Spatially Enabled Society
with AI and Digital Twin

인공지능과 디지털트윈으로 여는 공간정보사회

KRIHS 국토연구원

Spatially Enabled Society with AI and Digital Twin 인공지능과 디지털트윈으로 여는 공간정보사회

2019. 8

KRIHS 국토연구원

Smart GEO Expo 2019
2019 스마트국토엑스포

2019 ICGIS International Conference on Geospatial Information Science

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2019. 8. 8. (목), 13:00~18:00
코엑스 컨퍼런스룸 317호

KRIHS 국토연구원

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KRIHS 국토연구원

Program

Time	Contents
13:00~13:30	Registration | 등록
13:30~13:35	Opening Remarks | 개회사 President of KRIHS 국토연구원장
13:35~13:40	Congratulatory Address | 축사 Deputy Minister of House and Land Office, MOLIT 국토교통부 주택토지실장
13:40~14:20	**Keynote Speech 기조연설**
13:40~14:20	Senseable Cities 센서블 시티 Prof. Carlo Ratti, Senseable City Lab, MIT
14:20~14:40	Coffee break 휴식
14:40~16:40	**Invited Talk 발표세션**
14:40~15:10	Smart Partnerships 스마트 파트너쉽 Prof. Debra Lam, Georgia Institute of Technology
15:10~15:40	How Big Data Can Meaningfully Support Urban Design and Planning 빅데이터를 활용한 도시 디자인과 계획 Prof. Bige Tunçer, Singapore University of Technology and Design
15:40~16:00	Understanding Tourists' Image of Seoul with Geotagged Photos using Convolutional Neural Networks CNN딥러닝을 이용한 외국인 관광객의 서울 이미지 분석 Prof. Youngok Kang, Ewha Womans University 이화여자대학교 강영옥 교수
16:00~16:20	Use Cases of Geospatial Information in AI Applications 인공지능 응용에서의 공간정보 활용 사례 Prof. Hyeonkyu Lee, KAIST 한국과학기술원 이현규 교수
16:20~16:40	Monitoring Land Use and Land Cover Change using Geospatial A.I. 인공지능 기술을 활용한 국토모니터링 혁신 방안 Dr. Ki-Hwan Seo, KRIHS 국토연구원 서기환 연구위원
16:40~17:00	Coffee break 휴식
17:00~18:00	**Panel Discussion 종합토론**
17:00~18:00	Moderator | 좌장 Dr. Hosang Sakong, KRIHS | 국토연구원 사공호상 선임연구위원 Panels | 토론자 Prof. Do-Nyun Kim, Sungkyunkwan University | 성균관대학교 김도년 교수 Prof. Kyoung Jun Lee, Kyung Hee University | 경희대학교 이경전 교수 Dr. Seungbum Kim, VW LAB | 브이더블유랩 김승범 소장 Dong Min Han, MOLIT | 국토교통부 국토정보정책과 한동민 과장 Bo-Gyeong Mun, The Electronic Times | 전자신문 문보경 차장

Contents

Keynote Speech

Senseable Cities

[센서블 시티]

Prof. Carlo Ratti
Senseable City Lab, MIT

SENSEABLE CITIES

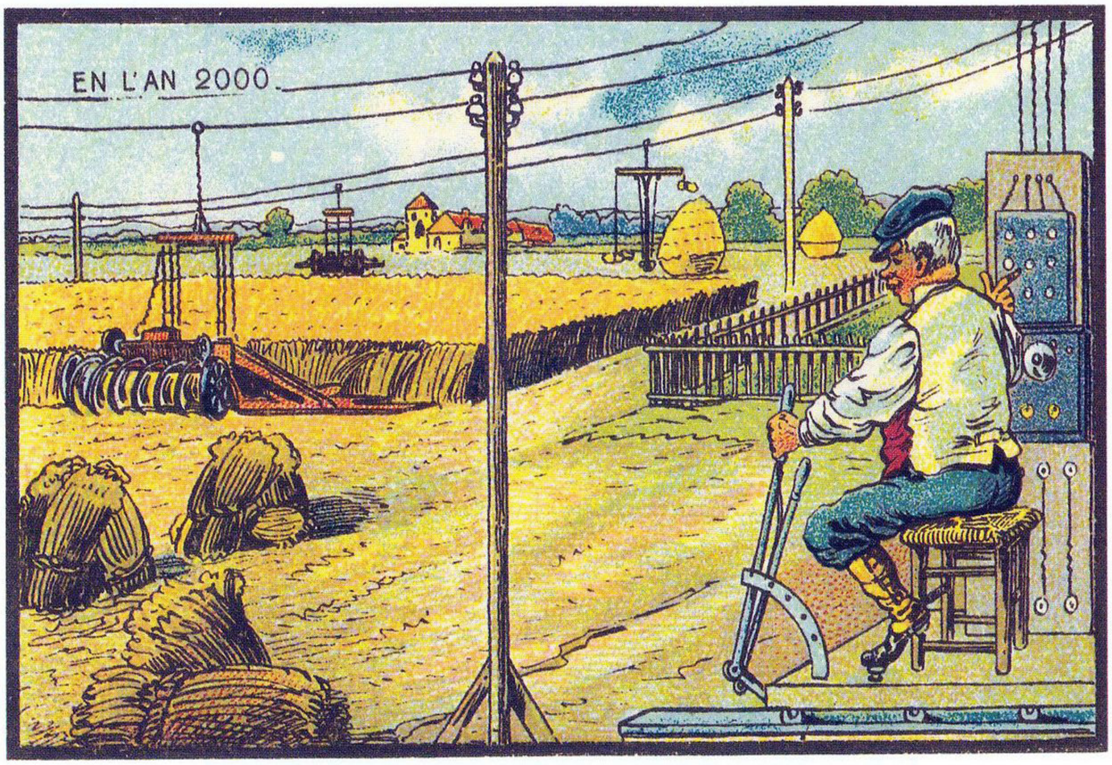
Carlo Ratti
ratti@mit.edu
Massachusetts Institute of Technology (MIT)

Abstract

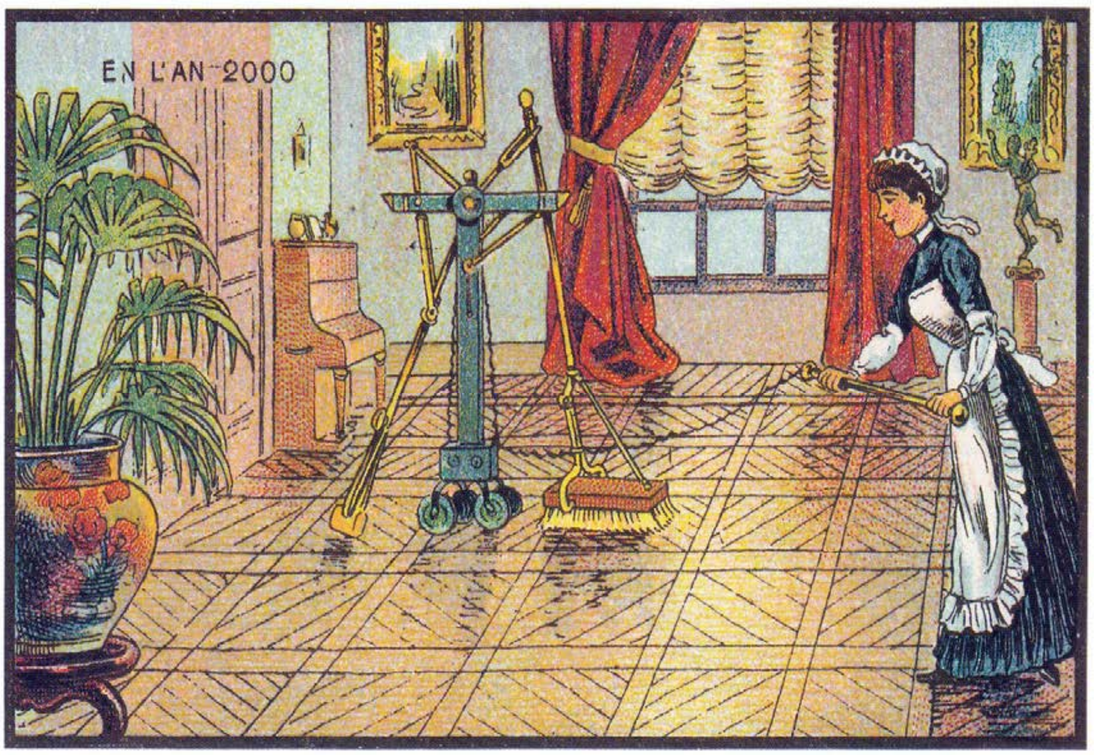
The way we live, work, and play is very different today than it was just a few decades ago, thanks in large part to a network of connectivity that now encompasses most people on the planet. In a similar way, today we are at the beginning of a new technological revolution: the Internet is entering the physical space – the traditional domain of architecture and design – becoming an “Internet of Things” or IoT. As such, it is opening the door to a variety of applications that – in a similar way to what happened with the first wave of the Internet - can encompass many domains: from energy to mobility, from production to citizen participation. The contribution from Prof. Carlo Ratti will address these issues from a critical point of view through projects by the Senseable City Laboratory, a research initiative at the Massachusetts Institute of Technology, and the design office Carlo Ratti Associati.


Seoul, 8 August 2019
ICGIS 2019 Conference
Senseable Cities
Big Data and Mobility
Carlo Ratti
Partner, Carlo Ratti Associati
Professor of the Practice of Urban Technologies, MIT

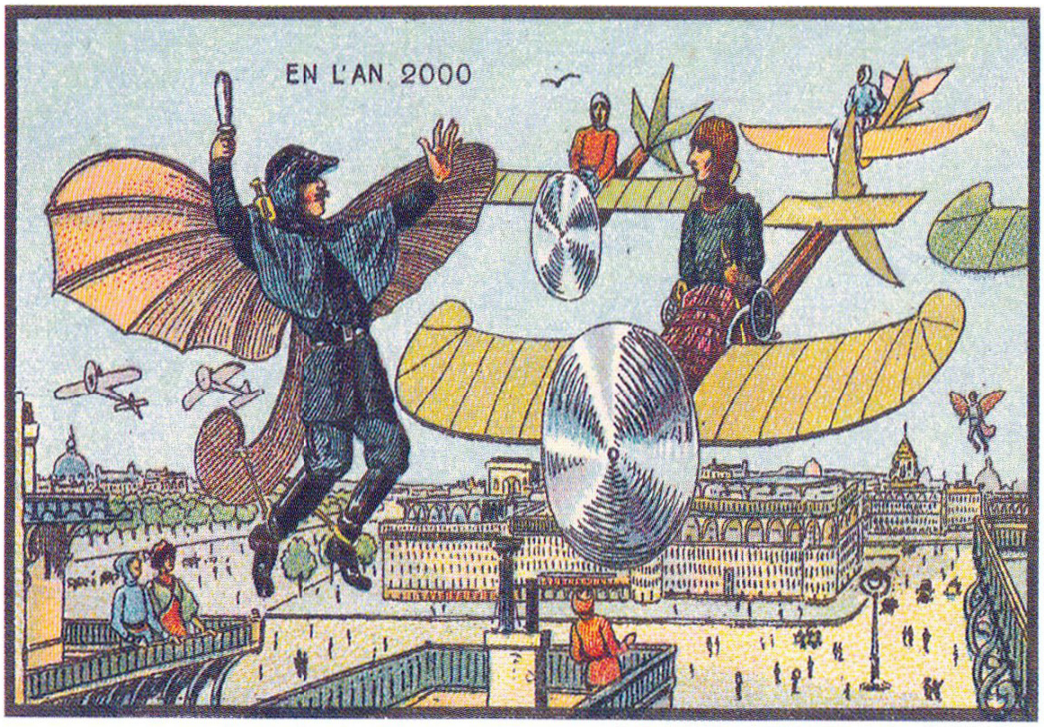

En l’en 2000…



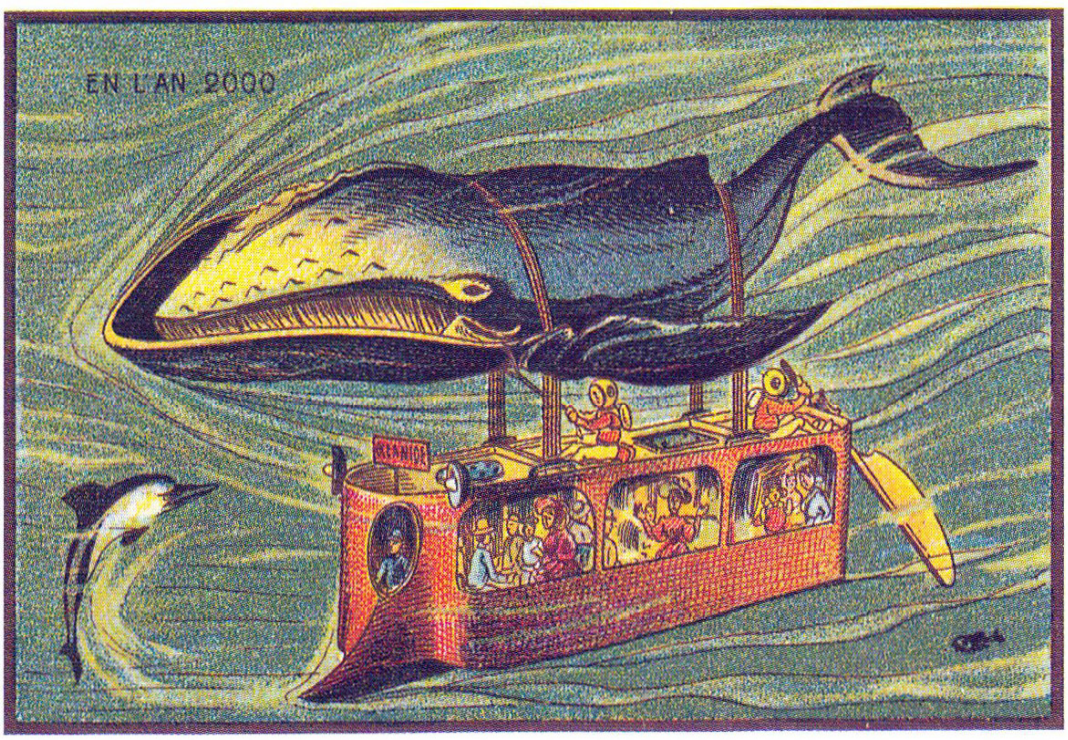
A Very Busy Farmer



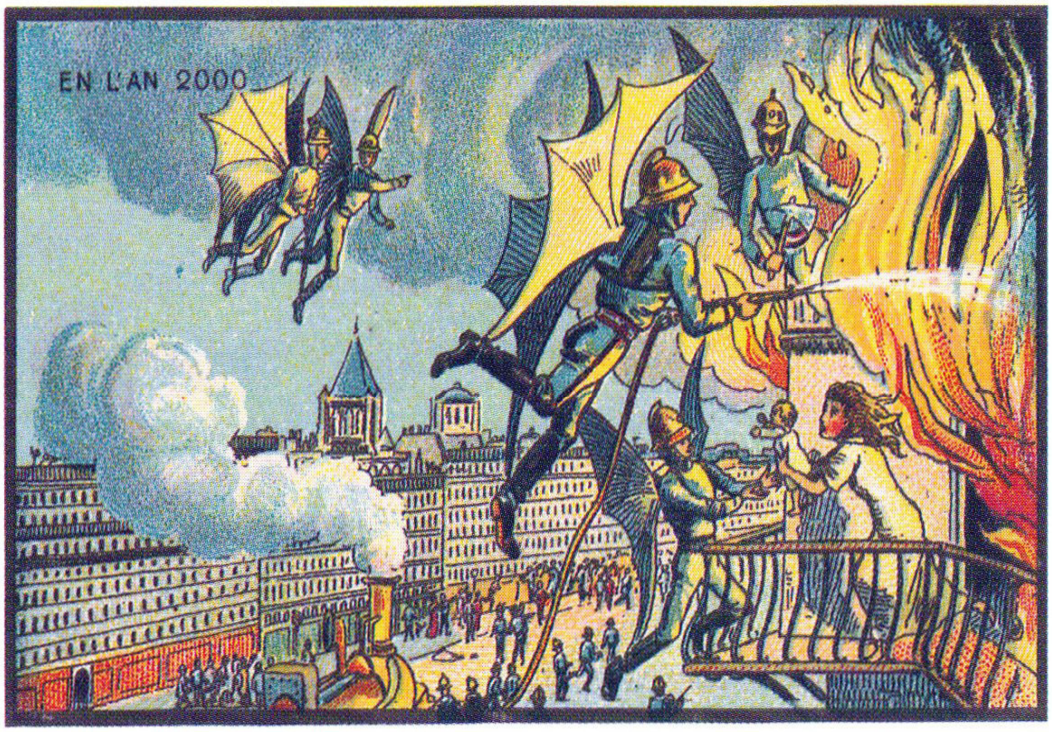
Electric Scrubbing



Aviation Police



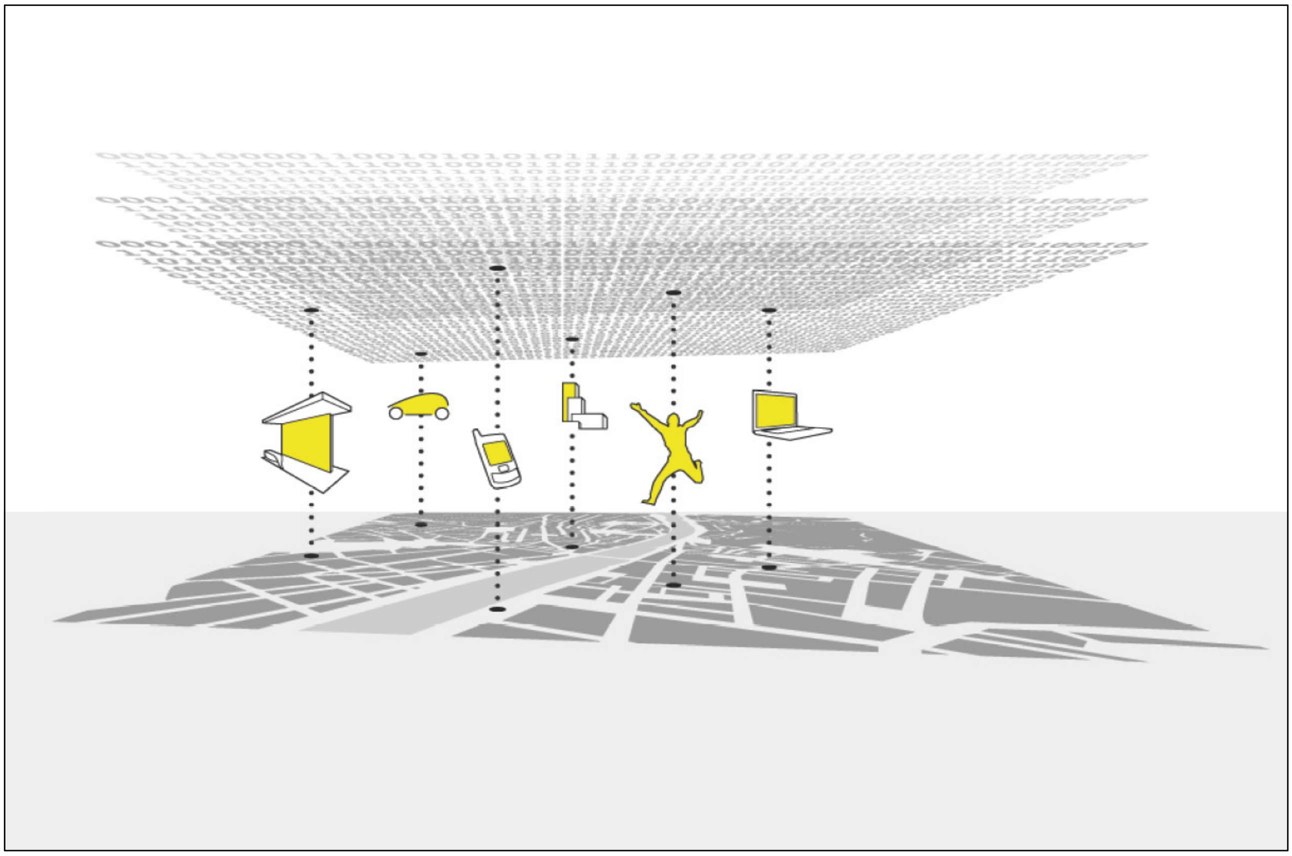
A Whale-Bus



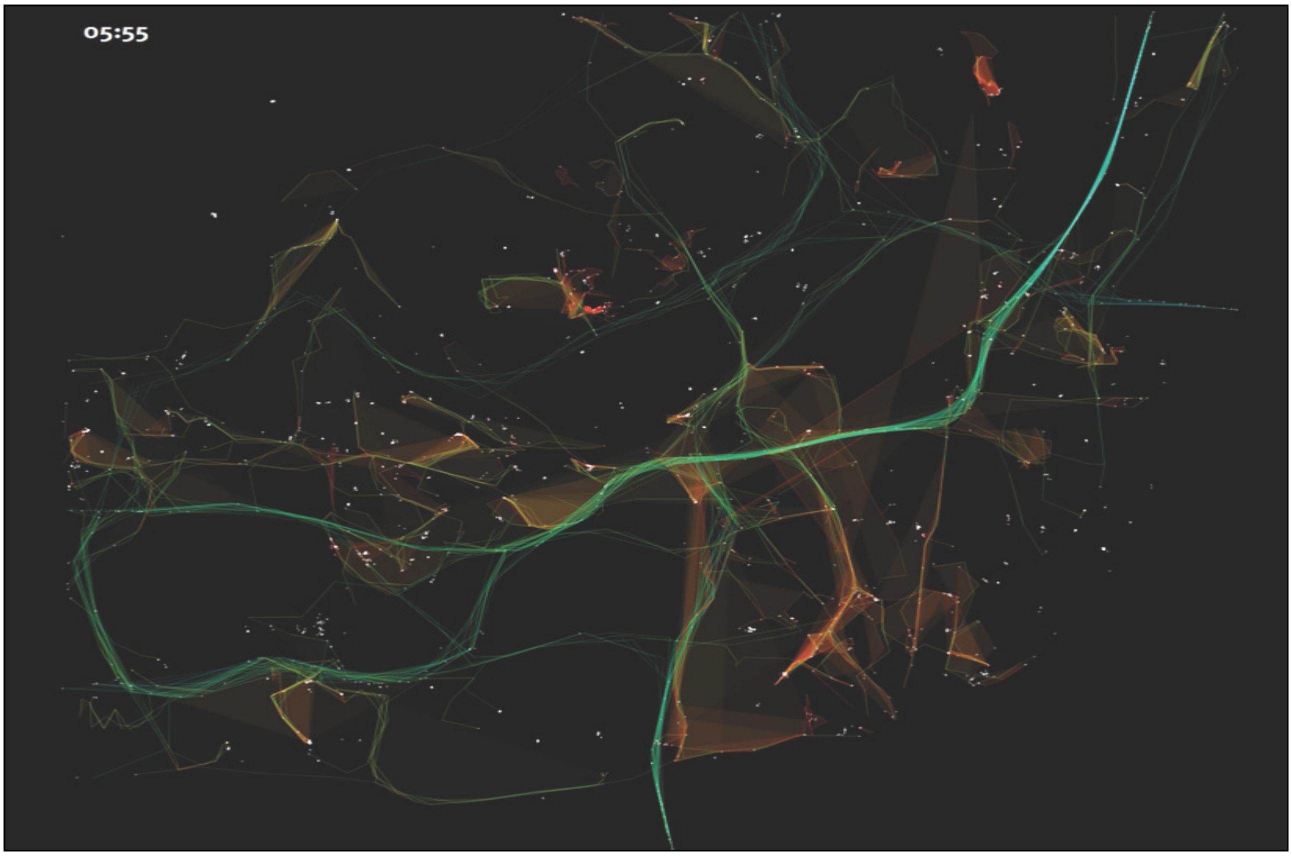
Aerial Firemen

"The future is open. It is not predetermined. No one can predict it, except by chance. We all contribute to determining it by what we do. We are all equally responsible for its success."

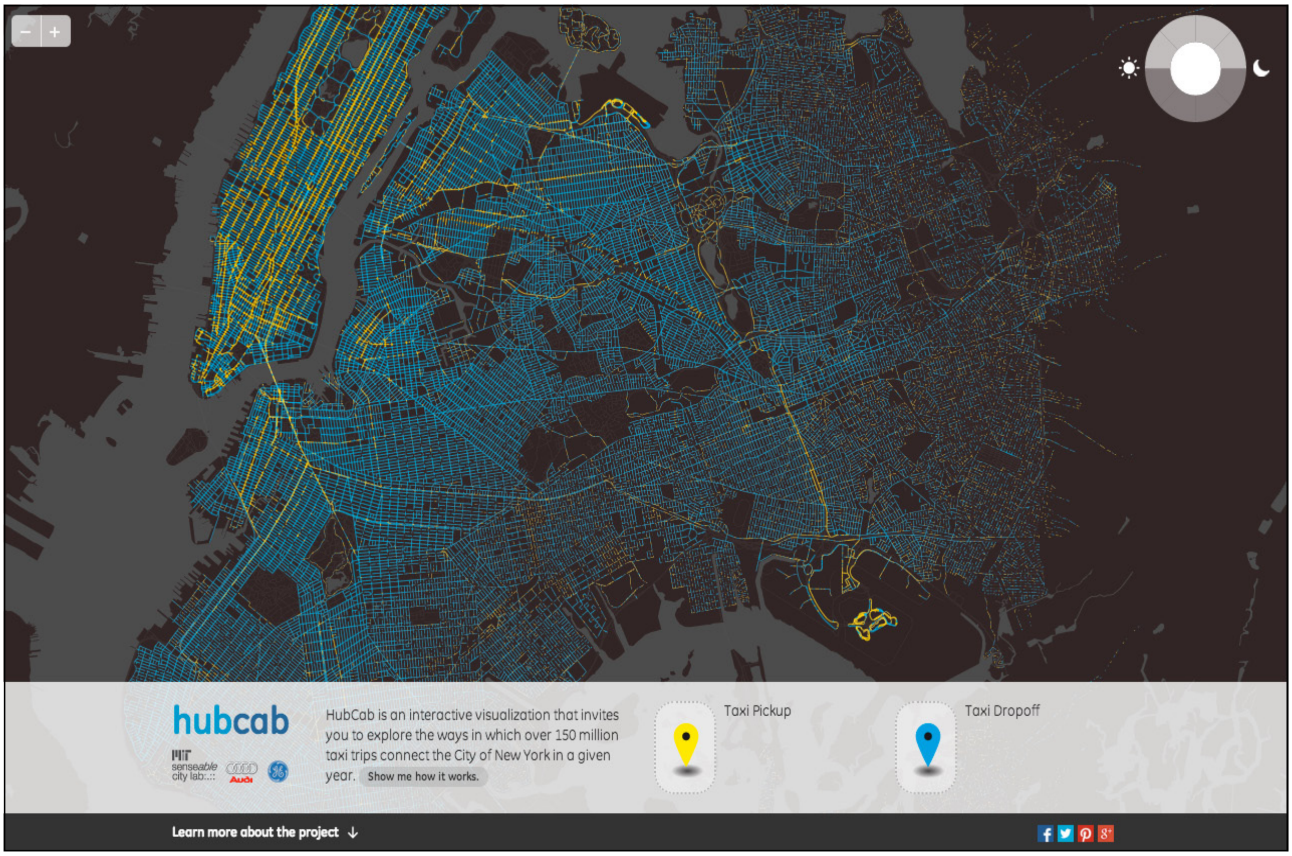
Karl Popper




CARLO RATTI ASSOCIATI
London, UK
CARLO RATTI ASSOCIATI
Turin, Italy
SUPERPEDESTRIAN
Cambridge, MA
MAKR SHAKR
Turin, Italy
CARLO RATTI ASSOCIATI
New York, NY
MIT SENSEABLE CITY LAB
Cambridge, MA
SENSEABLE CITY LAB
Singapore


05:55


Van Wyck Expressway
Van Wyck Expressway
hubcab
MIT
senseable city lab
Audi
HubCab is an interactive visualization that invites you to explore the ways in which over 150 million taxi trips connect the City of New York in a given year.
Show me how it works.
Taxi Pickup
Taxi Dropoff
Learn more about the project


hubcab
HubCab is an interactive visualization that invites you to explore the ways in which over 150 million taxi trips connect the City of New York in a given year.
Show me how it works.
Taxi Pickup
Taxi Dropoff
Learn more about the project


Sharing benefits
3,160,172 $
1,052,627 mi
445,261 kg
225k
214k
hubcab
HubCab is an interactive visualization that invites you to explore the ways in which over 150 million taxi trips connect the City of New York in a given year.
Show me how it works.
Taxi Pickup
Reset
West 15th Street
Total Pickups: 1069
Average duration: 12.4 min
Average distance: 3 mi
Taxi Dropoff
Reset
East 54th Street
Total Dropoffs: 1053
Average duration: 10.2 min
Average distance: 2.38 mi
Learn more about the project

PNAS

Quantifying the benefits of vehicle pooling with shareability networks

Paolo Santi[a,b], Giovanni Resta[b], Michael Szell[a,1], Stanislav Sobolevsky[a], Steven H. Strogatz[c], and Carlo Ratti[a]

[a]Senseable City Laboratory, Massachusetts Institute of Technology, Cambridge, MA 02139; [b]Istituto di Informatica e Telematica del Consiglio Nazionale delle Ricerche, 56124 Pisa, Italy; and [c]Department of Mathematics, Cornell University, Ithaca, NY 14853

Edited* by Michael F. Goodchild, University of California, Santa Barbara, CA, and approved July 25, 2014 (received for review March 3, 2014)

Taxi services are a vital part of urban transportation, and a considerable contributor to traffic congestion and air pollution causing substantial adverse effects on human health. Sharing taxi trips is a possible way of reducing the negative impact of taxi services on cities, but this comes at the expense of passenger discomfort quantifiable in terms of a longer travel time. Due to computational challenges, taxi sharing has traditionally been approached on small scales, such as within airport perimeters, or with dynamical ad hoc heuristics. However, a mathematical framework for the systematic understanding of the tradeoff between collective benefits of sharing and individual passenger discomfort is lacking. Here we introduce the notion of shareability network, which allows us to model the collective benefits of sharing as a function of passenger inconvenience, and to efficiently compute optimal

At the basis of a shared taxi service is the concept of ride sharing or carpooling, a long-standing proposition for decreasing road traffic, which originated during the oil crisis in the 1970s (6). During that time, economic incentives outbalanced the psychological barriers on which successful carpooling programs depend: giving up personalized transportation and accepting strangers in the same vehicle. Surveys indicate that the two most important deterrents to potential carpoolers are the extra time requirements and the loss of privacy (7, 8). However, the lack of correlations between socio-demographic variables and carpooling propensity (8), the design of appropriate economic incentives (9), and recent practical implementations of taxi-sharing systems in New York City (http://bandwagon.io) give ample hope that many social obstacles might be overcome in newly emerging "sharing economies" (10, 11).

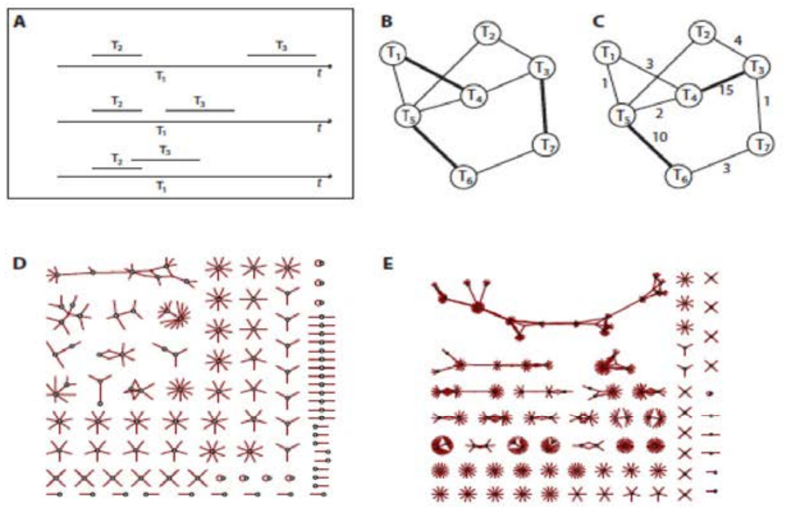
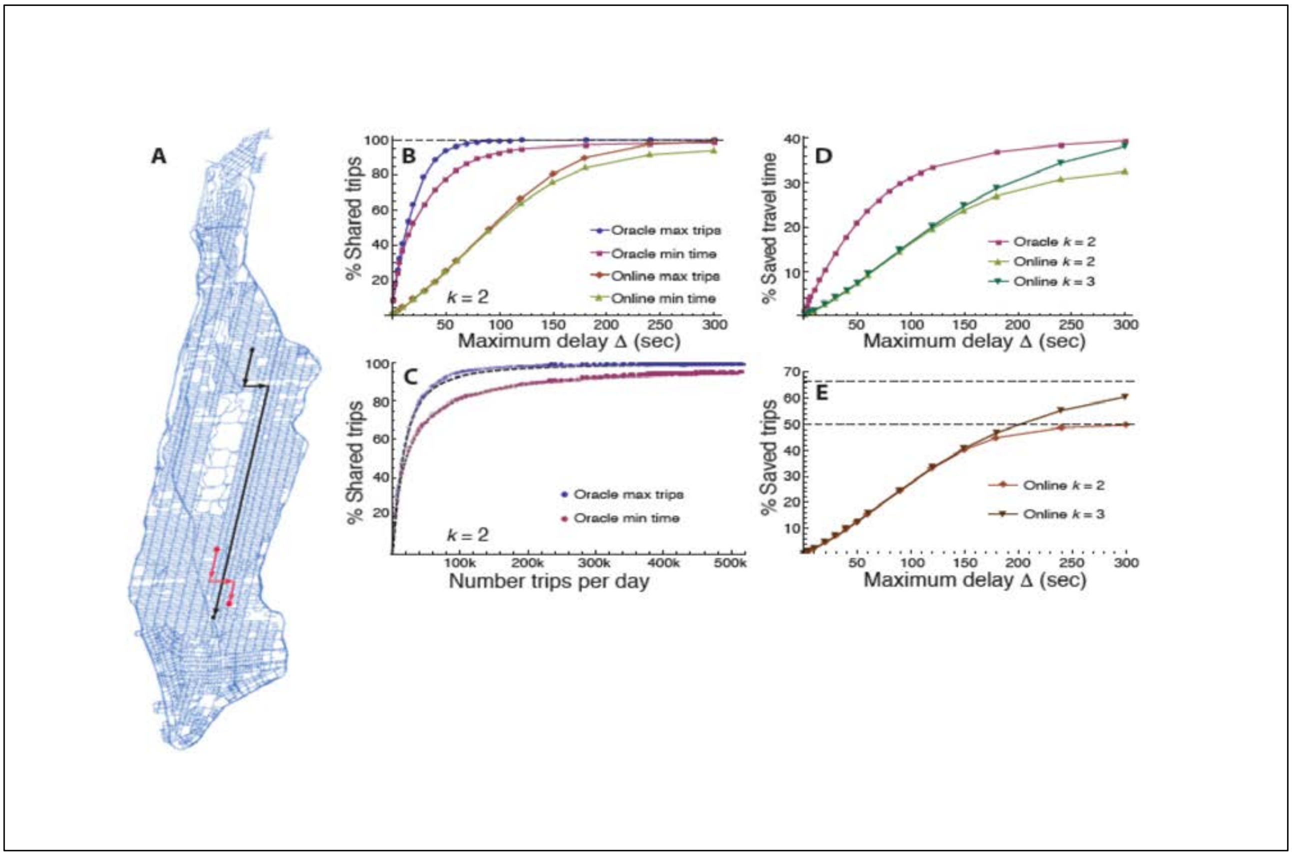
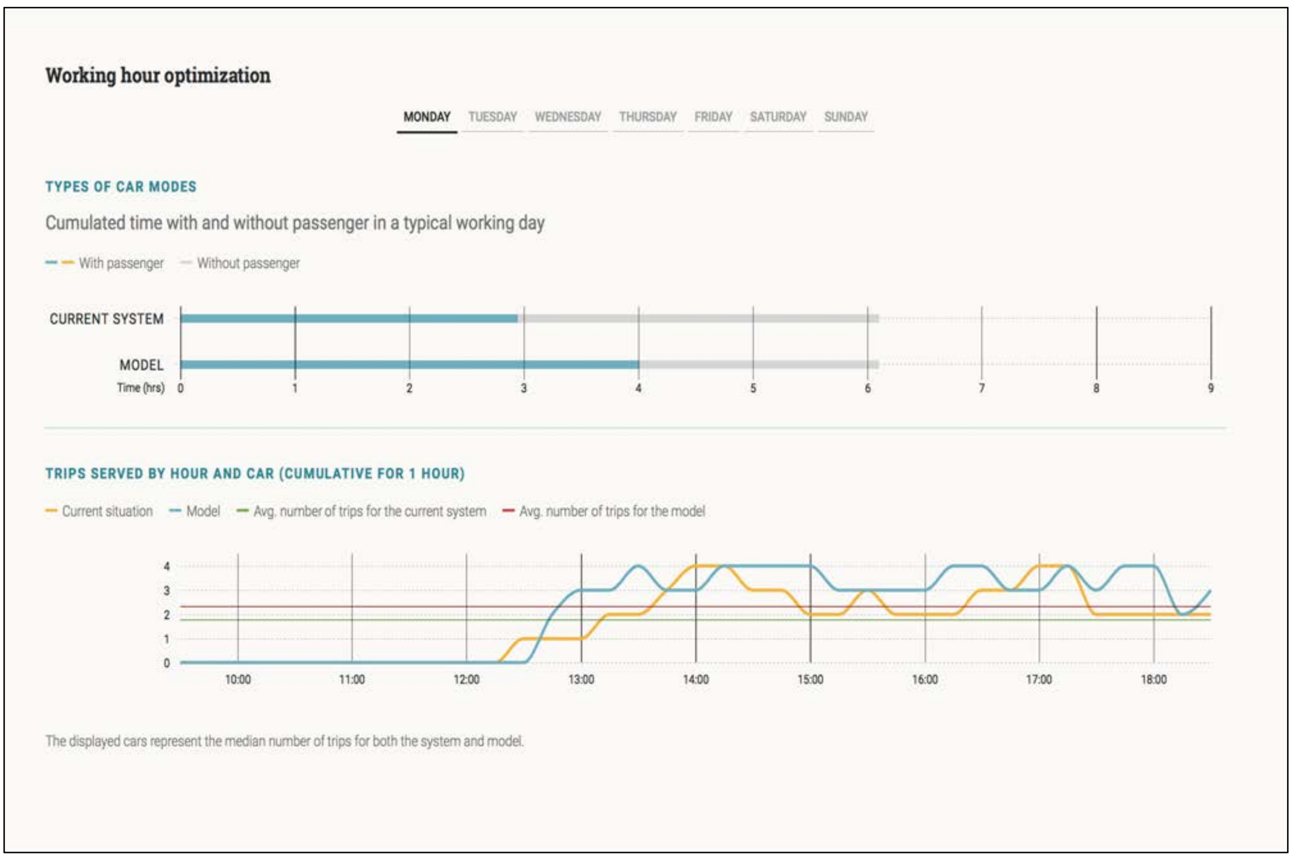
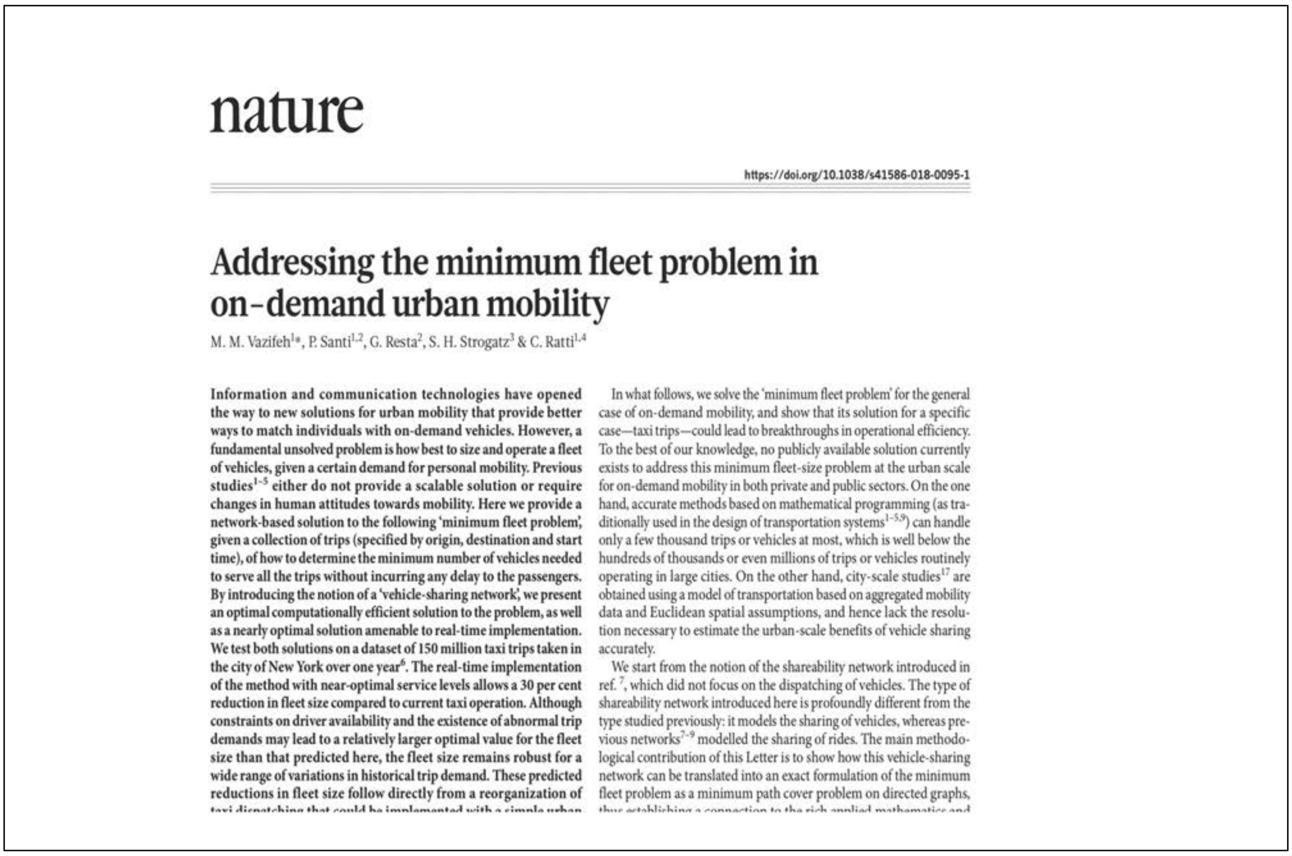


Figure 1: **Shareability networks. (A)** Trip sharing model and taxi capacity. Each of the three cases involves three trips T_1, T_2, and T_3 to be shared, but ordered differently in time t. The top case corresponds to a feasible sharing according to our model with $k = 2$, and the trips can be accommodated in a taxi with capacity ≥ 2. The middle case corresponds to a model with $k = 3$ since three trips are combined; notice that the three trips can be combined in a taxi with capacity two since two of the combined trips are non-overlapping. The bottom case corresponds to $k = 3$, but here a taxi capacity ≥ 3 is needed to accommodate the combined trips. **(B)** Example of maximum matching (*4*) in a simple shareability network. The links belonging to the maximum matching are displayed in bold. **(C)** Example of maximum weighted matching (*4*). **(D)** Exemplary subset of the shareability network corresponding to 100 consecutive trips for values of $\Delta = 30\,\mathrm{sec}$ and **(E)** $\Delta = 60\,\mathrm{sec}$, showing network densification effects and thus an increase of sharing opportunities with longer time-aggregation. Open links point to trips outside the considered set of trips. Isolated nodes are represented as self-loops. Node positions are not preserved across the networks.


A
B
% Shared trips
Maximum delay Δ (sec)
Oracle max trips
Oracle min time
Online max trips
Online min time
k = 2
C
Number trips per day
Oracle max trips
Oracle min time
D
% Saved travel time
Oracle k = 2
Online k = 2
Online k = 3
E
% Saved trips
Online k = 2
Online k = 3


Working hour optimization
MONDAY
TUESDAY
WEDNESDAY
THURSDAY
FRIDAY
SATURDAY
SUNDAY
TYPES OF CAR MODES
Cumulated time with and without passenger in a typical working day
With passenger
Without passenger
CURRENT SYSTEM
MODEL
Time (hrs)
TRIPS SERVED BY HOUR AND CAR (CUMULATIVE FOR 1 HOUR)
Current situation
Model
Avg. number of trips for the current system
Avg. number of trips for the model
The displayed cars represent the median number of trips for both the system and model.



nature

https://doi.org/10.1038/s41586-018-0095-1

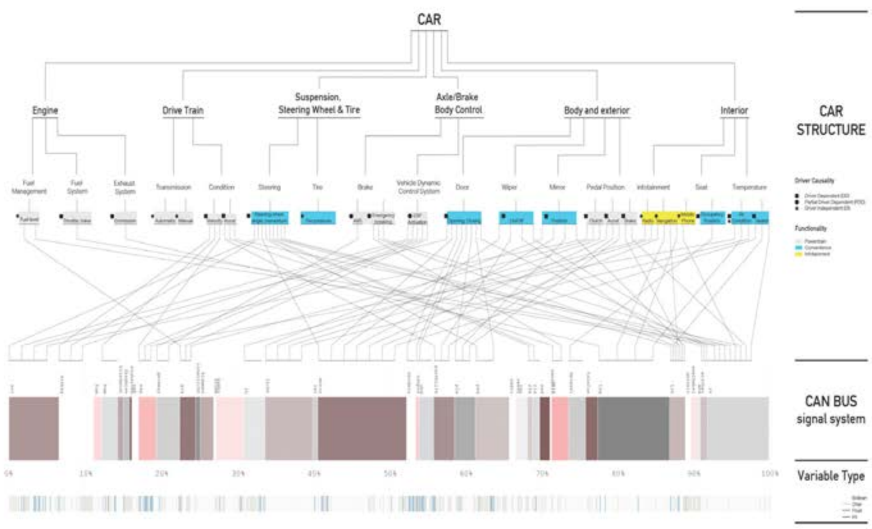
Addressing the minimum fleet problem in on-demand urban mobility

M. M. Vazifeh[1]*, P. Santi[1,2], G. Resta[2], S. H. Strogatz[3] & C. Ratti[1,4]

Information and communication technologies have opened the way to new solutions for urban mobility that provide better ways to match individuals with on-demand vehicles. However, a fundamental unsolved problem is how best to size and operate a fleet of vehicles, given a certain demand for personal mobility. Previous studies[1-5] either do not provide a scalable solution or require changes in human attitudes towards mobility. Here we provide a network-based solution to the following 'minimum fleet problem', given a collection of trips (specified by origin, destination and start time), of how to determine the minimum number of vehicles needed to serve all the trips without incurring any delay to the passengers. By introducing the notion of a 'vehicle-sharing network', we present an optimal computationally efficient solution to the problem, as well as a nearly optimal solution amenable to real-time implementation. We test both solutions on a dataset of 150 million taxi trips taken in the city of New York over one year[6]. The real-time implementation of the method with near-optimal service levels allows a 30 per cent reduction in fleet size compared to current taxi operation. Although constraints on driver availability and the existence of abnormal trip demands may lead to a relatively larger optimal value for the fleet size than that predicted here, the fleet size remains robust for a wide range of variations in historical trip demand. These predicted reductions in fleet size follow directly from a reorganization of

In what follows, we solve the 'minimum fleet problem' for the general case of on-demand mobility, and show that its solution for a specific case—taxi trips—could lead to breakthroughs in operational efficiency. To the best of our knowledge, no publicly available solution currently exists to address this minimum fleet-size problem at the urban scale for on-demand mobility in both private and public sectors. On the one hand, accurate methods based on mathematical programming (as traditionally used in the design of transportation systems[1-5,9]) can handle only a few thousand trips or vehicles at most, which is well below the hundreds of thousands or even millions of trips or vehicles routinely operating in large cities. On the other hand, city-scale studies[17] are obtained using a model of transportation based on aggregated mobility data and Euclidean spatial assumptions, and hence lack the resolution necessary to estimate the urban-scale benefits of vehicle sharing accurately.

We start from the notion of the shareability network introduced in ref. [7], which did not focus on the dispatching of vehicles. The type of shareability network introduced here is profoundly different from the type studied previously: it models the sharing of vehicles, whereas previous networks[7-9] modelled the sharing of rides. The main methodological contribution of this Letter is to show how this vehicle-sharing network can be translated into an exact formulation of the minimum fleet problem as a minimum path cover problem on directed graphs,



POINT OF VIEW

The Car as an Ambient Sensing Platform

BY EMANUELE MASSARO, CHAEWON AHN, AND CARLO RATTI
MIT Senseable City Lab, Cambridge, MA 02139 USA

PAOLO SANTI
MIT Senseable City Lab Cambridge, MA 02139 USA and Istituto di Informatica e Telematica del CNR, Pisa 56124, Italy

RAINER STAHLMANN AND ANDREAS LAMPRECHT
AUDI AG, Ingolstadt D-85045, Germany

MARTIN ROEHDER AND MARKUS HUBER
Volkswagen Group of America Electronics Research Lab Belmont, MA 02139 USA

Fig. 1. ***The vision of cars used as pervasive sensing platforms: CAN data are communicated to remote servers through wireless communication, possibly after onboard processing and aggregation. GPS signal is fundamental to build time- and spatially-resolved databases from the multiple data streams collected by a single vehicle, as well as from data generated by different vehicles.***

In recent years, cars have evolved from purely mechanical to veritable cyber-physical systems that generate large amounts of real-time data. These data are instrumental to the proper working of the vehicle itself, but make them amenable to a multitude of other uses. For instance, GPS information has recently been used for a large number of mobility studies in the academic community [1], [5], as well as to feed traffic apps such as Google Traffic and Waze. This use of vehicle data is already having a profound impact in science, industry, economy, and society at large. Now, imagine that instead of accessing one single source of vehicle-generated data (GPS), one can access the entire wealth of data exchanged on the controller area network (CAN) bus in near real time amounting to over 4000 signals sampled at high frequency, corresponding to a few gigabytes of data per hour. What would be the implications, opportunities, and challenges sparked by this transition?

This transition is now being made possible by the so-called connected car paradigm, which allows vehicle CAN bus data to be recorded and wirelessly transmitted to central servers for analysis. Thus, the car sensing dimension, which can be informally understood as the number of different signals that a vehicle records and makes available for data analysis, is increasing from 1 (or a few) to 1000 or above.

