Beyond Smart Cities

The Role of Technology in Resilient Urban Futures

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Director, Center for Urban Resilience and Analytics
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What makes cities “smarter”?

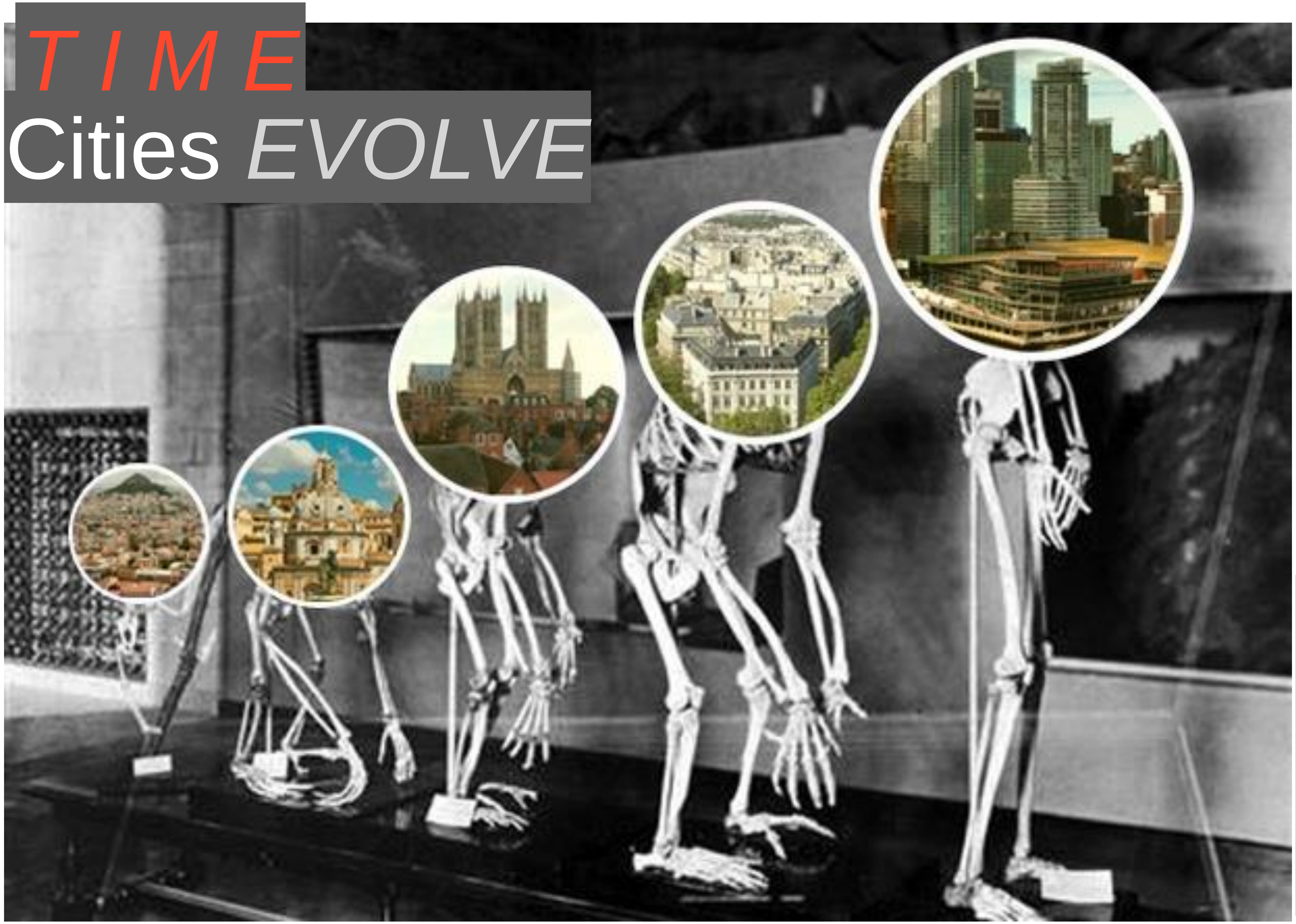
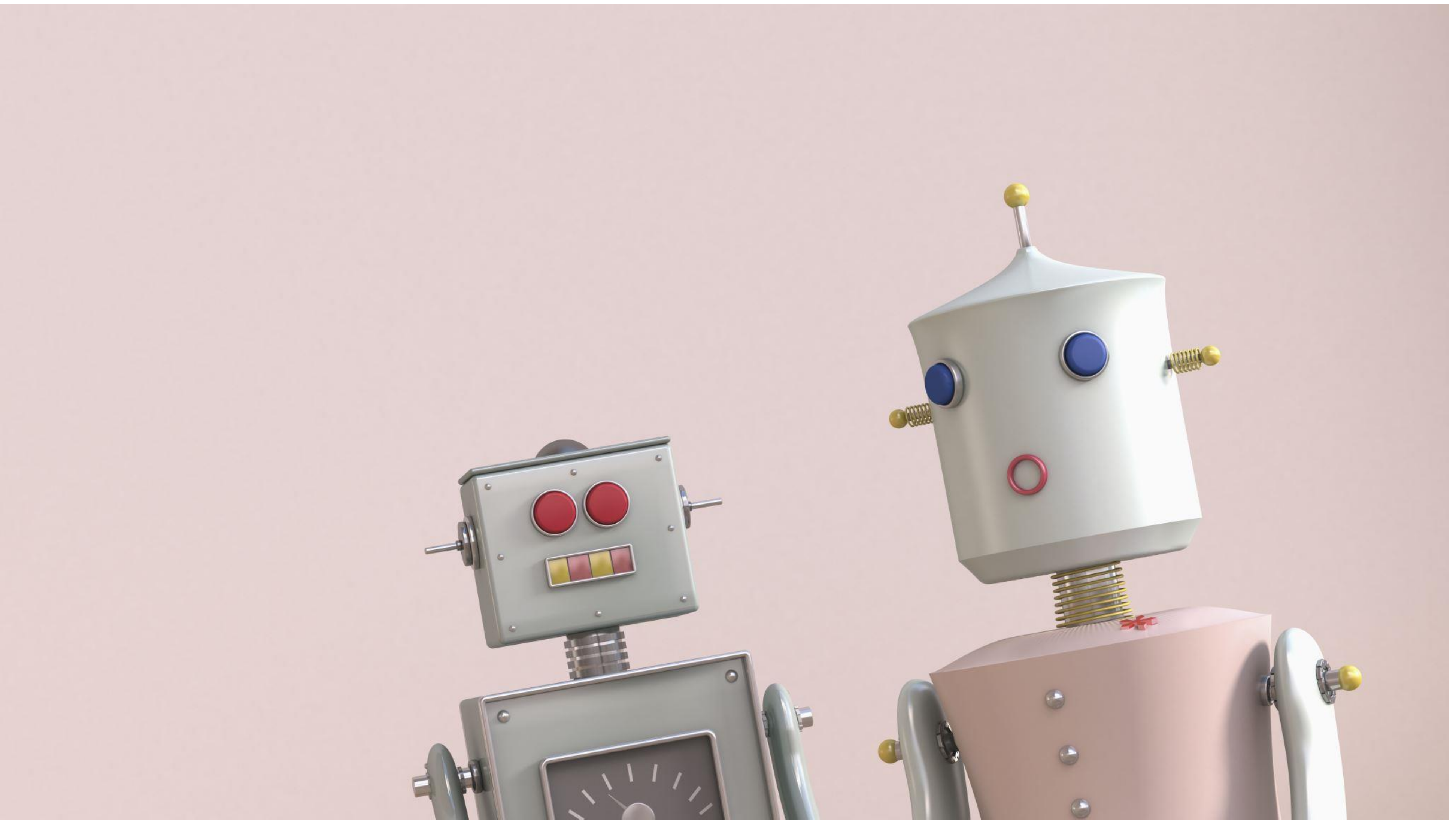


Image Mark Byrnes/CityLab

We make cities smarter by understanding its evolutionary trajectory and its “DNA,” which shapes its culture, society, traditions, and its way of life

≠



How did we “design” smart cities?

Arcosanti, Arizona

PlanIT Valley,
Portugal

Masdar City, Abu Dhabi

Songdo, South Korea

Tianjin Eco-City

What characteristics do these cities share?

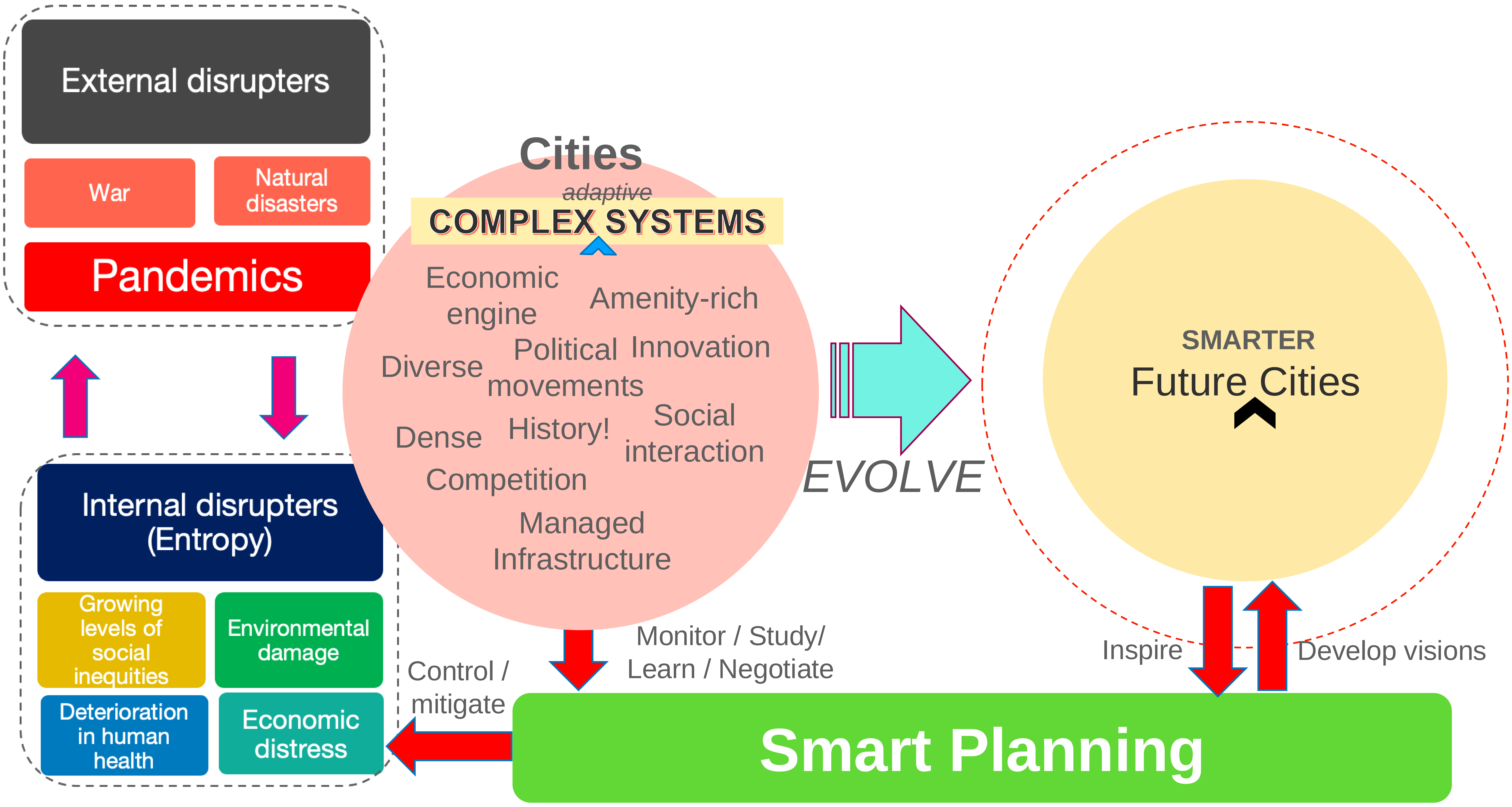
- Flat Cartesian plane
  – generic anyplace = no place

- People appear after the infrastructure is in place
  -- people adapt to the built environment rather than the environment adapting to culture and social norms of people

- A singular logic imposed by corporate entity on government
  -- Eschews conflict, difference, and internals distinctions in that logic

- Antiseptic! Devoid of a sense of wonder and joy

Smart Planning – A {complex} systems perspective


External disrupters
War
Natural disasters
Pandemics
Internal disrupters (Entropy)
Growing levels of social inequities
Environmental damage
Deterioration in human health
Economic distress
Cities
adaptive
COMPLEX SYSTEMS
Economic engine
Amenity-rich
Diverse
Political movements
Innovation
Dense
History!
Social interaction
Competition
Managed Infrastructure
EVOLVE
SMARTER
Future Cities
Monitor / Study/ Learn / Negotiate
Control / mitigate
Inspire
Develop visions
Smart Planning

How do we think about “SMART” {anything}?

