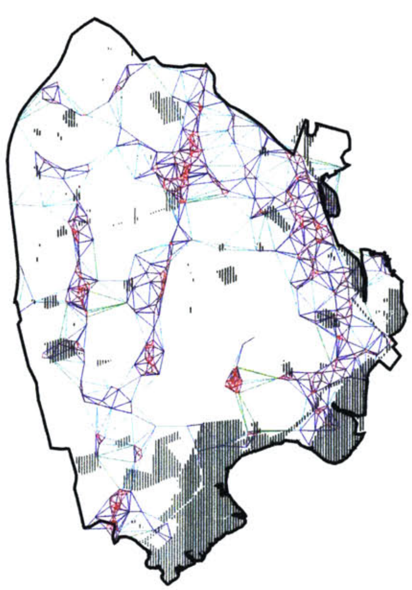
connection of locations whitin 500 m

Central

57.29m
Distance between public locations

33.82m
Distance between public and semi public locations

1,069
number of 'locations'

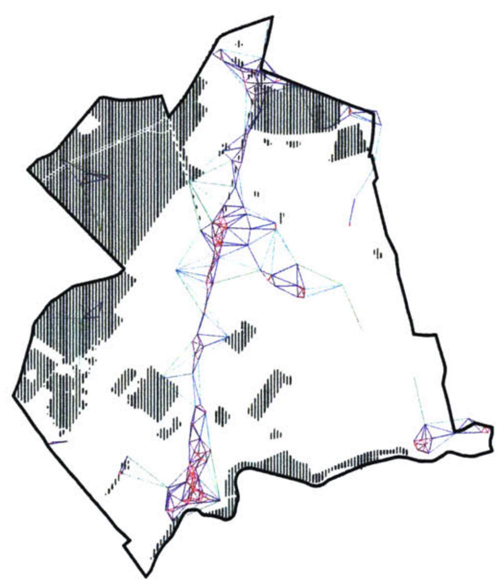


South Dorchester

73.06m
Distance between public locations

59.69m
Distance between public and semi public locations

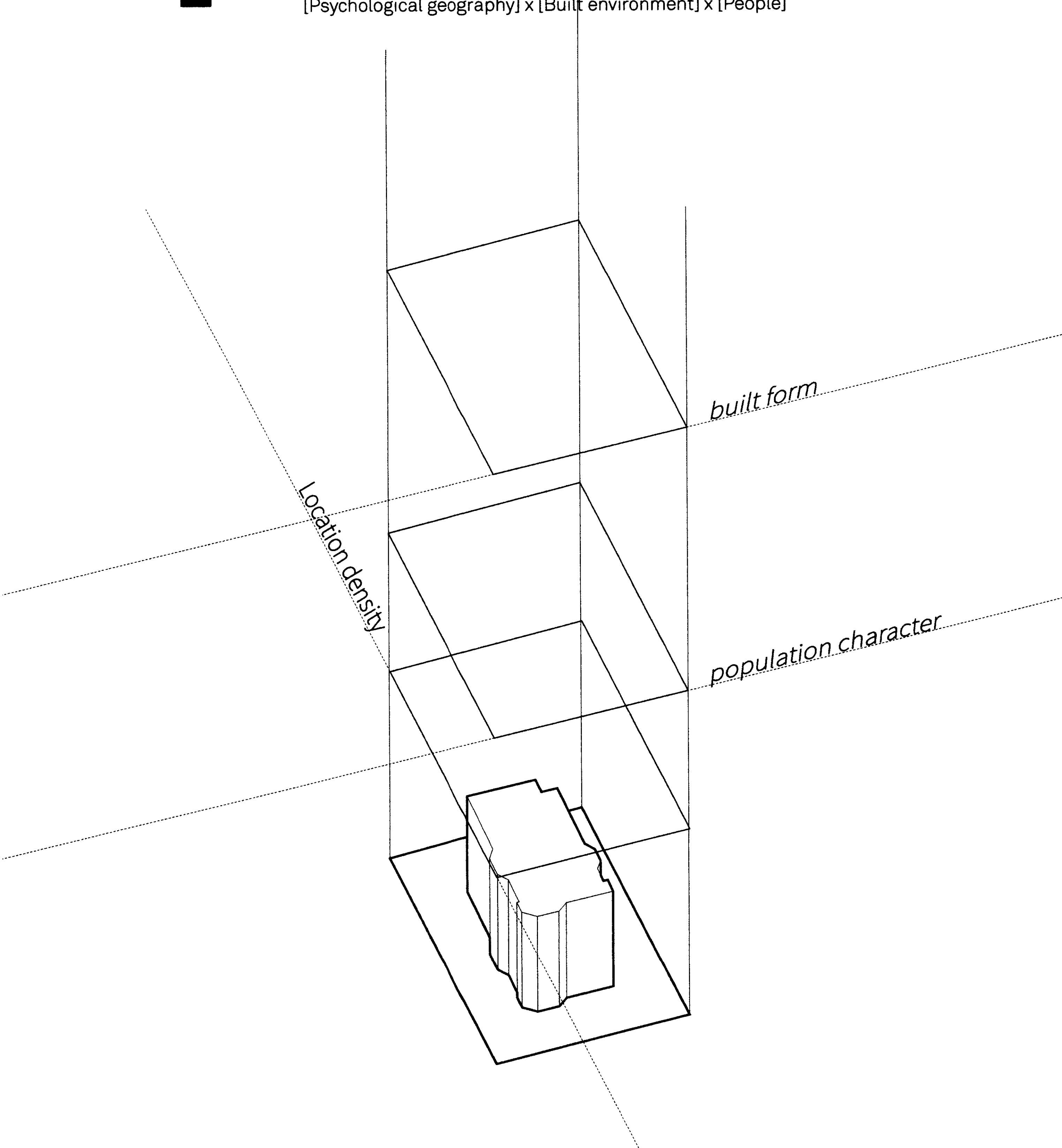
339
number of 'locations'



Mattapan

2 Three questions

[Psychological geography] x [Built environment] x [People]



There are some preconceptions about Social Network Service data in terms of the user demographics, the places people post from and its content. Prior to utilizing the data as a tool to capture human activities in neighborhoods, the research studies the behavior of such data to understand the nature of the Instagram location data itself. With these maps in hand, the research first, investigates in three main questions.

| **Does land use dictate the location density?**

| **What is the relationship between the demographic characteristic and the location density?**

| **What is the role of public space in the psychological geography of meaningful places?**

question 1

Does land use dictate posting activities?

One common bias towards Social Network Services, is that the geo-tagging activity is highly concentrated in commercial space. Therefore, the first section of the research explores the land use where the tag took place and categorizes the Instagram locations into public, commercial and private locations. The analysis measures the density of Instagram locations and the ratio of posts in relation to its program in Central Boston, South Dorchester, and Mattapan. So in plain language, what the section studies is whether people geo-tag their posts more in public space if the planning district has a high ratio of public space. This question is posed to understand not only whether the composition of different programs in the city predetermines human activity at all, but also if there is a tendency of geotagging activity in a specific type of program that transcends the character of neighborhood.

As mentioned in Chapter 3, the three planning districts — Central Boston, South Dorchester, and Mattapan — are selected because of their distinctively different composition of public & institutional land, commercial land and private land. Central Boston is the most commercial district in Boston with a relatively high ratio of public land and historical land marks. South Dorchester is one of the most public districts because of the waterfront on the east side accompanied with a high ratio of private space. Finally, Mattapan is one of the most private planning district of detached single family houses. Since the land use ratio of the three districts are distinctively different, they are considered as an independent variable on which the Instagram location data will be projected.

The ratio of locations in public & institutional land, commercial land and private land will be compared with the land use ratio that covers each district.

The ratio of public, commercial and private Instagram locations displayed distinct patterns in Central Boston, South Dorchester and Mattapan. Central Boston had 55 percent of 29,206 posts to be tagged in commercial space, which was followed with 30 percent of posts in public space and 15 percent in private space. This ratio of private posts matches the ratio of private land but in commercial space, but the ratio of commercial posts exceeded the ratio of commercial land, and that of public posts was lower than the ratio of public land. In South Dorchester, the ratio of posts did not follow the land use composition, because the ratio of public, commercial and private was 25 percent, 35 percent and 40 percent while the ratio of land use was 65 percent, 13 percent and 22 percent respectively. In other words, the most public district showed the commercial and private land to be tagged more than pubic land. In Mattapan, out of 1,580 posts 35 percent were made in public space, 31 percent in commercial space and 34 percent in private space. This result also shows a significant discrepancy between the land distribution and the geo-tagging activity.

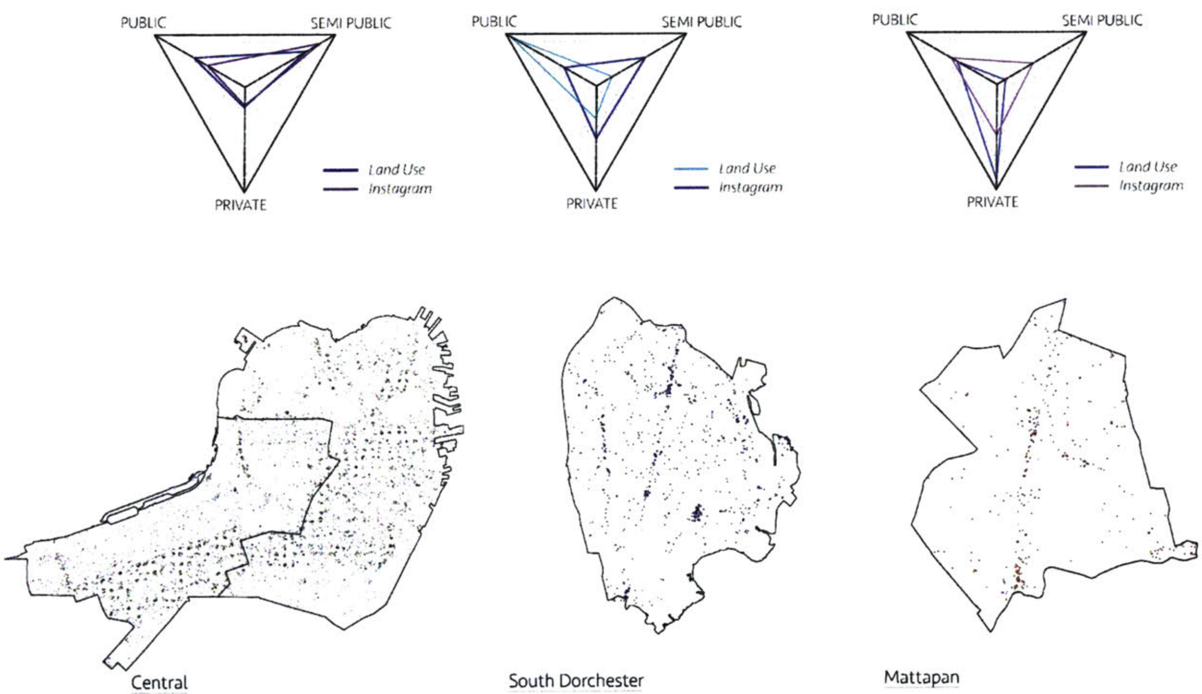
Within the overall impression that the land use composition does not necessarily dictate the geo-tagging behavior, there are some notable results both in public posts and commercial posts. The abundance of public space does not guarantee more location recognition activities. This discrepancy was observed the most severe in South Dorchester. South Dorchester is the overwhelmingly public district among the three with 65 percent of the land public, but the post ratio in public space indicates the lowest percentage (25%) among the three districts. Surprisingly, the second public district Mattapan demonstrated 35% of the posts in public space. Also Central Boston that has a strong public infrastructure integrated with commercial lands, the posts geo-tagged in public space where discovered less and posts would be more geo-tagged in commercial space. This incongruity challenges the general notion that the wealth of public space would lead more activities in public space. It rejects the idea of estimating human activity through a quantitative analysis that measures median park size or the percentage of acres dedicated to parks in a city.**3** Moreover, it leads to further questions wether there is a typology of public infrastructure that attracts people more in different neighborhood settings.

3 ParkScore does indicate that there is this much of Park(physical area) there, but should not suggest that this measure actually means that human activity in parks is more active where there are more parks.

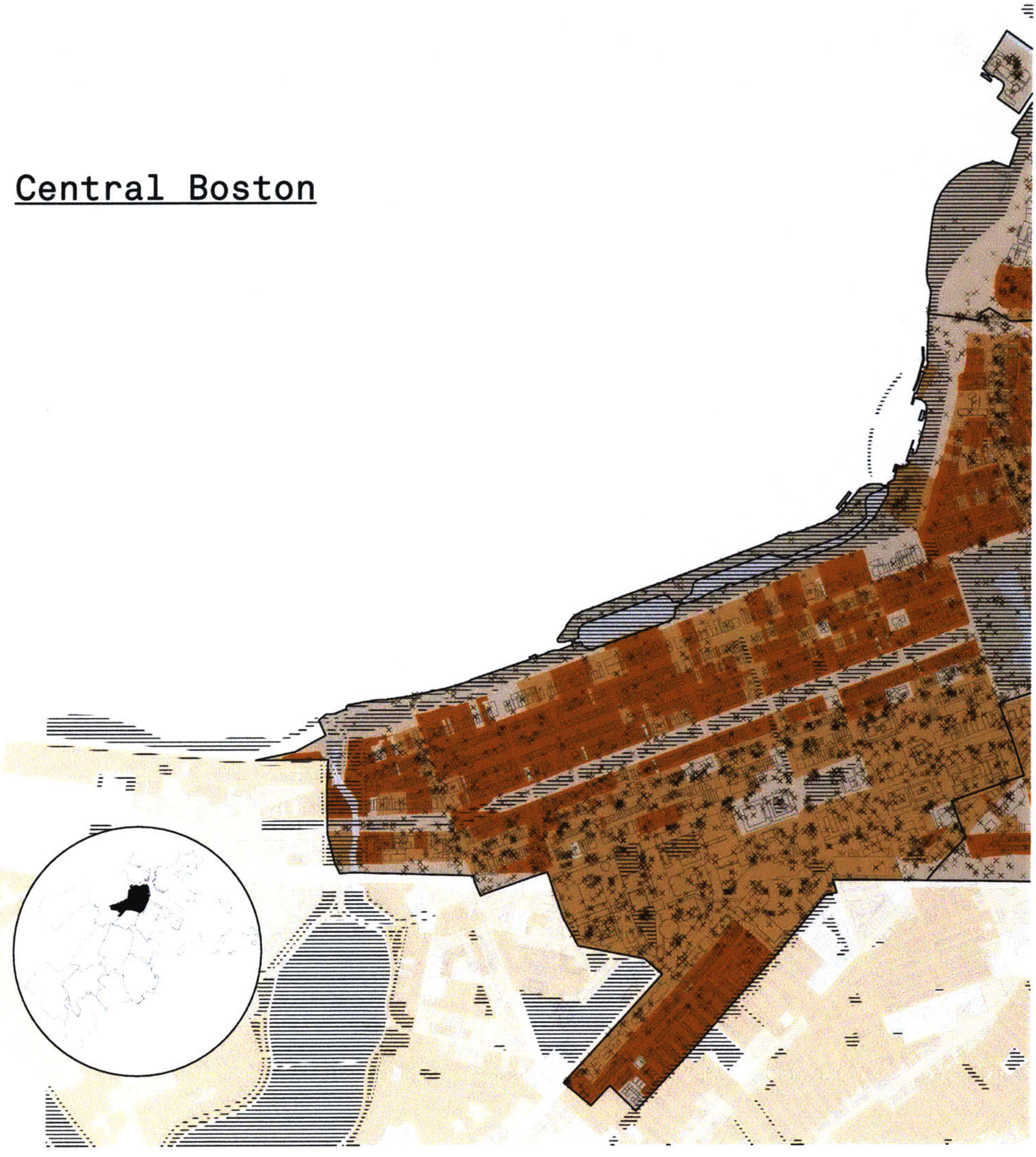
"Park Score methodology" 2015. Parcscore. Accessed May 21. http://parkscore.tpl.org/methodology.php

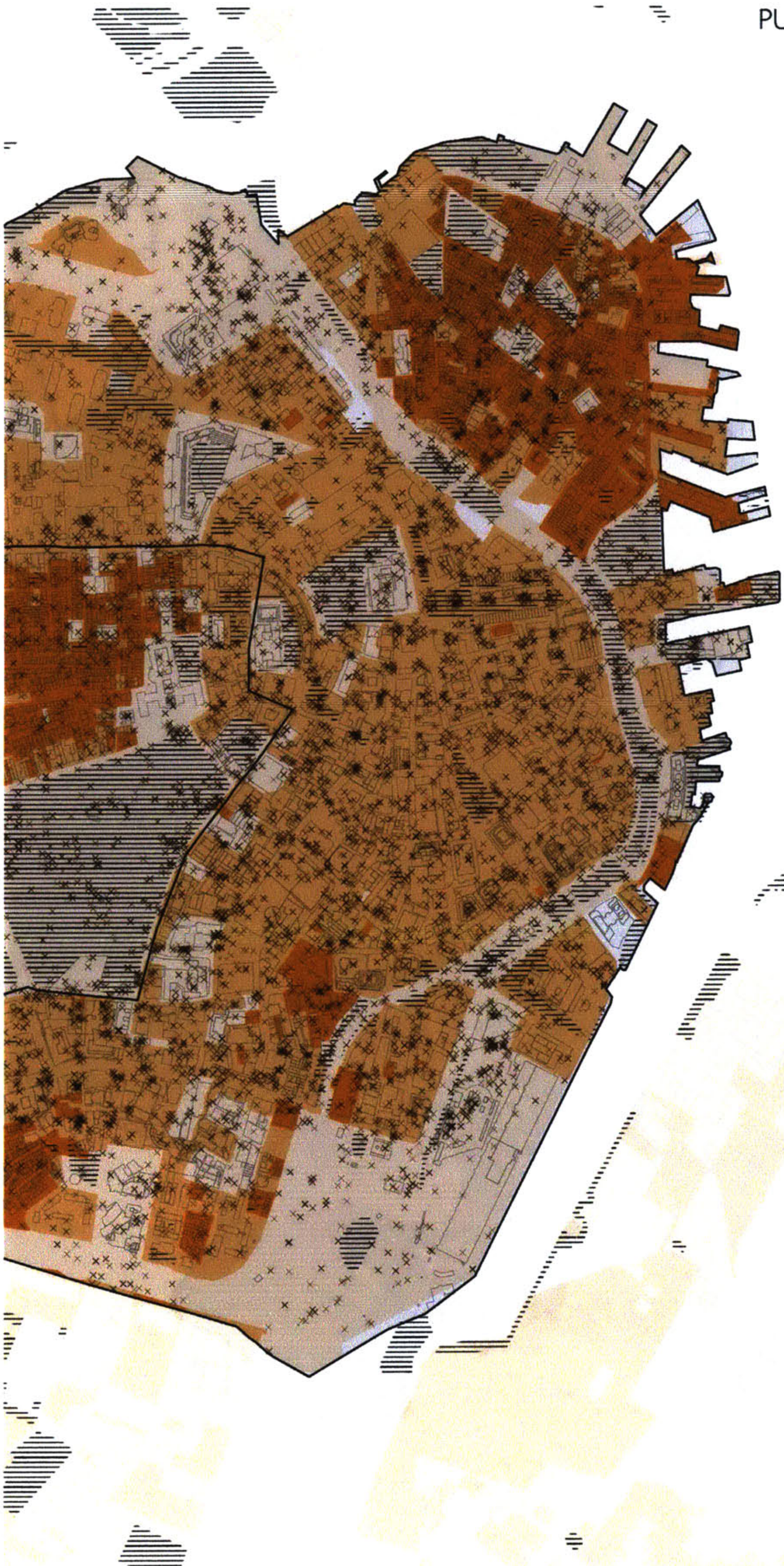
Observing the behavior in commercial space reconfirms the common notion that geo-tagging activities tend to be concentrated in commercial space. In all three planning districts, the ratio of posts in commercial space was higher than the ratio of land use. The gap between two ratios was the largest in South Dorchester, meaning that people would tend to geo-tag their posts more in commercial land despite the lack of commercial land in the district. A similar pattern emerges in Mattapan, maybe because both districts are mainly residential neighborhoods. Central Boston showed the least difference in ratio but still remained in absolute the district with the largest ratio of posts tagged in commercial space.

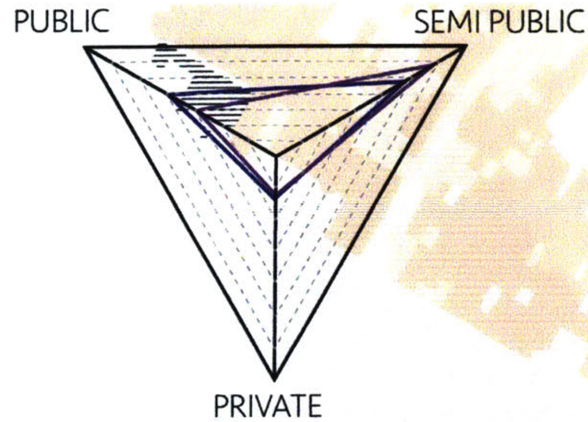
The result showed that the post ratio does not necessarily follow the land use ratio. Three planning districts with clearly different land use composition of public space, commercial space and private space are compared to see the relationship between the built environment and the form of the psychological landscape of collected Instagram locations. Whereas the hypothesis was that the ratio of a specific land use would drive more activities in such lands, leaving more digital traces by the people, the result showed an incongruity to the hypothesis. The analysis informs us that Central Boston, South Dorchester and Mattapan did follow the common perception that geo-tagging activity tends to happen more in commercial space overall, but also left some questions why it would generate so much gap even in districts that have abundant public space. Also, the discordance of post ratio and land use ratio in public space throughout the three planning districts provokes curiosity where the reason of this unexpected results lies.



Central Boston



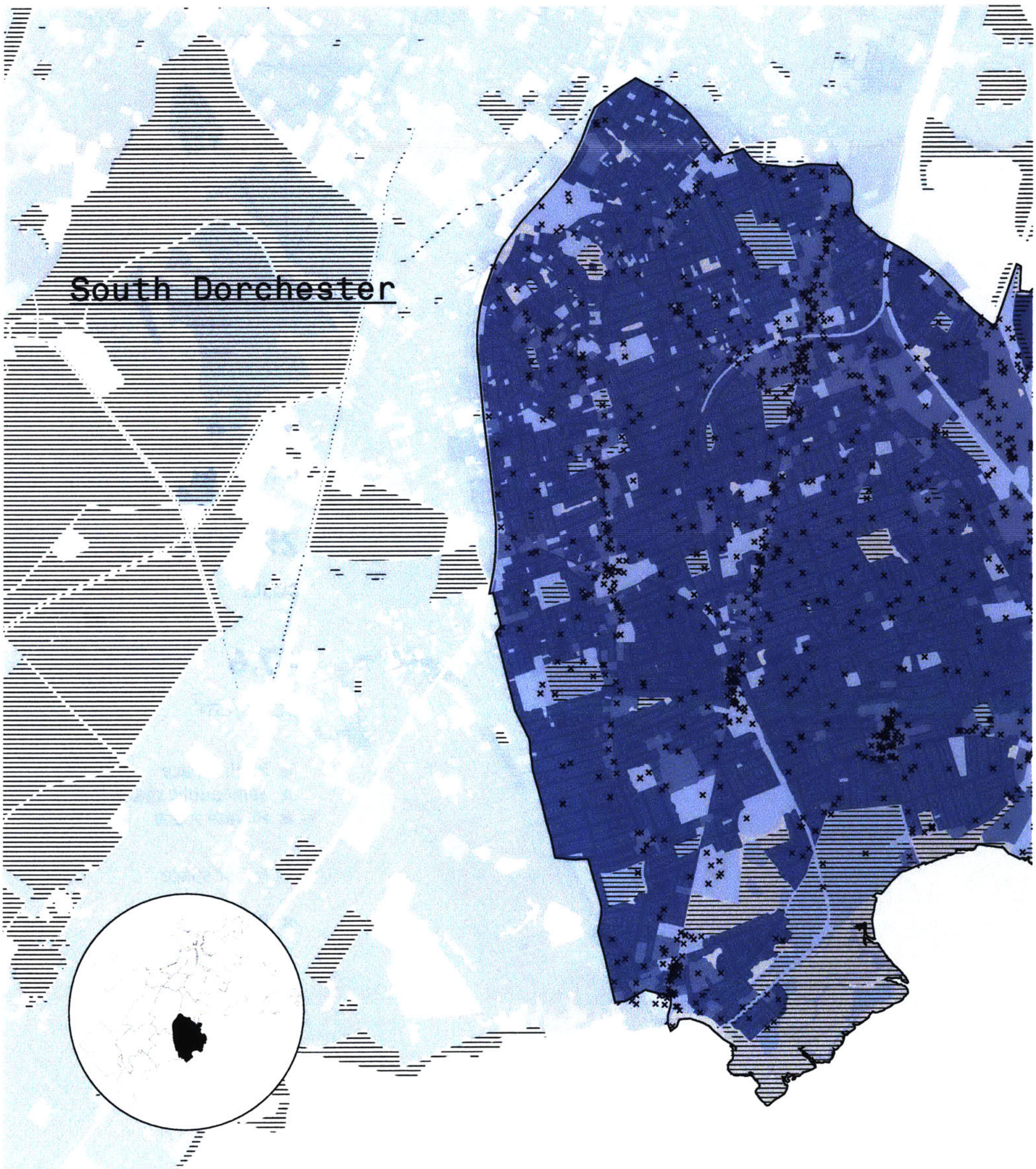


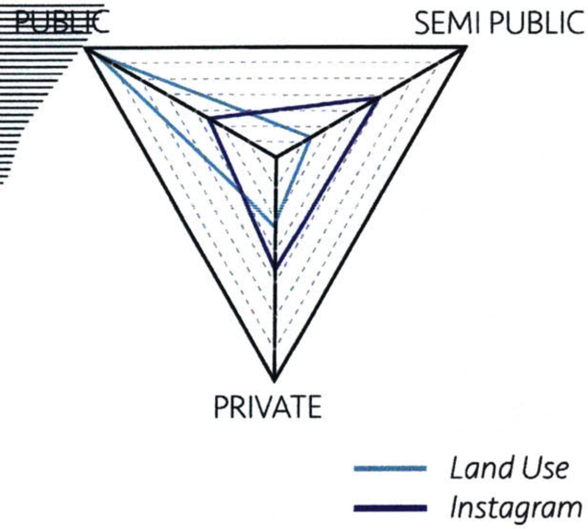


3,969
locations

29,206
posts

47.6
posts/cm^2


South Dorchester



1,069
locations

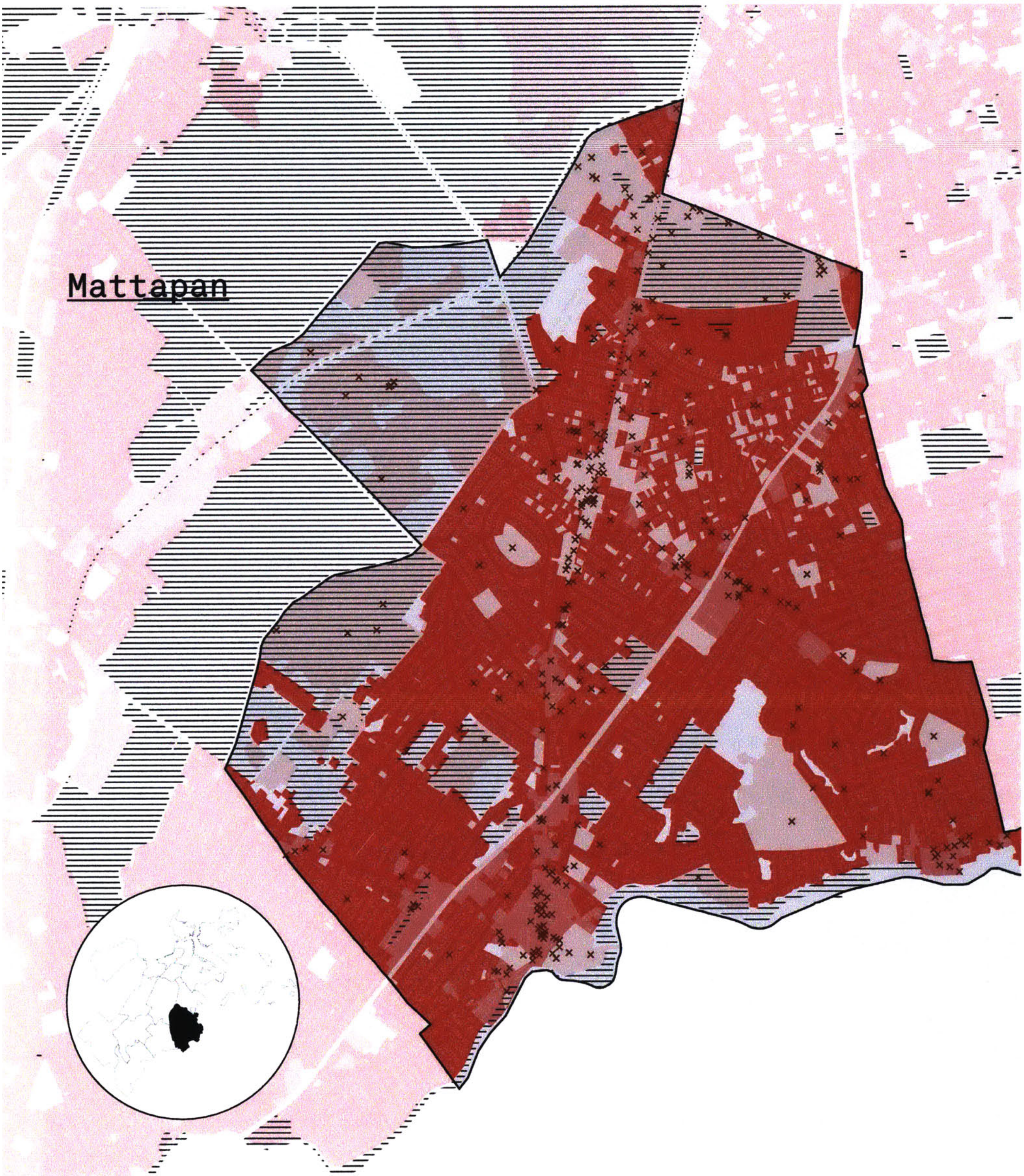
5,746
posts

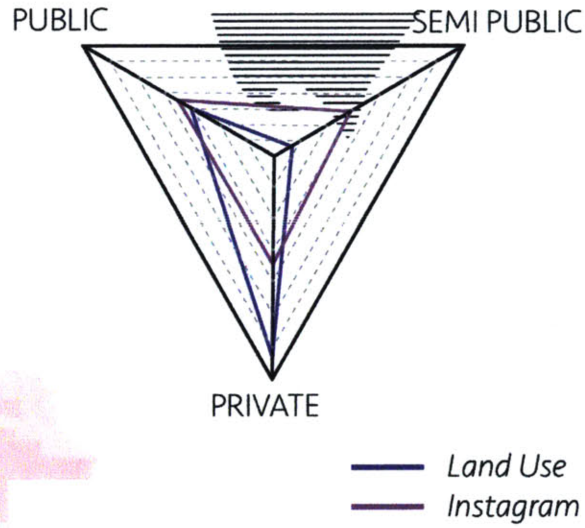
3
posts/cm^2

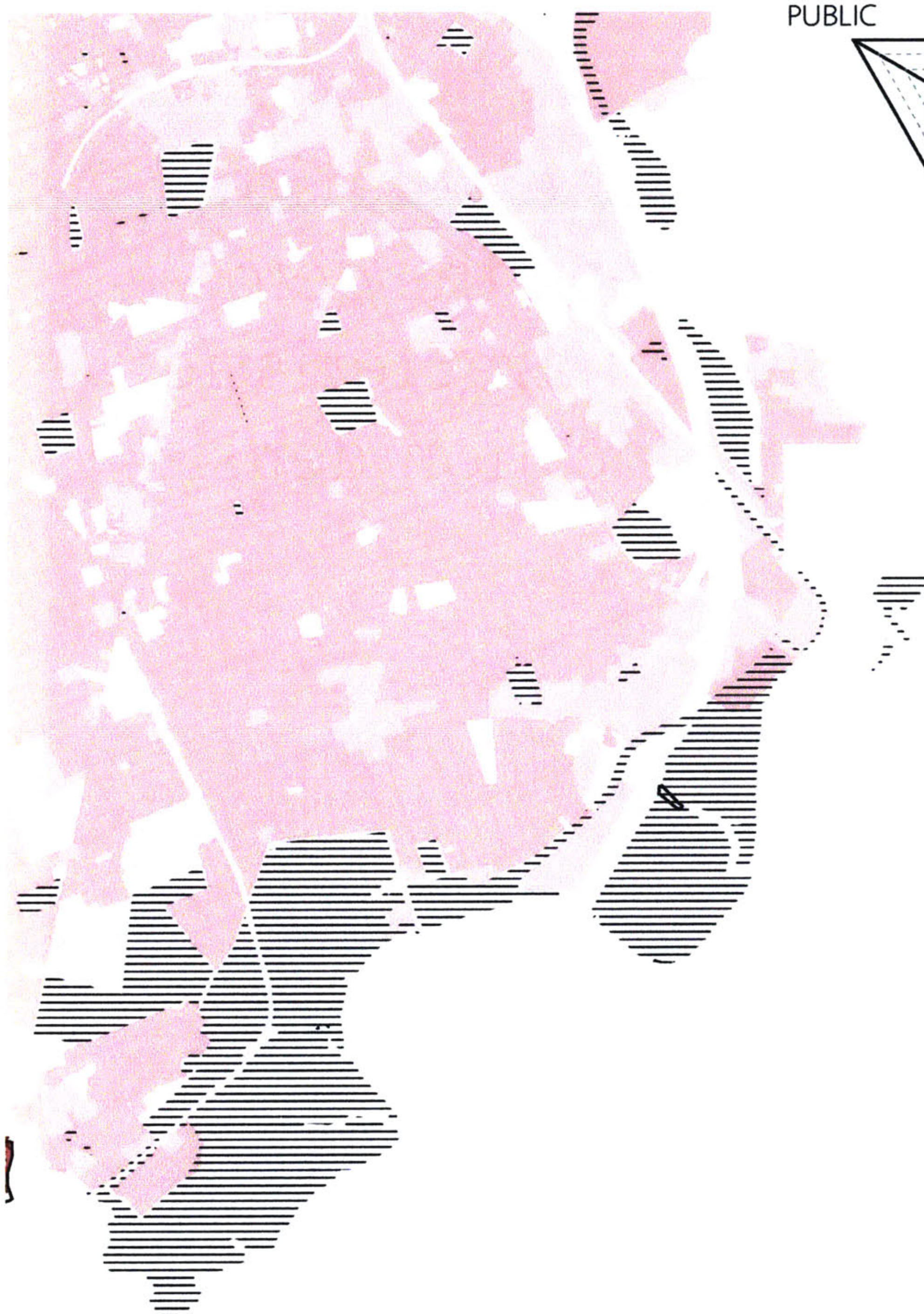
≡ open space

× posts

Public space
Semi public space
Private space


Mattapan





339

locations

1,580

posts

1.1

posts/cm^2

≡ open space

× posts

■ Public space
■ Semi public space
■ Private space

question 2

What is the relationship between the demographic characteristic and the location density?

This section studies the correlation between the demographic characteristic in different neighborhoods and the density of geo-tagged Instagram locations. The social network service data is inherently biased with the type of users that have access to it. We cannot and should not be able to trace the user's demographic profile, but with the link of space, we can relate the socio-economic character of the resident population and the density of places that are digitally marked. Here I am not questioning "Who posts where?". The question is rather: "Who is living where the location data concentrates and not?" In simple words, this section asks what the relationship between the location density and the character of the residents is.

To answer this question statistically with the data I have already collected, I chose to draw a graph that relates the index value of demographic data and Instagram location density data. The Instagram location density, calculated through the Kernel Density analysis, is the independent variable in this analysis and the socio-economic index which is made through an overlay of equally weighted rasters that map different categories in Census data, is the dependent variable. Each value is projected on parcels so that each parcel contains the two values. To extract the relationship between the two variables, I did a **scatter plot 4** of the two variables to locate the points that represent one parcel in Cartesian coordinates in the two dimensional graph.

4 "Scatter Plot." 2015. Wikipedia, the Free Encyclopedia. http://en.wikipedia.org/w/index.php?title=Scatter_plot&oldid=661825389.

The scatter plot gave each parcel a unique location in the XY graph. It is difficult to grasp the meaning of a scatter plot graph when dealing with such a large data set by just looking into it. Therefore, to understand the behavior of the data, the trend of the scatter plot graph is described through a **logarithmic curve**. A logarithmic graph is used to analyze the behavior of large scale data sets by reducing the actual value into a manageable range of numbers.