In the rest of the article, we discuss the groundbreaking effects this transition will have on our ability of sensing roads and the urban living environment. Guided by the preliminary

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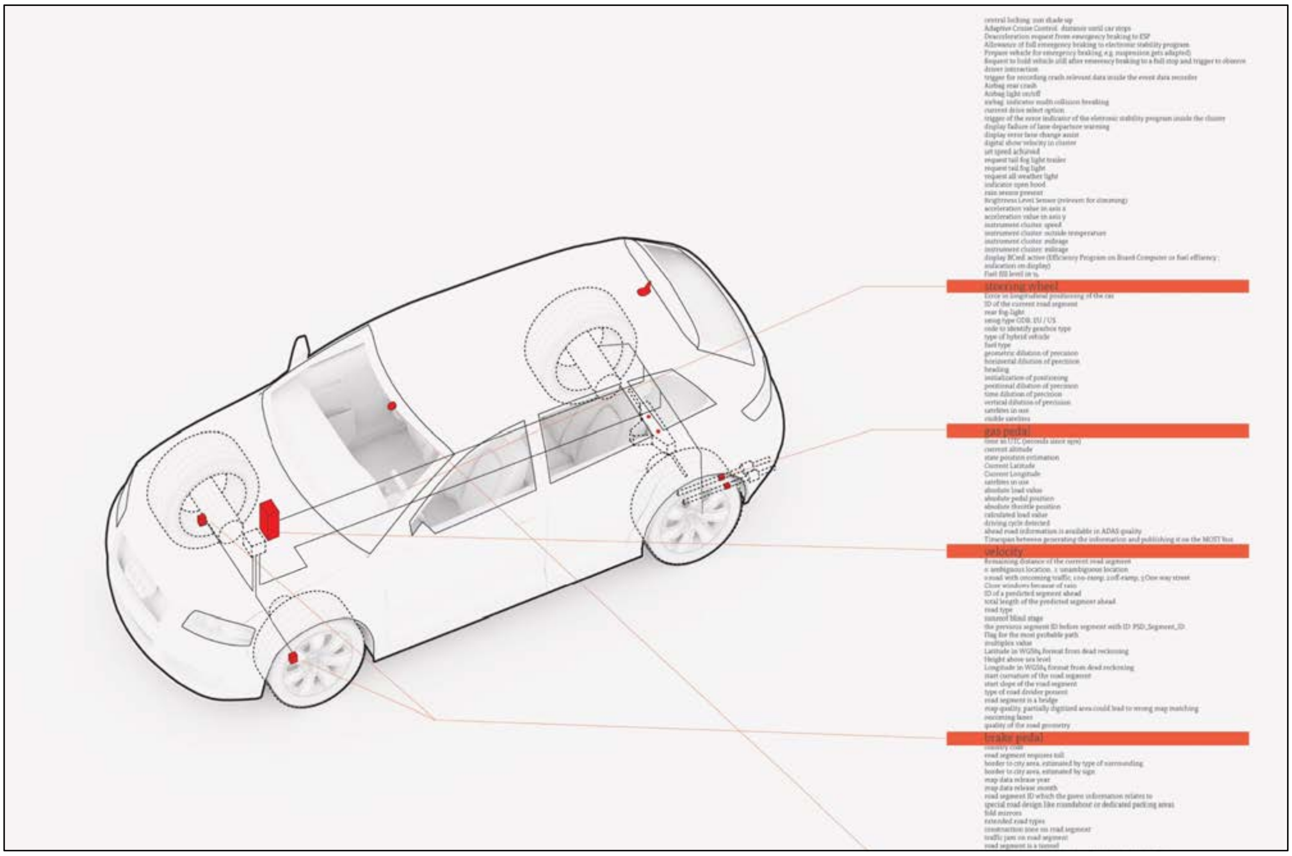
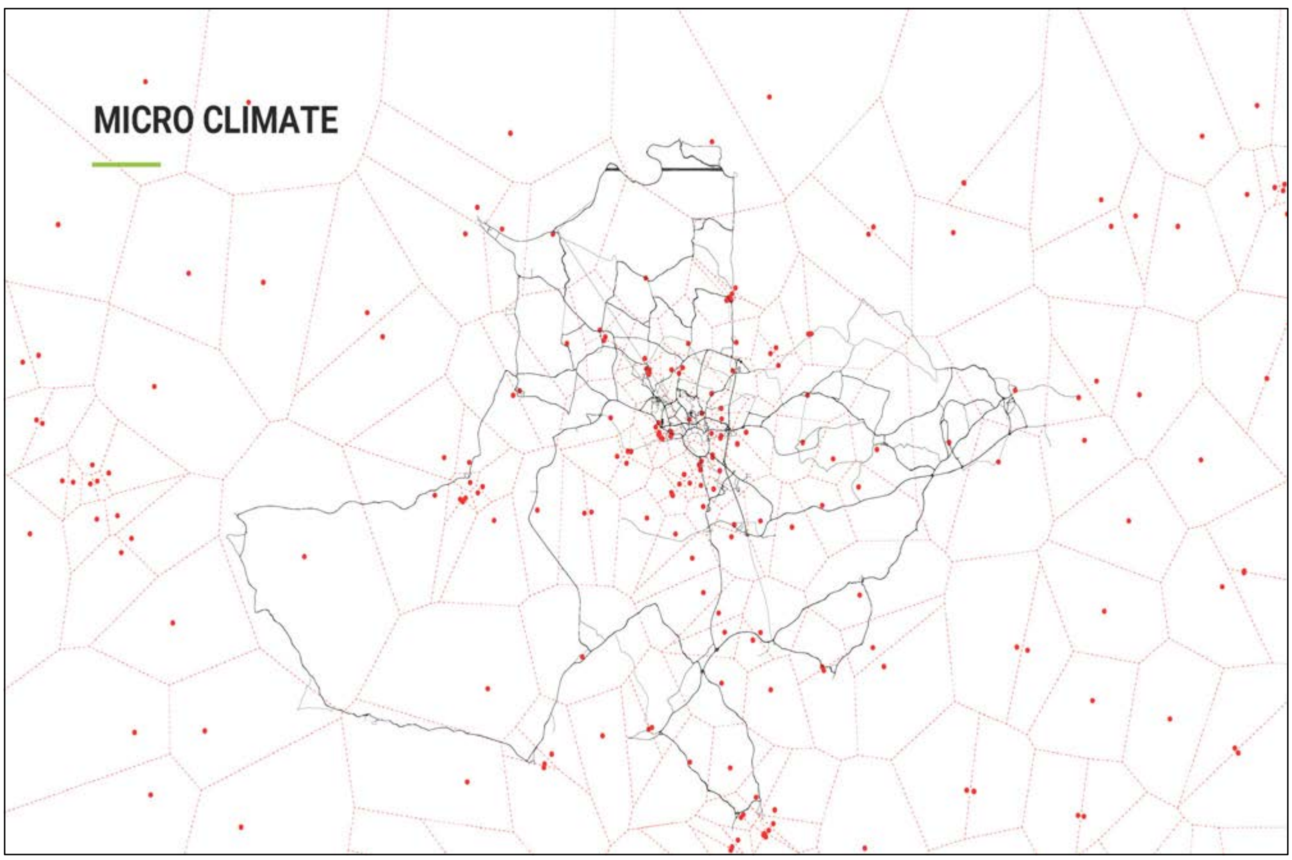

steering wheel
gas pedal
velocity
brake pedal

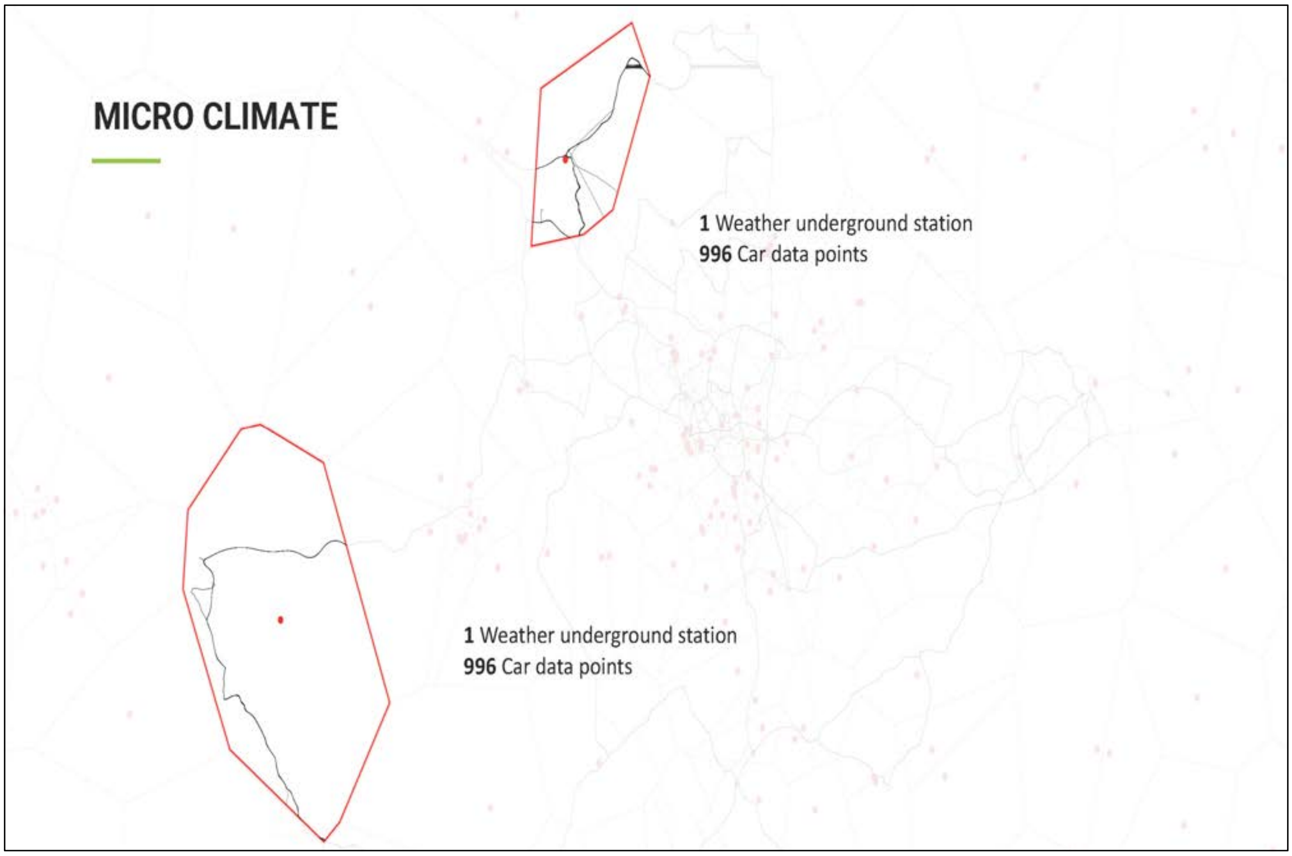

64 drivers
40 hours per driver (ave.)
2500+ hours of driving
1354 trips
0 3 6 12 Kilometers

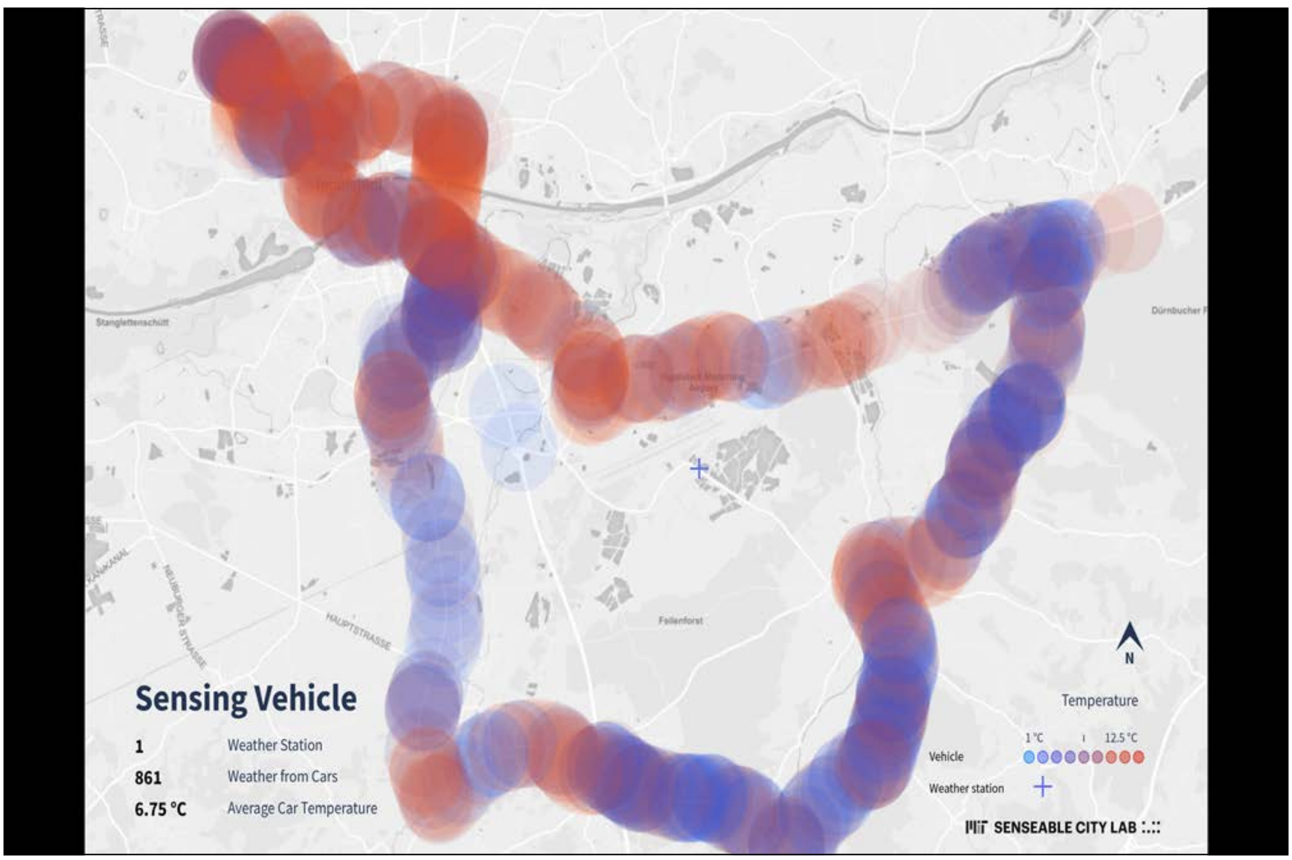

1354 trips
516 trips
424 trips
0
0.5
1
2 Kilometers


Desching
Ingolstadt
Oberschwaig
Sensing Vehicle
ABS ON
Velocity
5 km/h
134 km/h
N
SENSEABLE CITY LAB


ROAD SAFETY


MICRO CLIMATE


MICRO CLIMATE
1 Weather underground station
996 Car data points
1 Weather underground station
996 Car data points

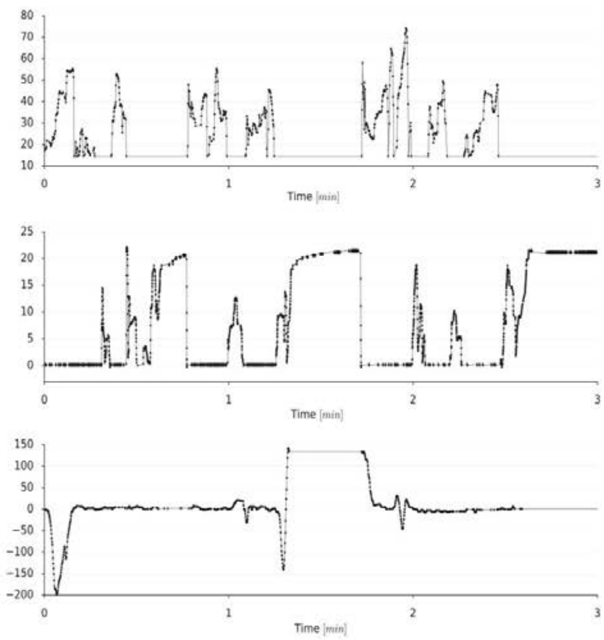

Sensing Vehicle
1 Weather Station
861 Weather from Cars
6.75 °C Average Car Temperature
N
Temperature
1 °C
12.5 °C
Vehicle
Weather station
MIT SENSEABLE CITY LAB

DRIVING BEHAVIOR

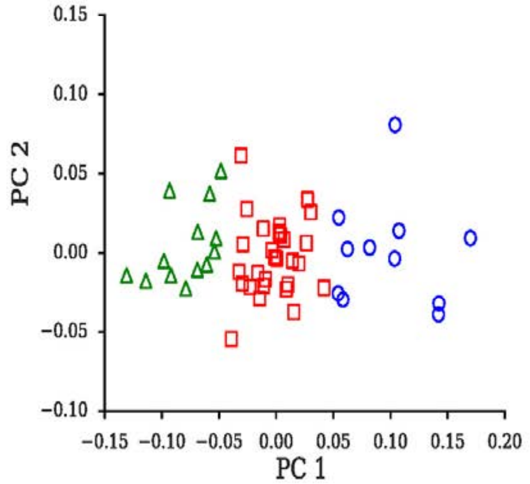
GAS PEDAL
pedal position

BRAKE PEDAL
pedal pressure

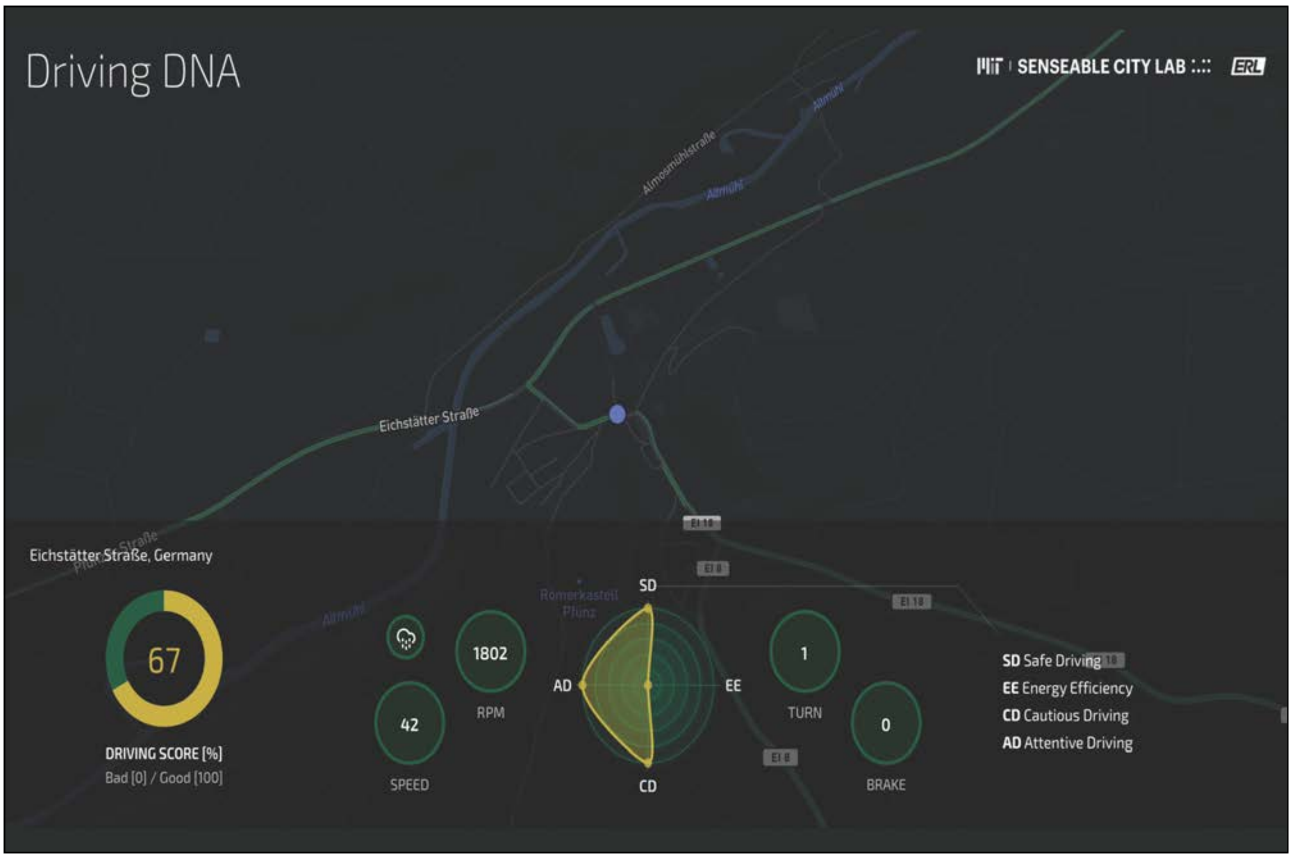
STEERING WHEEL
angle measure

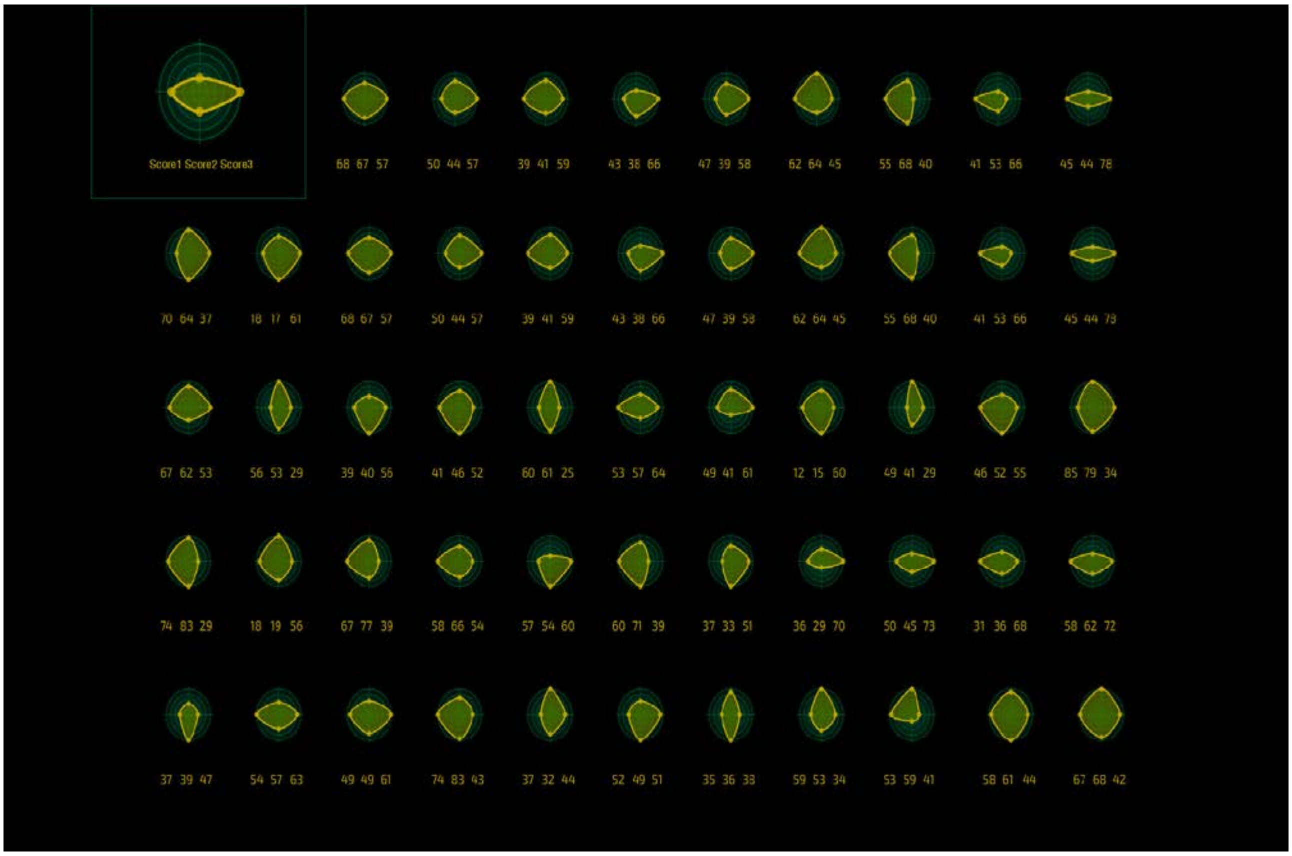


DRIVING BEHAVIOR



Using a clustering algorithm and Principal Components Analysis it is possible to cluster drivers according to their driving behavior, discovering similarities and outliers.




Score1 Score2 Score3
68 67 57
50 44 57
39 41 59
43 38 66
47 39 58
62 64 45
55 68 40
41 53 66
45 44 78
70 64 37
18 17 61
68 67 57
50 44 57
39 41 59
43 38 66
47 39 58
62 64 45
55 68 40
41 53 66
45 44 78
67 62 53
56 53 29
39 40 56
41 46 52
60 61 25
53 57 64
49 41 61
12 15 50
49 41 29
46 52 55
85 79 34
74 83 29
18 19 56
67 77 39
58 66 54
57 54 60
60 71 39
37 33 51
36 29 70
50 45 73
31 36 68
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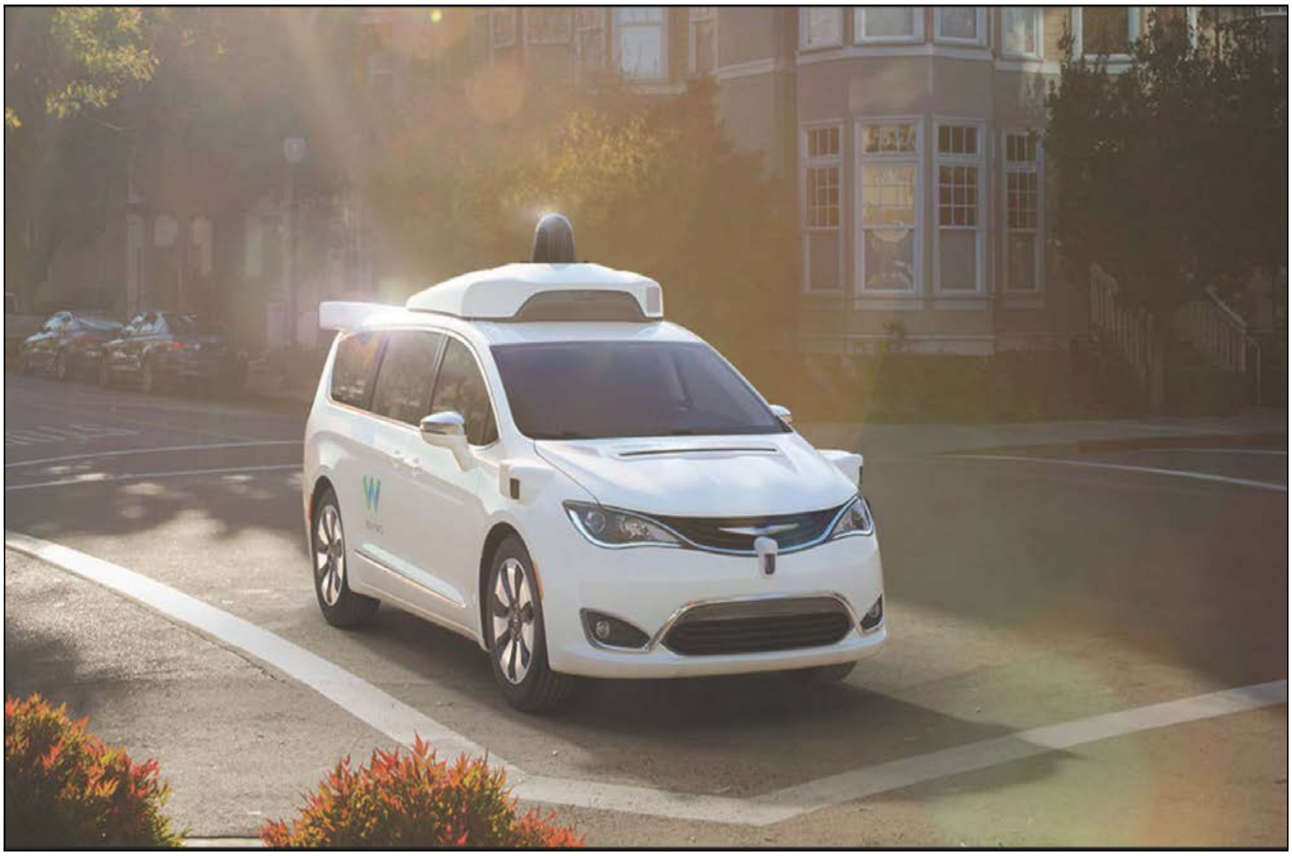
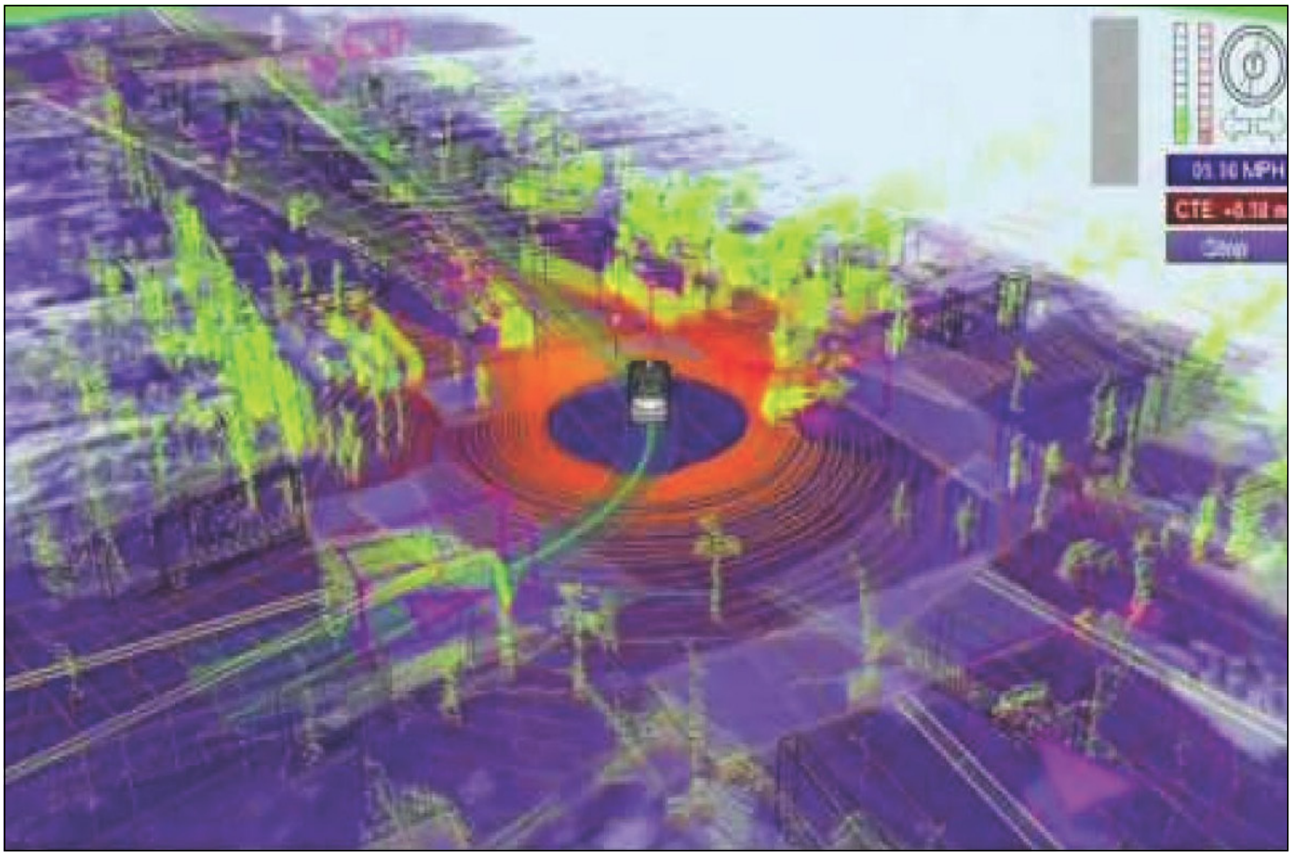
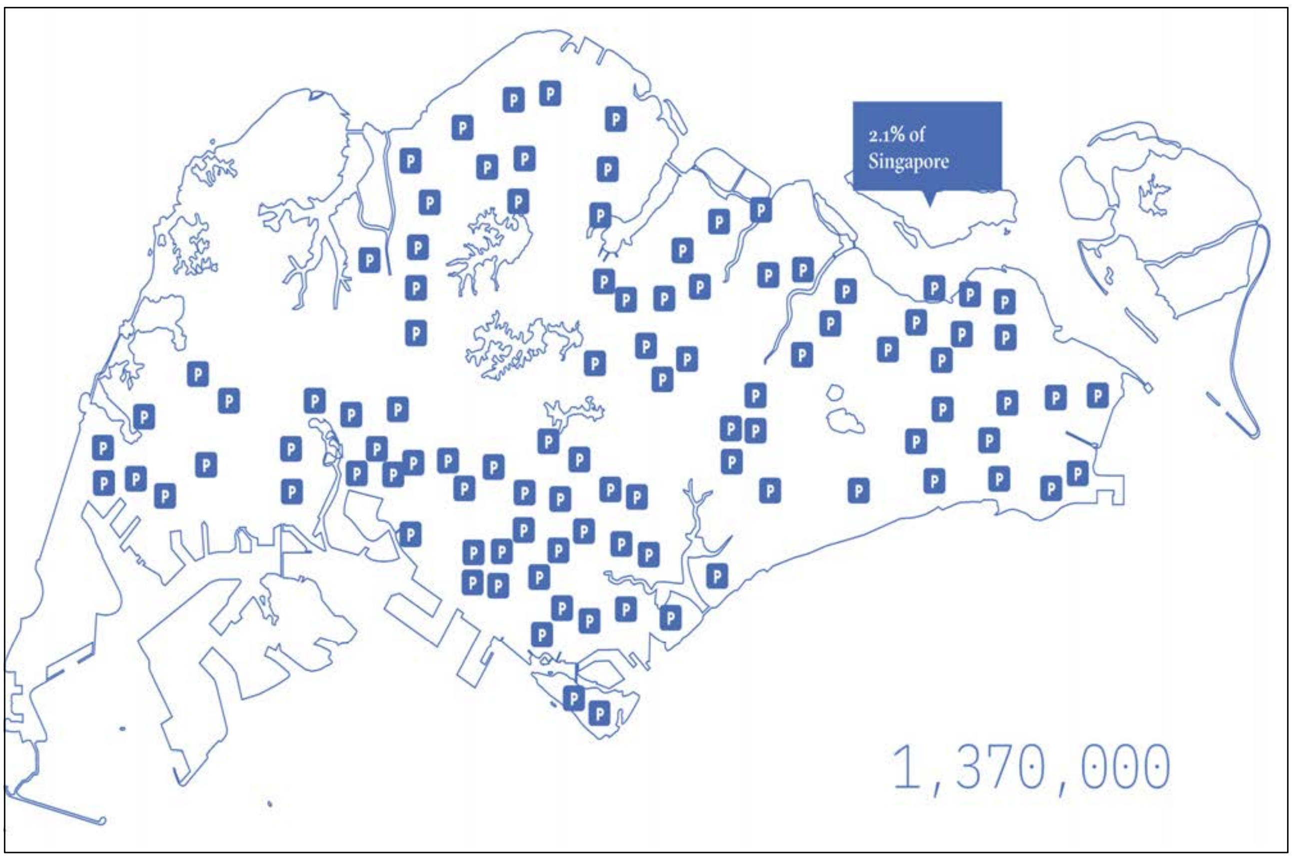
67 68 42

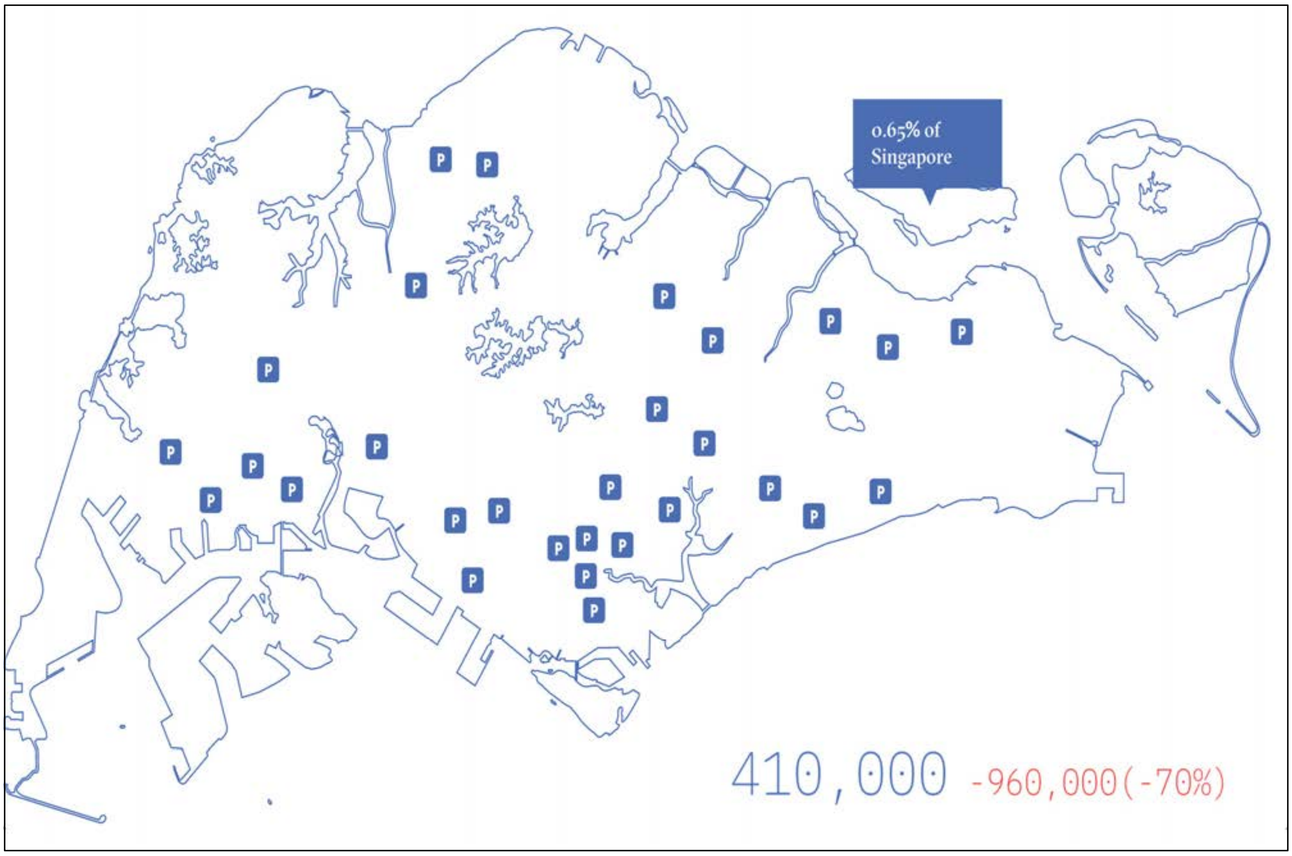




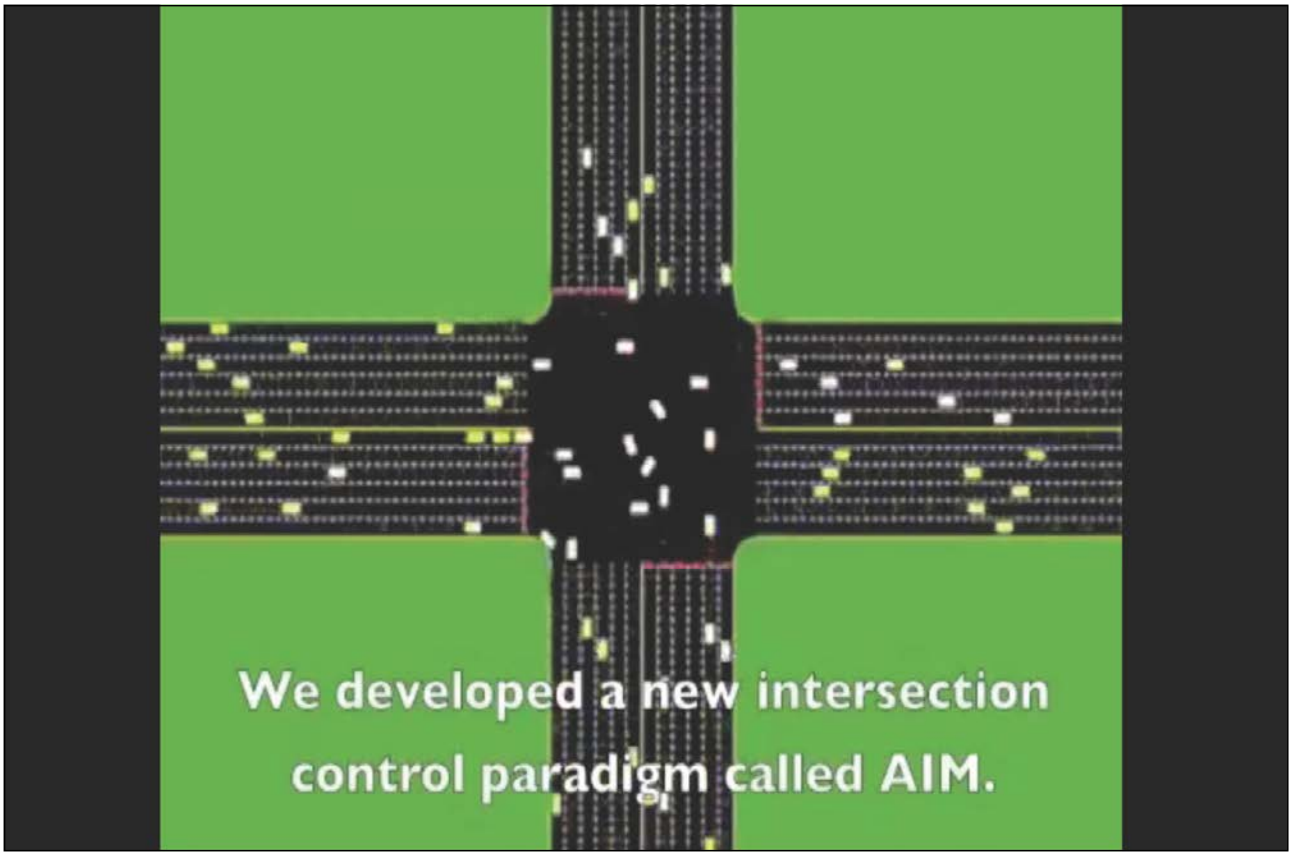

UBER


95%
Manheim, Pennsylvania (© Nearmap)


2.1% of Singapore
1,370,000

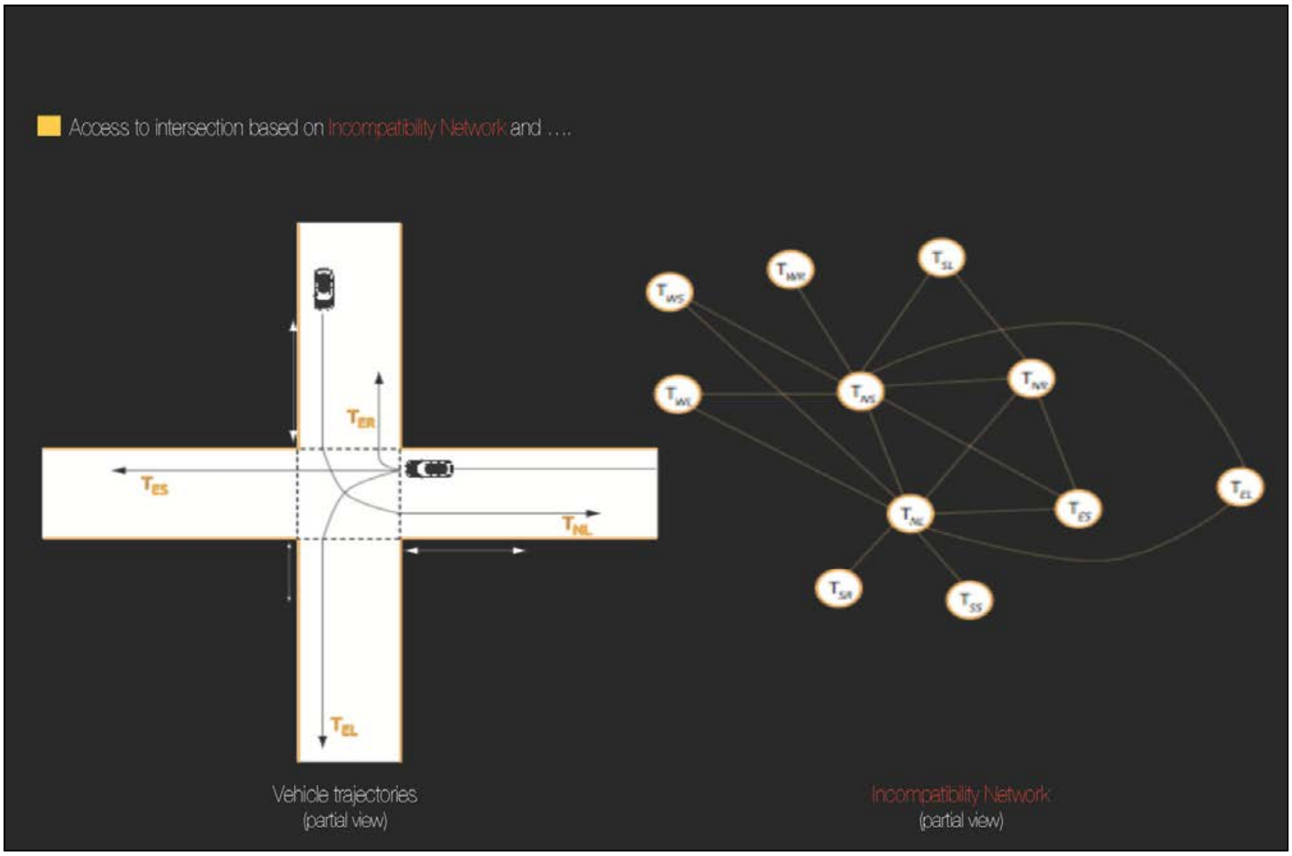

0.65% of
Singapore
410,000 -960,000(-70%)

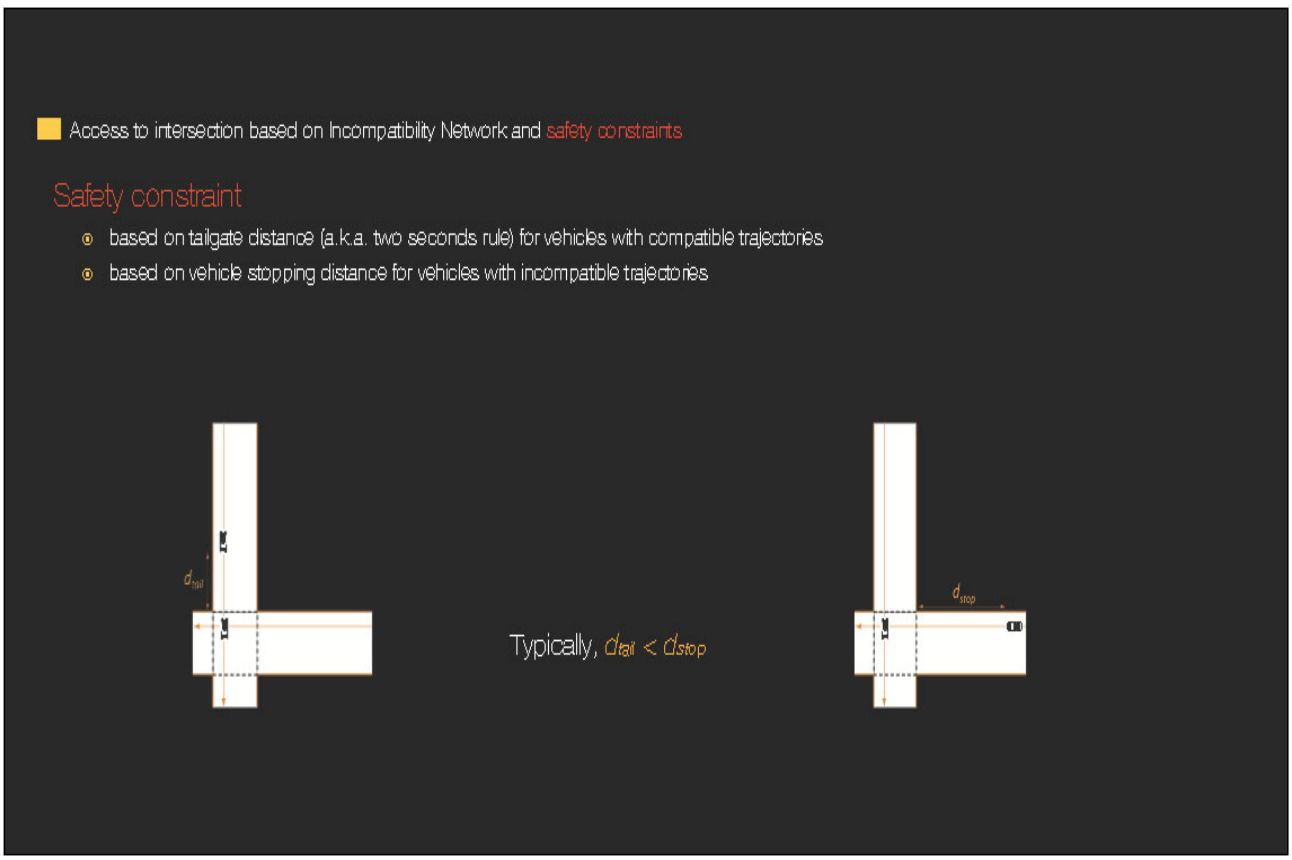

DRIVE
TO
RIGHT

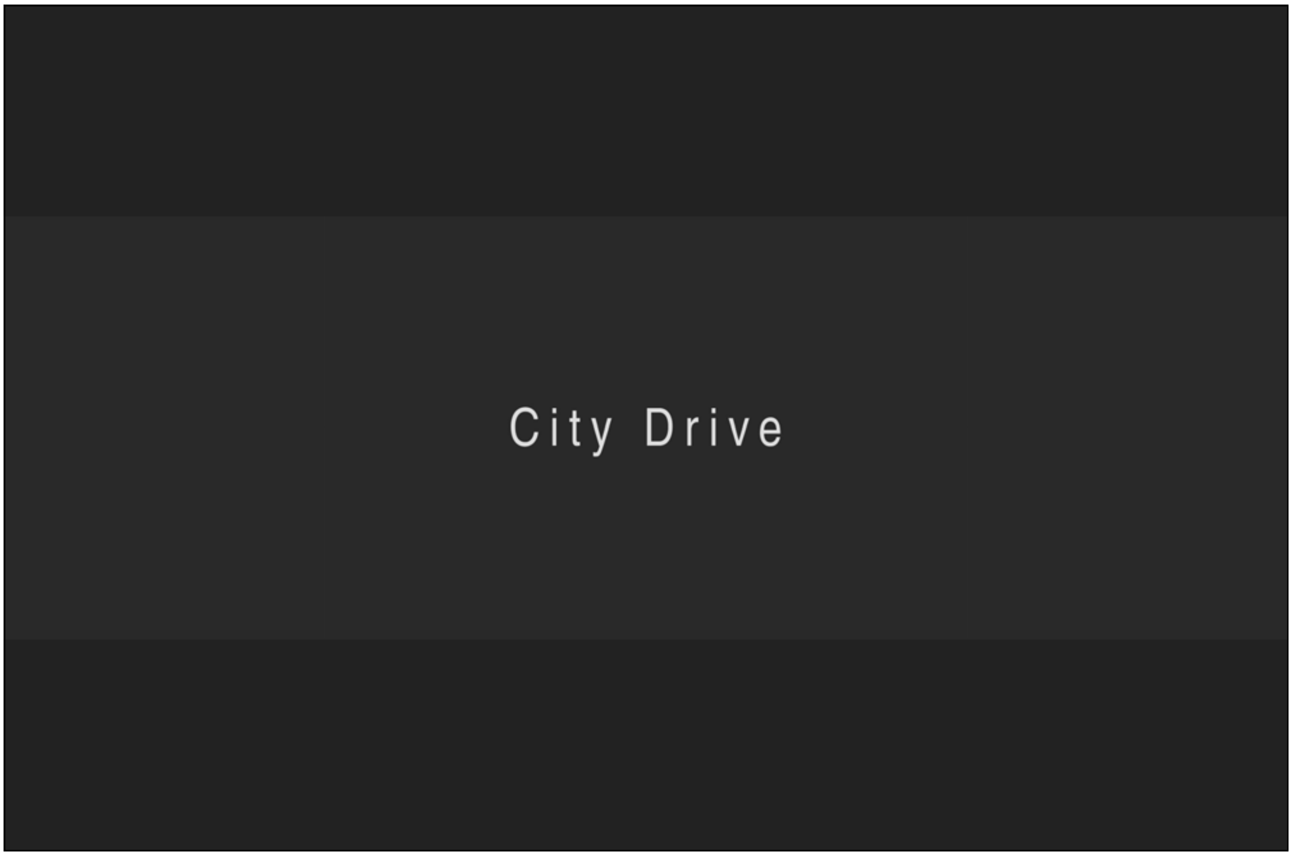


“In Milan, traffic lights are instructions.
In Rome, they are suggestions.
In Naples, they are Christmas decorations.”

Antonio Martino
Former Minister of Foreign Affairs (1994) and Minister of Defense (2001-2006)


Access to intersection based on Incompatibility Network and ….
T_ER
T_ES
T_NL
T_EL
T_WS
T_WR
T_SL
T_WL
T_NS
T_NR
T_EL
T_NL
T_ES
T_SR
T_SS
Vehicle trajectories
(partial view)
Incompatibility Network
(partial view)


Access to intersection based on Incompatibility Network and safety constraints
Safety constraint
based on tailgate distance (a.k.a. two seconds rule) for vehicles with compatible trajectories
based on vehicle stopping distance for vehicles with incompatible trajectories
d_{tail}
Typically, $d_{tail} < d_{stop}$
d_{stop}



PLOS | ONE

RESEARCH ARTICLE

Revisiting Street Intersections Using Slot-Based Systems

Remi Tachet[1], Paolo Santi[1,2]*, Stanislav Sobolevsky[1], Luis Ignacio Reyes-Castro[3], Emilio Frazzoli[3], Dirk Helbing[4], Carlo Ratti[1]

1 Senseable City Laboratory, Massachusetts Institute of Technology, 77 Massachusetts Avenue, Cambridge, MA 02139, United States of America, **2** Istituto di Informatica e Telematica del CNR, Pisa, Italy, **3** Laboratory for Information and Decision Systems, Massachusetts Institute of Technology, 77 Massachusetts Avenue, Cambridge, MA 02139, United States of America, **4** ETH Zurich, Computational Social Science, Clausiusstrasse 50, CH-8092, Zurich, SWITZERLAND

* psanti@mit.edu

CrossMark

OPEN ACCESS

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Editor: Tieqiao Tang, Beihang University, CHINA

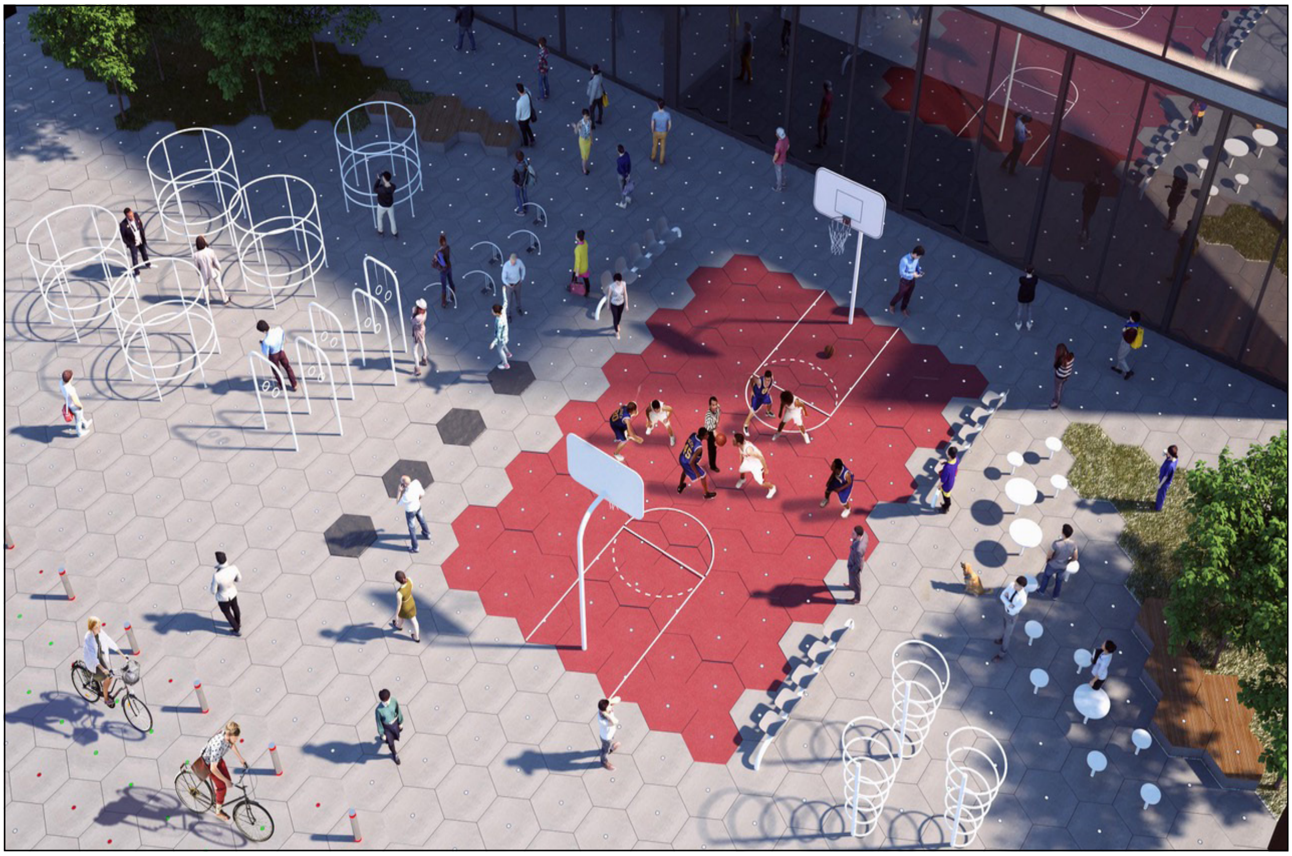
Received: October 29, 2015

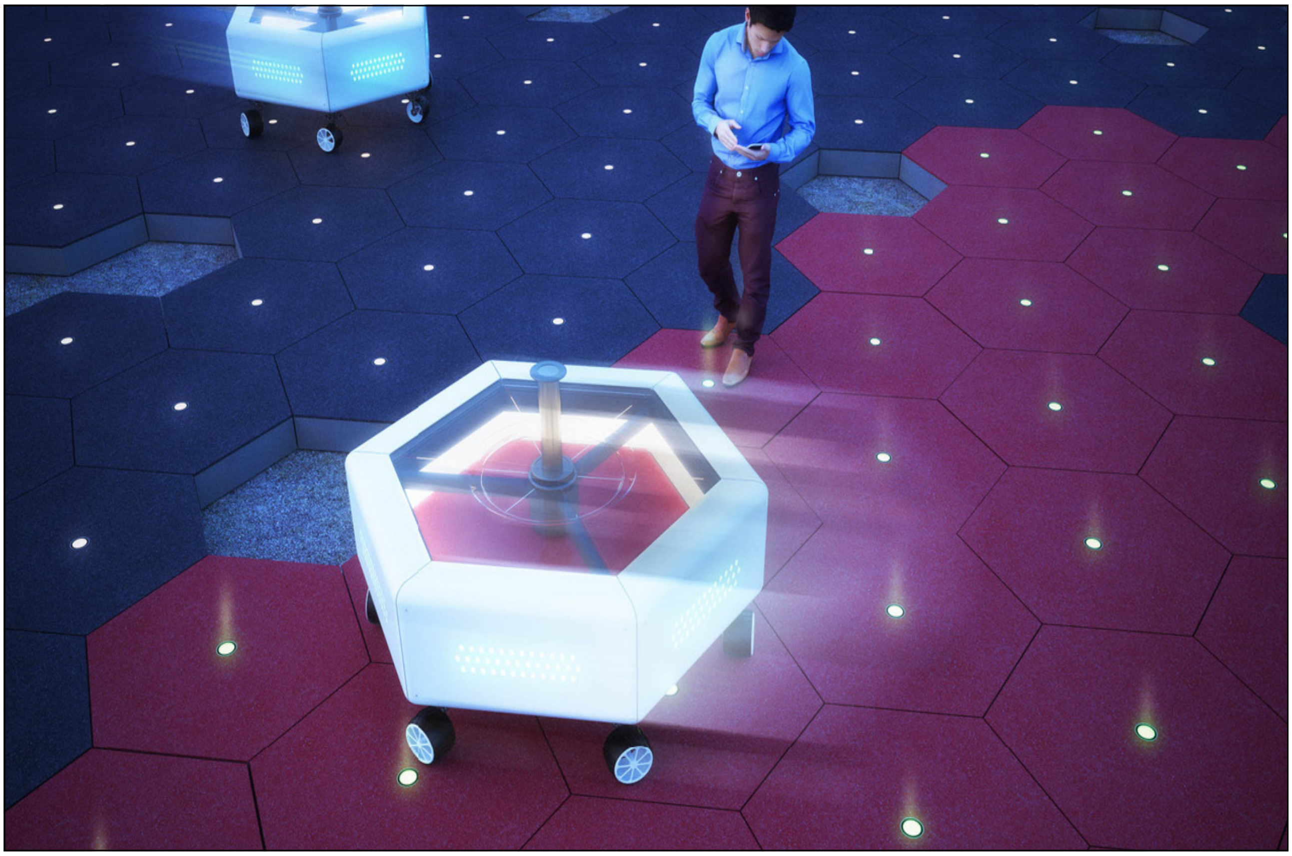
Accepted: February 3, 2016

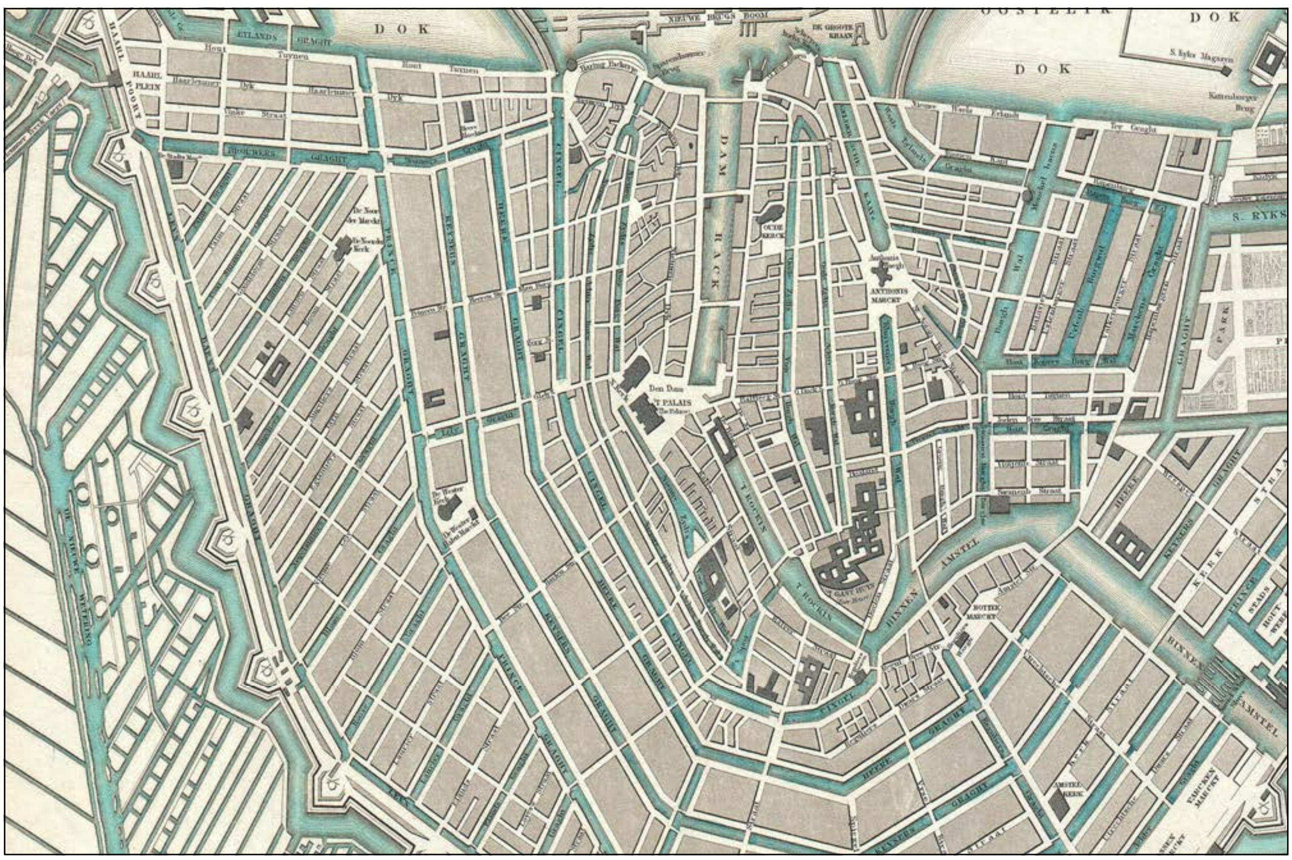
Published: March 16, 2016

Abstract

Since their appearance at the end of the 19th century, traffic lights have been the primary mode of granting access to road intersections. Today, this centuries-old technology is challenged by advances in intelligent transportation, which are opening the way to new solutions built upon slot-based systems similar to those commonly used in aerial traffic: what we call Slot-based Intersections (SIs). Despite simulation-based evidence of the potential benefits of SIs, a comprehensive, analytical framework to compare their relative performance with traffic lights is still lacking. Here, we develop such a framework. We approach the problem in a novel way, by generalizing classical queuing theory. Having defined safety conditions, we characterize capacity and delay of SIs. In the 2-road crossing configuration, we provide a capacity-optimal SI management system. For arbitrary intersection configurations, near-optimal solutions are developed. Results theoretically show that transitioning from a traffic light system to SI has the potential of doubling capacity and significantly reducing delays. This suggests a reduction of non-linear dynamics induced by intersection bottlenecks, with positive impact on the road network. Such findings can provide transportation engineers and planners with crucial insights as they prepare to manage the transition towards a more intelligent transportation infrastructure in cities.