SMART

GROWTH

CITIES

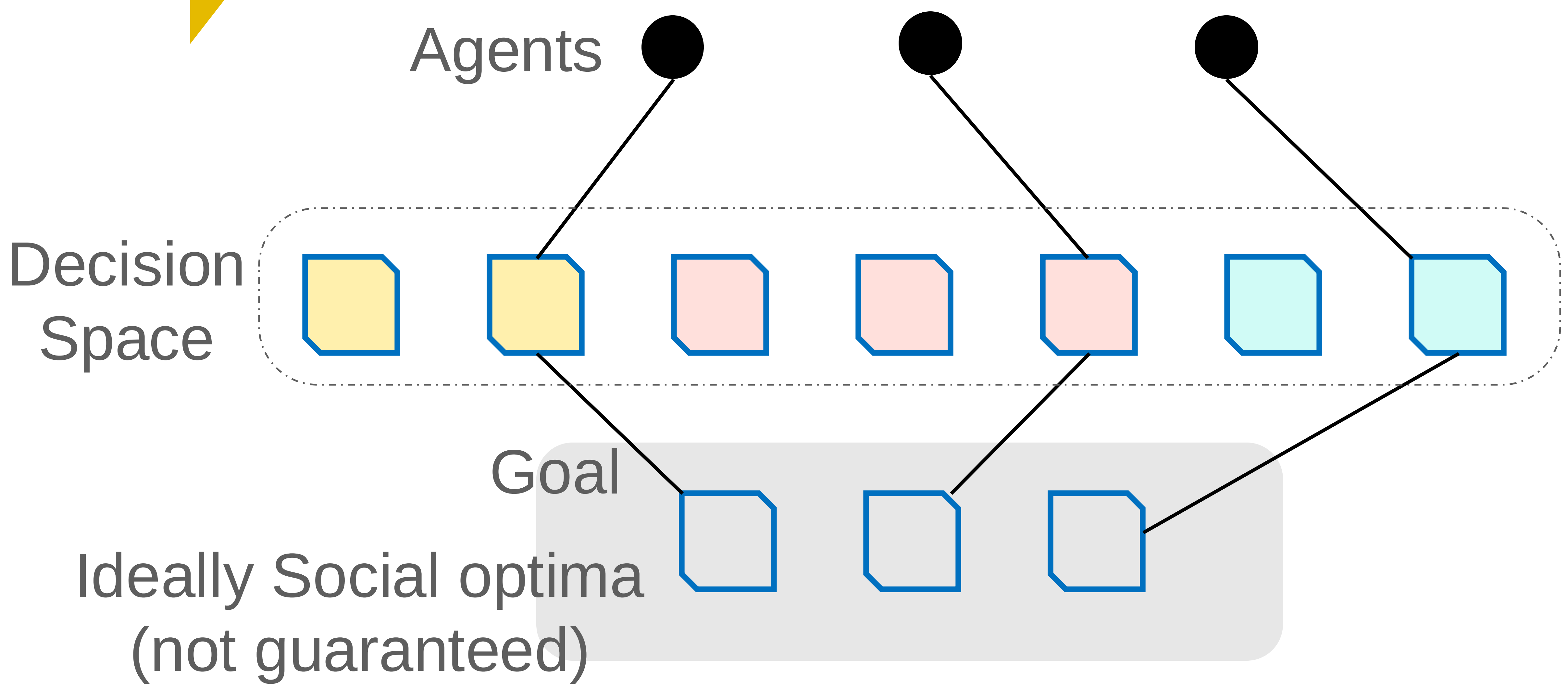
PLANNING

MOBILITY

GOVERNANCE

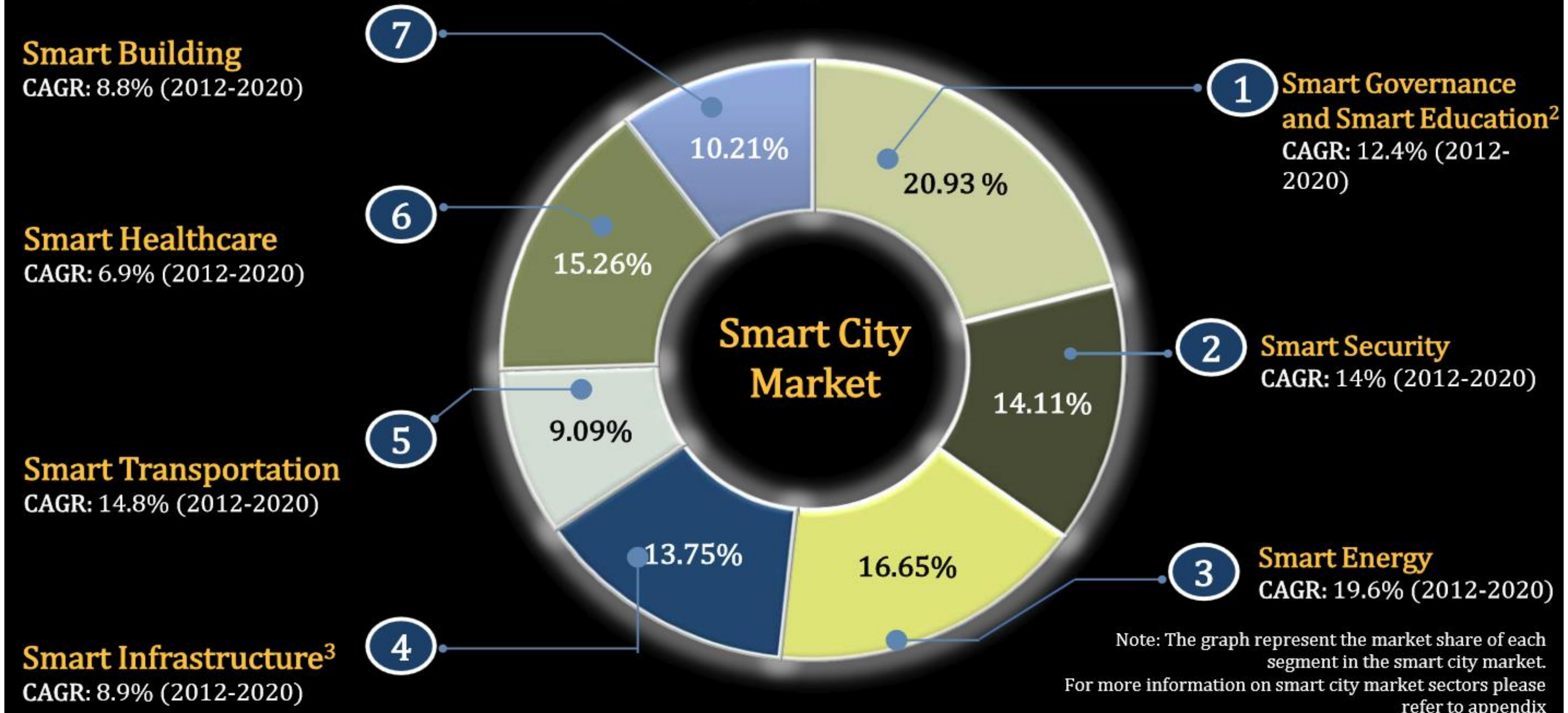
SECURITY

Making
{Knowledge / Information supported and goal oriented}
Decisions



Smart cities To Create Huge Business Opportunities With A Market Value Of $1.5 Trillion In 2020

Smart City Market by Segments,[1] Global, 2020



Note: The graph represent the market share of each segment in the smart city market.
For more information on smart city market sectors please refer to appendix

[1] These numbers represent the entire smart solutions eco-system in each segment for both urban and non-urban panoramas

[2] Smart Education includes eLearning services for schools, universities, enterprises, and government entities

[3] Other Smart Infrastructure such as sensor networks, digital management of water utilities not included in other segments

Source: Frost & Sullivan analysis.

FROST & SULLIVAN

Why we should be careful about the marketing hype

No accepted standards

- Proprietary technology
- Challenges of interoperability of different systems
- Increasing complexity
- Increasing specialization

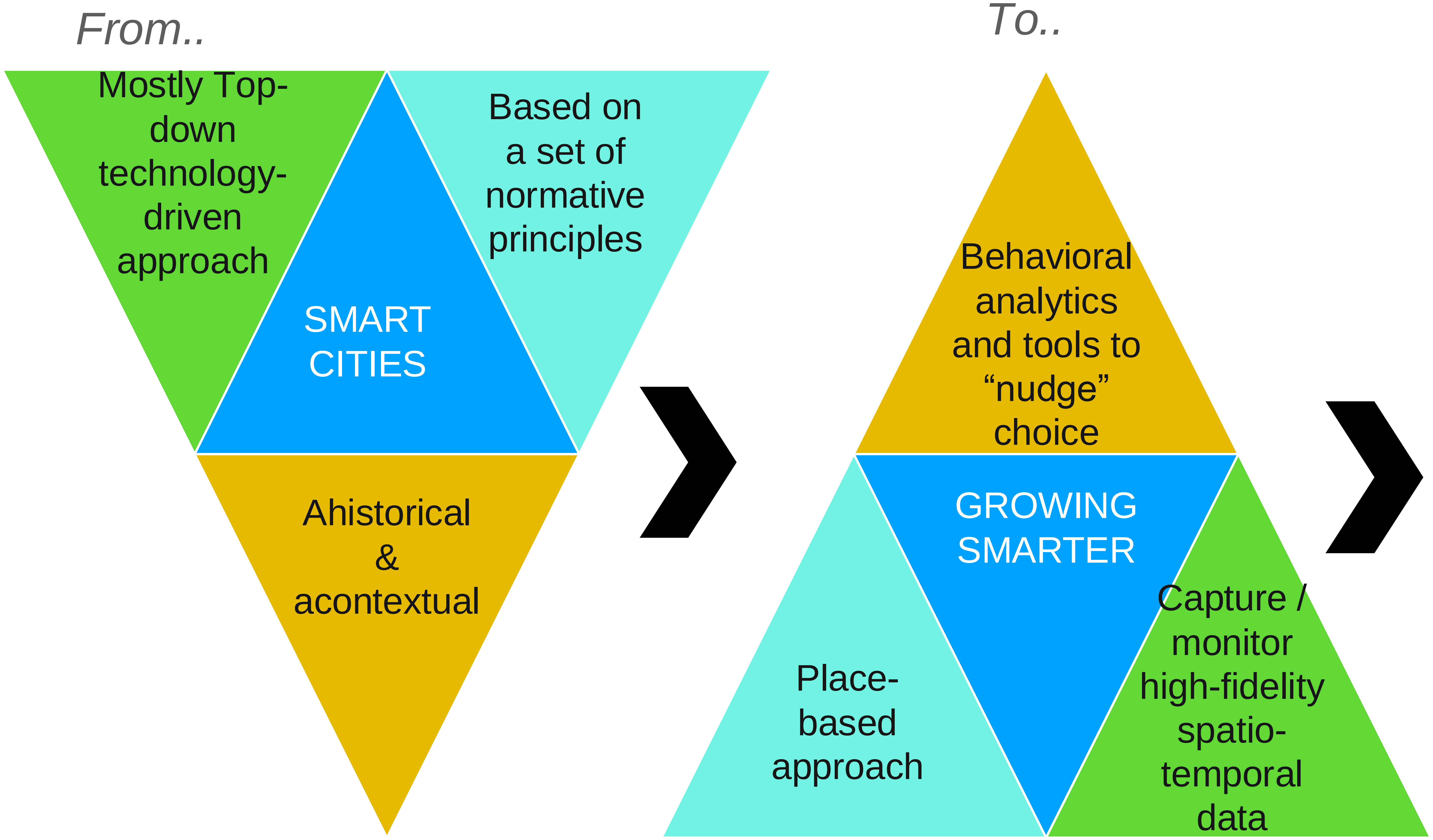
Lock –in!

- Expensive to shift if other more promising technologies are available
- Creating more natural monopolies
- Constrains on decision making
- Specialized administrative structure

Possible effect on social choices in future and on equity

Serious issues about data security and privacy – who manages the data and how?

Becoming Smarter



Seek knowledge of individual / social behavior by analyzing the decisions they make

Undertake place-based research and engage deeply with communities

Conduct experiments to determine what forms of intervention / messaging work

Promote success stories in more personal and engaging formats and multiple venues

Charting the path forward

In a world of uncertain facts, disputed values, high stakes, and urgent decisions

Groundedness

(Place-based solutions)

Wicked problems exist on the ground and often they cannot be generalized outside their context

"It is only through the critical examination of this groundedness can wicked problems be solved"

Brown 2010 quoting Rittel and Webber (1973)

The essential role of **smart design**

Design is about grounded solutions!

Smart Planning

- Engages multiple experts and stakeholders to address a problem
- Requires extended "peer" communities

Smarter Cities

- Socio-technical analytics using new forms of data to understand social behavior
- Experimental designs to see what messages and interventions matter for growing smarter
- Better (more personal and creative) storytelling

Strategic Approach in Adopting Technology in Urban Systems

- ✓ Evolutionary – Problem focused
  - ❑ Seek out “appropriate technologies” through public deliberation for specific solutions
  - ❑ Eschew large complex “systems integration” type approaches
  - ❑ Open standards should be emphasized
  - ❑ Should be able to evolve with new innovations with minimum costs
- ✓ Concentrate on “enabling” technologies
  - ❑ Opening up information / data (with appropriate security controls) for enabling innovative applications
  - ❑ Create a climate where small firms and individuals can use the ICT backbone to develop tailored solutions for different groups
- ✓ Enable large set of choices
  - ❑ Redundancy is preferred
  - ❑ Guard against solutions that are “too big to fail”

Exemplars

Our Work at CSPAV

- Pedestrian Navigation
- Walkability and livability
- Neighborhood Quality
- Biking and Complete Streets
- On-Demand Transit (equity)
- Urban growth scenarios of Atlanta

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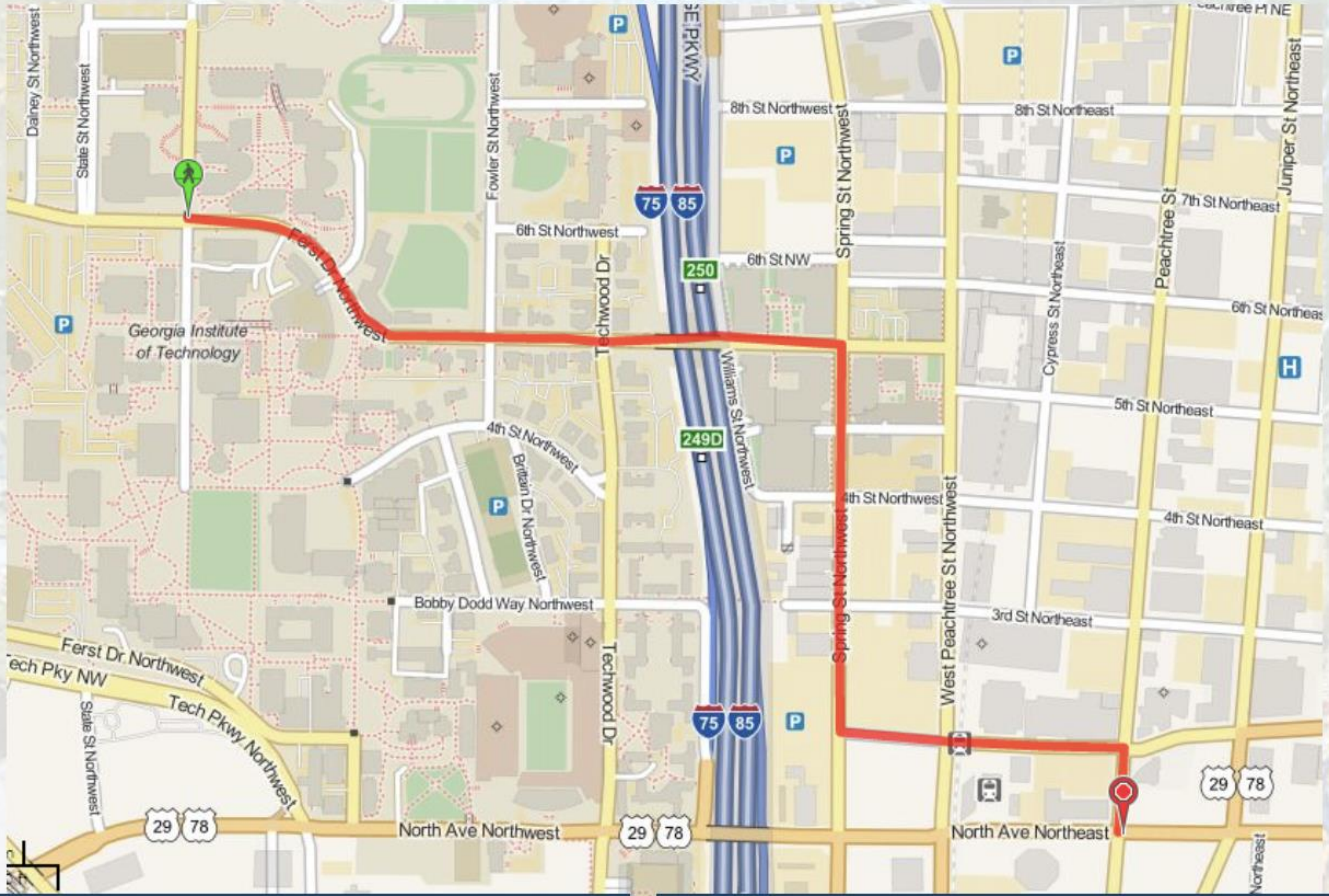
START EXPERIENCING



Find your best walk-route:

The shortest route may not always be the most walkable route if the user is not time constrained. People walk for various reasons and many of these reasons relate to enjoying the experience of walking through places that please the senses. Also, different persons respond differently to similar places, hence the walk route that is pleasing to one may not be the same to another. Indeed, the same individual might choose to walk along different routes depending upon the specific activities she

Prioritize your concerns

Our walk trip planner provides a range of attributes that users can select and weigh to

Most walkable vs. shortest routes

The planner calculates not only the shortest walking route but also the tailored walking route based on the users' choices. The detailed information for both routes can be retrieved from

Walking for health

Walkable environments have been associated with urban social life, economic regeneration, public health, and overall quality of life.

