인공지능과 공간정보가 함께하는 미래사회

The Future of Geospatial AI

국토연구원 KRIHS

국토교통부 Ministry of Land, Infrastructure and Transport

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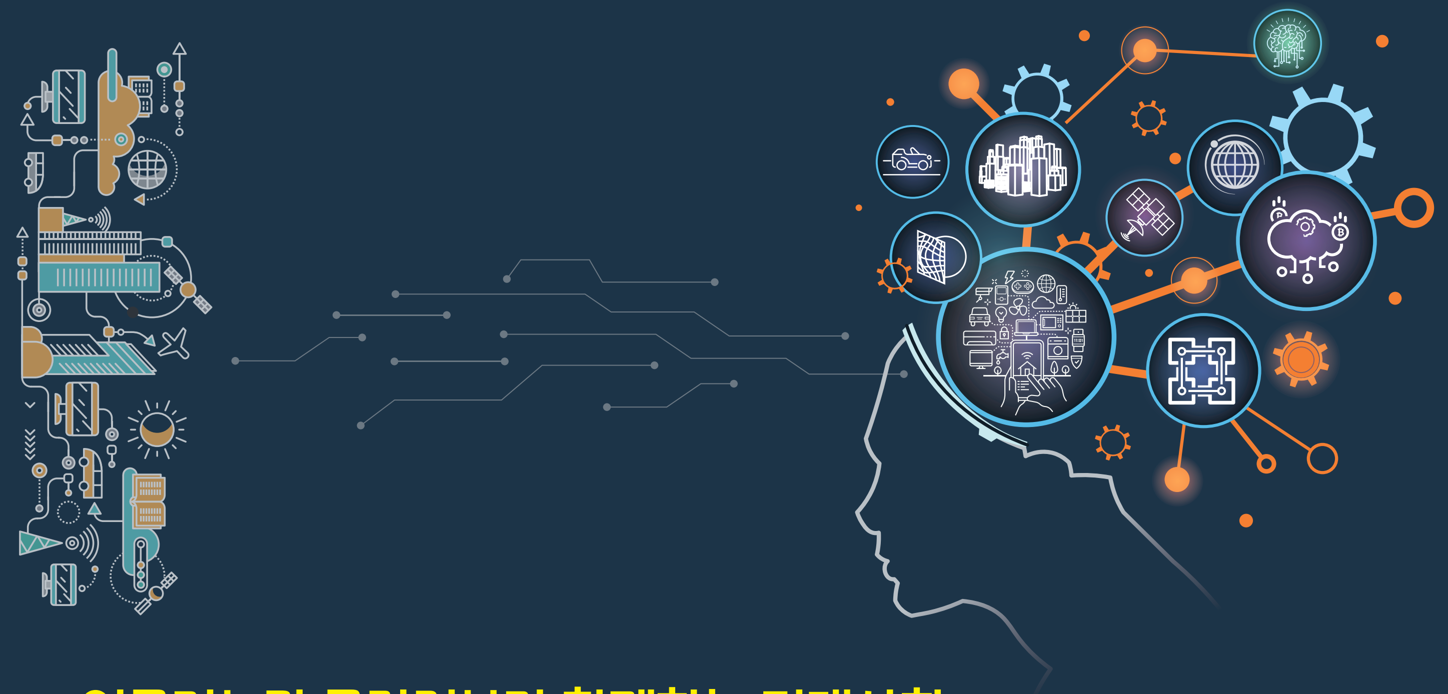
2018. 9

국토연구원 KRIHS

국토교통부 Ministry of Land, Infrastructure and Transport

International Conference on Geospatial Information Science
2018 ICGIS
공간정보 국제컨퍼런스