The result gave me a curve that shows a reciprocal relationship between the location density index and the socio-eco-

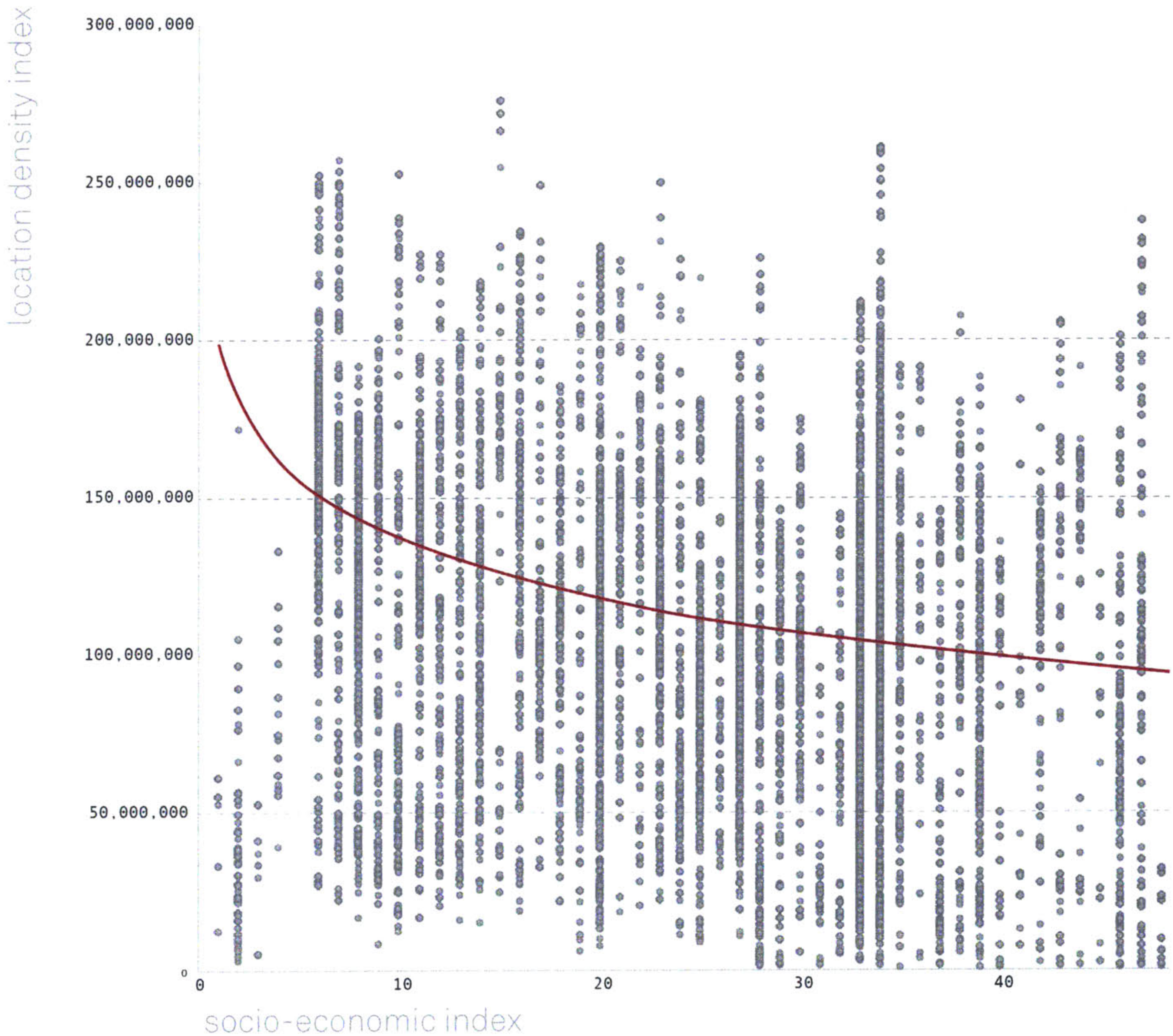
Instagram Location Density

Central / Back Bay

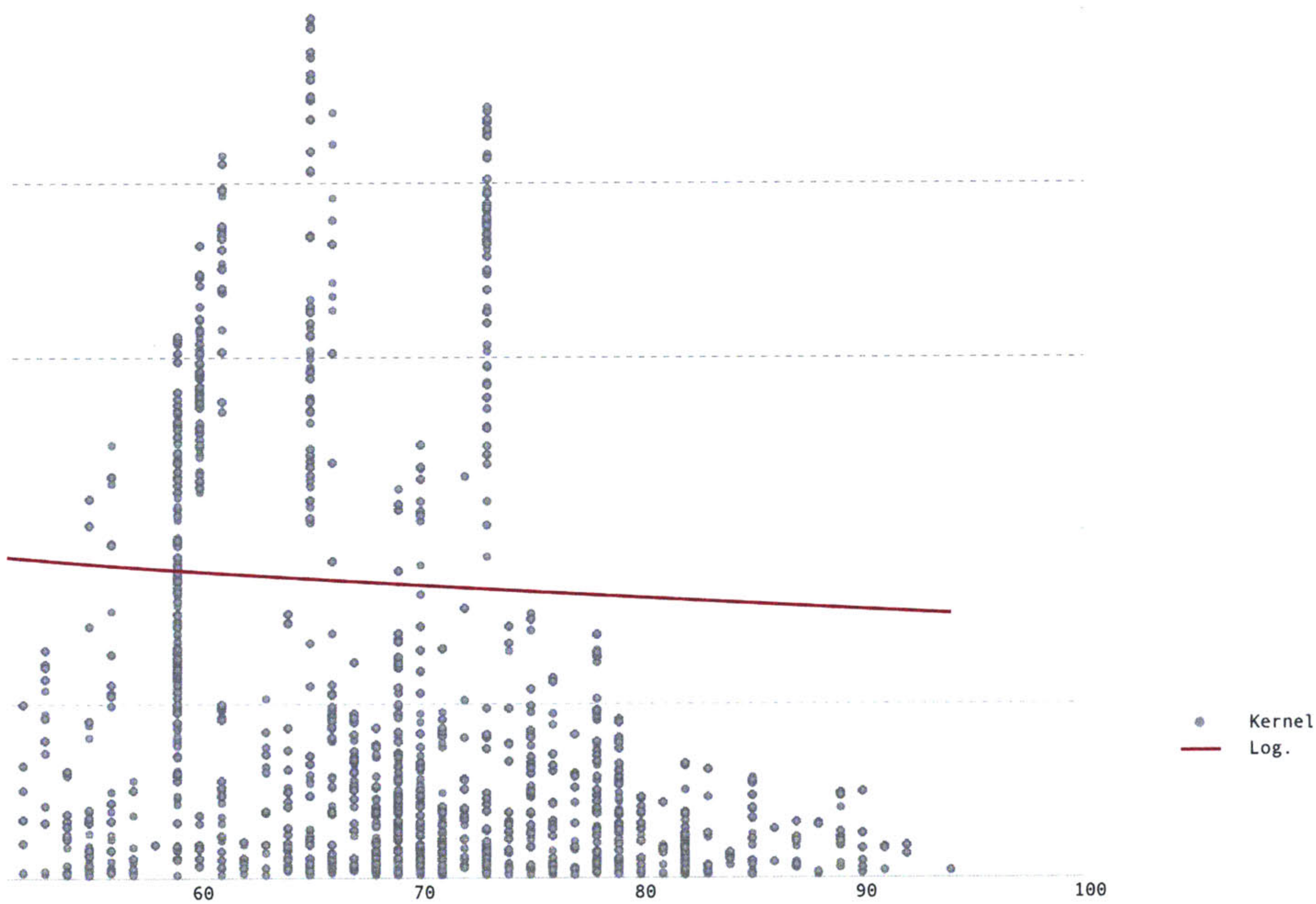
South

hester

Mattapan


location density index
300,000,000
250,000,000
200,000,000
150,000,000
100,000,000
50,000,000
0
0
10
20
30
40
socio-economic index

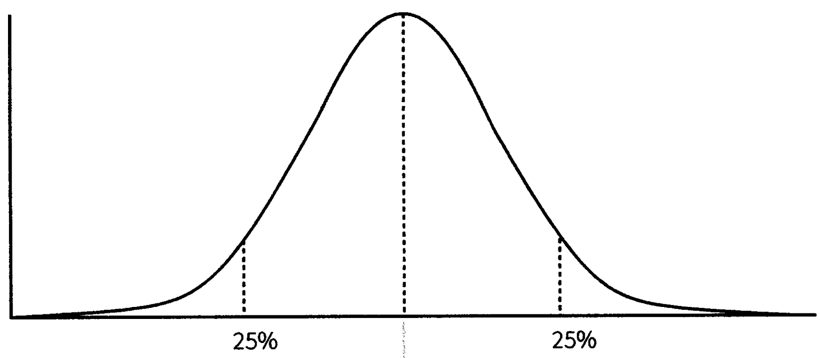
socio-economic status and location density



nomic index. This means that the socio-demographic status of the residential population of the calculated parcel became lower as the location density decreased. And as more posts were generated around each parcel, the neighborhood tended to be more well off. The inclination of the curve also changed dramatically between the parcels below average and over average of socio-economic characteristics. While the inclination of the location density increased rapidly approaching from average socio-economic index values towards the highest socio-economic index values, the inclination of the other half of the lower socio-economic class was marginal. In other words, the difference of location density among the neighborhoods with the lowest socio-economic status would change more gradually, showing less dramatic changes.

The overall behavior of the data expressed through the logarithmic curve is interesting because it follows Ziph's law. T h e relationship between the psychological geography and the population characteristic triggered the curiosity to understand what spatial structure drives this tendency, if it has any influence at all.

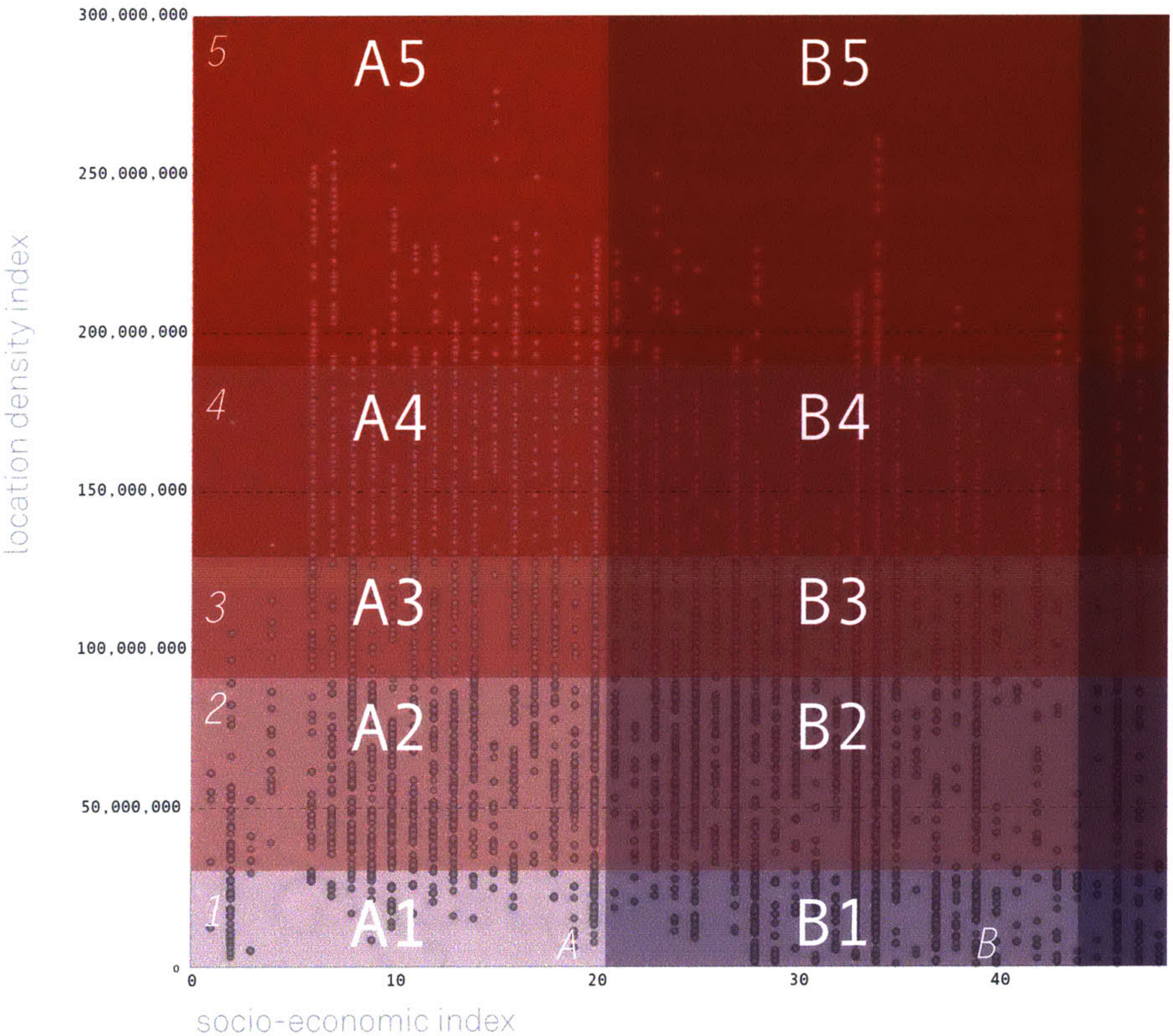
The values were projected to each parcels. However, cities are not entities of an aggregation of parcels, but a rather organic structure in which all different kinds of places together form a tree-like relationship. Therefore, it was necessary to define neighborhoods, clusters of parcels that retain different characters to make a comparison of the physical structure. The strategy was to define the data into several classes that represent different behaviors in location density and socio-economic index. Once the group of parcels is defined as a specific group, it becomes possible to identify neighborhoods that have a high concentration of parcels that behave in the assigned specific way. And that way, if we compare the built structure of each neighborhoods, it will be possible to know the relationship of the spatial composition of the neighborhood and its class that has a unique value in the location distribution and socio-economic index.



The classification is made through an overlap of a **standard deviation 5** of each axis value. I have chosen to use the standard deviation as a class division method among many other statistical methods, because of the entirely different nature of the two datasets that were compared and related. Standard deviation calculates the difference between the value dealt with and the mean of the whole dataset. The classes are broken according to the relative comparison of the value. This decision was made to ensure that the classes of the two different dataset become comparable to each other.

Standard deviation generated five classes for each dataset which breaks at 75%, 50%, and 25% and generates four classes. The classes were overlapped in the graph as in the following pages. The different size of each class reflects the difference in the number of parcel in each class. Also classes such as E5, E4 which are highly active with a low socio-economic class, do not contain any parcel in the studied planning districts.

5 "Standard Deviation Classification - GIS Dictionary." 2015. Accessed May 21. http://support.esri.com/en/knowledgebase/GISDictionary/term/standard%20deviation%20classification.


300,000,000
250,000,000
200,000,000
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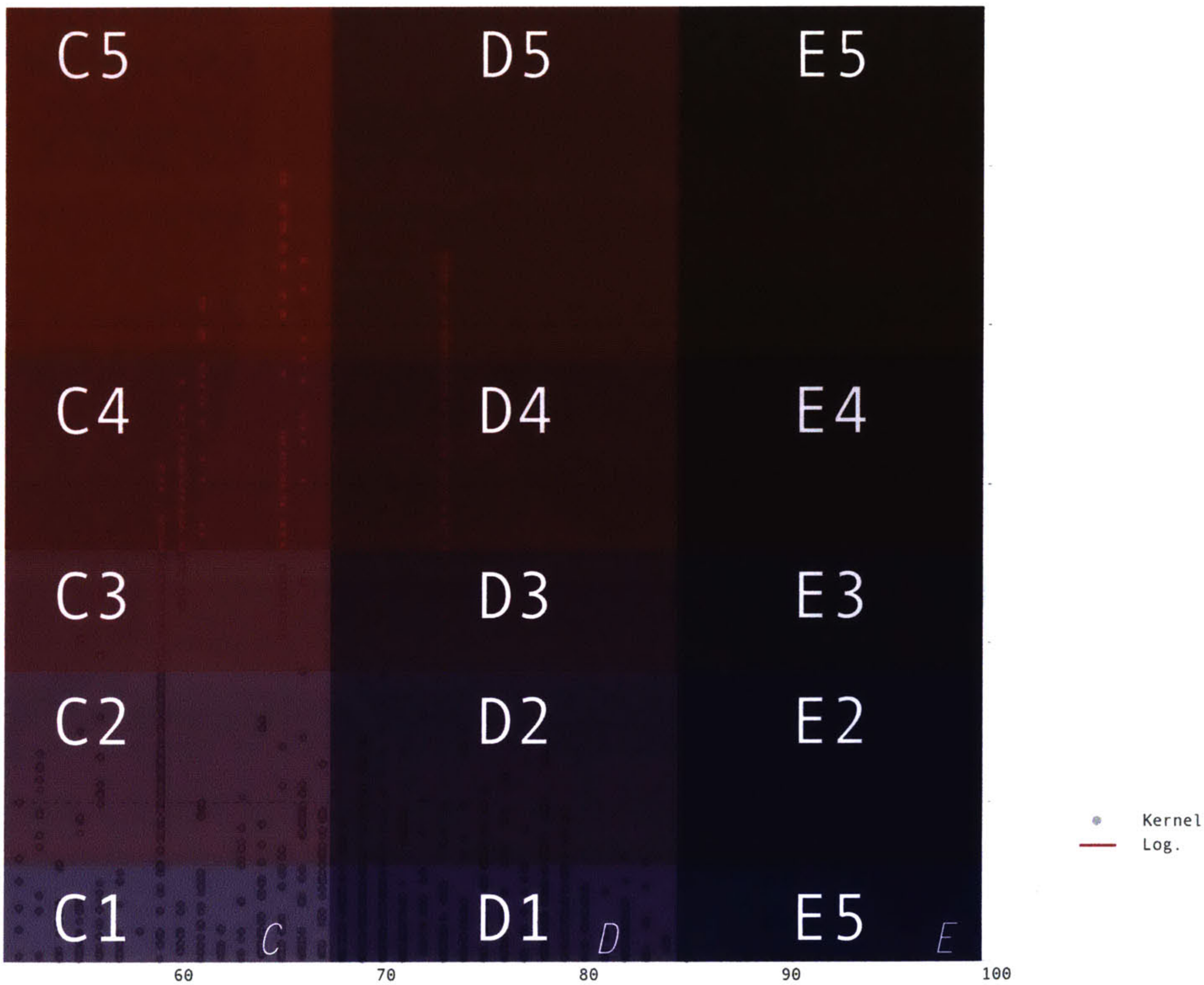
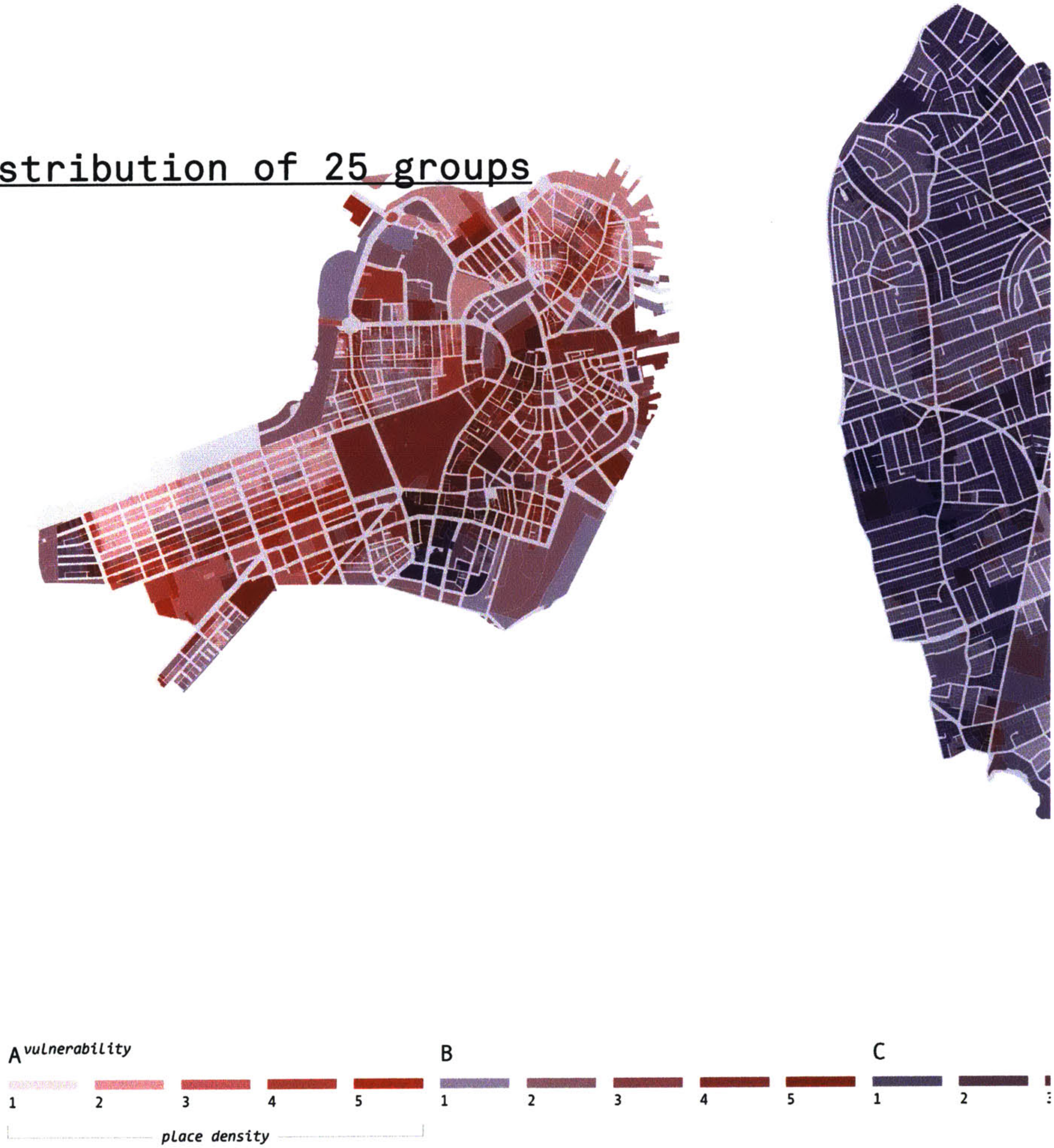
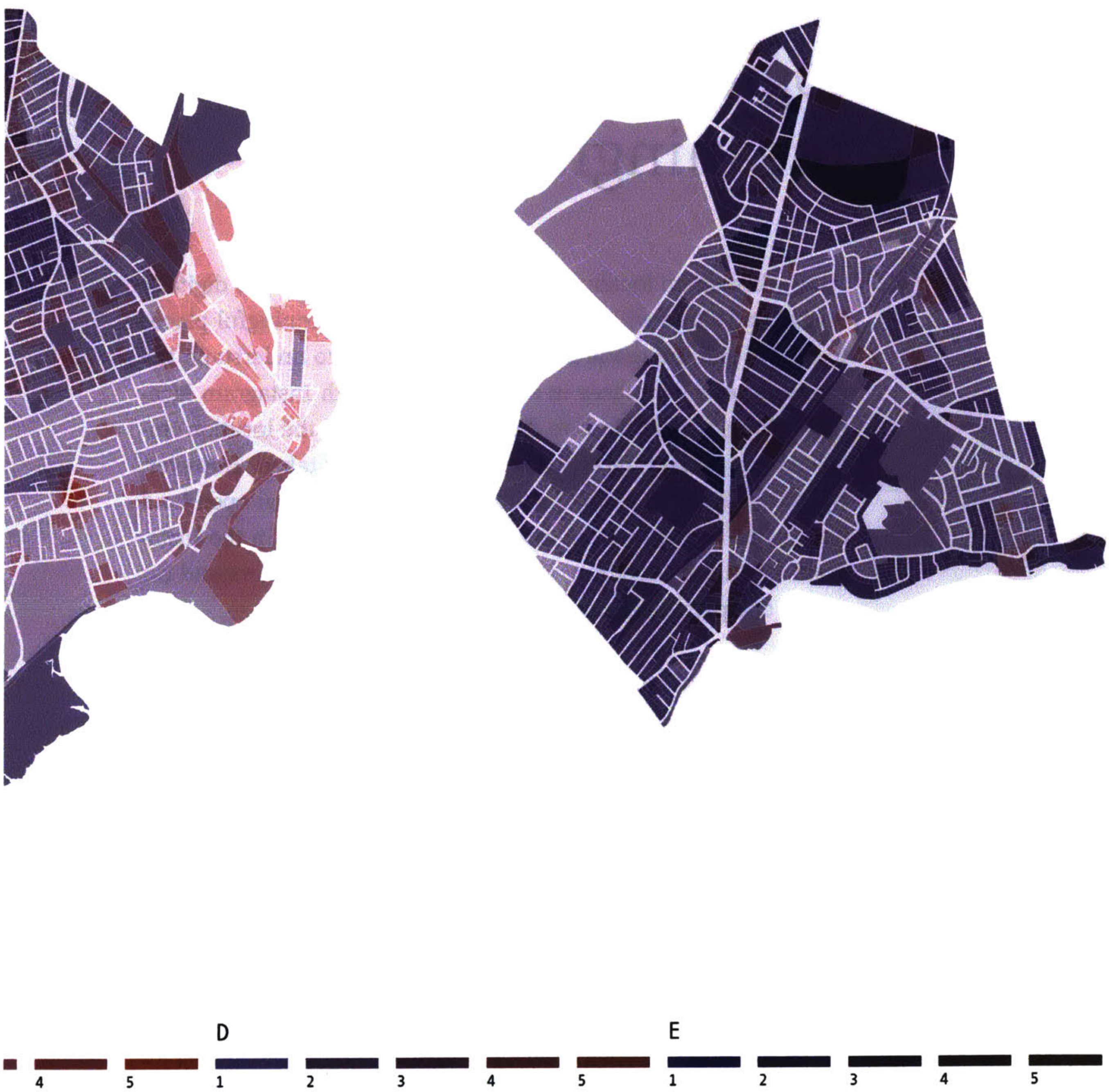
100,000,000
50,000,000
0
location density index
5
A5
B5
4
A4
B4
3
A3
B3
2
A2
B2
1
A1
A
B1
B
0
10
20
30
40
socio-economic index

Classification
based on standard deviation of x, Y axis



Distribution of 25 groups




D
E
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1
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3
4
5

question 3

What is the role of public space in the psychological geography of meaningful places?

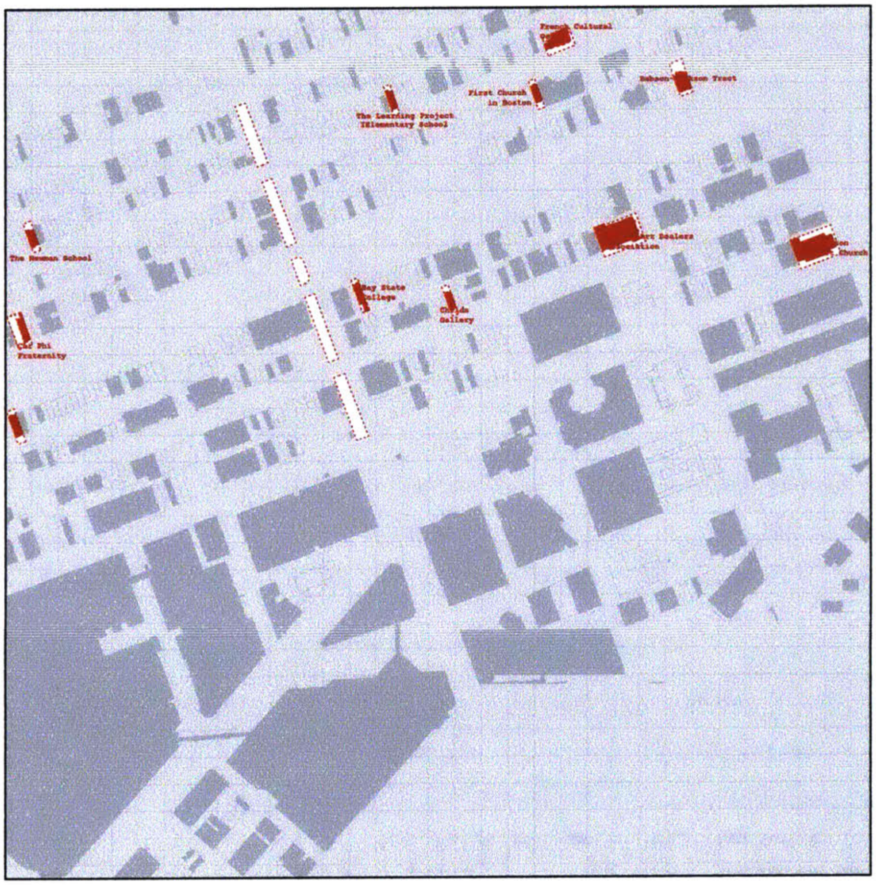
Instagram location data shows places that people digitally record and share with their friends. They are meaningful places to people and the research has been a process to understand the character of such places in a macro scale. With Instagram locations alone, it is difficult to distinguish whether the location involved any social interaction while the post was taken. However, by overlapping the public institutions and recreational open land enables us to measure the role of public institutions in the Instagram locations. Moreover, it makes it possible to understand ow public one psychological geography is over another.

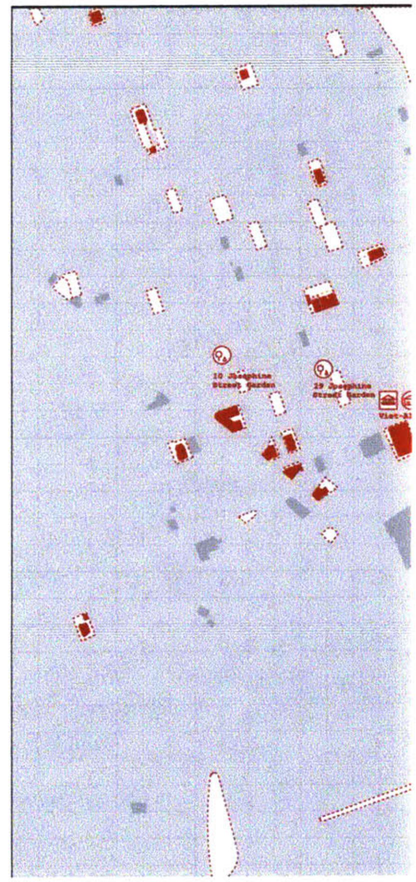
This section questions what role public institutions and recreational open lands play in the geography of meaningful places. The comparison made in the sampled neighborhoods of Back Bay(A4), Fields Corner(C2), and Blue hills avenue(E1). The selected neighborhoods have different level of location density and socio-economic status. The comparison is made by first, looking into the percentage of posts made in public institutions and recreational open space, and second by looking into the spaces that do not contain any posts during the last four years in Instagram.

Back Bay had 586 of posts, 122 locations and 27.69 square acre was dedicated to public institutions and recreational open land, while Fields Corner had 16 locations 135 posts in 23.8 square acre and 5 locations with 44 posts in 46.26 square acre. The basic condition indicates that the percentage of public space and recreational open land is the highest in Blue Hill Avenue followed with Back Bay and Fields Corner.

Interestingly, the ratio of posts that are tagged to locations that are public institutions and recreational open land showed significant difference between Back Bay and Blue Hills Avenue. 12 percent of posts in Back Bay were tagged in public space, while 6.8 percent in Fields Corner and 4.5 percent in Blue hills Avenue. This suggests that the less geo-tagging activities happen and the lower the socio-economic status of the residents in the studied area becomes, the lower posts are generated, and tagging public institutions and recreational open space.

In other words, this means that regardless of how much public space is provided, the meaningful places in neighborhoods tend to be more concentrated in private and commercial space as the neighborhood becomes more vulnerable.

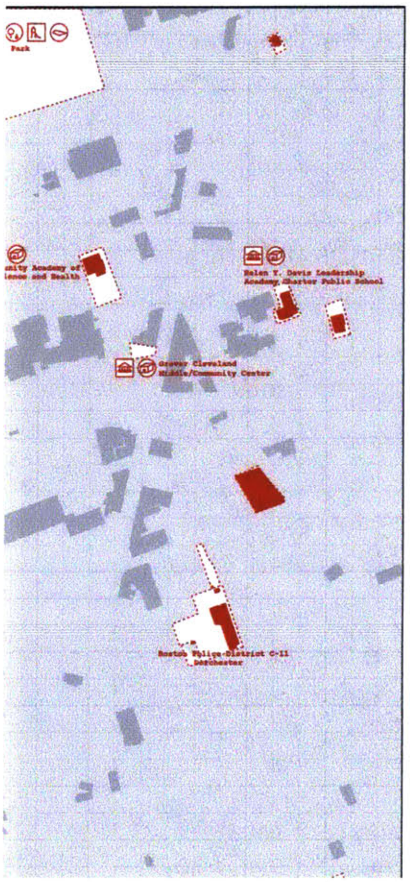


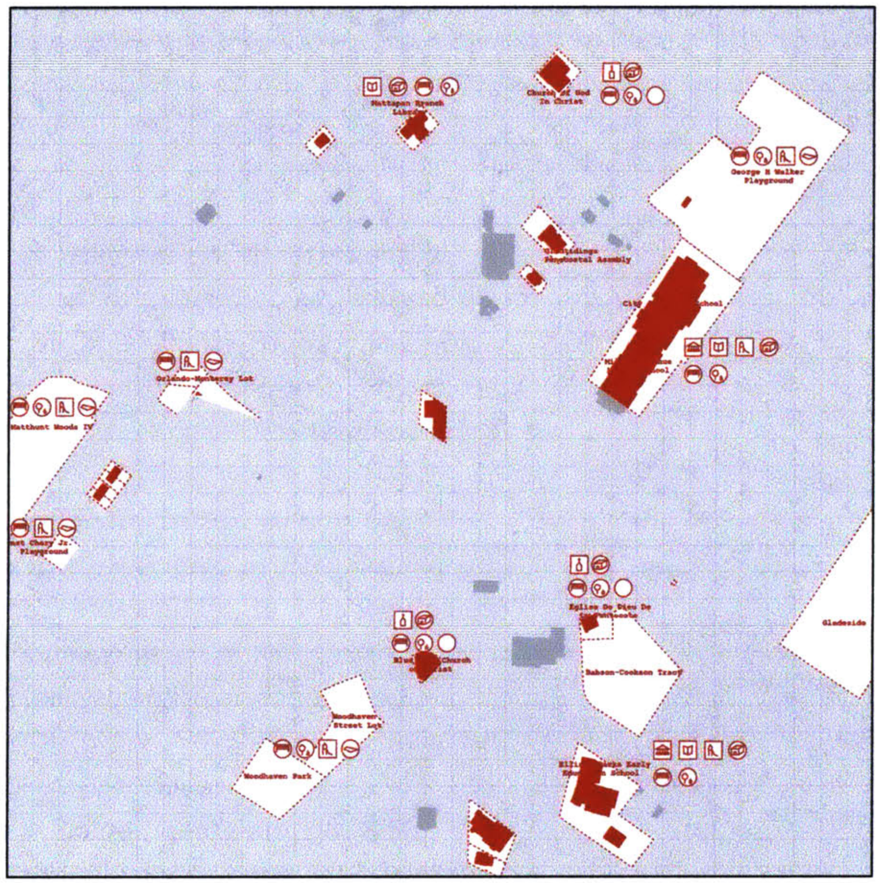


12%

A4 Back Bay

C2 Fiel





Corner

E1 Mattapan

Synthesis

findings and limitations

The research was intended to understand Instagram location density in a correlation to the land use distribution, and the socio-demographic structure. It provides insight to the research through its incongruity to the hypothesis and triggers questions for further research.

The land use distribution does not dictate people's geo-tagging behavior. Three planning districts with clearly different land use composition of public space, commercial space and private space are compared to see the relationship between the built environment and the form of the psychological landscape of collected Instagram locations.

The reciprocal relationship between Instagram location density and the socio-economic index of the resident population was a predictable result. However, the fact that the appearance of geo-tagged Instagram locations in public institution decreases as the neighborhood becomes more vulnerable contradicted the common notion. The fact that areas with a lower socio-economic class have a higher tendency of posting from commercial and private space made me wonder the reason.

These doubtful points lead the research towards a simple question: What are these places? Since the studied scope was to vast to grasp the spatial characteristic of the places with high or low location density, a more qualitative in-depth research is required. These limitations connect the research to the next level in which the physicality and program of places is examined in neighborhood scale.

FINDINGS

1. The Instagram location distribution does not necessarily follow the distribution of land uses. Behavior is not dictated by the provision of space.

2. The vulnerability of the population and the location density have a reciprocal relationship, showing that the location density decreases as the population becomes more vulnerable.

3. The mismatch between the public infrastructure and the digitally highlighted places grows moving towards neighborhoods that are more vulnerable and have less dense in location data along the curve. Meaningful places for people are outside public infrastructure the more vulnerable the neighborhood is.

CH5

Sampling neighborhoods
motivation, intention, methodology

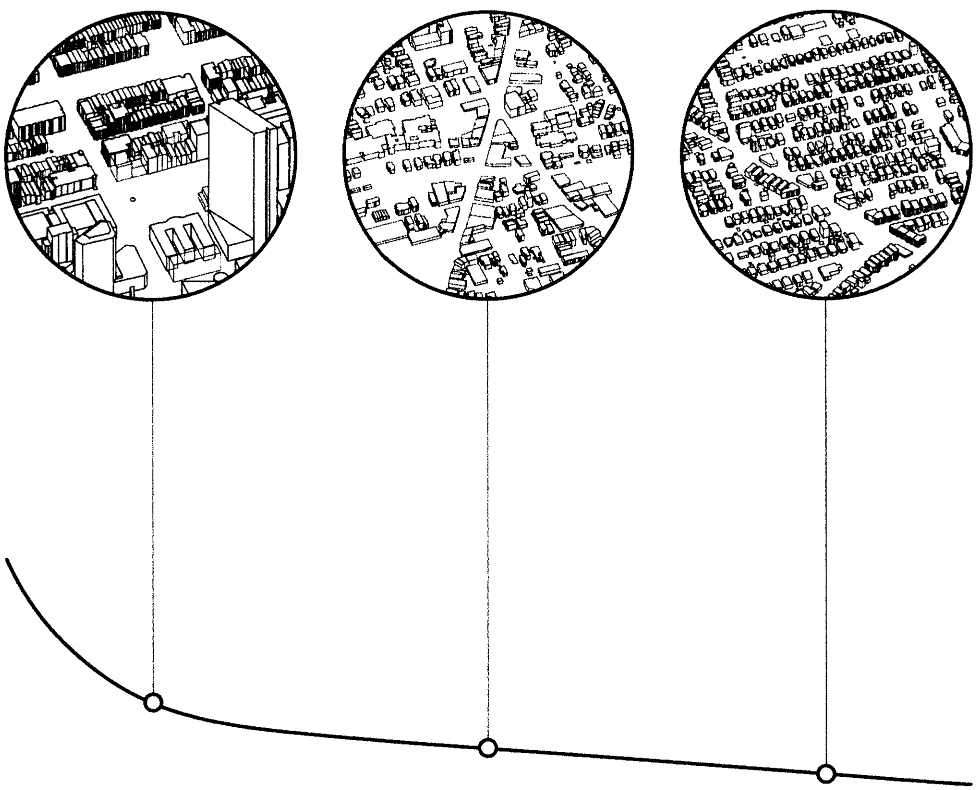
A manual
Purpuse, Method, Places in, Places out

The form of the psychological geography
in Fields Corner, South Dorchester

Comparative analysis
Back Bay, Fields Corner, Blue hills Avenue

1 Sampling neighborhoods

motivation, intention, methodology



The findings of the previous chapter guide us to an in-depth analysis on a neighborhood scale because it tells that the distribution of places people marked to be meaningful draw distinct patterns in different parts of the city. It proves that the behavior of people's geo-tagging activity cannot be estimated through quantitative measurements of public space or the land use composition. It suggests that there is something other than that, that forms a concentration or dearth of meaningful places in the city.

It makes one question what types of places are highlighted in different neighborhoods, if the significance of public institutions and open space changes through neighborhoods, and finally if the psychological geography helps one discover local patterns of social interaction. The in-depth analysis investigates in such questions through going into the spatial scale of the Instagram locations. It is going to be answered through the translation of the dots, shades and lines into space, physical elements, and programs, fundamentally answering the question: what are these places? And what are not these places?