Plan Trip | Plan Result | Plan Result

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Georgia Tech

Most Walkable:
Sun, Mar 5th 8:52am - Sun, Mar 5th 9:21am

Shortest:
Sun, Mar 5th 8:52am - Sun, Mar 5th 9:19am

Start at 5th Street Northwest

Walk to Active Oval

About 28 minutes - 1.3 mi

1. Walk **east** on **5th Street Northwest** - 99 ft
2. Left on **Spring Street Northwest** - 27 ft
3. Right on **unnamed street** - 0.4 mi
4. Right on **Peachtree Place Northeast** - 142 ft
5. Left on **unnamed street** - 259 ft
6. Right on **10th Street Northeast** - 0.2 mi
7. Left on **Juniper Street Northeast** - 37 ft
8. Right on **unnamed street** - 0.5 mi
9. Right on **Active Oval** - 0.2 mi

End at Active Oval

Advanced Options

Reverse

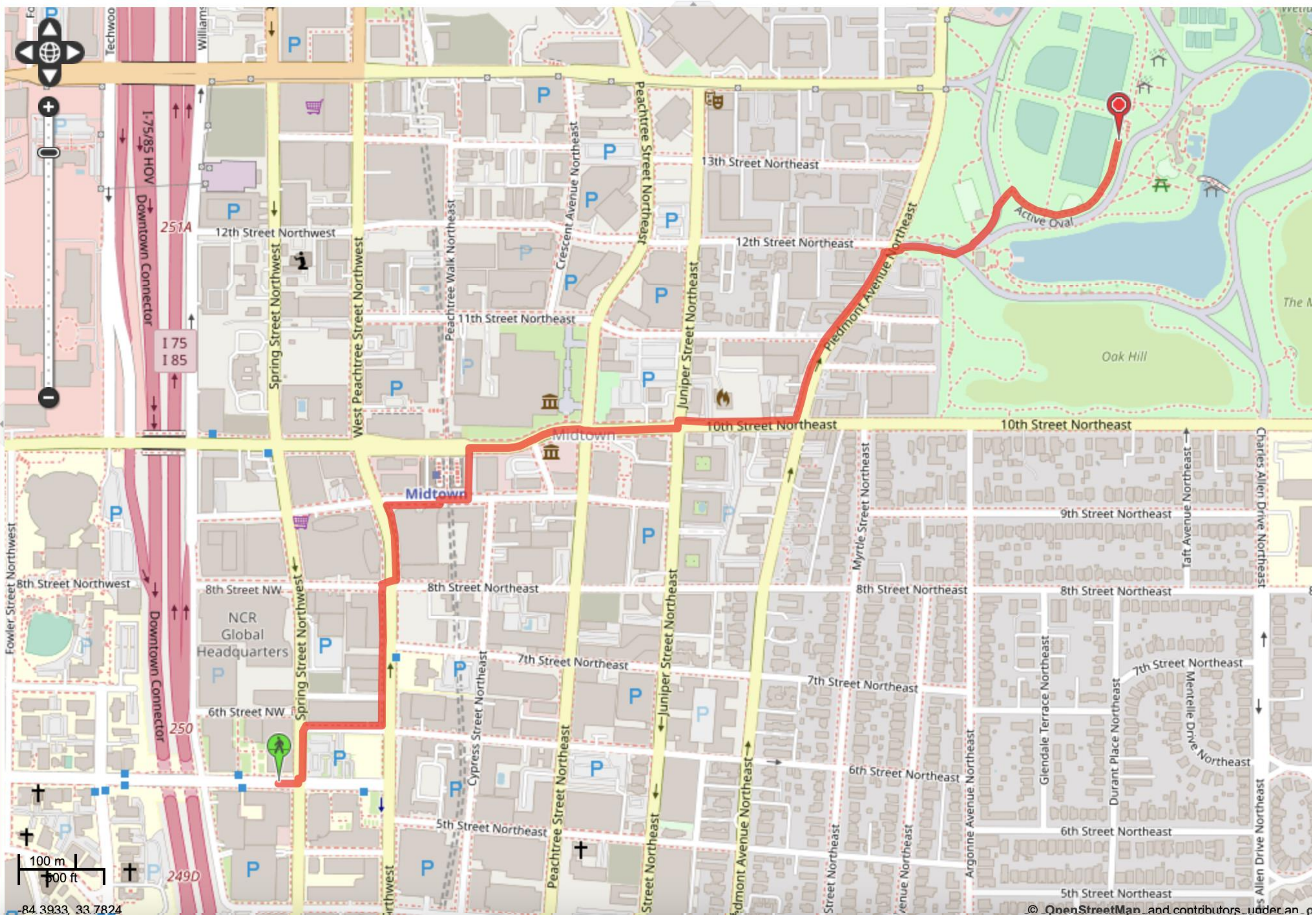
Edit

Print

Link

Trip details

Travel	Sun, Mar 5th 8:52am
Valid	March 5th, 2023 @ 8:53am
Time	26 minutes 1.3 mi



Selectable Parameters

1. Sidewalk:
-> Width
-> Shade
-> Slope

2. Traffic control:
-> Traffic lights
-> Stop signs

3. Street Crossing:
-> curb cuts
-> pedestrian signals
-> crosswalks
-> intersection density

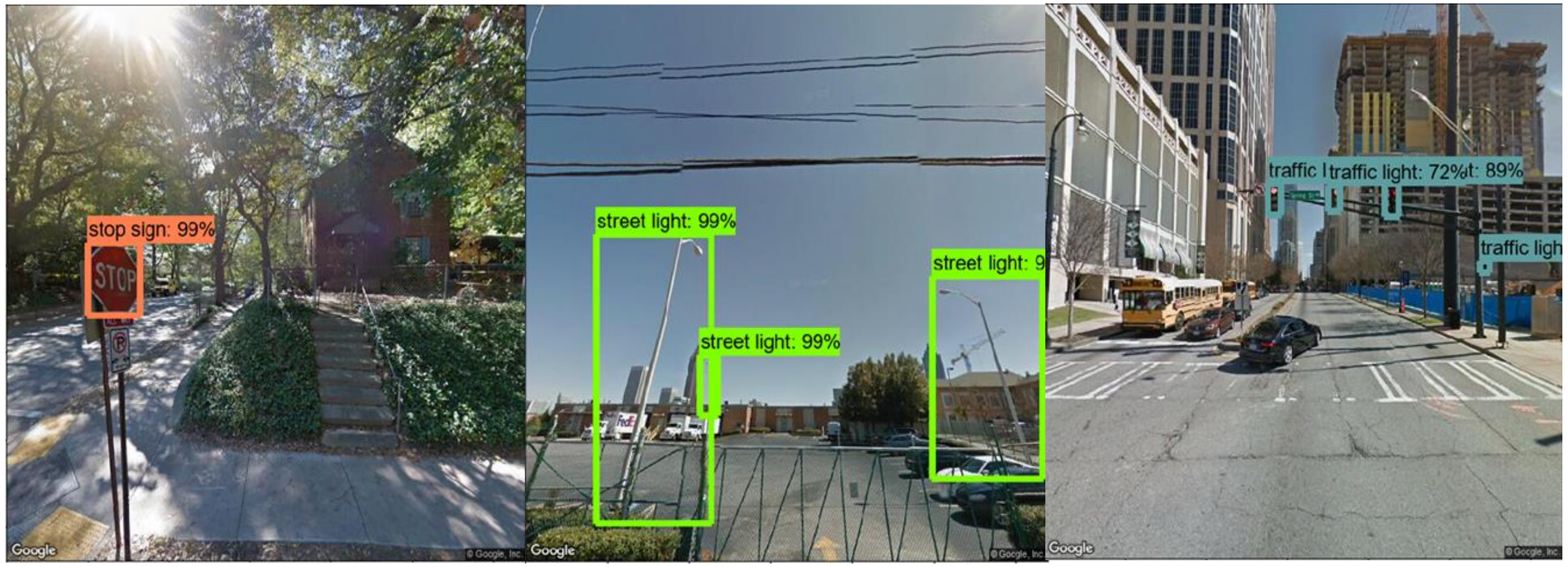
4. Building density:
-> Residential density
-> Business Safety:

5. Safety:
-> Streetlights
-> Traffic volume
-> Crime rate

6. Resting Areas:
-> Bus shelters

Using Computer Vision techniques on Google StreetView images

Google StreetView Feature Detection



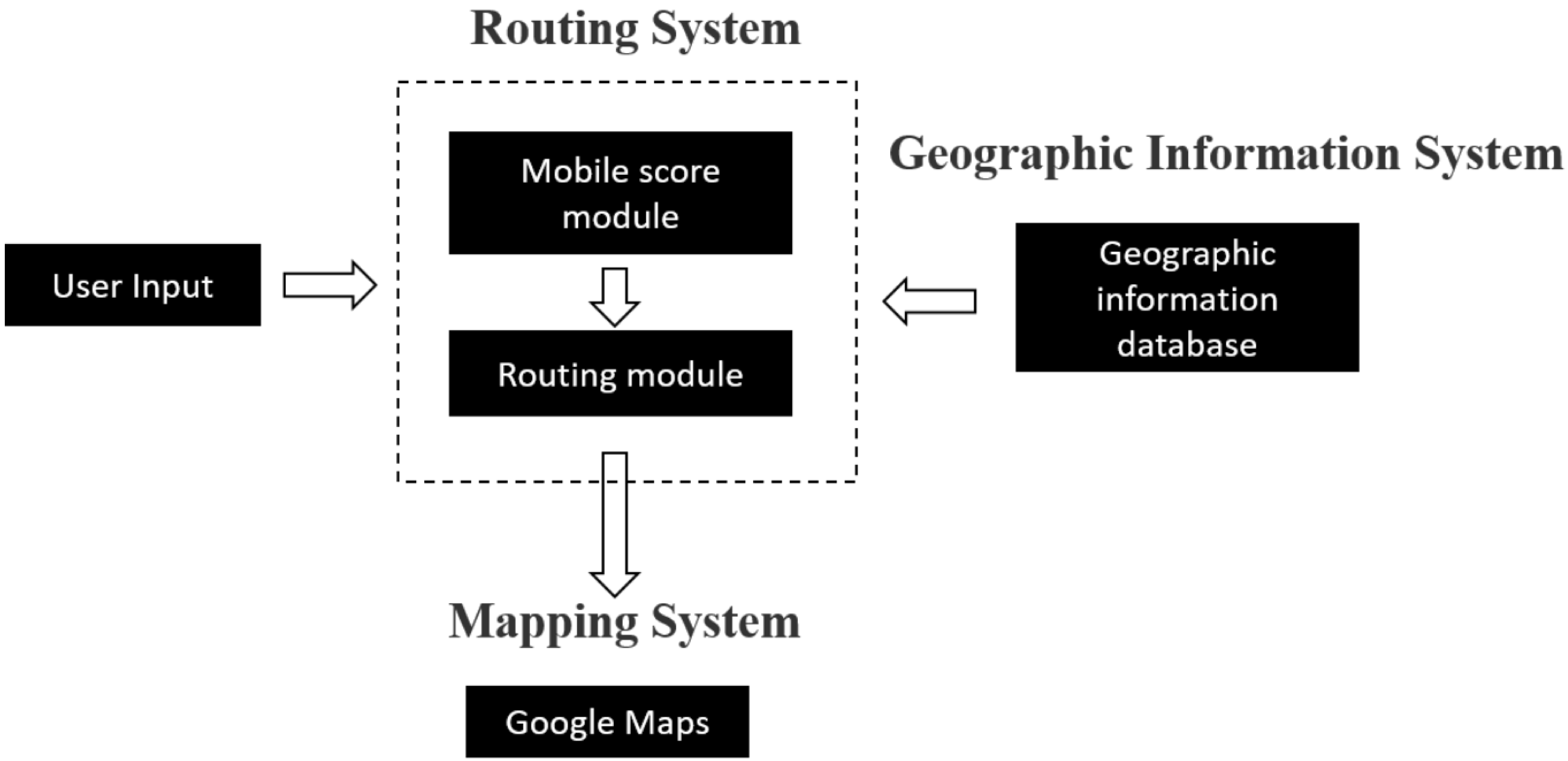
- We used a pretrained model called Faster R-CNN with Inception Resnet v2 atrous version for object detection.
- We used the **COCO** dataset for detecting **traffic light, bench, and stop sign**
- Since **COCO** dataset does not include **curb cut, crosswalk, streetlight and walk signal**, we prepared our own training dataset

How well do we predict?