Smart Geospatial Expo 2018
2018 스마트국토엑스포



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The Future of Geospatial AI

2018. 9. 13(THU.) 10:00~17:30

코엑스 컨퍼런스룸(남) 308호
COEX Conference Room(South) 308

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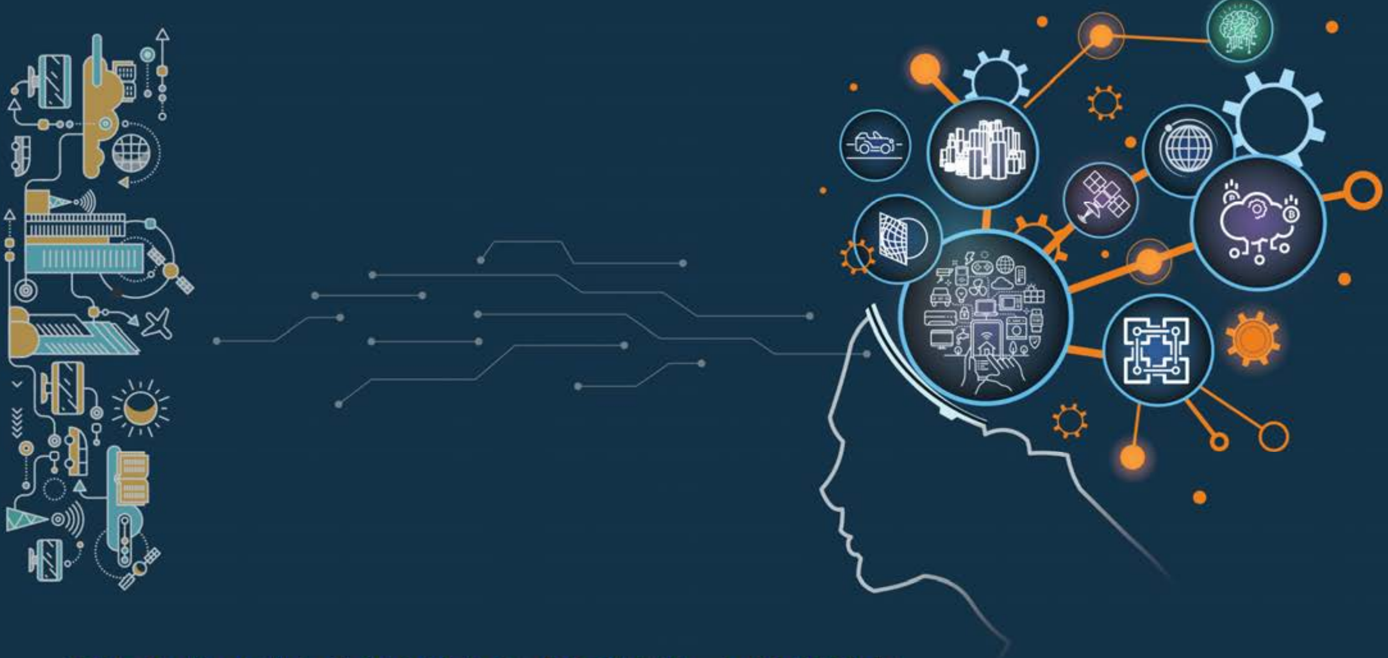

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2018 ICGIS Programs

The Future of Geospatial AI 인공지능과 공간정보가 함께하는 미래사회	
09:30~10:00	Registration 등록
10:00~10:10	**Opening Remarks/** ***Hyun-Soo Kang***, President of KRIHS 개회사/ 국토연구원 **강현수** 원장 **Congratulatory Address /** ***Woo-Jun Son***, Director General for Spatial Information Policy Bureau at MOLIT 축사/국토교통부 **손우준** 국토정보정책관
Session 1 : What is Geospatial AI 세션 1 : 공간정보 기반 인공지능	
10:10~10:40	**Keynote Speech 1** "Place in Geographic Information Science"/ ***Stephan Winter,*** Professor, The University of Melbourne **기조연설 1** "공간정보 과학기술에서의 장소"/ **스테판 윈터,** 호주 멜번대학 교수
10:40~11:10	"New Approaches to Space-Time Analytics of Human Dynamics" / ***May Yuan,*** Professor, The University of Texas at Dallas "휴먼 다이나믹스의 시공간 패턴 분석을 위한 새로운 접근방법"/ **메이 유안,** 텍사스(달라스) 대학 교수
11:10~11:40	"New Business Models integrating Artificial Intelligence and Geospatial Information" / ***Kyoung-Jun Lee,*** Professor, Kyung Hee University "인공지능과 공간정보를 융합한 새로운 비즈니스 모델"/ **이경전,** 경희대학 교수, 벤플 대표
11:40~13:30	Lunch 점심
Session 2 : New and Smart Geospatial Information Industries with AI 세션 2 : 인공지능을 융합한 새로운 도전과 산업진흥	
13:30~14:00	**Keynote Speech 2** "Geo AI for Smart New Industries"/ ***Brett Dixon,*** General Manager, Asia Pacific at ESRI **기조연설 2** "신산업 창출을 위한 Geo AI의 역할"/ **브레트 딕슨,** ESRI 아시아 태평양지부 총괄매니저
14:00~14:30	"AI for Smart Mobility" / ***Seung-Il You,*** Head of Datalab, Kakao Mobility "스마트 모빌리티를 위한 AI"/ **유승일,** 카카오모빌리티 데이터랩장
14:30~15:00	"Geospatial Information and Machine Learning Application in Japan" / ***Yoshiki Ogawa,*** Project Researcher, The University of Tokyo "공간정보와 머신러닝 -일본사례를 중심으로-"/ **요시키 오가와,** 도쿄대학 생산기술연구소 특임연구원
15:00~15:30	"Cloud-powered Machine Learnings on Geospatial Services - From the Earth to Your Home" / ***Channy Yun,*** Tech Evangelist, Amazon Web Service Korea "공간정보 서비스를 위한 클라우드 기반 머신러닝 활용" / **윤석찬,** 아마존웹서비스코리아 테크에반젤리스트
15:30~16:00	"A Deep Learning Approach for Simulating Urban Development"/ ***Donghan Kim,*** Research Fellow, KRIHS "딥러닝을 적용한 도시시뮬레이션"/ **김동한,** 국토연구원 연구위원
16:00~16:20	Coffee break 휴식
Round-Table Meeting 종합토론	
16:20~17:30	Round Table Meeting Moderator: ***Min-Hwa Lee,*** Chairman, KCERN(Korea Creative Economy Research Network) 좌장: **이민화,** 창조경제연구회 이사장
Closing 폐회	