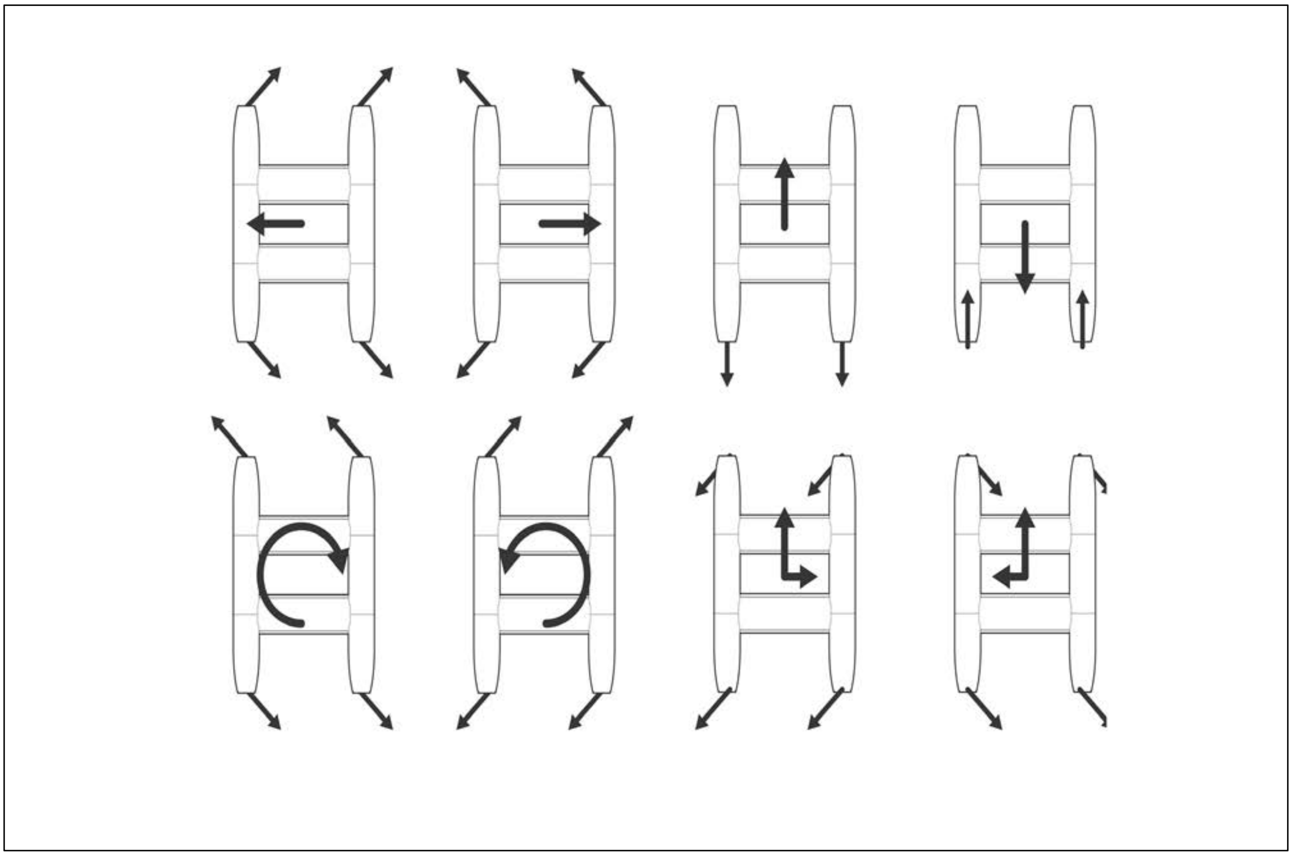

D O K
D O K
D O K
D A M
R A C K
Den Dam
S. RYKS
AMSTEL
AMSTEL

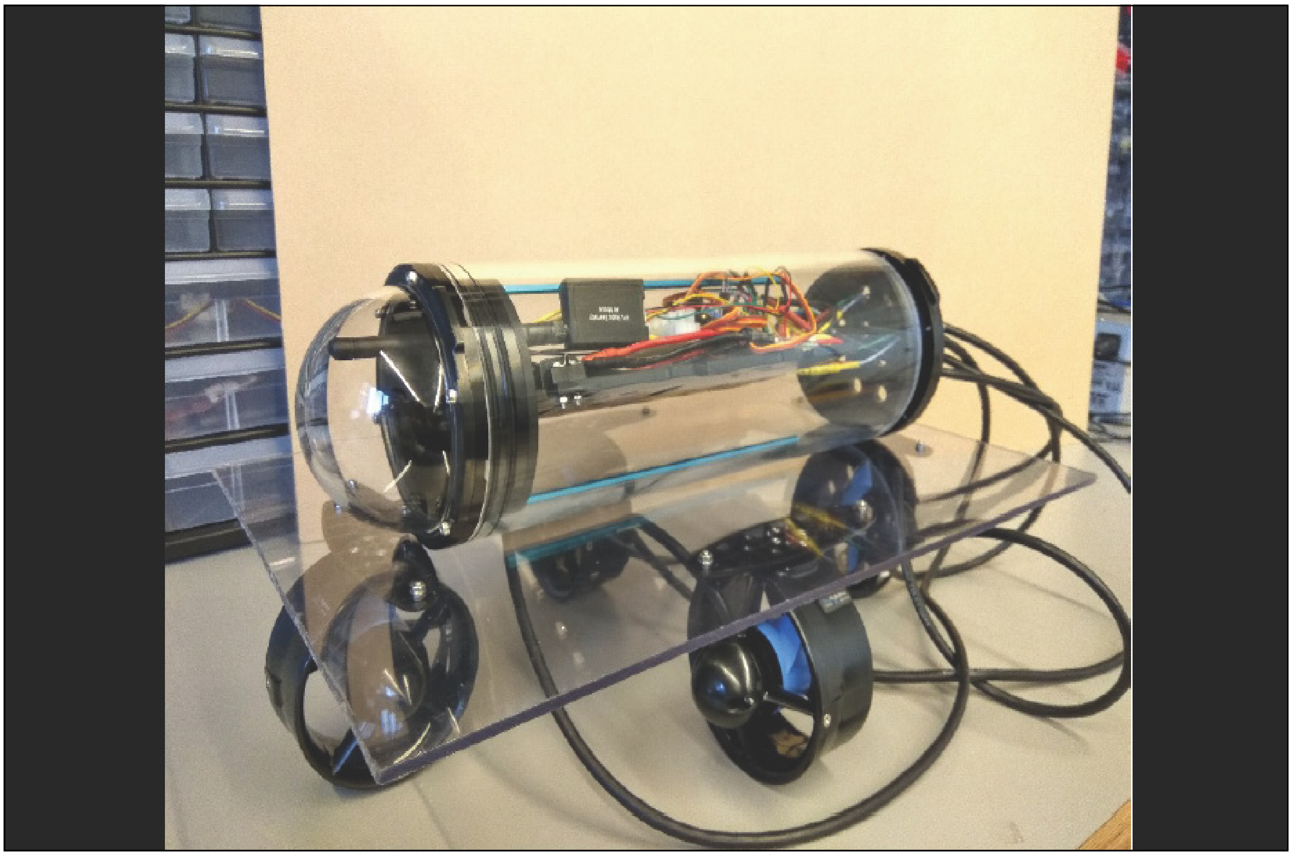

AMS

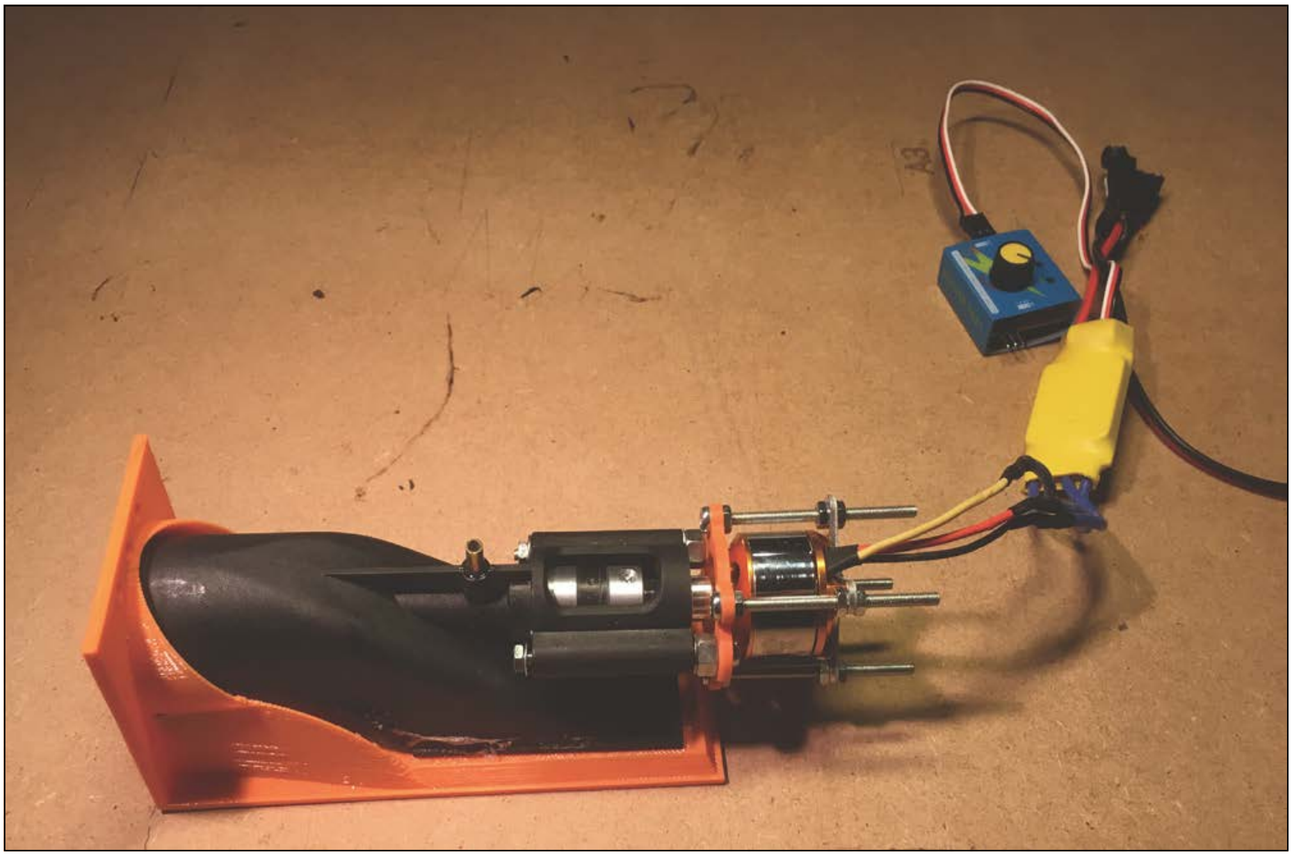

QUEENS
DHL
DHL EXPRESS AMSTERDAM

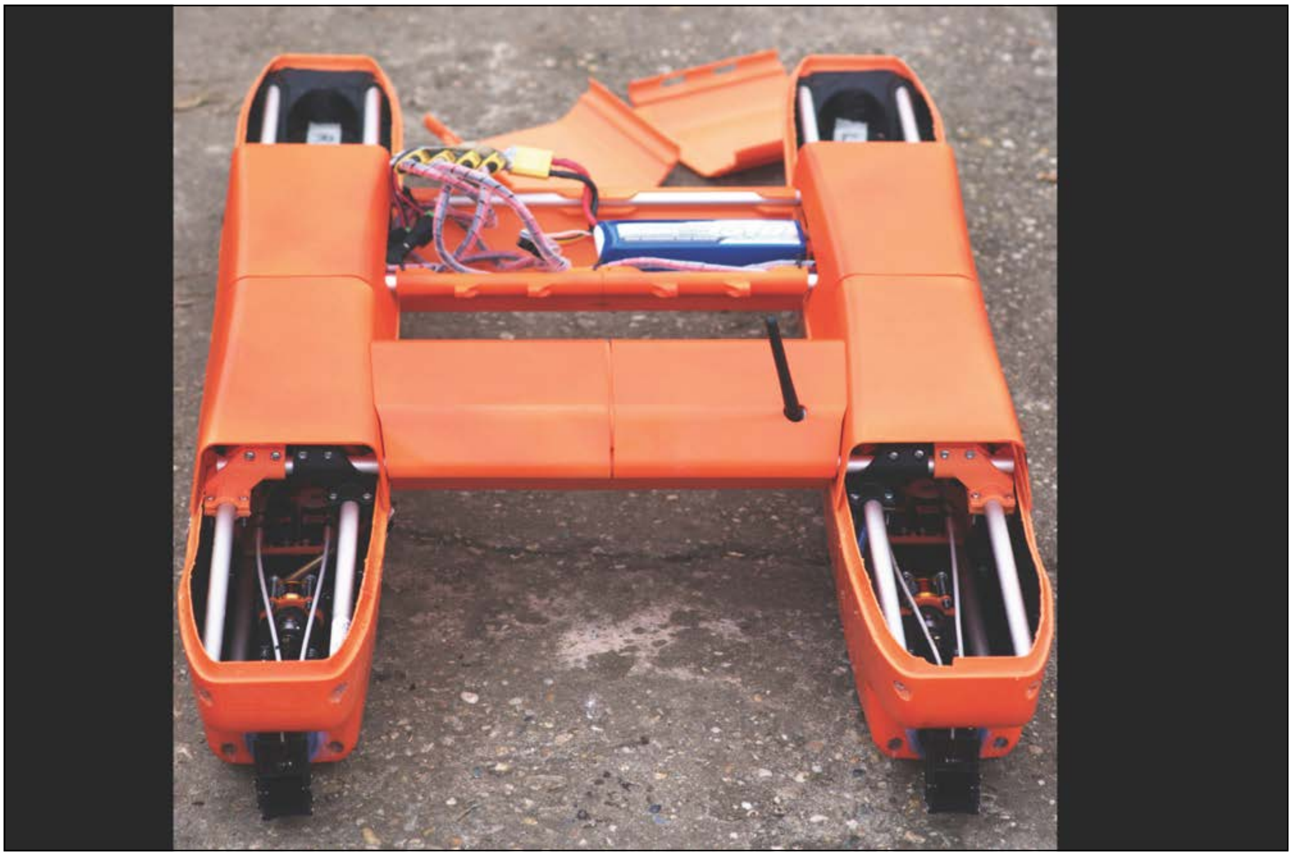

TWEE
WATER TAXI

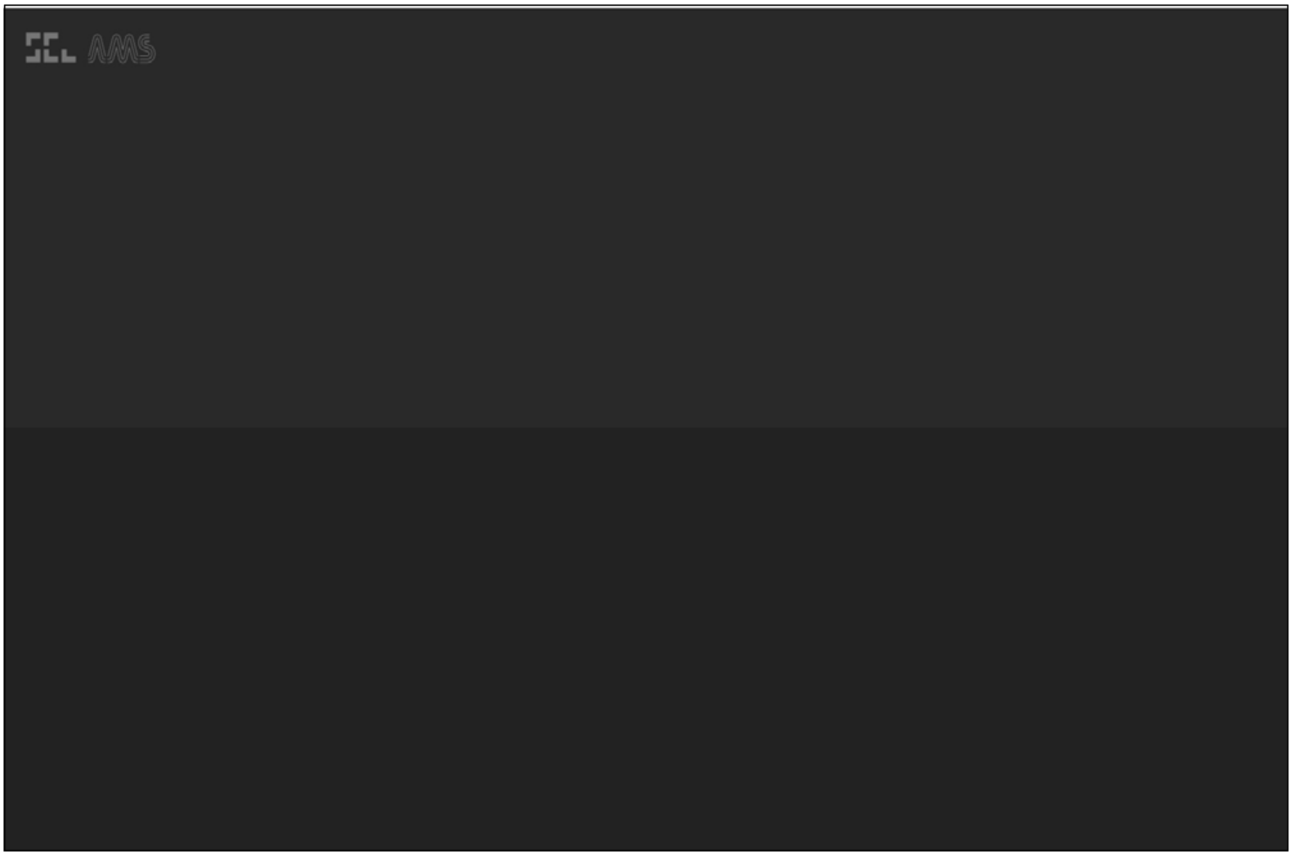

HANDLE WITH CARE

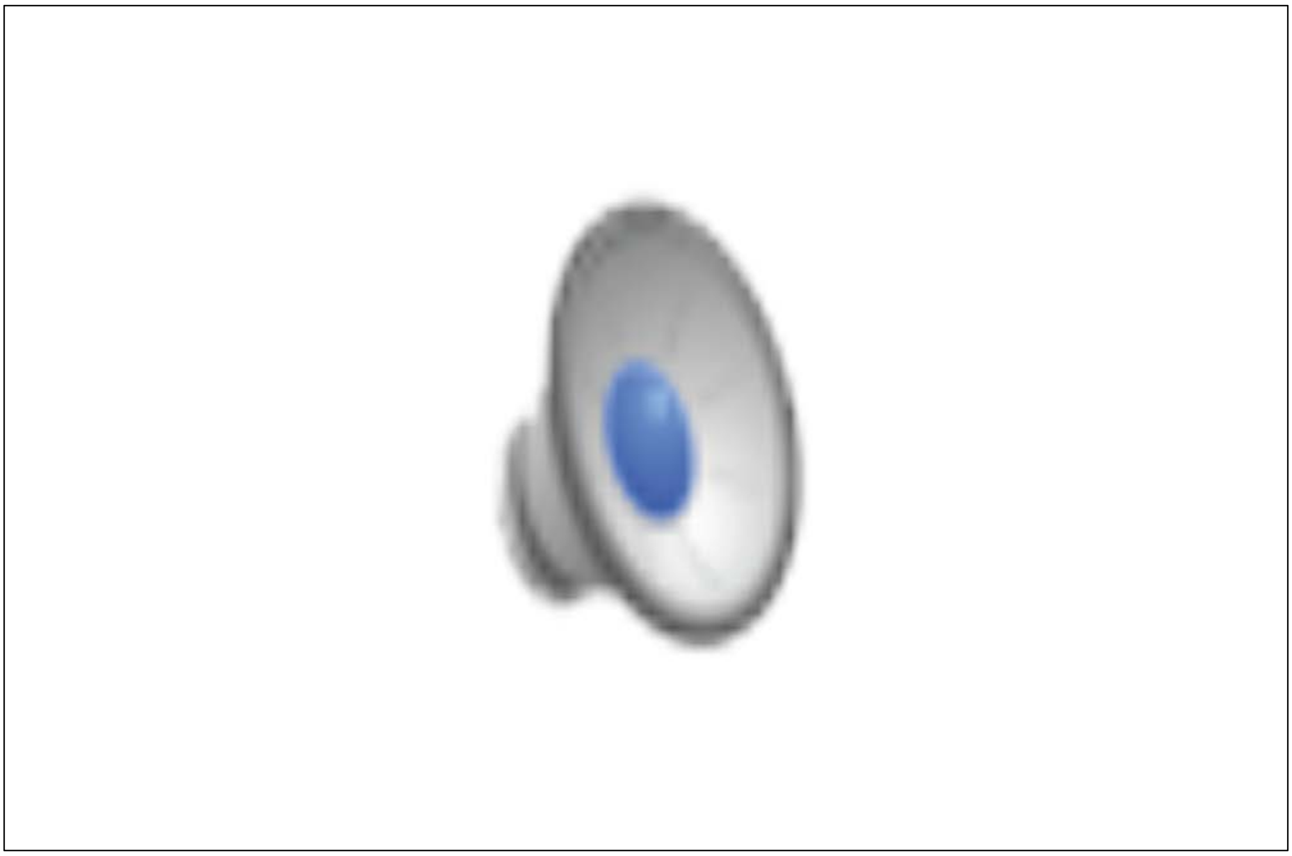


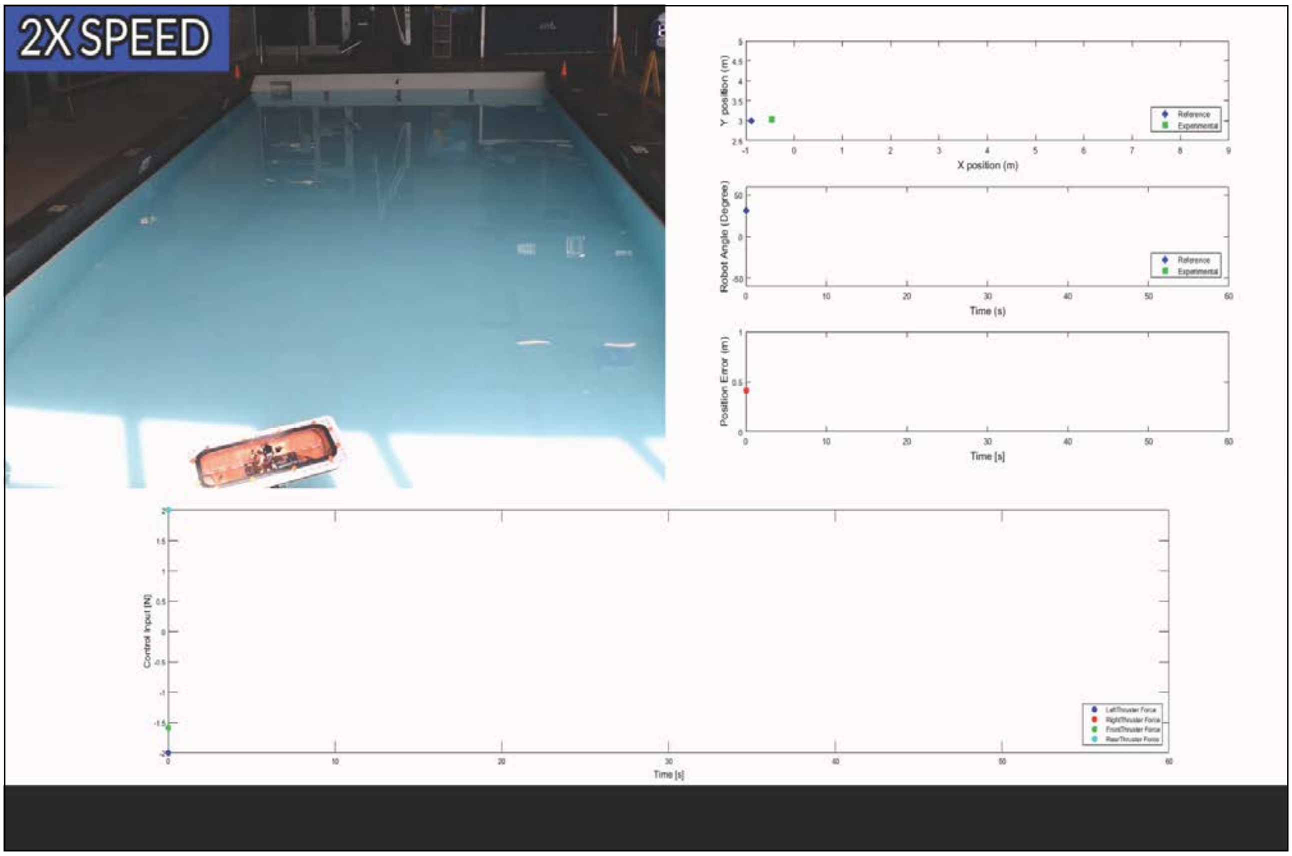


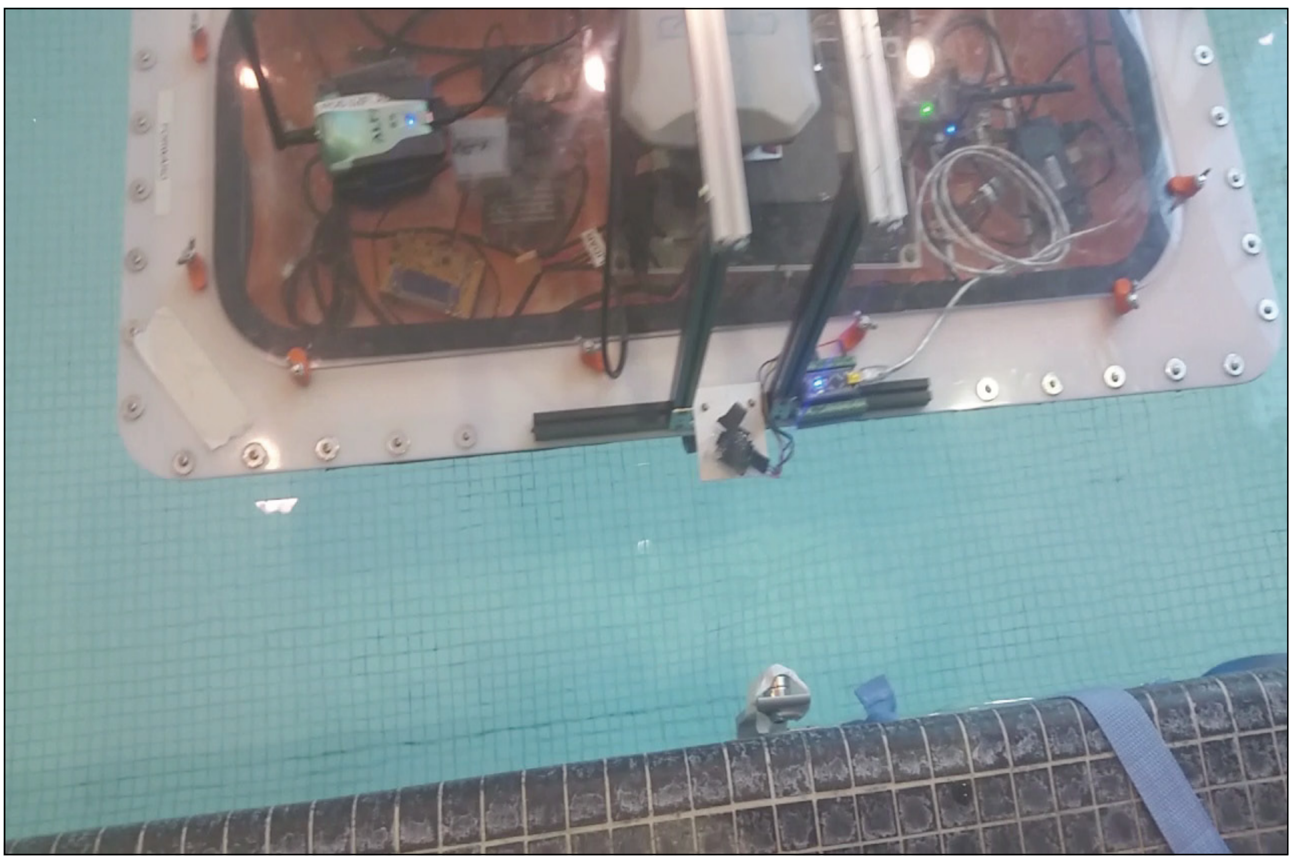


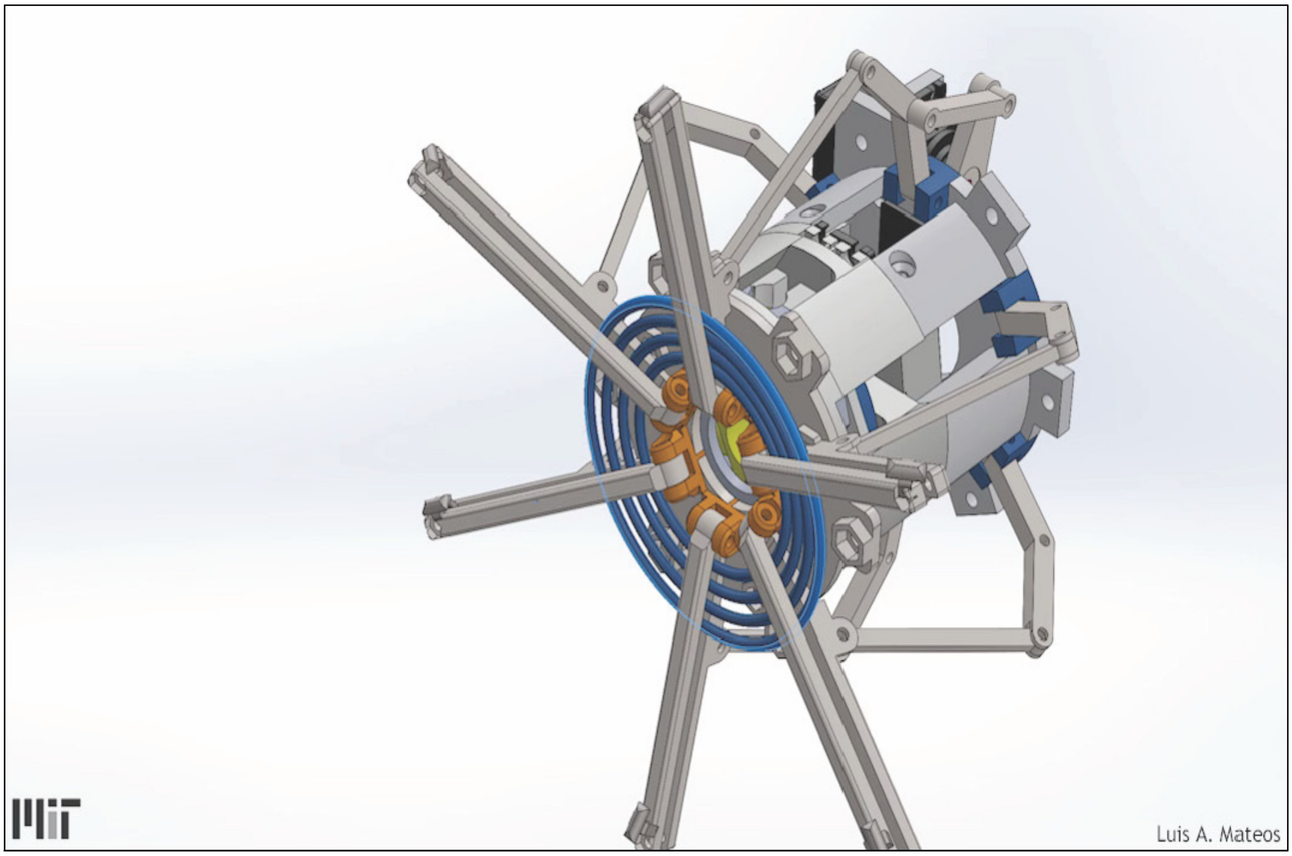




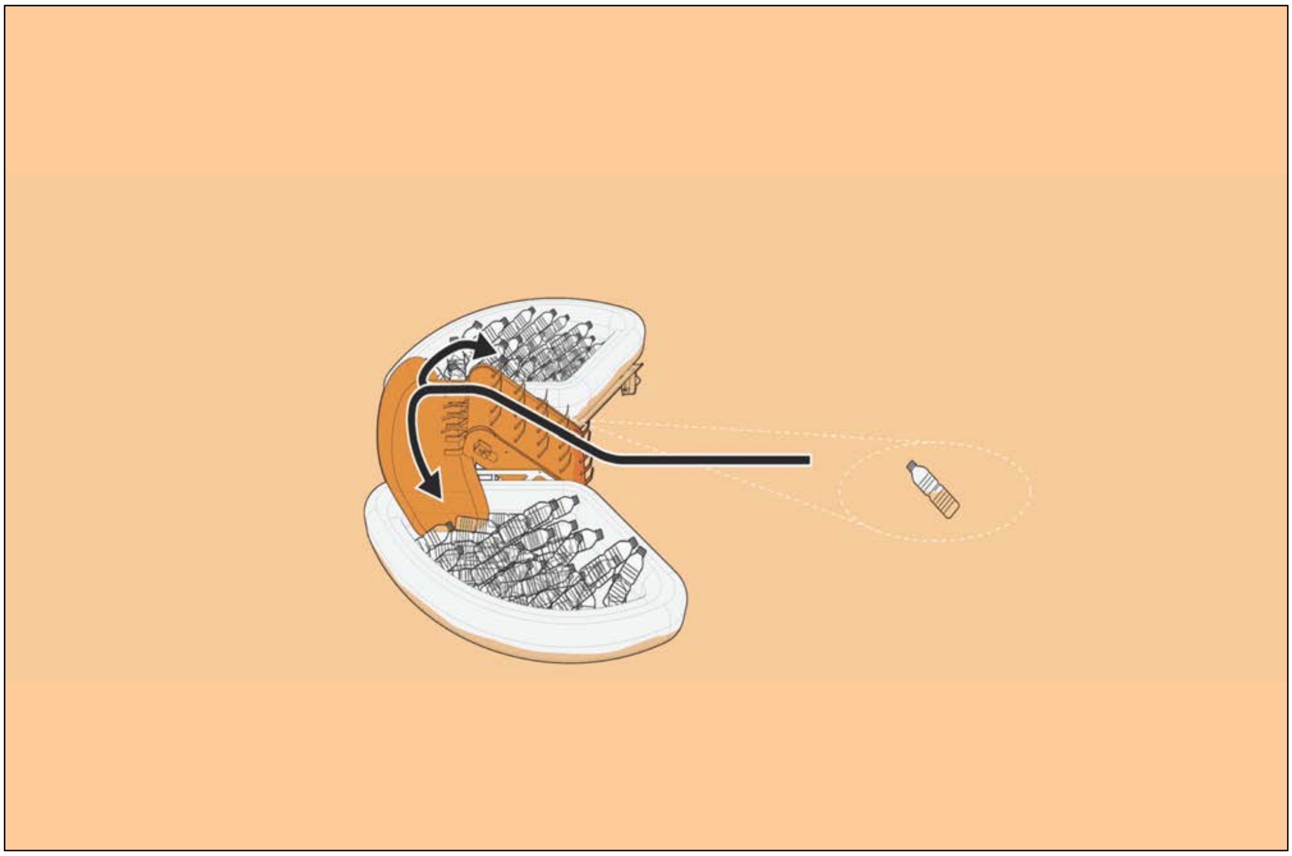


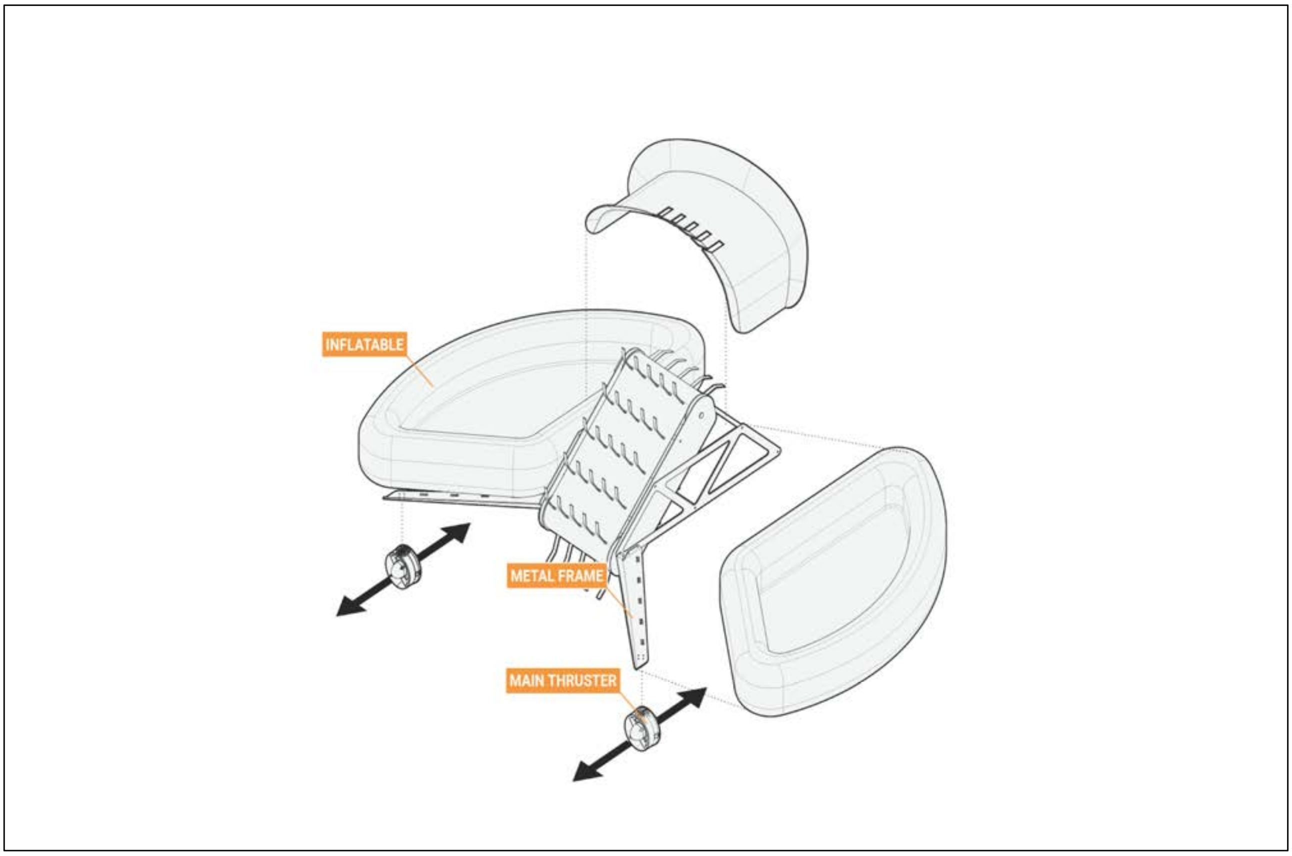

2X SPEED
Y position (m)
X position (m)
Reference
Experimental
Robot Angle (Degree)
Time (s)
Position Error (m)
Time [s]
Control Input [N]
Time [s]