500 randomly chosen objects of each type

	TP	FN	TN	FP	Accuracy	Recall	Precision
Traffic Light	115	1	377	7	0.98	0.99	0.94
Stop Sign	31	9	450	10	0.96	0.78	0.76
Walk Signal	107	5	331	57	0.88	0.96	0.65
Streetlight	181	12	259	48	0.88	0.94	0.79
Cross Walk	167	19	277	37	0.89	0.90	0.82
Curb Cut	123	25	342	10	0.93	0.83	0.92

Design Framework



Routing System

1. Calculate the mobility cost of each segment using the formula:

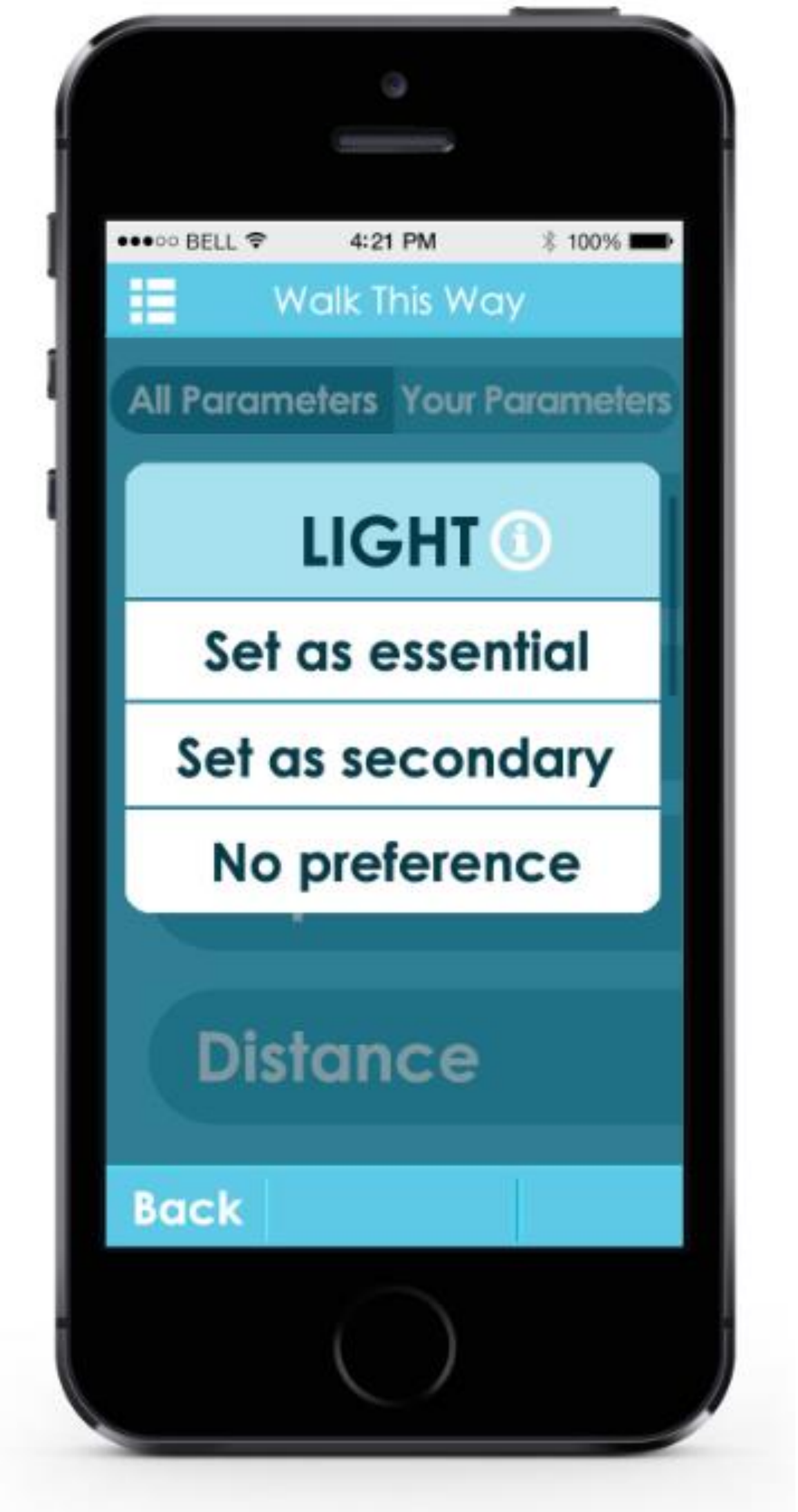
$$MC_j = \frac{D_j}{\sum_{i=1}^{n}(V_{ij}W_i)+1}$$

D_j = Length of Street Segment
V_{ij} = Value of the attribute selected for j (normalized)
W_i = Weight of the attribute selected (Primary or secondary)

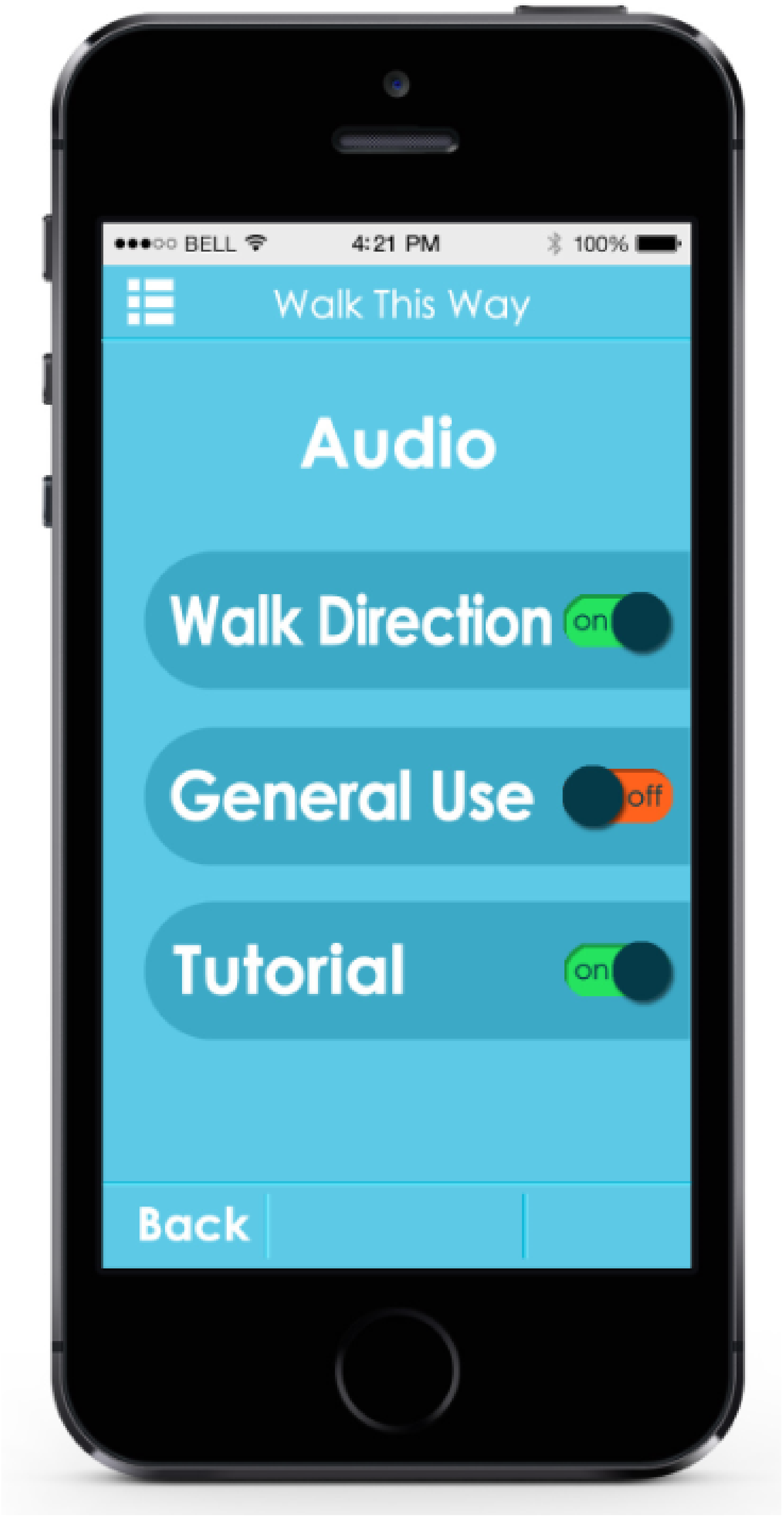
2. Dijkstra Shortest Path Algorithm

APP FOR LOCATIONAL INTELLIGENCE AND GEOSPATIAL NAVIGATION (ALIGN!)

Included Feedback on Route Conditions

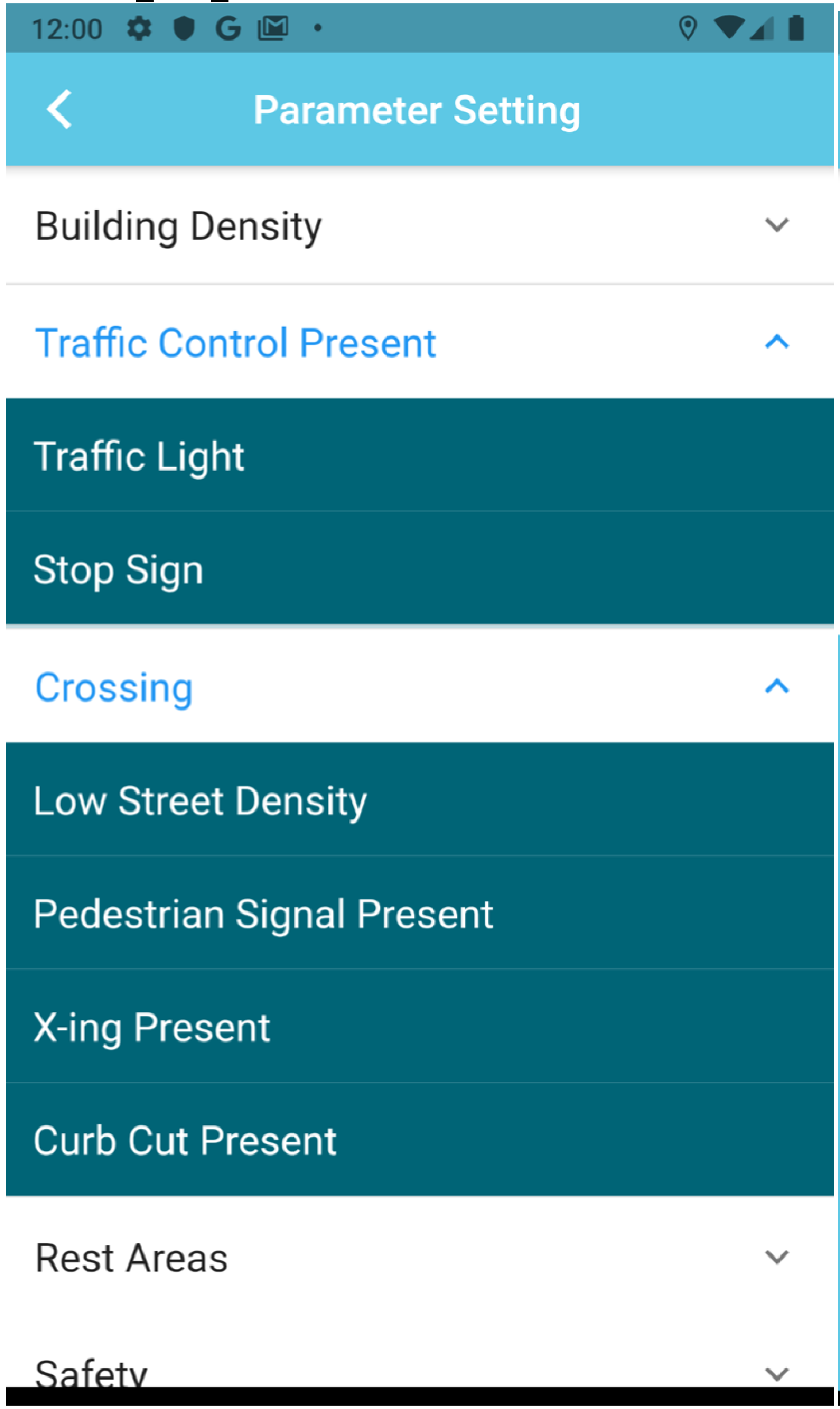


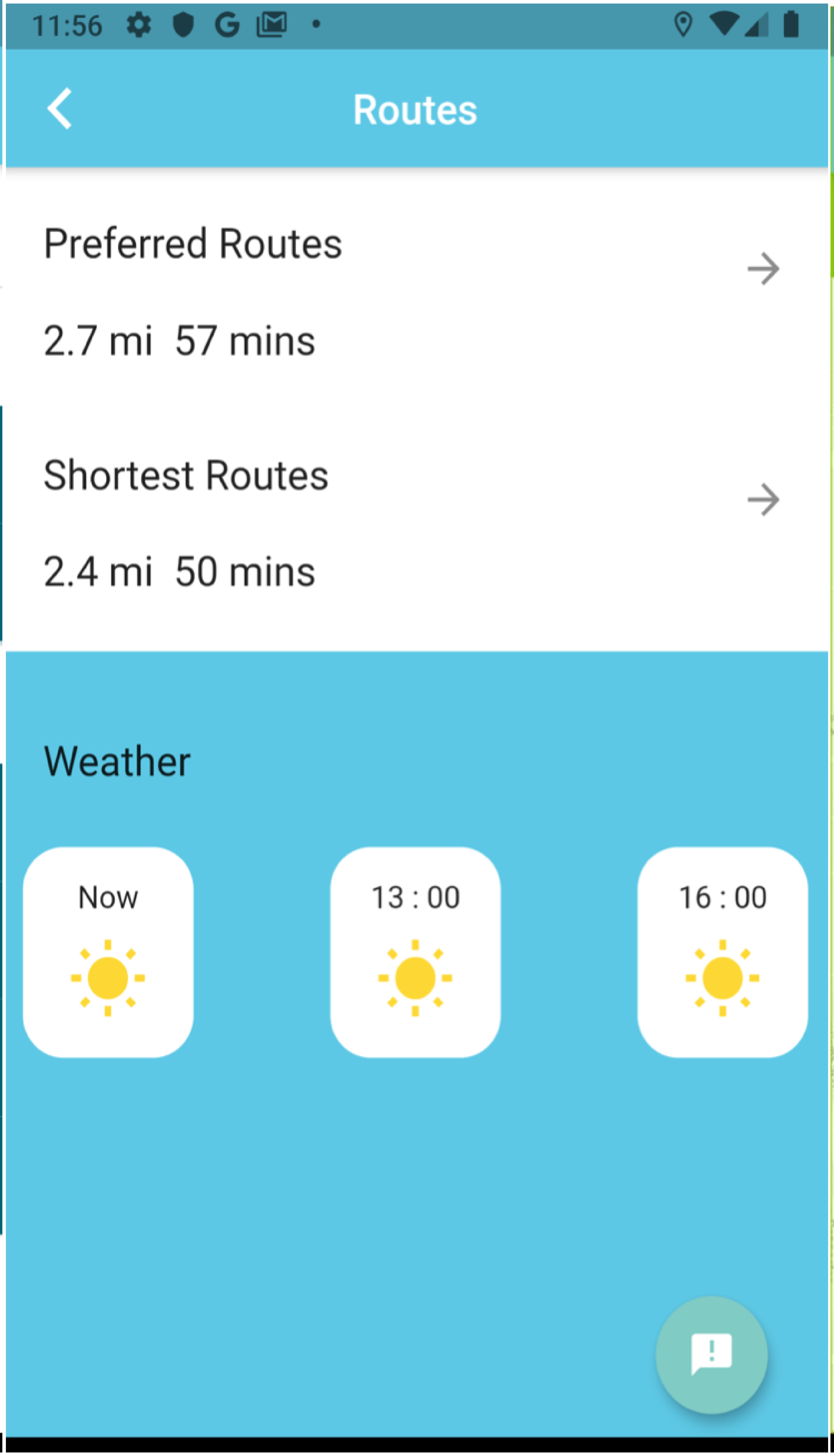
A Simpler Rating System (essential and secondary