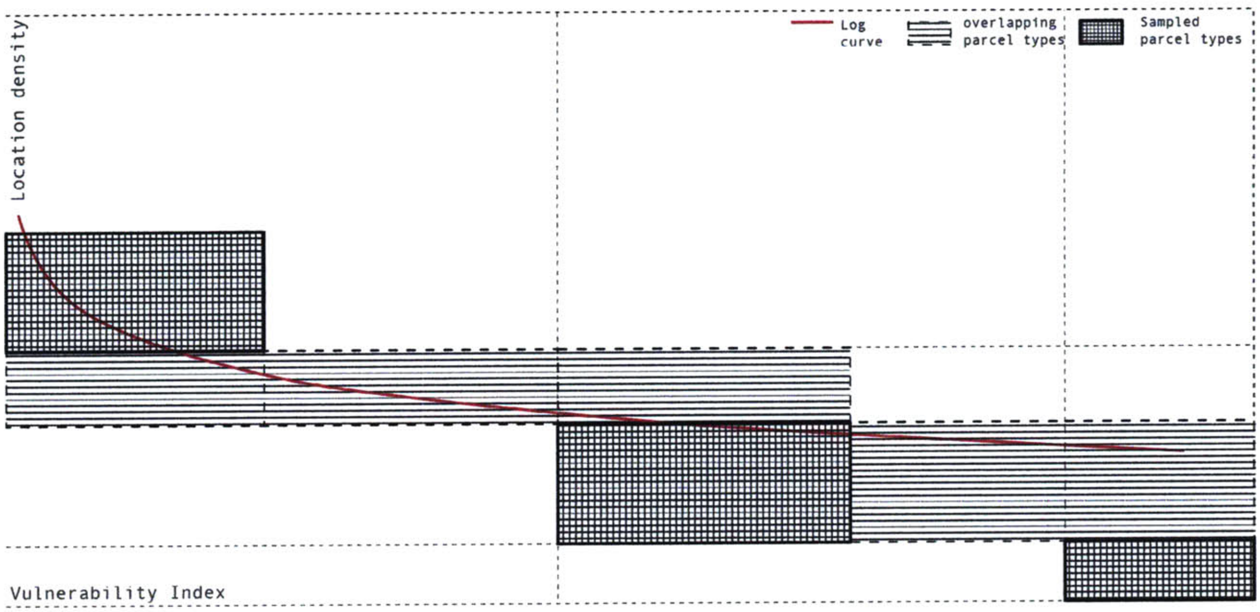
In this chapter the reading of meaningful places zooms into neighborhood scale, and this brought the nessecity to break this chapter up to three parts. First, I select the neighborhoods to be analyzed, second, I propose a manual for social space reading and finally I cunduct a comparative study of the selected three neighborhoods.

For an in-depth analysis, this chapter samples three neighborhoods representing different socio-economic classes and location data density to conduct a comparative analysis on the built form of the neighborhoods. This selection of different types of neighborhoods ensures that the analysis studies a broad range of neighborhoods and compares the physicality of each psychological geography. It not only avoids the analysis to be biased due to the specific user population one type of neighborhood might have, but also investigates in the question how the spatial characteristic of geo-tagged places changes as the population becomes more vulnerable and the geo-tagging activity becomes low.

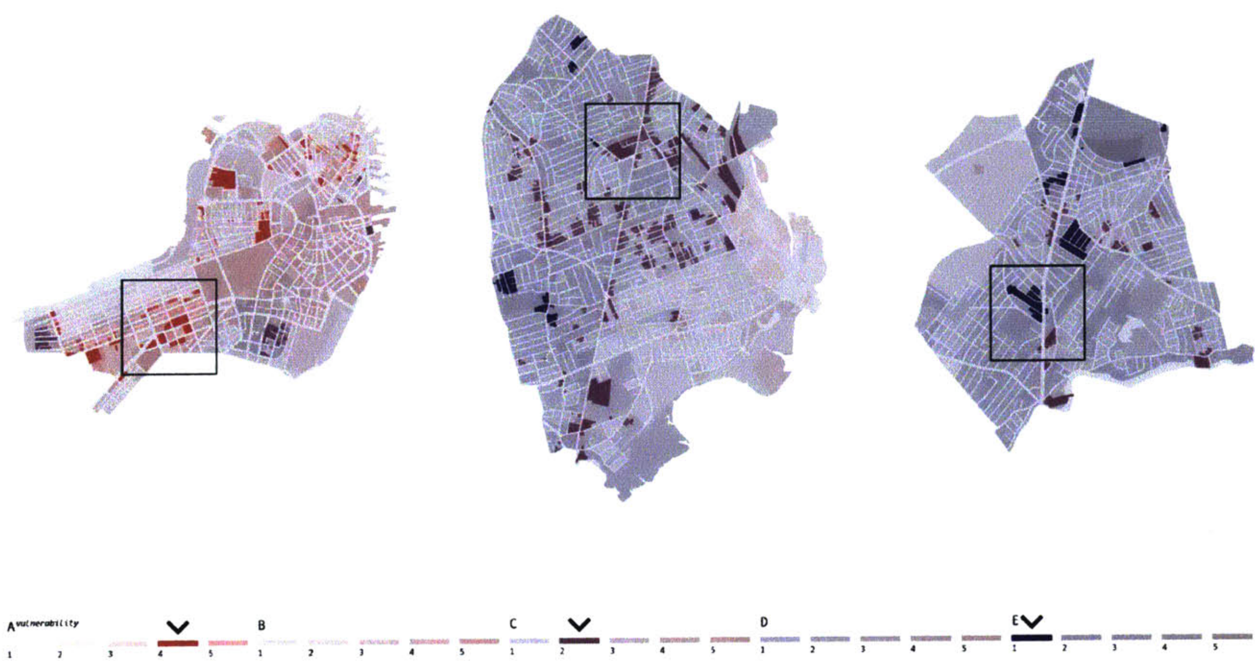
The demographic class, and the location data density act as independent variables to observe the built form of selected neighborhoods as a dependent variable. The neighborhoods are selected through the classification of 25 parcels types, generated through the overlap of the psychological geography and the demographic data. Given the fact that the logarithmic curve draws the trend line of all analyzed parcels according to demographic index and location data density index, I assume that the parcel class coinciding with the curve is a type that has a representative character over other parcels.

The classes coinciding with the curve are A5, A4, B3, C2, D2 and E1. To be able to compare neighborhoods with clearly different conditions, the further analysis selects neighborhoods with a high concentration of A4, C2, and E1 parcels. Moving from A4, C2 to E1 means that the socio-economic class becomes more and more lower and the location density also decreases. As a result three neighborhoods — back bay, fields corner and blue hill avenue — are selected, due to the high concentration of parcel type A4, C2 and E1 respectively.

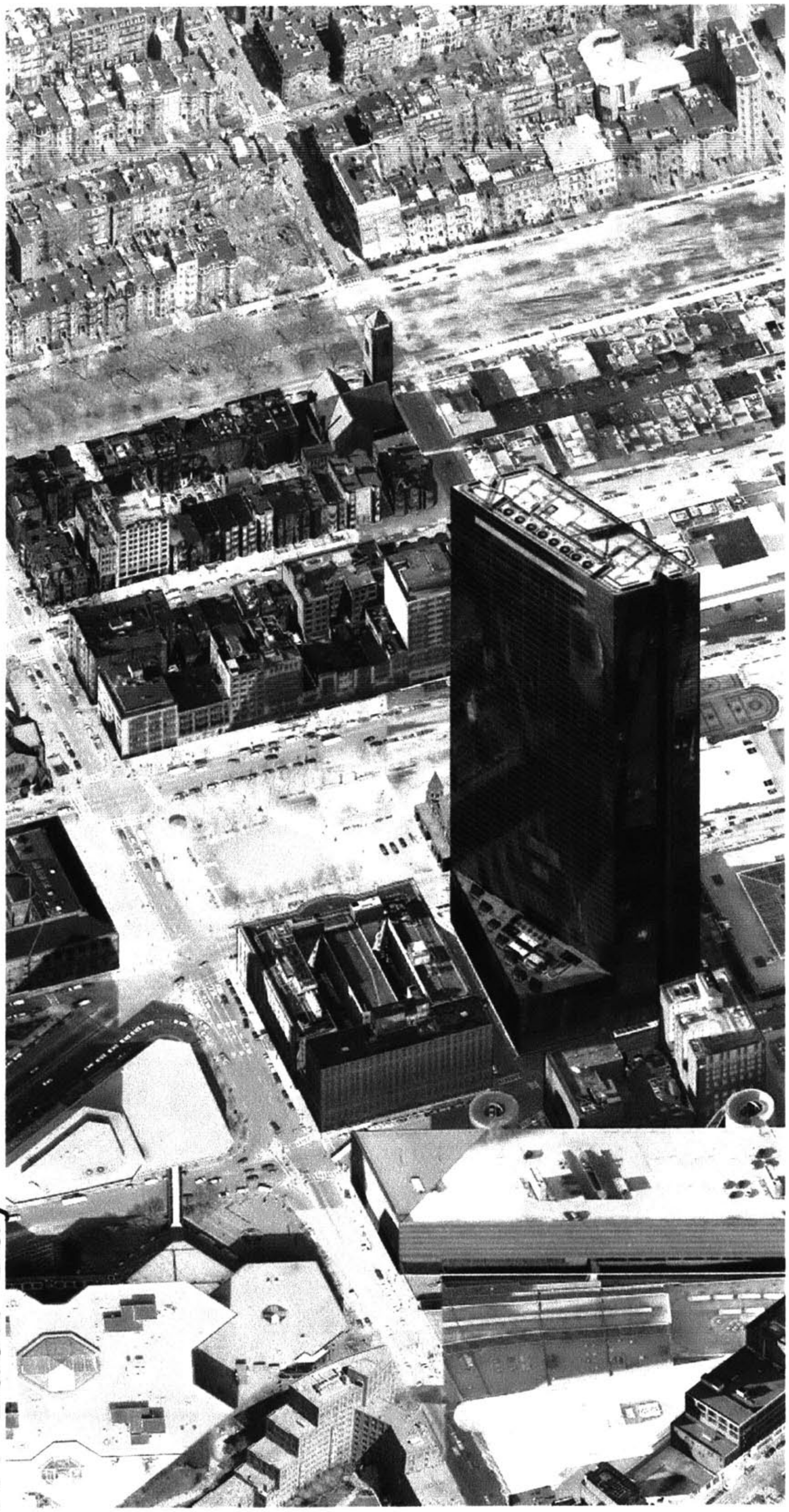
In this chapter, where I conduct a case study, I am analyzing Fields corner, having Back bay and Blue hill avenue as an object for comparisons.



Sampling Parcel Types

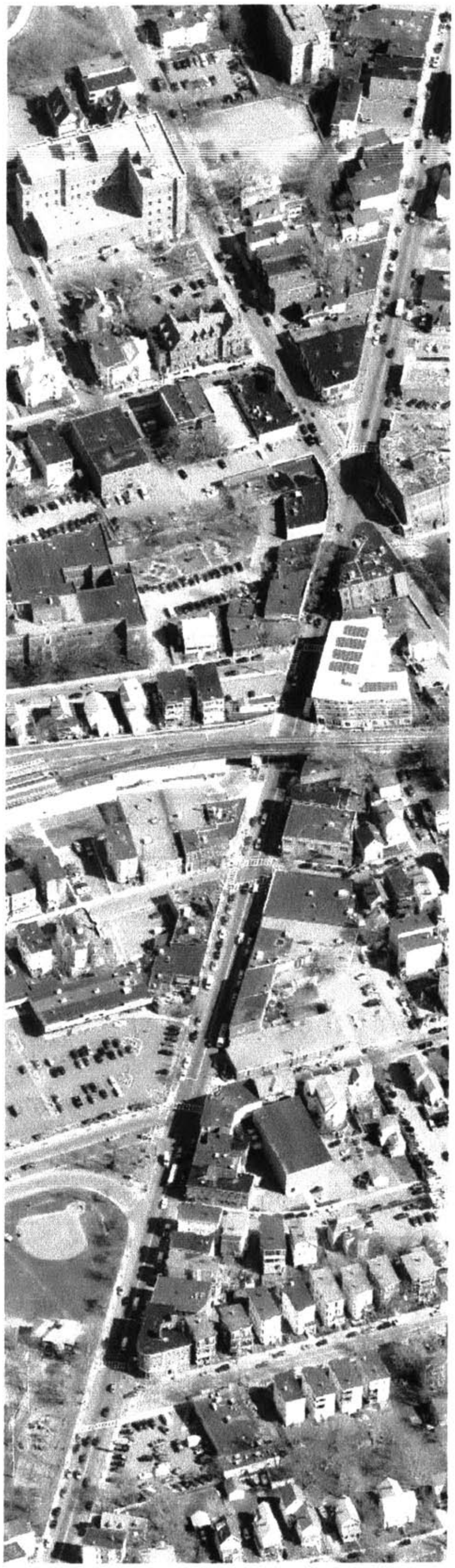


Sampling Neighborhoods



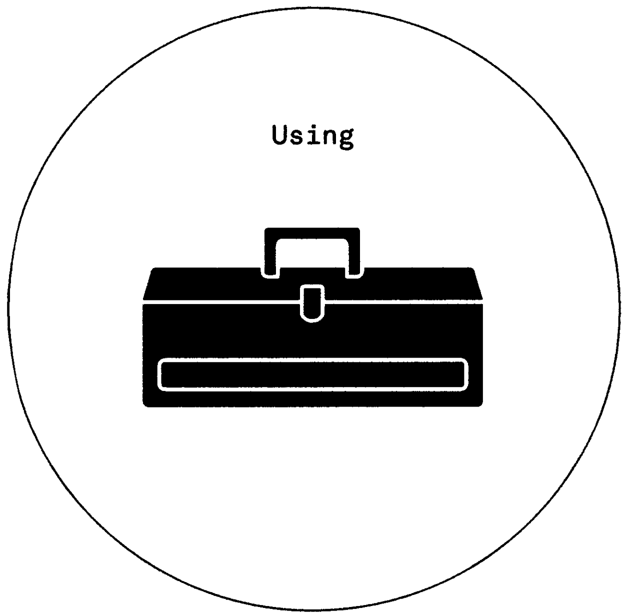
A4 Back Bay

C2 Fields Corner



E1 Mattapan

2 The Manual
Purpuse, Method



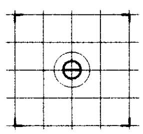
PURPUSE

The manual integrates the reading of the physical environment, the psychological geography, and the experiential reading of the site, informing architects, urban designers and urban planners the programs and spatial elements that form the locality of meaningful places in a neighborhood. The psychological geography of Instagram locations draws a border between places that are in this map and not. This distinction enables one to understand what places hold meanings for people. The manual's reading primarily relies on that border that was formerly unseen.

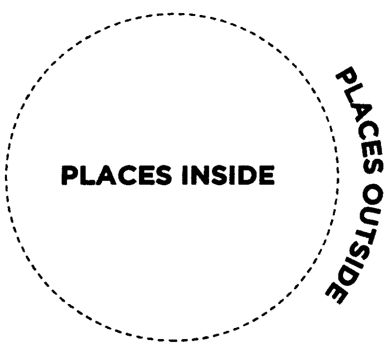
USER

Architects, Urban designers, Urban Planners

01 Psychological Reading



Detect physical subjects through the psychological geography of mesningful places



02 Physical Reading

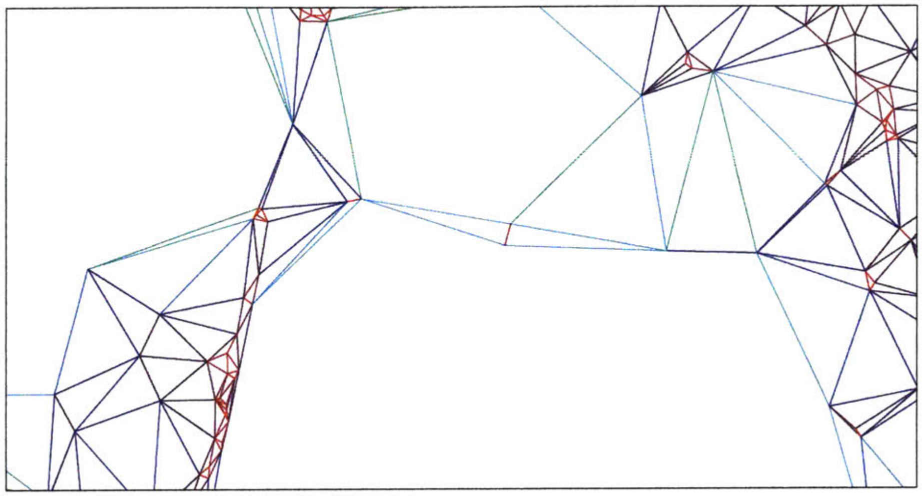
Read the them through traditional methods

METHOD

The method is twofold. First, the mapped psychological geography detects physical places that fall into the border or lie outside. These places are analyzed through traditional methods that define social space through the program and physical elements.

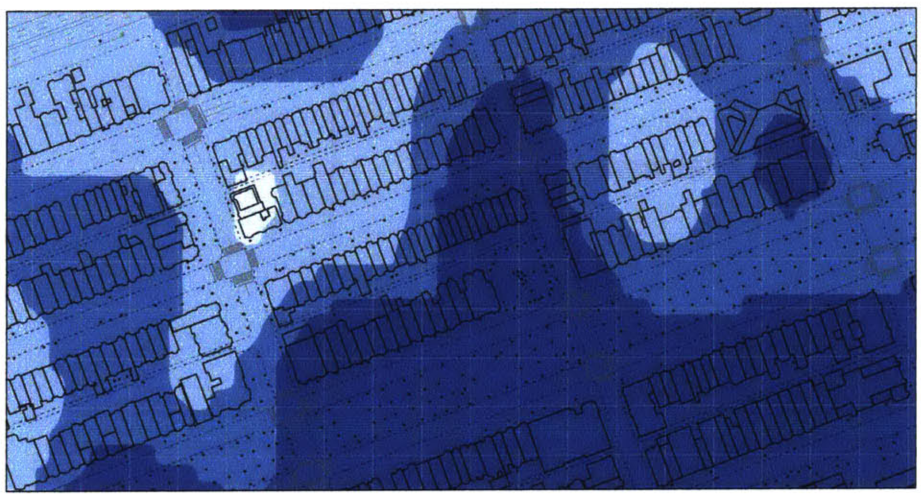
NET

If one connects the locations within a 5 minutes walking distance (800meters), it draws a net of locations that are accessible from one to another.



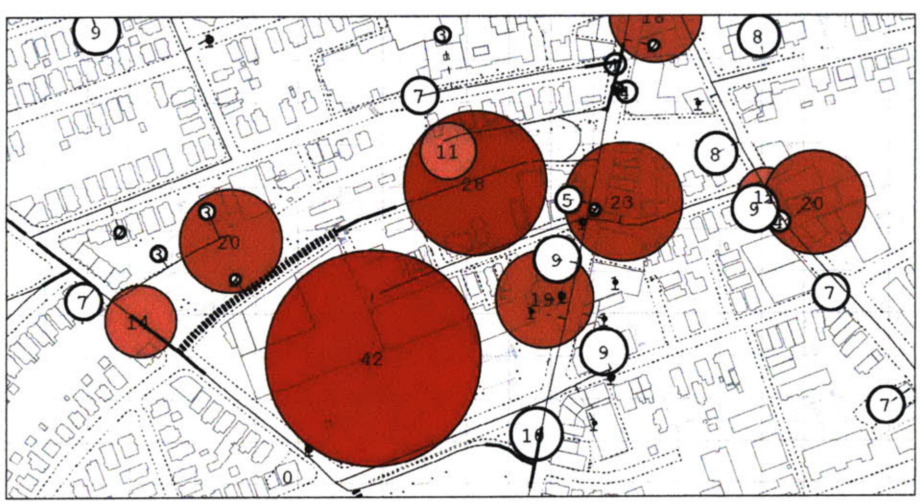
AREA

The Kernel density generates a heat map ofinstagram location density that shows the boundary of the core and the periphery of a neighborhood's meaningful area.



INTENSITY

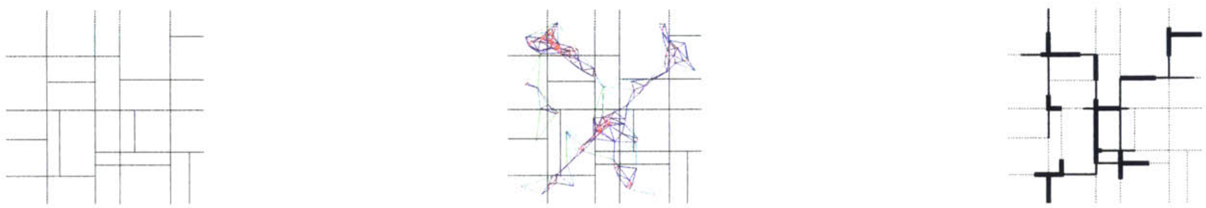
If one connects the locations within a 5 minutes walking distance (800meters), it draws a net of locations that are accessible from one to another.



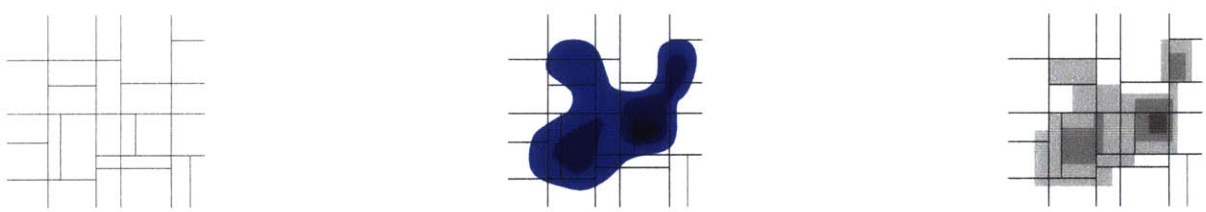
Psychological Reading

places inside and outside

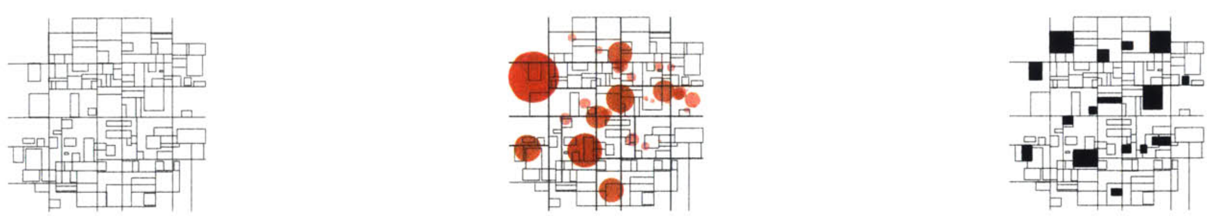
The visualization method of data predetermine what built form it illuminates. The in-depth analysis selects three different data visualization methods that illuminate three types of built environment. The first is a 'Delaunay triangulation' that will generate a hierarchy of the pathways. Delaunay triangulation is a technique for creating a mesh of contiguous, non overlapping triangles from a dataset of points. The primary mapping of a delaunay triangulation of location points within a distance of 500 meters forms a net of the locations. The net might be very dense in zones of agglomeration and disconnected where there are no points around one point within a 500-meter distance. The net shows the physical accessibility between each location, and therefore overlapping the road segments shows the segments with higher and lower accessibility to other locations. The second visualization method is the 'Kernel Density' tool. Kernel Density calculates a magnitude per unit area from point or polyline features using a kernel function to fit a smoothly tapered surface to each point or polyline. When computing the Instagram location data points, Kernel density tools generate a raster image that displays the density of points on each unit pixel. The smoothly tapered surface is transformed into a five stepped standard deviation of the kernel density value. In other words, standard deviation calculates the difference of the kernel density value of the examined unit and reclassifies the unit into these five new classes. This generates a boundary between each step and shows the center of the high density and periphery of low density. The research translates these boundaries as splitting edges of zones and draws a new map that includes all parcels that fall into one zone. Finally, I am adding all unique locations that situate in one parcel to understand the intensity of location numbers in each parcel. This first, generates a map of parcels that



NET - Pathway
The net of places forms a boundary that gives hierachy to the pathways that connect places.



AREA - CORE
The stepped boundary made through the Kernel density mappings indicates parcels that belong to the core and the periphery of the geography of meaningful places.

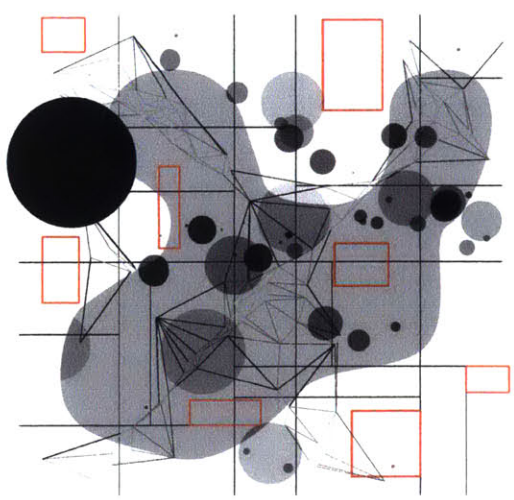


INTENSITY - Building
Projecting the aggregated number of posts to each parcel shows which parcels, moreover which buildings gain more importance in the psychological geography.

contain location data, but also a hierarchy among parcels according to the number of locations. Through this method it is possible to pinpoint the parcel, the building or open space it contains that will be the subject to be spatially examined.

The research starts by mapping the location data of each selected neighborhood with the above mentioned visualization methods. With this maps in hand, the research documents the spatial element, program and its relationship to the surrounding environment of the highlighted pathways, zones and buildings. This process is the moment when the abstraction becomes translated into our tangible reality and when the new layer of information finally integrates with traditional ways of reading the city.

But there are always places that might have importance to the community, yet completely invisible in the psychological geography of Instagram locations. Therefore, the second part of the manual looks into the program and spatial elements that form such places. The places in and out of the psychological geography generate a unique profile for each neighborhood.



OUTLIERS

The absence / presence of public institutions,recreational open spaces, and landmarks in the psychological geography shows how much people feel engaged to those places.

Physical Reading
program and physical elements

The places that are distinguished through the psychological reading become subject for a dissection that identifies the programs and elements that shapes the place. The program and physical element is derived from traditional city reading in Urban studies. This process links the psychological reading to the traditional reading of the city that studies the function and the built form of places, and allows us to grasp spatial meaning of a unique profile of places of the psychological geography of Instagram locations.

The programs come from Kevin Lynch's 'The image of the city' where he generates a mental map of important paths, nodes, edges, districts and landmarks through interviews on people. The paths, nodes, edges, and districts were marked only in terms of their importance in the studied area, therefore I took notice of marked landmarks because they are places with a specific function recognized in his reading. William Whyte's 'The social life of small Urban spaces' contains an empirical observation of the usage of different urban spaces. The chapters were structured around specific physical elements that are indispensable of the formation of the examined urban space typologies. Finally, the 'Urban Street Design Guide' by the National Association of City Transportation Officials provided the typology for pathways through the relationship of the examined pathway and the type of contiguous space.

The Manual

source **element** **space**

Kevin Lynch

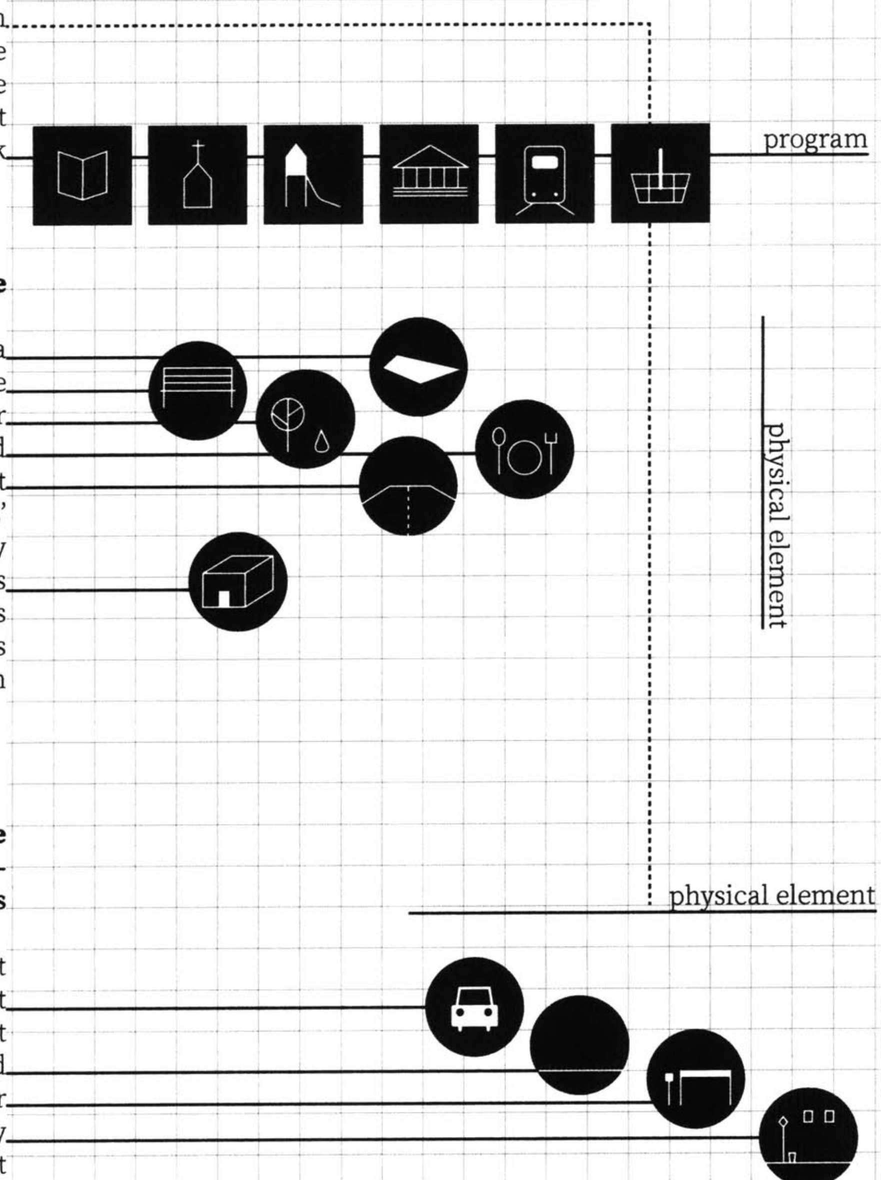
1. Path
2. Node
3. Edge
4. District
5. Landmark

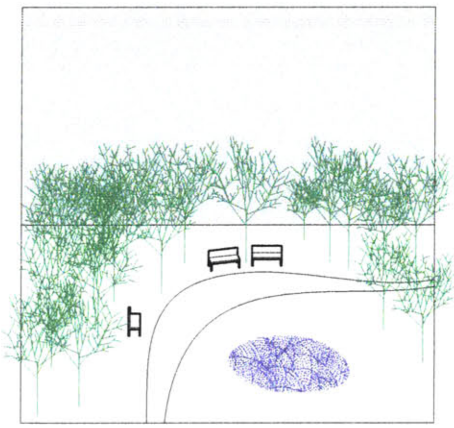
William Whyte

1. Plaza
2. Sitting space
3. Sun, wind, trees, water
4. Food
5. The street
6. The 'undesireables'
7. Effective capacity
8. Indoor spaces
9. Concourses and Megastructures
10. Smaller cities and places
11. Triangulation

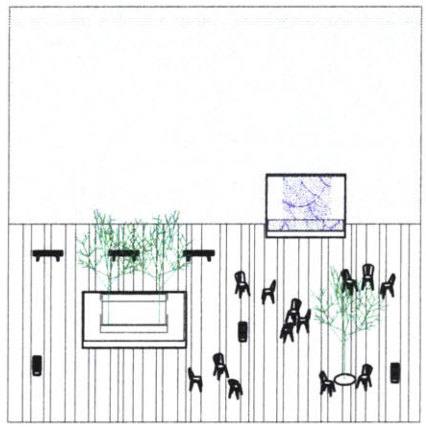
Urban Street Design Guide
National Association of City Transportation Officials