Keynote & Speaker

Stephan Winter, The University of Melbourne

Stephan Winter is Professor for Spatial Information Science in the Department of Infrastructure Engineering at The University of Melbourne.
His areas of research interest include wayfinding and navigation, intelligent transportation systems and computational transportation science.
He has also worked in the fields of mobile geosensor networks, smart cities (mobility, urban analytics), spatial cognitive engineering, spatial data mining and geographic information retrieval. His recent research in marrying the human and vague concept of place with the formal requirements of information systems aims to improve user interaction, especially voice assistants, with information systems.

Brett Dixon, Asia Pacific at ESRI

As the general manager for Asia Pacific at Esri, Brett Dixon is recognised as an authority on enterprise geospatial strategies. Brett has been working in the geospatial intelligence realm for almost two decades. He's passionate about using GIS and geomatics to assist in national security, emergency and recovery, and disaster response.
Now, he advises many agencies throughout the Asia Pacific region, leveraging his GIS skills and national security knowledge to stay ahead of geospatial trends and challenges.
Aside from his duty as a general manager, he was appointed as a member of global advisory board of Geospatial Media and Communications since 2017.

May Yuan, The University of Texas at Dallas

May Yuan is Ashbel Smith Professor of Geospatial Information Sciences in the School of Economic, Political, and Policy Sciences at the University of Texas at Dallas.
Her research interest expands upon space-time representation and analytics to understanding geographic dynamics. Over the years, she has been working to develop approaches to represent and model geographic processes and events in GIS databases to support space-time query, analytics, and knowledge discovery.

Yoshiki Ogawa, The University of Tokyo

Yoshiki Ogawa is Project Researcher for Spatial Information Science and Institute of Industrial Science at The University of Tokyo.
His area of research is Big data analysis of GIS data and developing integrated simulation system of gigantic earthquake and tsunami disasters.
He utilizes data from mobile phones GPS and various GIS data to observe and measure people phenomena in our urban/rural regions and develop and apply simulation models to understand the past and predict the future disaster damage by integrated simulation.

Kyoung-Jun Lee, Benple Inc., Kyung Hee University

Kyoung-Jun Lee is tenured professor of Information Systems at Business School, Kyung Hee University, Seoul, Korea.
He is a member of Government 3.0 Committee (vice-minister level) and plays a role of Information Sharing and Collaboration Committee Chair.
He has been also working as a head of IoT/IoE Division of the public-private partnership for e-Government.
He is currently the director of International Center for Electronic Commerce and Humanitas Big Data Research Center.
He founded Benple Inc., the Button Internet company, and Allwinware Inc., a patented group auction company, and serve as the CEO of Benple and an executive officer of Allwinware.

Seung-Il You, Kakao Mobility

Seungil You is the head of datalab at Kakao Mobility, where he is leading the research effort for building an AI system that leverages spatiotemporal data. He earned his PhD on mathematical optimization, and started his career at Google as a software engineer where he designed machine learning models to improve service qualities and open sourced TensorFlow Lattice. Currently, his main work is developing AI systems that can operate at scale and improve Kakao Mobility's core services. He also wrote many papers in machine learning, control and decision, and communication.