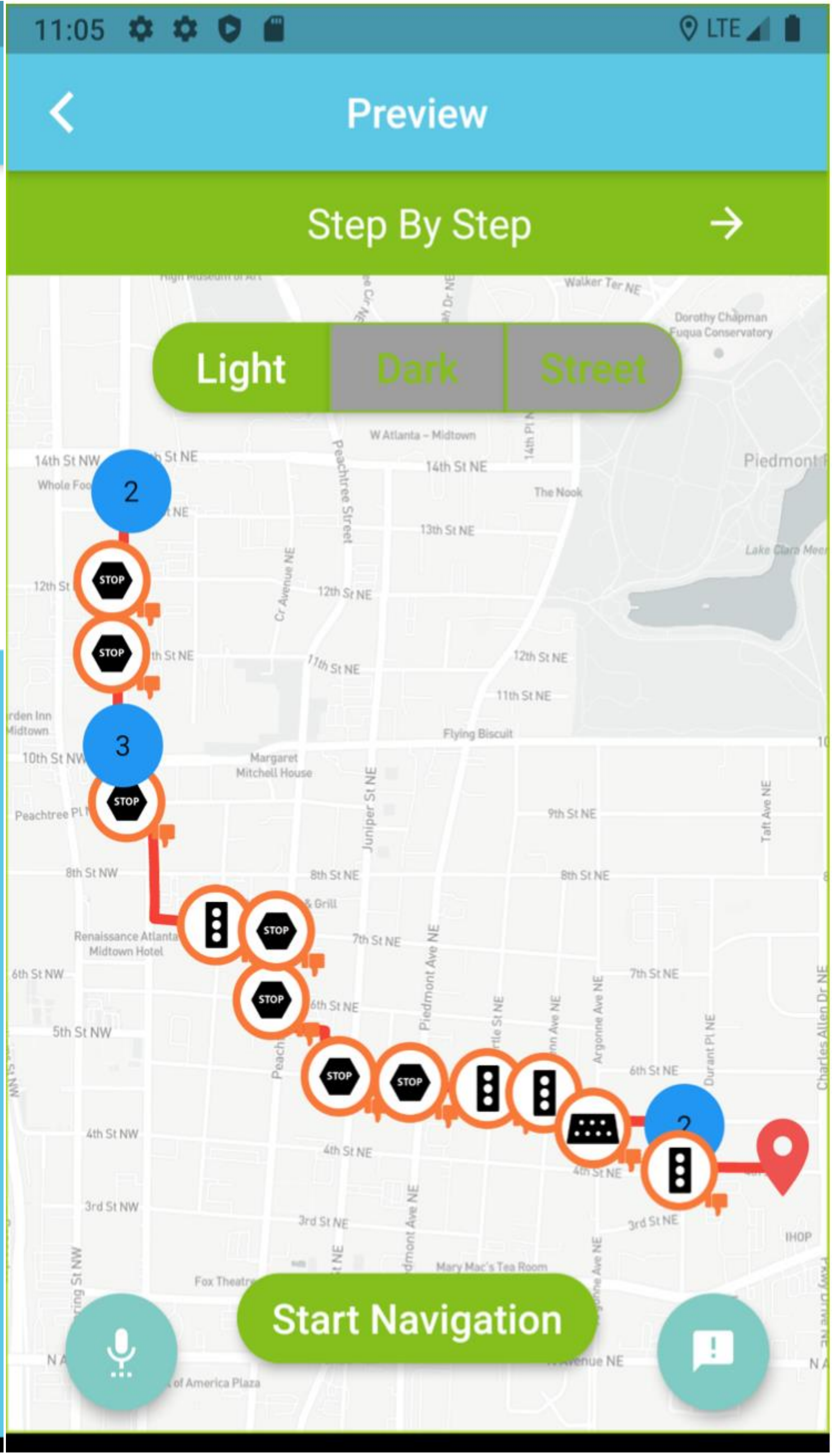


Included Audio Feedback

App Interface







Crowdsourcing transient and incorrect information

- Most routes have points where the user preferences are not met, and these are pointed out on the route plan
- Users can long press on a point on their route and upload images and comments about unexpected hurdles or facilitators
- Other users on the routes can see these images and comments and endorse with ”thumbs up” or “thumbs down”
- When enough users (three) offer “thumbs down” on a particular issue, that issue is removed from the information that is shared (resolved)

Crowdsourcing

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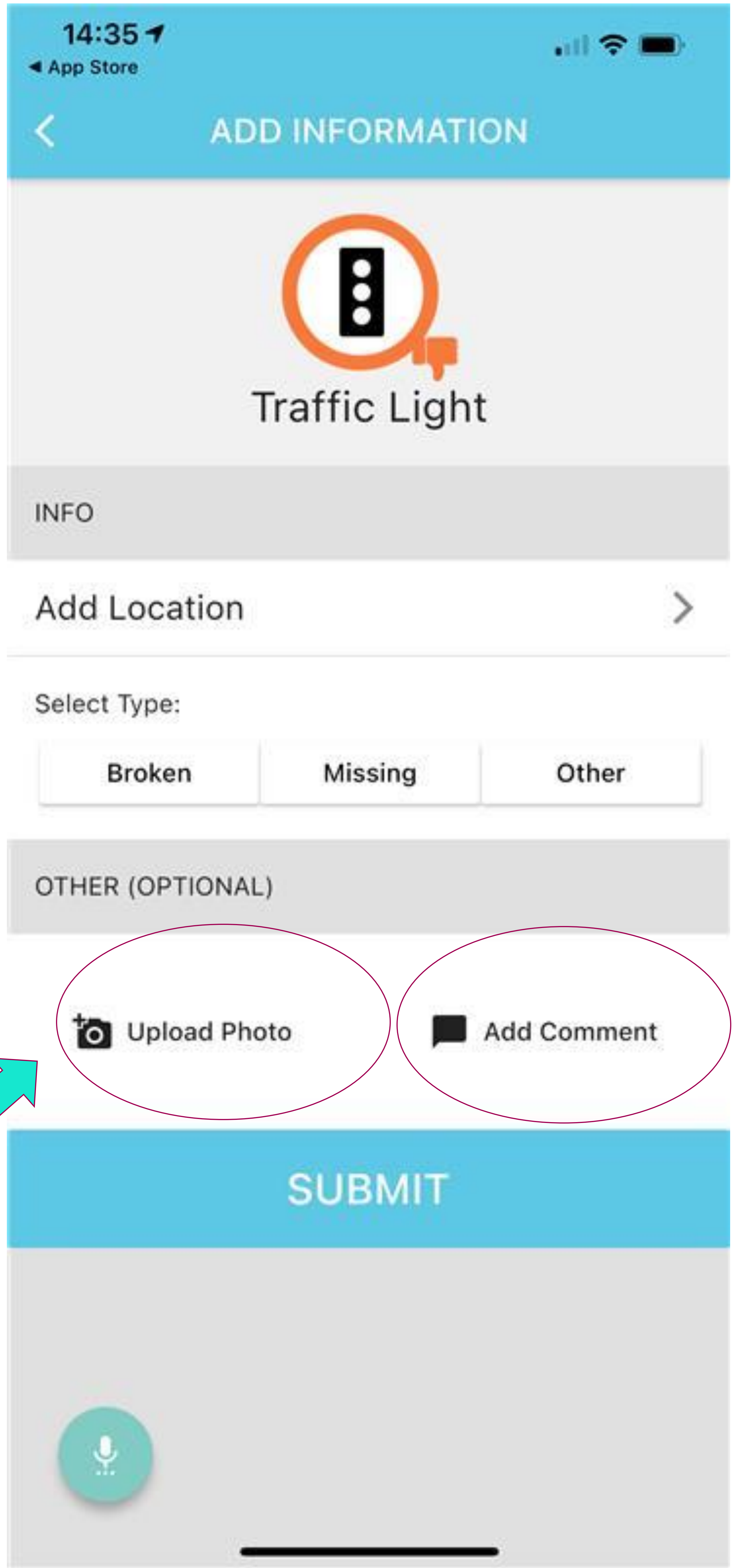
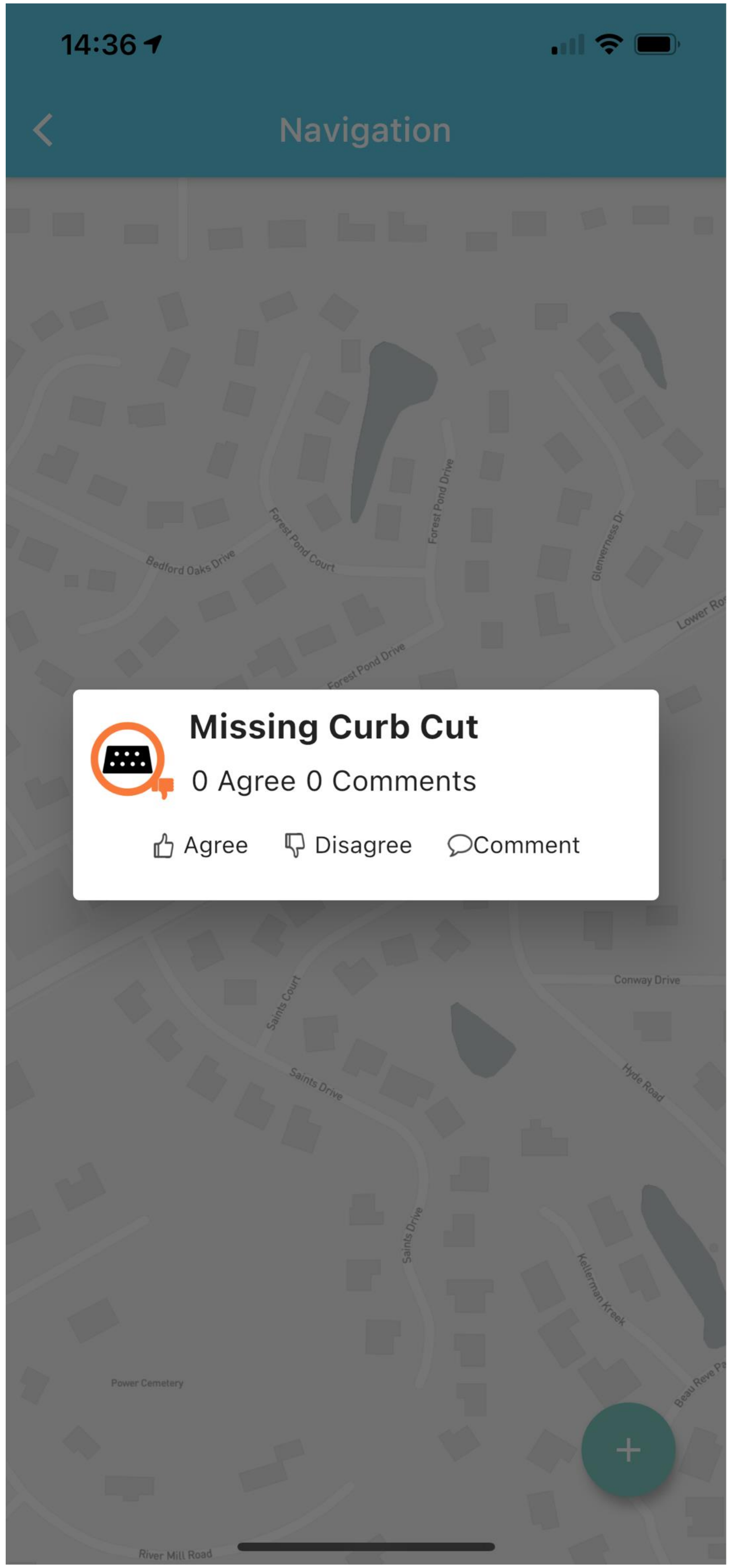
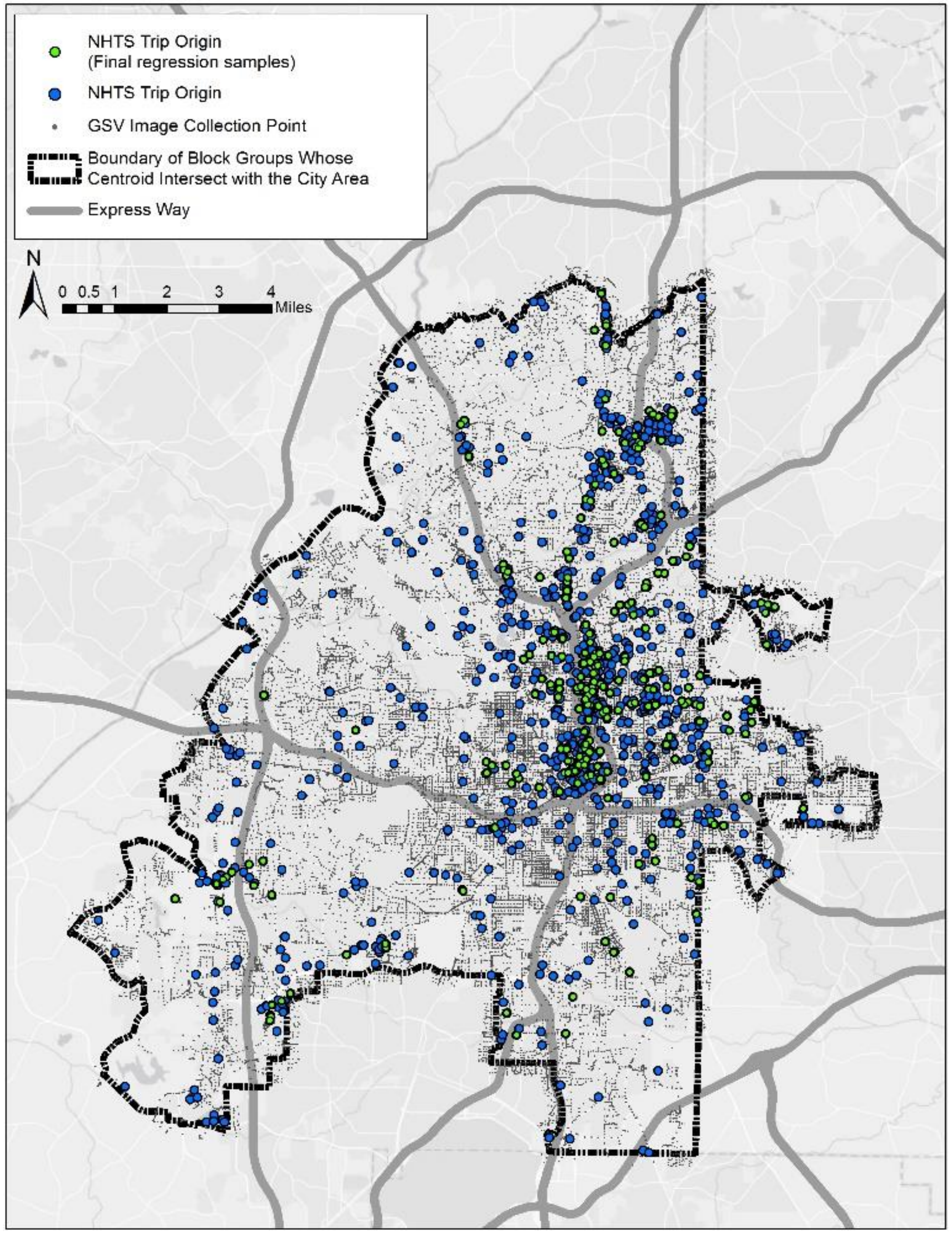