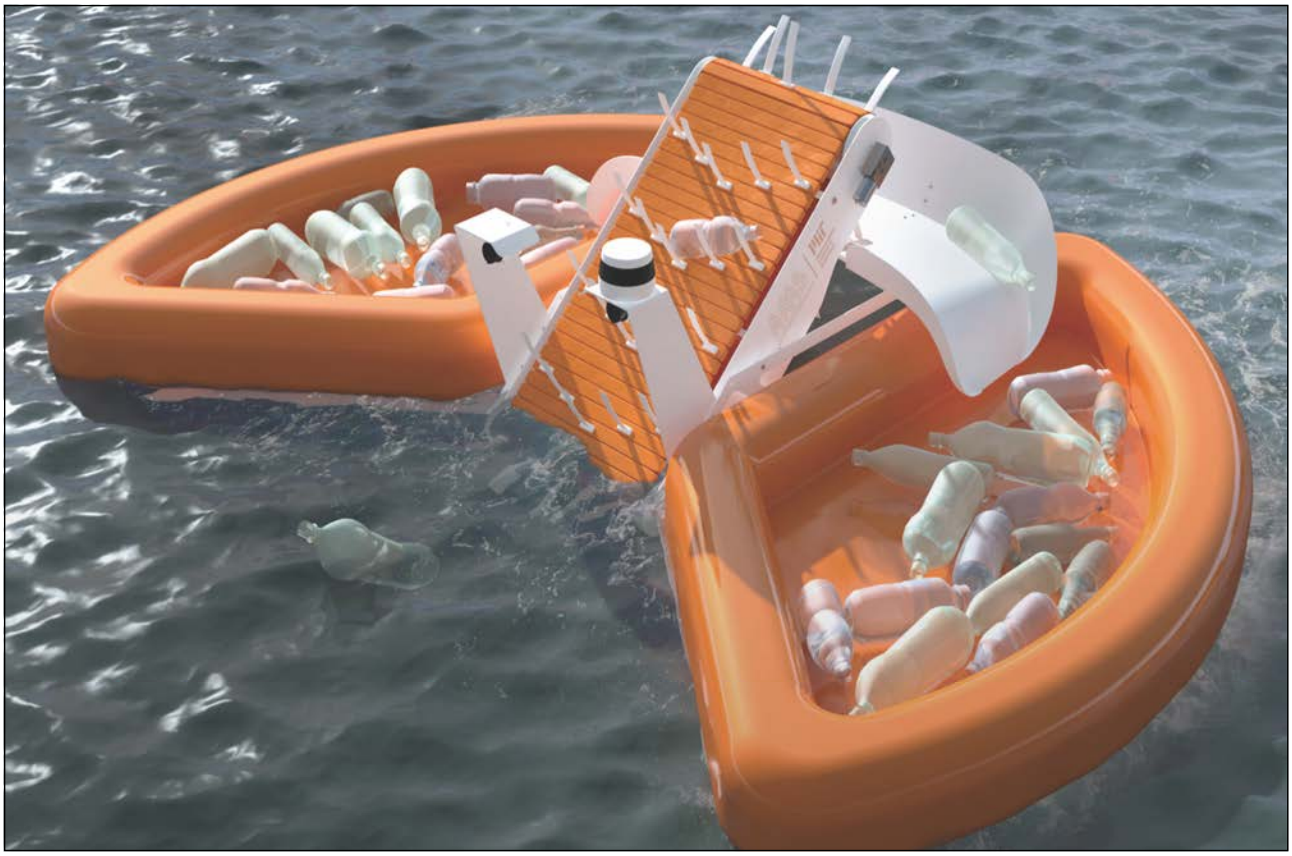


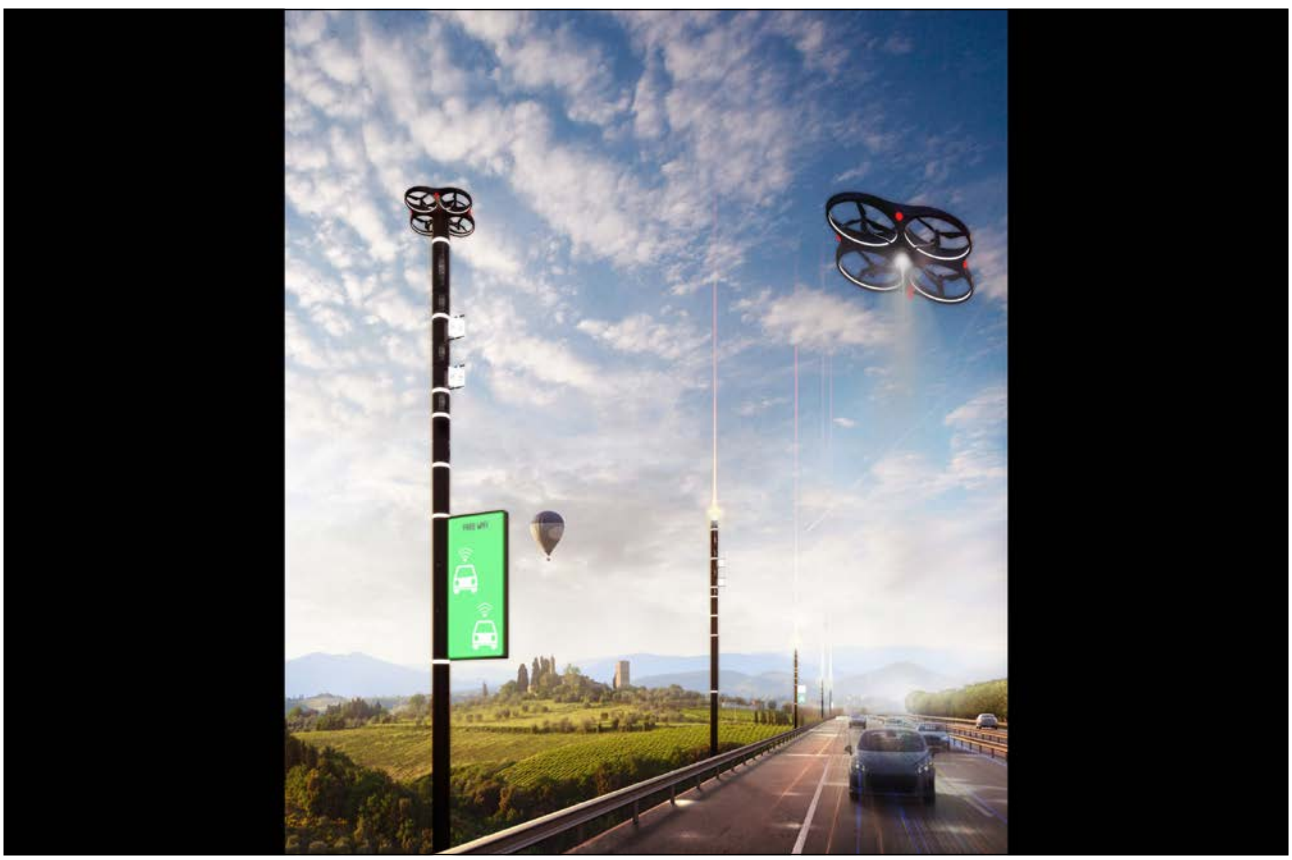

Luis A. Mateos

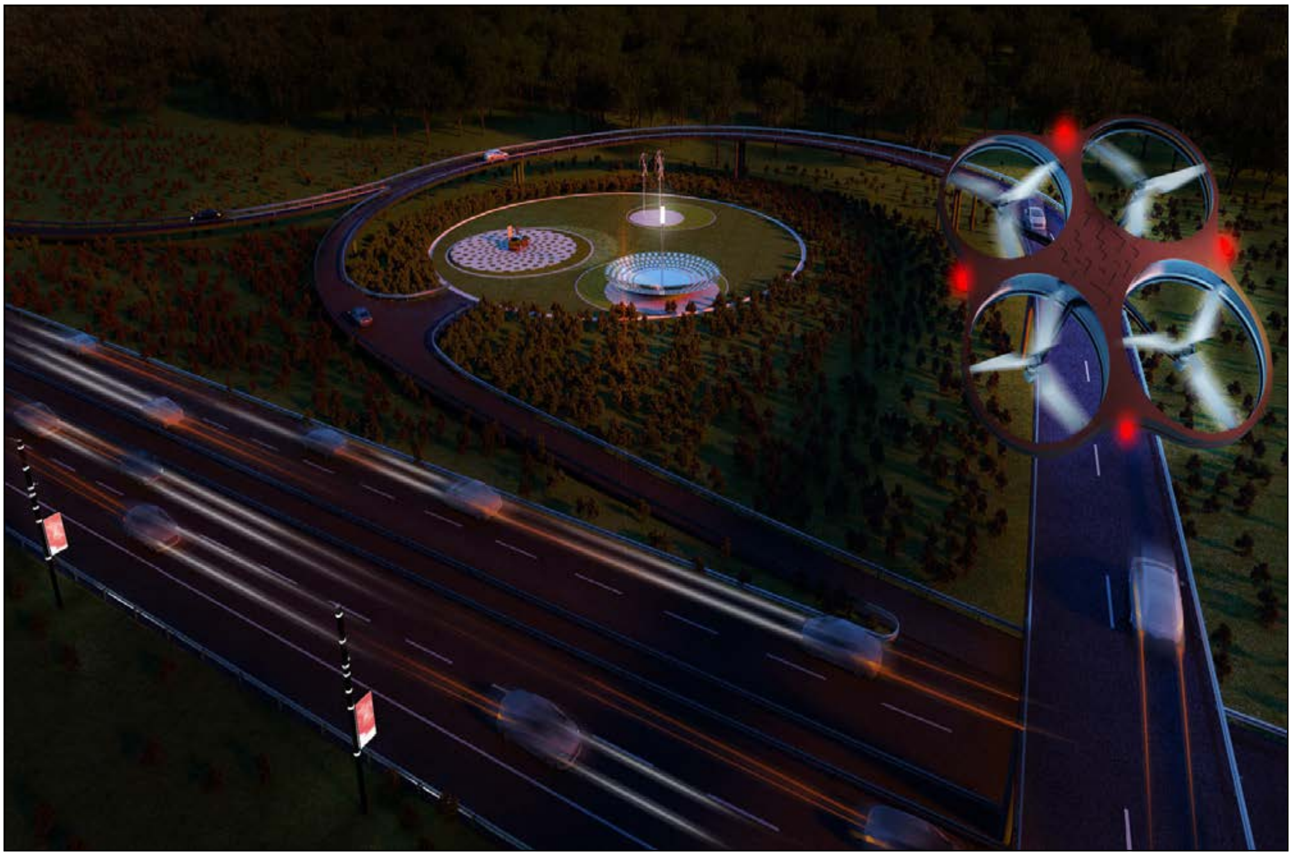

69% (35399 out of 51131)
of all households are served by the floating dumpsters

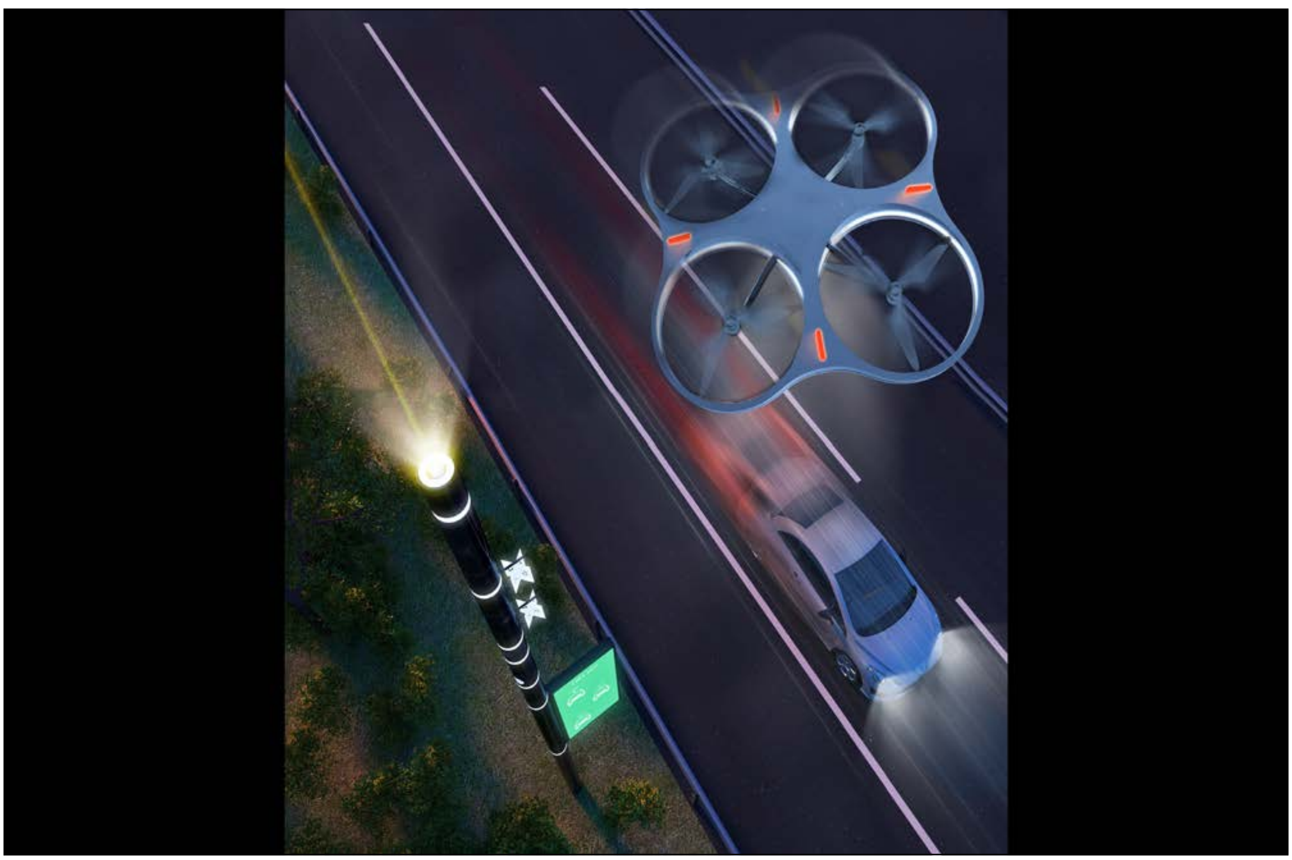



INFLATABLE
METAL FRAME
MAIN THRUSTER





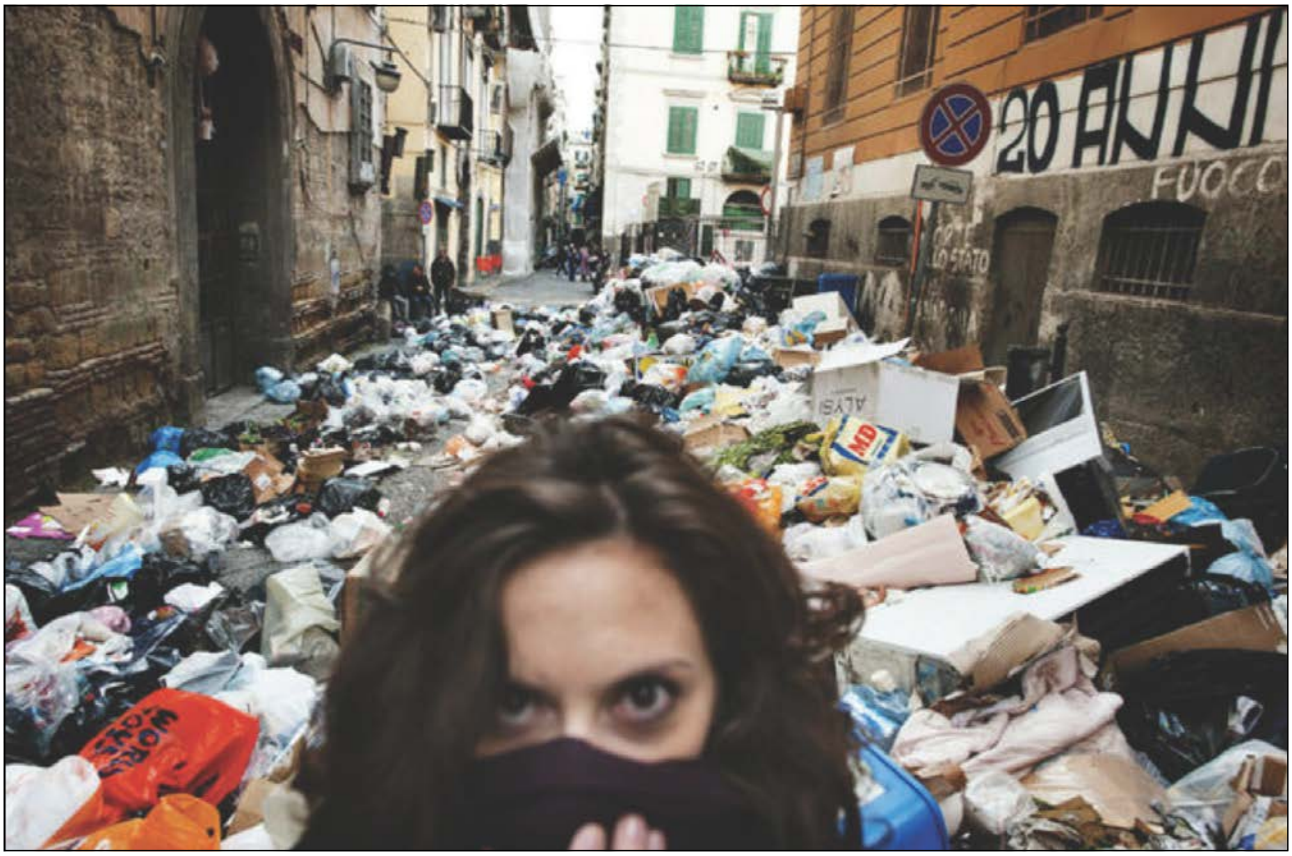




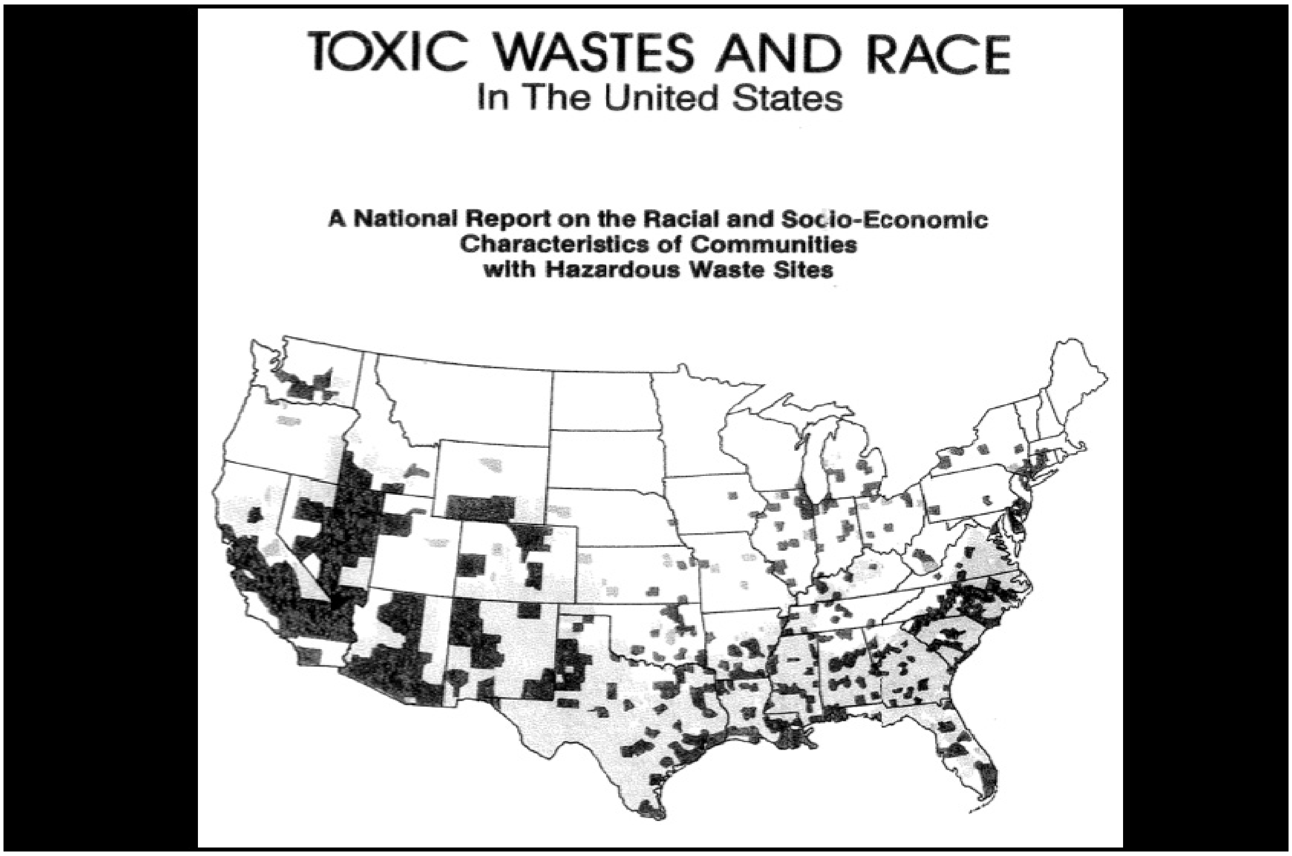

Sourcemap
Canada
United States
Brasil
Australia
India
Mongolia
Greenland

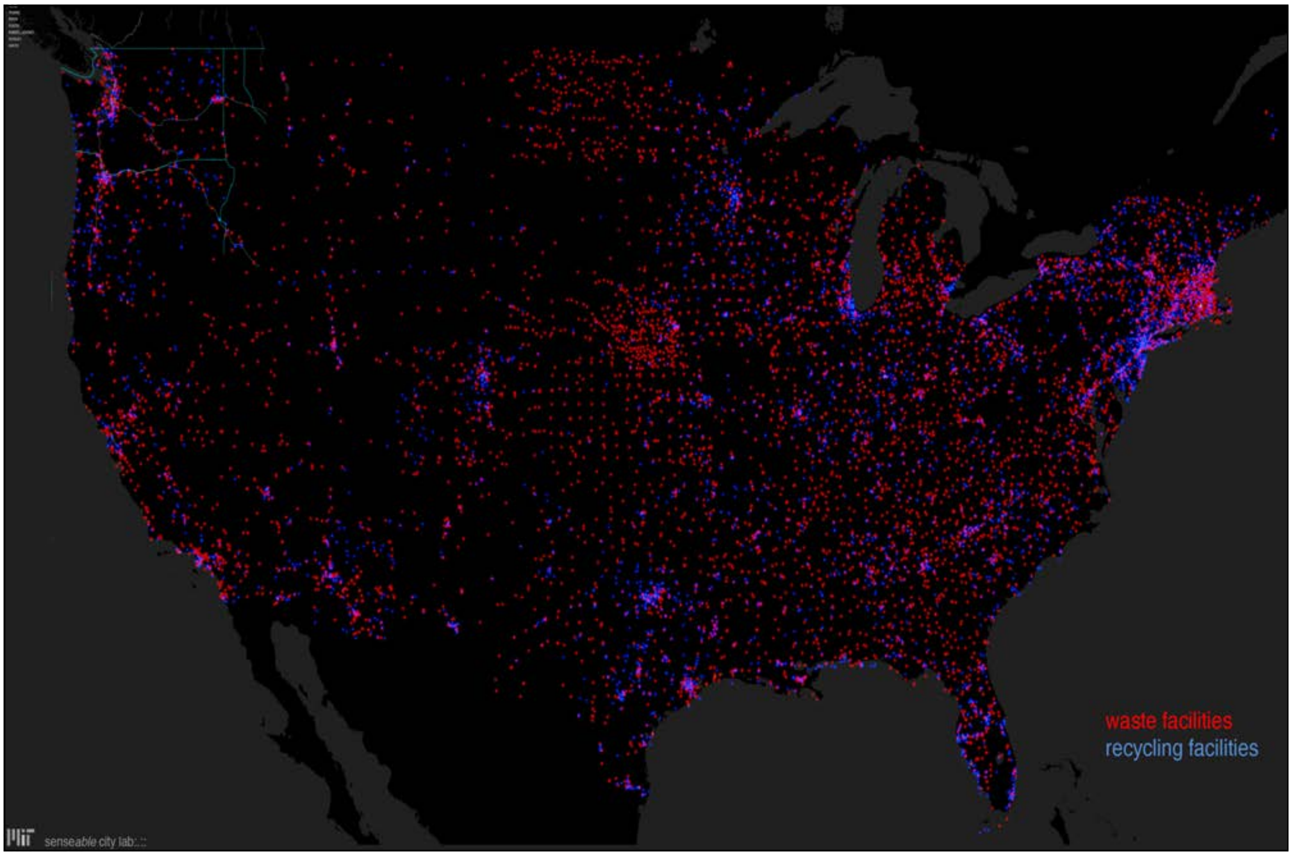
removal chain today/yesterday...

removal chain resilience...



environmental justice...

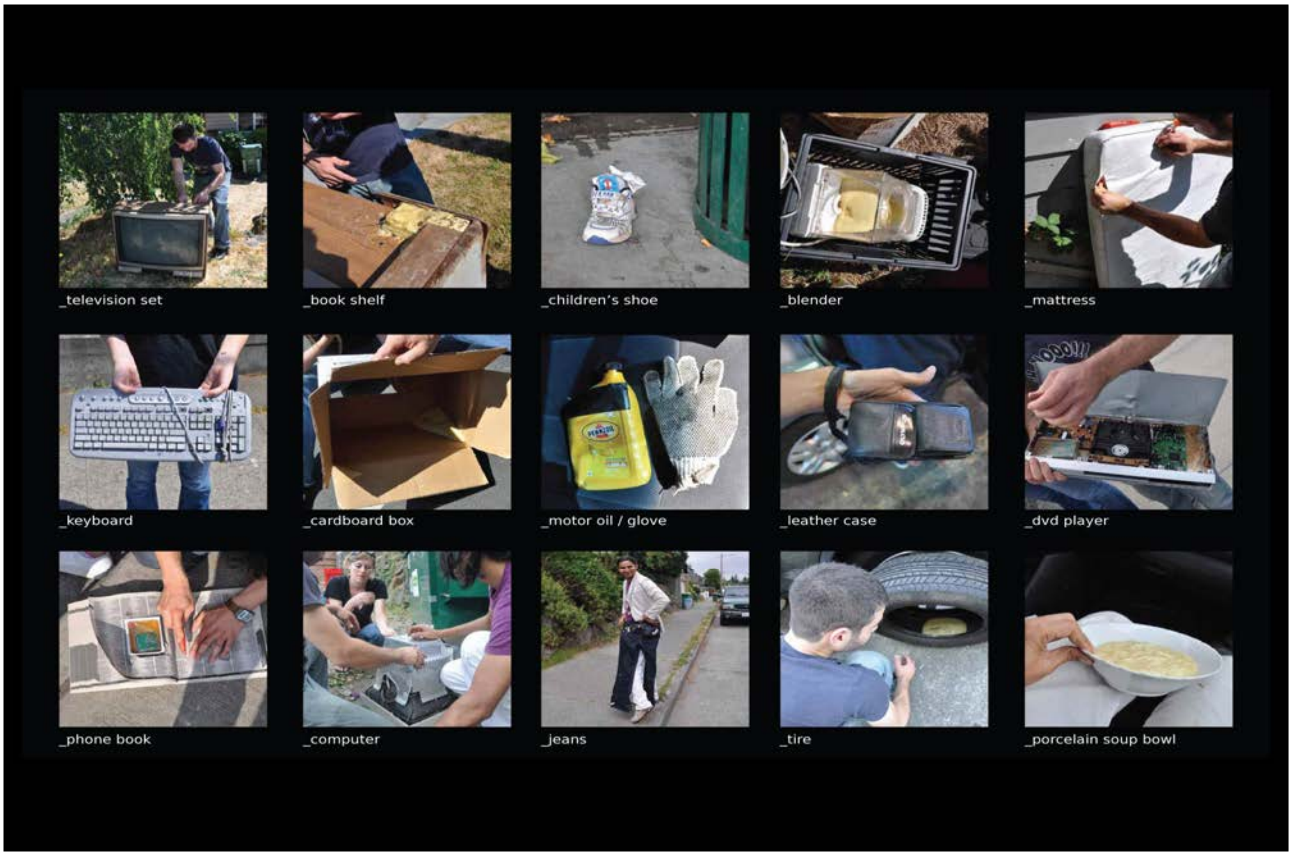

TOXIC WASTES AND RACE
In The United States
A National Report on the Racial and Socio-Economic
Characteristics of Communities
with Hazardous Waste Sites

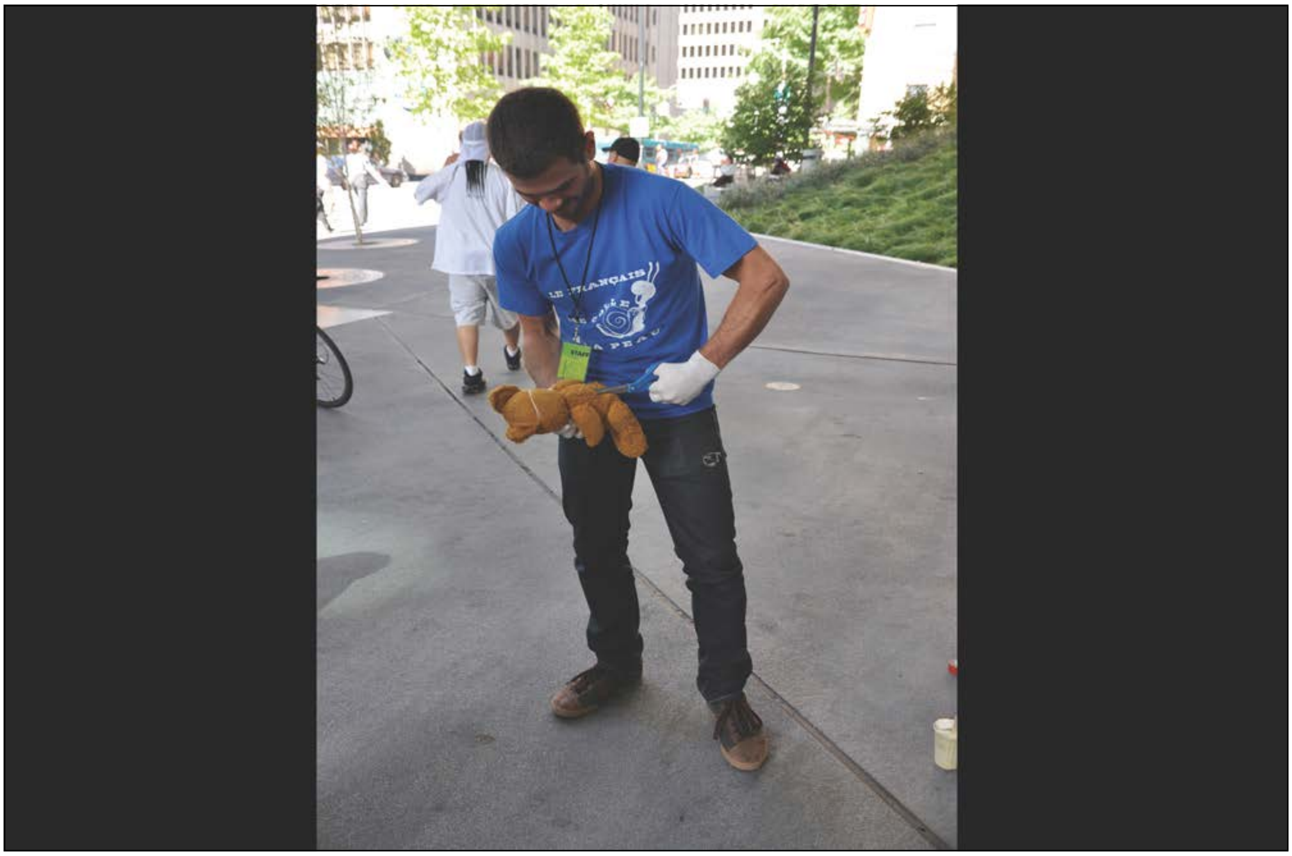

waste facilities
recycling facilities
senseable city lab

our idea...


Telit GE864-QUAD
CE0168


QUALCOMM
On | Off
LIBERTY
QUARTER DOLLAR


_television set
_book shelf
_children's shoe
_blender
_mattress
_keyboard
_cardboard box
_motor oil / glove
_leather case
_dvd player
_phone book
_computer
_jeans
_tire
_porcelain soup bowl

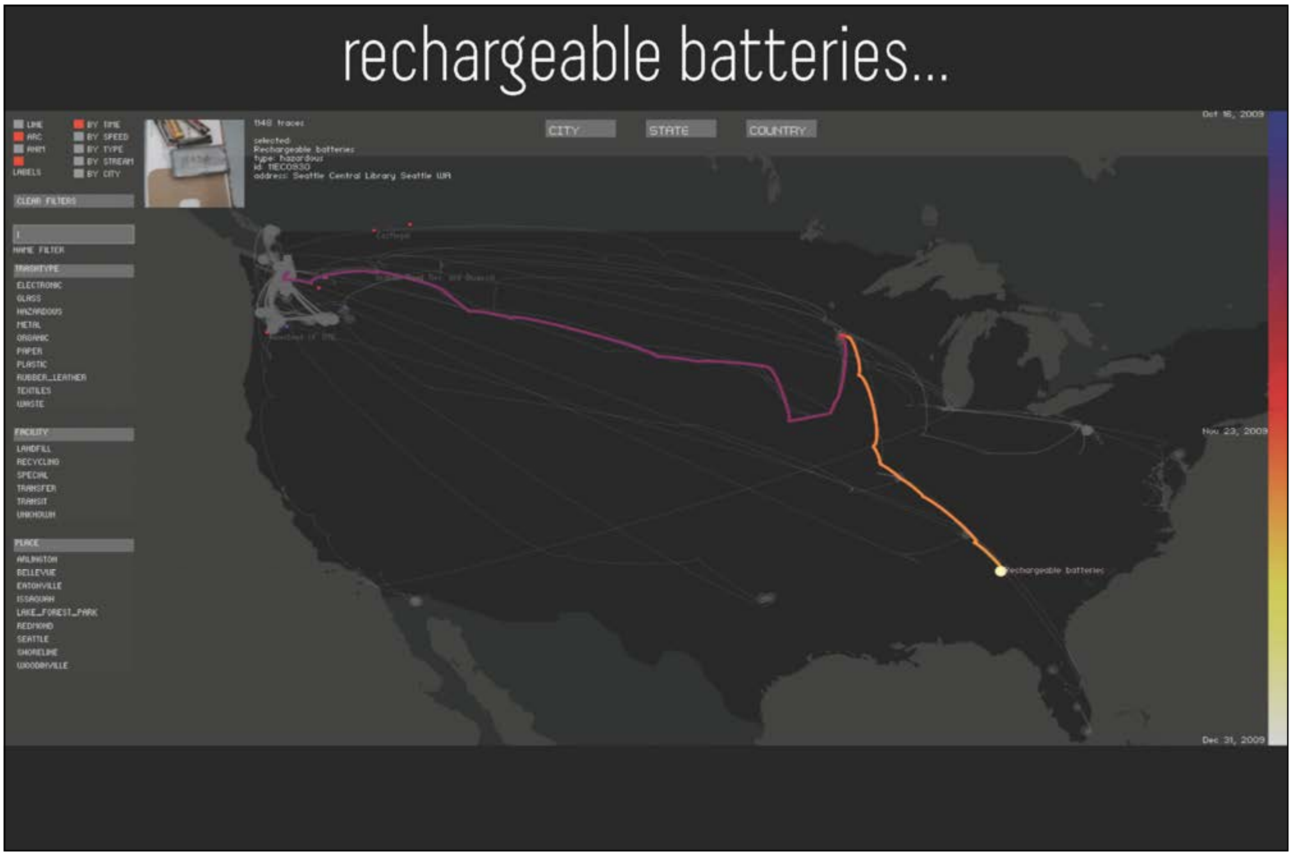


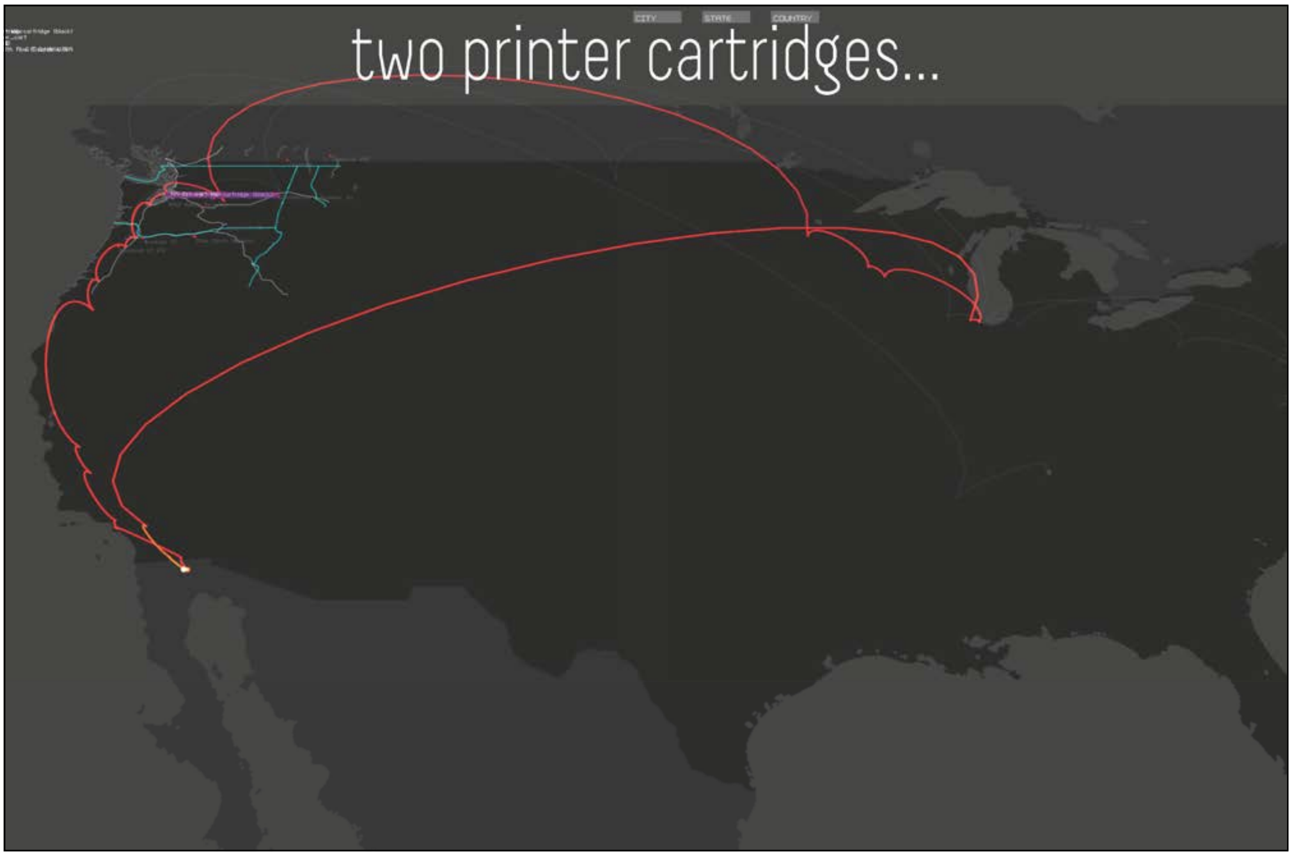

869-RZW

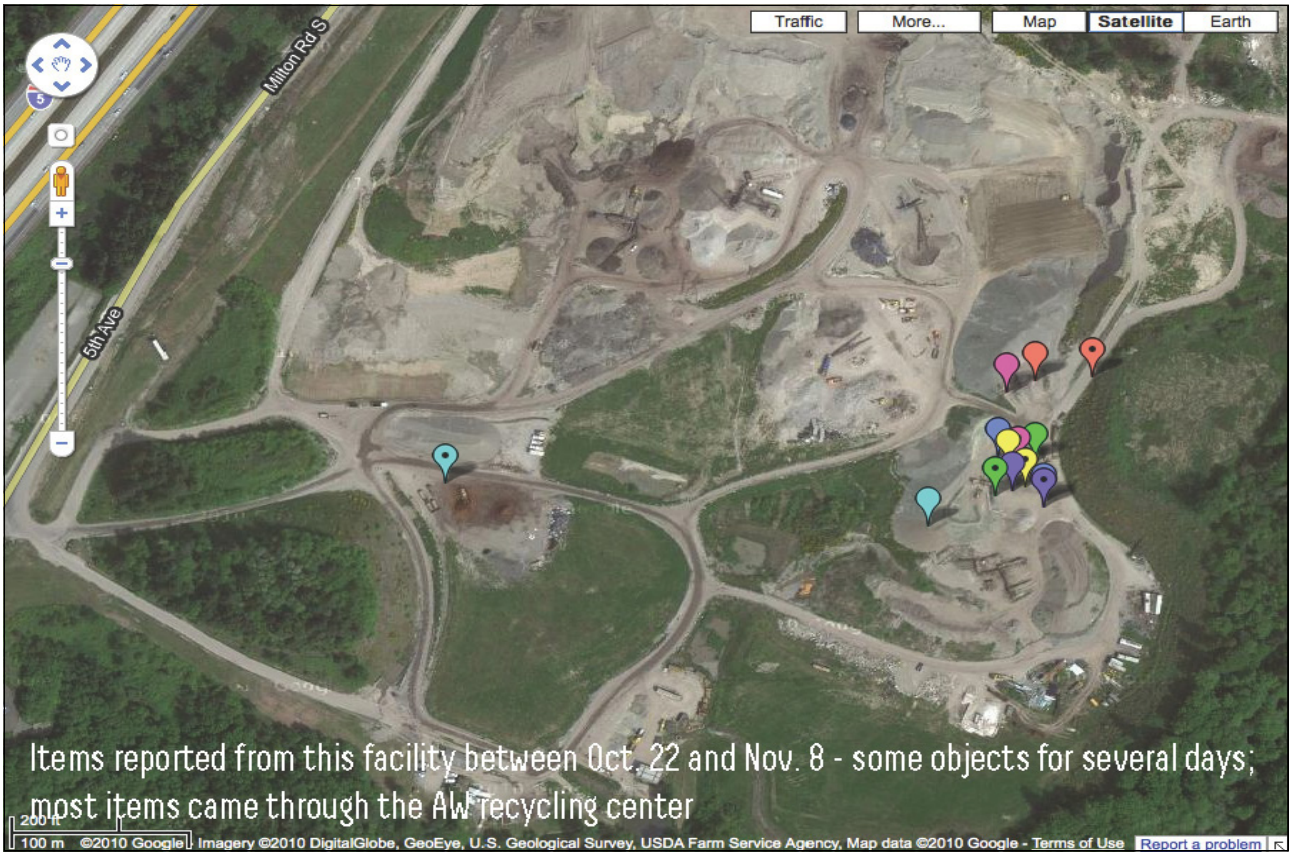

MIT / Trash Track
Volunteers
0+
August 20,
10:30 am

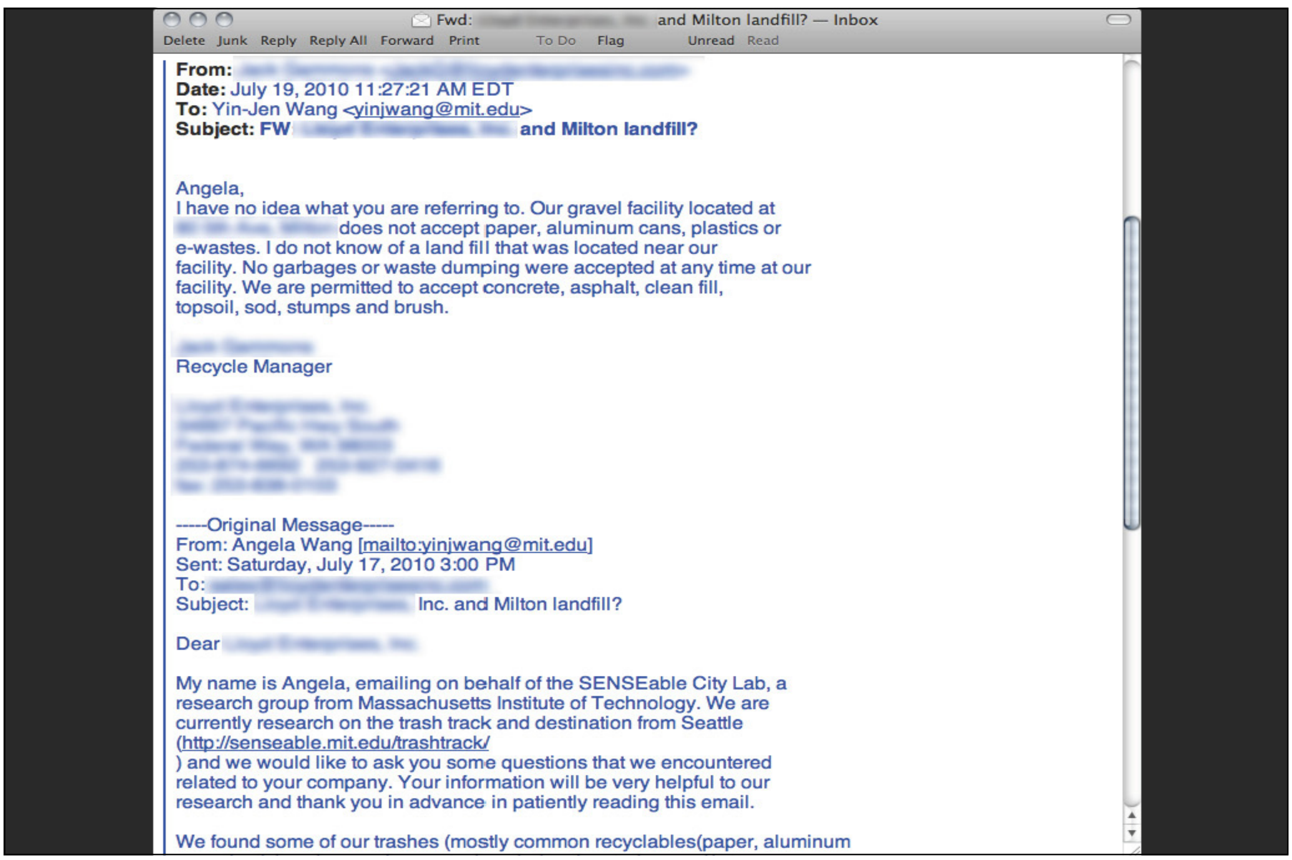
Lesson 1


Yogurt Container
Trashed at
1350 N 34th St
Seattle, WA 98103
Traveled
35.05 Miles,
3 Days and 16 Hours
Category
Plastic
Jul 12, 2009
+ 6 Days
Jul 12, 2009
Jul 12, 2009
Fremont
Wallingford
Queen Anne
SEATTLE
Alki
Beacon Hill
Aug 16, 2009, 1:11 PM
Aug 16, 2009, 1:11 PM
Aug 16, 2009, 1:11 PM
Aug 16, 2009, 1:11 PM
Aug 16, 2009, 1:11 PM
En Route
Yogurt
Container
Last seen from:
1350 N 34th St
Seattle, WA 98103


rechargeable batteries...
CITY
STATE
COUNTRY
Oct 16, 2009
Nov 23, 2009
Dec 31, 2009


two printer cartridges...
CITY
STATE
COUNTRY





Fwd: [redacted] and Milton landfill? — Inbox

Delete Junk Reply Reply All Forward Print To Do Flag Unread Read

From: [redacted]
Date: July 19, 2010 11:27:21 AM EDT
To: Yin-Jen Wang <yinjwang@mit.edu>
Subject: FW [redacted] **and Milton landfill?**

Angela,
I have no idea what you are referring to. Our gravel facility located at [redacted] does not accept paper, aluminum cans, plastics or e-wastes. I do not know of a land fill that was located near our facility. No garbages or waste dumping were accepted at any time at our facility. We are permitted to accept concrete, asphalt, clean fill, topsoil, sod, stumps and brush.

[redacted]
Recycle Manager

[redacted]

-----Original Message-----
From: Angela Wang [mailto:yinjwang@mit.edu]
Sent: Saturday, July 17, 2010 3:00 PM
To: [redacted]
Subject: [redacted] Inc. and Milton landfill?

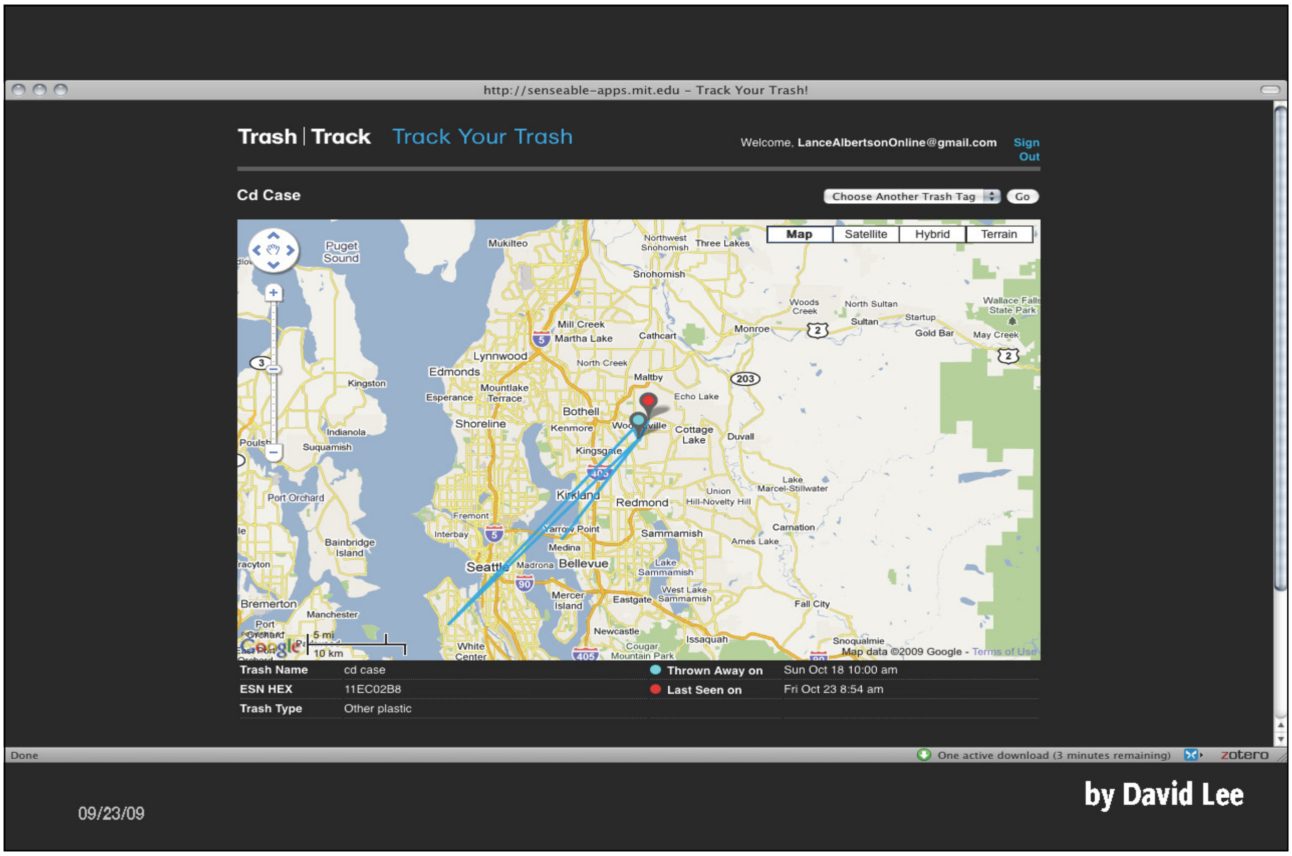
Dear [redacted]

My name is Angela, emailing on behalf of the SENSEable City Lab, a research group from Massachusetts Institute of Technology. We are currently research on the trash track and destination from Seattle (http://senseable.mit.edu/trashtrack/
) and we would like to ask you some questions that we encountered related to your company. Your information will be very helpful to our research and thank you in advance in patiently reading this email.

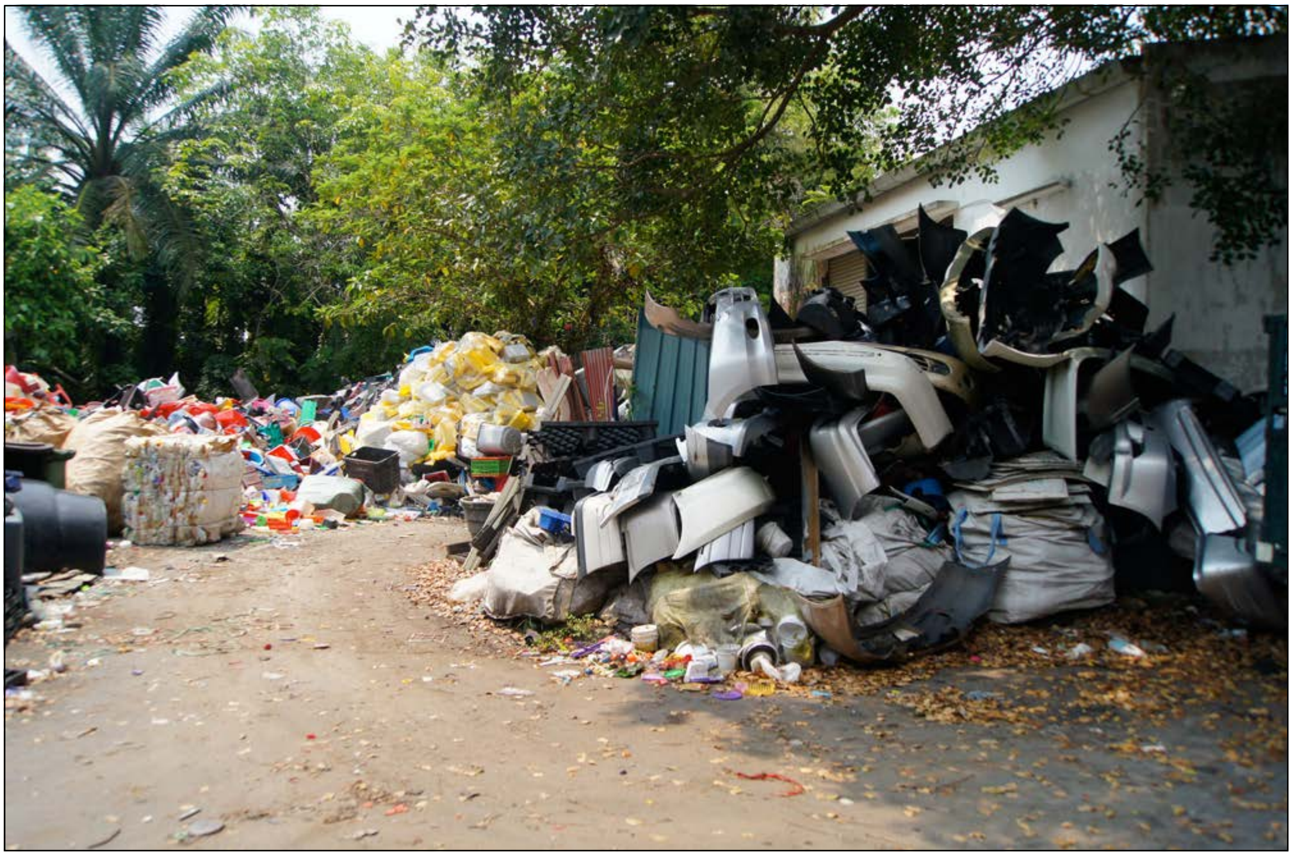
We found some of our trashes (mostly common recyclables(paper, aluminum

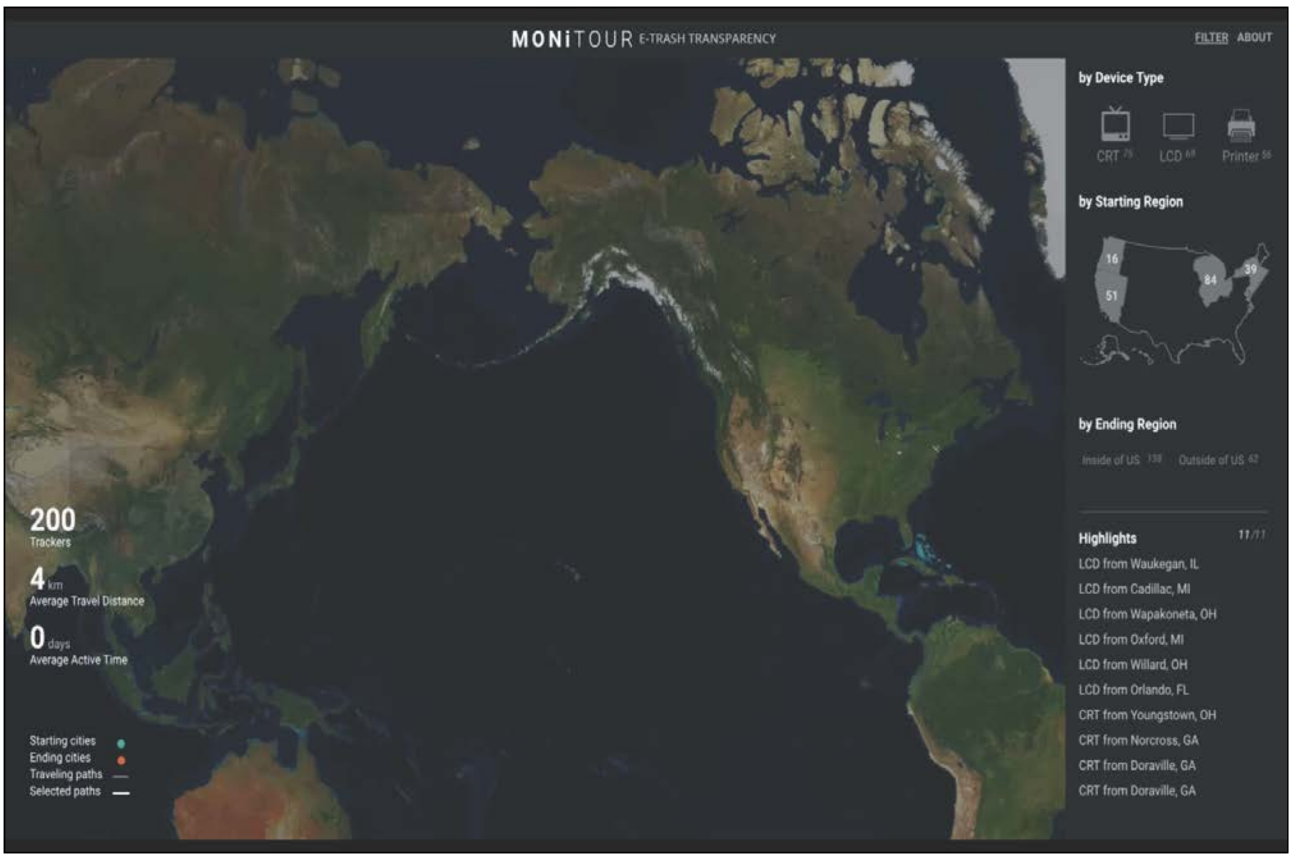

Reported Transportation Distance by Trash Category
distance log(km)
Trash Category
cell_phone
e_waste
glass
hhw
metals
mixed
paper
plastic_bottle
pcp
plastic_other
textiles
0.7
0.8
factor(endfactype)
landfill
recycling
special
transfer
transit
unknown

Lesson 2


http://senseable-apps.mit.edu – Track Your Trash!
Trash | Track
Track Your Trash
Welcome, LanceAlbertsonOnline@gmail.com
Sign Out
Cd Case
Choose Another Trash Tag
Go
Map
Satellite
Hybrid
Terrain
Trash Name
cd case
ESN HEX
11EC02B8
Trash Type
Other plastic
Thrown Away on
Sun Oct 18 10:00 am
Last Seen on
Fri Oct 23 8:54 am
Done
One active download (3 minutes remaining)
zotero
09/23/09
by David Lee

Lesson 3




MONiTOUR E-TRASH TRANSPARENCY
FILTER ABOUT
by Device Type
CRT
LCD
Printer
by Starting Region
16
51
84
39
by Ending Region
Inside of US
Outside of US
Highlights
11/11
LCD from Waukegan, IL
LCD from Cadillac, MI
LCD from Wapakoneta, OH
LCD from Oxford, MI
LCD from Willard, OH
LCD from Orlando, FL
CRT from Youngstown, OH
CRT from Norcross, GA
CRT from Doraville, GA
CRT from Doraville, GA
200
Trackers
4 km
Average Travel Distance
0 days
Average Active Time
Starting cities
Ending cities
Traveling paths
Selected paths

Lesson 4


Twitter
@CRASSOCIATI
@SENSEABLECITY

Memo

Memo

Invited Talk 1

Smart Partnerships

[스마트 파트너쉽]

Prof. Debra Lam
Georgia Institute of Technology

Smart Partnerships

(Public Innovation for inclusive growth)

Debra Lam

Debra.lam@georgiatech.edu

The Georgia Institute of Technology

Abstract

Whether measured by expected market valuation, speed of technological change, or potential of data collection and analytics, smart cities development has become a vital area of growth for governments, the public and corporations a like. However, the development has been misunderstood, overpromised, and produced unintended consequences like widen inequality.

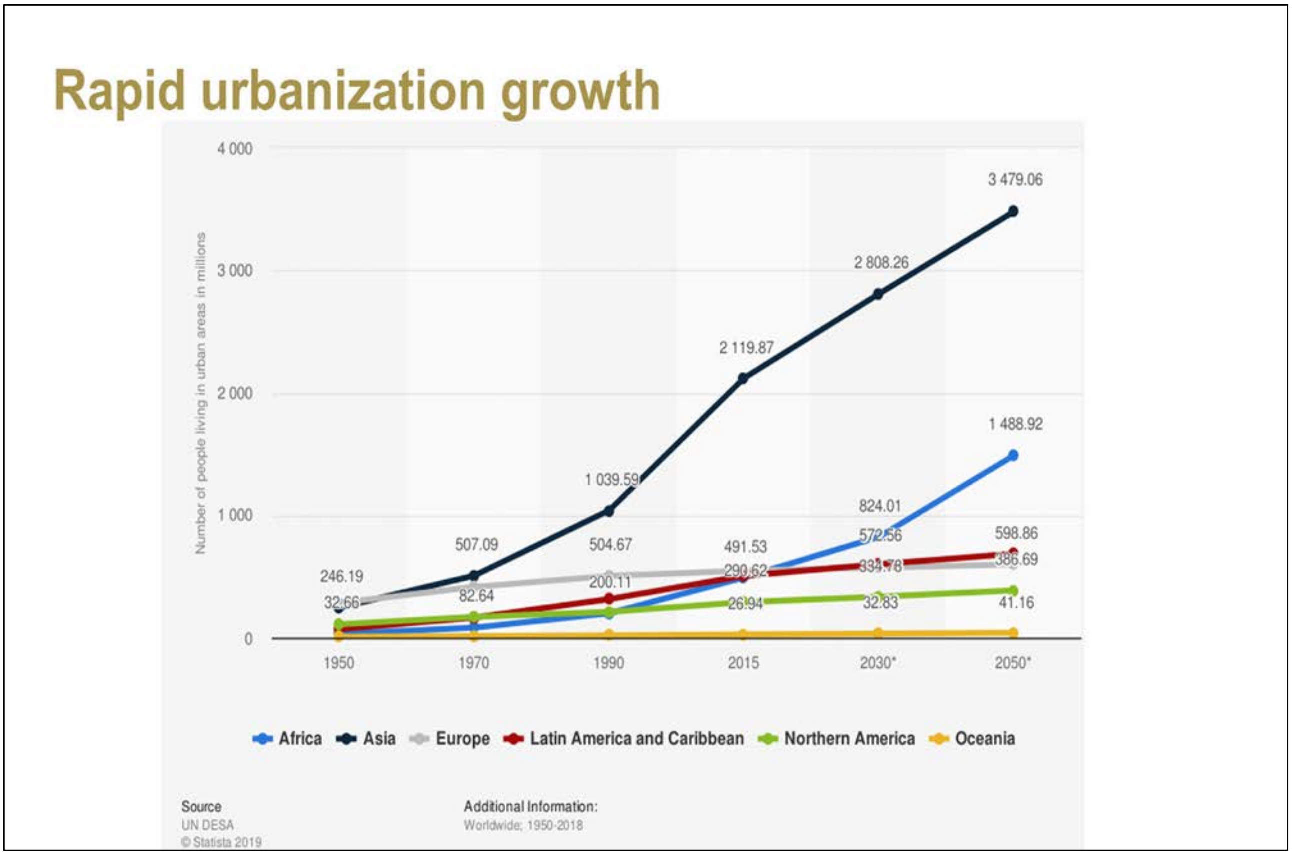
Deeper dialogue and more action are required to ensure that all communities can reap the benefits of technology and data. This talk will explore how public innovation with multisector engagement can empower communities to better address critical development challenges and evolving needs of their citizens. Technology and data are not the panacea, but they are part of a broader toolkit that allows governments to innovate, while providing a role for more actors to engage and be part of the solution.