Channy Yun, Amazon Web Service Korea

Channy Yun is a Principal Technical Evangelist at Amazon Web Services and works with Korean developers to enable them to use AWS cloud services. He has over 20 years of experience in various information systems such as geospatial, content management, e-commerce platform, and building their large-scale API systems such Daum Search and Maps APIs. Now he has special interests in cloud native architectures such as serverless, container, mobile/IoT, and machine learning.

Donghan Kim, Korea Research Institute for Human Settlements

Donghan Kim is a research fellow at the Geospatial Analytics Center in the Korea Research Institute for Human Settlements. His researches are focused on developing and applying urban and regional models for planning policy.
His recent modelling work covers the following themes: urban sprawl and growth, urban decay and regeneration, urban gentrification and segregation, firm dynamics and employment location, regional disparity and balanced development, etc.

Contents

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What is Geospatial AI

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New Business Models integrating Artificial Intelligence and Geospatial Information
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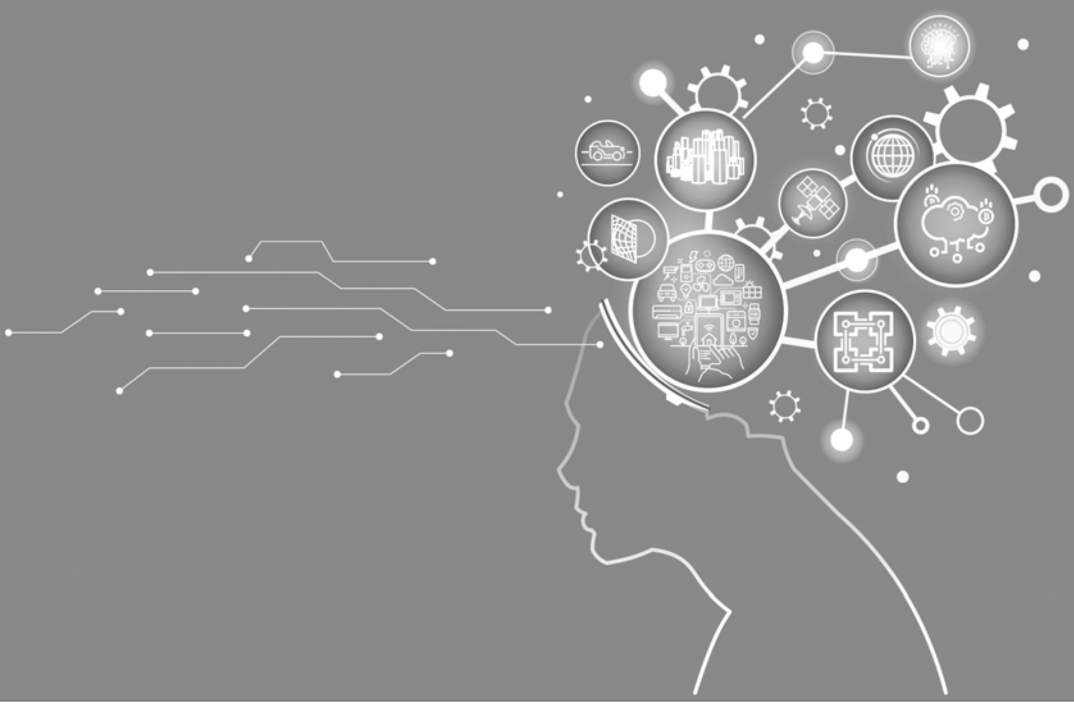

Keynote Speech 1

Place in Geographic Information Science

Stephan Winter
Professor, The University of Melbourne

Place in Geographic Information Science

Stephan Winter
winter@unimelb.edu.au
Department of Infrastructure Engineering, The University of Melbourne, Australia

Abstract

The human concept of place is not only vague in its meaning, but also often vague in the spatial extent of its instances (e.g., ‘Yellow Sea’, ‘Bukhansan’, or ‘downtown’). When people describe where something is, or how to find to somewhere, they refer to places. Their descriptions typically use qualitative spatial relationships (such as ‘near’, ‘at’, ‘in’, or ‘left’) of no less vagueness. Both concepts, places and their qualitative relationships, are not adequately matched with content of spatial databases. Thus, machines have substantial difficulties to interpret spatial common language (text or voice). I will report from our ongoing research on capturing the spatial knowledge in human place descriptions in a knowledge base, and linking this knowledge with spatial databases. Long-term we aim to achieve a meaningful, context-bound dialog between user and machine on locations.