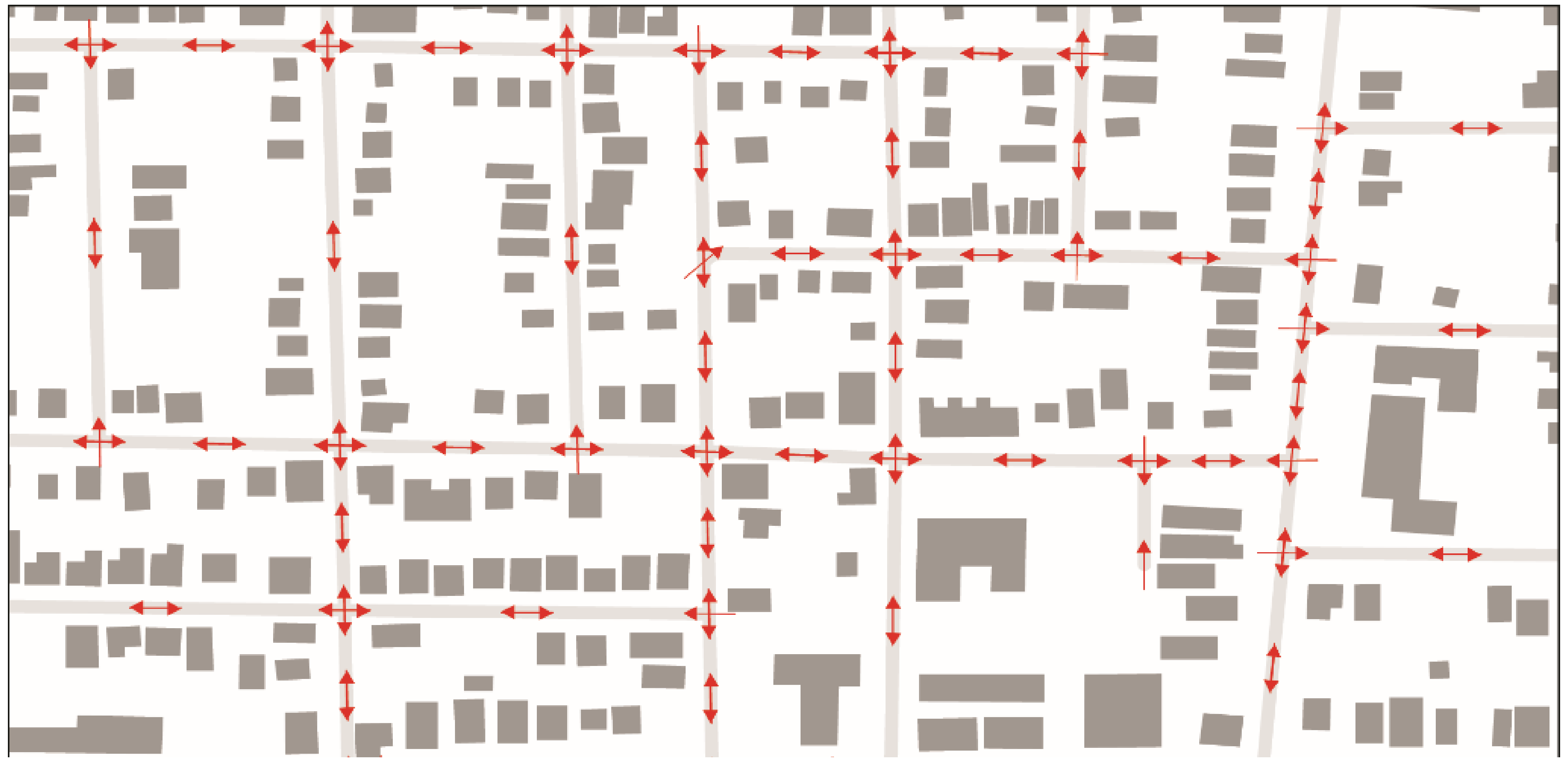


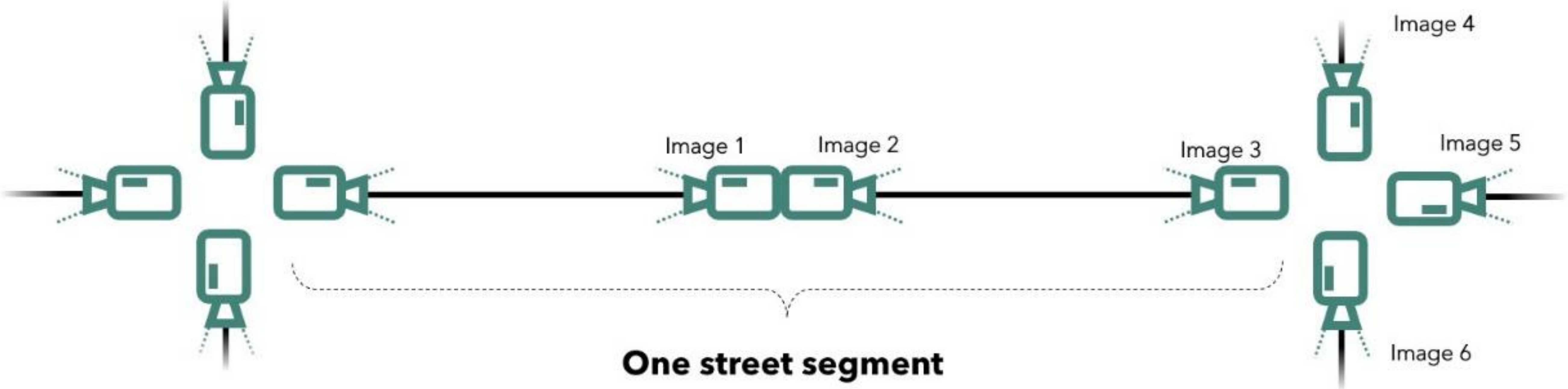
Measuring & validating walkable environments using Google Street View and computer vision

Bon Woo Koo

NHTS Walking Trip Origins in Atlanta (2016-2017)







Results of the logistic regression models using 600-meter GSV buffer (dependent variable = walking / non-walking in binary)

$$\textbf{building-to-street ratio} = \frac{share\ of\ building\ pixels}{sum\ of\ the\ share\ of\ sidewalk, road, and\ path\ pixels}$$

$$\textbf{greenness} = sum\ of\ the\ share\ of\ tree, grass, and\ plant\ pixels$$

$$\textbf{sidewalk-to-street proportion} = \frac{share\ of\ sidewalk\ pixels}{sum\ of\ the\ share\ of\ sidewalk, road, and\ path\ pixels}$$

- The regression results are in $\frac{Odds\ Ratio\ ***}{(z\text{-}statistic)}$ format, where the Odds Ratio is the exponent of the standardized coefficient from the logistic regression.

† Significant at the 10% level; * Significant at the 5% level; **Significant at the 1% level; *** Significant at < 1% level.

		Base Model	Model 1	Model 2	Model 3
	Constant	24.496*** (5.726)	3.157*** (5.231)	2.907*** (5.076)	3.11*** (5.060)
Personal-, trip-level covariates	Age	0.978* (-2.384)	0.732 (-1.62)	0.715† (-1.731)	0.737 (-1.553)
	Employment status (Unemployed)	0.239*** (-3.905)	0.314** (-2.741)	0.436† (-1.951)	0.438† (-1.860)
	Driver status (Not a driver)	6.805*** (3.411)	8.279** (3.135)	8.785*** (3.357)	7.185** (2.854)
	Number walking activities in the past 7 days	1.107*** (5.271)	2.617*** (5.041)	2.355*** (4.800)	2.58*** (4.884)
	Trip distance	0.006*** (-8.213)	0.287*** (-7.202)	0.287*** (-7.132)	0.285*** (-7.030)
Macro-scale	Employment Density		2.662** (2.949)		1.395 (0.816)
	Land Use Diversity		1.214 (1.170)		1.507* (2.034)
	Intersection Density		1.878** (2.694)		1.541† (1.651)
	(ln) Distance to Transit		1.390 (1.163)		1.239 (0.714)
	Walk Score®		0.997 (-0.015)		1.010 (0.043)
Meso-scale	Building-to-Street Ratio			5.879*** (4.361)	4.620** (2.97)
	Greenness			1.812* (2.015)	2.480* (2.507)
	sidewalk-to-street proportion			1.090 (0.420)	1.129 (0.537)
No. of observation		364	364	364	364
LL		-153.60	-135.74	-133.60	-130.06
Adj. McFadden's R^2		0.329	0.383	0.400	0.394
Bayesian Info. Criteria		342.59	336.36	320.28	342.68

Measuring Streetscape Attributes

Segment

Crossing

Computers, Environment and Urban Systems 106 (2023) 102030

Contents lists available at ScienceDirect

Computers, Environment and Urban Systems

journal homepage: www.elsevier.com/locate/ceus

Streetscapes as part of servicescapes: Can walkable streetscapes make local businesses more attractive?

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ARTICLE INFO

Keywords:
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Servicescapes
Walkability
Google Street View
Yelp review
Computer vision

ABSTRACT

Attractive local businesses can make cities more walkable by providing desirable destinations to walk to. The term servicescape has been used to describe the physical settings and environments that affect customers' inference of the service quality of businesses at that location. This study extends the concept of servicescapes to include walkable streetscapes and examines whether features that make streets more walkable also make local businesses on those streets more attractive. This study measures walkable streetscape features using street view images and computer vision, which are associated with customer satisfaction values derived from Yelp review

Contents lists available at ScienceDirect

Health and Place

journal homepage: www.elsevier.com/locate/healthplace

...validation of automated microscale walkability

...it Guhathakurta, Nisha Botchwey

...llege of Design, Georgia Institute of Technology, Atlanta, GA, USA

ABSTRACT

Measuring microscale factors of walkability has been labor-intensive and expensive. To reduce the cost, various efforts have been made including virtual audits (i.e., manual audits using street view images) and the introduction of computer vision techniques. Although studies have shown that virtual audits (i.e., manual audits using street view images) can reliably replicate in-person audits, they are still prohibitively expensive to be applied to a large geographic area. Past studies used computer vision techniques to help automate the audit process, but off-the-shelf models cannot detect some of the important microscale walkability characteristics, falling short of fully capturing the multi-facetted concept of walkability. This study is one of the earliest attempts to use the combination of custom-trained computer vision models, geographic information systems, and street view images to automatically audit a complete set of items of a validated microscale walkability audit tool. This study validates the reliability of the automated audit with virtual audit results. The automated audit results show high reliability, indicating automated audit can be a highly scalable and reliable replacement of virtual audit.

...Walk Score (Walk Score, n.d.) and EPA's ...mental Protection Agency, 2015), have ...acroscale factors such as land use mix ...macroscale factors of walkability are important for walkability, they are only a part of the multi-dimensional concept of walkability (Alfonzo, 2005). Recently, microscale factors of walkability, such as fine-grained urban design details and their main-

transport (Cain et al., 2014; Sallis et al., 2015). Furthermore, microscale factors are relatively easy, quick, and inexpensive to modify, making timely interventions for promoting active transport and physical activity much more feasible than macroscale factors.