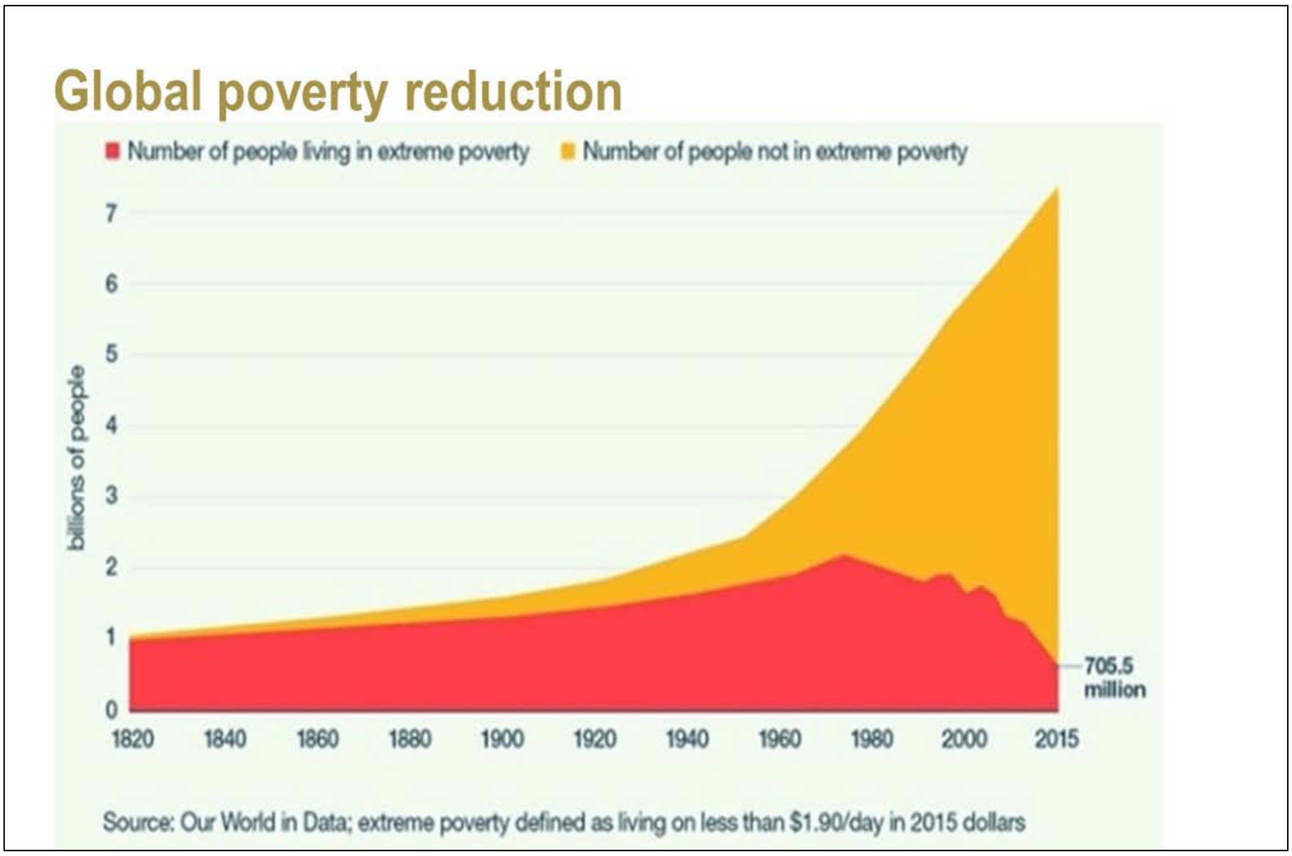
SMART Partnerships

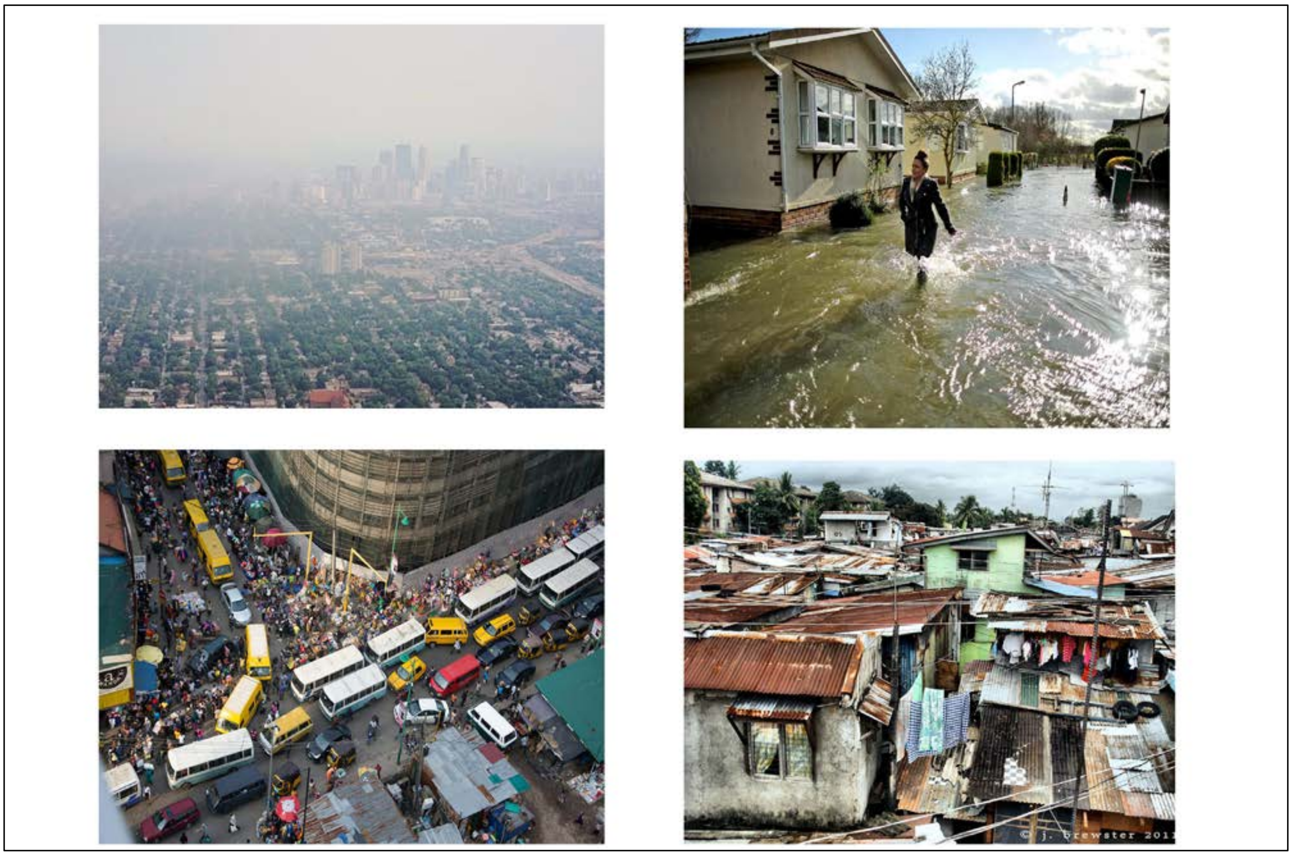
Creating new paths for smart cities and inclusive innovation

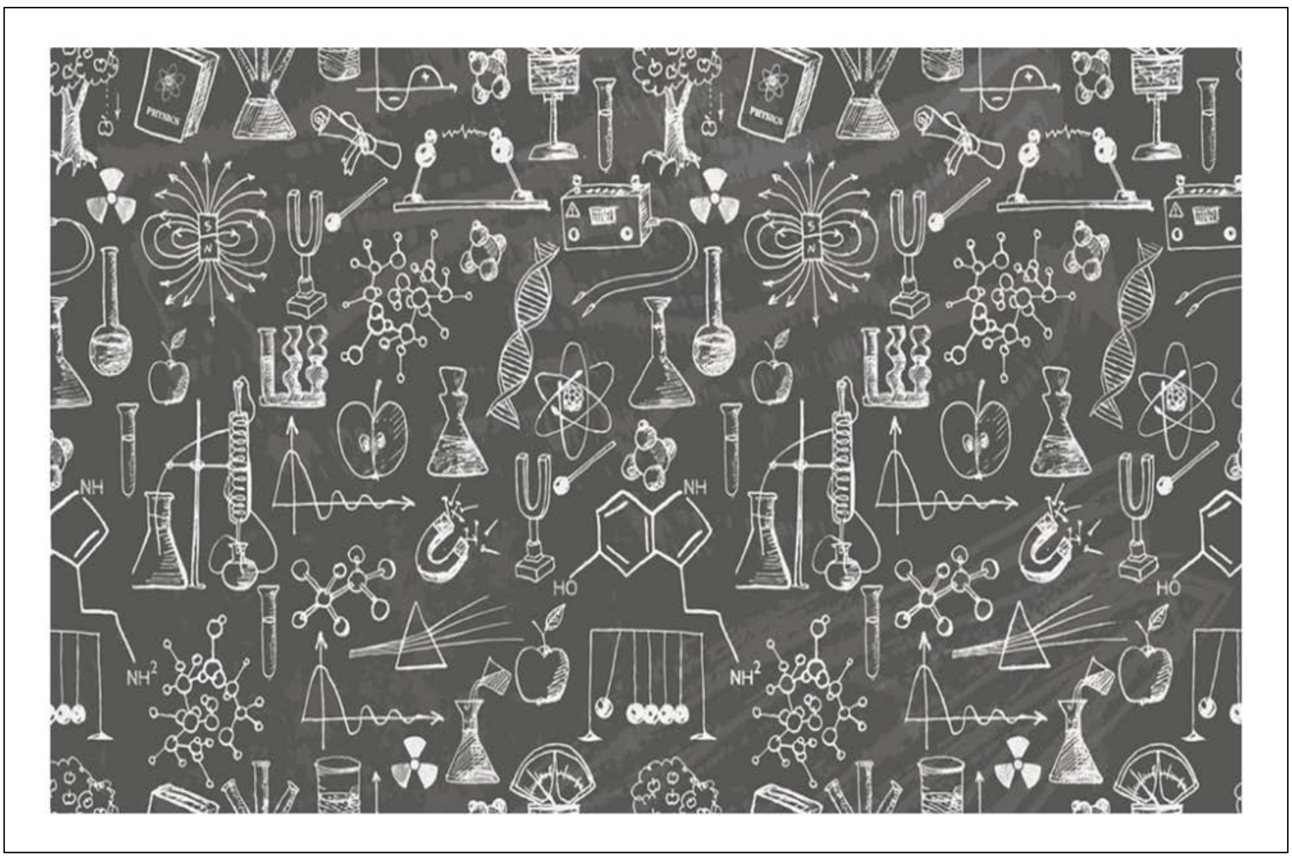
Debra Lam
ICGIS 2019
8 August 2019

Georgia Tech


Rapid urbanization growth
Number of people living in urban areas in millions
4 000
3 000
2 000
1 000
0
3 479.06
2 808.26
2 119.87
1 488.92
1 039.59
824.01
507.09
504.67
491.53
598.86
246.19
32.66
82.64
200.11
290.62
572.56
334.78
386.69
26.94
32.83
41.16
1950
1970
1990
2015
2030*
2050*
Africa Asia Europe Latin America and Caribbean Northern America Oceania
Source
UN DESA
© Statista 2019
Additional Information:
Worldwide; 1950-2018

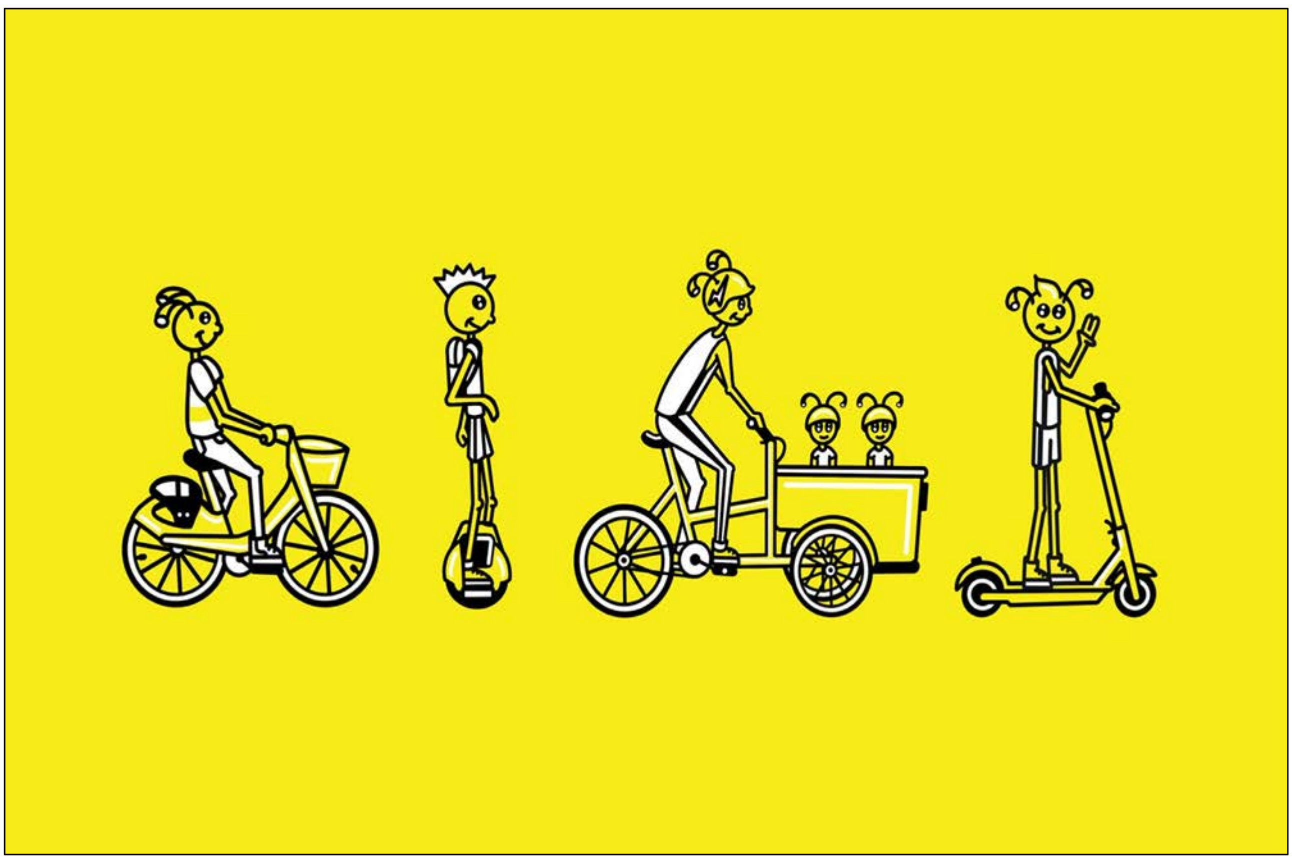

Global poverty reduction
Number of people living in extreme poverty
Number of people not in extreme poverty
billions of people
7
6
5
4
3
2
1
0
1820
1840
1860
1880
1900
1920
1940
1960
1980
2000
2015
705.5 million
Source: Our World in Data; extreme poverty defined as living on less than $1.90/day in 2015 dollars



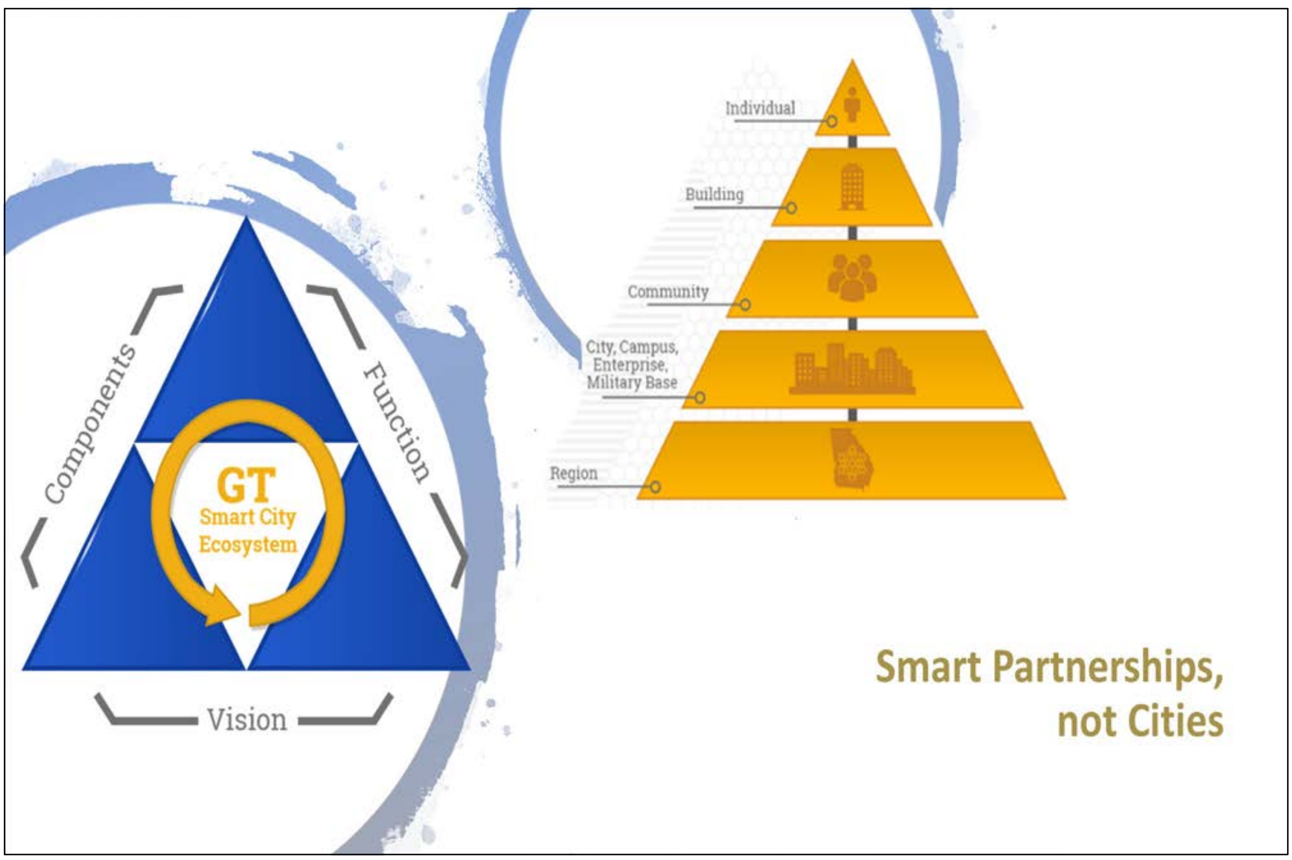


False Choice

VS




World Congress Ctr
Centennial Olympic Pk
EXIT 248C
Andrew Young Intl Blvd
Freedom Pkwy
Carter Center
Edgewood Ave
Auburn Ave
J W Dobbs Ave
Source: Travis Salters/Emily Hoberman, via Atlanta City Council Twitter

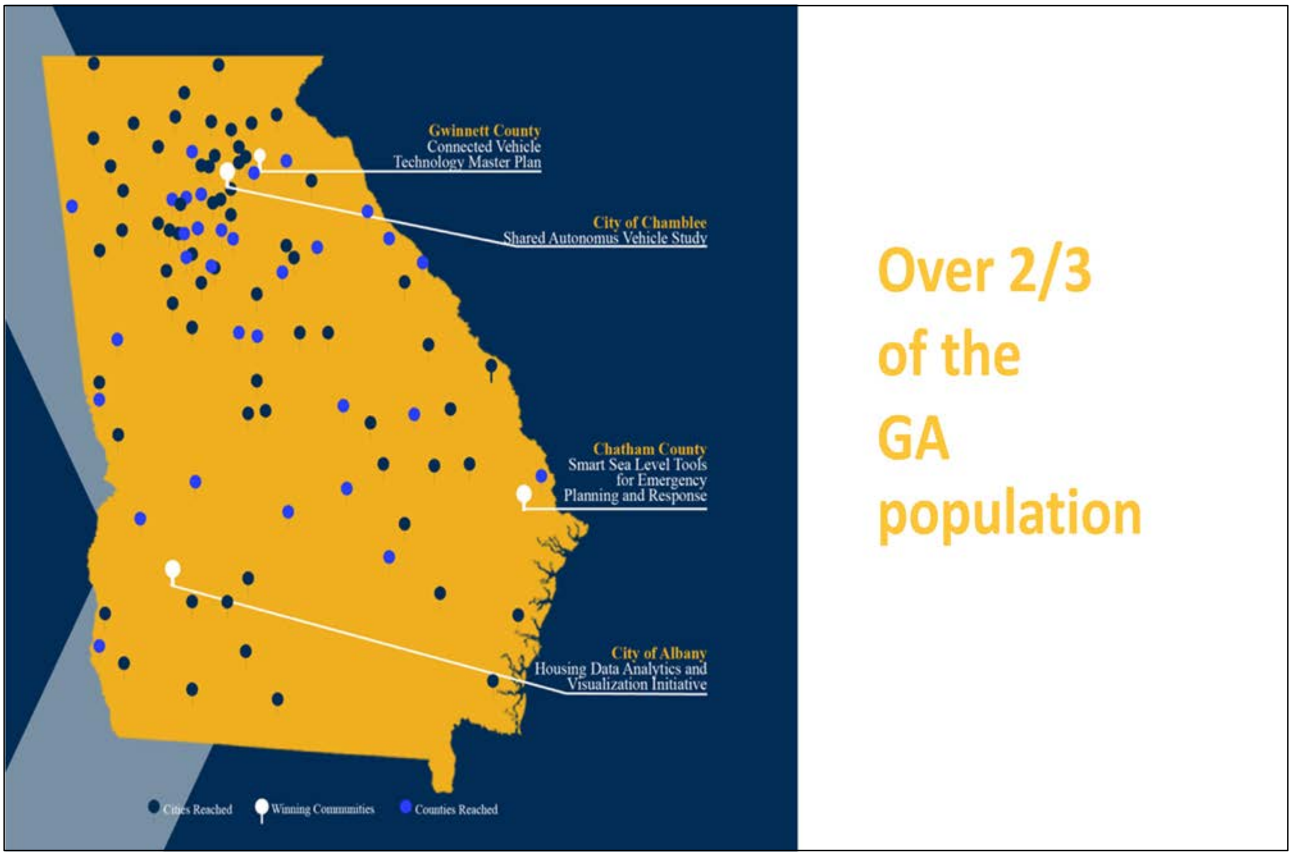

Components
Function
Vision
GT
Smart City
Ecosystem
Individual
Building
Community
City, Campus, Enterprise, Military Base
Region
Smart Partnerships,
not Cities

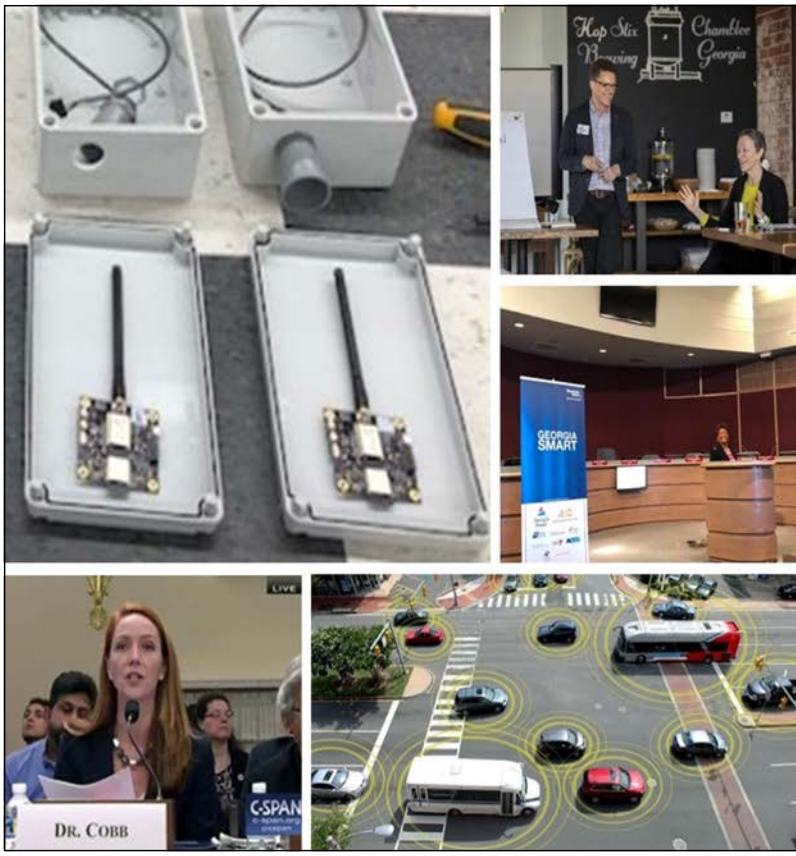

Smart Partnerships
Start with the Challenge
Research-based toolkit
Long-term engagement


GEORGIA SMART
COMMUNITIES CHALLENGE
GA Smart made possible by our partners
Georgia Power
The listing of corporate logos above does not constitute an endorsement by Georgia Tech


GA Smart Partners
Georgia Power
Atlanta Regional Commission
ACCG
Advancing Georgia's Counties.
Georgia USA
GEORGIACHAMBER
Georgia Department of Community Affairs
GEORGIA MUNICIPAL ASSOCIATION
TAG
Technology Associatic of Georgia
GLOBAL CITY TEAMS CHALLENGE
METRO ATLANTA CHAMBER
APA GA
American Planning Association Georgia Chapter
GARC


Georgia
Tech


Gwinnett County
Connected Vehicle
Technology Master Plan
City of Chamblee
Shared Autonomus Vehicle Study
Chatham County
Smart Sea Level Tools
for Emergency
Planning and Response
City of Albany
Housing Data Analytics and
Visualization Initiative
Cities Reached
Winning Communities
Counties Reached
Over 2/3
of the
GA
population



Making community impact

- Projects underway with active research and stakeholder engagement
- Innovative ways to use technology and data to advance goals
- Local and national attention
- Opportunities for additional research and funding
- Professional Credit for workshops

- Enabling students to tackle grand challenges
- Enhancing education beyond the classroom
- Empowering the next generation of leaders

GA Smart Field Guide

- Best practices and learnings distilled from communities
- Accessible to all GA Communities and beyond

Smart Partnerships

- Start with the Challenge
- Research-based toolkit
- Long-term engagement


Thank you
Georgia Tech

Memo

Memo

Smart GEO Expo 2019
2019 스마트국토엑스포
2019 ICGIS International Conference on Geospatial Information Science

Invited Talk 2

How Big Data Can Meaningfully Support Urban Design and Planning
[빅데이터를 활용한 도시 디자인과 계획]

Prof. Bige Tunçer
Singapore University of Technology and Design

How big data can meaningfully support urban design and planning

Bige Tunçer
bige_tuncer@sutd.edu.sg
Singapore University of Technology and Design

Abstract

Technology is more than ever available for providing designers with real-time data and information about many aspects of our environment, with the potential of being used in design processes to improve our built environment. Our goal is to take advantage of new and abundant forms of data, sensing technologies, and possibilities for interaction among people, communities and their physical environments. In this context, we ask ourselves “Can we integrate big data, user preferences, and designer knowledge for urban design and planning support?”

We use technology to foster evidence based design, and translate the rich and varied information sources to design support means. The research challenge lies in finding out which behavioral hypotheses can be drawn from specific urban data sets and their combination, and understanding the relationship of these hypotheses with spatial and organizational aspects of urban spaces.

This talk will present and discuss the focus on multi-source, multi-time and multi-scale data collection, analysis, and information visualization within design and decision support platforms for improving the livability of neighborhoods and cities.

Designers switch between various scales

Designers frame and solve various problems consecutively, simultaneously

Providing designers with

multi-source

multi-scale

multi-time

information, or evidence

an important contribution of big data to design support

EVIDENCE BASED DESIGN SUPPORT

The research challenge:

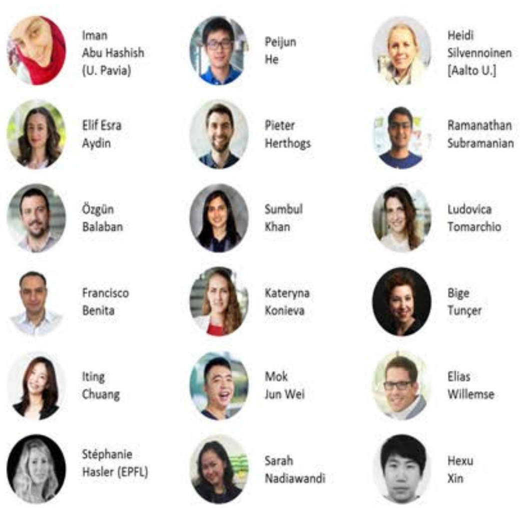
Which behavioral hypotheses can be drawn from specific urban data sets and their combination?

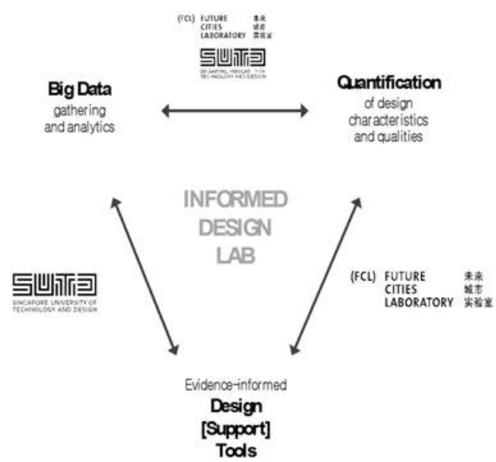
What is the relationship of these hypotheses with spatial and organizational aspects of urban spaces?

Can we integrate big data, user preferences, and designer knowledge for urban design and planning support?

INFORMED DESIGN LAB @ SUTD & FCL

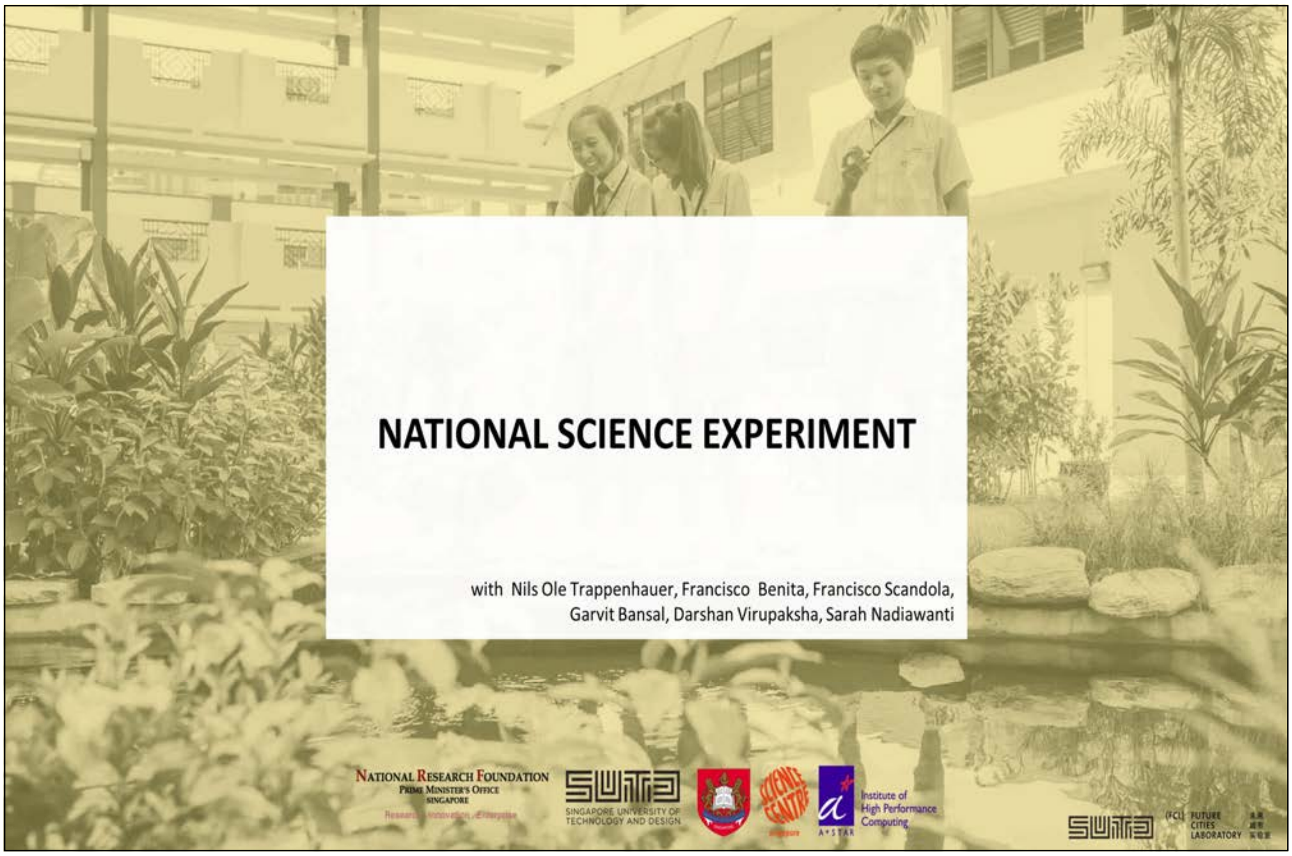
Multi-disciplinary group consisting of architects, software engineers, data scientists, also collaborating with social scientists

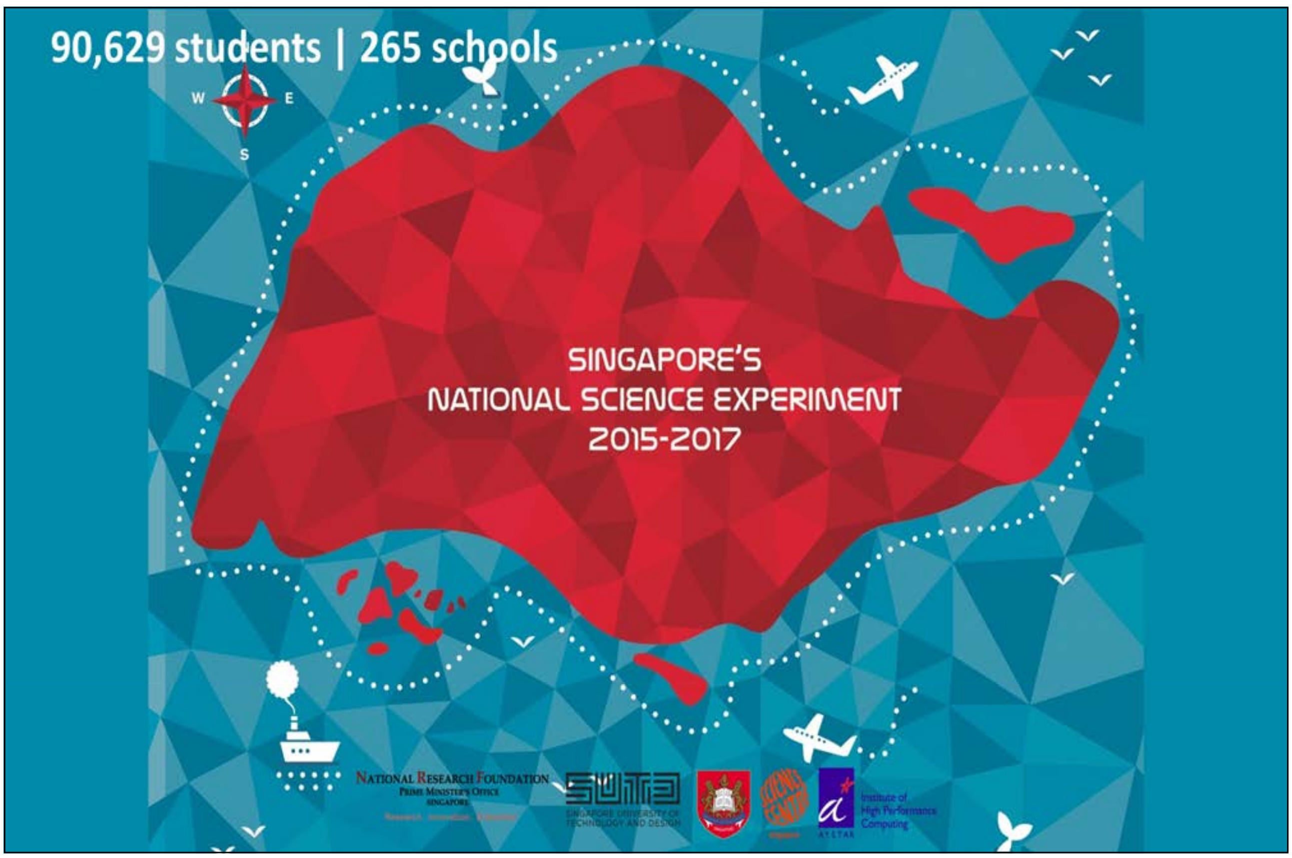




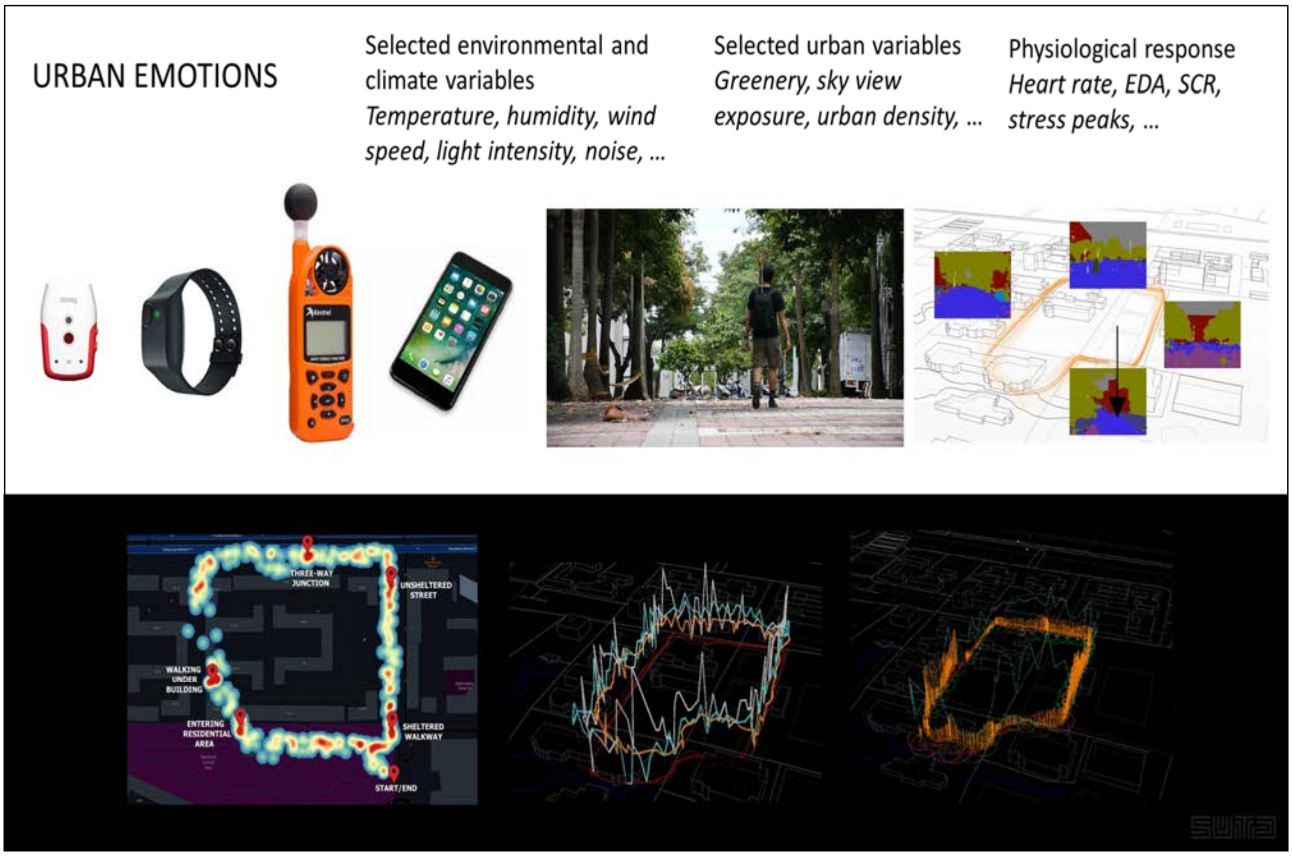

EXPLORING
ART PRODUCTION
AND CONSUMPTION
THROUGH SOCIAL MEDIA
with Ludovica Tomarchio
Yayoi Kusama's exhibition at the National Gallery PHOTO: NATIONAL GALLERY SINGAPORE
(FCL) FUTURE CITIES LABORATORY


HOW DO SOCIAL MEDIA
AFFECT ART?
Can we develop tools and methodologies
for responsive cultural city planning?
SOCIAL MEDIA DATA
• How can we describe Hybrid Art Venues?
• What kind of aesthetic results from the mix of art and social media?
• How effective are current cultural planning practices?
MAPPING ART LOCATIONS
• How can we define and map art venues through SM?
• Which types of analyses could be useful?
RESPONSIVE CULTURAL PLANNING
• What information from social media is useful?
• How can it be implemented in decision making?

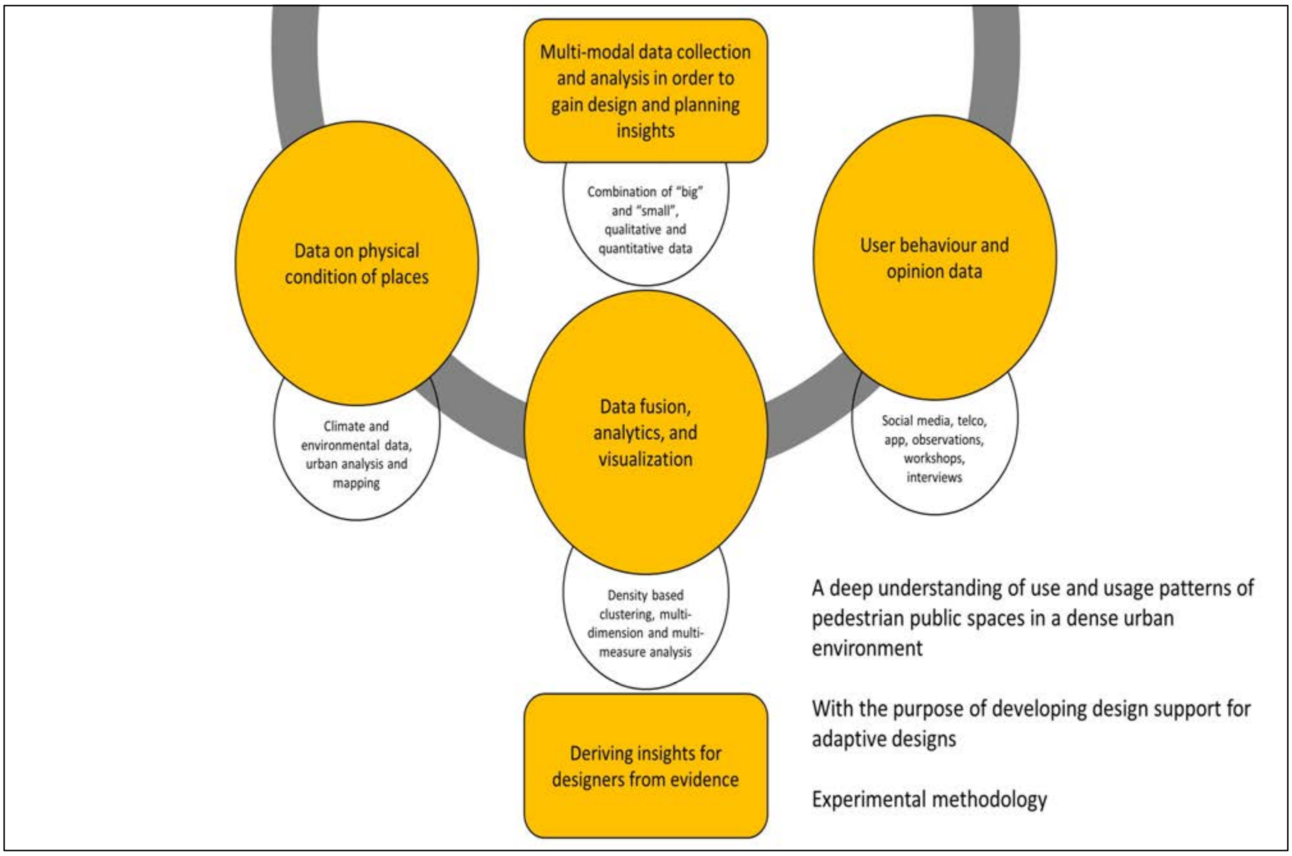

NATIONAL SCIENCE EXPERIMENT
with Nils Ole Trappenhauer, Francisco Benita, Francisco Scandola,
Garvit Bansal, Darshan Virupaksha, Sarah Nadiawanti
NATIONAL RESEARCH FOUNDATION
PRIME MINISTER'S OFFICE
SINGAPORE
SINGAPORE UNIVERSITY OF TECHNOLOGY AND DESIGN
Institute of High Performance Computing
A*STAR
FUTURE CITIES LABORATORY

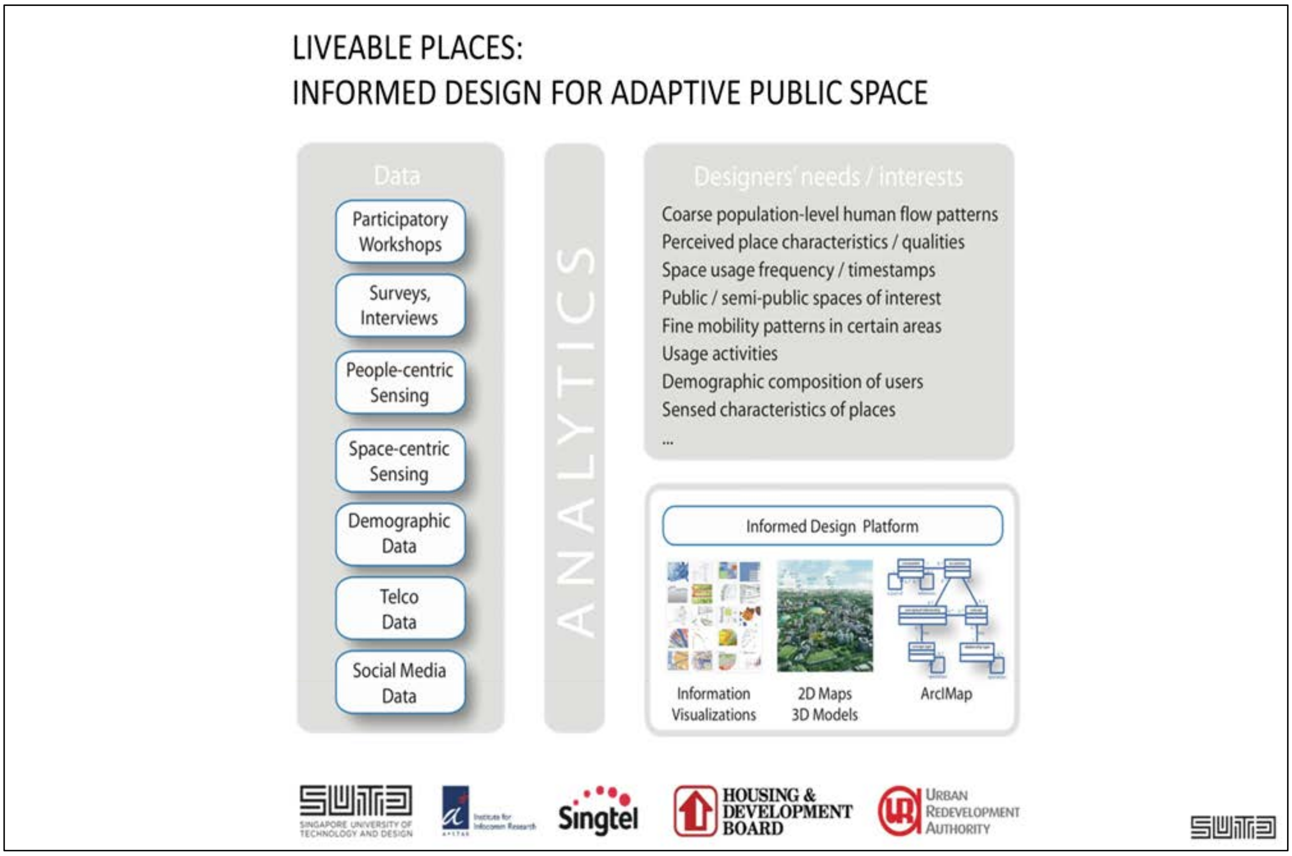

90,629 students | 265 schools
W
E
S
SINGAPORE'S
NATIONAL SCIENCE EXPERIMENT
2015-2017
NATIONAL RESEARCH FOUNDATION
PRIME MINISTER'S OFFICE
SINGAPORE
SINGAPORE UNIVERSITY OF TECHNOLOGY AND DESIGN
Institute of High Performance Computing
A*STAR


19.6%
30.5%
31.3%
18.6%
18.5%
30.5%
31.7%
19.3%
Secondary/JC
Primary
Heat map indicates density of homes, white points
Singapore
7 AM to noon
Noon to 8 PM
8 PM to 7 AM

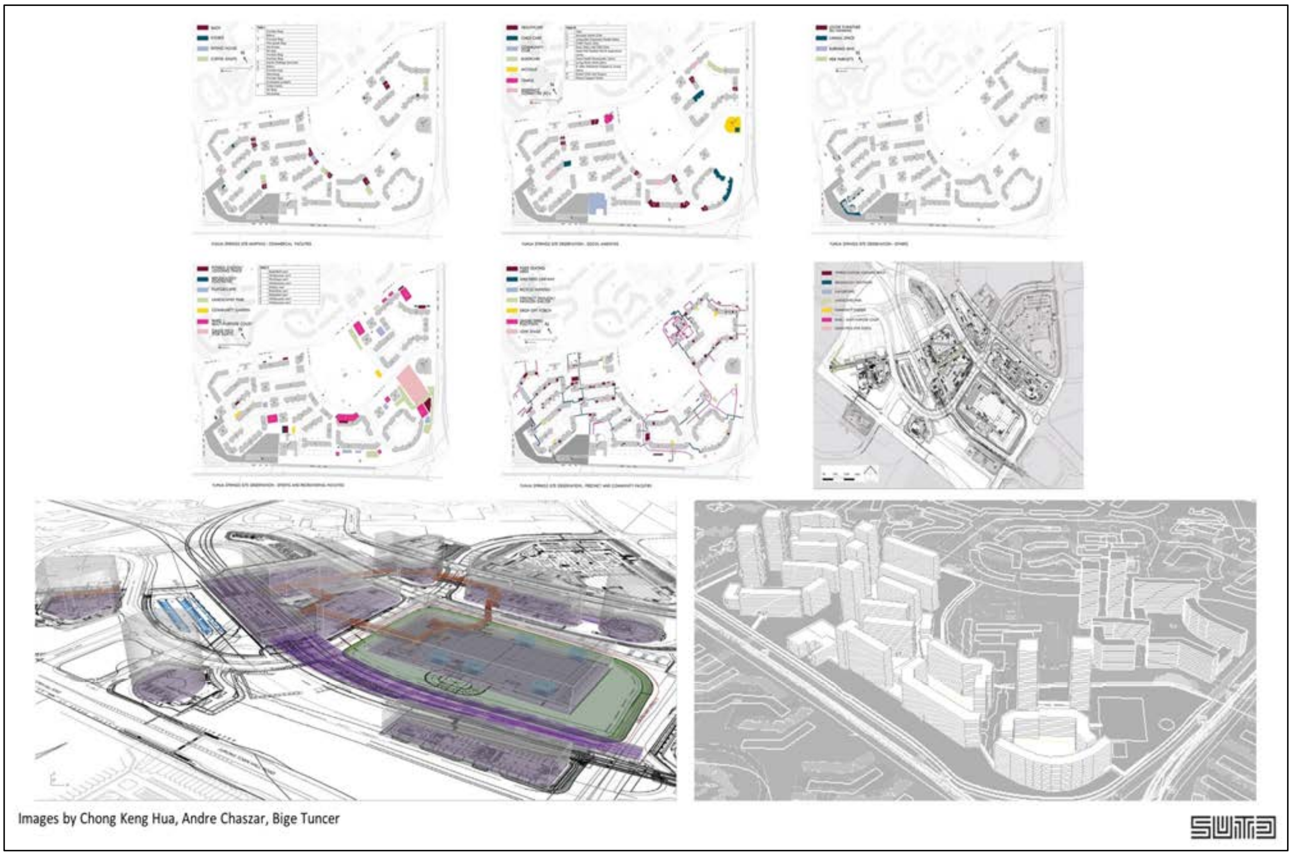

URBAN EMOTIONS
Selected environmental and climate variables
Temperature, humidity, wind speed, light intensity, noise, ...
Selected urban variables
Greenery, sky view exposure, urban density, ...
Physiological response
Heart rate, EDA, SCR, stress peaks, ...
THREE-WAY JUNCTION
UNSHELTERED STREET
WALKING UNDER BUILDING
ENTERING RESIDENTIAL AREA
SHELTERED WALKWAY
START/END

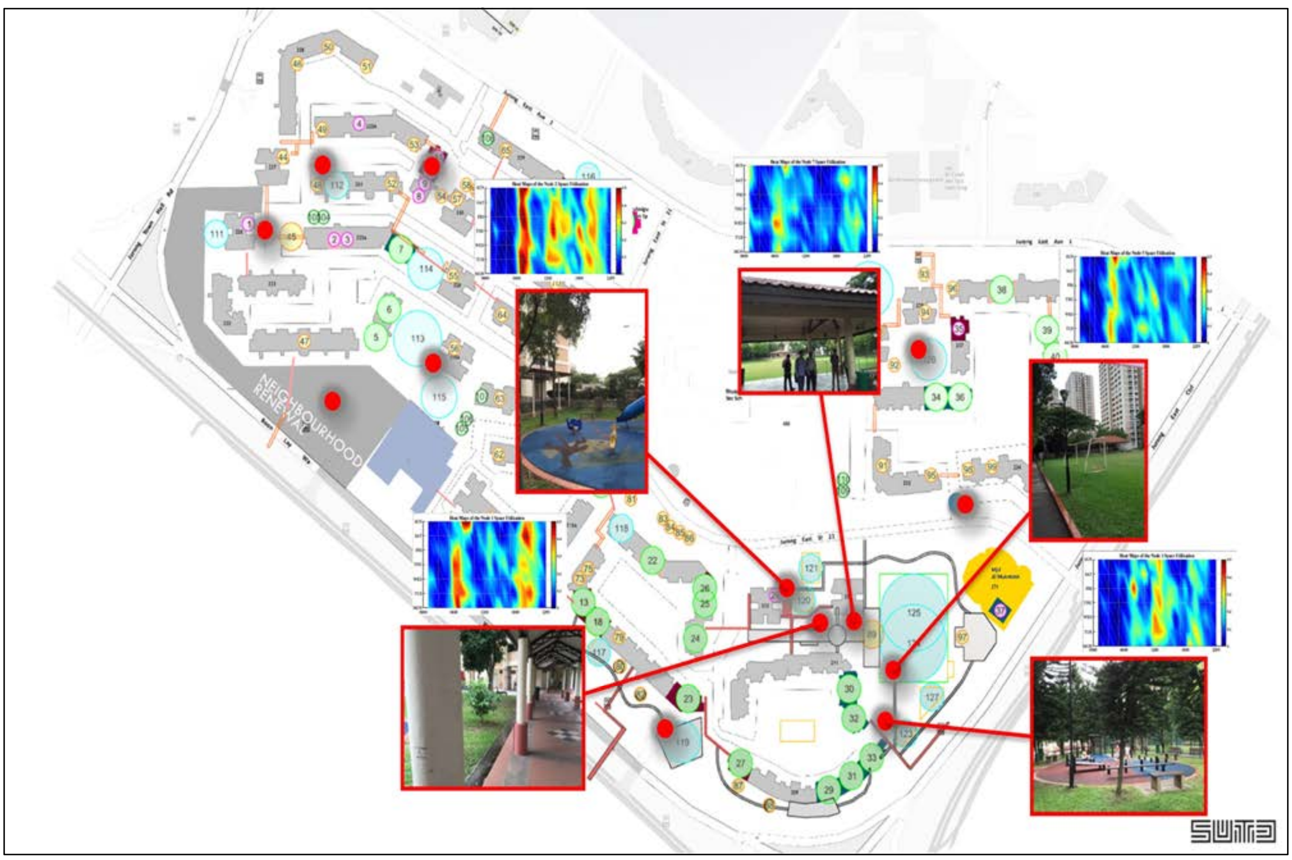

LIVEABLE PLACES:
INFORMED DESIGN FOR
ADAPTIVE PUBLIC SPACE
with Hexu Xin, Linlin You
Co-Is: Chong Heng Hua, Yuen Chau, Mihye Cho, Shili Xiang, Li Xiaoli
Photograph taken by Kien To
SINGAPORE UNIVERSITY OF TECHNOLOGY AND DESIGN
Singtel
HOUSING & DEVELOPMENT BOARD
URBAN REDEVELOPMENT AUTHORITY