1. Downtown street
2. Neighborhood street
3. Yield street
4. Boulevard
5. Transit corridor
6. Alley
7. Shared street

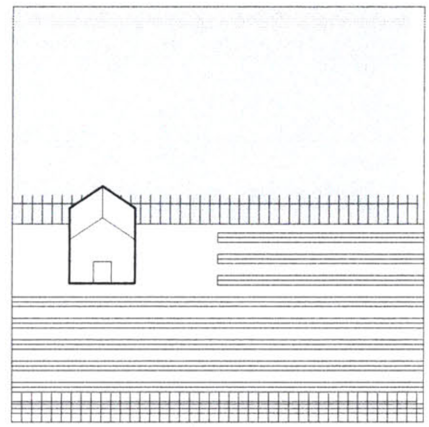




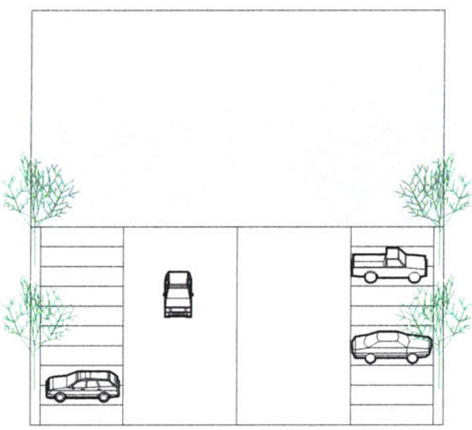
Park



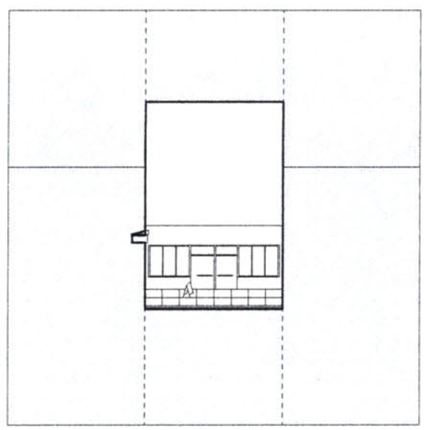
Plaza



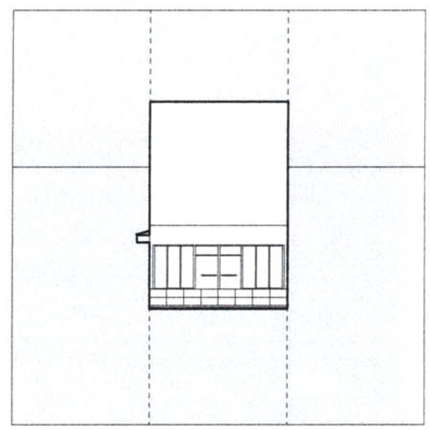
Community Garden



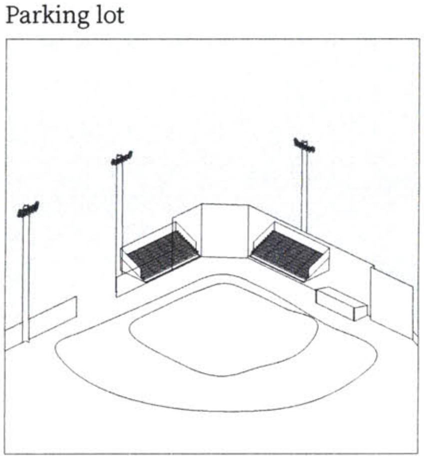
Parking lot



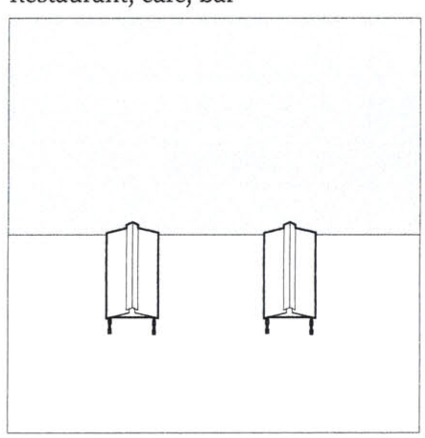
Restaurant, cafe, bar



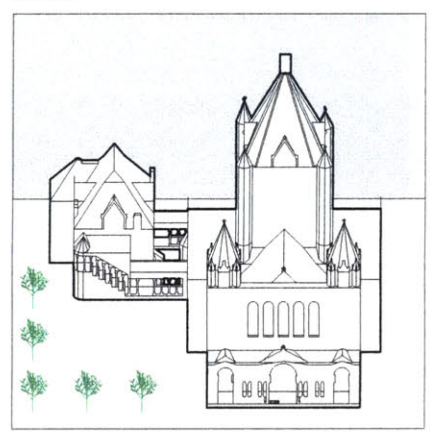
Retail



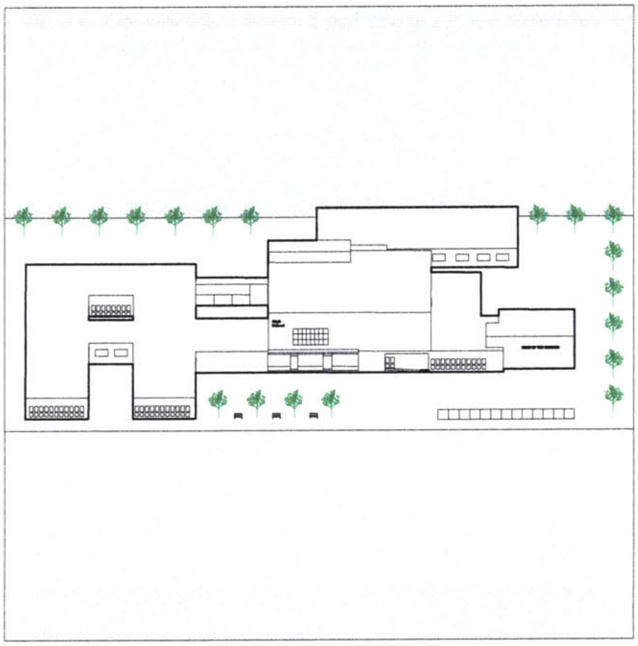
Sports field



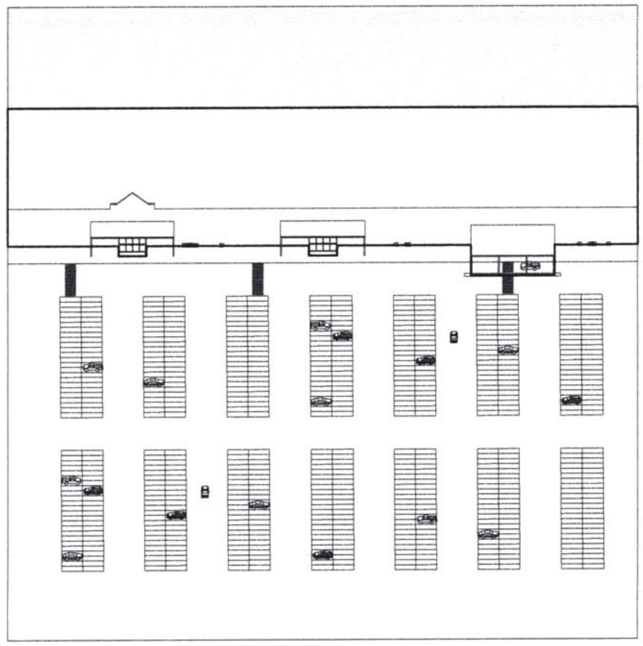
Farmers Market



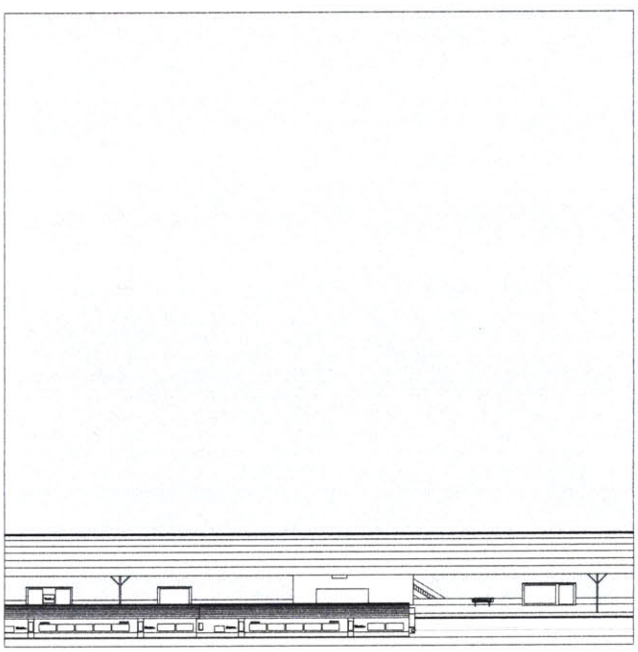
Religious building



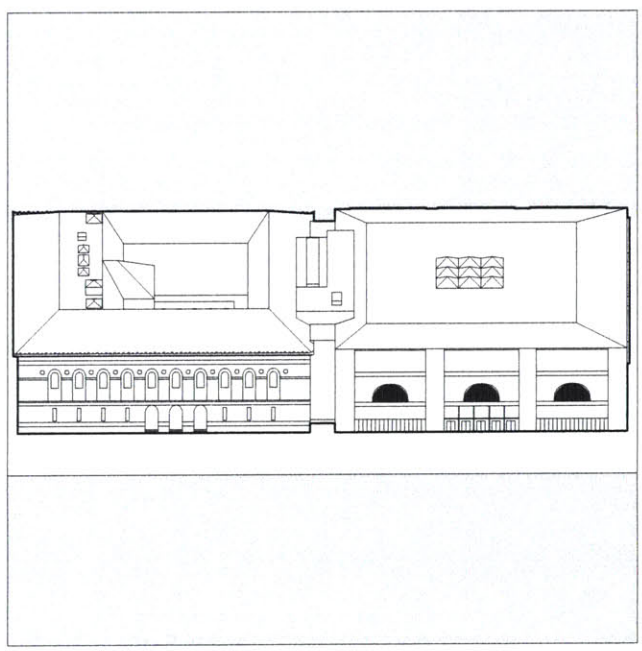
School



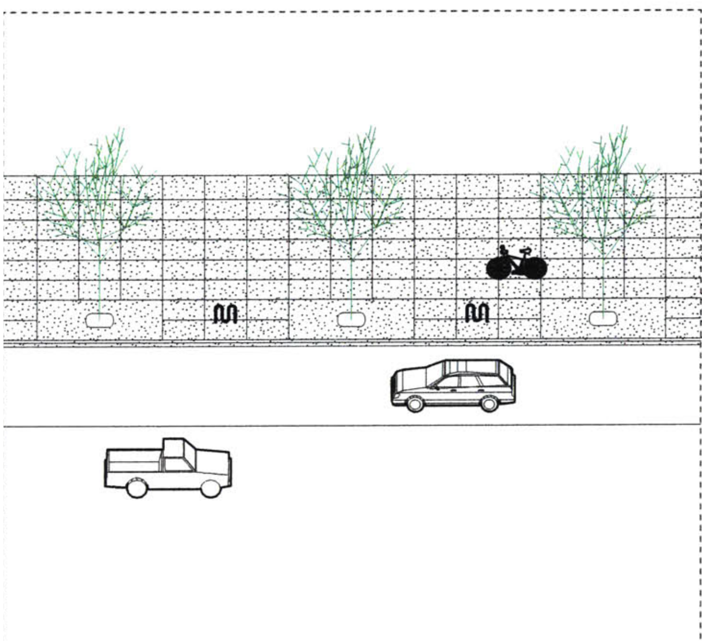
Mall



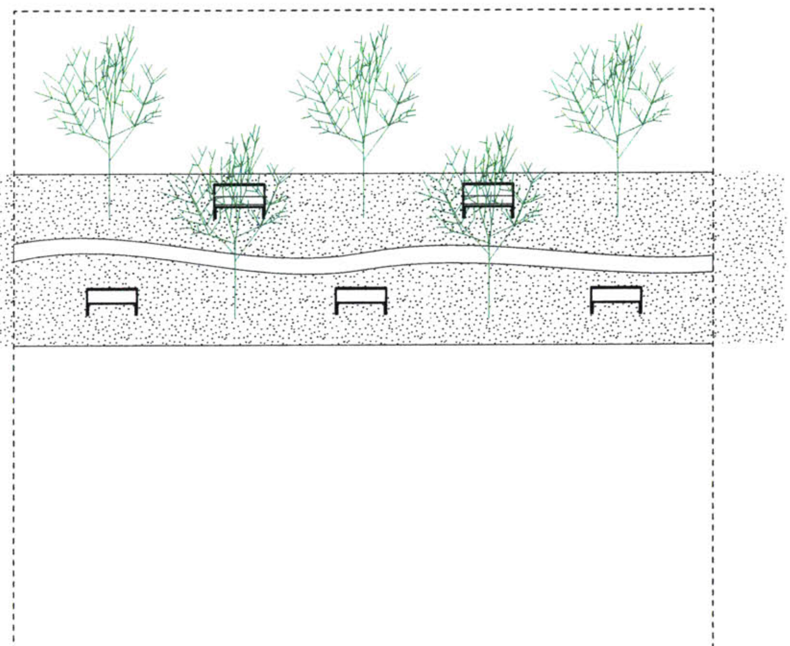
Stations



Library

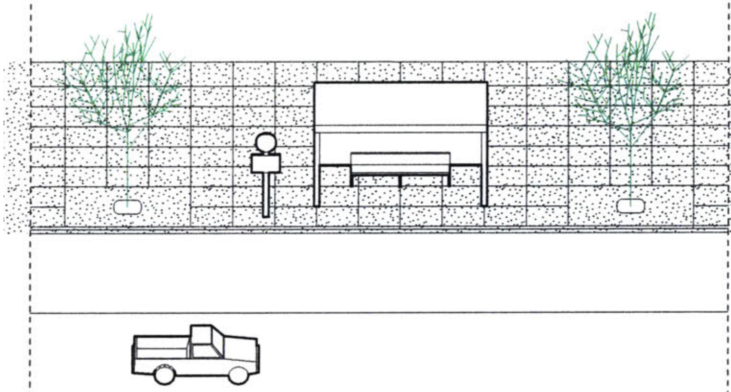


Pedestiran street

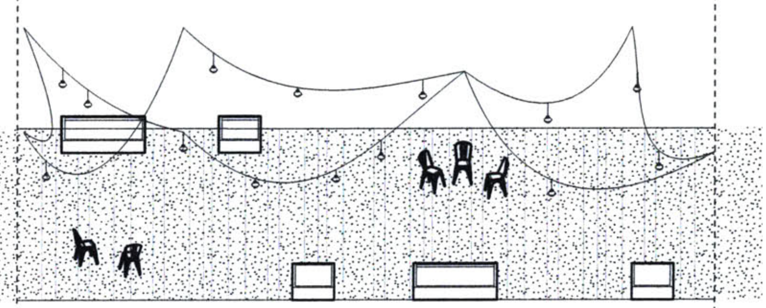


Park street

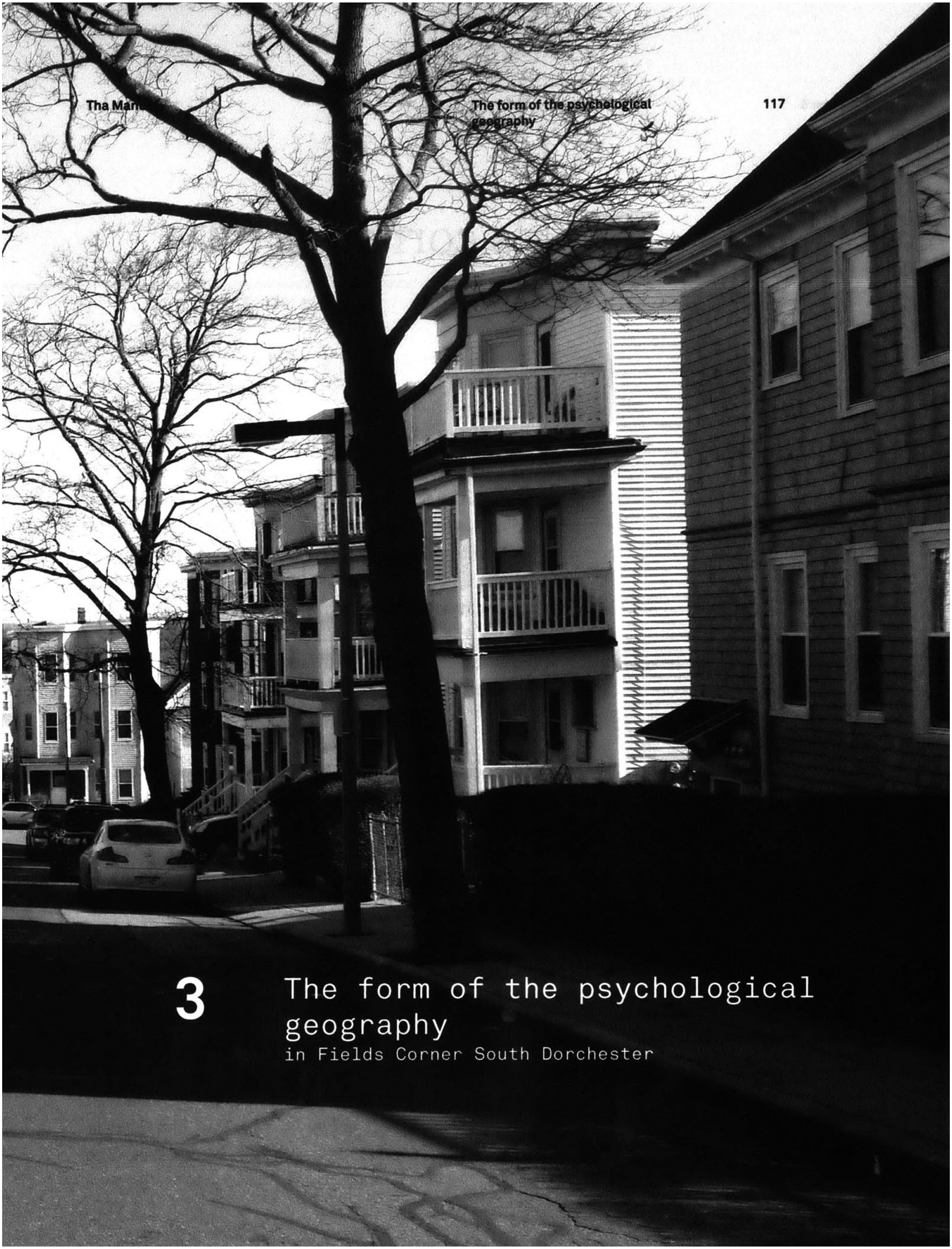
The Manual



Transit corridor



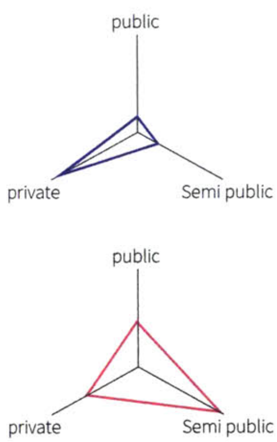
Alley



3 The form of the psychological geography

in Fields Corner South Dorchester

Fields corner as C2



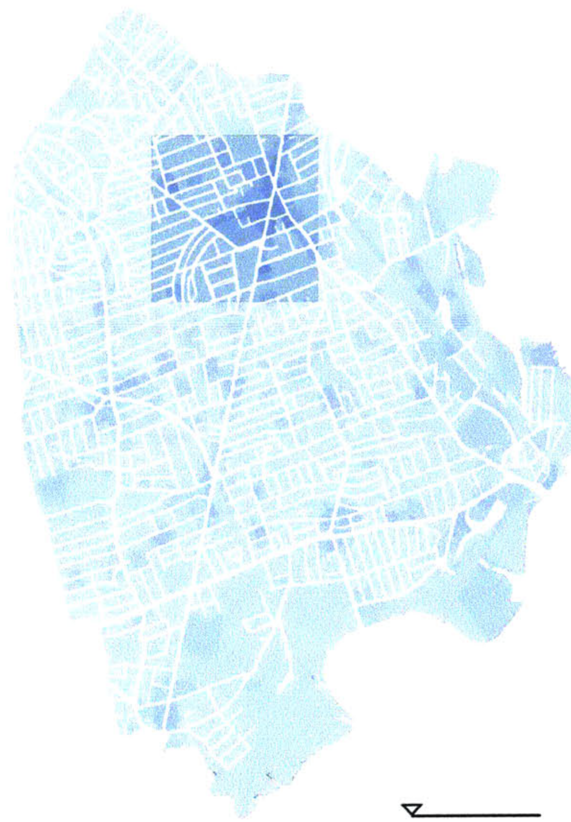
Fields Corner in South Dorchester is selected as a site for in-depth analysis due to the concentration of C2 parcels. C2 parcels refer to parcels that land in the fourth vulnerable class of population out of five classes, and shows a second low level in location density of five classes. In other words, the vulnerability of the population is right below average but not the most severe, and the Instagram location density is as well lower than average but more than that of the least active class. These parcels are mostly distributed in South Dorchester with 76% of the whole number of C2 parcels concentrated, followed by 21% in Mattapan and 3% in Central Boston.

Field corner is one of the locations where the agglomeration of C2 parcels in South Dorchester happens, with a mix of less vulnerable D2 parcels and less active C1, D1 parcels. The location density of Fields Corner is pretty low, compared to Back Bay and Central Boston. However, slight agglomerations of Instagram locations can be detected around intersections and and major T stations, that presumerably form subsenters within the suburban environment.

The sample area is highly private with detached single family houses being the main building typology for residential uses with a commercial corridor of shops and restaurants. Fields Corner is in general a highly vulnerable area, with an average population density, a very high unemployment rate, and a below average population that travels to work over 90 minutes. The

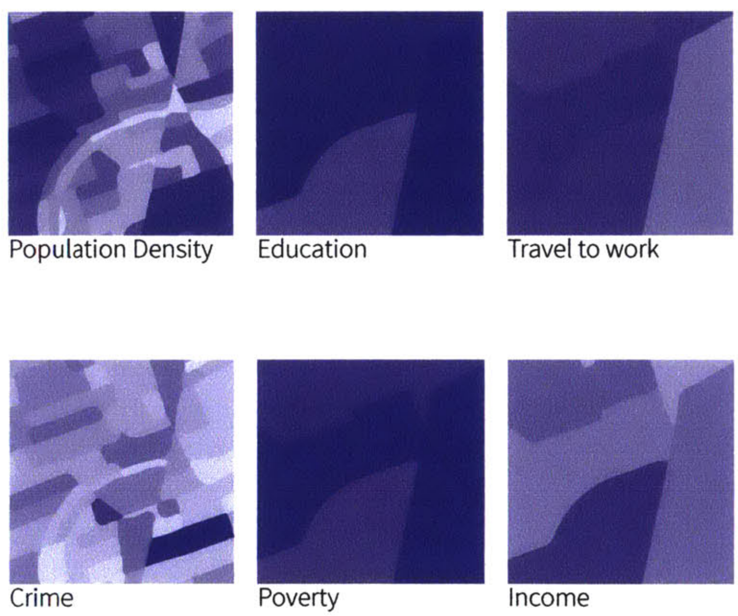
Class

Location data status

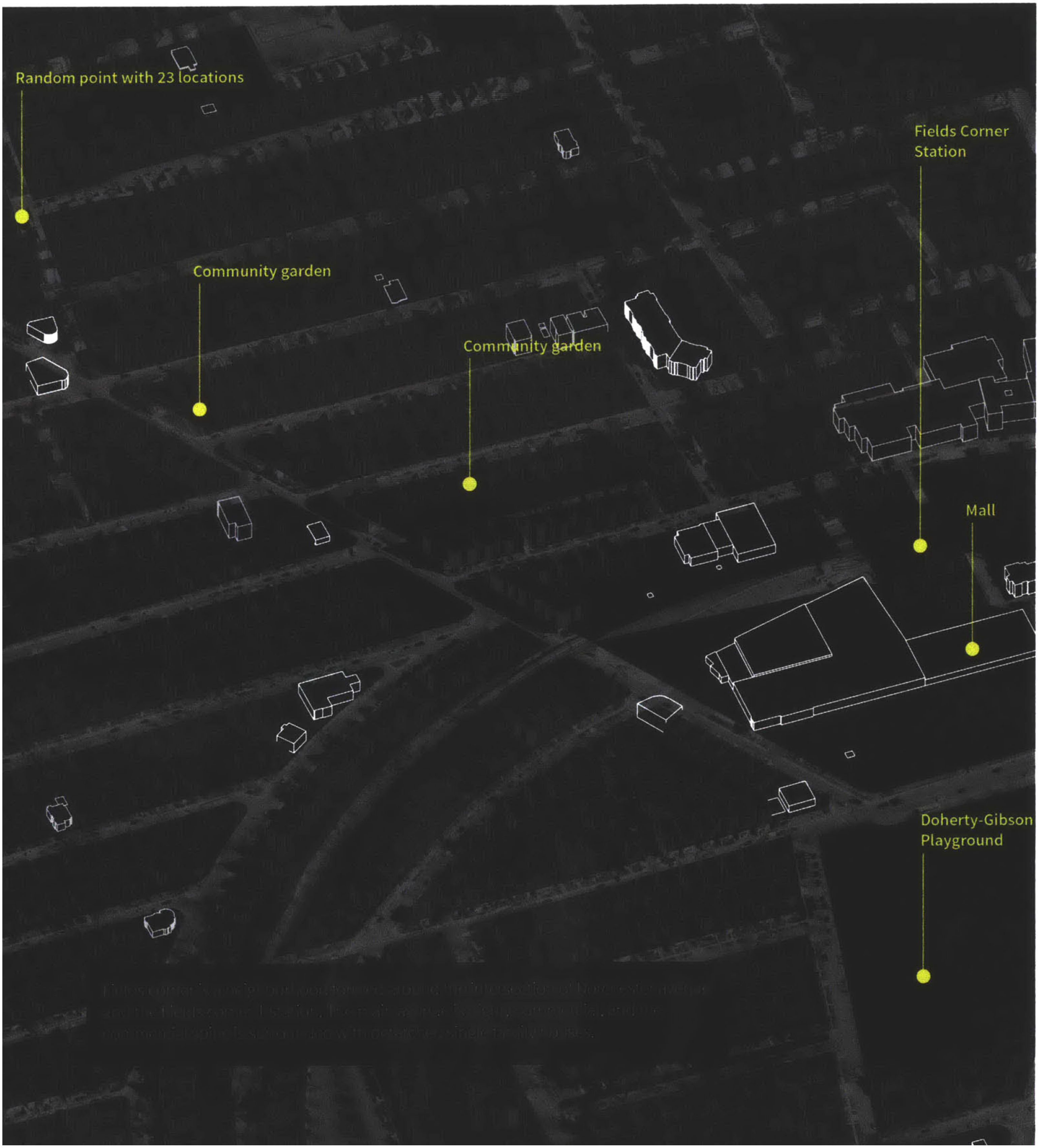


crime rate is lower than average, but the population below poverty line is very high. Finally the average income is slightly over average of all three planning districts. Simply put, Fields Corner is a neighborhood with a concentration of unemployed population that works nearby, with an income level that is just above average.

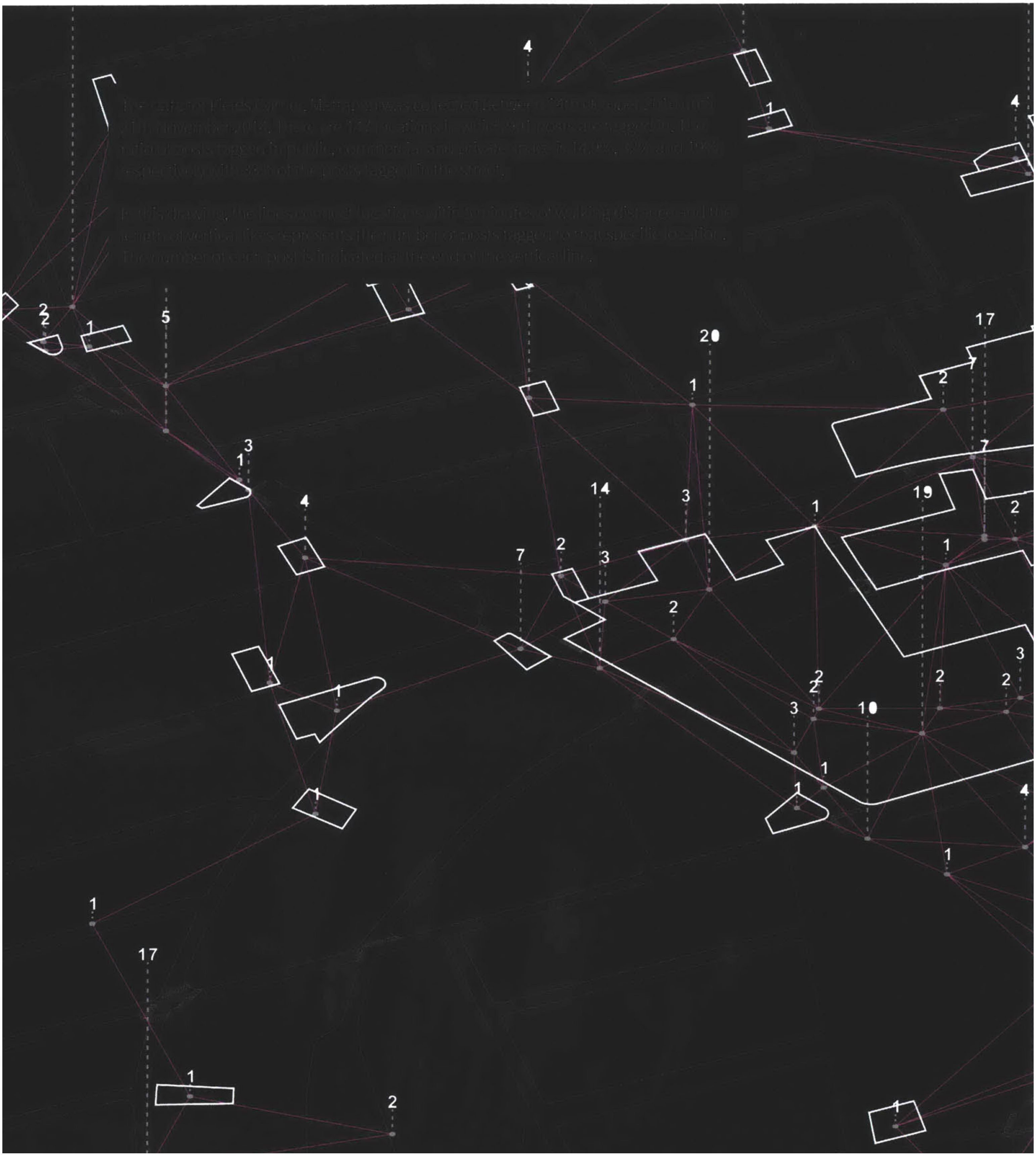
Zooming into the site, one can observe that a more educated, and wealthy population resides in the south west corner of the sampled area which is surrounded by a more vulnerable population. The crime rate peaks in one of the census blocks on the south east part of the neighborhood.



Socio-economic status


Random point with 23 locations
Fields Corner
Station
Community garden
Community garden
Mall
Doherty-Gibson
Playground


Dorchester Avenue
@ Adams Ave
Dorchester Avenue


4
1
4
2
2
1
5
20
17
1
2
7
3
1
7
14
3
19
4
1
2
7
2
3
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4
1
1
17
1
2
1

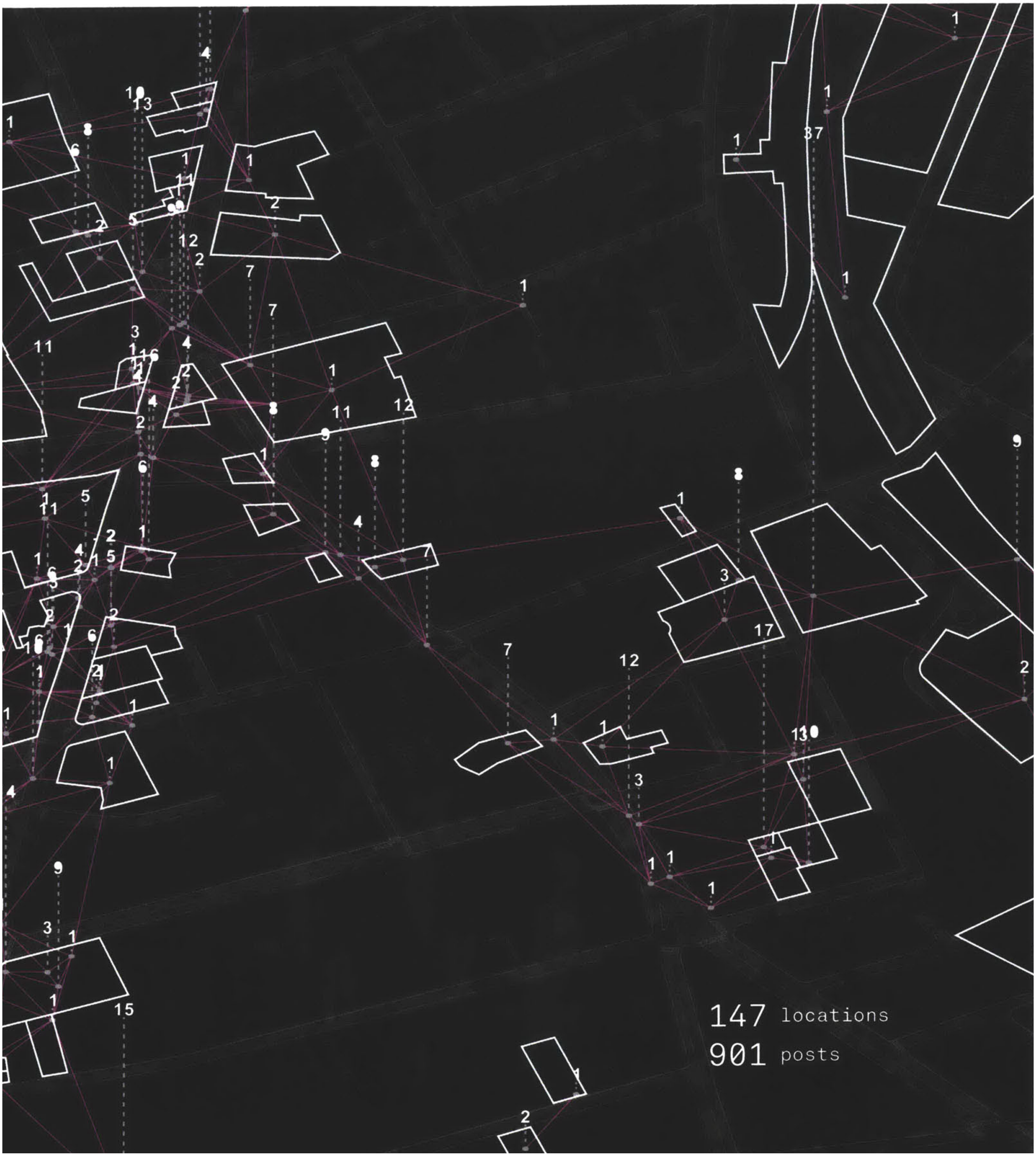
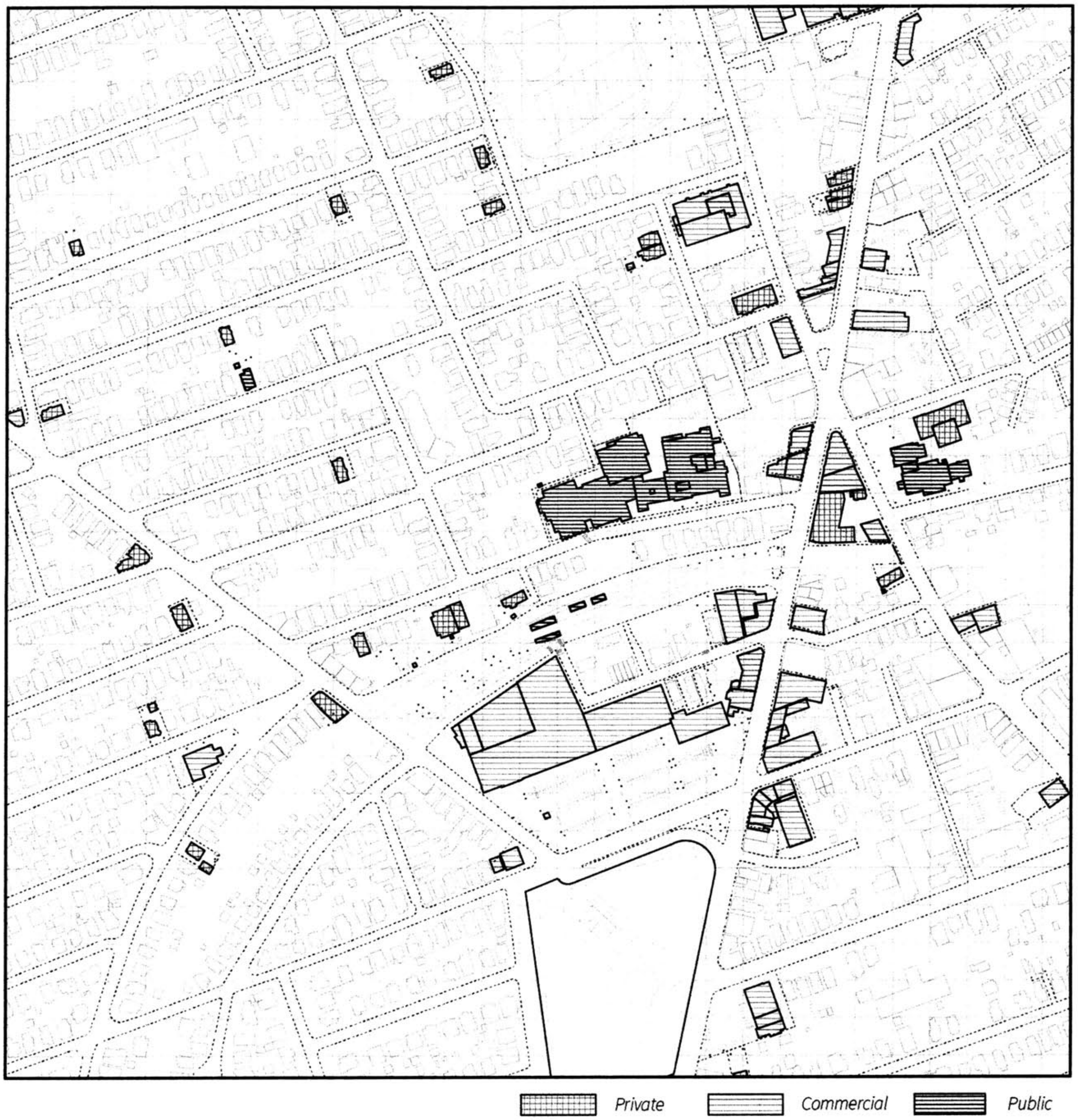

147 locations
901 posts

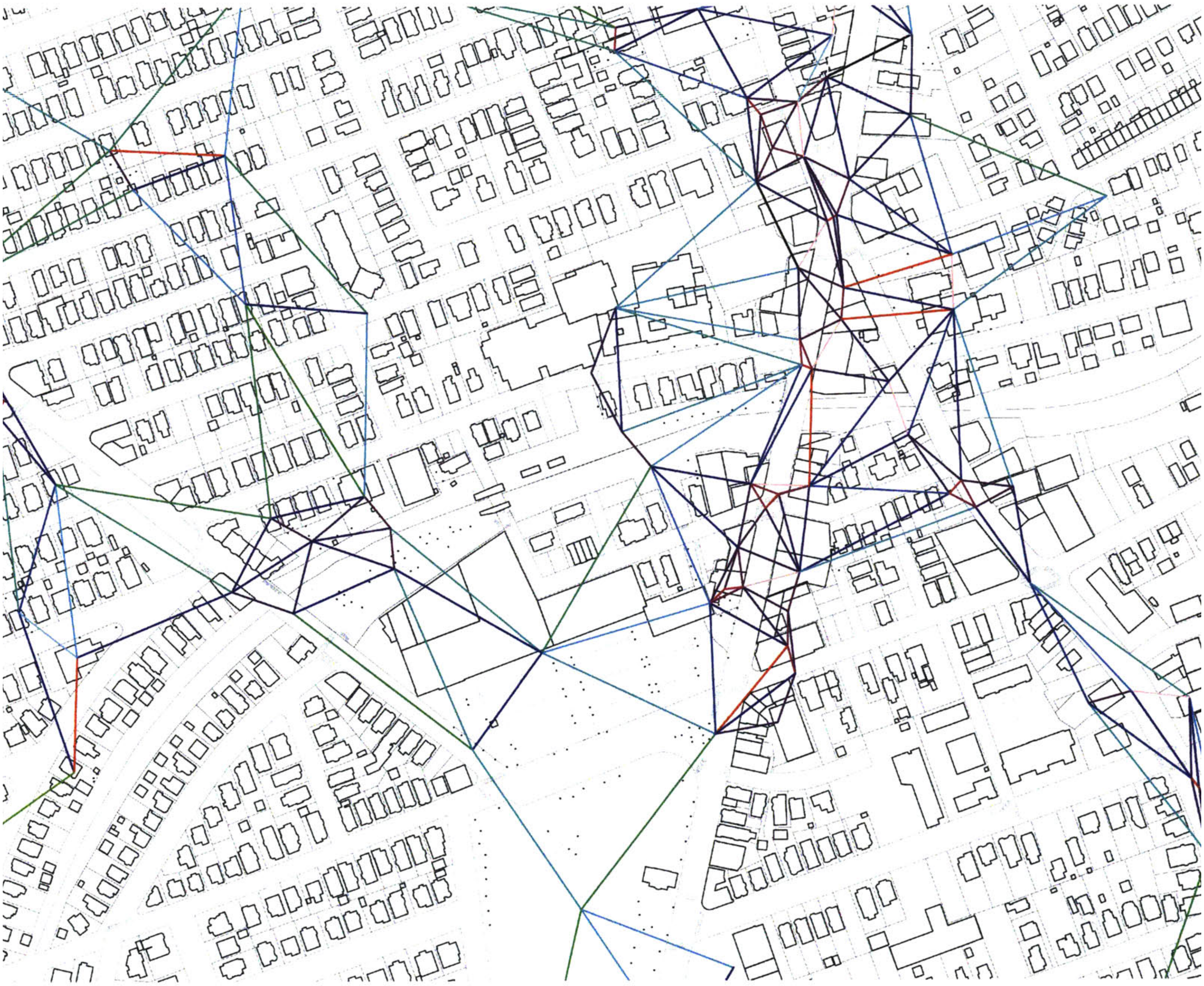
FIGURE AND GROUND

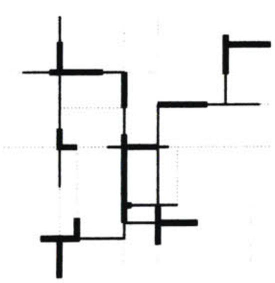
The way the building footprints are layed out shows the suburban nature of Fields Corner. Larger buildings are located along the commercial strip of Dorchester Avenue, and single detatched famliy housing surrounds the neighborhood.



Nolli Map

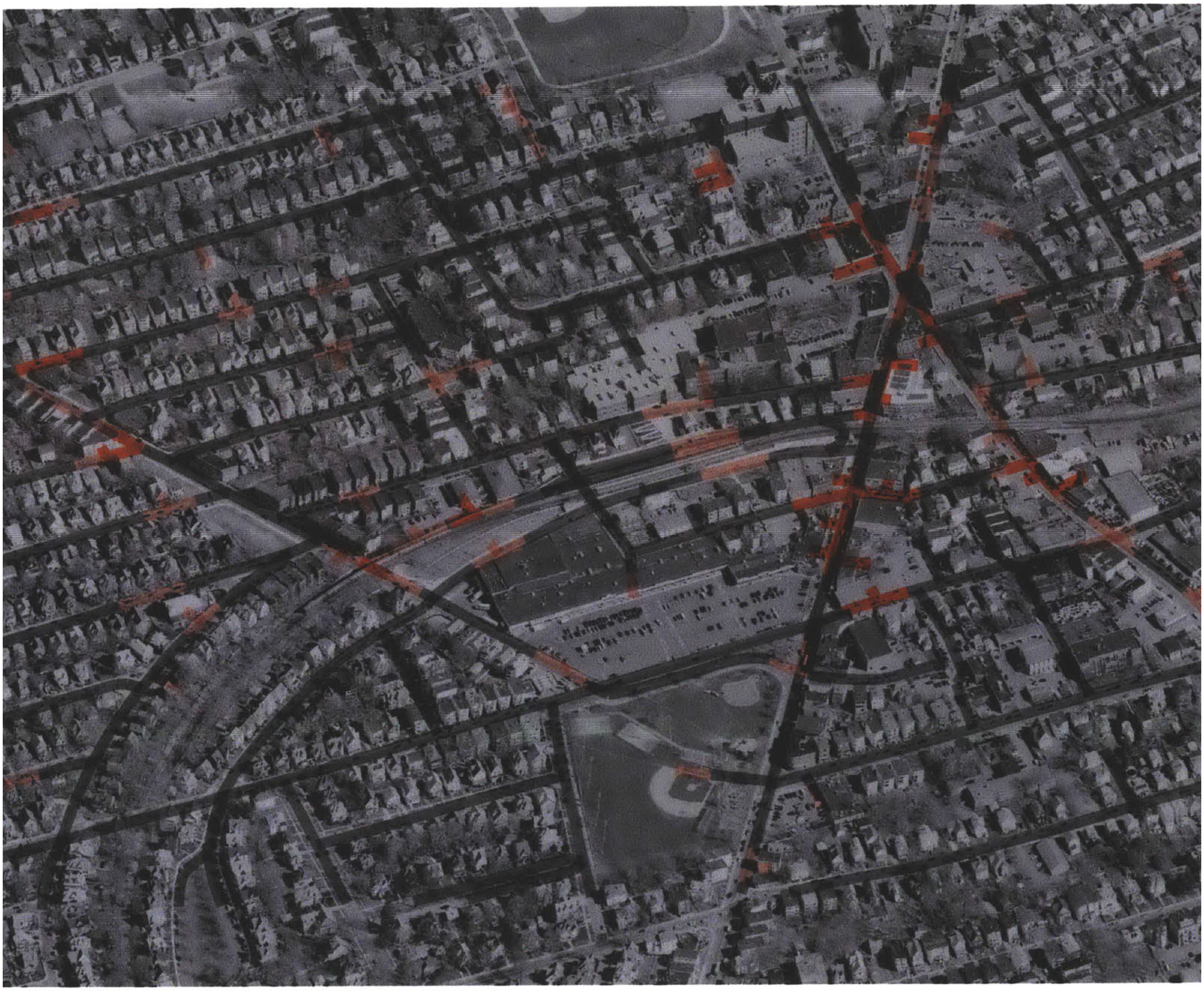
This drawing highlights the buldsings and open space in which geo-tagging activities took place, and the hatch indicates whether the place was public, commercial, or private.