Despite these strengths, microscale factors have been rarely incorporated into widely used walkability indices such as Walk Score because its measurements have heavily relied on on-site, manual audits or surveys. With the introduction of street view image services such as Google Street View, many studies examined the possibility of replicating in-

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1–31
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How are Neighborhood and Street-Level Walkability Factors Associated with Walking Behaviors? A Big Data Approach Using Street View Images

Bon Woo Koo[1], Subhrajit Guhathakurta[1], and Nisha Botchwey[1]

Abstract

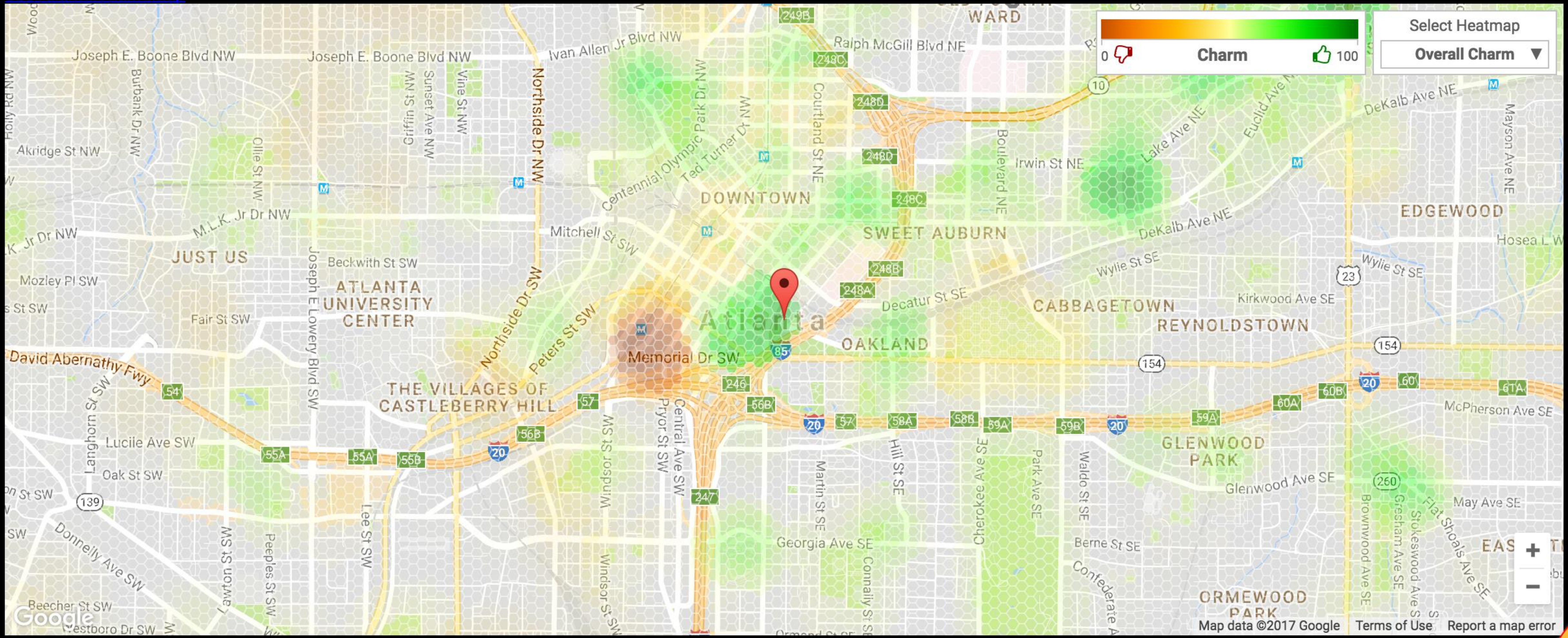
The built environment characteristics associated with walkability range from neighborhood-level urban form factors to street-level urban design factors. However, many existing walkability indices are based on neighborhood-level factors and lack consideration for street-level factors. Arguably, this omission is due to the lack of a scalable way to measure them. This paper uses computer vision to quantify street-level factors from street view images in Atlanta, Georgia, USA. Correlation analysis shows that some streetscape factors are highly correlated with neighborhood-level factors. Binary logistic regressions indicate that the streetscape factors can significantly contribute to explaining walking mode choice and that streetscape factors can have a greater association with walking mode choice than neighborhood-level factors. A potential explanation for the result is that the image-based streetscape factors may perform as proxies for some macroscale factors

Is Neighborhood Perception Close to Reality?

Charming Spot?

RentLingo Charm Index

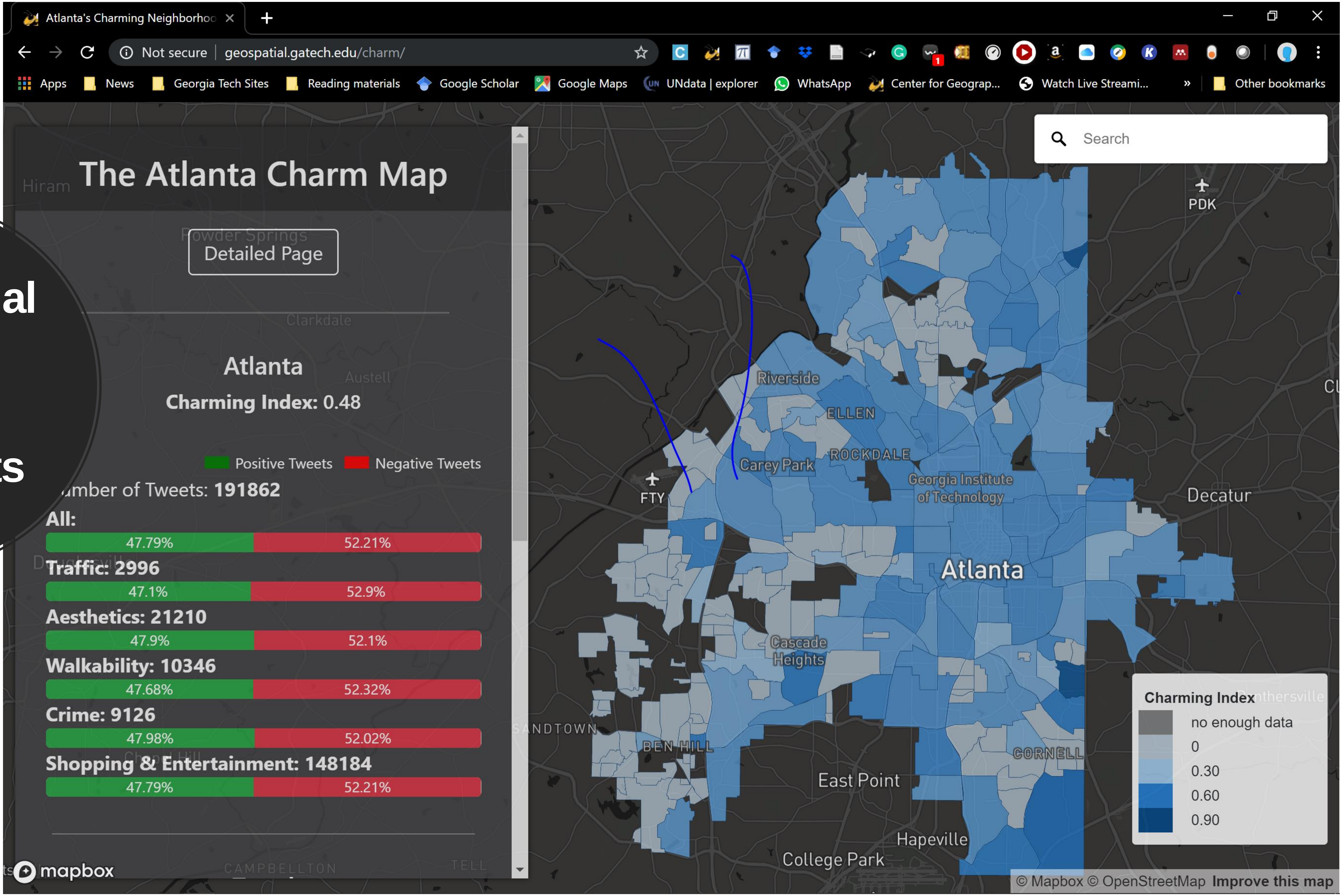
See Atlanta Charm Map

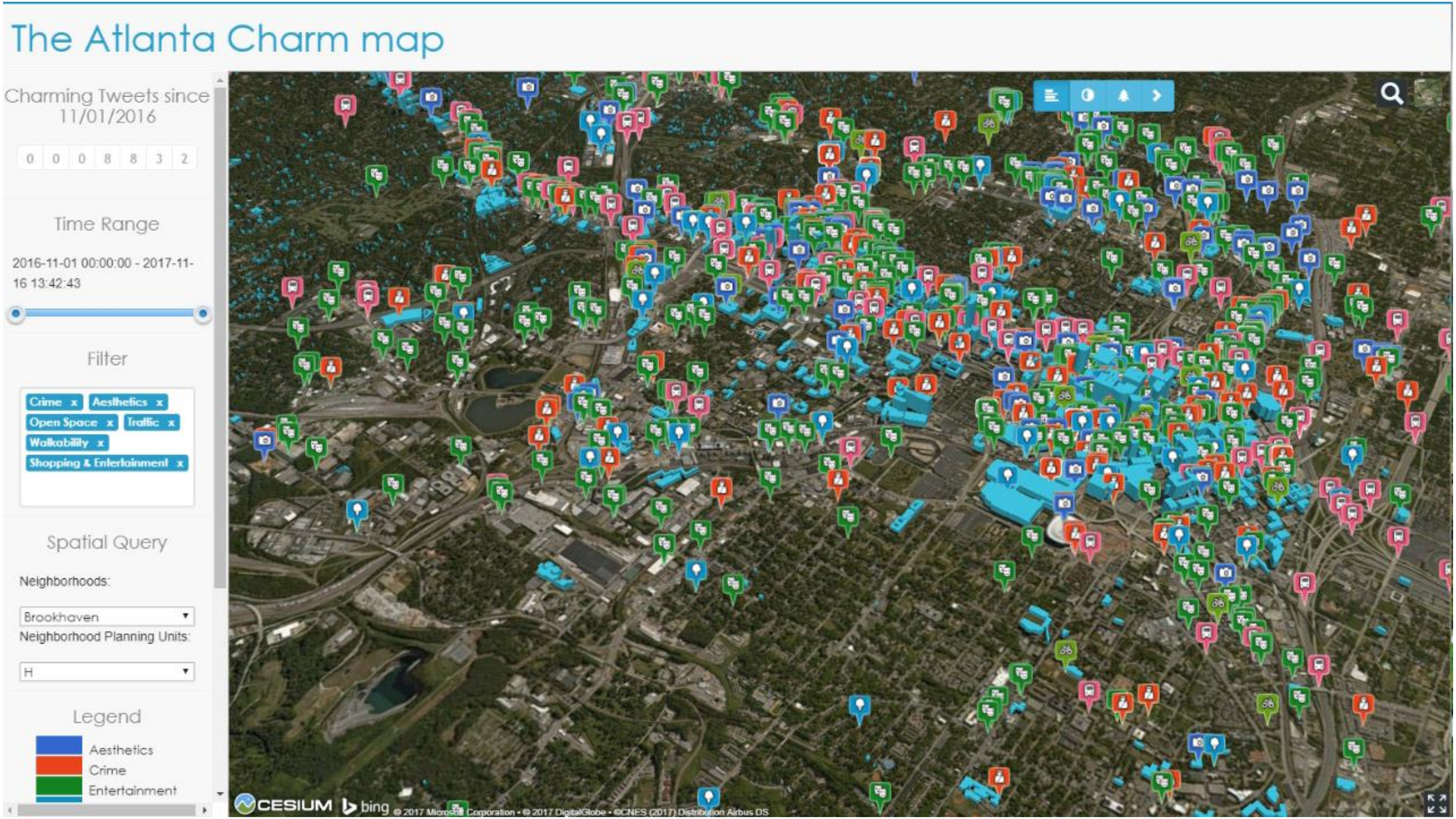


Charm

(Source: http://neighborhoodnexus.org/ && http://www.rentlingo.com/)

Using Social Media to Assess Popular Sentiments




The Atlanta Charm map
Charming Tweets since 11/01/2016
0 0 0 8 8 3 2
Time Range
2016-11-01 00:00:00 - 2017-11-16 13:42:43
Filter
Crime x
Aesthetics x
Open Space x
Traffic x
Walkability x
Shopping & Entertainment x
Spatial Query
Neighborhoods:
Brookhaven
Neighborhood Planning Units:
H
Legend
Aesthetics
Crime
Entertainment
CESIUM
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Classification Results: Neighborhood related or not

Classifier	Accuracy (%)	Precision (%)		Recall (%)		F_1-score (%)	
		Neighborhood	Non-Neighborhood	Neighborhood	Non-Neighborhood	Neighborhood	Non-Neighborhood
NB	80.06	75.25	82.75	71.13	85.55	73.12	84.12
10NN	82.91	82.10	83.28	70.64	90.48	75.93	86.73
SLAP	82.36	76.07	86.45	78.47	84.78	77.22	85.59
SVM	86.71	85.71	87.23	78.22	91.96	81.78	89.52

NB: Naïve Bayes
10NN: Nearest Neighbor
SLAP: A Supervised Learning Approach to Priority Cuts
SVM: Support Vector Machine

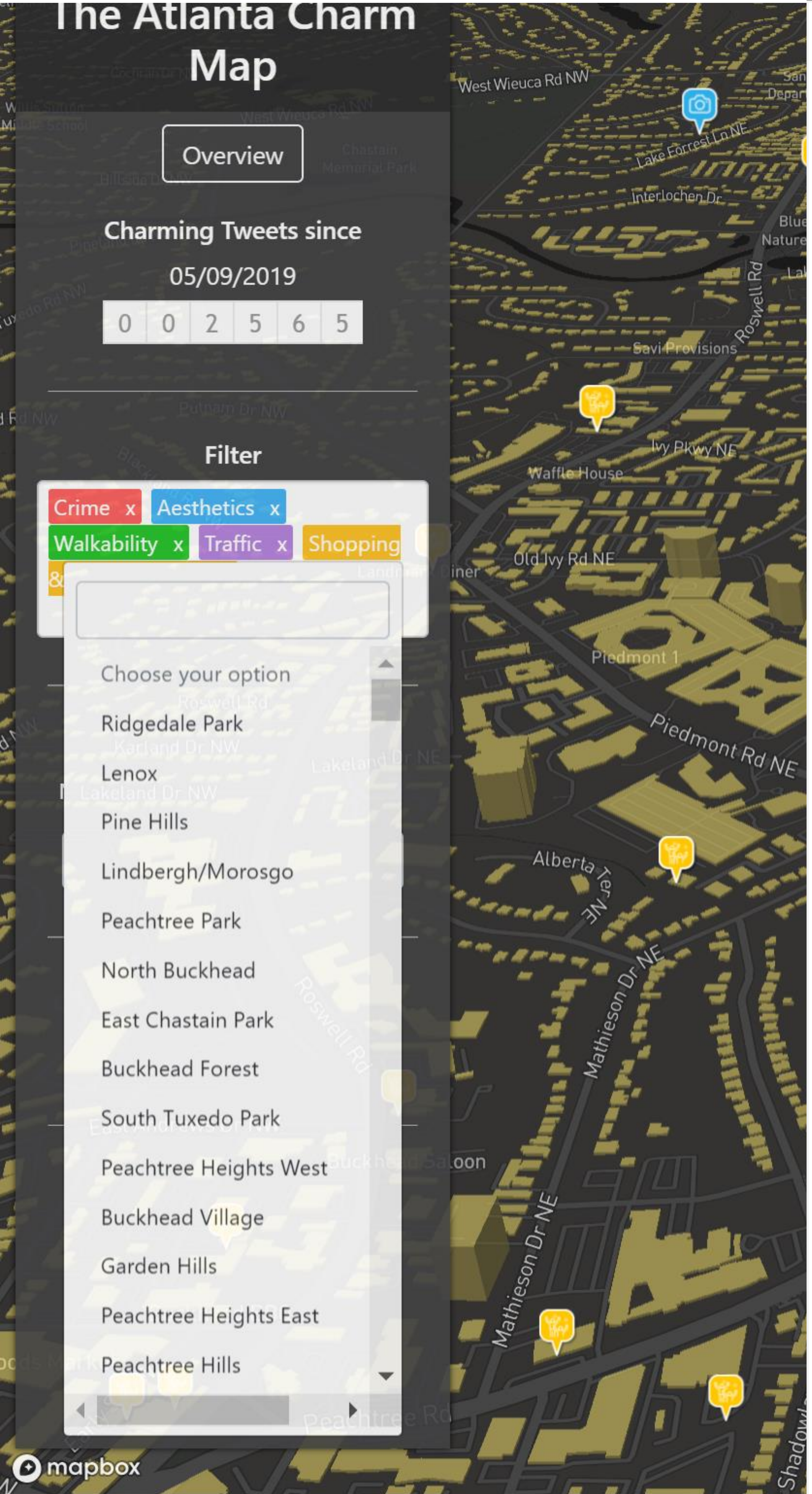
Classification Results: Positive or Negative?