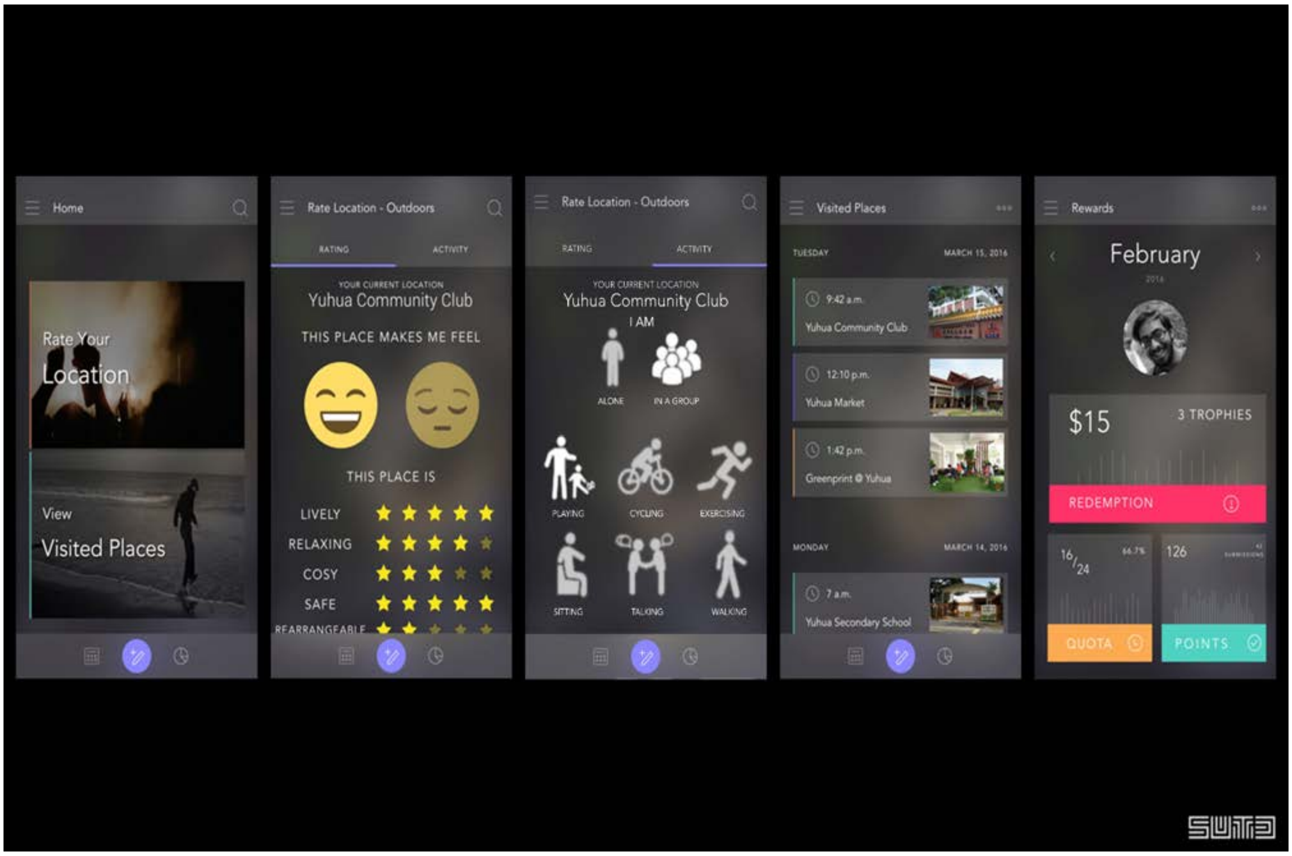

Multi-modal data collection and analysis in order to gain design and planning insights
Combination of "big" and "small", qualitative and quantitative data
Data on physical condition of places
Climate and environmental data, urban analysis and mapping
User behaviour and opinion data
Social media, telco, app, observations, workshops, interviews
Data fusion, analytics, and visualization
Density based clustering, multi-dimension and multi-measure analysis
Deriving insights for designers from evidence
A deep understanding of use and usage patterns of pedestrian public spaces in a dense urban environment
With the purpose of developing design support for adaptive designs
Experimental methodology

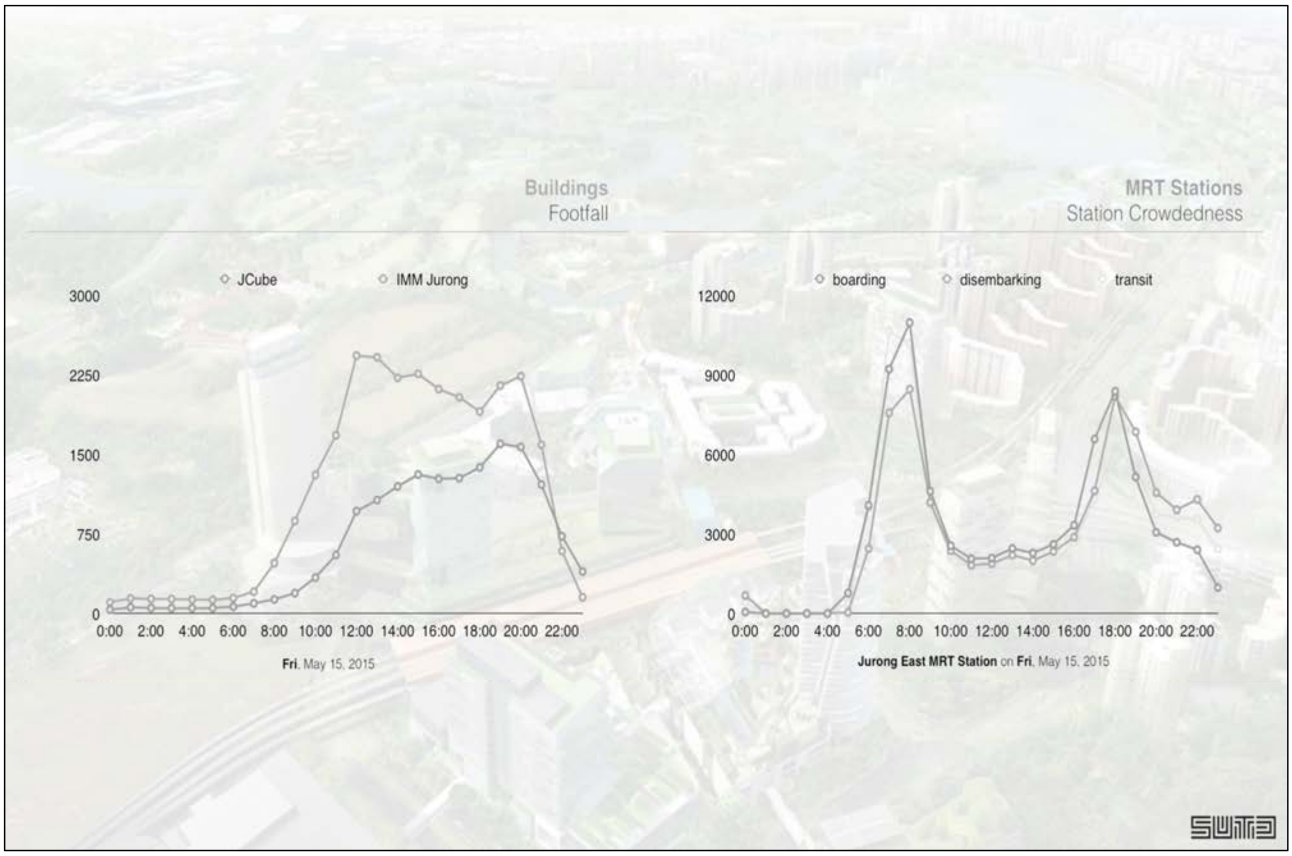

LIVEABLE PLACES:
INFORMED DESIGN FOR ADAPTIVE PUBLIC SPACE
Data
Participatory Workshops
Surveys, Interviews
People-centric Sensing
Space-centric Sensing
Demographic Data
Telco Data
Social Media Data
ANALYTICS
Designers' needs / interests
Coarse population-level human flow patterns
Perceived place characteristics / qualities
Space usage frequency / timestamps
Public / semi-public spaces of interest
Fine mobility patterns in certain areas
Usage activities
Demographic composition of users
Sensed characteristics of places
...
Informed Design Platform
Information Visualizations
2D Maps 3D Models
ArcMap
Singtel
HOUSING & DEVELOPMENT BOARD
URBAN REDEVELOPMENT AUTHORITY

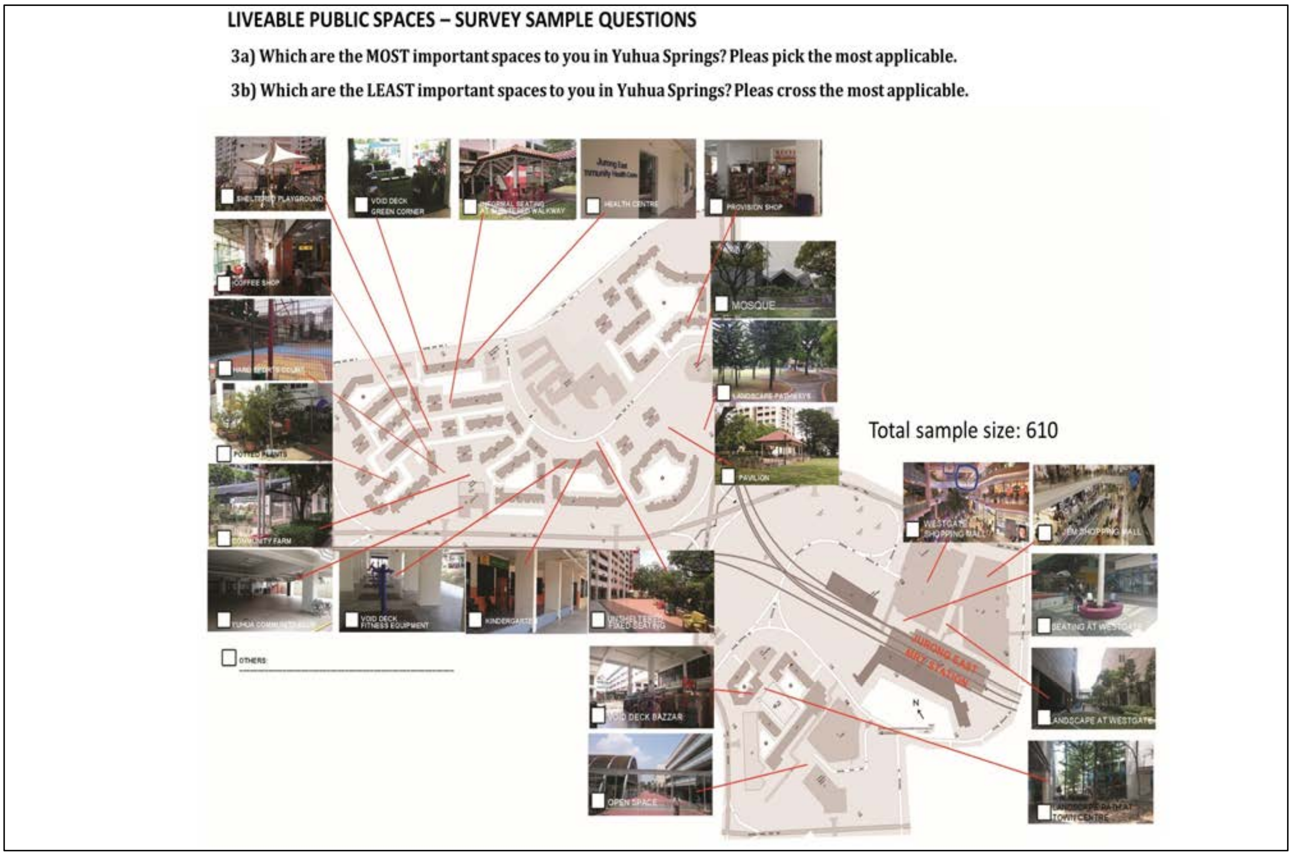

Photograph taken by Kien To
Singtel
HOUSING & DEVELOPMENT BOARD
URBAN REDEVELOPMENT AUTHORITY


Images by Chong Keng Hua, Andre Chaszar, Bige Tuncer

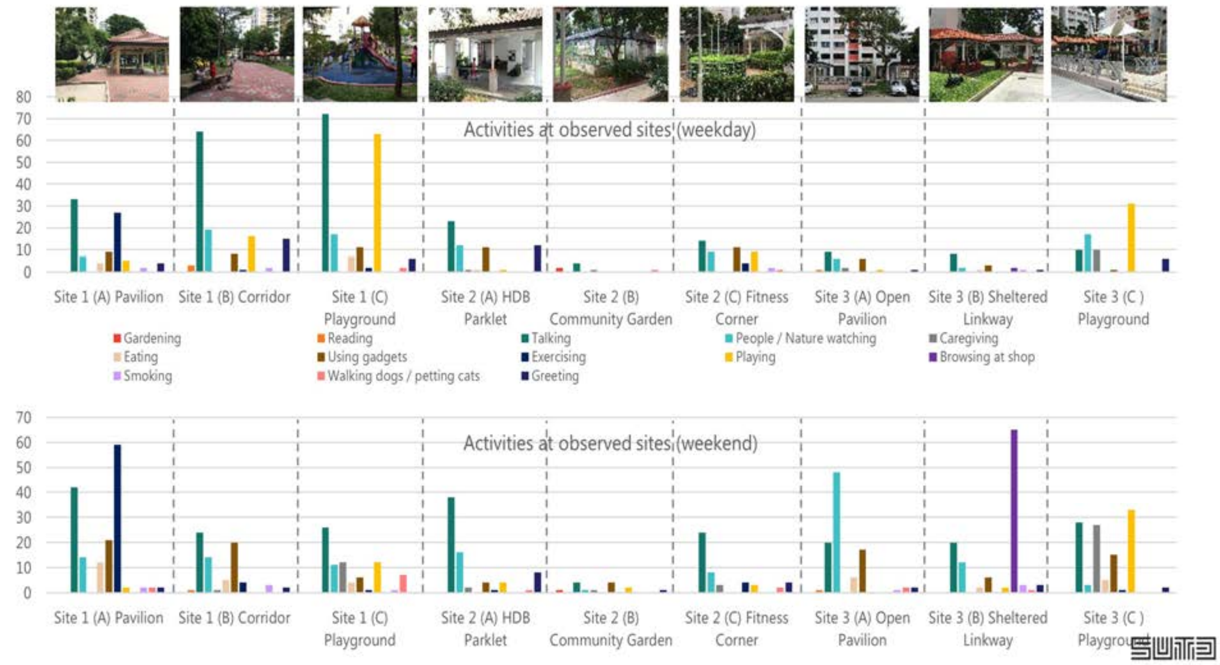

NEIGHBOURHOOD RENEWAL

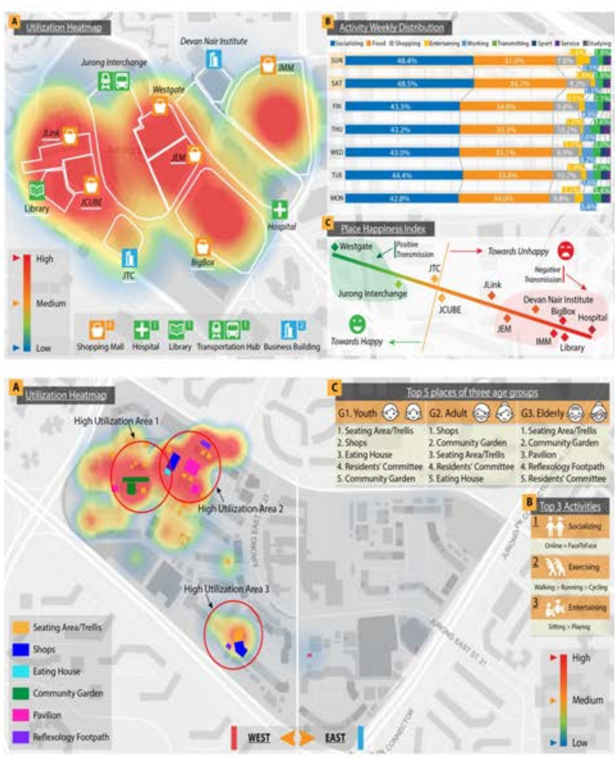

Home
Rate Your Location
View
Visited Places
Rate Location - Outdoors
RATING
ACTIVITY
YOUR CURRENT LOCATION
Yuhua Community Club
THIS PLACE MAKES ME FEEL
THIS PLACE IS
LIVELY
RELAXING
COSY
SAFE
I AM
ALONE
IN A GROUP
PLAYING
CYCLING
EXERCISING
SITTING
TALKING
WALKING
Visited Places
TUESDAY
MARCH 15, 2016
9:42 a.m.
Yuhua Community Club
12:10 p.m.
Yuhua Market
1:42 p.m.
Greenprint @ Yuhua
MONDAY
MARCH 14, 2016
7 a.m.
Yuhua Secondary School
Rewards
February
$15
3 TROPHIES
REDEMPTION
126
QUOTA
POINTS

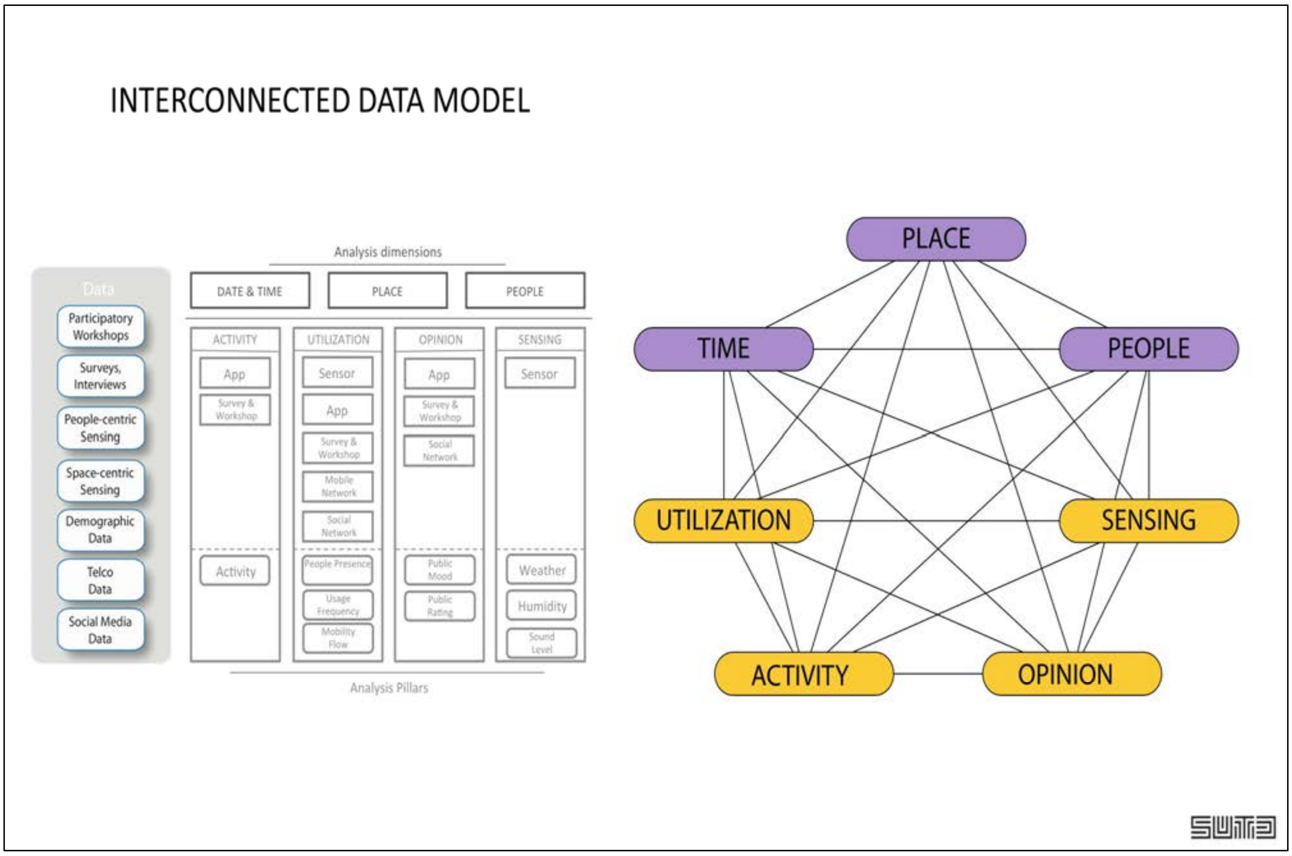

Buildings
Footfall
JCube
IMM Jurong
3000
2250
1500
750
0
0:00 2:00 4:00 6:00 8:00 10:00 12:00 14:00 16:00 18:00 20:00 22:00
Fri, May 15, 2015
MRT Stations
Station Crowdedness
boarding
disembarking
transit
12000
9000
6000
3000
0
0:00 2:00 4:00 6:00 8:00 10:00 12:00 14:00 16:00 18:00 20:00 22:00
Jurong East MRT Station on Fri, May 15, 2015

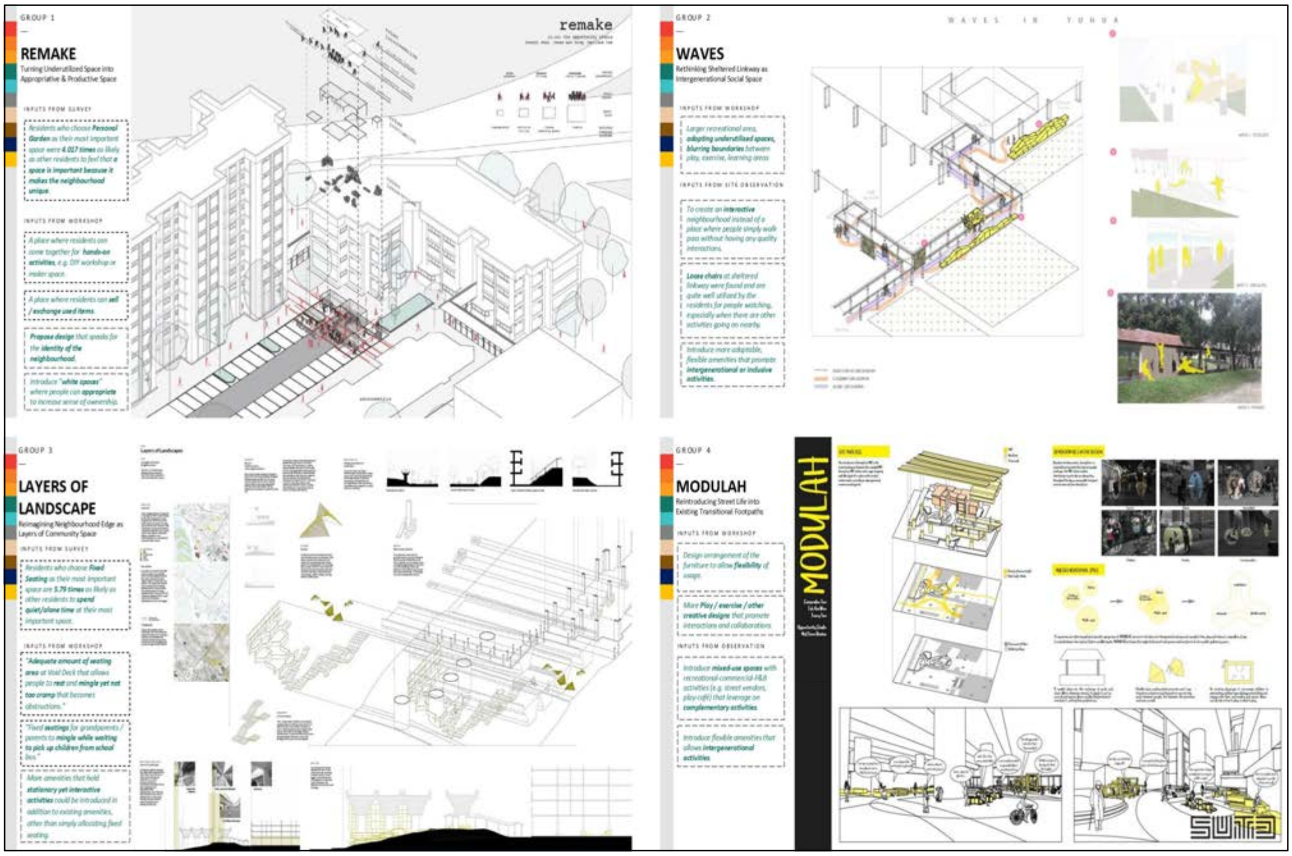

LIVEABLE PUBLIC SPACES – SURVEY SAMPLE QUESTIONS
3a) Which are the MOST important spaces to you in Yuhua Springs? Pleas pick the most applicable.
3b) Which are the LEAST important spaces to you in Yuhua Springs? Pleas cross the most applicable.
MOSQUE
Total sample size: 610
VOID DECK BAZZAR
OPEN SPACE

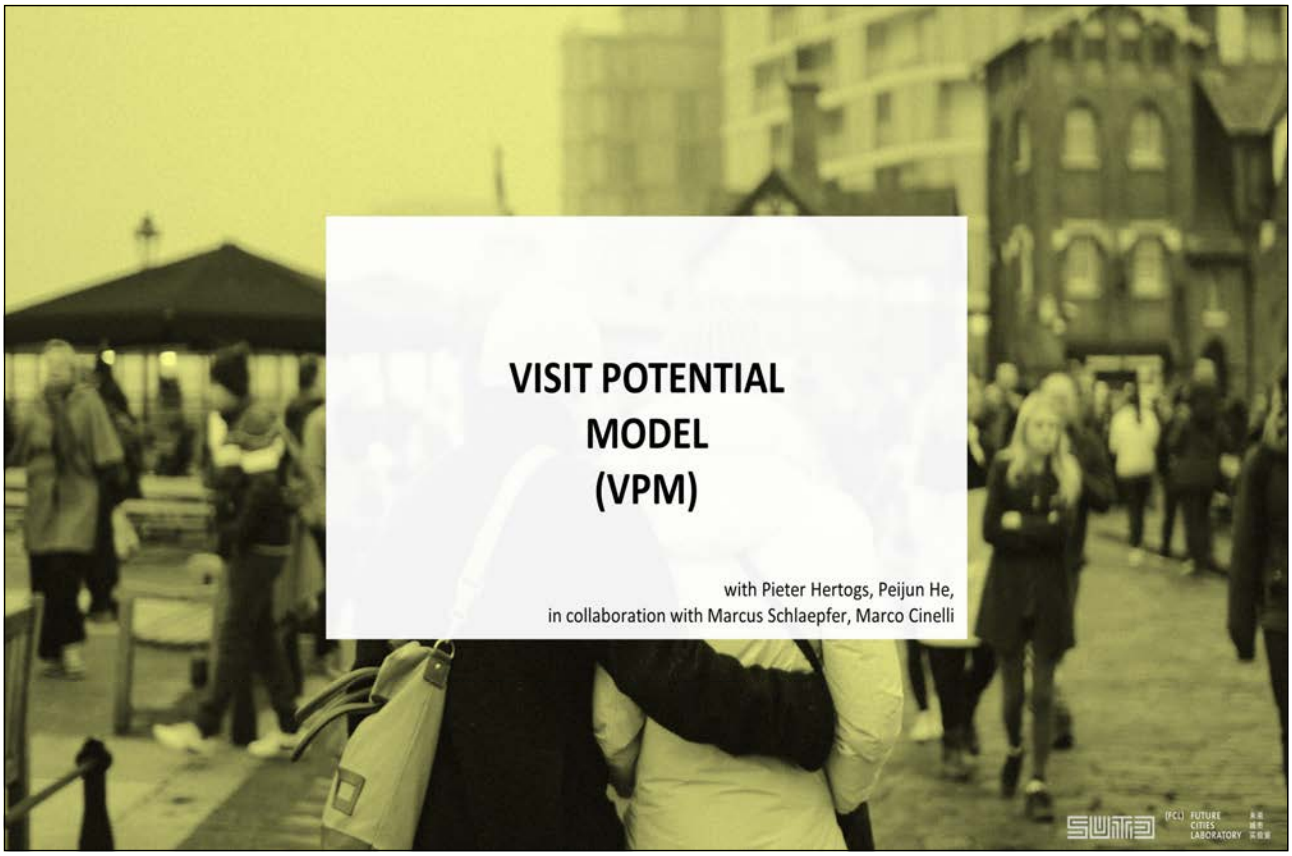

LOW STAGE


Activities at observed sites (weekday)
80
70
60
50
40
30
20
10
0
Site 1 (A) Pavilion
Site 1 (B) Corridor
Site 1 (C) Playground
Site 2 (A) HDB Parklet
Site 2 (B) Community Garden
Site 2 (C) Fitness Corner
Site 3 (A) Open Pavilion
Site 3 (B) Sheltered Linkway
Site 3 (C) Playground
Gardening
Eating
Smoking
Reading
Using gadgets
Walking dogs / petting cats
Talking
Exercising
Greeting
People / Nature watching
Playing
Caregiving
Browsing at shop
Activities at observed sites (weekend)
70
60
50
40
30
20
10
0
Site 1 (A) Pavilion
Site 1 (B) Corridor
Site 1 (C) Playground
Site 2 (A) HDB Parklet
Site 2 (B) Community Garden
Site 2 (C) Fitness Corner
Site 3 (A) Open Pavilion
Site 3 (B) Sheltered Linkway
Site 3 (C) Playground


Utilization Heatmap
Activity Weekly Distribution
Place Happiness Index
High
Medium
Low
Towards Unhappy
Towards Happy
Utilization Heatmap
Top 5 places of three age groups
G1. Youth
G2. Adult
G3. Elderly
Top 3 Activities
High Utilization Area 1
High Utilization Area 2
High Utilization Area 3
WEST
EAST

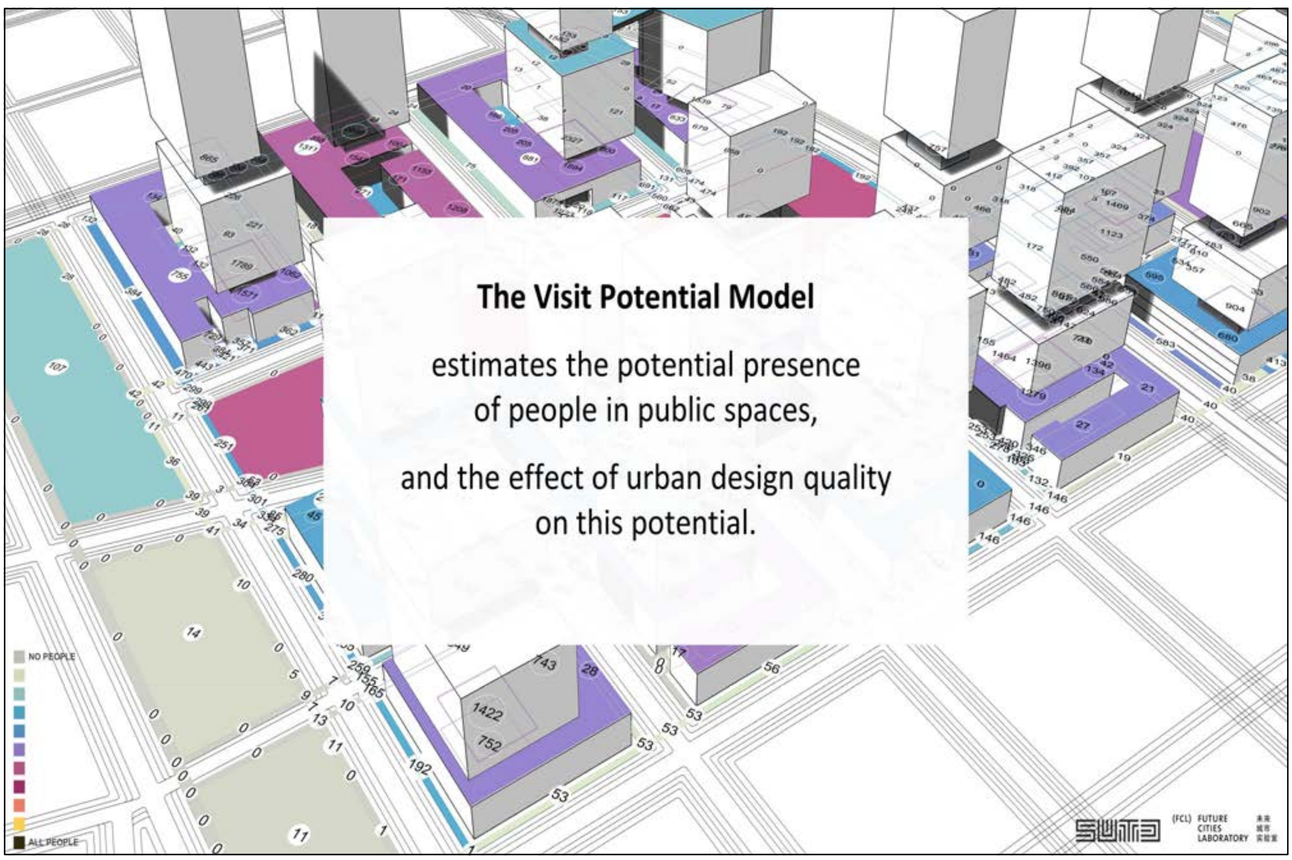

INTERCONNECTED DATA MODEL
Analysis dimensions
Data
Participatory Workshops
Surveys, Interviews
People-centric Sensing
Space-centric Sensing
Demographic Data
Telco Data
Social Media Data
DATE & TIME
PLACE
PEOPLE
ACTIVITY
UTILIZATION
OPINION
SENSING
App
Survey & Workshop
Sensor
App
Survey & Workshop
Mobile Network
Social Network
App
Survey & Workshop
Social Network
Sensor
Activity
People Presence
Usage Frequency
Mobility Flow
Public Mood
Public Rating
Weather
Humidity
Sound Level
Analysis Pillars
PLACE
TIME
PEOPLE
UTILIZATION
SENSING
ACTIVITY
OPINION

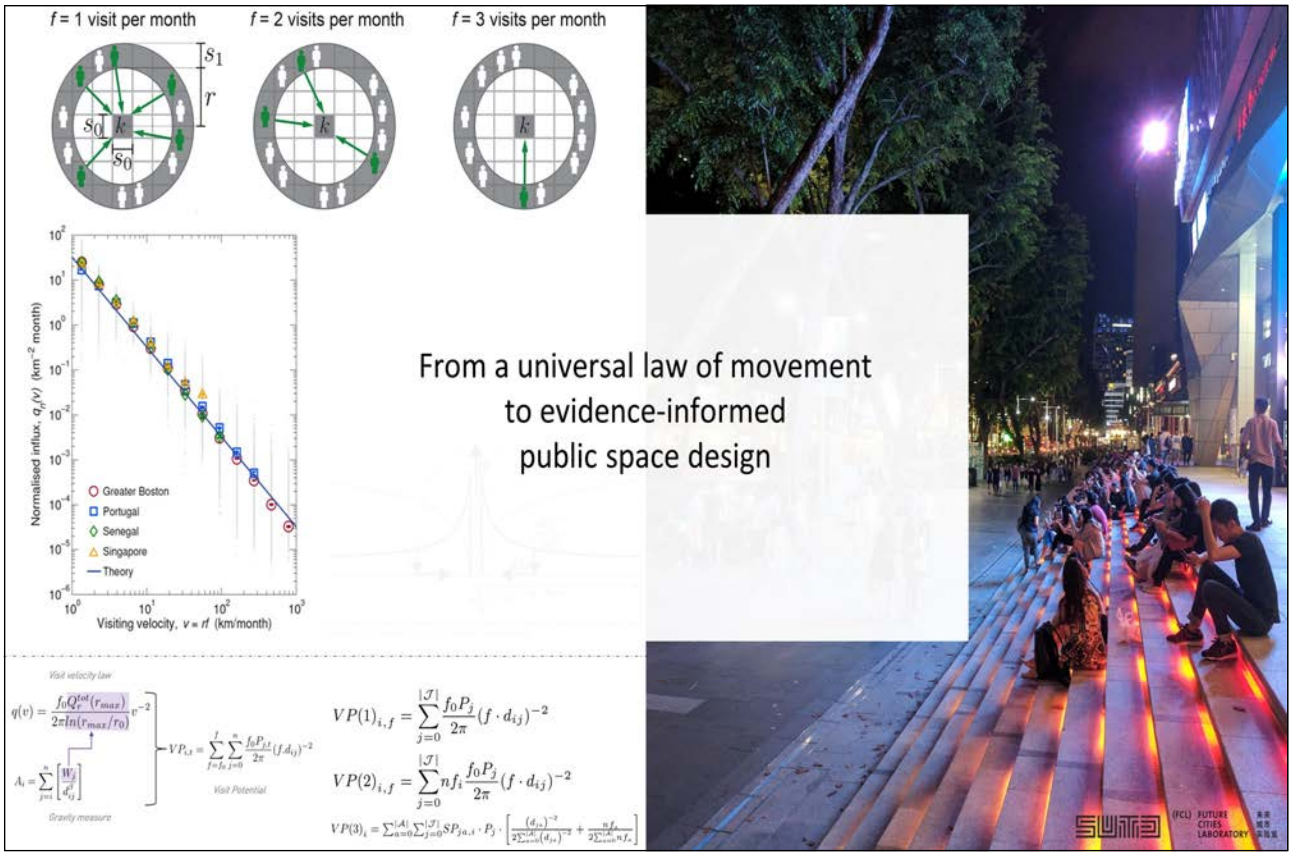

GROUP 1
REMAKE
Turning Underutilized Space into Appropriate & Productive Space
remake
GROUP 2
WAVES
Rethinking Sheltered Linkway as Intergenerational Social Space
GROUP 3
LAYERS OF LANDSCAPE
Reimagining Neighbourhood Edge as Layers of Community Space
GROUP 4
MODULAH
Reintroducing Street Life into Existing Transitional Footpaths
MODULAH

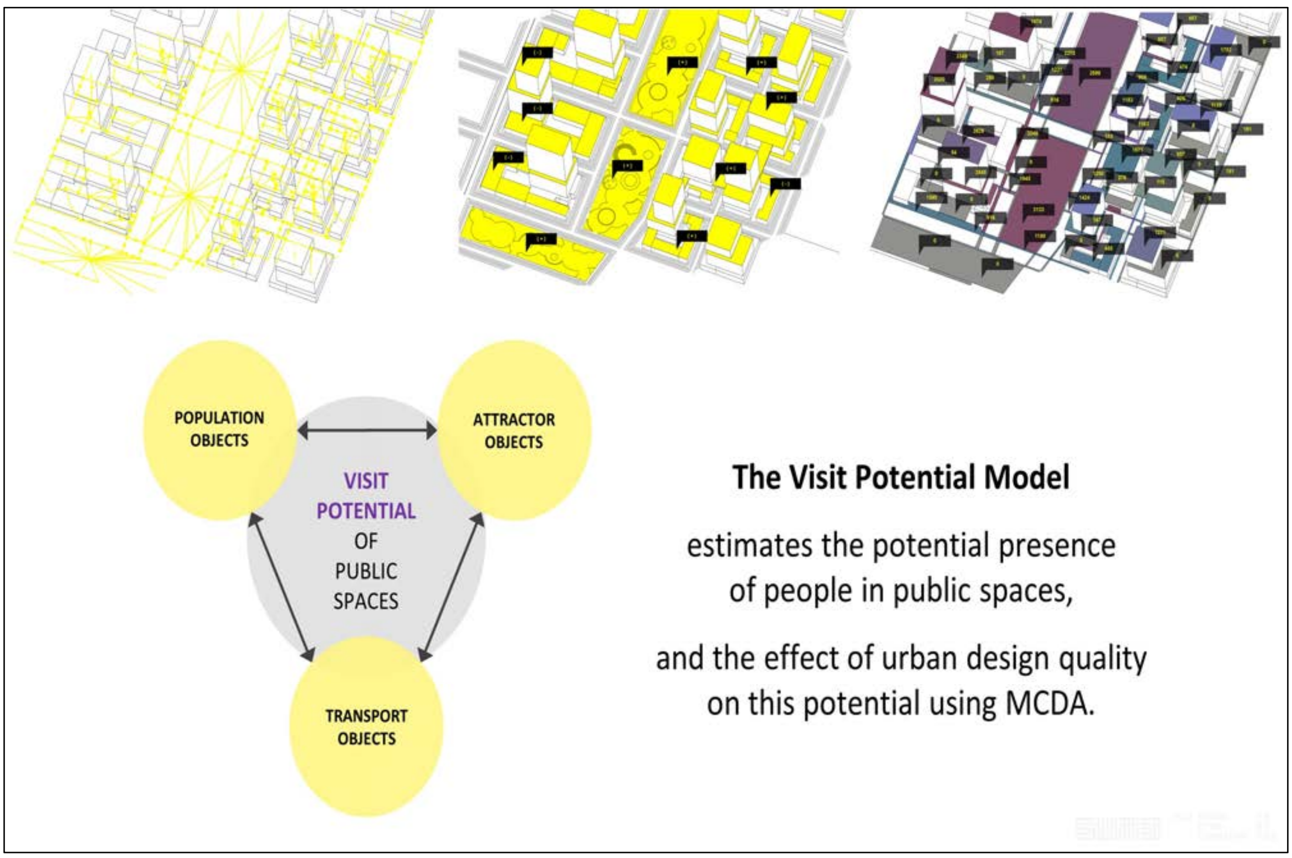

VISIT POTENTIAL
MODEL
(VPM)
with Pieter Hertogs, Peijun He,
in collaboration with Marcus Schlaepfer, Marco Cinelli
(FCL) FUTURE
CITIES
LABORATORY

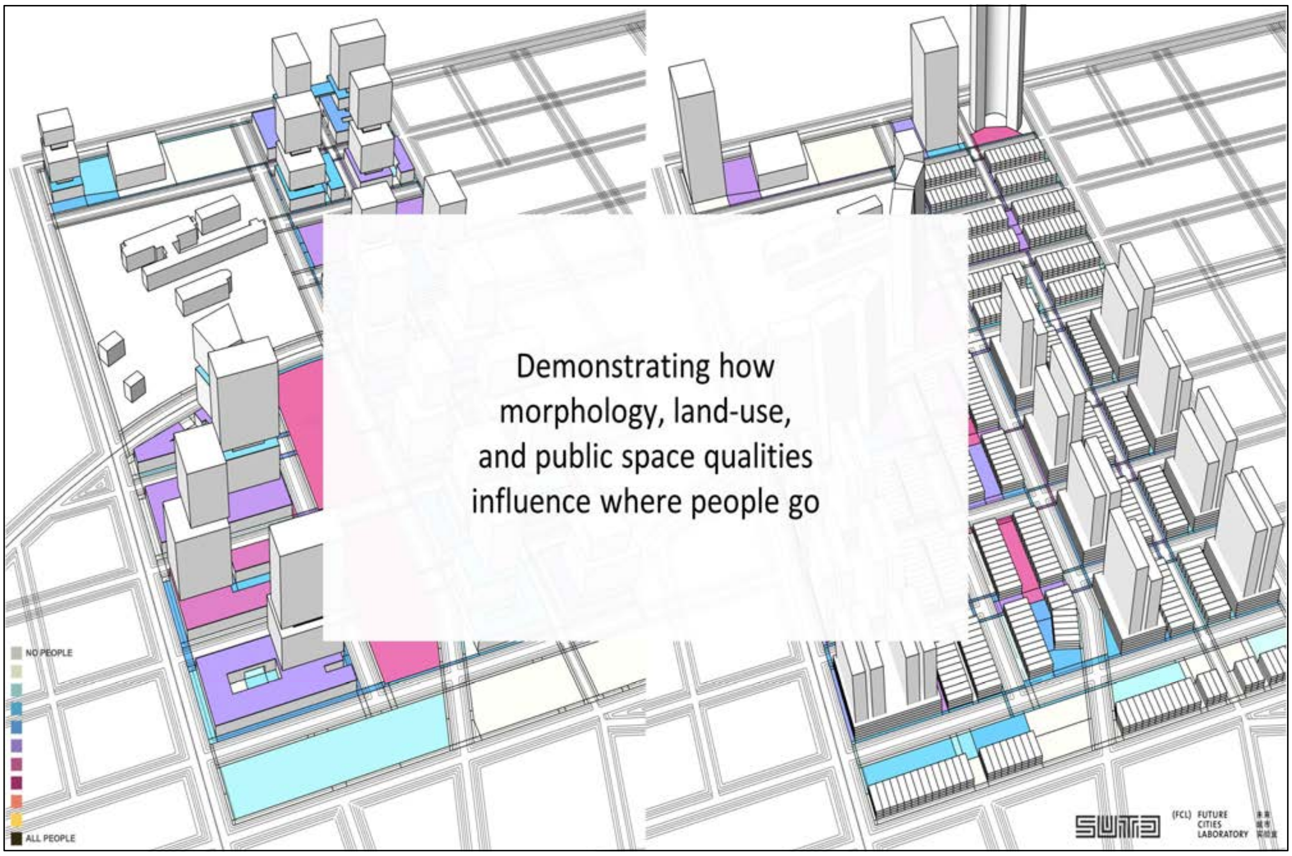
Can we predict
the liveliness of public spaces
in new designs?

(FCL) FUTURE CITIES LABORATORY




f = 1 visit per month
f = 2 visits per month
f = 3 visits per month
From a universal law of movement
to evidence-informed
public space design
Normalised influx, $q_r(v)$ (km^{-2} month)
Visiting velocity, $v = rf$ (km/month)
Greater Boston
Portugal
Senegal
Singapore
Theory
Visit velocity law
Gravity measure
Visit Potential
$VP(1)_{i,f} = \sum_{j=0}^{|\mathcal{J}|} \frac{f_0 P_j}{2\pi} (f \cdot d_{ij})^{-2}$
$VP(2)_{i,f} = \sum_{j=0}^{|\mathcal{J}|} n f_i \frac{f_0 P_j}{2\pi} (f \cdot d_{ij})^{-2}$


POPULATION OBJECTS
ATTRACTOR OBJECTS
TRANSPORT OBJECTS
VISIT POTENTIAL OF PUBLIC SPACES
The Visit Potential Model
estimates the potential presence of people in public spaces,
and the effect of urban design quality on this potential using MCDA.



SOME LIMITATIONS

Data collected may not represent all users of spaces

Evidence and insights derived shed light on only a subset of design parameters that are important for design

Data privacy concerns

SOME CONCLUSIONS

Deep understanding of both real and perceived utilization and appreciation of existing public spaces

Starting to relate these to physical attributes of places

Developing the methodology and technical infrastructure for this

Ongoing work

Memo

Memo

Invited Talk 3

Understanding Tourists' Image of Seoul with Geotagged Photos using Convolutional Neural Networks

[CNN딥러닝을 이용한 외국인 관광객의 서울 이미지 분석]

Prof. Youngok Kang
Ewha Womans University

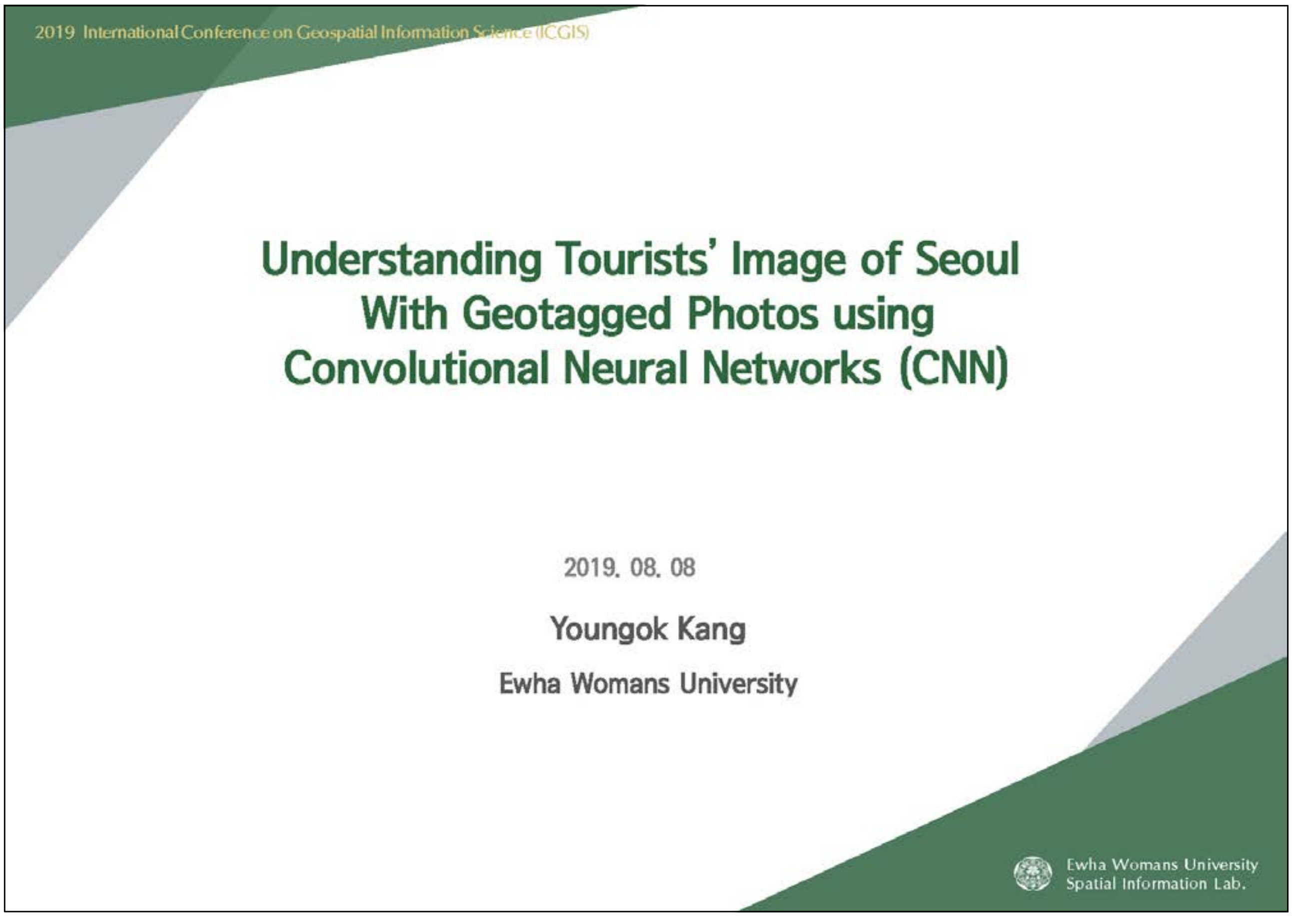
Understanding Tourists' Image of Seoul with Geotagged Photos using Convolutional Neural Networks (CNN)

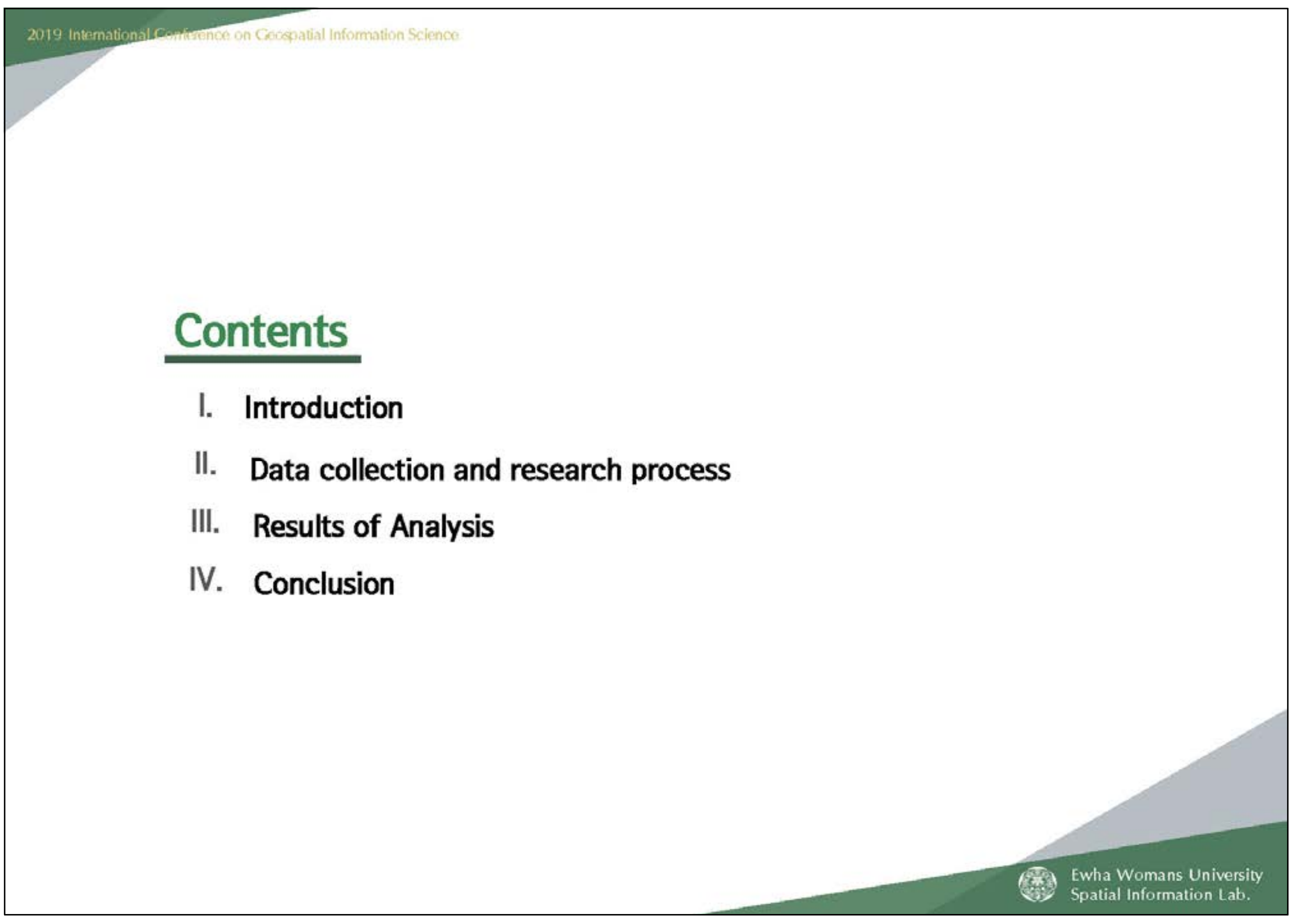
Youngok Kang
Professor, Ewha Womans University

Abstract

Today people prefer to share the posts such as texts, images, and videos via Social Network Services (SNS) with others without regard to time and location. Moreover, the geo-tagged photos uploaded on the site by tourists display the perception and the action of tourists as well as the images that tourists feel about the sightseeing attractions. As the images of touristic sites are closely associated with the tourists' attraction and intention, they serve as a reference for other tourists who seek to travel to those sites. In addition, as the touristic images on SNS can be continually produced and reproduced, we are able to ascertain the perceptions and the trends of representative sightseeing elements and locations by analyzing the images uploaded on SNS.