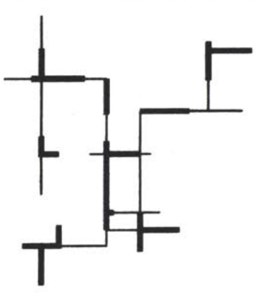




NET

In this drawing, the lines connect locations witin 5 minutes of walking distance and the length of vertical likes represents the number of posts tagged to that specific location. The number of each post is indicated at the end of the vertical line.





PATHWAYS

The net brings a hierachy to the pathways, The red streets mark the highest connectivity to Instagram locations, while pink indicates medium connectivity. The connectivity is decided by the number of adjacent locations.

Most connective paths

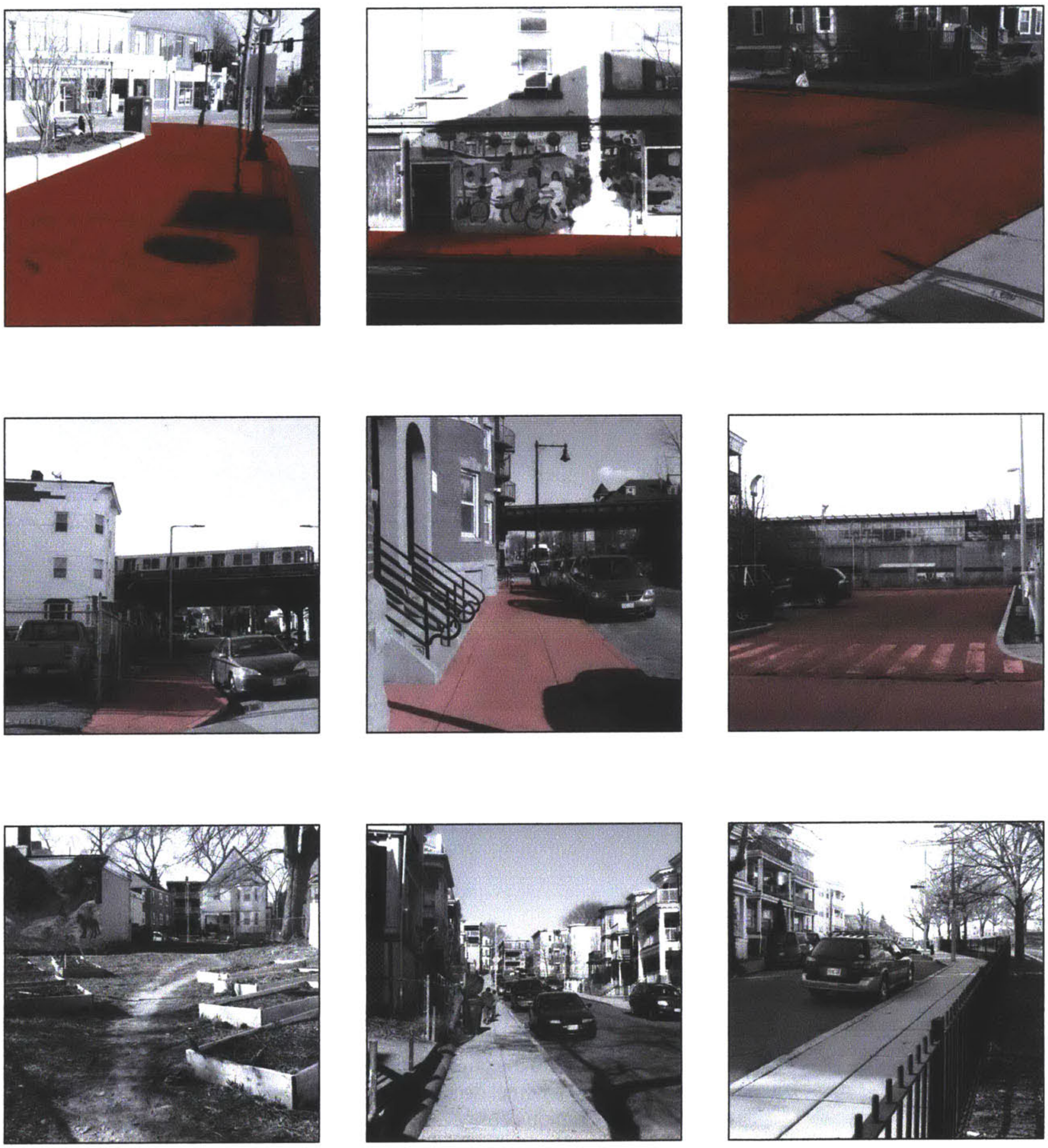
Medium connective paths

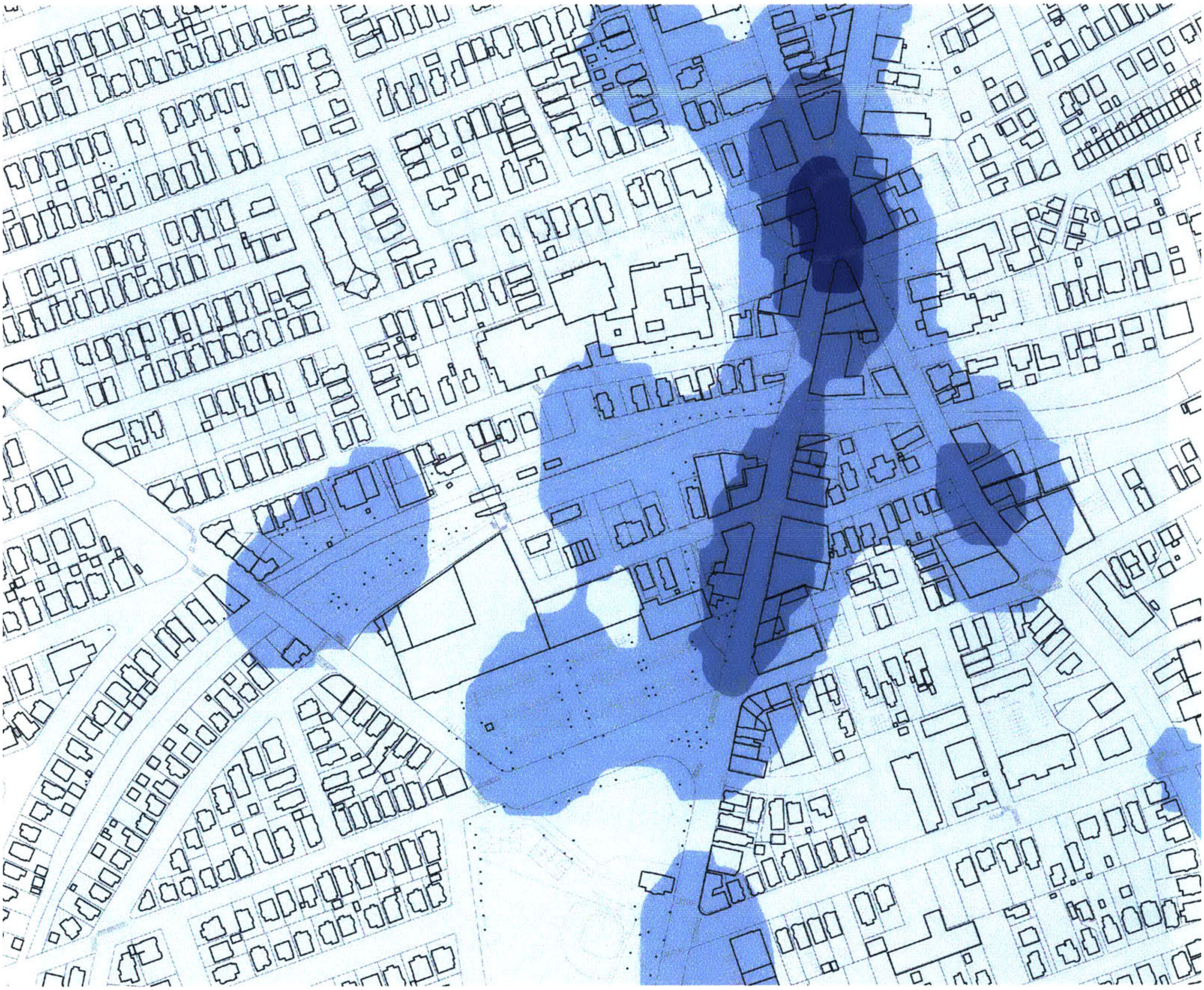
Least connective paths

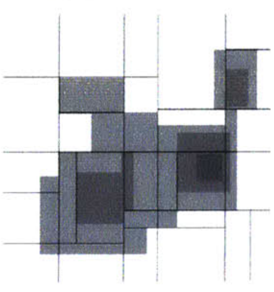
Pathways

The connectivity of a path is measured through the number of adjacent locations within a certain distance to each other. The number of posts tagged in each location did not influence the connectivity measurement.

The net becomes dense along Dorchester avenue and Geneva avenue. The intersection around Dorchester avenue has a high concentration of Instagram locations, which makes it a pathway that connects more locations than others. Pathways of higher connectivity are mainly along the commercial corridor, the less important parts connect the T station with those corridors. The least connective paths mainly run through the housing neighborhood.

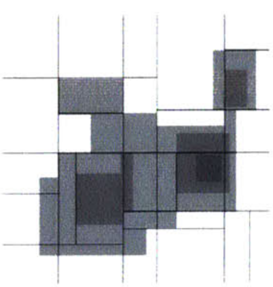






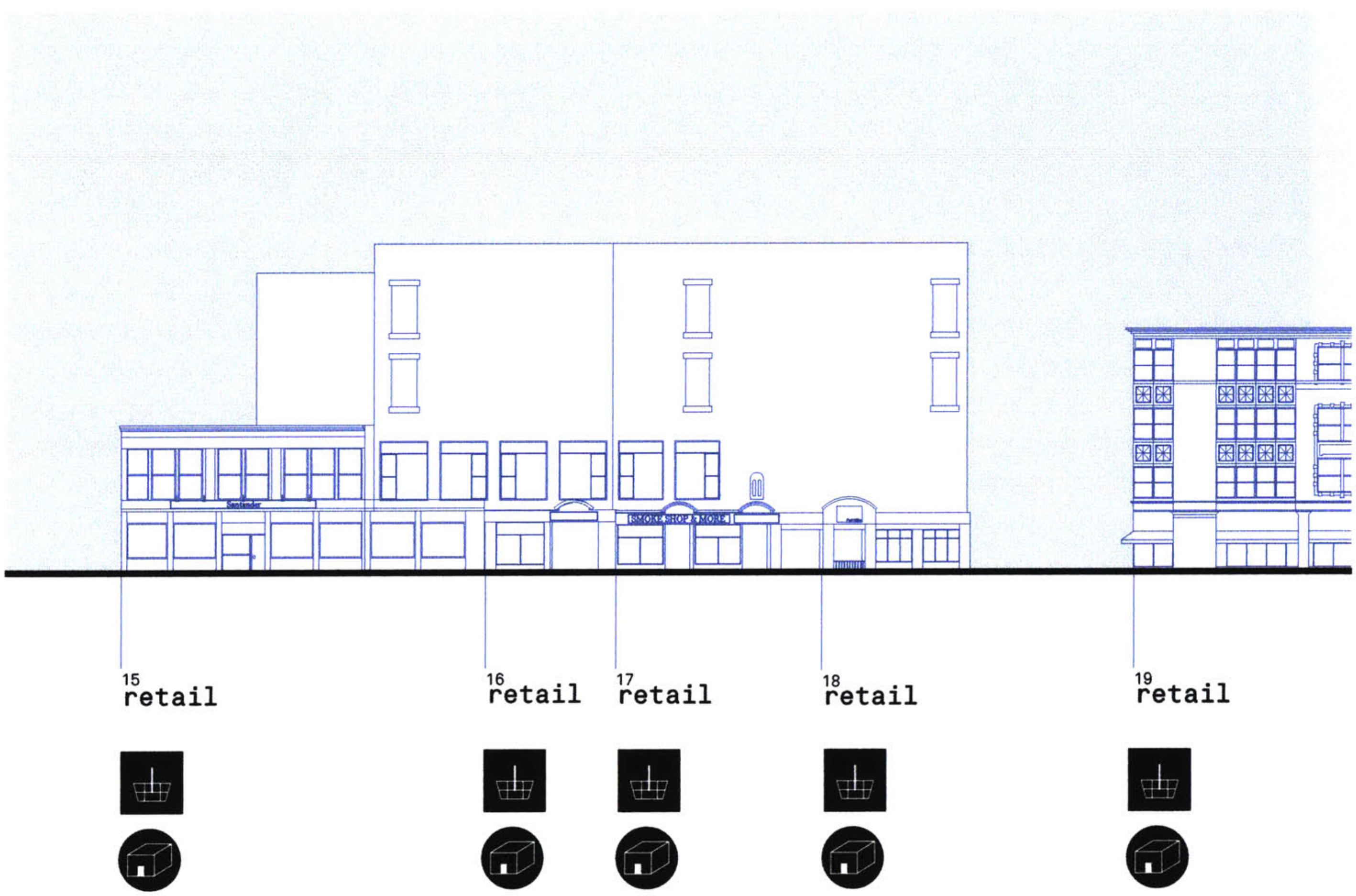
AREA

The map shows the center and periphery of the pshychological geography of the neighborhood. The boundaries of each post density class generate zones that assign discticntions to the physical structure of the neighborhood.The shades are made through a Kernel density mapping, that was translated into stepped boundaries of location density.



CORES AND PERIPHERIES

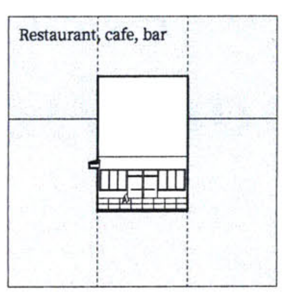
The stepped boundary identifies a cores and peripheries of the neighborhood.



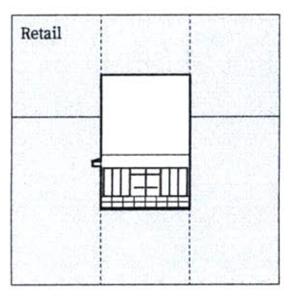
One core

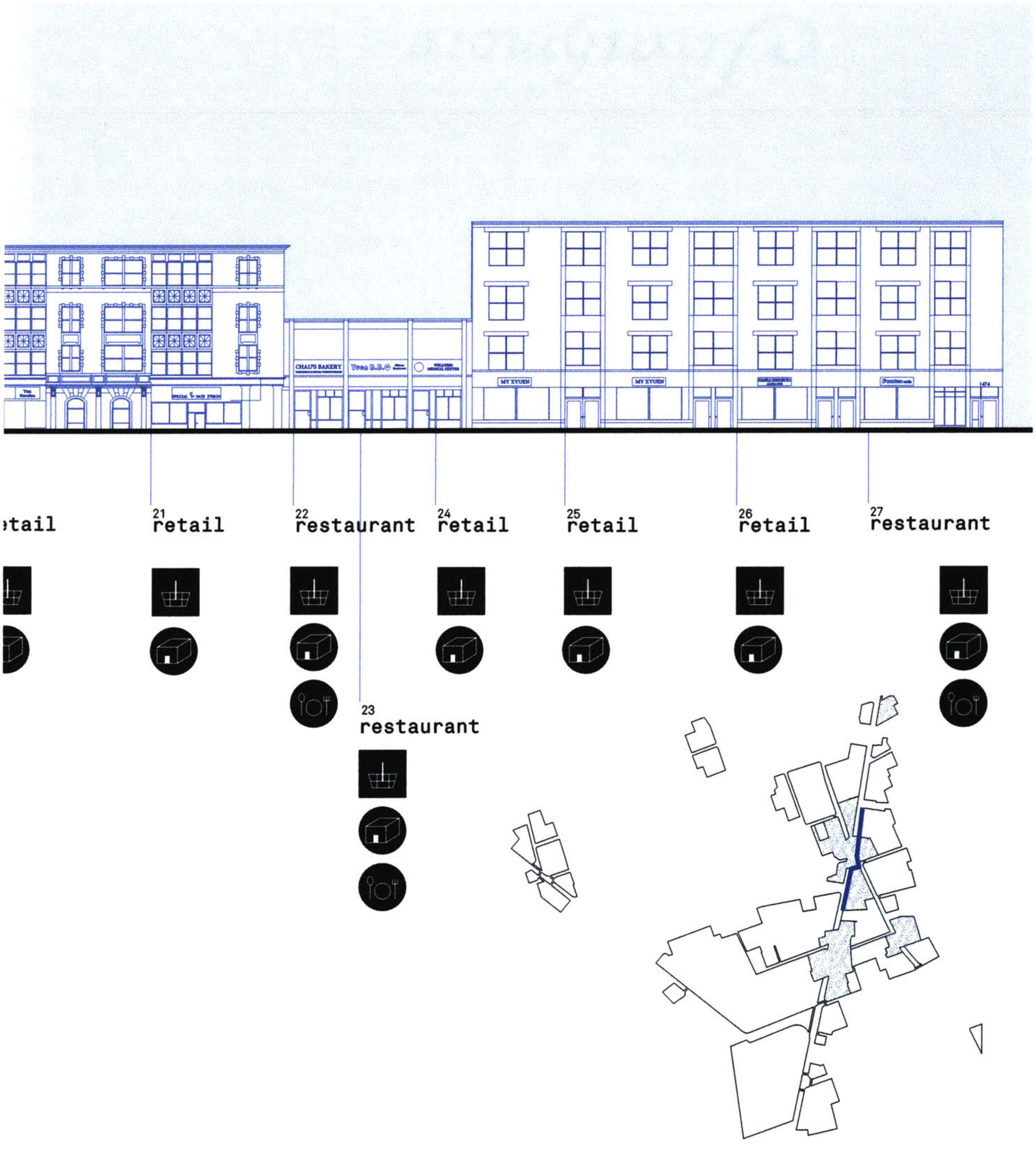
A high concentration of commercial space

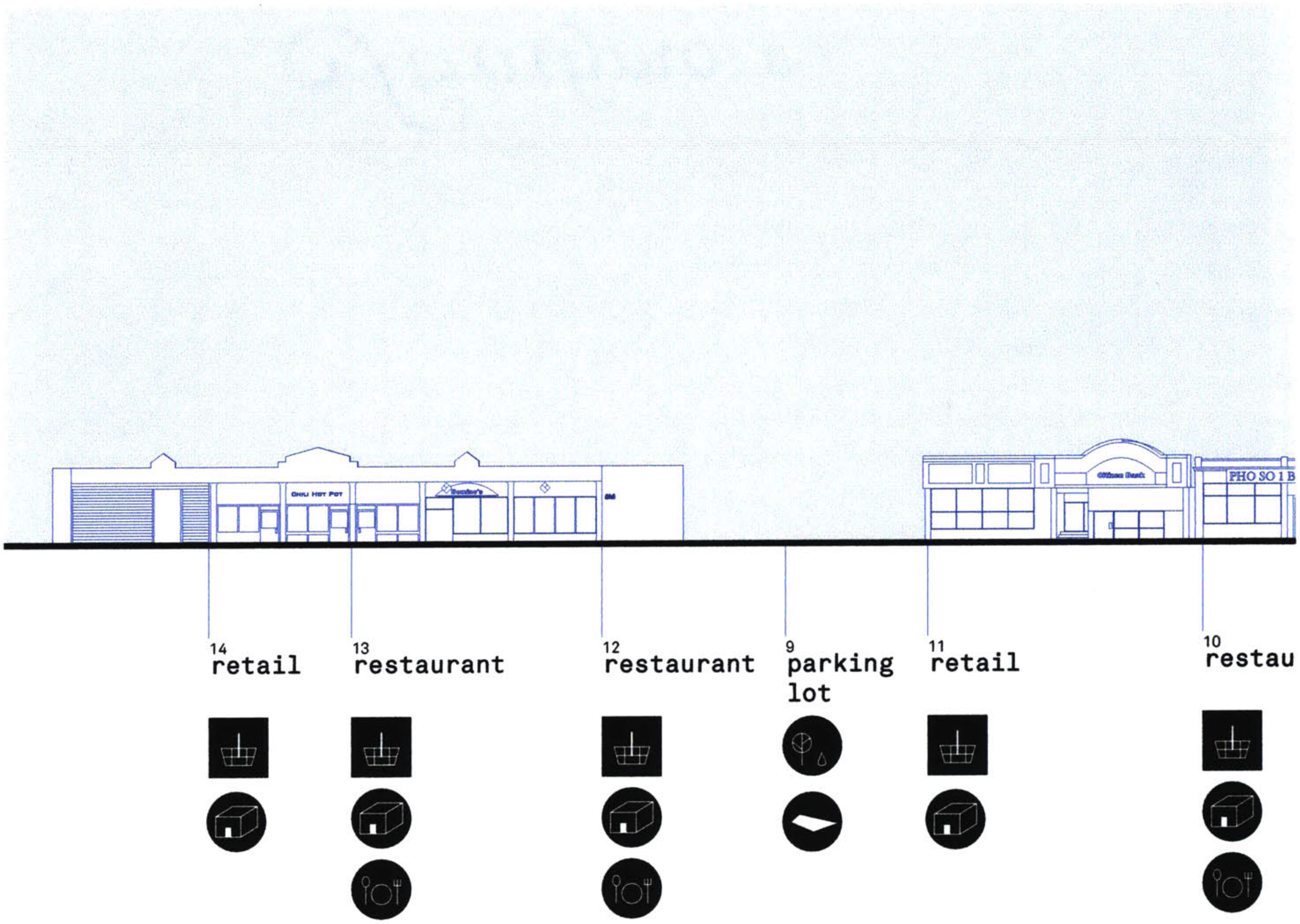
3



10



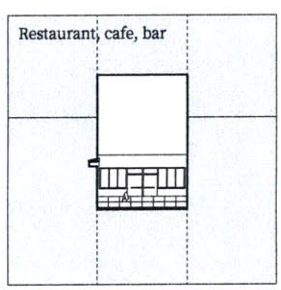

CHAU'S BAKERY
MY XYUEN
MY XYUEN
1474
etail
21 retail
22 restaurant
24 retail
25 retail
26 retail
27 restaurant
23 restaurant



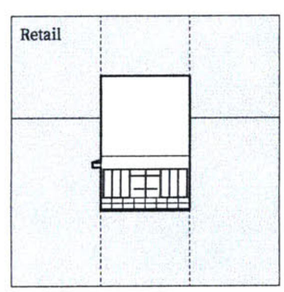
One core

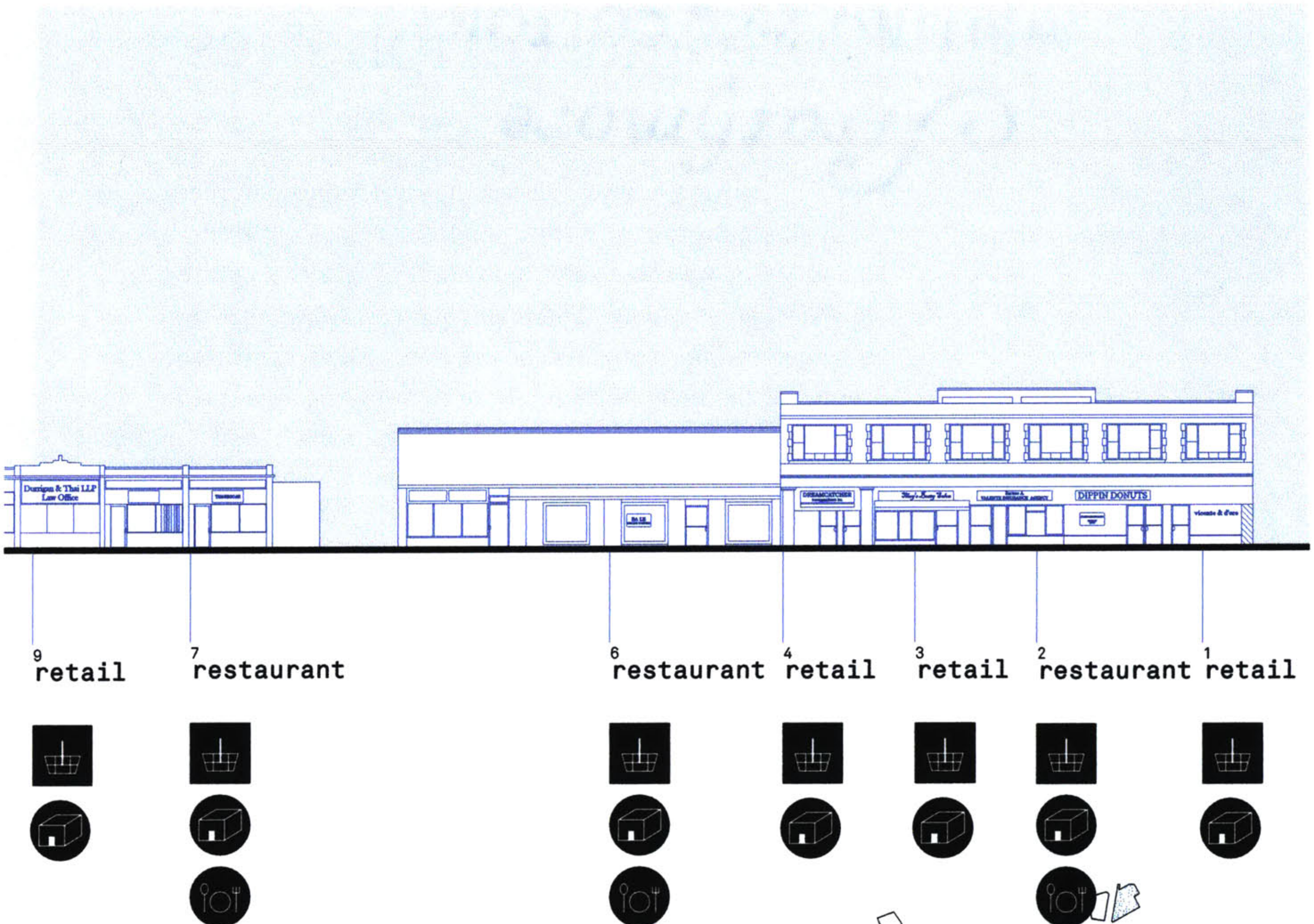
A high concentration of eating space with vietnamese culture

6



6




DIPPIN DONUTS
9 retail
7 restaurant
6 restaurant
4 retail
3 retail
2 restaurant
1 retail

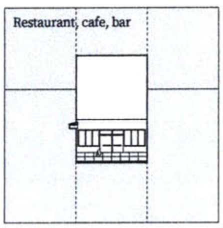
1


Parking lot

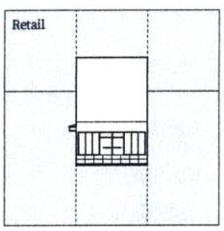
Core and Peripheries

zone 1

23



14



3

7 PRIVATE

The Area analysis shows the center and periphery of the neighborhood. With the boundary drawn through the analysis, we can cluster new kinds of blocks according to the location density. The map(page 133) shows that theses intersections along Dorchester Avenue clearly form the center of the neighborhood. I am naming the area inside the boundary with the highest intensity 'zone 1' and the next area that surrounds 'zone 1', yet surrounded with another border 'zone2'.

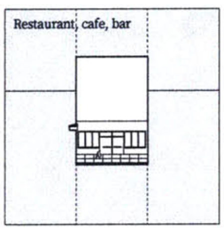
Zooming in into one of the 'zone 1' centers allows us to understand what program and physical element forms this zone. The zoomed in intersection contained 9 restaurants, 16 retail shops, one parking lot and no private space. It clearly seems like the commercial center. One interesting thing is that the high concentration of vietnamese restaurants reflects the cultural identity of the Fields Corner.

Zone one was mainly a commercial part of the neighborhood with a concentration of retail and restaurants. Throughout the total site, zone one contained 23 restaurants, 14 retail shops, 3 parking lot and 7 private locations, and zone two contained less commercial programs but 165 private locations. This shows that the center of fields corner is mainly formed around commercial space, and a high activity in private space forms the periphery.

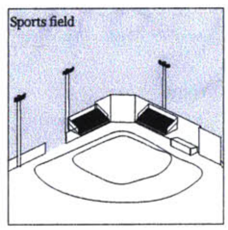
The findings in Fileds Corner prove the capacity of this method capturing the cultural cross section of a neighborhood. Even though the geo-tagging activity shows

zone 2

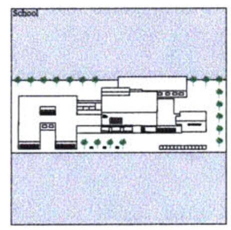
6



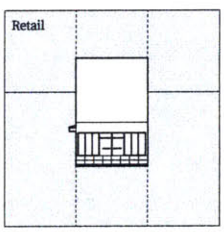
1



2



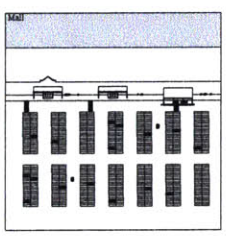
3



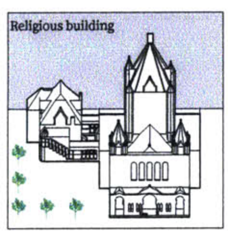
1

165 PRIVATE

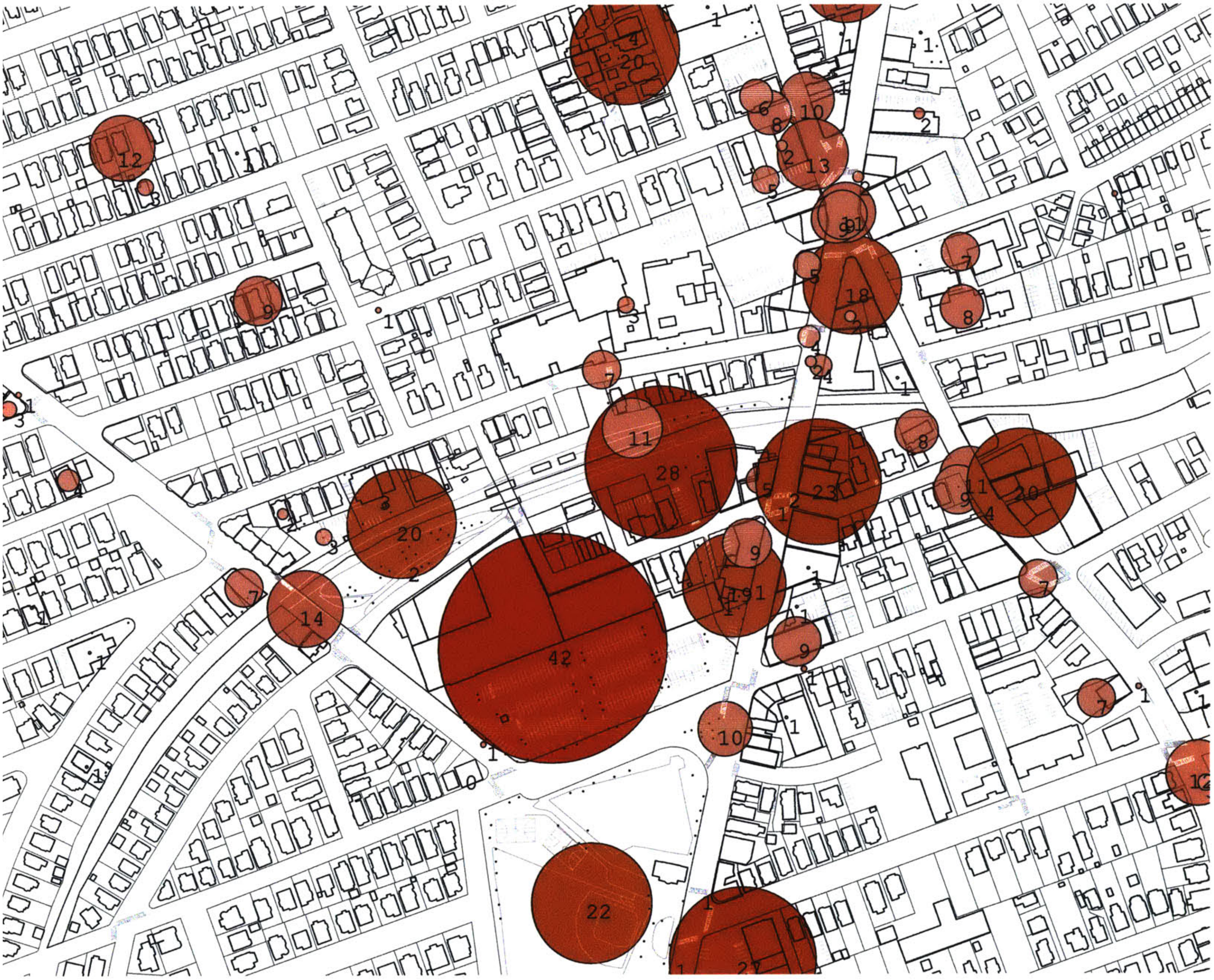
2

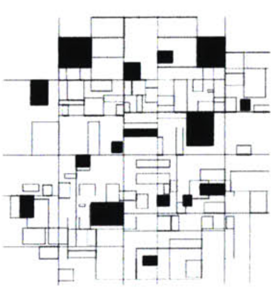


1



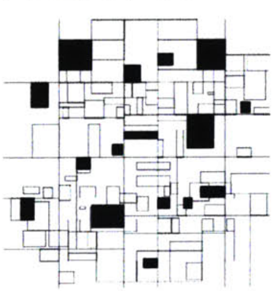
a high emphasis on commercial space, it provides evidence about the locality of the neighborhood through the places that people digitally recorded to be meaningful.





INTENSITY OF LOCATIONS

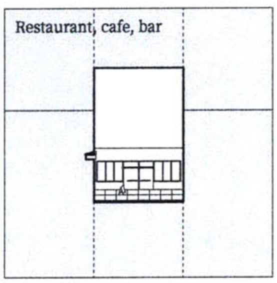
Instagram locations tend to be multiple points in one parcels. The radius of the circle represents the number of posts of all Instagram locations that fall in each parcel boundary.

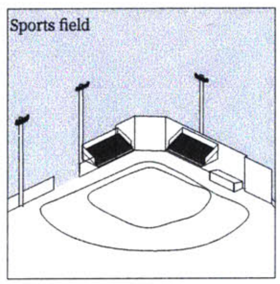


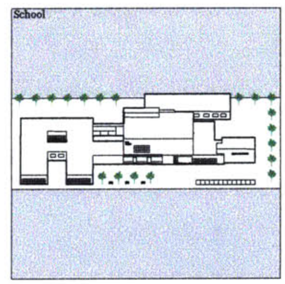
IMPORTANT BUILDINGS

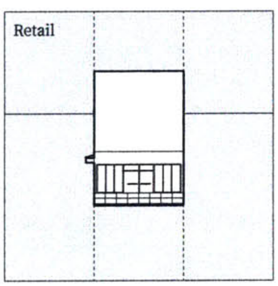
It is possible to display a hierachy of buildings according to the visibility in Instagram location data. The intensity of color reflects the number of posts from all locations within the specific parcel.

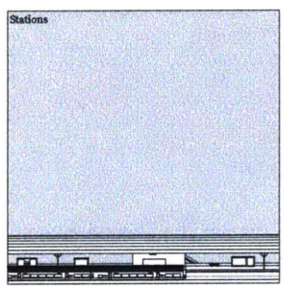
139 PRIVATE

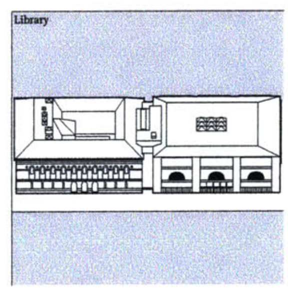
59


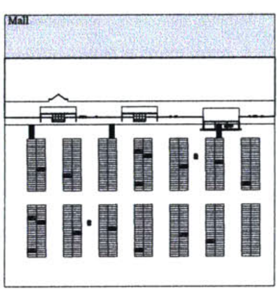
22


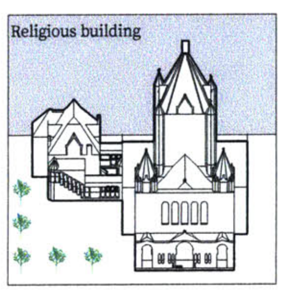
16


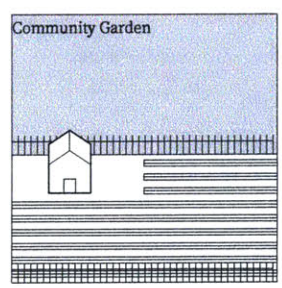
59


61


9


69


8


3


Buildings

Each parcel tends to contain multiple Instagram locations. This analysis takes only locations that are inside a parcel and adds up all locations and posts that happened in the parcel to detect important buildings. It is different from the 'Area' analysis because it rather measures the intensity of each parcel. Looking into the intensity of geo-tagging activities in buildings and open space bound to parcels, informs more clearly what program and spatial element coincides with more digital recognition.

Interestingly, this analysis demonstrated a mismatch with the 'Area' analysis. While the center of the neighborhood identified through the previous analysis was the intersection of dorchester avenue, the building ranked with the most posts is observed to be the mall in the middle of the neighborhood, which was followed by the T station. Both buildings are included in 'Zone 2', while only one of the buildings in 'Zone 1' made it into the top 10 of the list.