Classifier	Accuracy (%)	Precision (%)		Recall (%)		F_1-score (%)	
		Positive	Negative	Positive	Negative	Positive	Negative
NB	91.42	97.40	28.02	93.50	50.32	95.40	34.95
10NN	94.62	96.23	42.25	98.22	24.00	97.20	28.53
SLAP	94.29	97.24	42.31	96.75	45.62	96.99	42.89
SVM	95.88	96.09	84.17	99.73	19.61	97.87	30.62

NB: Naïve Bayes
10NN: Nearest Neighbor
SLAP: A Supervised Learning Approach to Priority Cuts
SVM: Support Vector Machine

Classification Results: Identifying Attributes Noted

Classifier		NB	10NN	SLAP	SVM
Accuracy (%)	OVERALL	86.61	88.71	90.4	90.27
Precision (%)	Aesthetics	53.1	51.54	57.34	54.54
	Crime	56.15	94.17	92.38	95.83
	Maintenance	81.38	58.68	77	70.78
	OpenSpace	34.74	50.07	38.18	54.35
	Entertainment	78.82	86.02	83.49	84.31
	Traffic	51.32	49.44	49.65	47.73
	Walkability	36.82	84.26	64.28	75.62



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Mining Social Media to Measure Neighborhood Quality in the City of Atlanta

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ABSTRACT

This article presents a model to classify perceptions of various Atlanta neighborhoods based on social media. Tweets were extracted using Twitter's API and categorized to determine 1) whether they are neighborhood related; 2) whether a positive or negative sentiment could be assigned, and 3) whether they belong to one of eight categories of neighborhood quality assessments. These eight categories are public safety, transportation, density, walkability, maintenance, aesthetics, open space, and quality of dining and entertainment venues. Tweets that were related to neighborhood quality and geo-tagged accounted for 4% of all filtered Tweets. Overall 49% of neighborhood perception related Tweets were extracted to create an indicator of perceived neighborhood quality. The study then compared the perception of neighborhoods from social media analysis with quantitative indicators of neighborhood quality.

KEYWORDS

Amenities, Machine Learning, Neighborhood, Perception, Quality of Life, Social Media

1. INTRODUCTION

Since neighborhood quality is an important attribute of residents' quality of life, choosing the right neighborhood is a critical task undertaken by households at one or more points during their lifecycle (Sirgy and Cornwell, 2002). Given that neighborhood quality is closely related to housing satisfaction, moving to a new area requires substantial research about the potential neighborhoods where a household might choose to live (Lee et al., 2008; Lovejoy et al., 2010; Lu, 1999; Oakley et al., 2013). During 2015-2016, around 1 out of 9 people in the U.S. moved to a new residence, and this statistic has been consistent in the recent past (U.S. Census 2016). The perception of a neighborhood is also closely tied to housing values (McCluskey and Rausser, 2001; Poor et al., 2001). Housing in desirable neighborhoods tends to maintain high resale values compared to similar housing in less desirable areas. Also, a household's social status is often partly derived from the perceived quality of the neighborhood where the household is located. While neighborhood quality matters for households'

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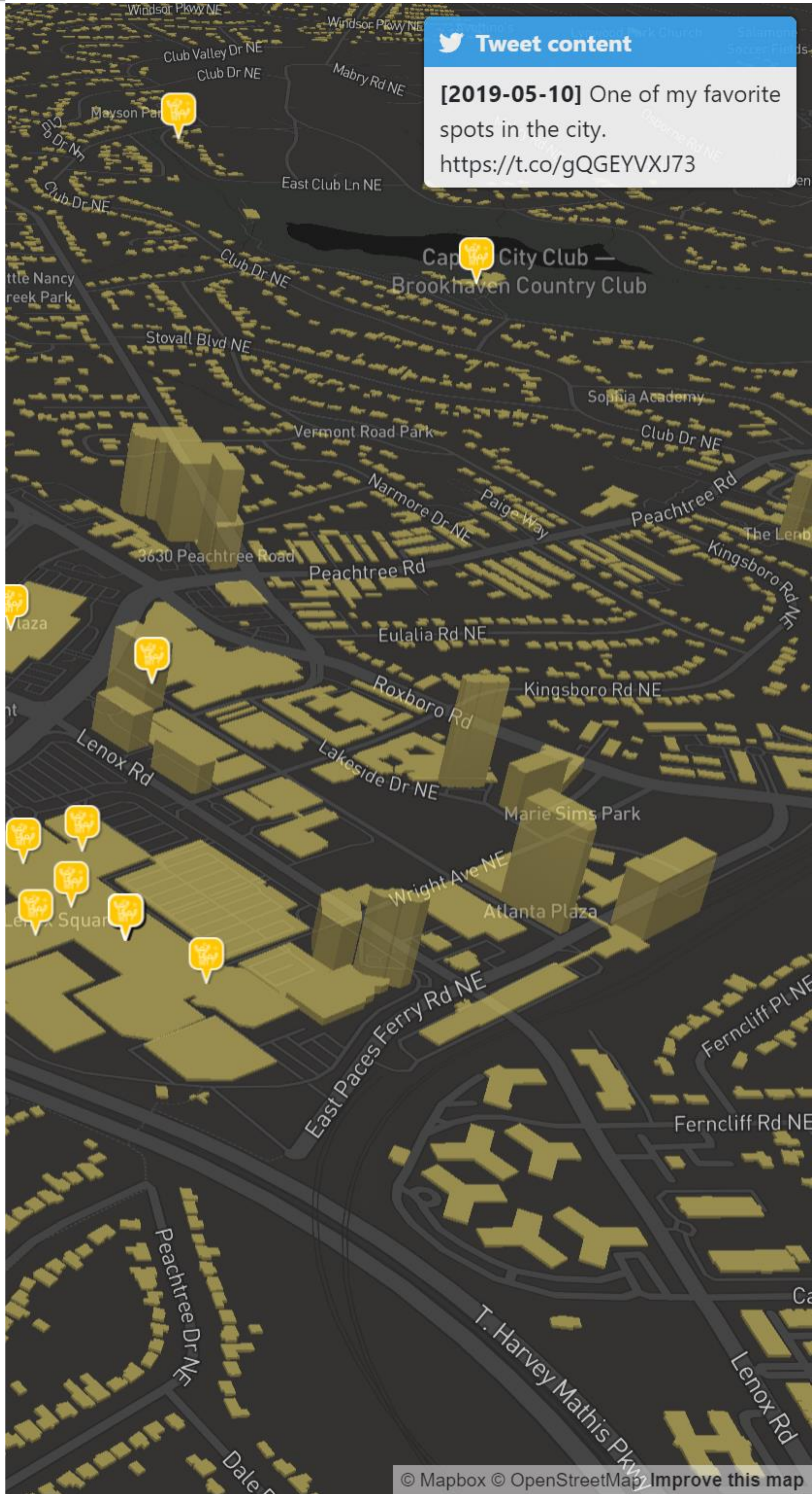

Summary “take-home” message

- ❖ Cities evolve together with the environment, culture, history, economy, and customs of a place and its inhabitants
- ❖ The joy of experiencing cities is embedded in the significance and meaning that places imbibe over time – it highlights particular moments in its history through its physical character and its people
- ❖ Smart cities are cities that celebrate the culture and history of the place and enable appropriate technologies to enhance livability of all inhabitants without compromising democracy and social choice in all spheres of city life
- ❖ Smart cities focus on enabling technologies that allow multiple solutions to emerge to enhance quality of life and offer choices with minimal constrains on making similar choices in the future

The Shoulders I Stand On

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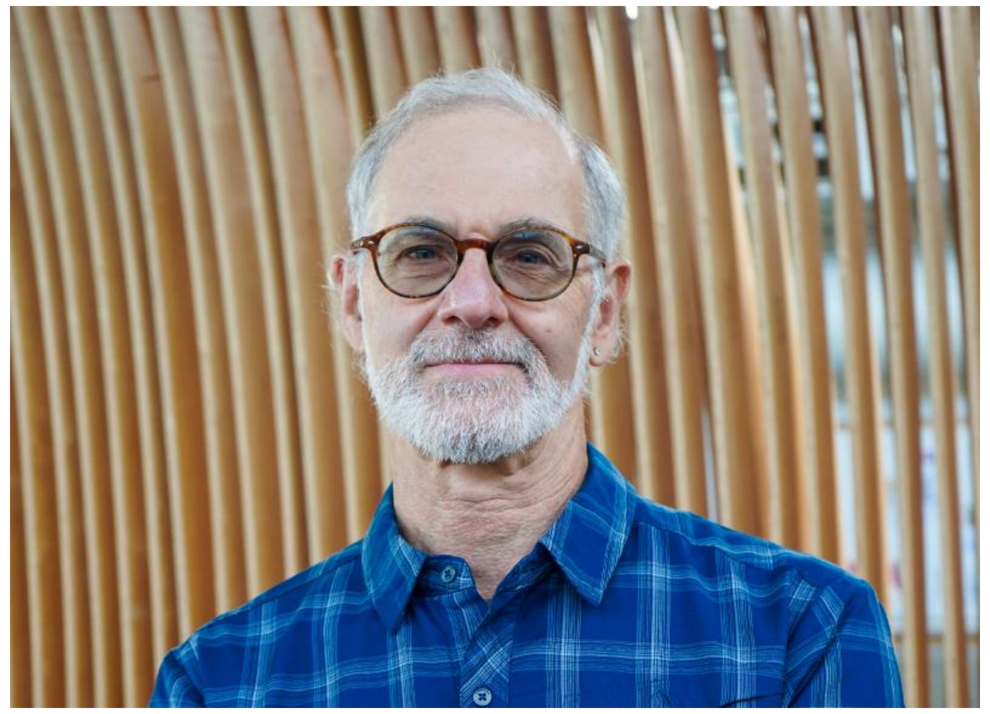
Florina Dutt

Bon Woo Koo

Jon Sanford



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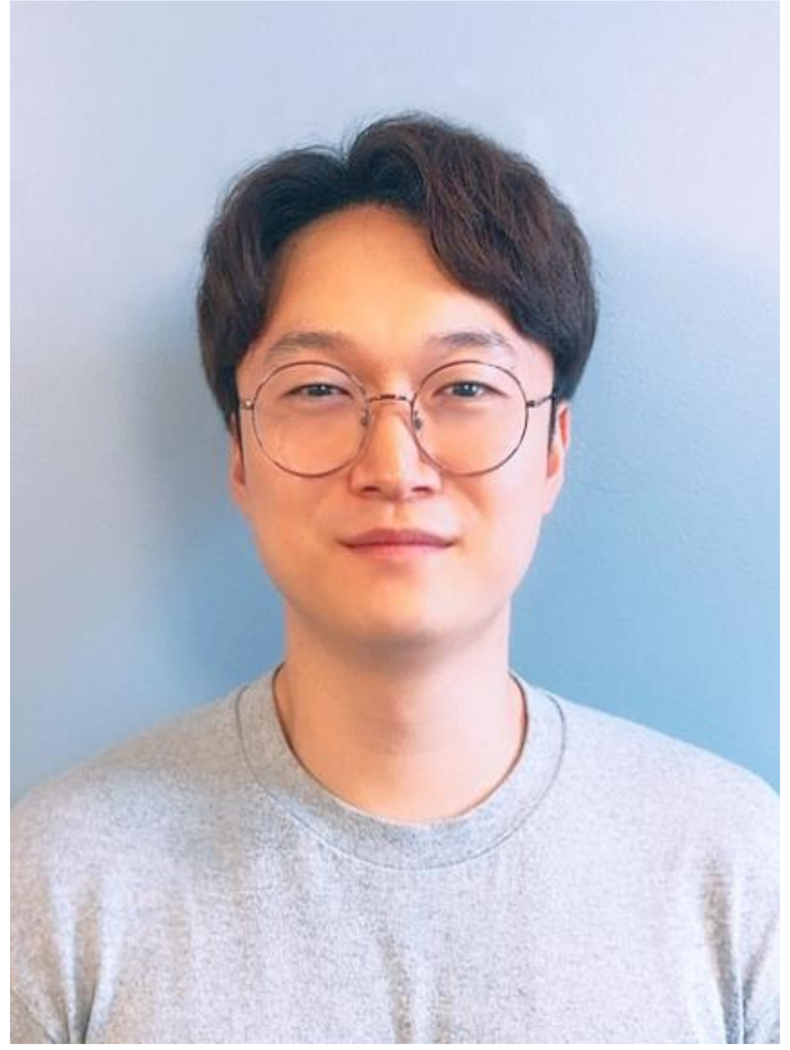

Nisha Botchwey

Thank You!

I look forward to your questions and comments

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