This study aims to track down representative images and elements of sightseeing attractions by analyzing the photos uploaded on Flickr by Seoul tourists with the image mining technique. For this purpose, we crawled the photos uploaded on Flickr and classified users into residents and tourists; drew 11 RoA (Region of Attractions) in Seoul by analyzing the spatial density of the photos; classified the photos into 1000 categories and then 14 categories by grouping 1,000 categories by utilizing Inception V3 model; analyzed the characteristics of the photo image by RoA. Key findings of this study are that tourists are interested in old palaces, historical monuments, stores, food, etc. and those key elements are distinguished from the major sightseeing attractions in Seoul. This study is meaningful in three folds: First, it tries to analyze urban image through the photos posted on SNS by tourists. Second, it uses deep learning technique to analyze the photos. Third, it classifies and analyzes the whole photos posted by Seoul tourists while most of other researches focus on only specific objects. However, this study has a limitation because the Inception v3 model which has been used in this research is a pre-trained model created by training the ImageNet data. In future research, it is necessary to classify photo categories according to the purpose of tourism and retrain the model by creating new training data set focusing on elements of Korea.


2019 International Conference on Geospatial Information Science (ICGIS)
Understanding Tourists' Image of Seoul With Geotagged Photos using Convolutional Neural Networks (CNN)
2019. 08. 08
Youngok Kang
Ewha Womans University
Ewha Womans University
Spatial Information Lab.


2019 International Conference on Geospatial Information Science
Contents
I. Introduction
II. Data collection and research process
III. Results of Analysis
IV. Conclusion
Ewha Womans University
Spatial Information Lab.

I. Introduction

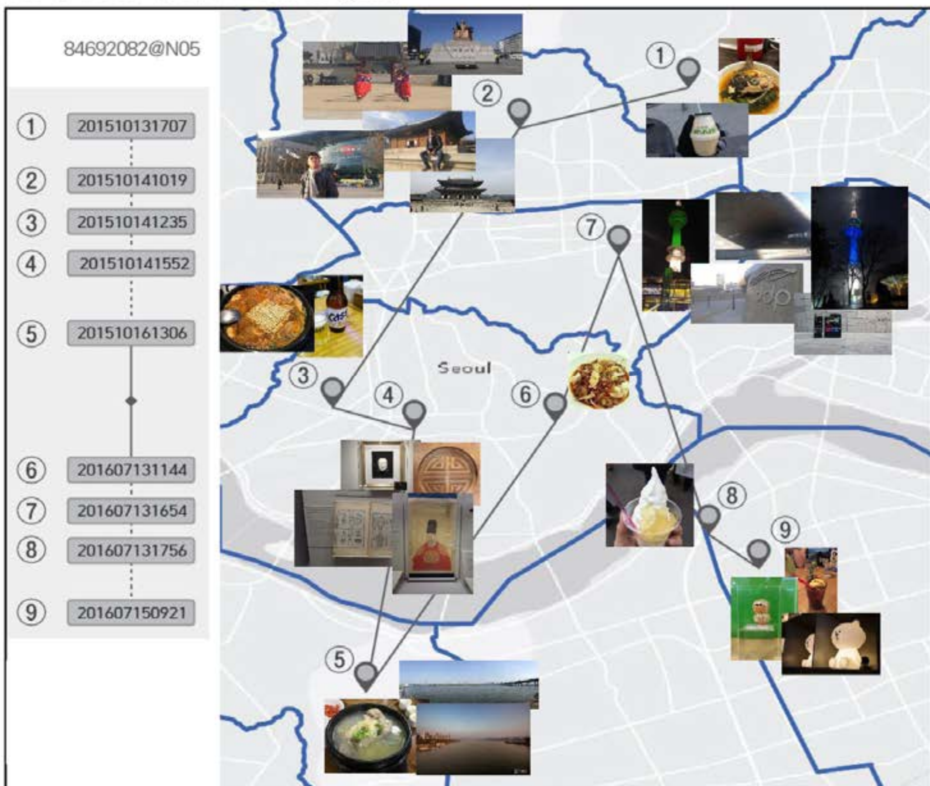
SNS (Social Network Service)

- People prefer to share the posts via SNS
- enables people communicate, share information, network among users
- Flickr : share geotagged photos

Example of crawled Flickr data

Owner ID	Latitude	Longitude	Taken Time	Owner Location	Picture URL	Tags	Titles
84692082 @N05	37.58417	126.9986	2016-11-17 7:18	Taipei, Taiwan	https://farm.staticflickr.com/585.jpg	['sony','ultra']	Please be seated.

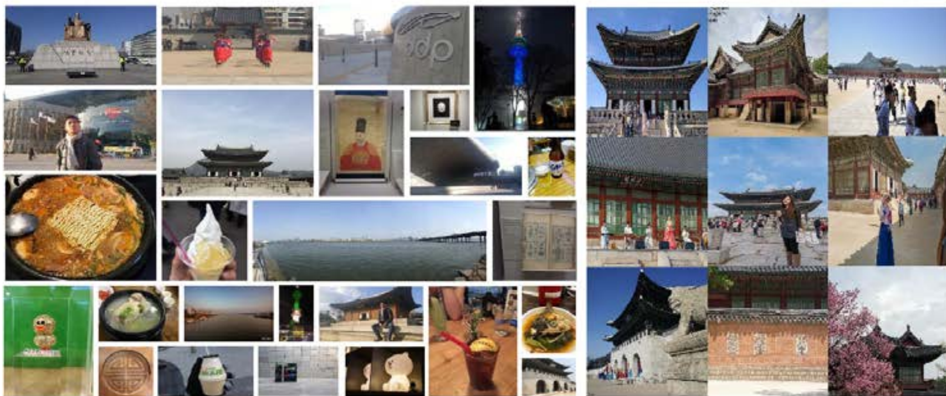
Example of Flickr (user ID : 84692082@N05)



I. Introduction

Photos uploaded on SNS by tourists

- display the perception and the action of tourists
- display the image of sightseeing attractions by tourists
- serve as a reference for other tourists who seek to travel to those sites
- continually produce and reproduce touristic images.



I. Introduction

Analysis of geotagged photos

- Previous studies which have utilized geotagged data on SNS have mostly analyzed
  - RoA (Region of Attraction)
  - patterns of user movement
  - texts included in the photos
- Recently, analyzing the photos on SNS have been increasing due to development of image data mining technique.

Image data mining

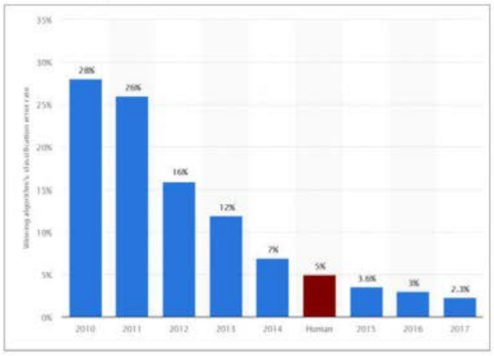
- the process of extracting information or knowledge from image data
- with the increase in the volume of image data as well as the improvement of training algorithm, image data mining using artificial neural networks have been applied to various fields such as medicine, environmental studies, information science, and computer graphics

I. Introduction

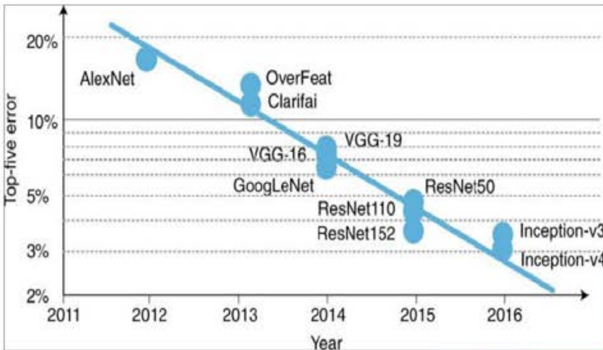
Convolutional Neural Network(CNN)

- one of artificial neural networks has been developed base on neurological knowledge surrounding the visual cortex of humans and animals.
- in image data mining research, it has become a trend to make use of it
- effective in distinguishing and categorizing the photo images

Winning algorithm's classification error rate



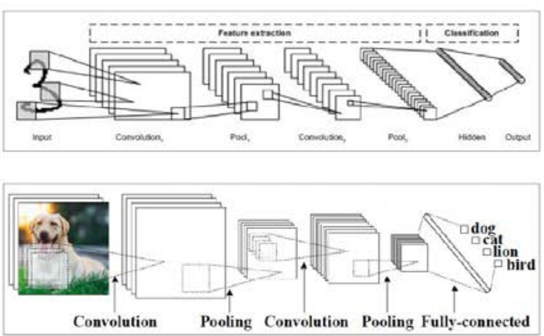
Top 5 error



I. Introduction

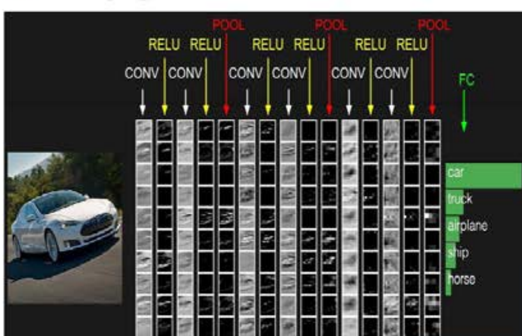
Convolutional Neural Network(CNN)

- basically composed of three layers such as a convolutional layer, a pooling layer, and a fully connected layer.
- users can produce a variety of models by changing the CNN structures & retrain the CNN model



▲ Examples of a CNN structure (https://www.ibm.com, http://www.ayasdi.com)

Winning algorithm's classification error rate



2019 International Conference on Geospatial Information Science

I. Introduction

Goal of this research :

Understand tourists' urban images with geotagged photos using CNN

Contents of research

- crawled the photos uploaded on Flickr
- classified users into residents and tourists
- drew 11 RoA in Seoul by analyzing the spatial density of the photos
- classified the photos into 1000 categories and 14 categories using Inception v3 Model
- analyzed the characteristics of the image by RoA
- performed accuracy test by comparing results of Inception v3 model & manual labelling

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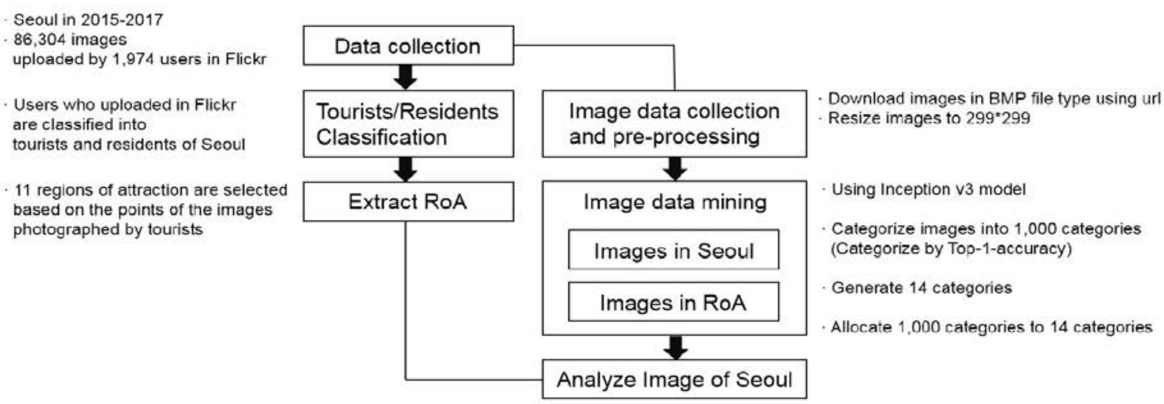
Spatial Information Lab.

2019 International Conference on Geospatial Information Science

II. Data Collection and research method

Research Flow



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II. Data Collection and research method

1. Data collection

- used open API provided by Flickr
- method : flickr.photos.search / flickr.photo.getInfo
- temporal range : January 1, 2015 ~ December 31, 2017
- spatial range : latitude of 37.4°~37.8°, longitude of 126.8° ~ 127.2

No.	Owner ID	Latitude	Longitude	Taken Time	Owner Location	Picture URL	Picture
1	15419854@N06	36.643333	127.431666	2018-01-10 AM 7:32:06	Seoul, Korea, Republic of	https://farm1.staticflickr.com/936/30067473458_d5a37fd967.jpg	
2	41053536@N08	37.567524	127.008776	2018-01-07 PM 6:12:01	Cambridg, Cambridgeshire	https://farm5.staticflickr.com/4751/39686286244_298c113767.jpg	
3	95331993@N06	37.295922	127.001802	2018-01-09 PM 1:56:07		https://farm5.staticflickr.com/4606/28184426809_fbef170556.jpg	
4	148448016@N05	37.57147	126.994614	2018-01-08 PM 9:15:14	Bangkok, Thailand	https://farm5.staticflickr.com/4718/39673594872_b98f62aa18.jpg	

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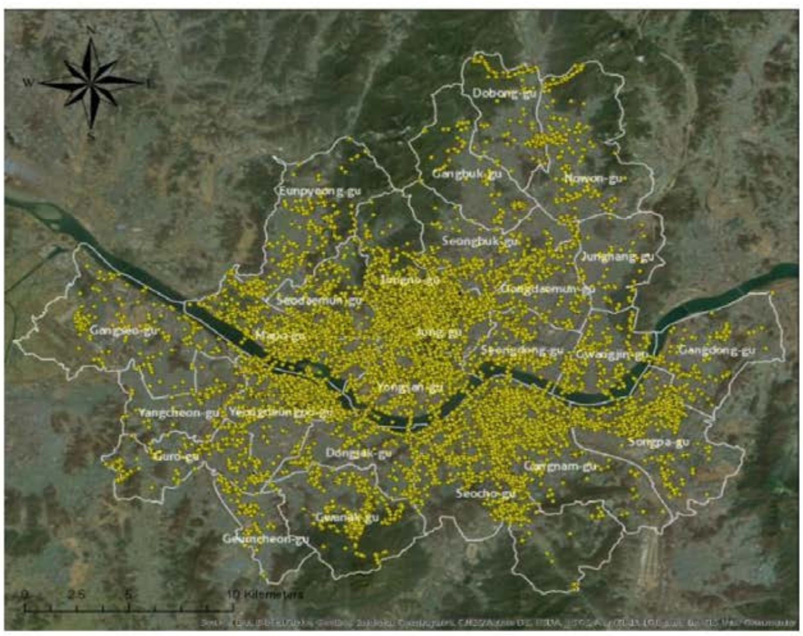
II. Data Collection and research method

1. Data collection



- Distribution of collected data
  : 86,291 photos
  : 1,974 users

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II. Data Collection and research method

2. Tourists / residents classification

- If the time difference between the first photo and the last photo posted by a user in Seoul is more than a certain threshold, it is classified as a resident, otherwise it is classified as a tourist
- In order to derive the optimal threshold, the model is evaluated through the data containing owner location information
  - among 1,974 users, 868 were valid
  - develop confusion matrix and evaluate accuracy ratio
  - Accuracy ratio = $\frac{Vv+Rr}{Vv+Vr+Rr+Rv} \times 100$

Vv: Number of actual tourists classified as tourists, Vr: Number of actual tourists classified as residents
Rv: Number of actual residents classified as tourists, Rr: Number of actual residents classified as residents

- 30day threshold was the highest with the accuracy of 88.979%

7day: 85.452%, 10day : 85.693%, 15day: 85.795%, 30day : 88.979%, 40day : 88.748%, 60day : 88.665%

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II. Data Collection and research method

2. Tourists / residents classification

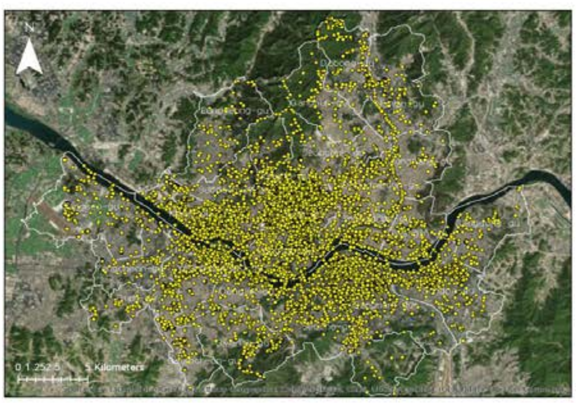
Tourists / residents classification based on 30 day threshold

Confusion matrix based on valid data (person)

		Results of classification		
		tourists	residents	total
Valid data	tourists	549	140	689
	residents	68	111	179
	total	617	251	868

Classification results of whole collected data

	# of photo		# of users	
	tourists	residents	tourists	residents
Results of classification	39,157 photos	47,147 photos	1,476 people	498 people
계	86,304 photos		1,974 people	

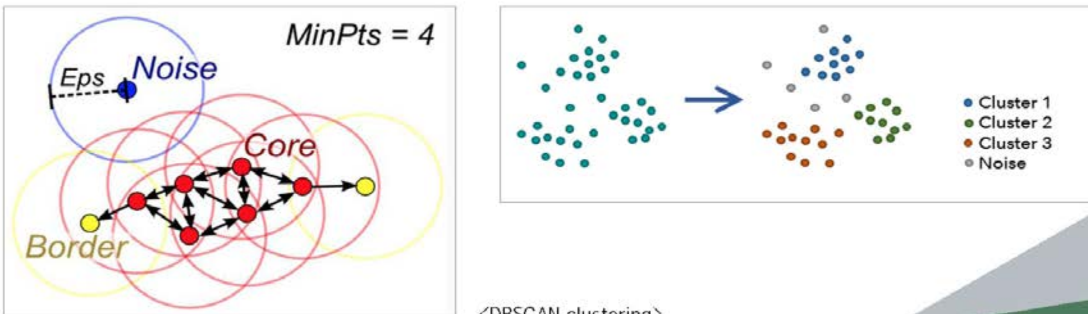


<distribution of tourist data>

II. Data Collection and research method

3. Extraction of RoA (Region of Attraction)

- DBSCAN (Density Based Spatial Clustering of Application with Noise) algorithm has been used to extract RoA
  - Density based clustering algorithm to identify clusters in a dataset containing noise and outliers
  - requires two parameters to form a dense region: ε (eps) and the minimum number of points
  - minimum # of points of 350 & minimum search radius of 250m were set after experimenting various combination



<DBSCAN clustering>

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II. Data Collection and research method

3. Extraction of RoA (Region of Attraction)

- 11 RoA from the 39,157 Flickr data

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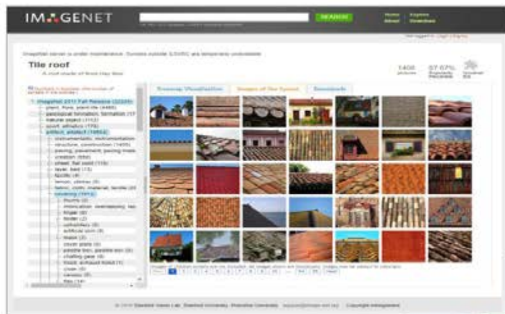
II. Data Collection and research method

4. Image data mining technique : Inception v3 Model

- one of various CNN models, for the photo data mining
- pre-trained model with ImageNet's data set, which comprises of 14,197,122 images divided into 1,000 categories.
- In case of categorizing images with the Inception v3 model, the model generates the category name that most resembles with the input image among 1000 categories and its accuracy value.



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II. Data Collection and research method

4. Image data mining technique : Inception v3 Model

Examples of data categories of ImageNet

Primary categories	Examples of secondary categories
amphibian	tench, Tinca tinca/ goldfish, Carassius auratus/ great white shark, white shark, great white shark, white shark, man-eater, man-eating shark, Carcharodon carcharias/ etc
animal	tiger cat/ Persian cat/ leopard, Panthera pardus/ etc
appliance	espresso maker/ desktop computer/ home theater, home theatre/ etc
bird	cock/ hen/ ostrich, Struthio camelus/ etc
covering	manhole cover/ book jacket, dust cover, dust jacket, dust wrapper/ lens cap, lens cover/etc
device	cash machine, cash dispenser, automated teller machine, automatic teller machine, automated teller, automatic teller, ATM/ cassette player/ CD player/ etc
fabric	academic gown, academic robe, judge's robe/ kimono/ apron/ etc
fish	eft/ conch/ jellyfish/ etc
flower	cauliflower/ daisy/ hip, rose hip, rosehip/ etc
food	guacamole/hot pot, hotpot/ pretzel/ etc
fruit	strawberry/ lemon/ banana/ etc
furniture	barber chair/ folding chair/ studio couch, day bed/ etc
geological formation	geyser/ lakeside, lakeshore/ seashore, coast, seacoast, sea-coast/ etc

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II. Data Collection and research method

4. Image data mining technique : Inception v3 Model

Example of photo classification using inception v3 model

```
In [109]: class_names[most_likely_class_index]
Out[109]: 'hoopskirt, crinoline#r'

In [110]: top_5 = np.argpartition(predictions_val[0], -5)[-5:]
          top_5 = reversed(top_5[np.argsort(predictions_val[0][top_5])])
          for i in top_5:
              print("{0}: {1:.2f}%".format(class_names[i], 100 * predictions_val[0][i]))

: 68.29%t, crinoline
: 6.44%bridegroom
: 5.61%
: 3.94% poke bonnet
: 3.56%o
```

```
In [34]: class_names[most_likely_class_index]
Out[34]: 'grocery store, grocery, food market, market#r'

In [35]: top_5 = np.argpartition(predictions_val[0], -5)[-5:]
         top_5 = reversed(top_5[np.argsort(predictions_val[0][top_5])])
         for i in top_5:
             print("{0}: {1:.2f}%".format(class_names[i], 100 * predictions_val[0][i]))

: 55.96%store, grocery, food market, market
: 16.66%nt, eating house, eating place, eatery
: 14.48%shop, meat market
: 2.60% bakeshop, bakehouse
: 1.72%
```


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II. Data Collection and research method

5. Generating 14 new categories

- Generate 14 new categories for tourism purpose
  - refered the categories of major activities on the "survey of the current state of foreign tourists" conducted by the Korea Tourism Organization in 2017

Primary Categories	Examples of Secondary Categories
food	bakery, bakeshop, bakehouse/ coffee mug/ restaurant, eating house, eating place, eatery, etc.
entertainment	beer bottle/ horizontal bar/ wine bottle, etc.
shopping	barbershop/ cinema, movie theatre, movie house, picture palace/ confectionery, confectionery, candy store, etc.
transportation	ambulance/ bicycle-built-for-two, tandem bicycle, tandem/ canoe, etc.
cityscape	cab, hack, taxi, taxicab/ spotlight, spot/ volcano
facilities	beacon, lighthouse, beacon light, Pharos/greenhouse, nursery, glasshouse/ fountain, etc.
residence	mobile home, manufactured home/ prison, prison house
natural views/ flora and fauna	trench, Tinca tinca/ goldfish, Carassius auratus/ lakeside, lakeshore, etc.
people	ballplayer, baseball player/ groom, bridegroom/ scuba diver
religion	altar/ church, church building/ stupa, tope
clothing	gown/ kimono/ neck brace, etc.
palace/ historical monuments/ cultural properties	abacus/ bell cote, bell cot/ palace, etc.
objects/miscellaneous	accordion, piano accordion, squeeze box/ ashcan, trash can, garbage can, wastebin, ash bin, ash bin, ashbin/ candle, taper, wax light, etc.
exhibits/sculptures	balloon/ pedestal, plinth, footstall/ totem pole, etc.

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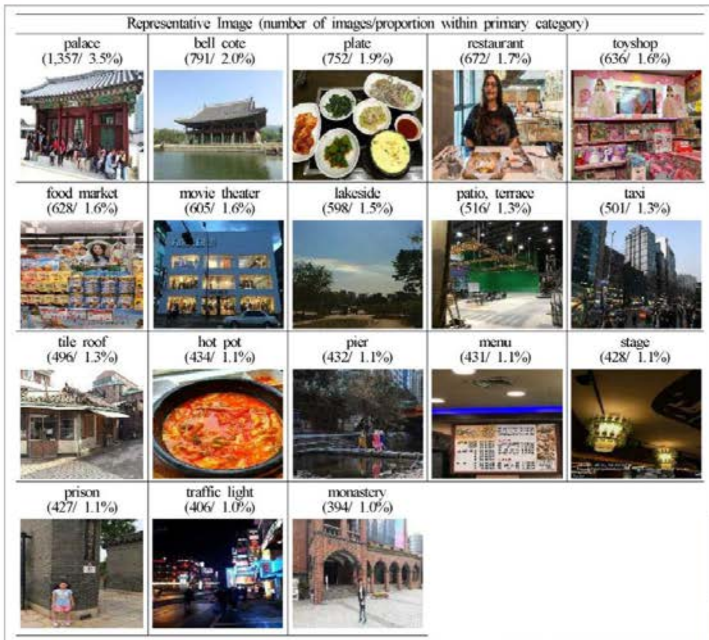
III. Results of Analysis

1. Image of Seoul

- As a result of classification of the 38,691 photos, we were able to produce 858 of 1,000 categories.
- the tourists' perception of Seoul in which owns palaces, food, buildings, and facilities

categories with a proportion of 1% or above



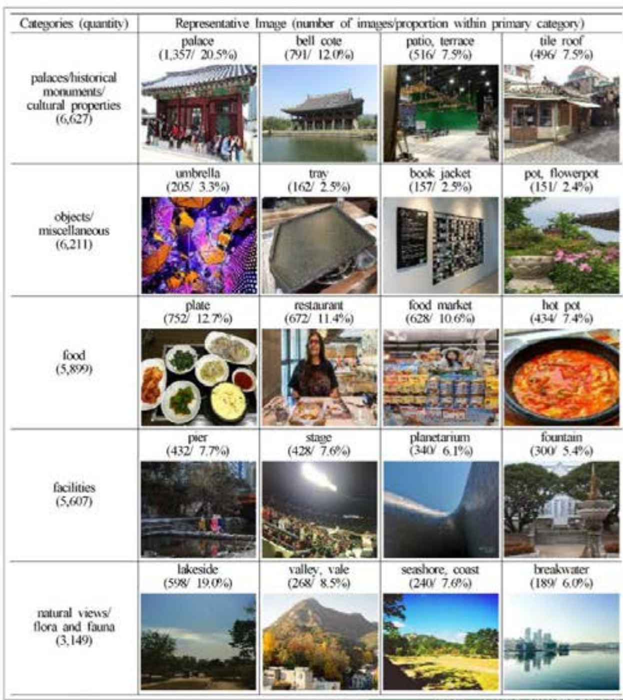
III. Results of Analysis

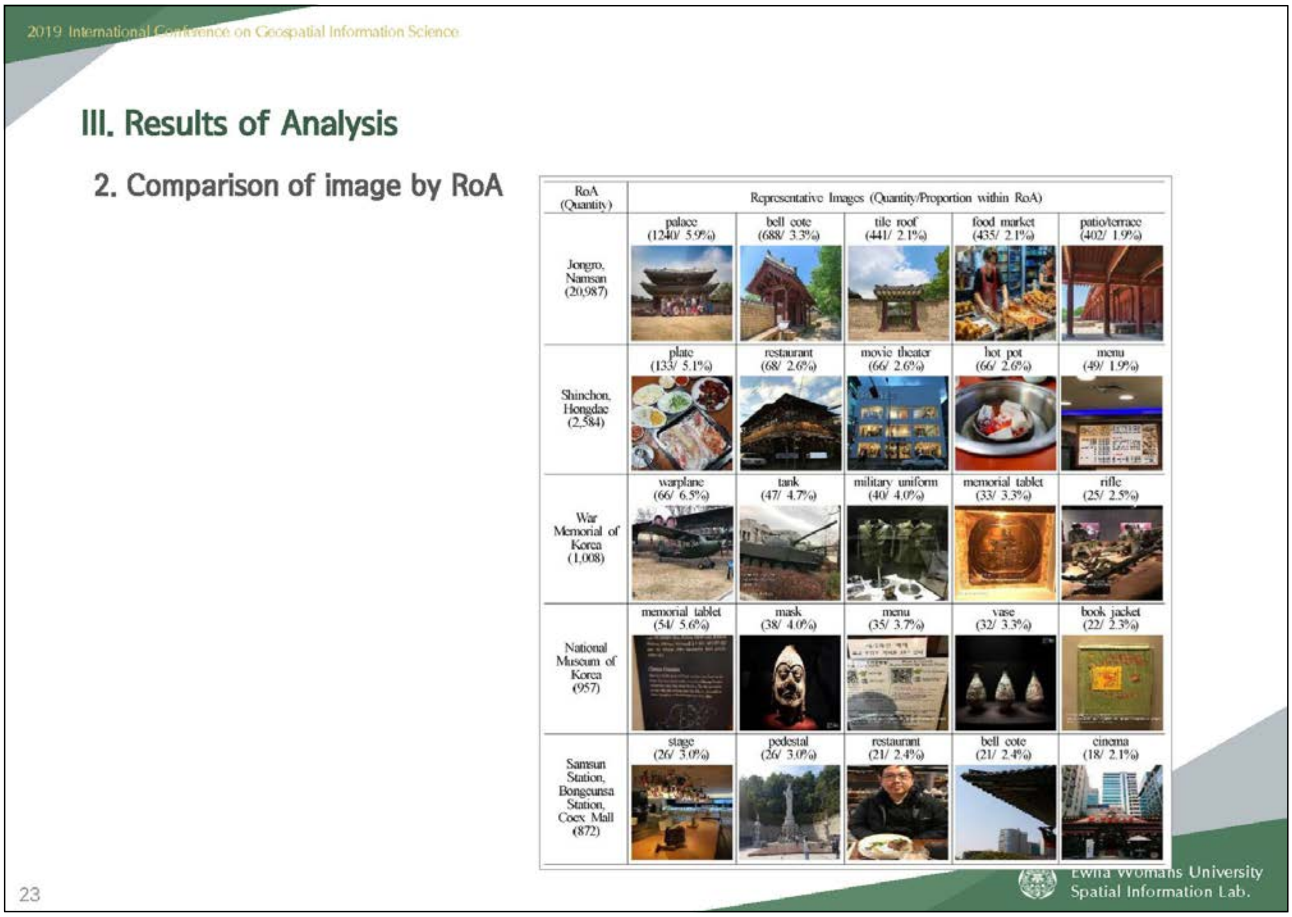
1. Image of Seoul

Categories	Number of Photos	Proportion (%)
palaces/historical monuments/cultural properties	6,627	17.1
objects/miscellaneous	6,211	16.1
food	5,899	15.2
facilities	5,607	14.5
natural views/flora and fauna	3,149	8.1
shopping	2,316	6.0
clothing	2,273	5.9
transportation	2,204	5.7
urbanscape	1,469	3.8
exhibits/sculptures	1,452	3.8
religion	502	1.3
residence	465	1.2
entertainment	296	0.8
people	221	0.6
Total	38,691	100.0

Tourists are generally interested in palaces, historical monuments, cultural properties, objects, food, facilities, natural views, and flora and fauna

Top 5 and corresponding subcategories

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III. Results of Analysis
2. Comparison of image by RoA
RoA (Quantity)
Representative Images (Quantity/Proportion within RoA)
Jongro, Namsan (20,987)
palace (1240/ 5.9%)
bell cote (688/ 3.3%)
tile roof (441/ 2.1%)
food market (435/ 2.1%)
patio/terrace (402/ 1.9%)
Shinchon, Hongdae (2,584)
plate (133/ 5.1%)
restaurant (68/ 2.6%)
movie theater (66/ 2.6%)
hot pot (66/ 2.6%)
menu (49/ 1.9%)
War Memorial of Korea (1,008)
warplane (66/ 6.5%)
tank (47/ 4.7%)
military uniform (40/ 4.0%)
memorial tablet (33/ 3.3%)
rifle (25/ 2.5%)
National Museum of Korea (957)
memorial tablet (54/ 5.6%)
mask (38/ 4.0%)
menu (35/ 3.7%)
vase (32/ 3.3%)
book jacket (22/ 2.3%)
Samsun Station, Bongeunsa Station, Coex Mall (872)
stage (26/ 3.0%)
pedestal (26/ 3.0%)
restaurant (21/ 2.4%)
bell cote (21/ 2.4%)
cinema (18/ 2.1%)
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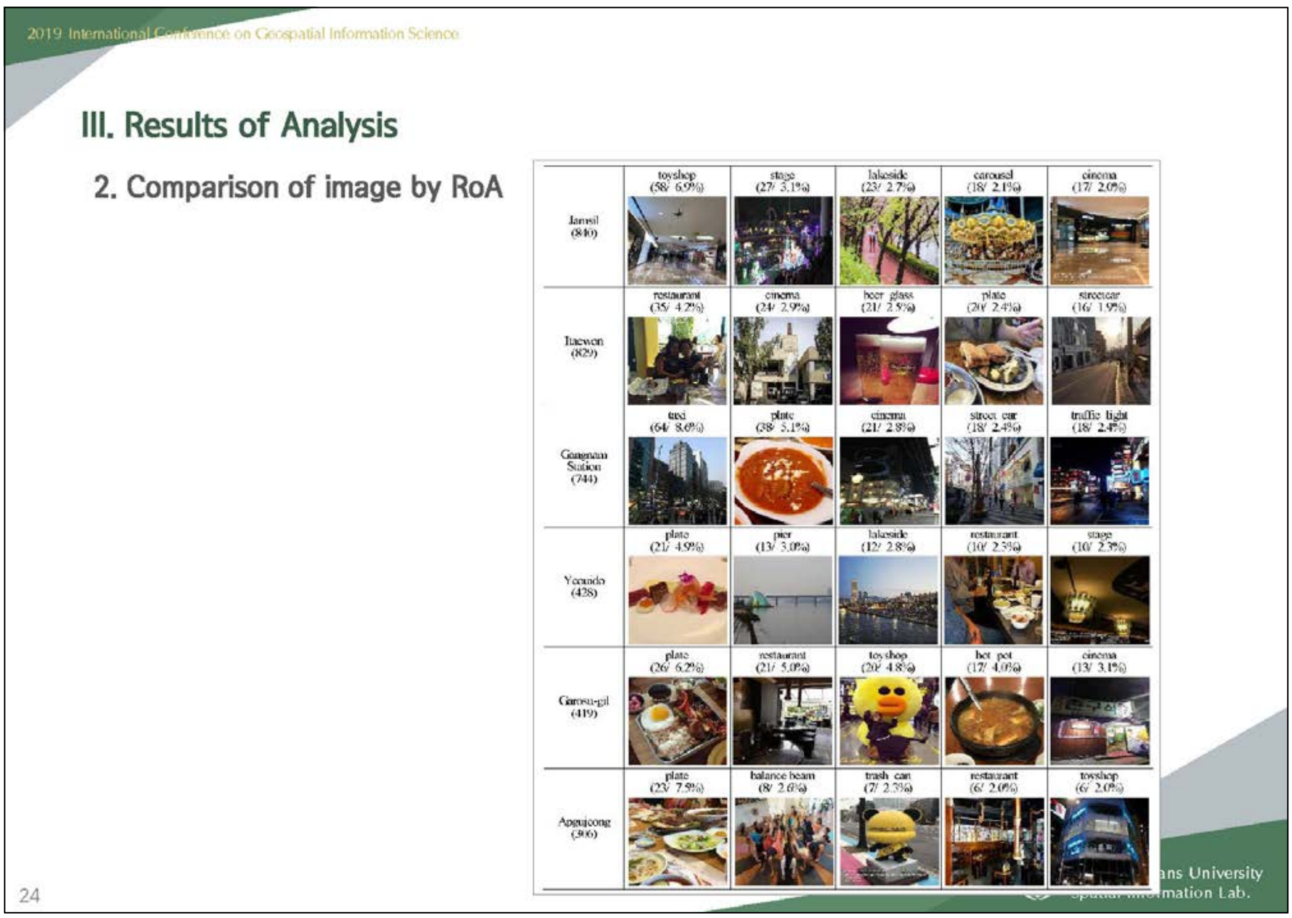
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III. Results of Analysis
2. Comparison of image by RoA
Jamsil (840)
toyshop (58/ 6.9%)
stage (27/ 3.1%)
lakeside (23/ 2.7%)
carousel (18/ 2.1%)
cinema (17/ 2.0%)
Itaewon (829)
restaurant (35/ 4.2%)
cinema (24/ 2.9%)
beer glass (21/ 2.5%)
plate (20/ 2.4%)
streetcar (16/ 1.9%)
Gangnam Station (744)
taxi (64/ 8.6%)
plate (38/ 5.1%)
cinema (21/ 2.8%)
street car (18/ 2.4%)
traffic light (18/ 2.4%)
Yeouido (428)
plate (21/ 4.9%)
pier (13/ 3.0%)
lakeside (12/ 2.8%)
restaurant (10/ 2.3%)
stage (10/ 2.3%)
Garosu-gil (419)
plate (26/ 6.2%)
restaurant (21/ 5.0%)
toyshop (20/ 4.8%)
hot pot (17/ 4.0%)
cinema (13/ 3.1%)
Apgujeong (306)
plate (23/ 7.5%)
balance beam (8/ 2.6%)
trash can (7/ 2.3%)
restaurant (6/ 2.0%)
toyshop (6/ 2.0%)
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III. Results of Analysis

2. Comparison of image by RoA

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III. Results of Analysis

3. Accuracy assessment

- In order to evaluate the accuracy of the classification results of the Inception v3 model, we conducted manual labeling for 38,691 photos.
- If the classification result of the Inception v3 model matches the results of manual labeling, the photo is correctly classified and given "True", otherwise "False.
  - the highest matching categories : 'plate', 'tile roof', 'restaurant', 'hot pot'
  - the lowest matching categories : 'monastery', 'prison', 'bell cote', and 'movie theater'.

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III. Results of Analysis

3. Accuracy assessment

- Accuracy ratio by categories based on Inception v3 model and manual labeling

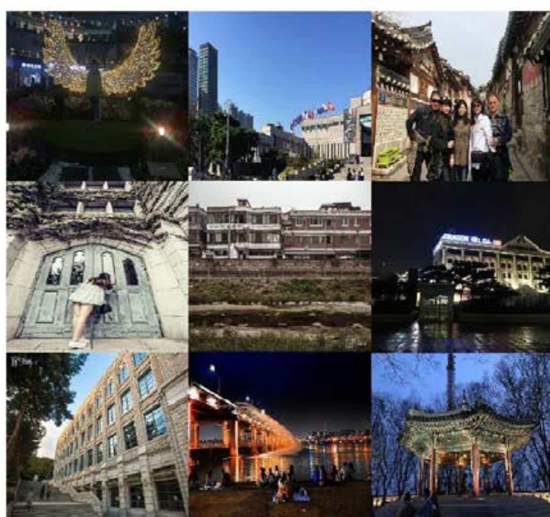
Predicted Categories	Total	True	False	Accuracy(%)
palace	1357	1070	287	78.85
bell cote, bell cot	791	25	766	3.16
plate	752	750	2	99.73
restaurant, eating house, eating place, eatery	672	450	222	66.96
toyshop	636	201	435	31.60
grocery store, grocery, food market, market	628	317	311	50.48
cinema, movie theater, movie theatre, movie house, picture palace	605	37	568	6.12
lakeside, lakeshore	598	168	430	28.09
patio, terrace	516	140	376	27.13
cab, hack, taxi, taxicab	501	84	417	16.77
tile roof	496	415	81	83.67
hot pot, hotpot	434	290	144	66.82
pier	432	216	216	50.00
menu	431	134	297	31.09
stage	428	185	243	43.22
prison, prison house	427	16	411	3.75
traffic light, traffic signal, stoplight	406	139	267	34.24
monastery	394	2	392	0.51
Total	38,691	10,807	27,884	27.93

III. Results of Analysis

3. Accuracy assessment

- palace : 78.85%

▲ True cases



▲ False cases

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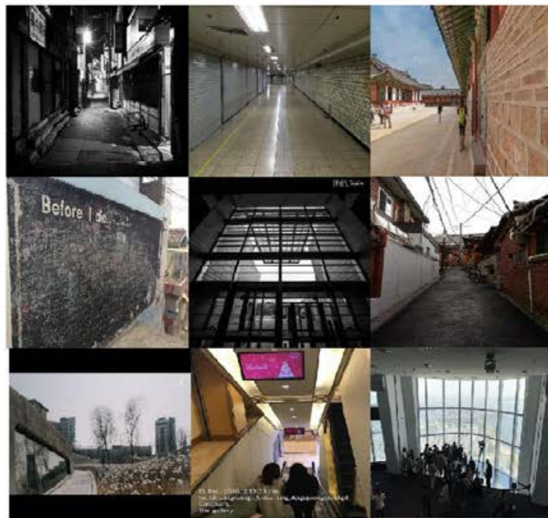
III. Results of Analysis

3. Accuracy assessment

- prison, prison house: 3.75%

▲ True cases



▲ False cases

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IV. Conclusion

- **Significance of research**
  - analyze urban image with the geotagged photos posted on the SNS by tourists
  - use deep learning technique to analyze the photos
  - classify and analyze the whole photos posted by tourists while most researches focus on only specific objects.

- **Limitation**
  - Inception v3 model which has been used in this research is a pre-trained model created by training the ImageNet data.
  - It was not possible to accurately categorize certain iconic landmarks of Korea
  - The photos related to palaces and Hanok villages were scattered in the categories such as 'Palace', 'bell cote' and 'terrace'.

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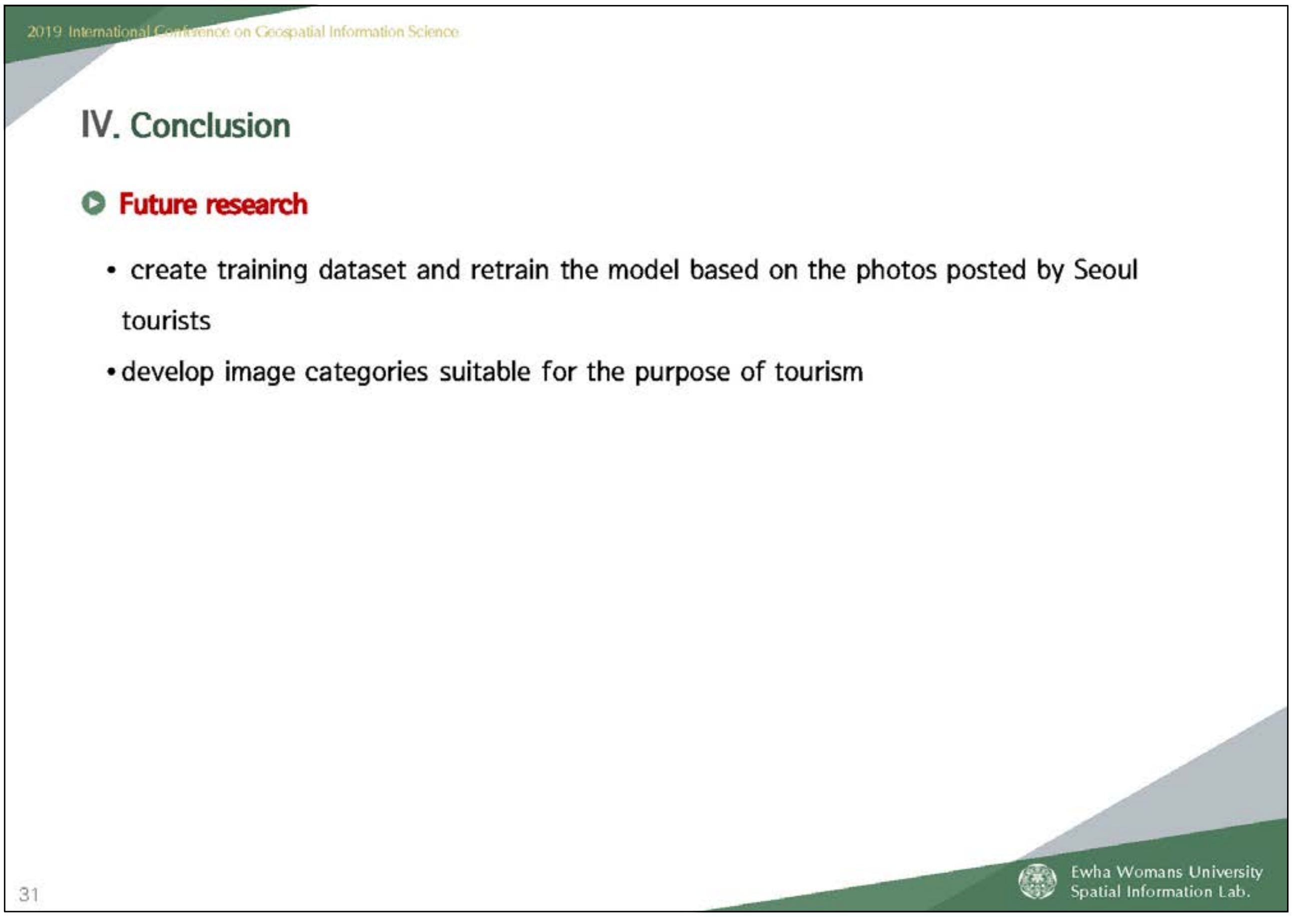
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IV. Conclusion
Future research
• create training dataset and retrain the model based on the photos posted by Seoul tourists
• develop image categories suitable for the purpose of tourism
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Thank you!
Youngok Kang : ykang@ewha.ac.kr
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Memo

Memo

Invited Talk 4

Use Cases of Geospatial Information in AI Applications

[인공지능 응용에서의 공간정보 활용 사례]

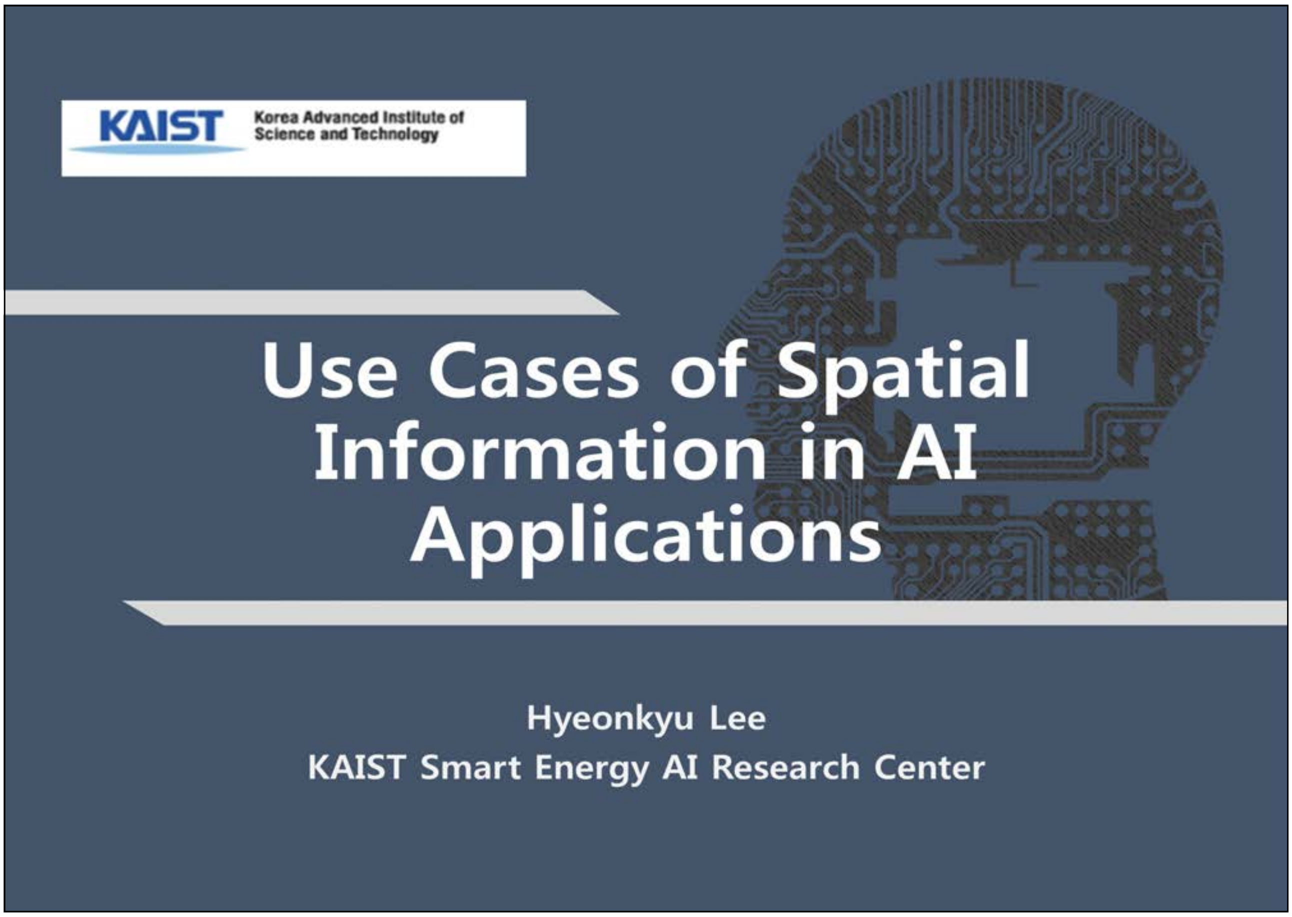
Prof. Hyeonkyu Lee
Korea Institute of Science and Technology

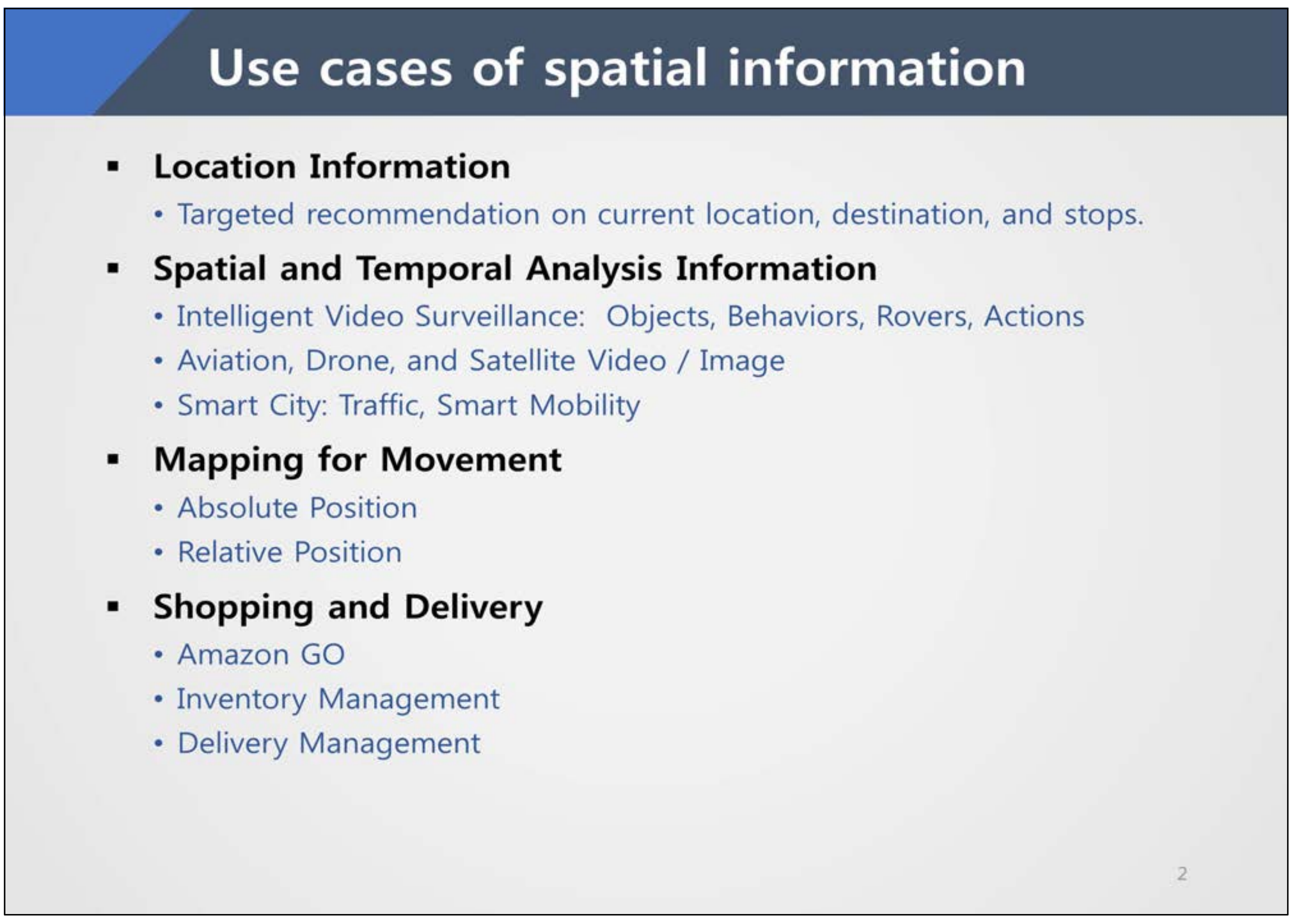
Use Cases of Geospatial Information in AI Applications

Hyeonkyu Lee
Prof, Korea Institute of Science and Technology

Abstract

As the AI-First era approaches, interaction and relative / absolute spatial information as information for understanding the context become the most important information in AI applications. In particular, spatial information plays an important role in making more sophisticated decisions about real-time response by understanding the situation in real time with time information. This presentation explains how spatial information is used in AI applications via use cases.