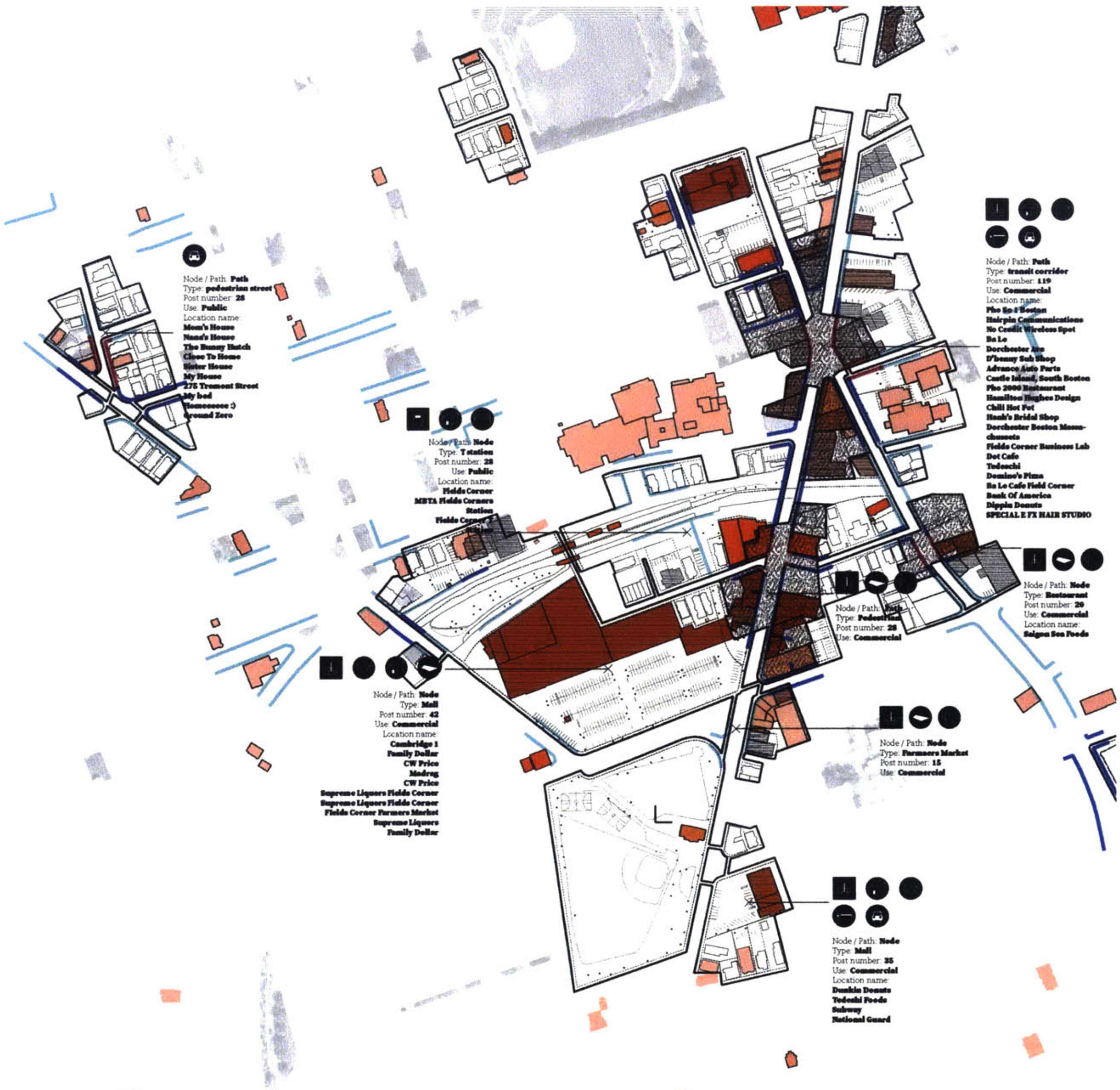
Also, while the type of building showed a very high concentration in commercial places, buildings discovered through the process showed a more wider range of programs, including more public places like sports fields, schools libraries and religious buildings.

What is this place?

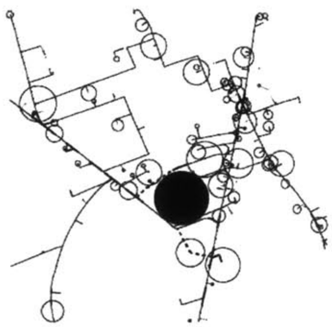
The mapping of the connectivity of pathways, the cores and peripheries, and the important buildings generated a map as in the right side. With this map, I went on a site visit to experience the places in person. The marked pathways, cores, and buildings served as a guide for the visit. The places highlighted became the places to be observed with more attention.

The site visit provided a whole new perspective in understanding the locality of the neighborhood, since it was an experience where I could see things that are not captured in any of the analysis process. The sound, the way people use the places, the atmosphere helped to understand the reason why these places were geo-tagged in social network services.

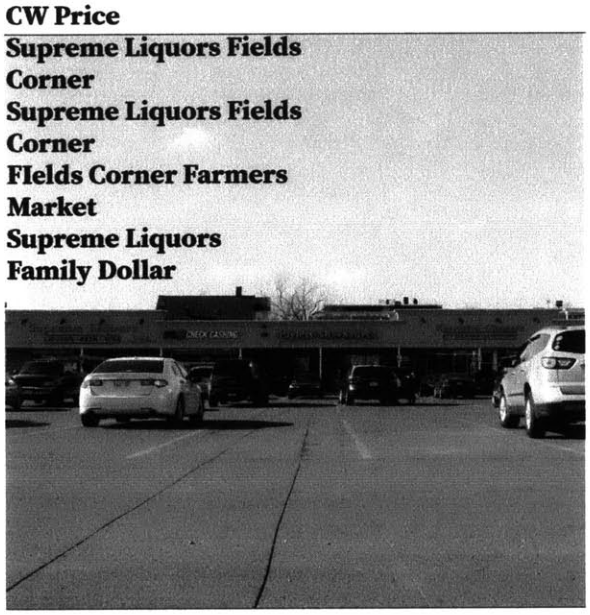
The following is a documentation of the experiences coupled with the status of the places in the psychological geography.


Node / Path: Path
Type: pedestrian street
Post number: 28
Use: Public
Location name:
Mom's House
Nana's House
The Bunny Hutch
Close To Home
Sister House
My House
275 Tremont Street
My bed
Homeeeeeee :)
Ground Zero
Node / Path: Node
Type: T station
Post number: 28
Use: Public
Location name:
Fields Corner
MBTA Fields Corners Station
Node / Path: Path
Type: transit corridor
Post number: 119
Use: Commercial
Location name:
Pho So 1 Boston
Hairpin Communications
No Credit Wireless Spot
Ba Le
Dorchester Ave
D'benny Sub Shop
Advance Auto Parts
Castle Island, South Boston
Pho 2000 Restaurant
Hamilton Hughes Design
Chili Hot Pot
Hanh's Bridal Shop
Dorchester Boston Massachusetts
Fields Corner Business Lab
Dot Cafe
Tedeschi
Domino's Pizza
Ba Le Cafe Field Corner
Bank Of America
Dippin Donuts
SPECIAL E FX HAIR STUDIO
Node / Path: Node
Type: Restaurant
Post number: 20
Use: Commercial
Location name:
Saigon Sea Foods
Node / Path: Path
Type: Pedestrian
Post number: 28
Use: Commercial
Node / Path: Node
Type: Mall
Post number: 42
Use: Commercial
Location name:
Cambridge 1
Family Dollar
CW Price
Madrag
CW Price
Supreme Liquors Fields Corner
Supreme Liquors Fields Corner
Fields Corner Farmers Market
Supreme Liquors
Family Dollar
Node / Path: Node
Type: Farmers Market
Post number: 15
Use: Commercial
Node / Path: Node
Type: Mall
Post number: 35
Use: Commercial
Location name:
Dunkin Donuts
Tedeshi Foods
Subway
National Guard

1 Mall

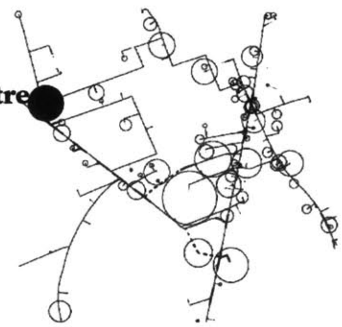


Node / Path: **Node**
Type: **Mall**
Post number: **42**
Use: **Commercial**
Location name:
Cambridge 1
Family Dollar
CW Price
Madrag
CW Price
Supreme Liquors Fields Corner
Supreme Liquors Fields Corner
FIelds Corner Farmers Market
Supreme Liquors
Family Dollar



The Mall contained the most numbers of posts projected on single buildings. By the time of my visit, which was late Saturday afternoon, it was a busy place with a lot of families shopping. Many people were using their car, giving the impression of a place people visit once in a while even from some distances.

2 Ridgewood street

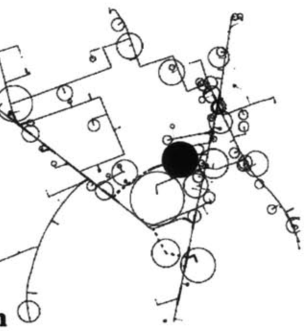


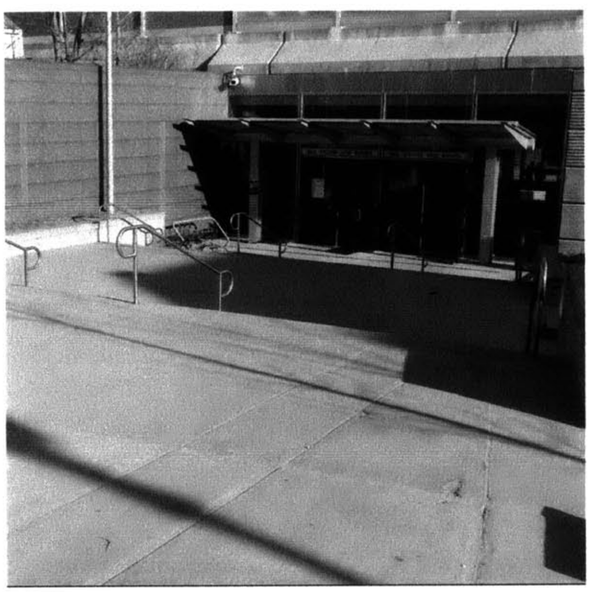
Node / Path: **Path**
Type: **pedestrian stre**
Post number: **28**
Use: **Public**
Location name:
Mom's House
Nana's House
The Bunny Hutch
Close To Home
Sister House

This spot is in the middle of the street, containing 28 posts. The street is within the residential neighborhood. But there is nothing around memorable. Later, once I got back from the trip when I was collecting location names, I realized that this location contains a lot of names like 'home', ' mom's house'.

3 Fields Cornder Station

Node / Path: **Node**
Type: **T station**
Post number: **28**
Use: **Public**
Location name:
Fields Corner
MBTA Fields Corners Station
Fields Corner T Station

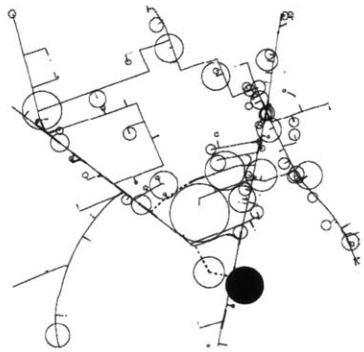


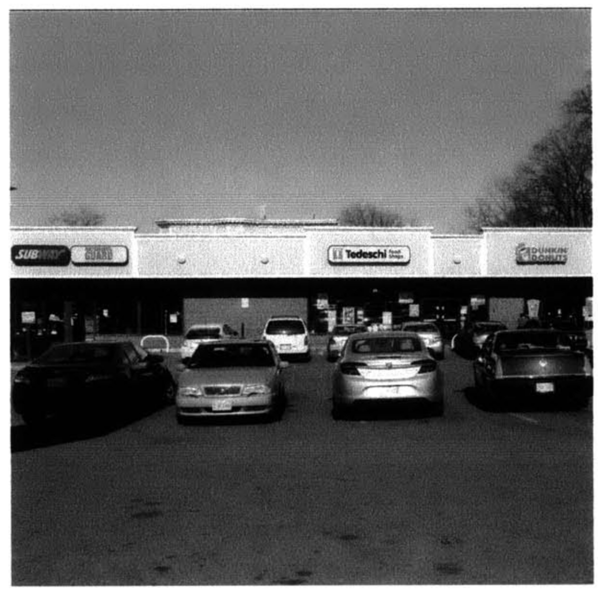


Fields Corner T station is the place one would meet the first, arriving to the neighborhood. Reflecting the waiting time, the number of posts were understandable. Posting from here seemed like a way to spend the waiting time.

4 Tedeschi

Node / Path: **Node**
Type: **Mall**
Post number: **26**
Use: **Commercial**
Location name:
Dunkin Donuts
Subway
Tedeschi food
National guards

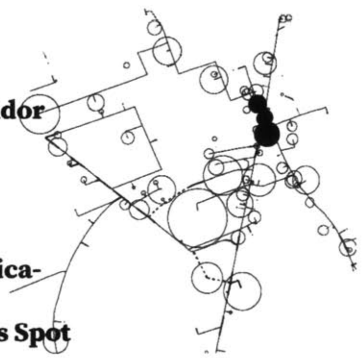




Tedeshi food is a drive in mall that has a Dunkin Donuts, Subway, Tedeschi food, and National guards store. The store itself did not appear really interesting, I thought that maybe the fact that it was located right next to the park could be the reason for the high appearances.

5 Dorchester Avenue

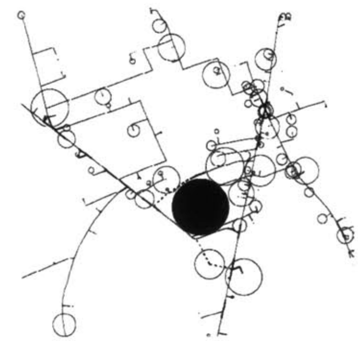
Node / Path: **Path**
Type: **transit corridor**
Post number: **119**
Use: **Commercial**
Location name:
Pho So 1 Boston
Hairpin Communications
No Credit Wireless Spot
Ba Le
Dorchester Ave
D'Benny Sub Shop
Advance Auto Parts
Castle Island, South Boston
Pho 2000 Restaurant
Hamilton Hughes Design
Chili Hot Pot
Hanh's Bridal Shop
Dorchester Boston Massachussets
Fields Corner Business Lab
Dot Cafe
Tedeschi



The intersection of Dorchester avenue was clearly a center of all commercial activities, with a very large percentage of Vietnamese restaurants and Asian retail stores. The strong presence of Vietnamese culture in this area gave the sense that this is a very important cultural component of the neighborhood.

6 Fieds corner playground

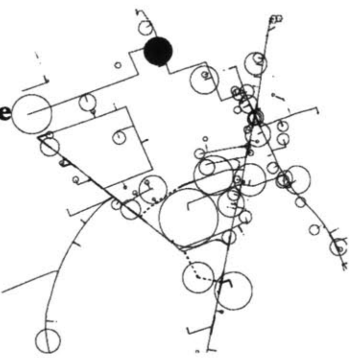
Node / Path: **Node**
Type: **Sports field**
Post number: **22**
Use: **Public**



Fileds Corner's sports filed was mostly under construction and only a small playground was operational. It was crowded with kids playing and parents or baby sitters watching the kids play.

7 Draper street

Node / Path: **Node**
Type: **private house**
Post number: **20**
Use: **Private**



The house on Draper street was one of the private locations where a lot of posts happened. Unlike in Ridgewood street, theis seemed like a location from which one user posts constantly.

8 Sai gon Seafood restaurant

Node / Path: **Node**
Type: **Restaurant**
Post number: **20**
Use: **Commercial**

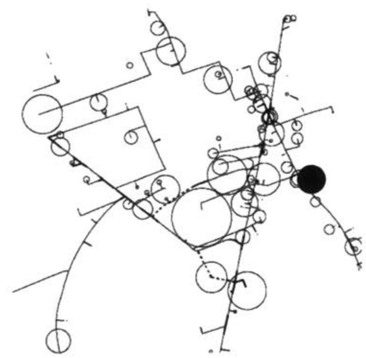


image source: google street view

The Saigon food restaurant is one of the places I did not take notice when I was doing the site visit. It was an unexpected location to be an important spot of the neighborhood.

What is not this place?

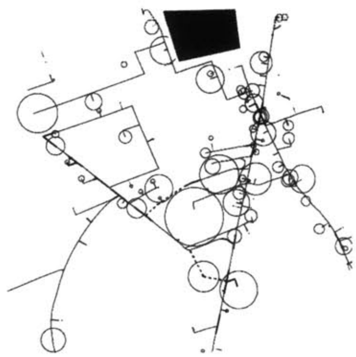
Public spaces are places intentionally designed for the purpose of gathering and social interaction. Therefore, the public institutions and recreational open spaces that never appeared between the year of 2010 and 2014 in Instagram triggered the curiosity.

The site visit provided an opportunity to understand why this happens, and also left some questions. Some spaces like police stations or schools are public in the sense that one can freely enter the place, but not social because they perform a specific function that not necessarily encourages geo-tagging activities. Therefore, I put emphasis on the observation of people's usage of the place as a priority of the site visit.

The following is a documentation of the experiences coupled with the status of the places in the psychological geography.

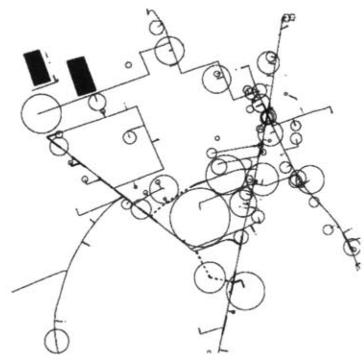

Community Academy of
Science and Health
Helen Y. Davis Leadership
Academy Charter Public School
10 Josephine
Street Garden
29 Josephine
Street Garden
Grover Cleveland
Middle/Community Center
Boston Police District C-11
Dorchester

1 Ronan Park



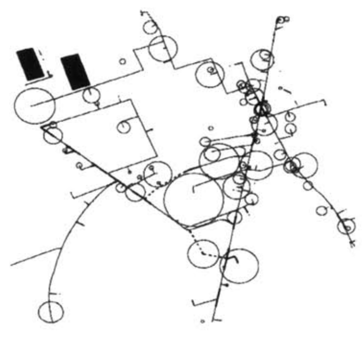
Ronan Park was one of the locations that totally drew my attention during the primary research. The complete absense from Instagram location data was difficult to explain. Some theories were that the place might be poorly maintained or subject to crime, hence lacking personal activities taking place. However, at the time I visited, I realized that it is a perfectly fine park with a lot of people sitting, doing sports and having a good time.

2 Josephine street garden



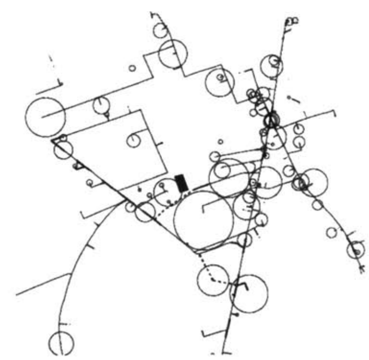
Josephine street garden is located in the middle of a single family housing area. Since it was early spring, nothing was grown in the park but people were fixing the fense. The small pocket space looked like being well maintained by people.

3 street garden



This street garden is located at the corner of a street. The mural on the wall and the boxes where seeds were planted showed traces of maintainence, and I saw a lot of people traveling through this open land.

4 VIET-AID

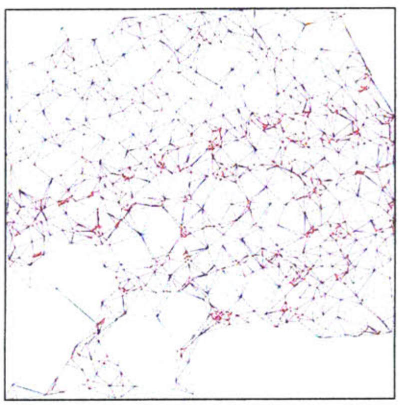


Viet-Aid was one of the places that had unexpectedly no action captured in Instagram. It is a community center for the Vietnamese community in Fields Corner, and their website displays a lot of content about their events. It seemed like a good resource to be used.

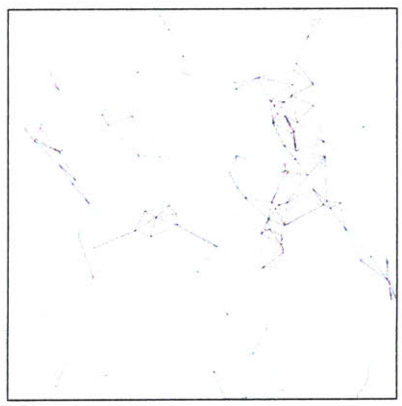
3 Comparative analysis

Back Bay, Fields Corner, Blue hills Avenue

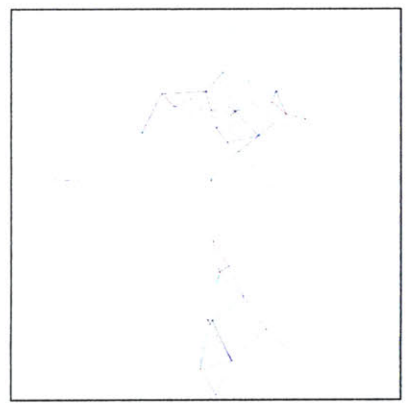
Net -Pathway analysis



A4 Back Bay



C2 Fields Corner

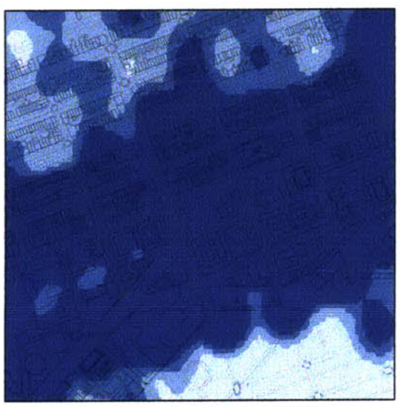


E1 Mattapan

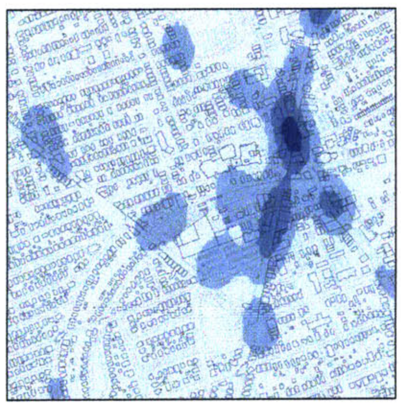
The comparison between Back Bay, Fields Corner, and Mattapan in the 'Net' analysis shows that the fineness of the net significantly drops from Back Bay, to Fields Corner and then in Mattapan. Overlapped with the type of streets showed that the sparse connection in Mattapan is mainly on commercial corridor, whereas that of Back Bay includes both commercial and public corridors.

In a lens of socio-economic status, this analysis shows that the lower the socio-econimic class becomes, the pathways that are marked as important become more the commercial corridors.

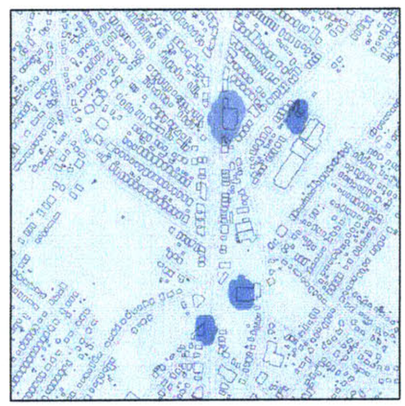
Area - Core analysis



A4 Back Bay



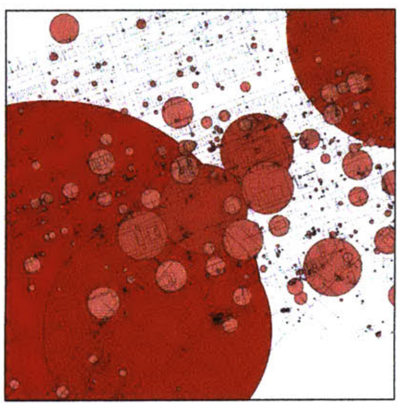
C2 Fields Corner



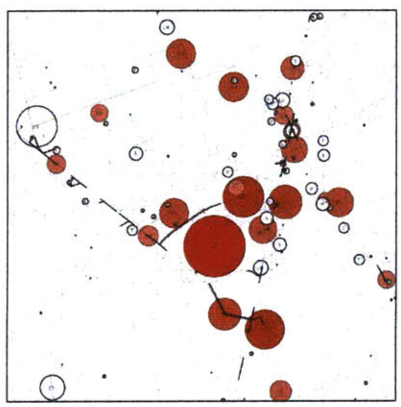
E1 Mattapan

Comparing the central areas in Back Bay, Fields Corner, and Mattapan shows that the core of the neighborhood is easier to detect in Mattapan rather than Back Bay, because the center defined through the borders in Back bay includes most of the studied area, while the core areas in Mattapan are very few.

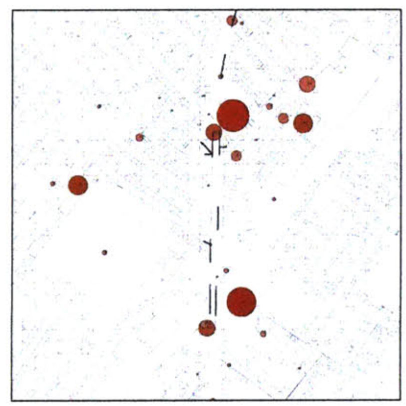
Intensity - Building analysis



A4 Back Bay



C2 Fields Corner

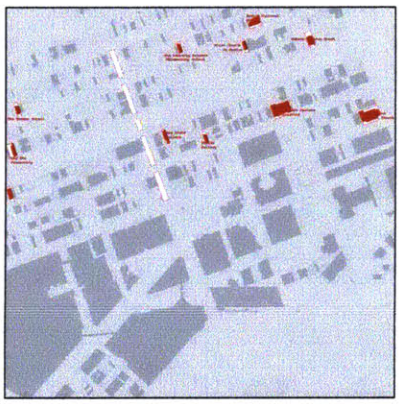


E1 Mattapan

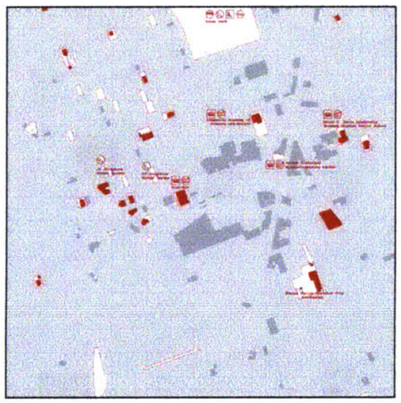
The intensity map of geo-tagging activities per parcel have an extreme distinction in the three studied areas. In Back Bay the largest circles are drawn around the Prudential Center and the Boston Common, followed with the Copely plaza and the Copely square. In Mattapan, the biggest circle was drawn on the public library followed by a shopping center.

The intensity of geo-tagging activities varied a lot among the sites, but fact that the type of buildings range from commercial space to public space was a similarity captured throughout.

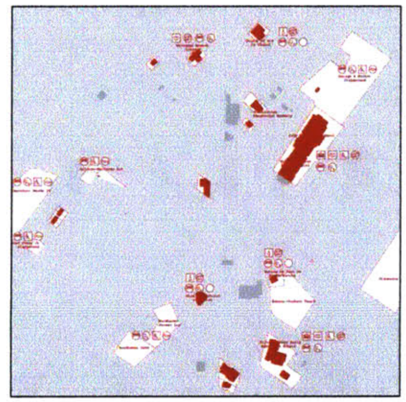
Places Out



A4 Back Bay



C2 Fields Corner

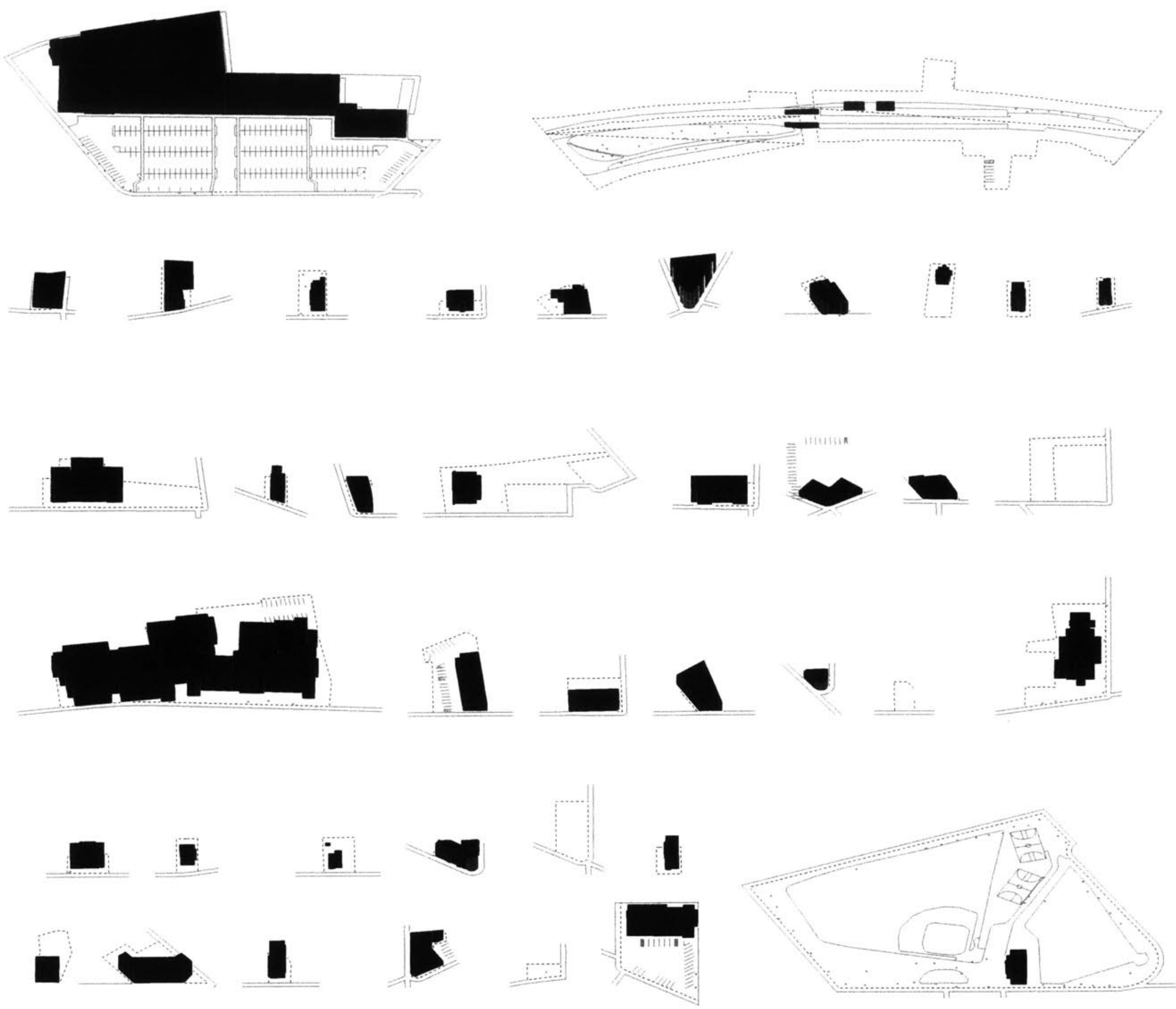


E1 Mattapan

The ratio of locations in public space decreased from Back Bay to Mattapan, indicating that meaningful places are more private and commercial as the density of locations decreases and the socio-economic status becomes lower. One surprising thing is that the geo-tagging activity in public spaces was the lowest despite the fact that Mattapan has the largest coverage of public institutions among the three sites.

The type of places that fall outside the psychological geography naturally differ. In Back bay, there was a high ratio of educational institutions, while community gardens were added in Fields Corner, and parks and religious buildings were added to the list in Mattapan.

4 Conclusion



The Manual to read social space in neighborhood scale operates in two different scales and purposes. One is to identify the locality of the given neighborhood through an analysis that clarifies the program and spatial element that forming the pathway, core and building. And the other is to compare neighborhoods with these measures.

The first scale demonstrates its capacity to capture the cultural landscape of the neighborhood because of the specific places that are emphasized through the analysis. However, questions on whether the user resides within the neighborhood or not remains unresolved, making it still unclear what role these places actually play in individual's life. For instance, the mall that was pointed out as the most important building could include more long distance travelers who visit it, and therefore receive more geo-tagged posts. Therefore, future work could include additionally a user analysis that identifies residents from non-residents.

The second scale shows that different patterns emerge in each neighborhood that can be characterized through the analysis of the first scale. With an addition research it will be able to compare different neighborhoods with the same depth of the research on Fields Corner.

While the research show a possibility to utilize social network service data as a tool to understand the local character of a given area, it also opens possibilities to future work that can be initiated through this approach. One of them could be identifying the sub centers of the city and conducting a comparative analysis on their spatial character. And another interesting direction would be going deeper in the content or user analysis to understand the psychological geography that might not be nessecarily bound to physical space.