This research has been funded by the Australian Research Council, grants LP100200199 and DP17100109.


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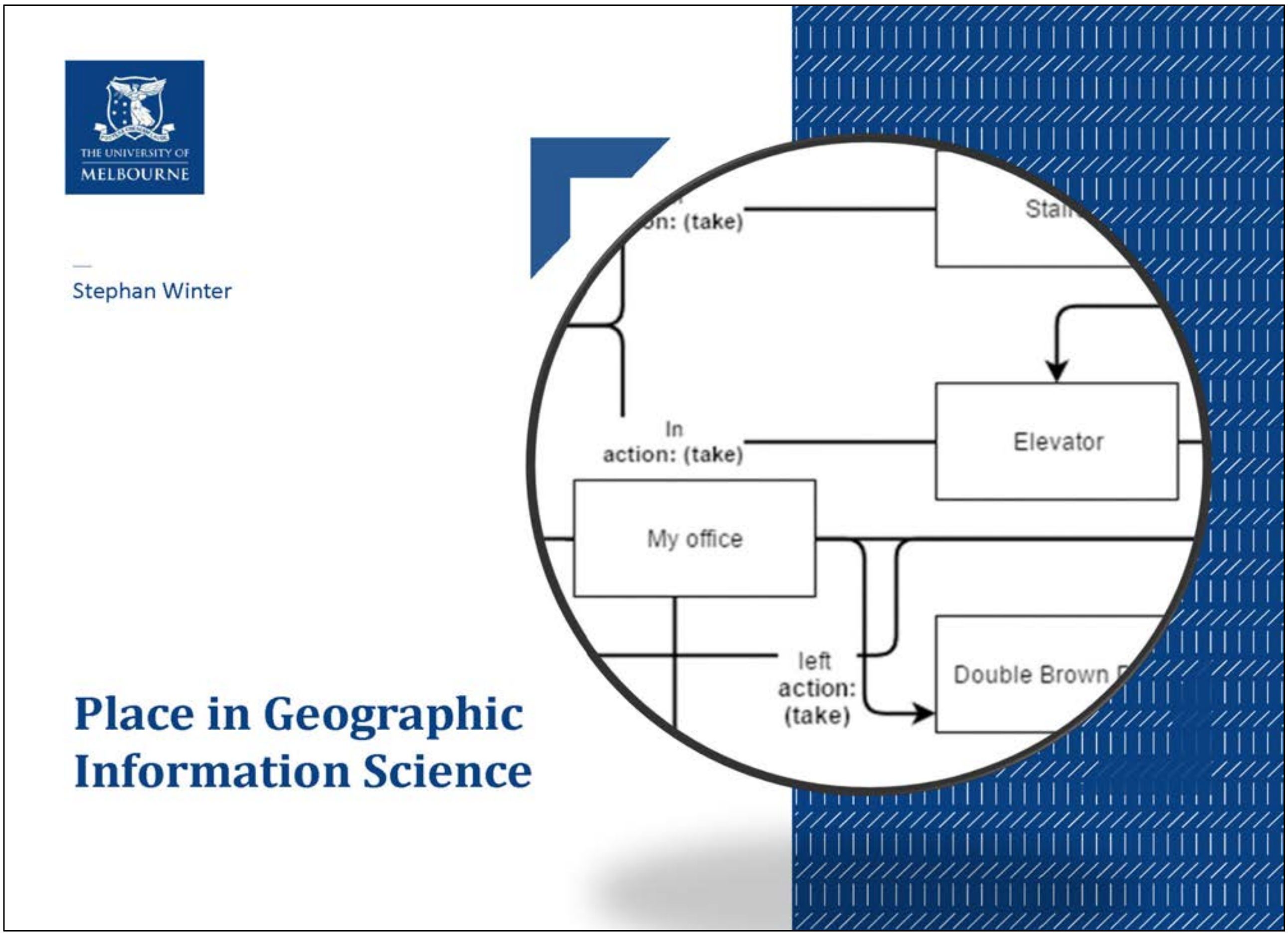
2018 International Conference on Geospatial Information Science
Place in Geographic Information Science
Stephan Winter(winter@unimelb.edu.au)
The University of Melbourne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Stephan Winter
Place in Geographic Information Science
In
action: (take)
Elevator
My office
left
action:
(take)