Korea Advanced Institute of Science and Technology
Use Cases of Spatial Information in AI Applications
Hyeonkyu Lee
KAIST Smart Energy AI Research Center


Use cases of spatial information
Location Information
Targeted recommendation on current location, destination, and stops.
Spatial and Temporal Analysis Information
Intelligent Video Surveillance: Objects, Behaviors, Rovers, Actions
Aviation, Drone, and Satellite Video / Image
Smart City: Traffic, Smart Mobility
Mapping for Movement
Absolute Position
Relative Position
Shopping and Delivery
Amazon GO
Inventory Management
Delivery Management
2

Smart Home - Google

- **Roomba, iRobot**
  - Mapping: iAdapt 3.0 (Visual SLAM)
  - Naming: Imprint Smart Mapping
- **Google and iRobot Partnership**
  - iRobot
    - ➢ Building a home map using Roomba
    - ➢ Voice control of Roomba with Google Assistant
  - Google
    - ➢ Provides easy Smart Home configuration and control by using home map created by Roomba
- **Google Fuchsia (Smart Home OS)**
- **Building 10,000 houses at Mountain View area**

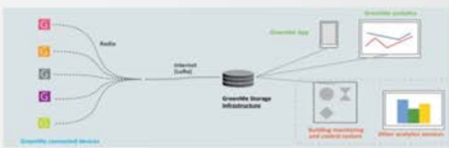
Source: Big Tech in the Smart Home, CB Insights (2018)

3

Smart Building

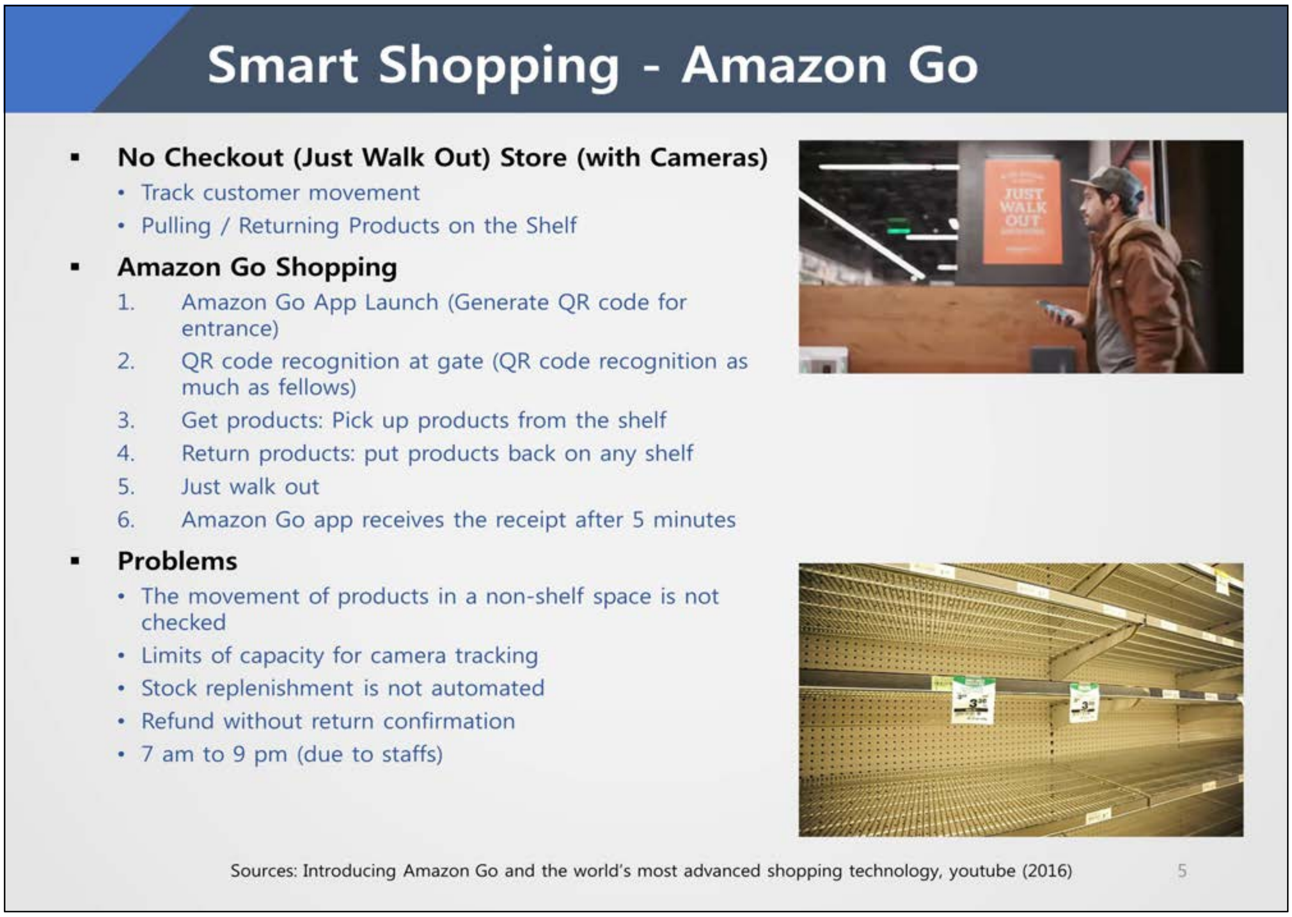
Maximizes Comfort, Wellness, and Efficiency

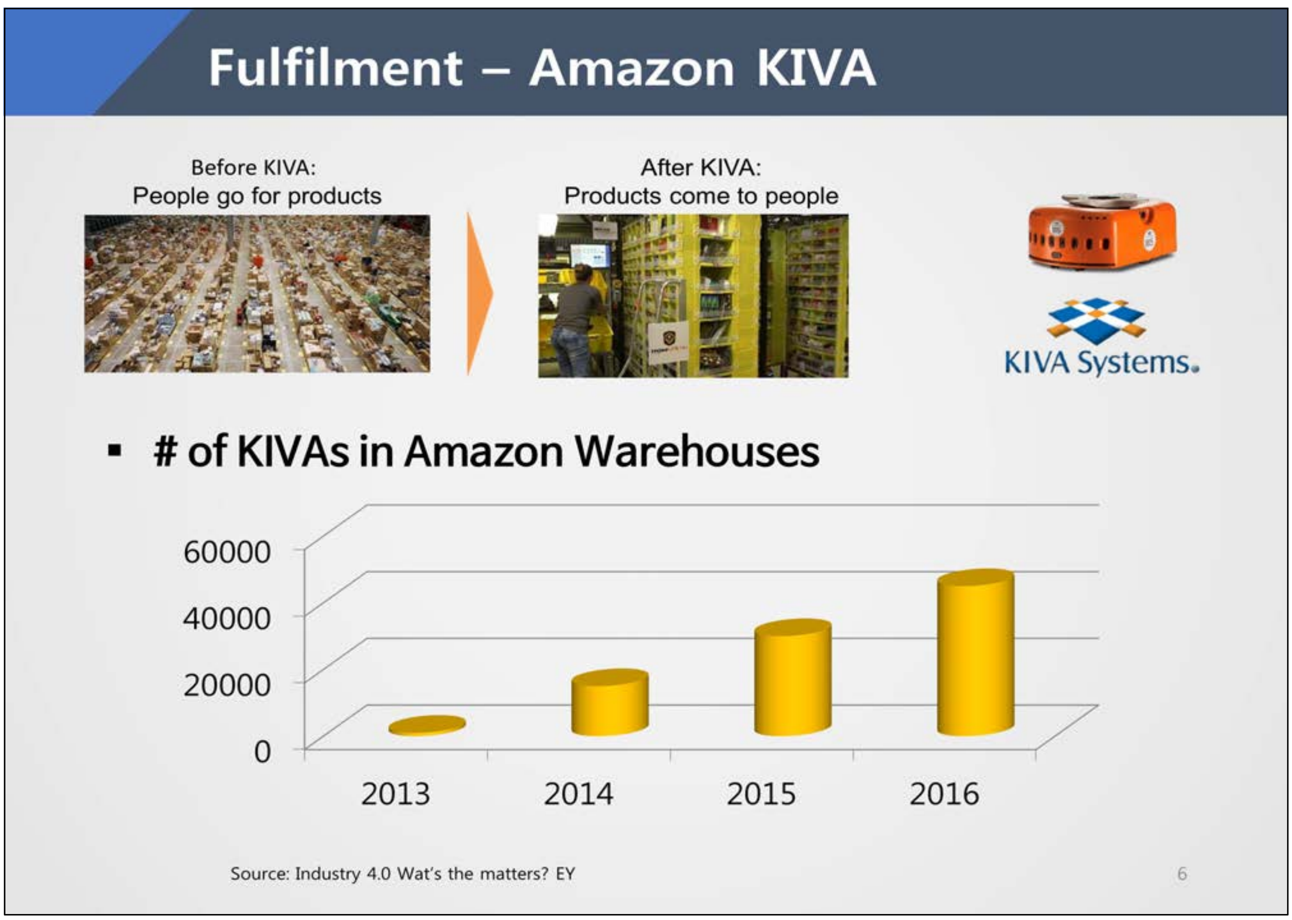
- **Amazon-backed ecobee detects occupancy and cools or heats rooms accordingly**
  - Sensors might track the movement of an elderly member to detect changes in behavior
- **GreenMe's Cubes small enough to be placed on individual desks**
  - Measures parameters from lighting and temperature to air quality, noise level, and light flickering.
  - Feeds into a building monitoring and control system for consensus on heating and cooling norms.
  - Workers can monitor how cold or warm they like their workplaces.
- **Comfy (Acquired by Siemens, 2018)**
  - Installs sensors and IoT devices in buildings so that occupants can adjust temperature and lighting.



Source : Big Tech in the Smart Home, CB Insights (2018)
14 Trends Shaping Tech, CB Insights (2019)

4


Smart Shopping - Amazon Go
▪ No Checkout (Just Walk Out) Store (with Cameras)
• Track customer movement
• Pulling / Returning Products on the Shelf
▪ Amazon Go Shopping
1. Amazon Go App Launch (Generate QR code for entrance)
2. QR code recognition at gate (QR code recognition as much as fellows)
3. Get products: Pick up products from the shelf
4. Return products: put products back on any shelf
5. Just walk out
6. Amazon Go app receives the receipt after 5 minutes
▪ Problems
• The movement of products in a non-shelf space is not checked
• Limits of capacity for camera tracking
• Stock replenishment is not automated
• Refund without return confirmation
• 7 am to 9 pm (due to staffs)
JUST WALK OUT
Sources: Introducing Amazon Go and the world's most advanced shopping technology, youtube (2016)
5


Fulfilment – Amazon KIVA
Before KIVA:
People go for products
After KIVA:
Products come to people
KIVA Systems.
▪ # of KIVAs in Amazon Warehouses
60000
40000
20000
0
2013
2014
2015
2016
Source: Industry 4.0 Wat's the matters? EY
6

Robot Delivery - Dispatch

- **Dispatch (Researchers of MIT & U. Penn)**
  - Autonomous Delivery Robot with Computer Vision and Machine Learning (2014)
  - Plans to build a platform for autonomous delivery robots with a fee
  - Campus as a Testbed: Dynamic env. with bicycles, skateboards, and pedestrians
- **Carry: Autonomous Delivery Robot**
  - Deliver parcels and / or foods via sidewalks and campus
  - For last-mile delivery
    - ➢ Reduced shipping cost compared to drones
    - ➢ Reducing concerns about privacy issues

Source: NIA AI Plus Series (2017)

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Last-mile delivery gets automated

Last-mile delivery may be the first place where we see fully autonomous fleets deployed.

- **Kroger partnered with self-driving startup Nuro, 2018**
  - to deliver groceries from its Fry's Food Stores to residents in Scottsdale, Arizona

- **Ford and Domino's partnership, 2018**
  - Customers would order food and have Ford Fusion hybrids deliver it.

Source: 14 Trends Shaping Tech, CB Insights (2019)

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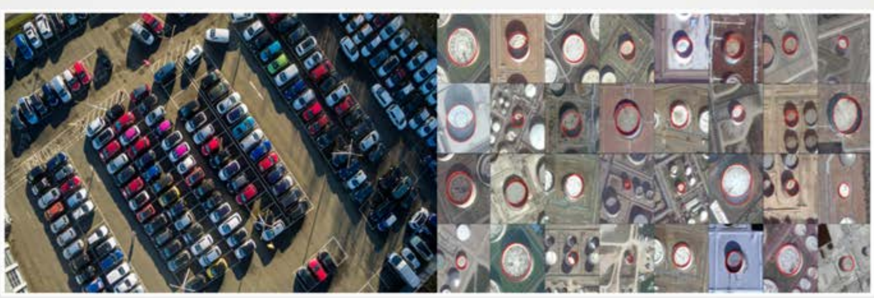
Smart Farm - Blue River Technology

- **Blue River Technology**
  - Developed an alternative to chemical-intensive agriculture in 2011
  - Innovation Endeavors (Established by Eric Schmidt) invested $10M
- **AI-based Weed Removal Robot**
  - Lettuce Bot : Identify weeds and selectively remove unwanted plants
    - ➢ Remove weeds and plants harmful to crop growth
    - ➢ Spread herbicide on weeds not on soil or crops → Reduce the use of chemicals by 90%
  - Identifies 5,000 plants/min, increases farm yield by 10%.
    - ➢ Lettuce Bot: 10% of the US-produced lettuce

Source: NIA AI Plus Series (2017), http://www.bluerivertechnology.com/ 9

Satellite Image Analysis – Orbital Insight

- **Orbital Insight**
  - Established in 2013 by James Crawford (Built NASA's intelligent system, Tech Director of Google Books)
  - Forecasting service that analyzes images taken by satellites and unmanned aerial vehicles using deep learning
  - Major Customers: Non-profit organizations and US government agencies
  - Partnership with the World Bank to better identify poverty-stricken areas in 2015
- **Economic / Industrial Forecasting based on Spatial Information**
  - Forecasting Economic / Social Trend: Cars, roads, airplanes, lakes, farmlands, buildings, oil tanks, etc.
  - Forecasting Oil Price: Changes in the surroundings of oil tanks of major oil-producing countries captured by satellites
  - Economic trends in the retail sector: # of cars, type of vehicles, and parking time (satellite images of 60 large US malls)
  - Predicting Chinese Construction Industry Status: # of construction works, site area, speed of constructions, and progresses (for each major construction site in China)
  - Calculating China's Unpublished Petroleum Supply and Storage Capacity: Satellite Image Analysis on Storage Facilities

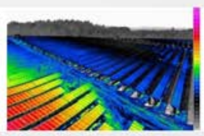
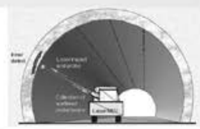


Source: NIA AI Plus Series (2017), https://orbitalinsight.com 10

Monitoring & Inspection


- **Public**
  - Missing person search
  - Security / disaster prevention
  - Traffic situation analysis
- **Facility Management**
  - Detection of external cracks in overpasses, bridges, railways, etc.
  - Inspection and maintenance of facilities such as power transmission towers and drilling towers
  - Prediction of flooding and collapse risk around hydroelectric power plants
  - Safety inspection of outer wall condition of nuclear power plant and analysis of cooling water environmental impact
  - Solar power plant and wind turbine facility condition check and maintenance
  - Tunnel and Sewer Detection of hazardous materials inside the underground space and safety inspection of structures
  - Safety inspection and maintenance of vents inside large buildings

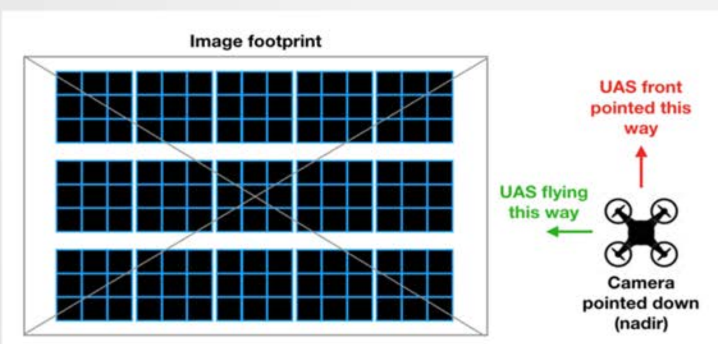


11

Predictive Maintenance

- **Use Drones to Inspect Managing Assets**
  - Reduces Time-spent and Risks caused by Manual Operations
- **Use Deep Learning**
  - Defect Detection Automation
  - Error Forecasting without Interrupting Operations

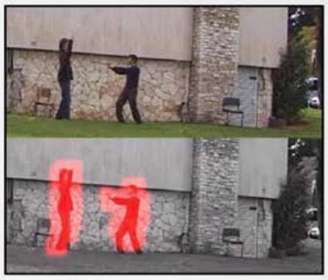


Source: How to Inspect Solar Farms with Drones, Nikhil (2017)

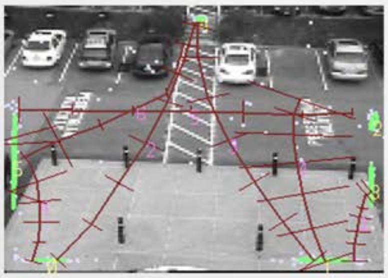
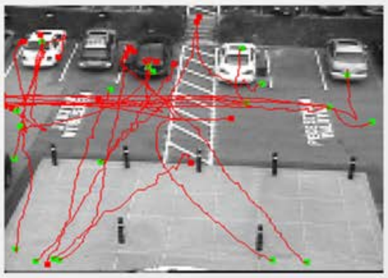
12

Video Surveillance - Behaviors

- **Suspicious Behaviors**

- **Management of Objects Entering and Exiting a Building / Area**

Sources: IBM Behavior Analysis, IBM TJ Watson Research Center, Rogerio Feris

13

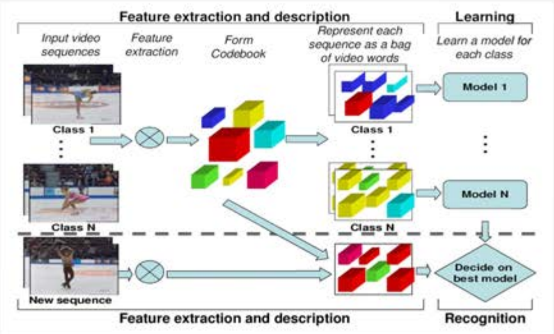
Video Surveillance – Template-based

- **Remote Motion Recognition**

- 300-pixel man
- Limb tracking

- 3-pixel man
- Blob tracking


- **Spatio-Temporal Analysis**



Source : Spatial-Temporal Bag of Word, Niebles, 2006

14


Video Surveillance - Events
The ability to quickly identify and respond to problems is essential to keeping the event safe and cautious.
Monitoring key areas
Send IVA Informatioin to IOC
Provides intelligent response to issues identified in IVA
Source : IBM's Intelligent Video Analytics & IBM Intelligent Public Safety, IBM
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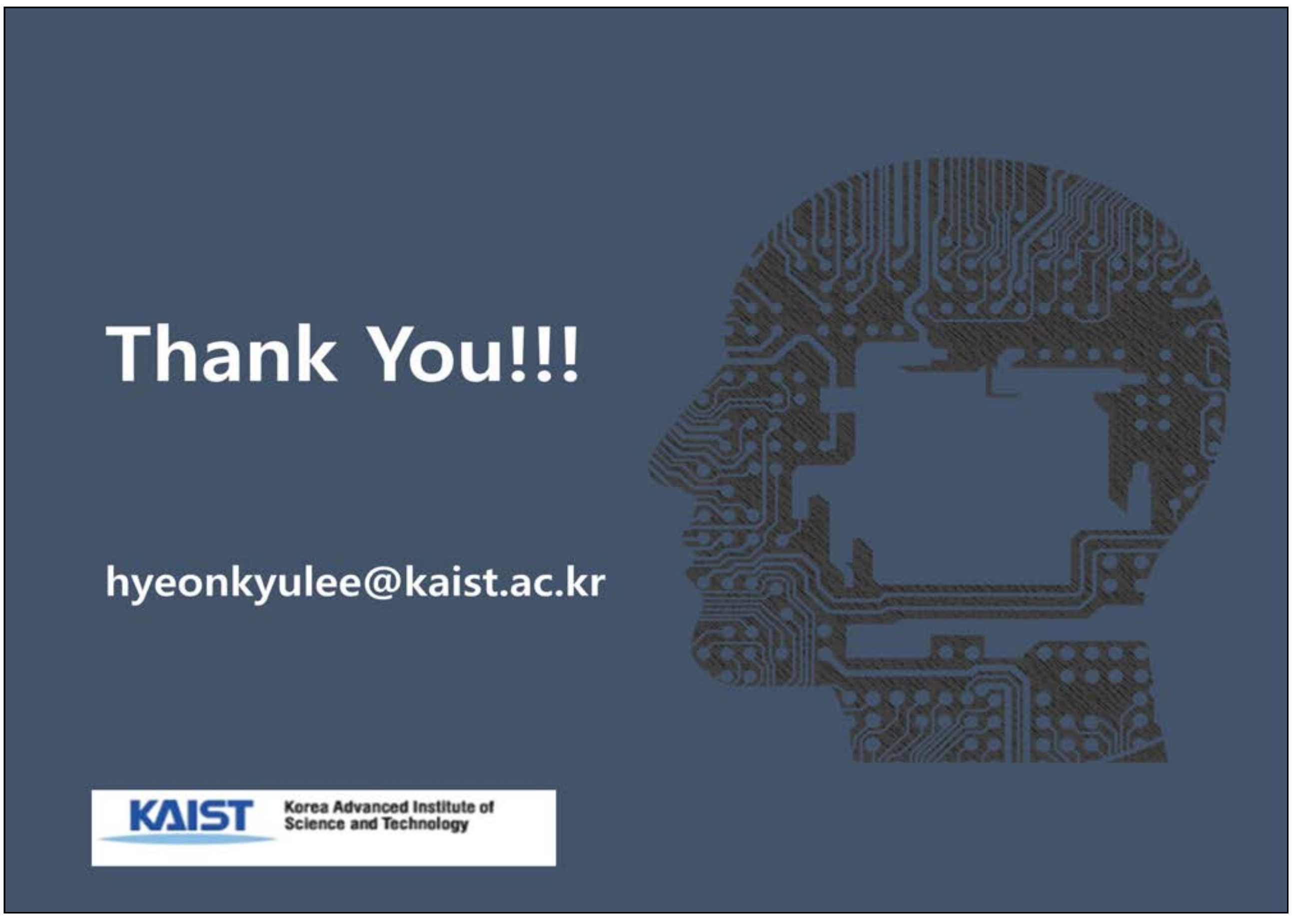
Thank You!!!
hyeonkyulee@kaist.ac.kr
KAIST
Korea Advanced Institute of Science and Technology

Memo

Memo

Invited Talk 5

Monitoring Land Use and Land Cover Change using Geospatial A.I

[인공지능 기술을 활용한 국토모니터링 혁신 방안]

Dr. Ki-hwan Seo

Korea Research Institute for Human Settlements

KRIHS Korea Research Institute for Human Settlements

Monitoring Land Use and Land Cover Change using Geospatial A.I.

August 8th, 2019

Kihwan Seo

KRIHS Korea Research Institute for Human Settlements

Why do we need to monitor changes in land use and land cover?

- Information about land use and land cover changes is important and essential for many applications such as resources (i.e., water, soil, forest, and so on) management, disaster management, planning activities, conservation, and sustainable growth.

- Time series land use & land cover data can be used for predicting future land use and more.

2

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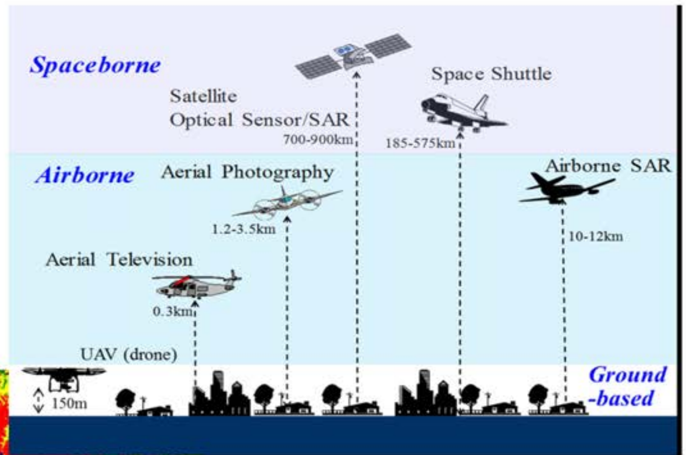
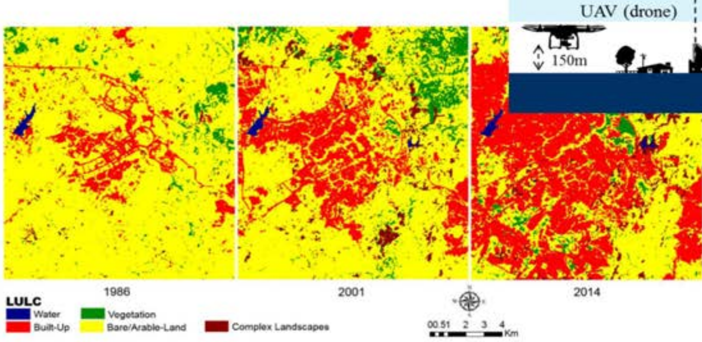
Conventional approach to obtain land use & land cover data

- ➢ Remote Sensing
  - ✓ Satellite
  - ✓ Airplane
  - ✓ Drone (UAV)
- ➢ Field Survey





3

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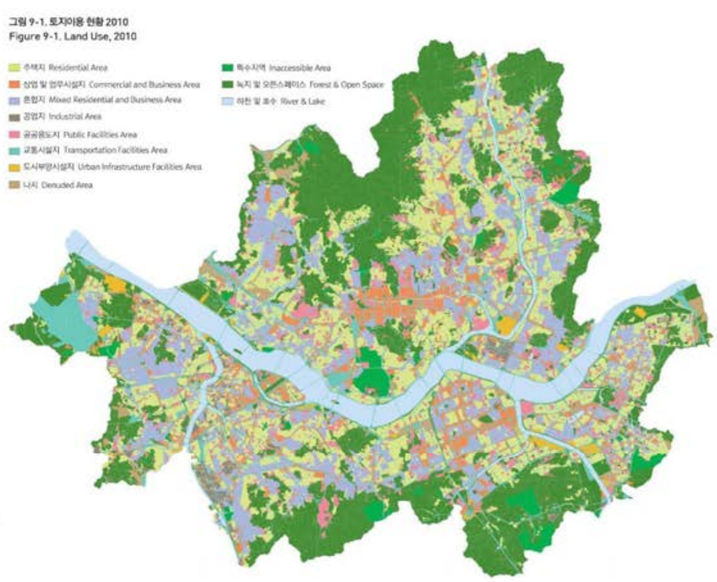
Monitoring land use & land cover change in Korea

- ➢ Ministry of Land, Infrastructure and Transportation (MOLIT)
  - ✓ National Geographic Information Institute (NGII) produces and disseminates **land use maps**
  - ✓ Using aerial photo (screen digitizing) and field survey
  - ✓ Conventional image processing is labor-intensive and time-consuming
- ➢ In 2002, land use mapping was suspended due to the recommendation of the Board of Audit and Inspection of Korea.
  - ✓ Redundant investment issue



4

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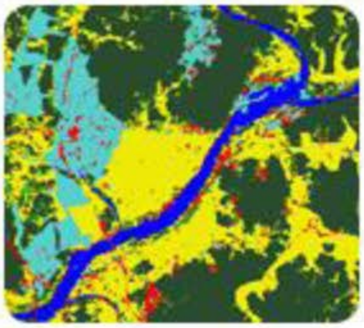
Monitoring land use & land cover change in Korea

- Ministry of Environment (MOE)
  - ✓ Produce and disseminate **land cover maps**



- Class: 7
- Coverage: Korean Peninsula
- Update: every 10 year
- Source: Landsat 7 ETM+
- Time series: 1989/1999/2009 /2019(now updating)

- Class: 22
- Coverage: South Korea
- Update: partly
- Source: IRS-1C, 1D, SPOT-5, KOMPSAT 2, Aerial photo
- Time series: 2004/2007

- Class: 41
- Coverage: South Korea
- Update: none
- Source: Aerial photo, KOMPSAT 2
- Time series: 2019 (now updating)

5

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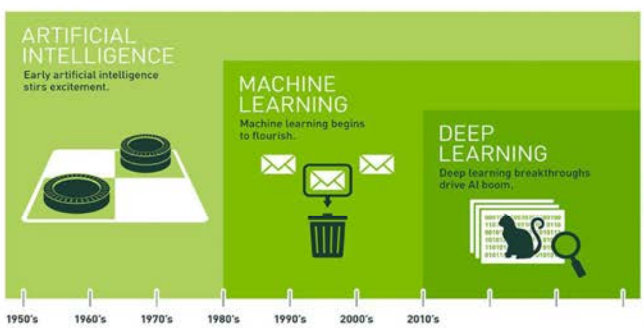
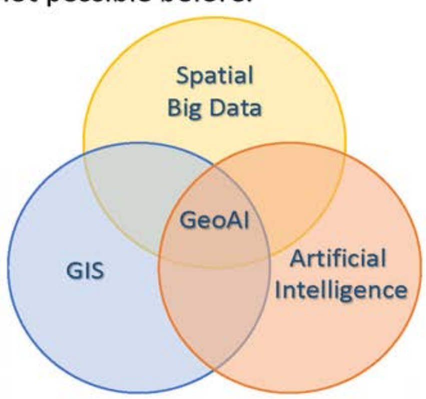
What is Geospatial Artificial Intelligence (GeoAI)

- "Geospatial Artificial Intelligence (GeoAI) is an emerging scientific discipline that combines innovations in spatial science, artificial intelligence methods in machine learning (e.g., deep learning), data mining, and high-performance computing to extract knowledge from spatial big data." (VoPham et al, 2018)

- GeoAI is unlocking many possibilities that were not possible before.





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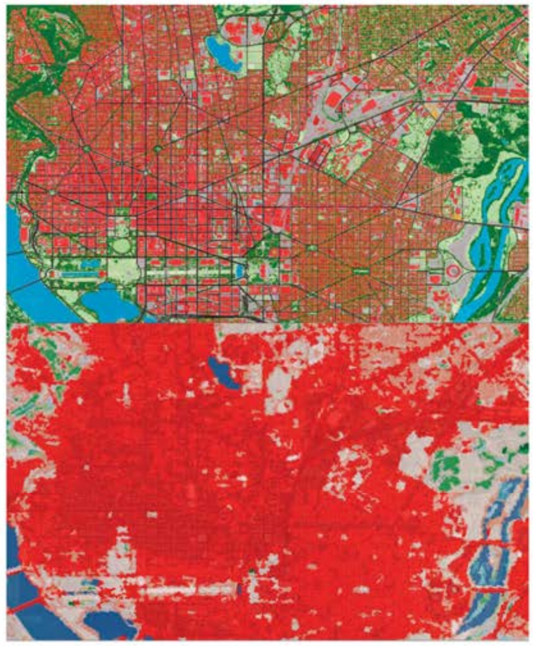
Trend & Applications in GeoAI

- Microsoft & ESRI teamed up for "AI for Earth Project" in 2017.
  - ✓ Microsoft provided a deep learning framework (Cognitive Toolkit) on Azure (MS cloud service).
  - ✓ ArcGIS Pro is installed in the GeoAI Data Science Virtual Machine (GeoAI DSVM).
  - ✓ ArcGIS Pro + Azure + Deep learning framework → GeoAI DSVM
  - ✓ Chesapeake Conservancy provided aerial imageries.



Source: ESRI newsroom

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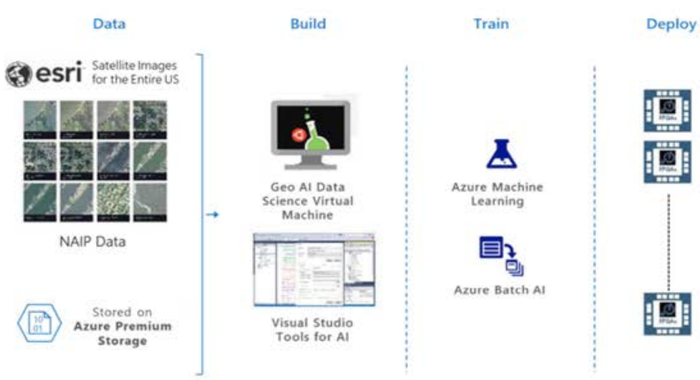
Trend & Applications in GeoAI

- To date, AI for Earth program awards the grants to support 393 projects with 63 countries.
  - ✓ MS invests $50 million over the next four years to fund AI development across five key areas — agriculture, biodiversity, conservation, climate change, and water.



200M Images, 20TB
Land cover mapping for the whole of US in
10+ minutes

Source: Lucas Joppa. 2018. Microsoft blog

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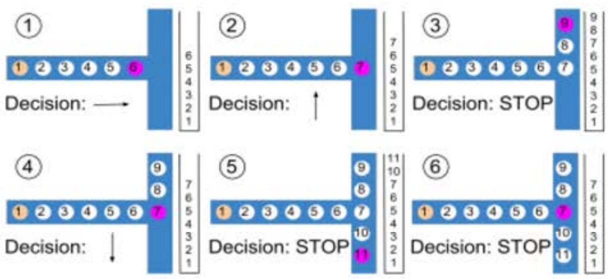
Trend & Applications in GeoAI

- RoadTracer: Automatic Extraction of Road Network from Aerial Images (Bastani et al, 2018)
  - ✓ Iterative graph construction method using CNN-guided search returned lower error rate with capturing 45% more junctions than segmentation approach.
  - ✓ Split dataset into a training set with 25 cities and a test set with 15 other cities.



Exploring a T intersection in the search process

9

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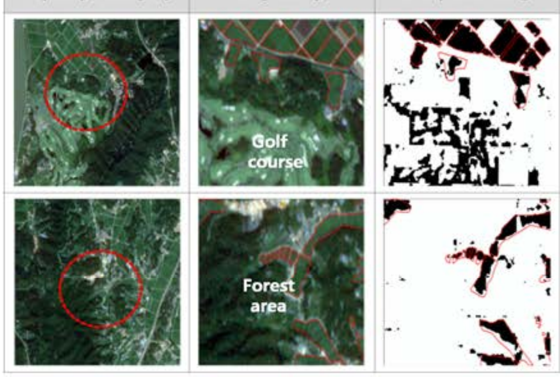
Trend & Applications in GeoAI

- Statistics Korea
  - ✓ Since 2012, paddy field inventory using remote sensing
  - ✓ In 2017, pilot project using RapidEye imagery and deep learning technique
- Data
  - ✓ RapidEye Imagery
  - ✓ Training dataset 2013 ~2015
  - ✓ Test set 2017
- Classification methods
  - ✓ Support Vector Machine
  - ✓ Random Forest
  - ✓ U- net (Deep Learning) → Highest accuracy

› Classification Accuracy

	Iksan-si	Sangju-si
Accuracy	87.6%	81.0%

RapidEye imagery	Digitizing	Deep Learning



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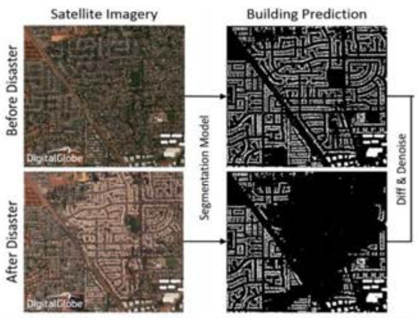
Trend & Applications in GeoAI

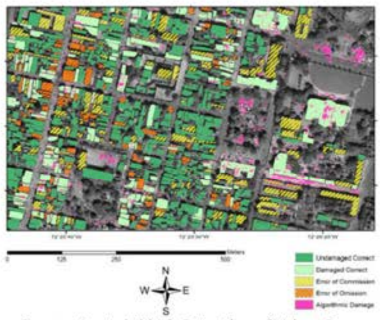
- Other applications
  - ✓ Damage detection (e.g., road crack, pothole, damaged building, etc)
  - ✓ Automated D3 building modeling and change detection

    and many more….
  - ✓ Mostly CNN-based semantic segmentation models were used.

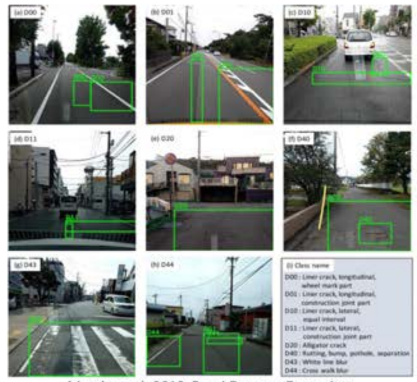
ESRI pilot project: ArcGIS Pro + deep learning + point cloud



Doshi et al. 2018. From Satellite Imagery to Disaster Insights



Corner, A. et al. 2016. Detection of Urban Damage using RS and Machine Learning Algorithms



Maeda et al. 2018. Road Damage Detection Using Deep Neural Networks with Images Captured Through a Smartphone

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Pilot Study in Korea:

Residential building extraction using aerial orthophoto and deep learning model

- Purpose: reduce time and cost updating land cover maps.
  - ✓ Study area: City of Daejeon where various residential buildings are built.
  - ✓ Data: aerial orthophoto / 25cm spatial resolution / 2016 imageries
  - ✓ Reference data: building vector data from Integrated building information system by MOLIT

Producer	National Geographic Information Institute (NGII)
Year	2016
Spatial resolution	25cm
Spectral resolution	RGB band
Radiometric resolution	8 bit
Data type	Geo TIFF
Area	2300 x 2880 m / Scene
Location	City of Daejeon

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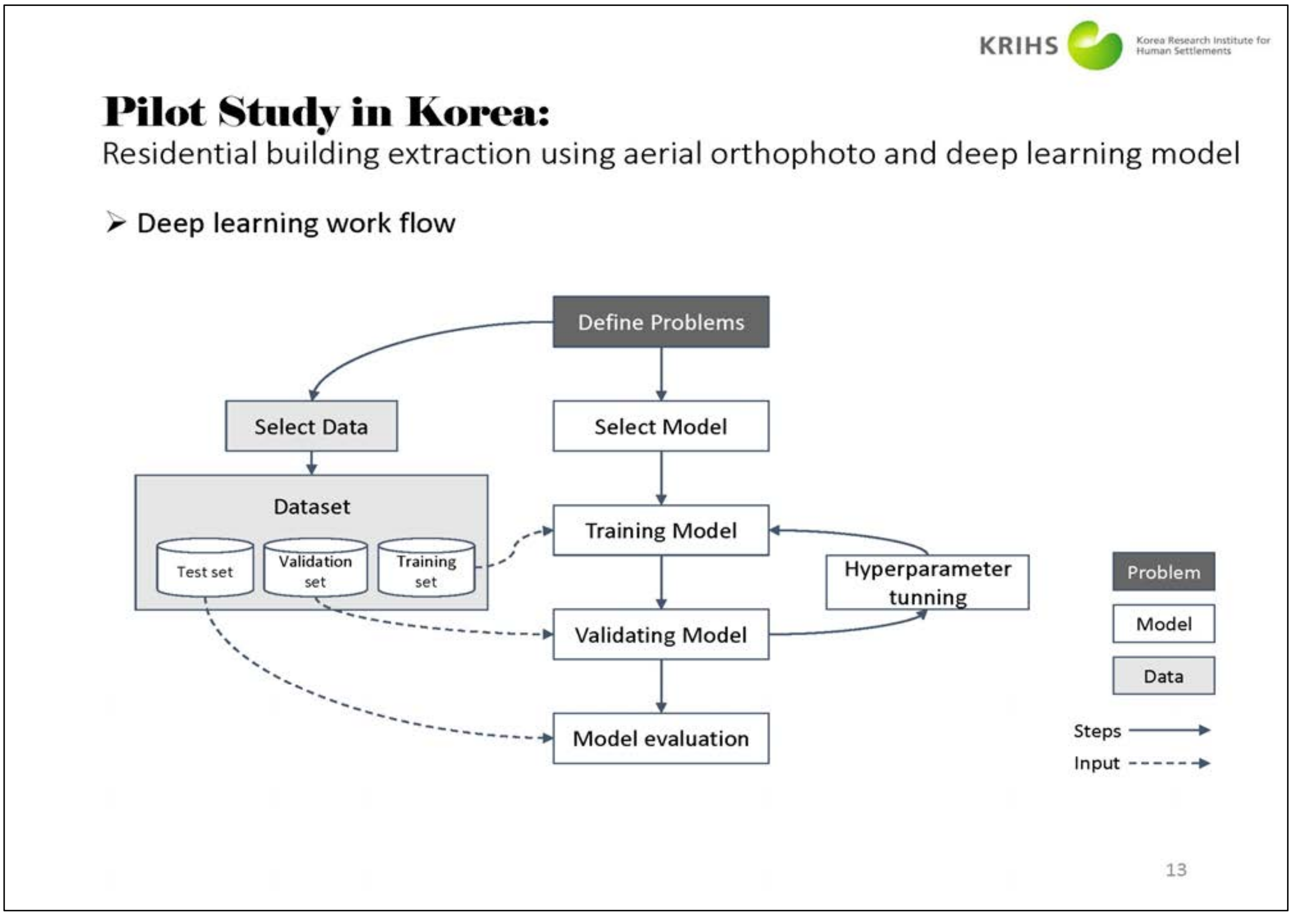
KRIHS
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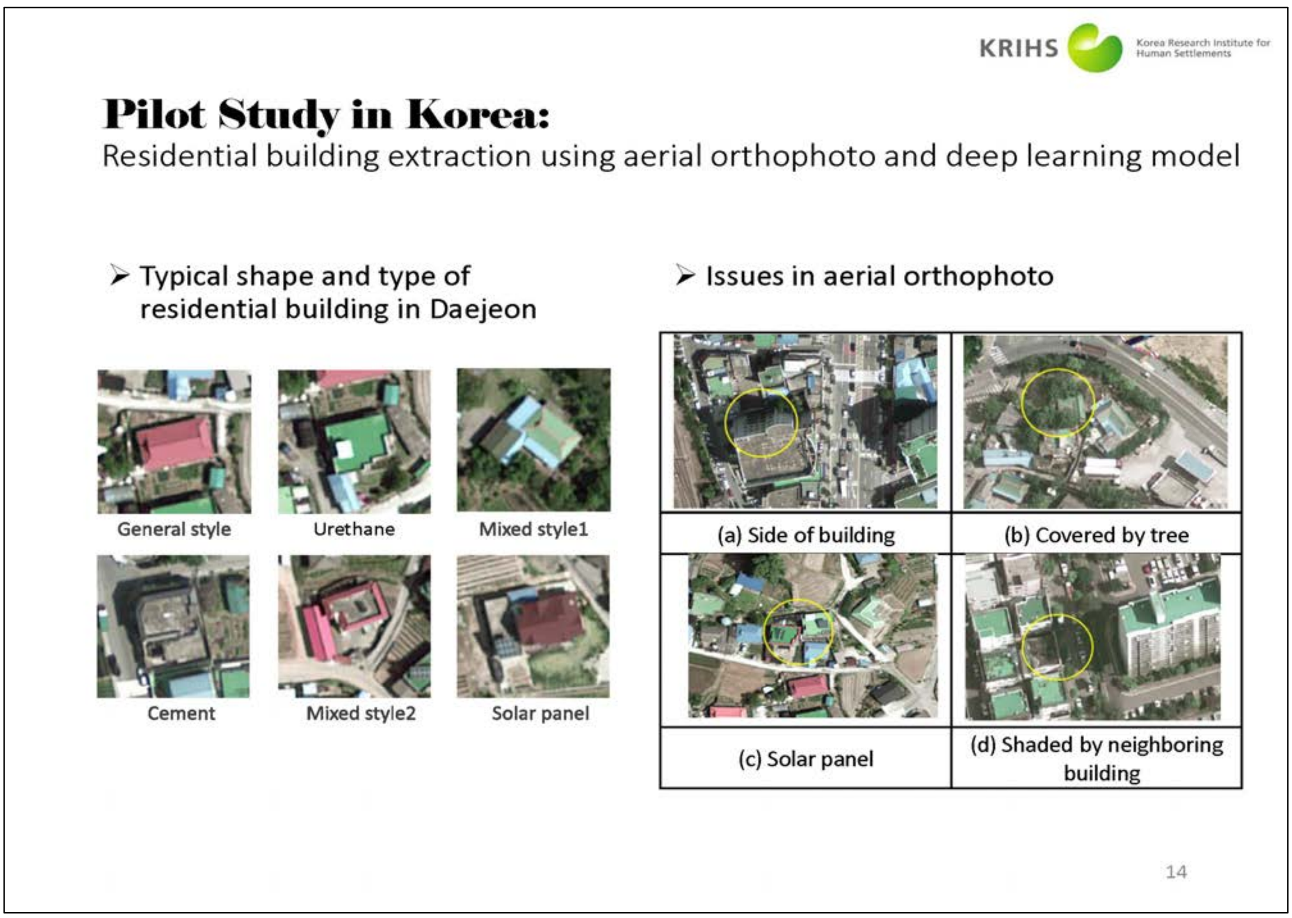
Pilot Study in Korea:
Residential building extraction using aerial orthophoto and deep learning model
➢ Deep learning work flow
Define Problems
Select Data
Select Model
Dataset
Test set
Validation set
Training set
Training Model
Hyperparameter tunning
Validating Model
Model evaluation
Problem
Model
Data
Steps
Input
13


KRIHS
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Pilot Study in Korea:
Residential building extraction using aerial orthophoto and deep learning model
➢ Typical shape and type of residential building in Daejeon
General style
Urethane
Mixed style1
Cement
Mixed style2
Solar panel
➢ Issues in aerial orthophoto
(a) Side of building
(b) Covered by tree
(c) Solar panel
(d) Shaded by neighboring building
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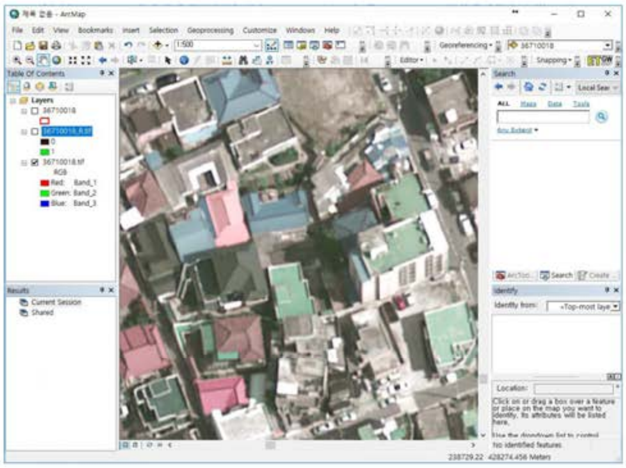
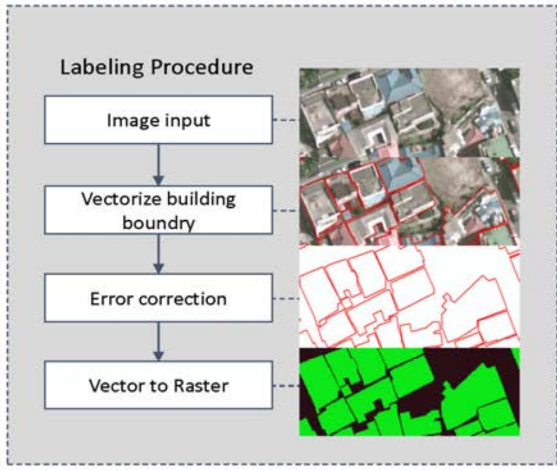
Pilot Study in Korea:

Residential building extraction using aerial orthophoto and deep learning model

- Labeling procedure
  - ✓ Tool for labeling: ArcGIS 10.1





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Pilot Study in Korea:

Residential building extraction using aerial orthophoto and deep learning model

- Labeling for datasets
  - ✓ 1 set of data = image & label
  - ✓ Pixel size : 0.25m/pixel
  - ✓ Ground size of a dataset : 64m x 64m (256 x 256 pixel)

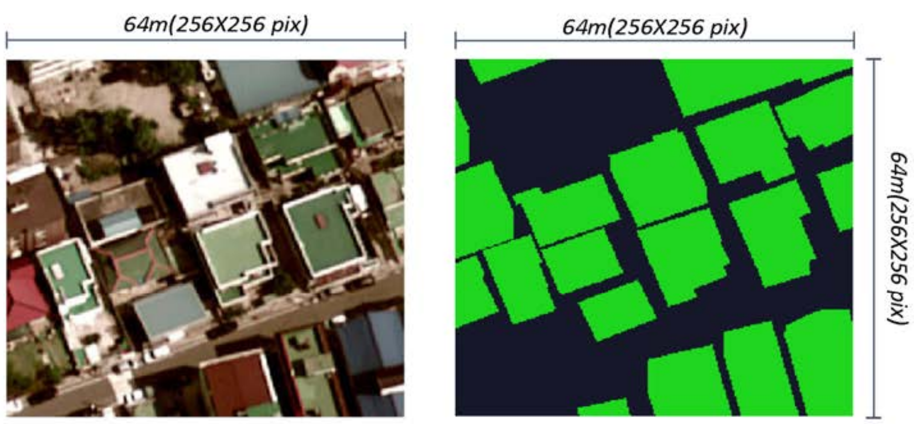

Image Label

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Pilot Study in Korea:
Residential building extraction using aerial orthophoto and deep learning model

- Labeling and # of datasets
  - ✓ Using sliding window : 32m from left to right
  - ✓ Number of datasets : 32,400 sets (1,620 sets / scene)

Sliding window

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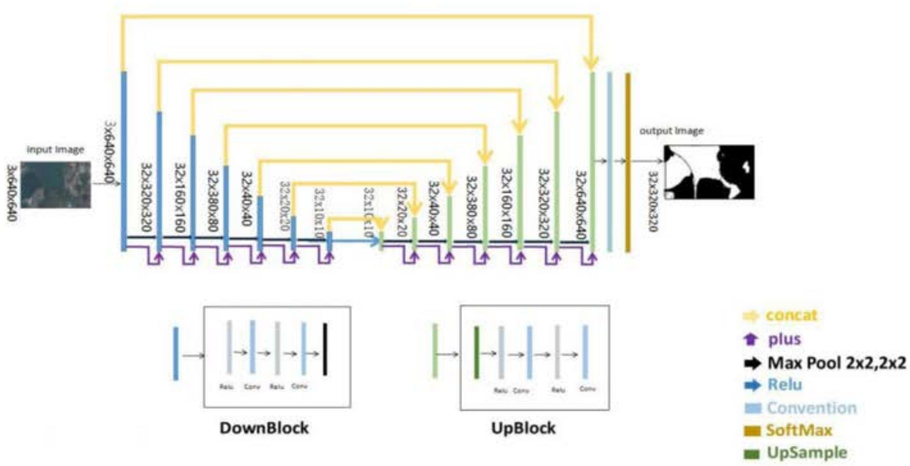
Pilot Study in Korea:
Residential building extraction using aerial orthophoto and deep learning model

- Deep learning model candidates : Deep Unet / DeepLab V3+



Deep Unet detailed structure and annotation

Source: Li et all. 2017. DeepUNet: A Deep Fully Convolutional Network for Pixel-level Sea-Land Segmentation

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Pilot Study in Korea:

Residential building extraction using aerial orthophoto and deep learning model

➢ Ratio of dataset for test, validation, and training

Dataset	# of dataset	Ratio
Test set	374	1.2%
Vaildation set	1,505	5.0%
Training set	28,221	93.8%
Total	30,100	100.0%

➢ Hyperparameter tunning

Contents	Value
Batch Size	11
Epoch	10,000
Momentum	0.9
Learning rate	0.1

➢ Average time for each model

Average time	Deep U-net	DeepLab V3+
1 Epoch	180 second	1900 second
150 Epoch	8 hours	80 hours

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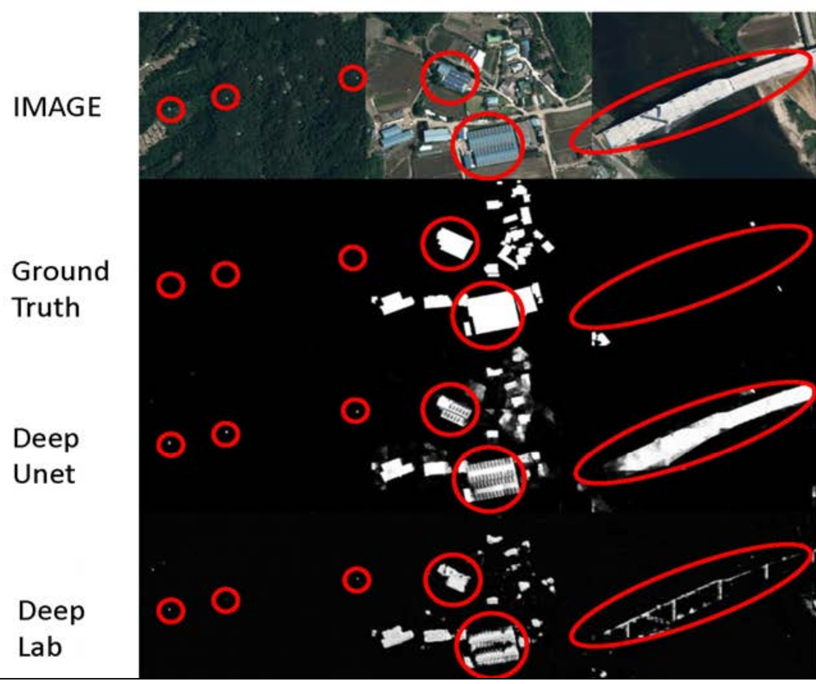
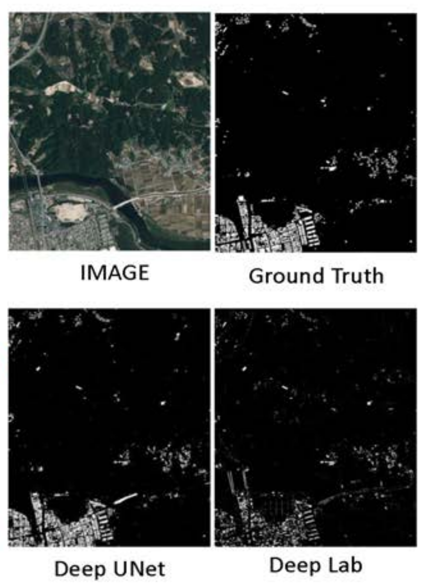
Pilot Study in Korea:

Residential building extraction using aerial orthophoto and deep learning model

➢ Types of error





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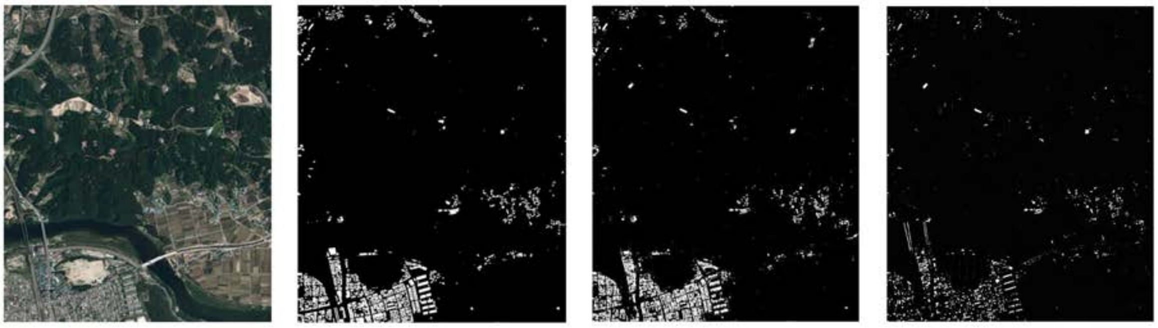
Pilot Study in Korea:
Residential building extraction using aerial orthophoto and deep learning model

➢ Validation set results



(a) Image (b) Ground truth (c) Deep UNet (d) DeepLab V3+

	Deep UNet	DeepLab V3+
Precision	0.7716 (77.2%)	0.3387 (33.9%)
Recall	0.7795 (78.0%)	0.7690 (76.9%)
Accuracy	0.9796 (98.0%)	0.9652 (96.5%)

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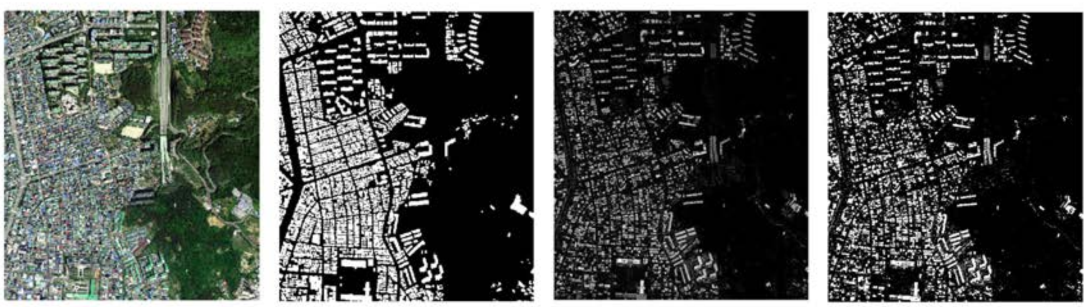
Pilot Study in Korea:
Residential building extraction using aerial orthophoto and deep learning model

➢ Test set results



(a) Image (b) Ground truth (c) Deep UNet (d) Binary image

	Residential building	**Other building**
Precision	0.1809 (18.1%)	0.0306 (3.1%)
Recall	0.2689 (26.9%)	0.1327 (13.3%)
Accuracy	0.7609 (76.1%)	0.8913 (89.1%)

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Challenges of GeoAI in Korea

- Significant computational resources and optimized AI algorithms are required for fast processing speed and classification accuracy
- Lack of adequate geospatial big data (e.g., time-series areal photo and satellite imagery that covers entire south Korea)
  - ✓ Lack of varying temporal resolution
  - ✓ Regional variation of spatial data
- Human challenges
  - ✓ People using and developing a GeoAI need to have knowledge in data science, deep learning, and geography.
  - ✓ Most of all, they should be able to collaborate with experts from other areas.

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Thank You!

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Memo

Memo