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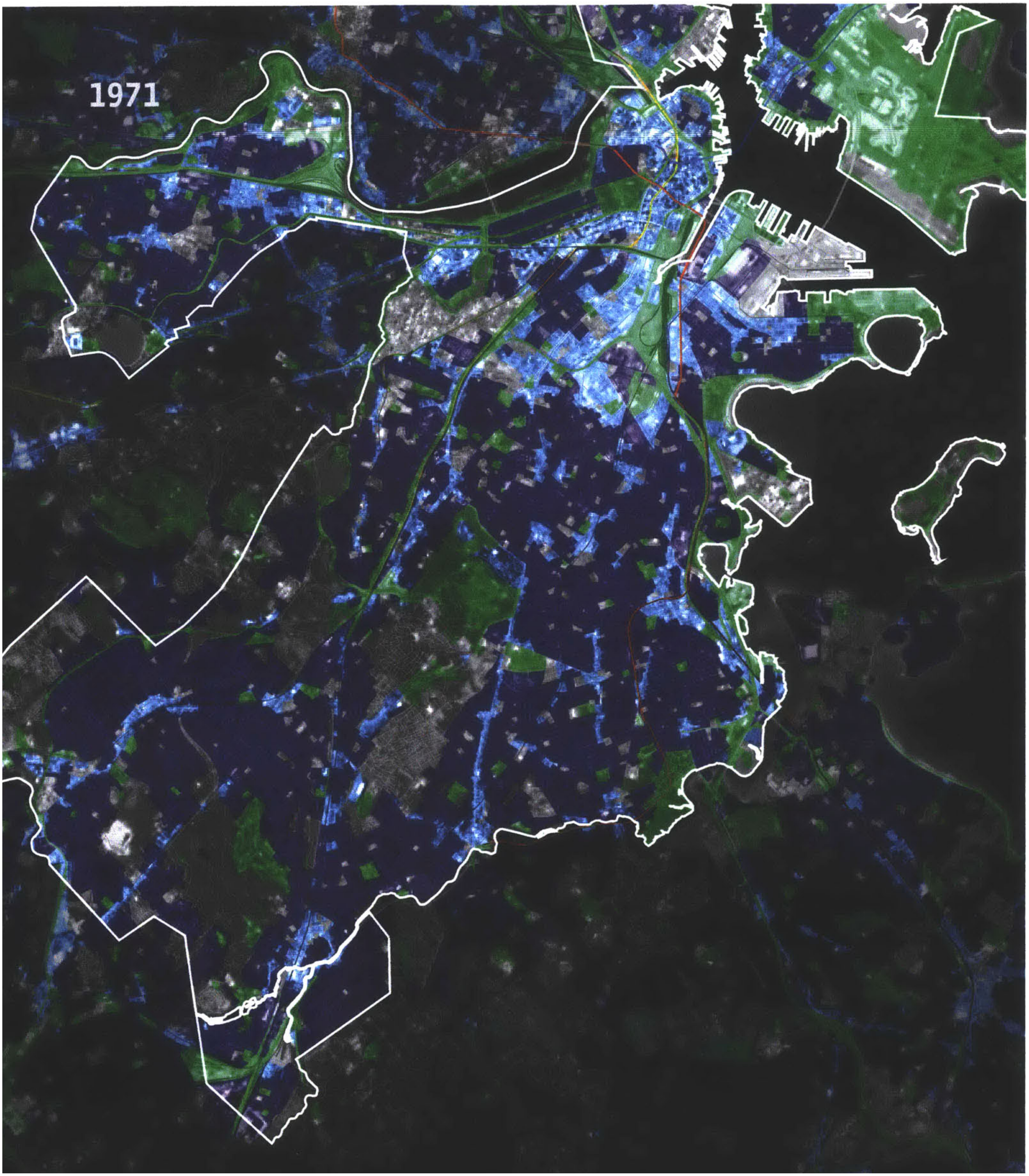
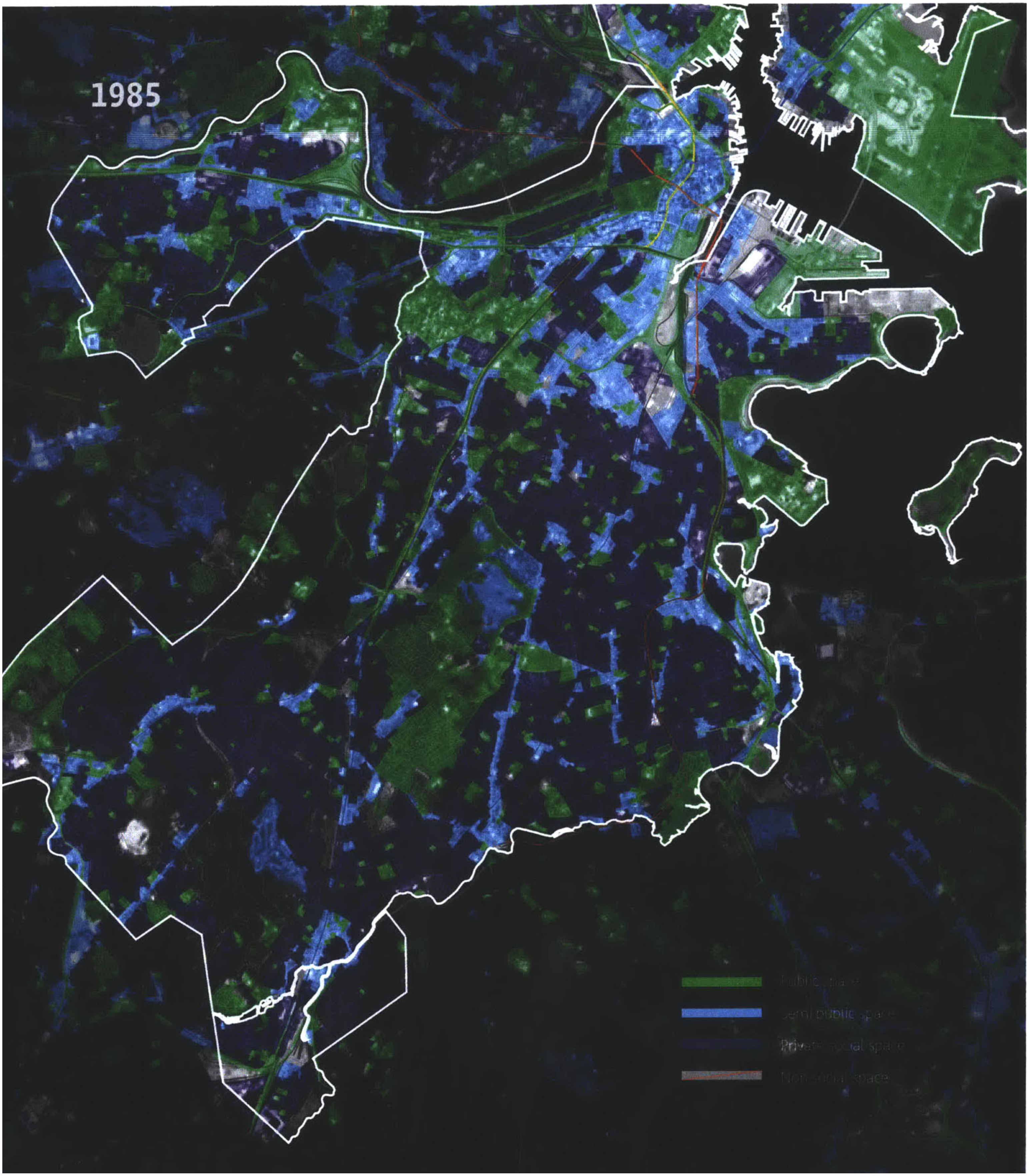
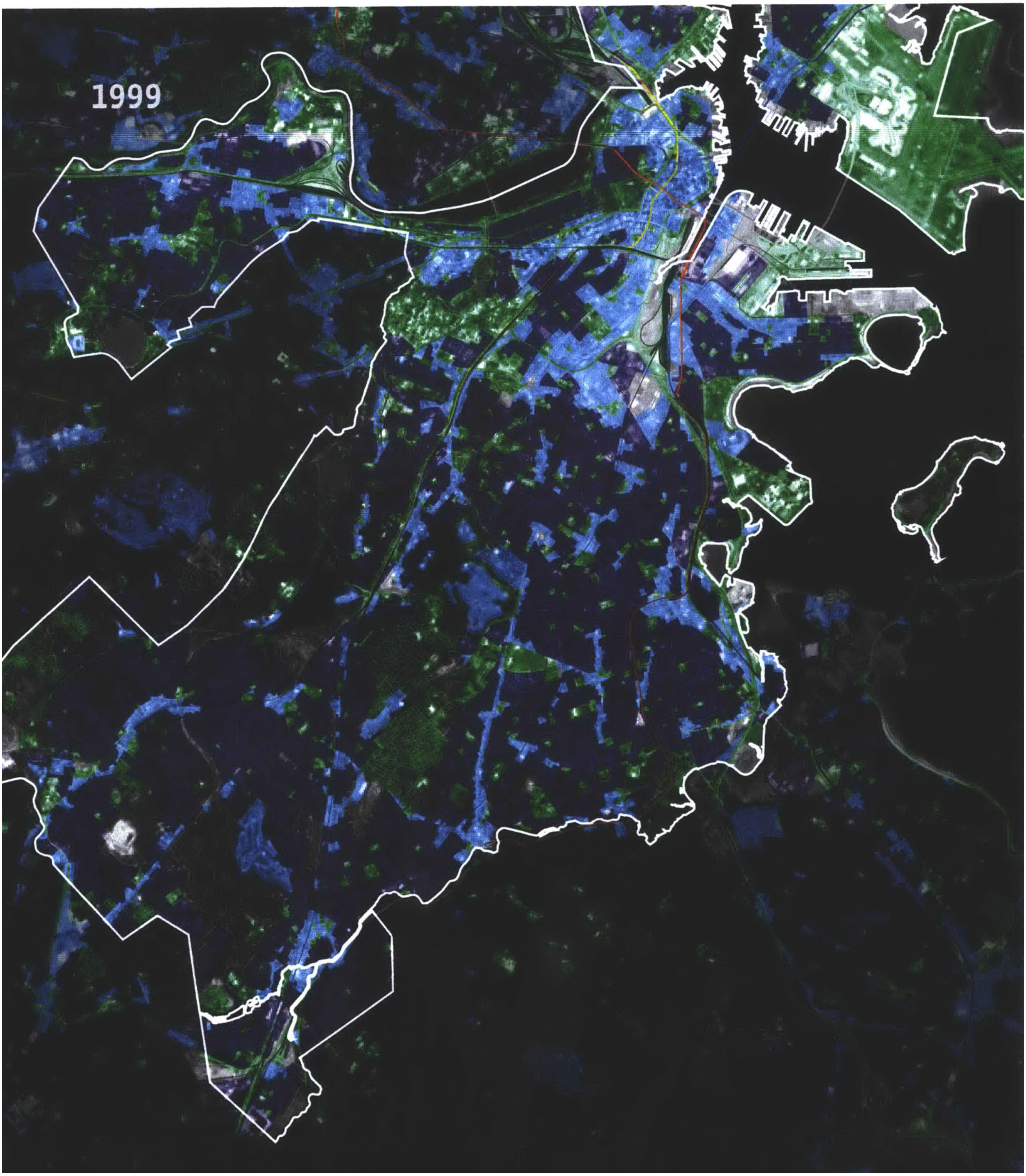
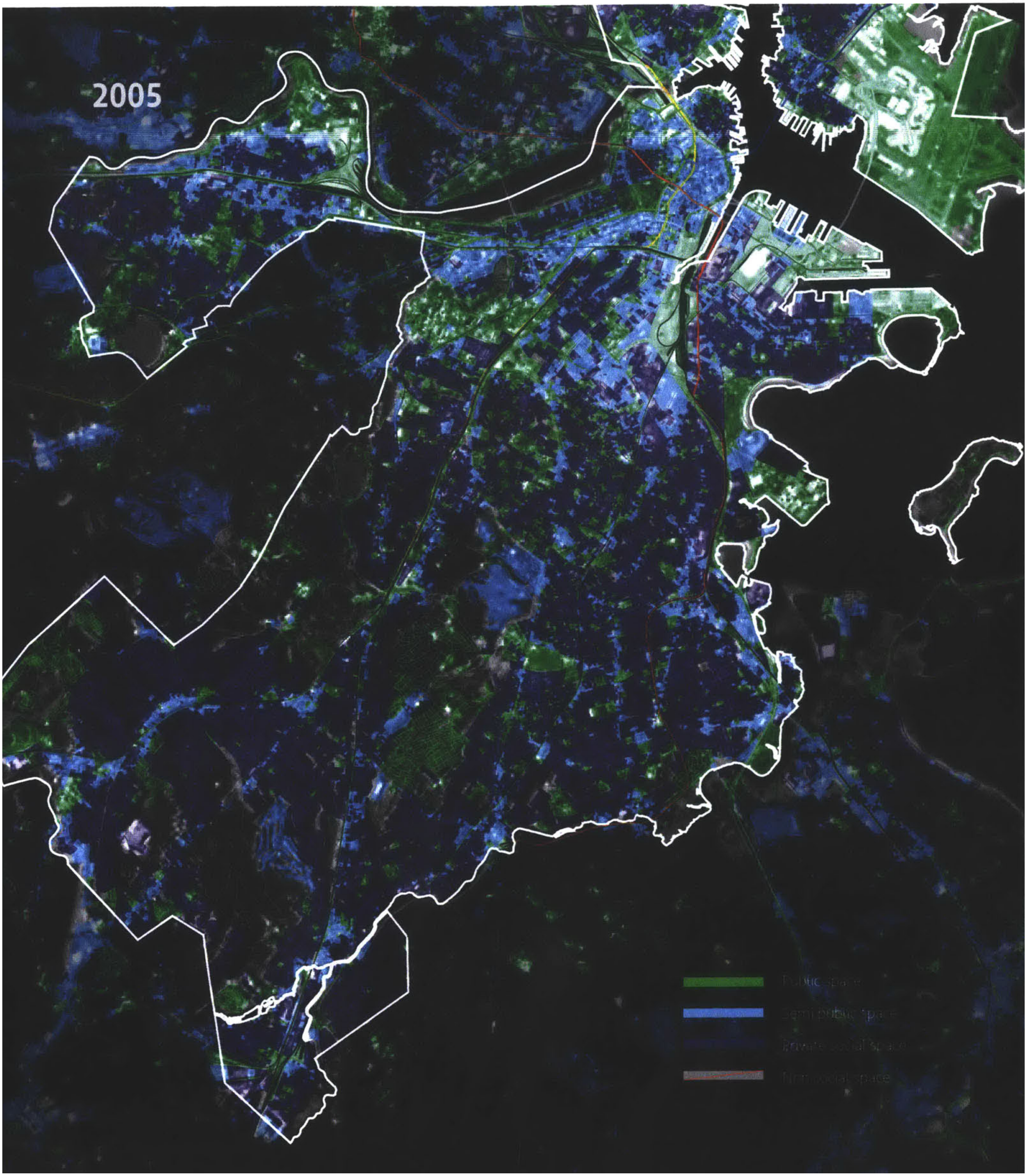
[Fig 1] “Map Gallery — CartoDB.” 2015. Accessed May 21. http://cartodb.com/gallery/.
[Fig 2] Lynch, Kevin, The Image of the City. 1960. MIT Press. page 146
[Fig 3] Whyte, William, The social life of small Urban spaces, 1980, Project for public spaces, page 70
[Fig 4] “Data, technology and urban design”, Urban Design: Data, technology and urban design, 132, Autumn 2014: 20-36. Cover page

Appendix 1
land use change from 1971 to 2005




1985
Public space
Semi public space
Private social space
Non social space


1999


2005
Public space
Semi public space
Private social space
Non social space

Appendix 2

Python code for data collection

```python
import argparse
import json
from pprint import pprint
import sys
import urllib
import urllib2

import oauth2
import requests

API_HOST = 'api.instagram.com'
DEFAULT_LAT = '42.39584072'
DEFAULT_LNG = '-70.99859869'
DEFAULT_DISTANCE = 1000

SEARCH_LIMIT = 5000
SEARCH_PATH = '/v1/locations/search'
LOCATION_PATH = 'v1/locations/'

TOKEN_SECRET = '1369186.26f3b2c.22ca9809bcc14a90876af4f0f5ac3680'

def request(path, url_params=None):
    """"Makes a request do the API_HOST, and can add url_params
    adds access_token by default
    """
    url_params = url_params or {}
    url = u'https://{0}{1}'.format(API_HOST, path)

    url_params['access_token'] = TOKEN_SECRET

    result = requests.get(url, params=url_params)
    try:
        print "got result from", result.url
        results = result.json()
        return results
    except:
        print "couldn't get json"
```

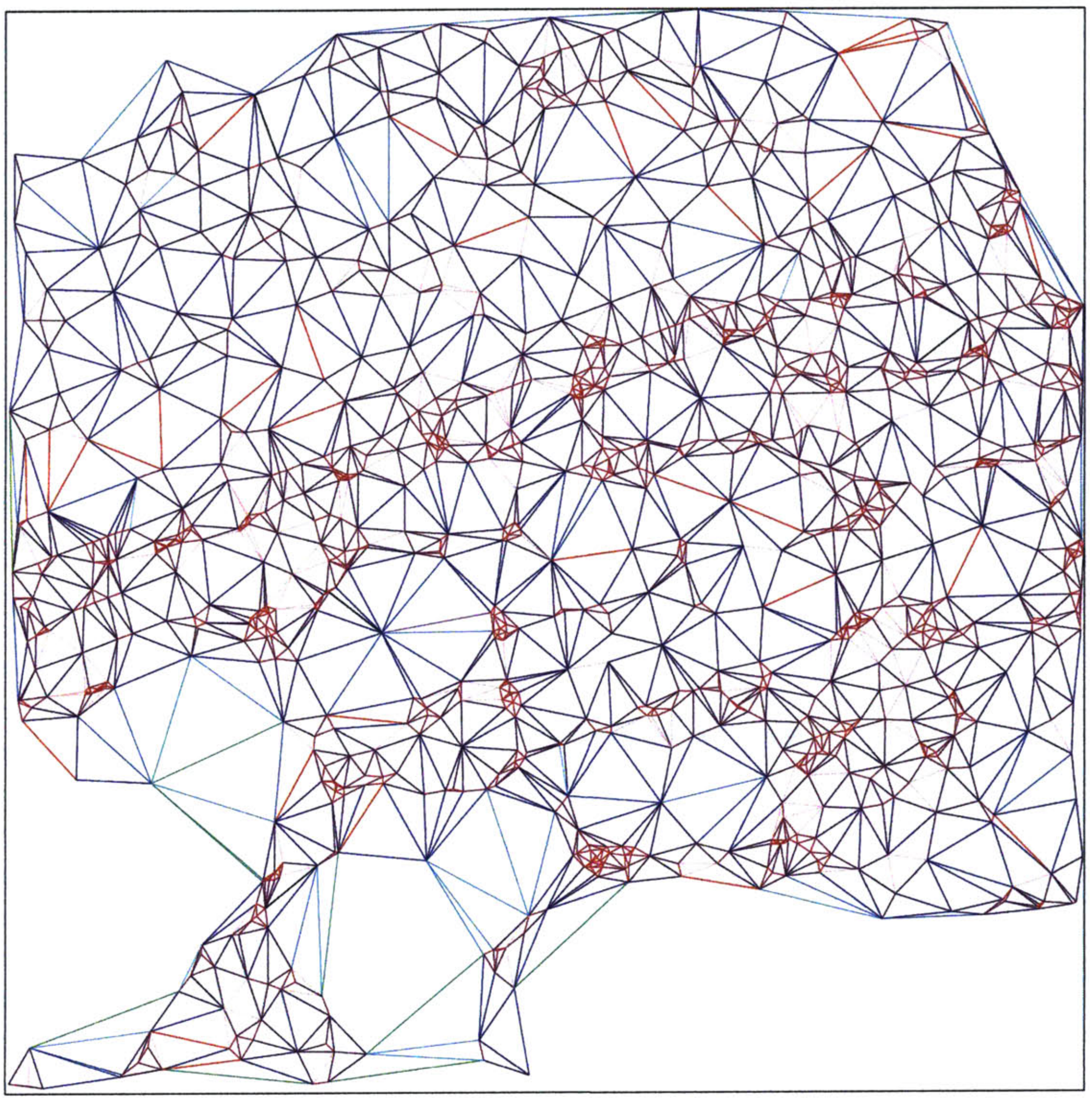
```python
import os
from pprint import pprint
import urllib2

from unicodecsv import DictReader, DictWriter
import csv

from instagram import request


API_HOST = 'api.instagram.com'
DEFAULT_LAT = '42.350457'
DEFAULT_LNG = '-71.079759'
TIMESTAMP = ''
DEFAULT_DISTANCE = 100

SEARCH_LIMIT = 5000
SEARCH_PATH = '/v1/locations/search'
LOCATION_PATH = 'v1/locations/'

TOKEN = '1369186.26f3b2c.22ca9809bcc14a90876af4f0f5ac3680'

post_csv = 'posts.csv'
point_csv = 'points.csv'
locations_csv = 'locations.csv'

DATA = {}

LOCATION_FIELDS = [
    'id',
    'latitude',
    'longitude',
    'num_media',
        ]

POST_FIELDS = [
    'id',
    'type',
    'users_in_photo',
    'tags',
    'comments',
    'created_time',
    'likes',
    'latitude',
    'longitude',
    'name',
    'uid',
    'url',
        ]


POINT_FIELDS = [
        'point_id',
        'lat',
        'lon',
        'num_locations',
        ]

def read_csv(path):
    if os.path.isfile(path):
        with open(path, 'rU') as f:
            reader = DictReader(f, encoding='utf-8')
            data = [row for row in reader]
    else:
        data = []
    return data

def write_csv(path, data, fields):
    with open(path, 'wb') as f:
        w = DictWriter(f, fieldnames=fields, encoding='utf-8', quotechar='"',
                quoting=csv.QUOTE_NONNUMERIC)
        w.writeheader()
        for row in data:
            w.writerow(row)

def get_media(location):
    distance = DEFAULT_DISTANCE
    path = '/v1/locations/' + str(location['id']) + '/media/recent'
    media = request(path)
    return media
```

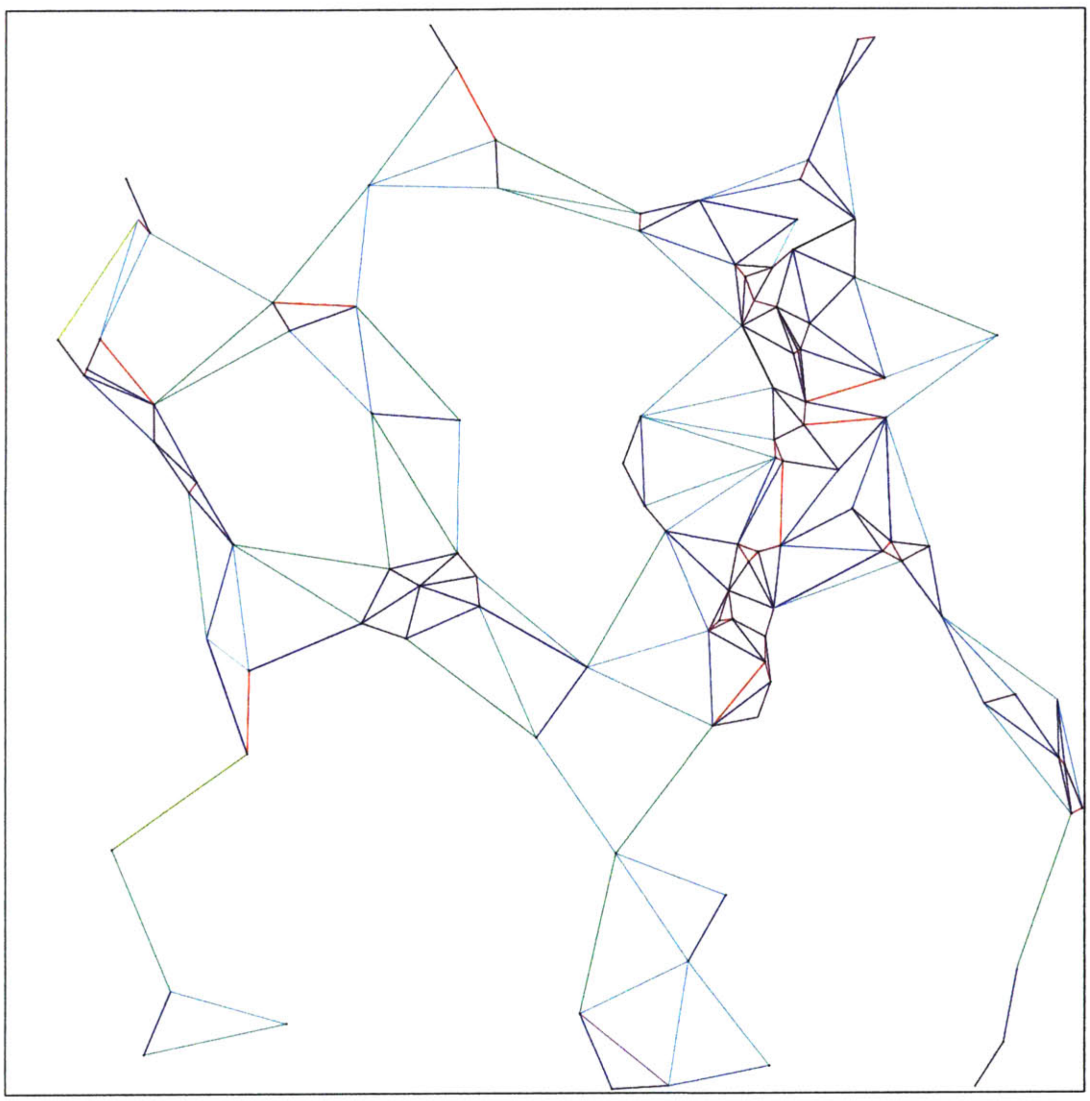
```
def get_locations(point):
    distance = DEFAULT_DISTANCE
    path = '/v1/locations/search'
    locations = request(path, {
        'distance': distance,
        'lat': point['lat'],
        'lng': point['lon'],
        })
    return locations['data']

def read_points():
    return read_csv(point_csv)

def write_points():
    write_csv(point_csv, DATA['points'], POINT_FIELDS)
    print "saved", len(DATA['points']), "points"

def read_csv_to_dictionary(filename, id_key='id'):
    data = {}
    rows = read_csv(filename)
    for row in rows:
        key = row[id_key]
        data[key] = row
    return data

def write_media():
    data = DATA['posts'].values()
    write_csv(post_csv, data, POST_FIELDS)
    print "saved", len(DATA['posts']), "posts"

def write_locations():
    write_csv(locations_csv, DATA['locations'].values(), LOCATION_FIELDS)
    print "saved", len(DATA['locations']), "locations"


def media_format(json):
    post_jsons = json['data']
    posts = []
    for json in post_jsons:
        obj = {}
        obj['id'] = json['id']
        obj['type'] = json['type']
        if 'users_in_photo' in json:
            obj['users_in_photo'] = len(json['users_in_photo'])
        else:
            obj['users_in_photo']= ''
        if 'tags' in json:
            obj['tags'] = ','.join(json['tags'])
        else:
            obj['tags']= ''
        if 'comments' in json:
            obj['comments'] = json['comments']['count']
        else:
            obj['comments']= ''
        obj['created_time'] = json['created_time']
        if 'likes' in json:
            obj['likes'] = json['likes']['count']
        else:
            obj['likes']= ''
        obj['latitude'] =  json['location']['latitude']
        obj['longitude'] = json['location']['longitude']
        obj['name'] = json['location']['name']
        obj['uid'] = json['user']['id']
        obj['url'] = json['images']['thumbnail']['url']
        posts.append(obj)
    return posts

def location_format(json):
    obj = {}
    for key in ['id', 'latitude', 'longitude']:
        obj[key] = json[key]
    obj['num_media'] = 0
    return obj

def add_new_media(json):
    posts = media_format(json)
    for post in posts:
        key = post['id']
        if key not in DATA['posts']:
            DATA['posts'][key] = post

def add_new_locations(jsons):
    locations = []
    for json in jsons:
        location = location_format(json)
        locations.append(location)
        key = location['id']
        if key not in DATA['locations']:
            DATA['locations'][key] = location
    return locations

def do_missing_searches():
    for point in DATA['points']:
        if int(point['num_locations']) < 1:
            loc_data = get_locations(point)
            locations = add_new_locations(loc_data)
            write_locations()
```

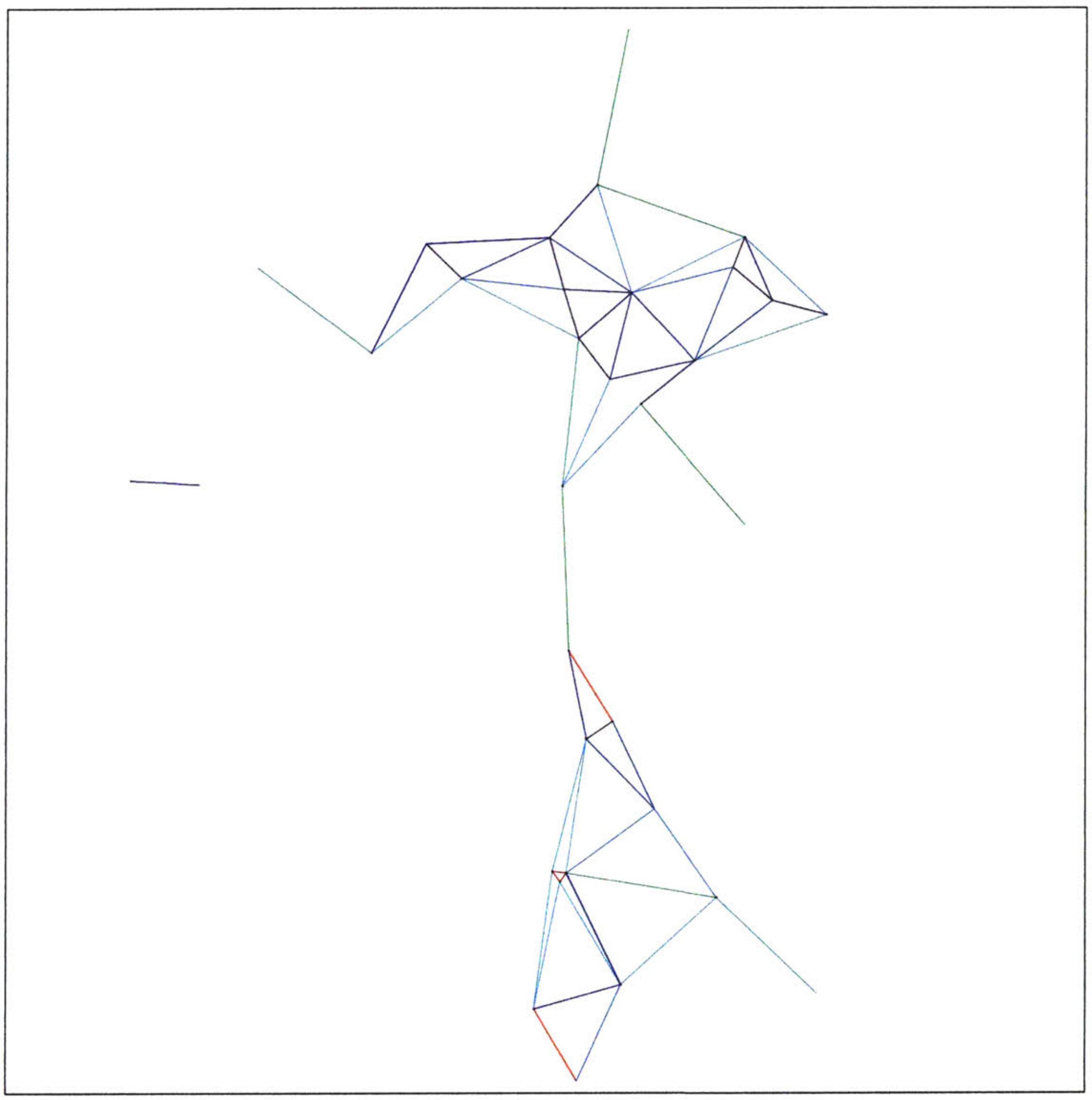
```
            point['num_locations'] = len(locations)
            for location in locations:
                if int(location['num_media']) < 1:
                    new_media = get_media(location)
                    add_new_media(new_media)
                    write_media()
                write_locations()
        write_points()

def main():
    DATA['points'] = read_points()
    DATA['locations'] = read_csv_to_dictionary(locations_csv)
    DATA['posts'] = read_csv_to_dictionary(post_csv)
    do_missing_searches()


if __name__ == '__main__':
    main()
```