Place in cognition and communication

- "place cells", "grid cells"
  (O'Keefe and Nadel 1979, Moser et al. 2008)
- "cognitive graph"
  (Chrastil and Warren 2014)
- landmark – route – survey knowledge
  (Siegel and White 1975)
- learning from environment and from abstractions of environment
  (Thorndyke and Hayes-Roth 1982)

- Maps
- Sketches
  (e.g., Lynch 1960, Krukar et al. 2018 – route vs survey)
- Verbal
  (identifiers and relationships; e.g., Vasardani et al. 2013, Belouaer et al. 2013: directional vs configurational)
- Pointing
  (polar coordinates / path integration)
- Behaviour
  (e.g., leading)

"Naïve geography"

(Egenhofer & Mark 1995)

- *Naive Physics* is the body of knowledge that people have about the surrounding physical world (Hayes 1978)

- *Naive Geography* is the body of knowledge that people have about the surrounding geographic world
- Requires a set of theories that provide the basis for designing systems that follow human intuition

"Naïve geography"

(today's view)

The set of theories should comprise:

- Core spatial concepts
- Relationships between concepts
- Reasoning

... and be based on cognitive principles:

- Inaccessible; but externalized in language, graphical communication, and behaviour
- Different from neuroscience

Ontology of core spatial concepts

(Kuhn et al. 2012, 2016)

base concept

- Location

content concepts

- Object
- Field
- Network
- Event

© Werner Kuhn

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Qualitative spatial relationships

(Egenhofer 1989, Randell et al. 1992, Mark et al. 1995)

- Qualitative spatial relations
  - unary, binary, ternary
  - expressed in prepositions, verbs, sketches, or formally in topology, geometry and first order logic
- Formal models for
  - topological relations (Egenhofer 1989, Randell et al. 1992)
  - directions (cardinal, relative) (Frank 1991, Freksa 1991)
  - distances (Worboys 2001)

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Qualitative spatial relationships

(Egenhofer 1989, Randell et al

- Quali
  - una
  - exp
    top
- Form
  - top
  - dire
  - dist

Challenging:

- non-binary relations, and ambiguous relations
  - e.g., "between", "surrounded by", "at"
- various ontological commitments possible
  - e.g., point set topology or first-order logic
- context-dependence
  - e.g., reference frames
- linguistic flexibility, indeterminacy, non-universality
  - e.g., some prepositions not translatable
- cognitive adequacy (Mark 1989, 1999, Mark & Egenhofer 1994)
  - e.g., cardinal direction systems

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Qualitative spatial reasoning

(Freksa 1991, Frank 1991, Egenhofer 1991, Cohn 1996, Renz 2002, Ligozat 2013)

- By formal models:
  - Composition tables (Egenhofer 1991)
  - Calculi (Cohn 1996)
  - SparQ (Wolter 2009)
- Limited tools for cross-family reasoning

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Qualitative spatial reasoning

(Freksa 1991, Frank 1991, Egenhofer 1991, Cohn 1996, Renz 2002, Ligozat 2013)

- By formal models:
  - Composition tables (Egenhofer 1991)
  - Calculi (Cohn 1996)
  - Sp
- Limit

Challenging:

- consistency is a hard problem
- limited cross-family reasoning

- cognitive adequacy:
  - lack of context
  - hierarchical and default reasoning
    "topology defines, geometry refines" (Mark 1999)

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Place

- A matter for communication
  - news items, travel guides, websites, social media, captions, search queries, navigation systems, location-based services, voice assistants

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Place

- A matter for communication
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On Q&A websites:

"Most people began their business question with the words 'Where can I find/get/buy', 'What is the location of' or 'How do I find'."

Amanda Spink and Okan Gunar. 2001. E-commerce Web queries: Excite and Ask Jeeves study. First Monday 6, 7 (2001)

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Place

- A matter for communication
  - news items, travel guides, websites, social media, captions, search queries, navigation systems, location-based services, voice assistants

In general search:

"About 1 in 3 of queries that people just type into a standard Google search bar are about places, they are about finding out information about locations."