Appendix 4

Net analysis on Back Bay, Fields Corner and Mattapan

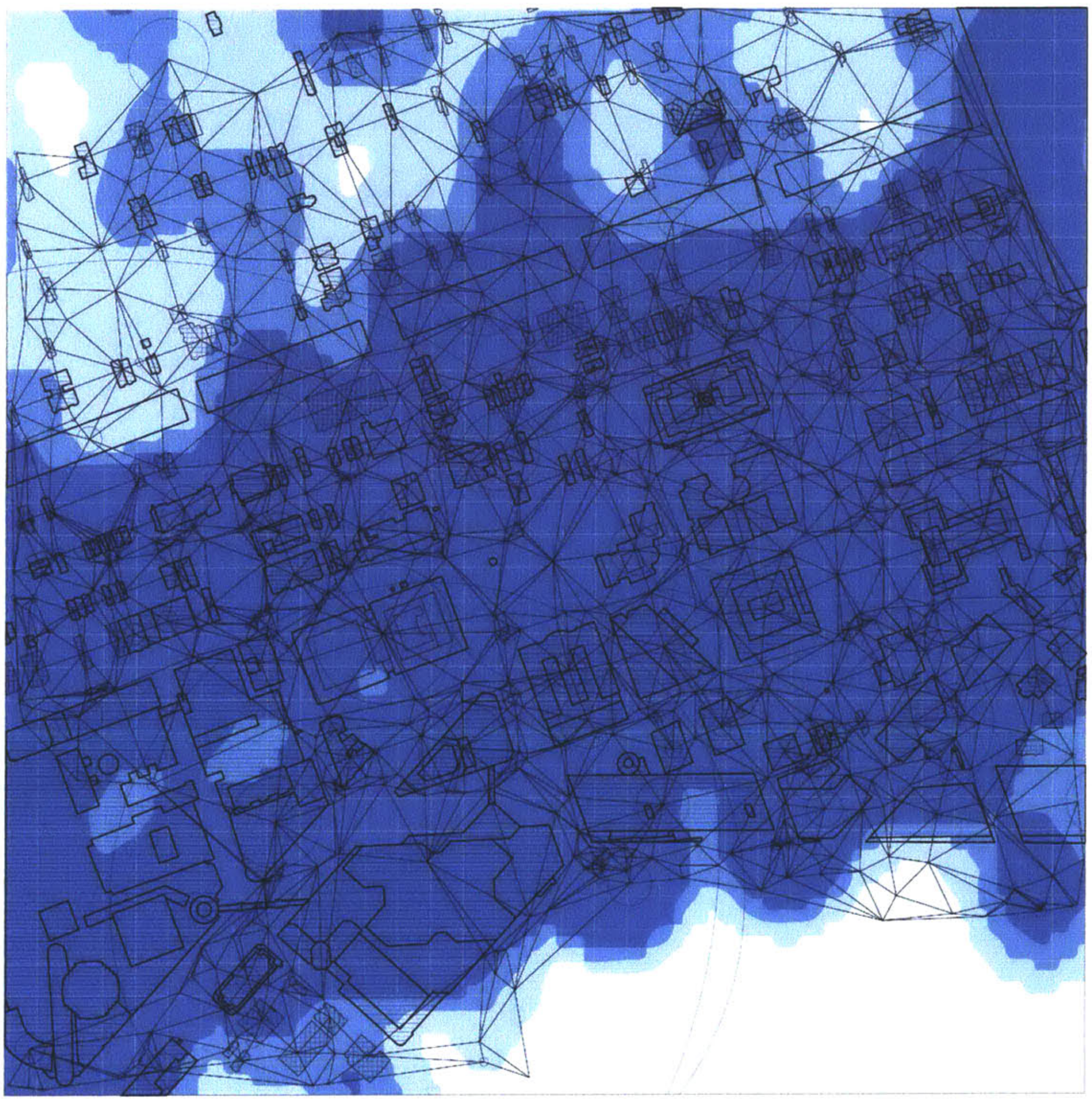


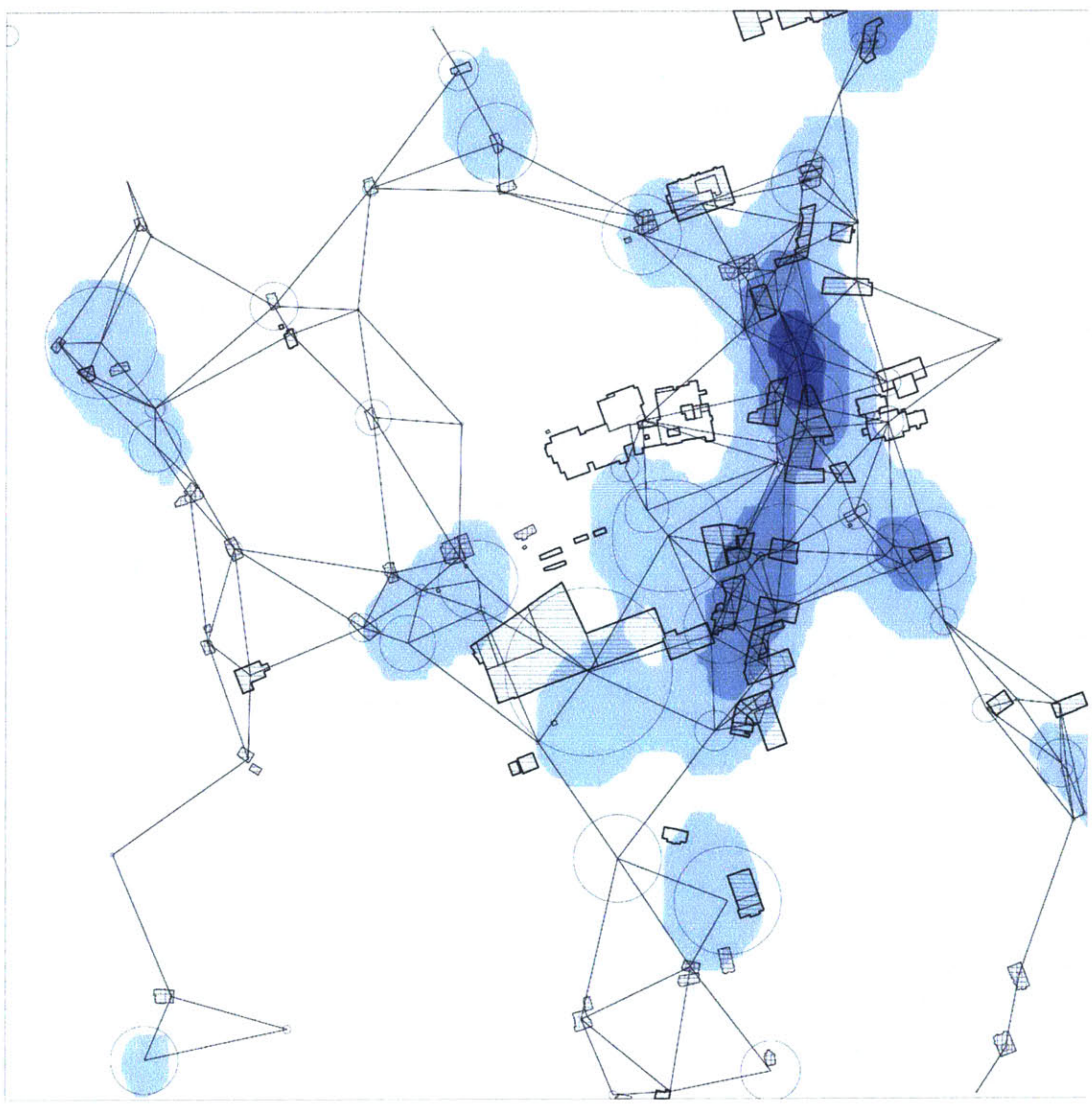


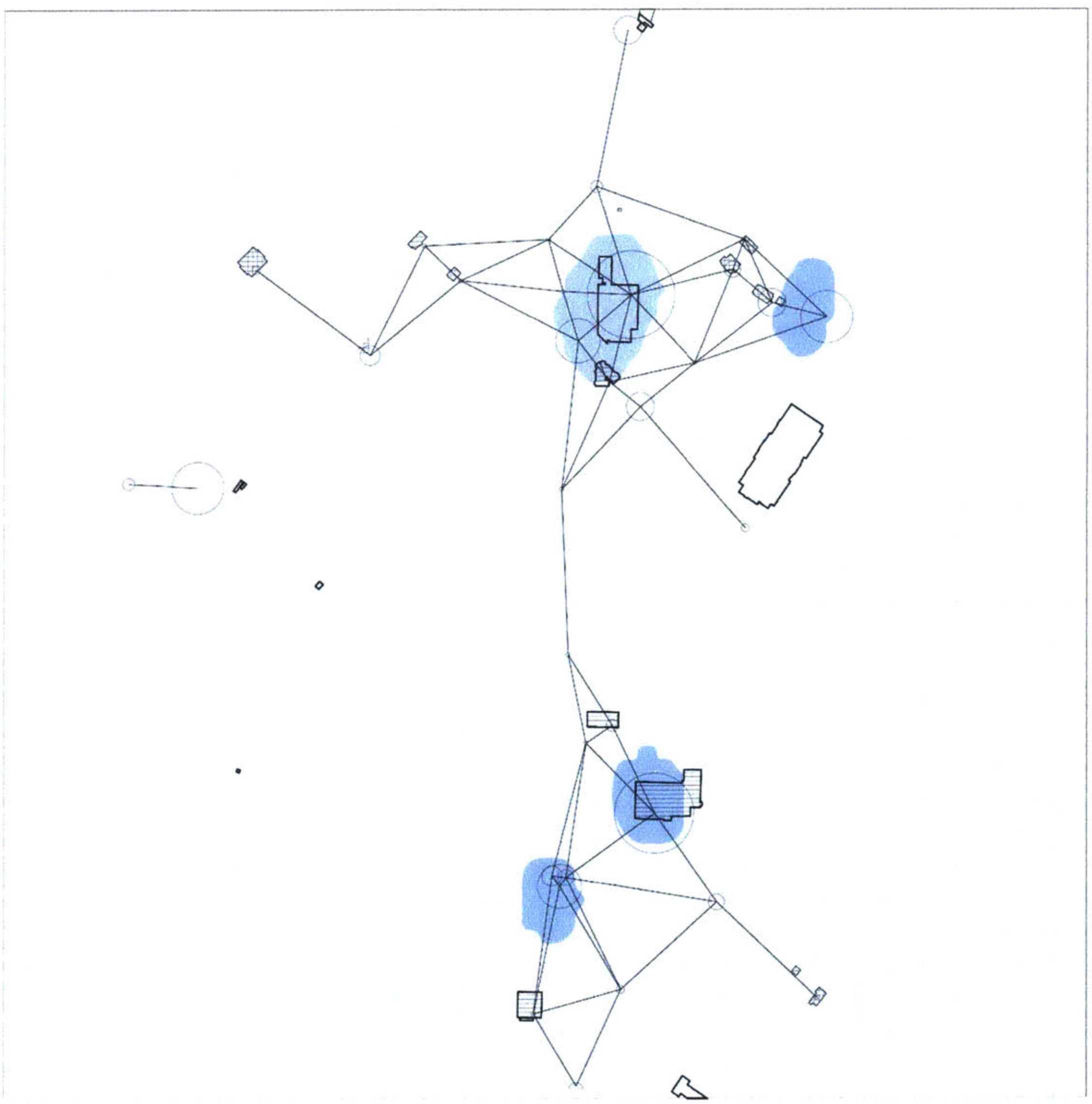


Appendix 5

AREA analysis on Back Bay, Fields Corner and Mattapan

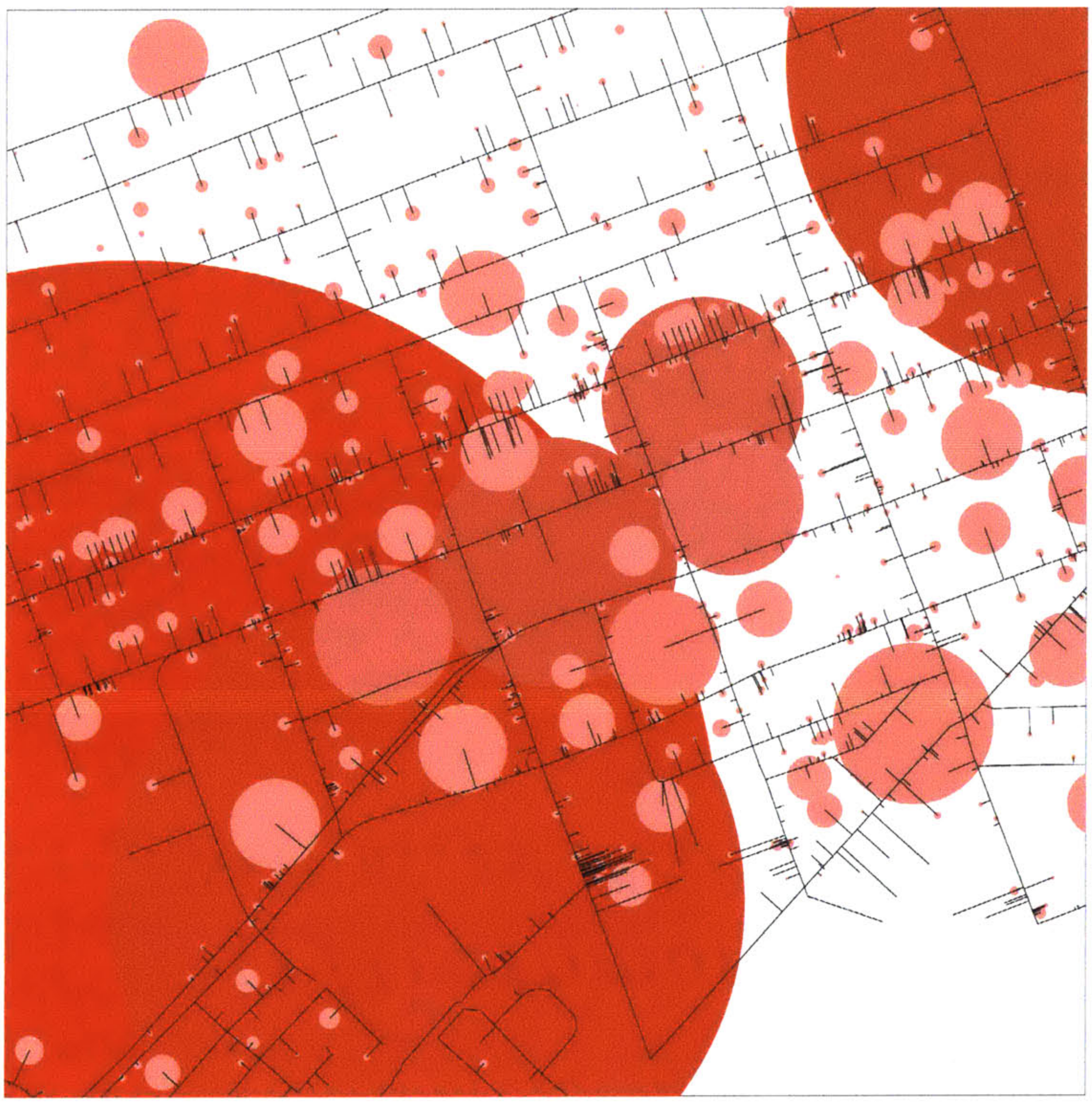


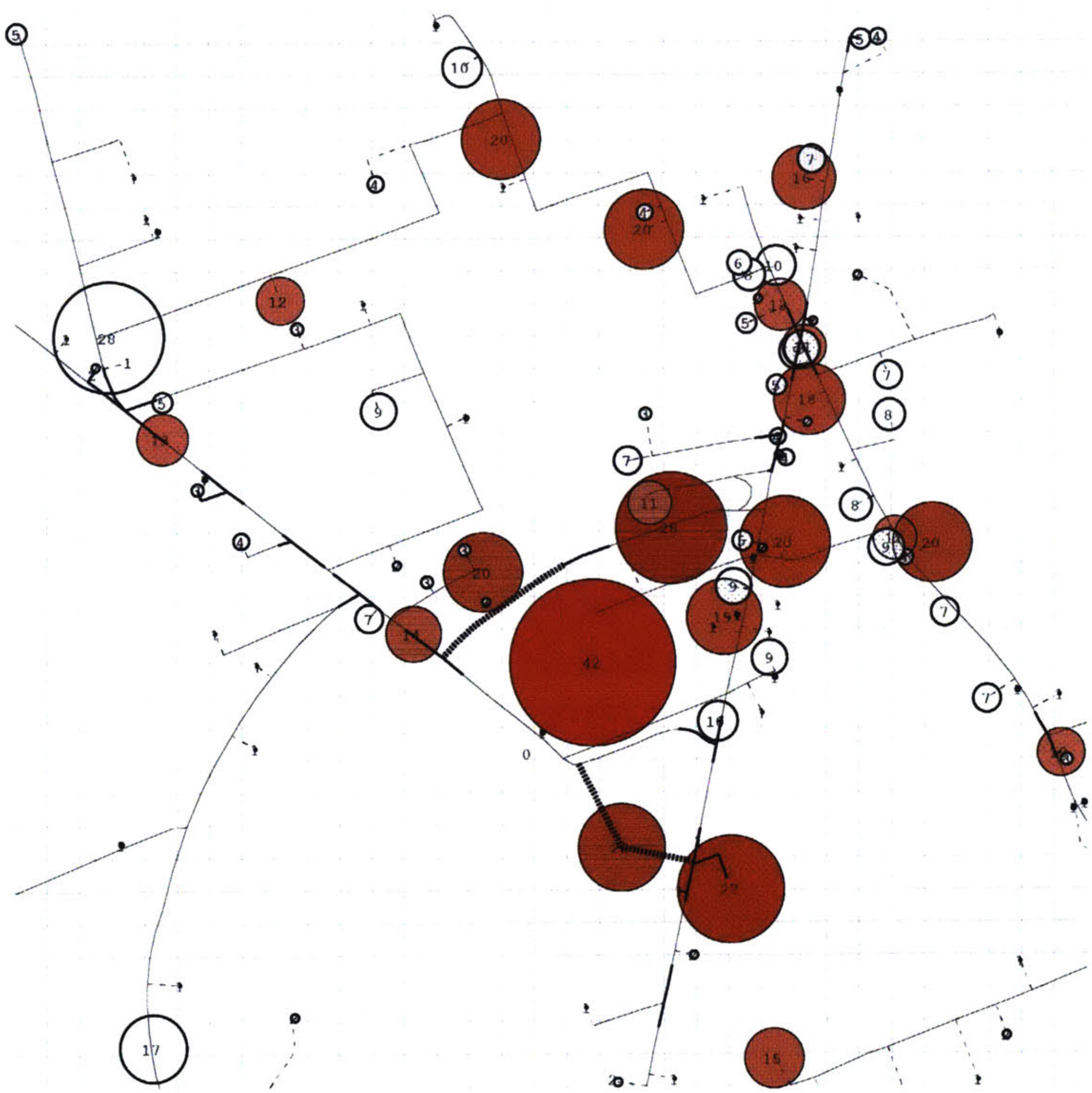


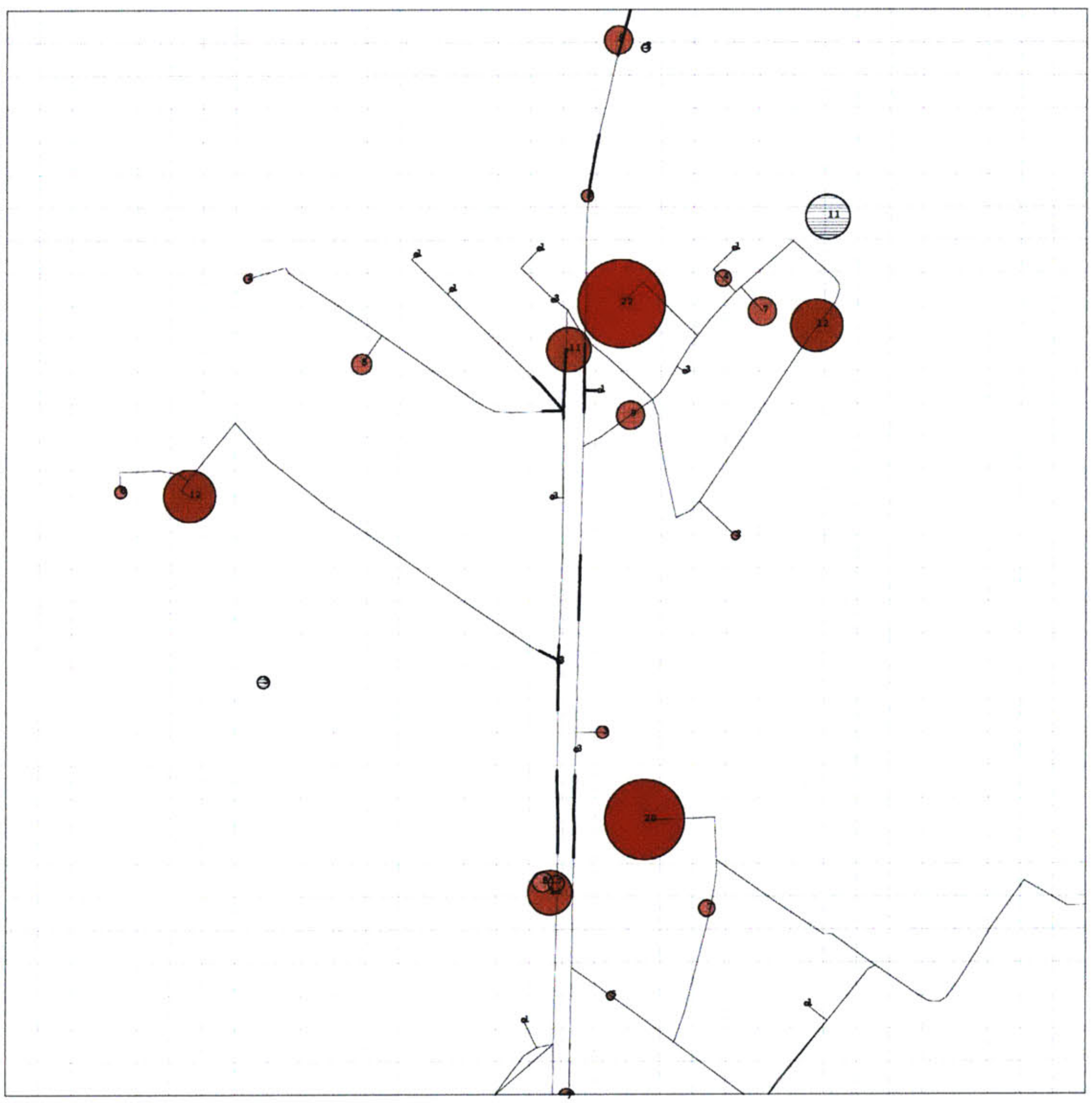


Appendix 6

Intensity analysis on Back Bay, Fields Corner and Mattapan

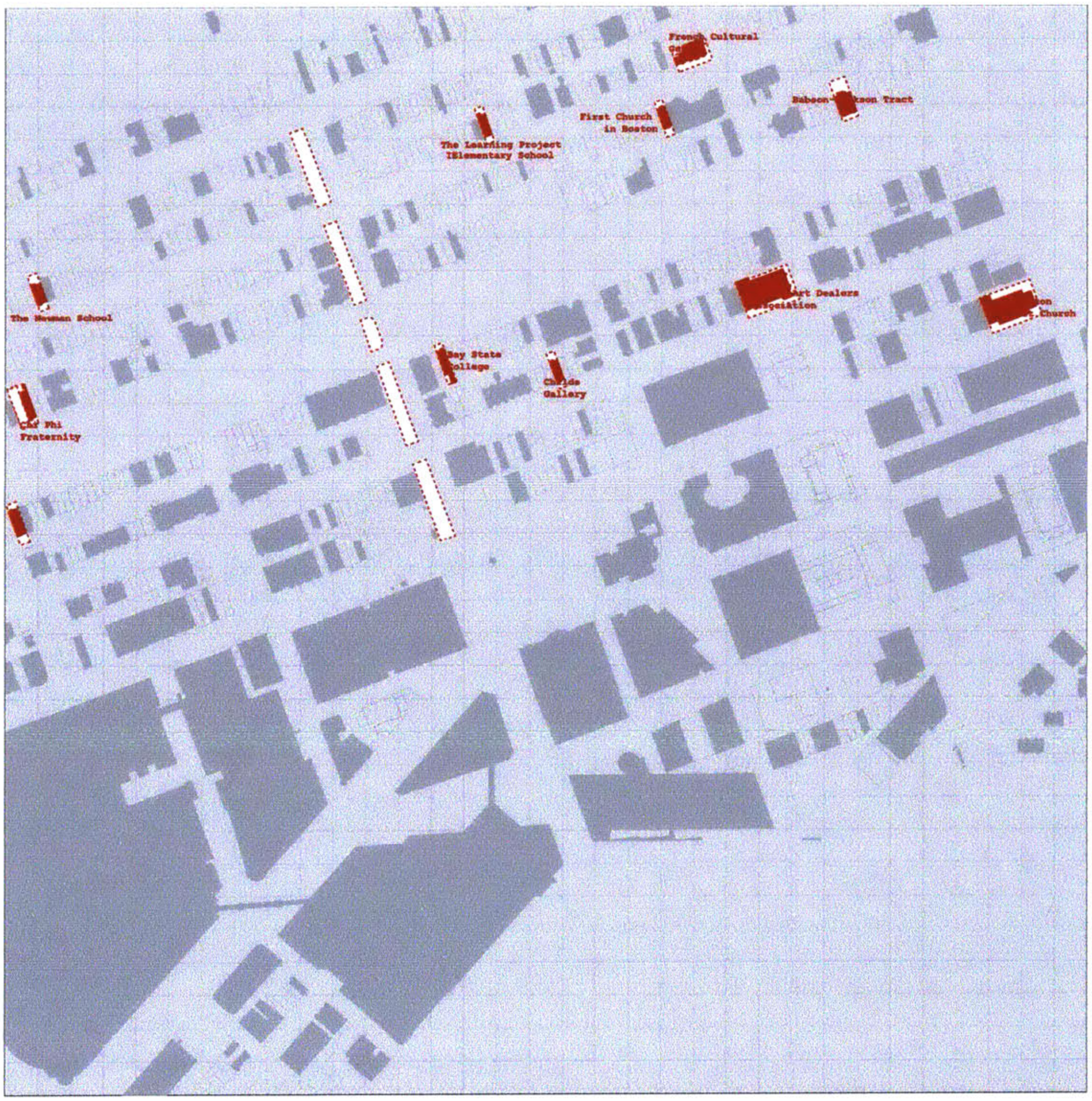


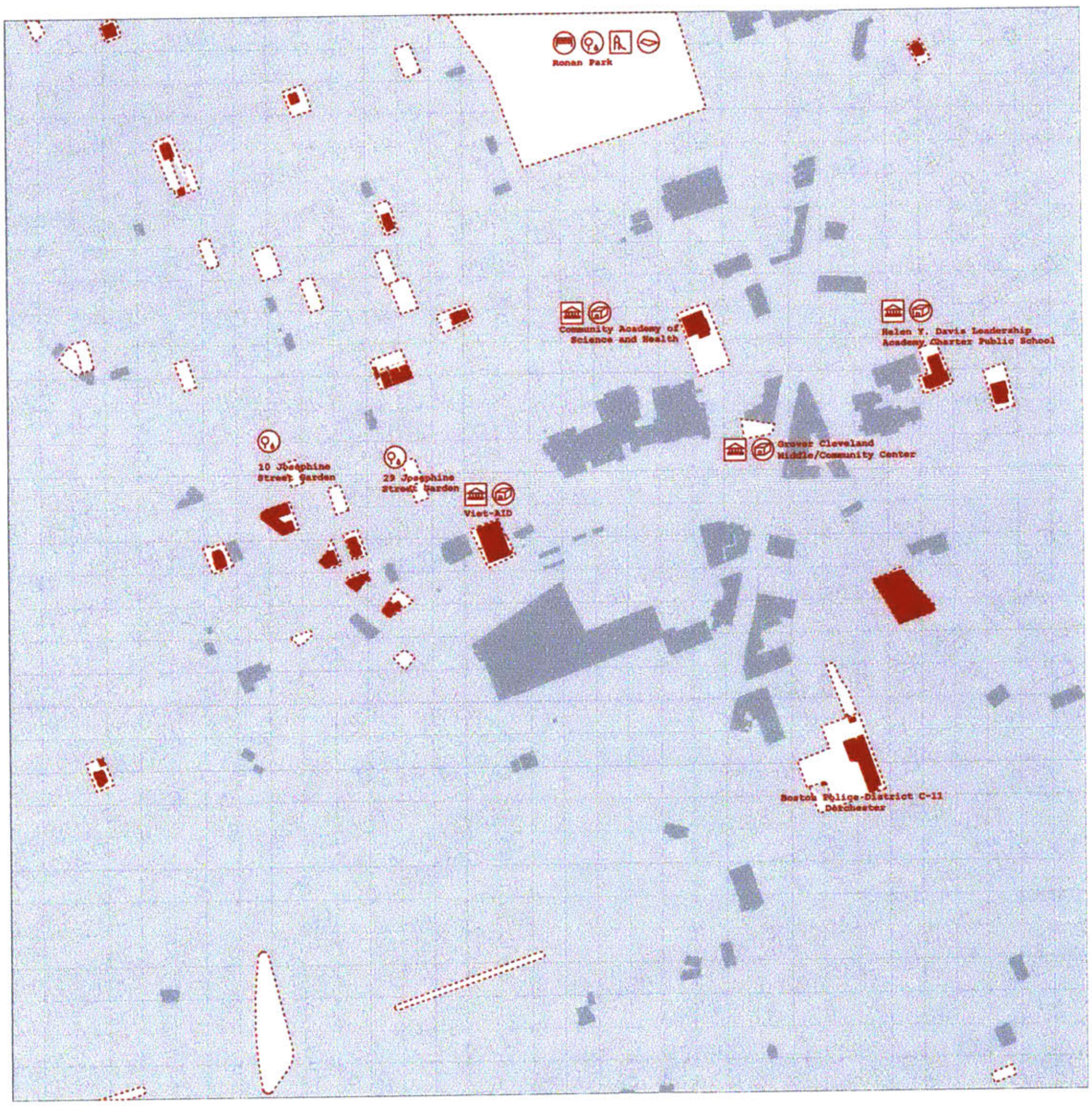


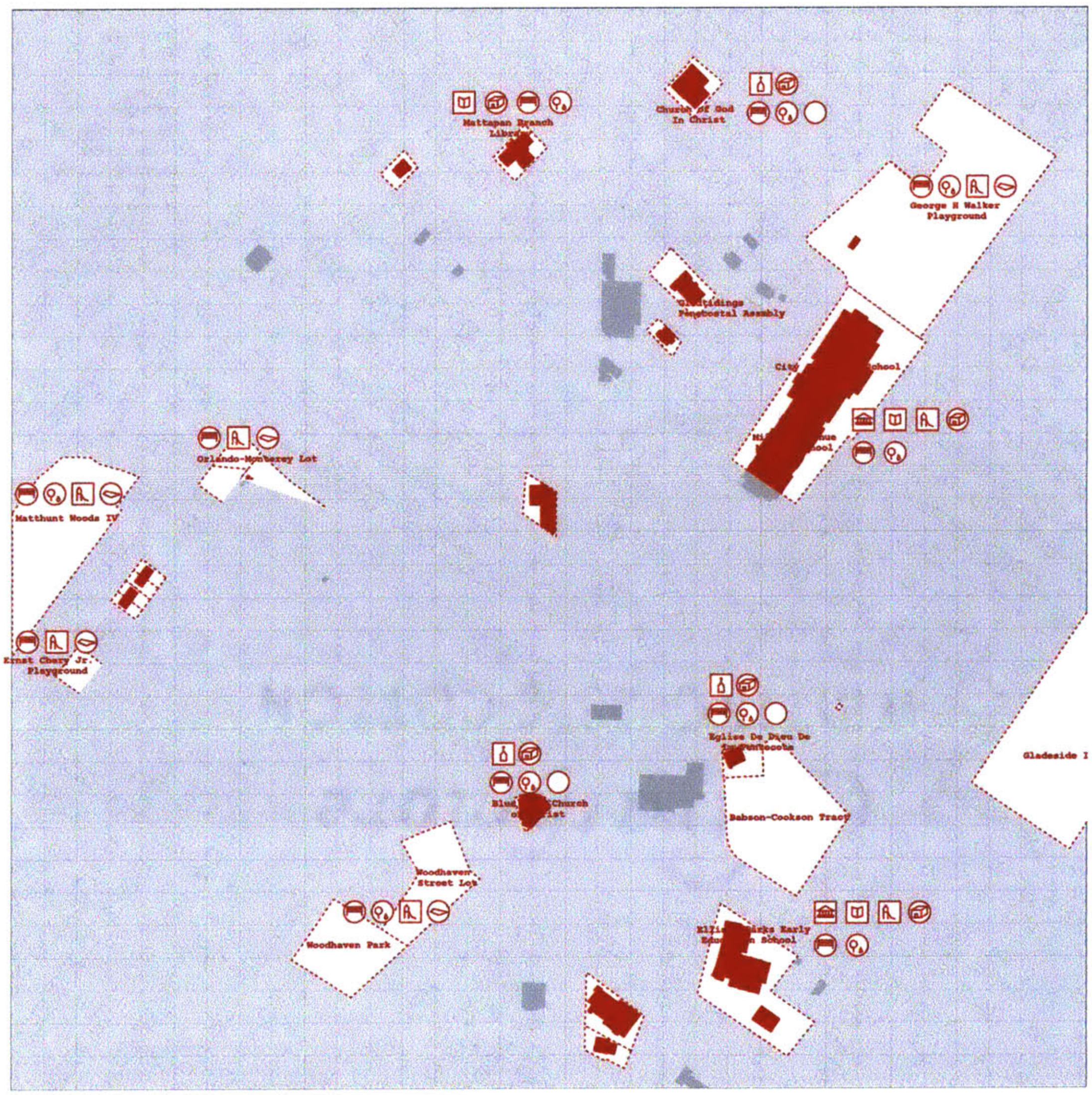


Appendix 7

Public institutions outside the psychological geography in Back Bay, Fields Corner and Mattapan




Ronan Park
Community Academy of Science and Health
Helen Y. Davis Leadership Academy Charter Public School
Grover Cleveland Middle/Community Center
10 Josephine Street Garden
29 Josephine Street Garden
Viet-AID
Boston Police-District C-11 Dorchester



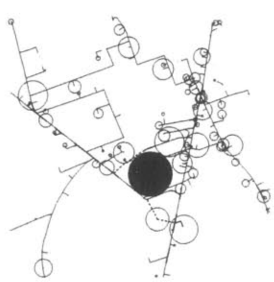
Church of God
In Christ
George H Walker
Playground
Orlando-Monterey Lot
Matthunt Woods IV
Ernst Chery Jr.
Playground
Gladeside I
Babson-Cookson Tract
Woodhaven
Street Lot
Woodhaven Park

Appendix 8

Instagram hashtags and location names of places in Fields corner

Mall

Node / Path: **Node**
Type: **Mall**
Post number: **42**
Use: **Commercial**
Location name:
Cambridge 1
Family Dollar
CW Price
Madrag
CW Price
Supreme Liquors
Fields Corner
Supreme Liquors
Fields Corner
Fields Corner
Farmers Market
Supreme Liquors
Family Dollar

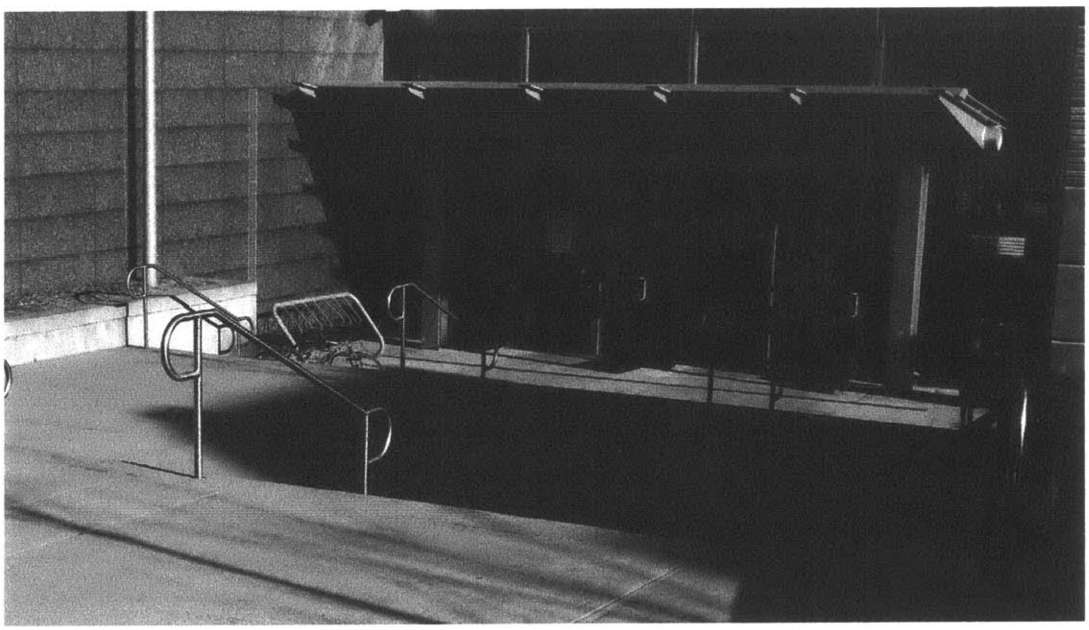


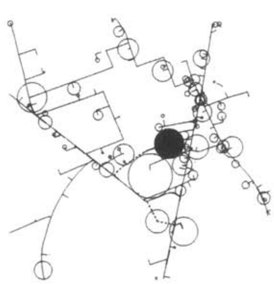
\#

nofilter,spicychicken,pankochicken,bosbingo,buffalo chickenfingers,cheers,goodnight,teamwork,hardhit,dorchester,
myhood,stella,belgiumsoriginal,stellaartois,tryit,americas-
foodbasket,localbiz,dorchester,boycott,dinnerwithdad,bostonevenings,ahk,beautiful,foodgasm,tagstagram,foodporn,
yumyum,sweet,tagsta,delicious,sharefood,love,foodpics,eat,getinmybelly,munchies,yummy,favorite,instafoodie,myfav
,comida,instafood,food,dinner,eating,homemade,yum,picoftheday,tagsta_food,boston,practice,breaklife,blizzard2015,
bboy,respect,graffiti,floroc,dyc,meat,ckc,foodporn,foodislife,finishedproduct,happy,easter,eat,ham,haters,roomies,yu
ck,celebrate,success,royaleandharpcudnthandleit,teachpeace,fleece,catnap,animal,boston,feline,westpaw,cat,bboy,art
,dorchester,boston,respect,graffiti,practice,firstworkshop,tlaw,meat,family,food,midnighthungry,deenor,thanksgiving,
dinner,throwback,friends,eat,winter,superbowl,sundayfunday,patriots,boston,inthewindow,schilling,instagram,win,b
ostonstrong,superbowl,patriots,christmas,merry,hashtag,boston,happyholidays,happysunday,happynewyears,hoophu
stler,situationenthusiast,getloud,enddeathtraps,bangladesh,solidarity,makenoise,dollarstoretreasures,hifipizza,felixar
royo,Dorchester,tlaw,hiphop,music,rap,sexism,homophobia,racism,clouds,nature,s3,boston,samsung,sky,outside,sun
set,sun,nofilter,teamnosleep,selfie,workgrind,workflow,blarneystone,stpaddysday,Dorchester,byob,m,buildingyourow
nbrand,shipyard,library,latergram,takeout,food,chinesefood,thestruggle,yesterday,suckstobu,safetyschool,bcrejects,ar
cadefun,foodie,dorchester,foodporn,food,boston,farmersmarket,15now,informal_noun,wcw,romanticcommunists,d3
100,romcoms,tlaw,teamwork,cooperation,teambuilding,food,fastfood,thestruggle,yesterday,lharperstylechannel,midn
ightrelease,dorchester,gamestop,nba2k13,videogames,boston,theorder1886,instagood,loveher,food,boston,lol,fun,smil
e,girl,friends,happy,tunnelvision,art,dreamchaser,dreamcatcher,selfie,asweetplace,myvision,dreams,inspiration,bride
smaid,mygurl,bosbingo,goodtimes,drinkwithafriend,arthur,teachersolutions,lol,hypebeast,desu,nofilter,hipster,gethy
pe,ultimatechallenge,nasty,touchdown,sundayfunday,patriots,family,permissibangladesh,justice,worker,protest,safety
,international,action,health,workersrights,boutikey,dorchesterforaday

Fields Corner

Node / Path: **Node**
Type: **T station**
Post number: **28**
Use: **Public**
Location name:
Fields Corner
MBTA Fields Corners Station
Fields Corner T Station



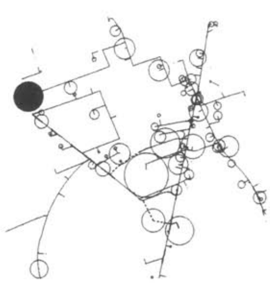


#

hsdailyfeature,rising_masters,communityfirst,hot_shotz,vsco-
best,alwaysshooting,noticeeverything,passionpassport,traveldeeper,welovethiscity,featuremeinstagood,visitboston,far
toodope,beautyindecay,gramoftheday,iheartboston,uncalculated,arteverywhere,the_v,demdoors,progressive,whiteboys
hit,city,vscocam,boston,bostonma,vsco,museumoffineartsboston,meandchris,stunnashades,tuesdaychillin,dentaltues
day,monstertime,dinosaur,fingerpuppetbook,kidding,hsdailyfeature,rising_masters,communityfirst,boston,passionpa
ssport,postmoreportraits,welovethiscity,featuremeinstagood,strideby,postthepeople,strangersinmyfeed,tagsforlikes,kil
ltheunderground,iheartboston,exploreeverything,ishootstrangers,the_visionarie,mbta,missedtrain,tooslow,hsdailyfeat
ure,rising_masters,communityfirst,todays_simplicity,boston,bandw,alwaysshooting,passionpassport,traveldeeper,wel
ovethiscity,featuremeinstagood,visitboston,strangersinmyfeed,strideby,exploreeverything,beautifuldestinations,world
wanderlust,uncal,mfa,tbt,freethenipple,day138,flower,my_365,beautiful,igers,instadaily,photooftheday,instagramers,i
nstagood,hsdailyfeature,peoplescreatives,vscogrid,publicimage,top_masters,hypebeast,huffpostgram,postmoreportrai
ts,silhouette,postthepeople,moodylover,bostondotcom,premiumposts,ink361,allshots_,igmasters,livefolk,streetdream
smag,vscogood,liveauthentic,makeportrai,top_masters,rising_masters,communityfirst,boston,alwaysshooting,noticee
verything,most_deserving,traveldeeper,graffiti,visitboston,featuremeinstagood,bostonusa,beautyindecay,shootermag,
vscogood,the_visionaries,iphoneonly,bestfeeds,streetdreamsmag,killing,tinymiracles,sunflowers,myhood,sunlight,hs
dailyfeature,igboston,tripadvisor,communityfirst,streetshots,boston,alwaysshooting,noticeeverything,passionpassport
,myownshots,igersboston,instaboston,killtheunderground,iheartboston,exploreeverything,instafollow,travel,iphoneo
nly,worldwanderlust,uncal,hsdailyfeature,igboston,rising_masters,communityfirst,pro_shooters,boston,alwaysshooti
ng,lifeisgood,passionpassport,traveldeeper,igersboston,shoot2kill,paid2shoot,flipgram,instaboston,killtheundergroun
d,iheartboston,exploreeverything,outcastamerica,travel,ass,casualfriday,gowns,oldhollywood,glam,uncalculated,risin
g_masters,communityfirst,alwaysshooting,sh_003,passionpassport,traveldeeper,postmoreportraits,urbanromantix,fea
turemeinstagood,visitboston,postthepeople,exploreeverything,dorchesterave,strangersinmyfeed,worldwanderlust,isho
otwhereyouwon,fields,Dorchester,fieldscorner,hoodrich,18k

Ridgewood street

Node / Path: **Path**
Type: **pedestrian street**
Post number: **28**
Use: **Public**
Location name:
Mom's House
Nana's House
The Bunny Hutch
Close To Home
Sister House
My House
275 Tremont Street
My bed
Homeeeeee :)

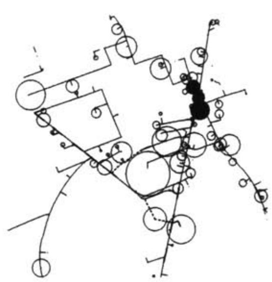


#

jordan,myfirst,thankmymom,awesome,miracle,latethough,catsof-
instagram,cat,tech,jack,1997,truth,angrybirdie,battenkill,gfys,snowing,winter,troubleinthings,snoot,nose,face,boston,
catsofinstagram,cat,9,neverforget,underbarboston,dance,latin,bostonnightlife,club,boston,drinks

Dorchester - Fields Corner

Node / Path: **Path**
Type: **transit corridor**
Post number: **119**
Use: **Commercial**
Location name:
Pho So 1 Boston
Hairpin Communications
No Credit Wireless Spot
Ba Le
Dorchester Ave
D'benny Sub Shop
Advance Auto Parts
Castle Island, South Boston
[illegible] 2000 Restau-[illegible]
Hamilton Hughes Design
Chili Hot Pot
Hanh's Bridal Shop
Dorchester Boston Massachusetts
Fields Corner Business Lab
Dot Cafe
Tedeschi
Domino's Pizza
Ba Le Cafe Field Corner
Bank Of America
Dippin Donuts
SPECIAL E FX HAIR STUDIO

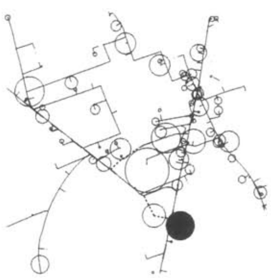


#

life,hardlife,boston,gangsta,dontfckwithme,dotpride,catsofinstagram,petsofinstagram,cat,yamaha,gig,morninggig,musicians,music,m√É¬∫sicos,piano,event,stage,vscocam,rnb,keithsweat,gooddadgang,antique,homedecor,vintage,ghostchair,interiordesign,sale,books,diy,desk,target,pillow,Dorchester,evento,dontstopthemusic,yamaha,gig,morninggig,live,musicians,music,m√É¬∫sicos,event,stage,pork,glutenfree,primal,dairyfree,-jerf,paleo,instapaleo,paleoeats,cleaneating,caulirice,eatclean,1996,kevinmckidd,monrowemagazine,trainspotting,film,dannyboyle,coffee,dorchester,spring,beer,outside,prettythings,boston,breakfast,nom,paleo,eatclean,stud,breakfast,jerf,bacon,nom,paleo,avocado,jerf,bacon,cleaneating,overeasy,eatclean,breakfast,fishes,goldfish,pets,fishtank,chairmanmeow,love,work,photoshoot,pic,cool,boston,the,cleaning,pool,tired,vscocam,exploreeverything,streetdreamsmag,iphoneography,lookup,shoot2kill,justgoshoot,vsco,phoneography,jj_forum_0927,vscocam,love,iphone,color,engagement,ugglytruth

Tedeschi Foods

Node / Path: **Node**
Type: **Mall**
Post number: **26**
Use: **Commercial**
Location name:
Dunkin Donuts
Subway
Tedeschi food
National guards

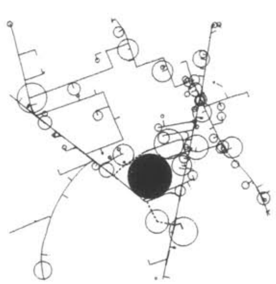


#

stone,stpaddysday,Dorchester,byob,m,buildingyourownbrand,ship-
yard,library,latergram,takeout,food,chinesefood,thestruggle,yesterday,suckstobu,safetyschool,bcrejects,arcadefun,foo
die,dorchester,foodporn,food,boston,farmersmarket,15now,informal_noun,wcw,romanticcommunists,d3100,romcom
s,tlaw,teamwork,cooperation,teambuilding,food,fastfood,thestruggle,yesterday,lharperstylechannel,midnightrelease,d
orchester,gamestop,nba2k13,videogames,boston,theorder1886,instagood,loveher,food,boston,lol,fun,smile,girl,friend
s,happy,tunnelvision,art,dreamchaser,dreamcatcher,selfie,asweetplace,myvision,dreams,inspiration,bridesmaid,myg
url,bosbingo,goodtimes,drinkwithafriend,arthur,teachersolutions,lol,hypebeast,desu,nofilter,hipster,gethype,ultimate
challenge,nasty,touchdown,sundayfunday,patriots,family,permissibangladesh,justice,worker,protest,safety,internatio
nal,action,health,workersrights,boutikey,dorchesterforaday

Fieds corner playground

Node / Path: **Node**
Type: **Sports field**
Post number: **22**
Use: **Public**

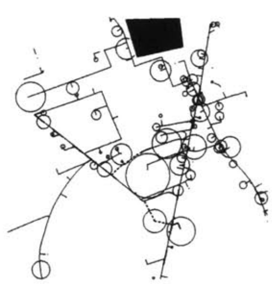


#

restinparadise, walkingtomakeadifference,walkforpeace, whatyouknowaboutblack, bla,dragons, teachpeace,boston, bostonstrong,walkforpeace, brotherfromanothermother, 2014,stopthestreetviolence,cityinpain,mothersdaywalkfor-peace,boston, purple,crutch, dorchesterdayparade, boston,remyology,parktime,gooddadgang, thisusedtobemyplay-ground,picstitch,beauty, 2014,purpleribbon,riptoallwehavelost,boston,stopthestreetvio-lence,bostonstrong,mothersdaywalkforpeace

Ronan Park

Node / Path: **Node**
Type: **Park**
Post number: **0**
Use: **Public**



Josephine Street Garden

Node / Path: **Node**
Type: **Community garden**
Post number: **0**
Use: **Public**