Ed Parsons, Geospatial Chief Technologist of Google, 2012

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Place

- A matter for communication
  - news items, travel guides, websites, social media, captions, search queries, navigation systems, location-based services, voice assistants

In voice assistants:

Voice assistants in self-driving cars

CES 2018, MBUX

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Place

- A matter for communication
  - news items, travel guides, websites, social media, captions, search queries, navigation systems, location-based services, voice assistants

- … but not a core concept

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Place

- A matter for communication
  - news items, travel guides, websites, social media, captions, search queries, navigation systems, location-based services, voice assistants

- Human experience, social construct
- Incompatible with geometric foundations of spatial IS
  - GIS, spatial databases, big data / IoT, POI, gazetteers

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Place

- Compatible with core spatial concepts:
- A *place* is an *object* resulting from a shared identification of a *location*
  - social construct
  - has a location
  - has unique identity, properties, relationships
  - properties are debated, but cognitive/perceptual

  (Alexander 2002, Vasardani & Winter 2016)

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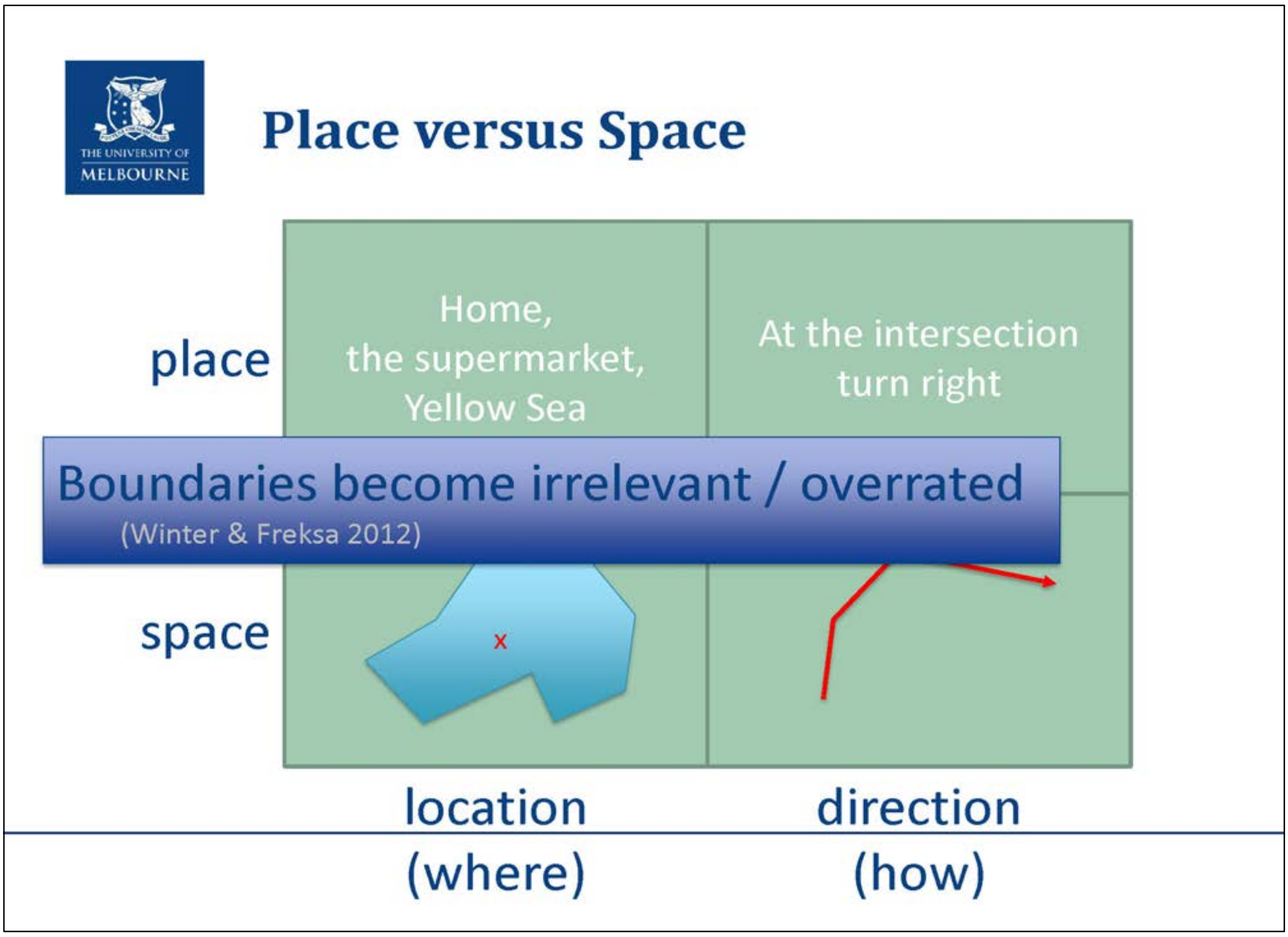
Place versus Space

	location (where)	direction (how)
place	Home, the supermarket, Yellow Sea	At the intersection turn right
space		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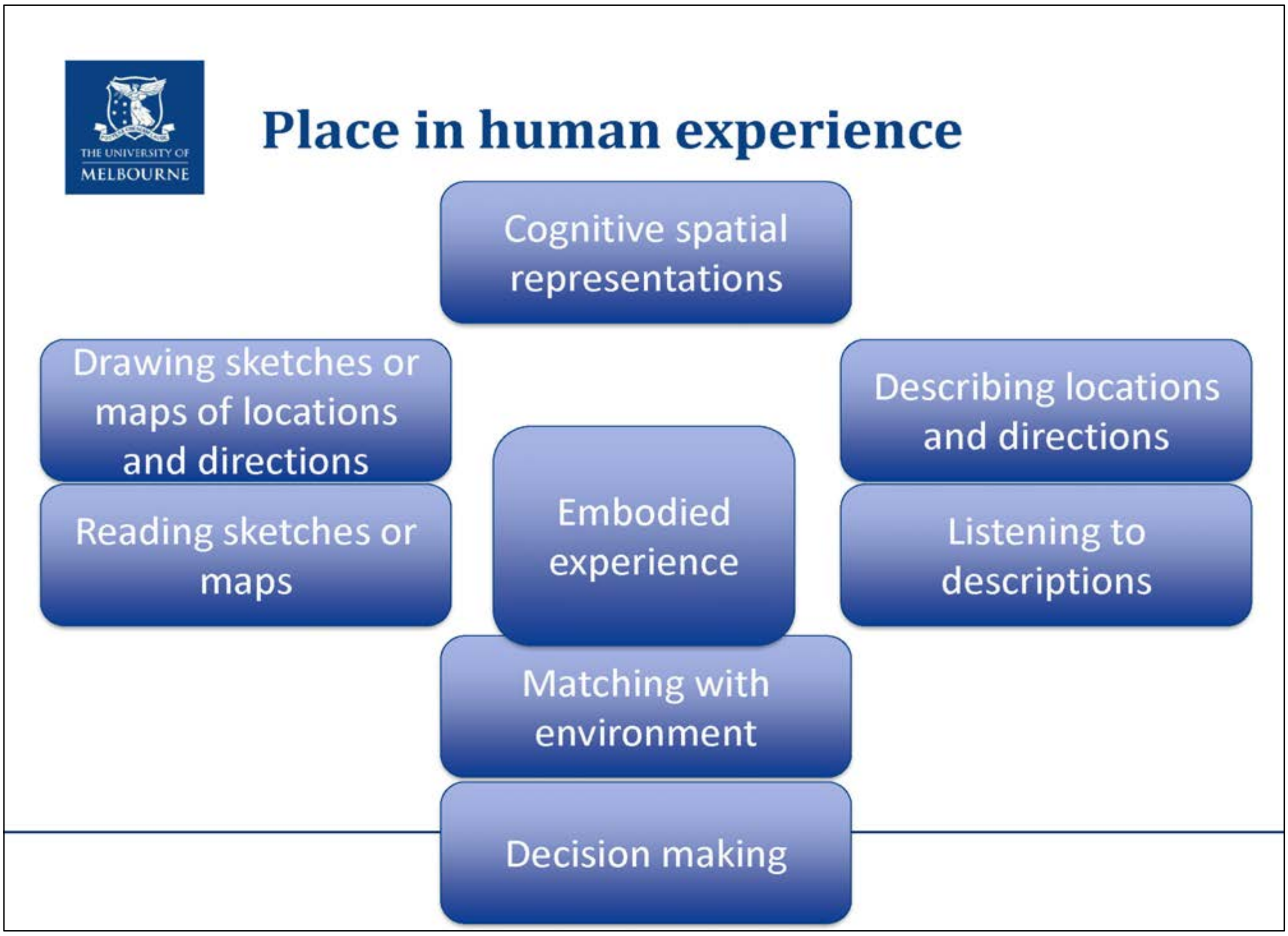
Place versus Space
place
Home,
the supermarket,
Yellow Sea
At the intersection
turn right
Boundaries become irrelevant / overrated
(Winter & Freksa 2012)
space
x
location
(where)
direction
(how)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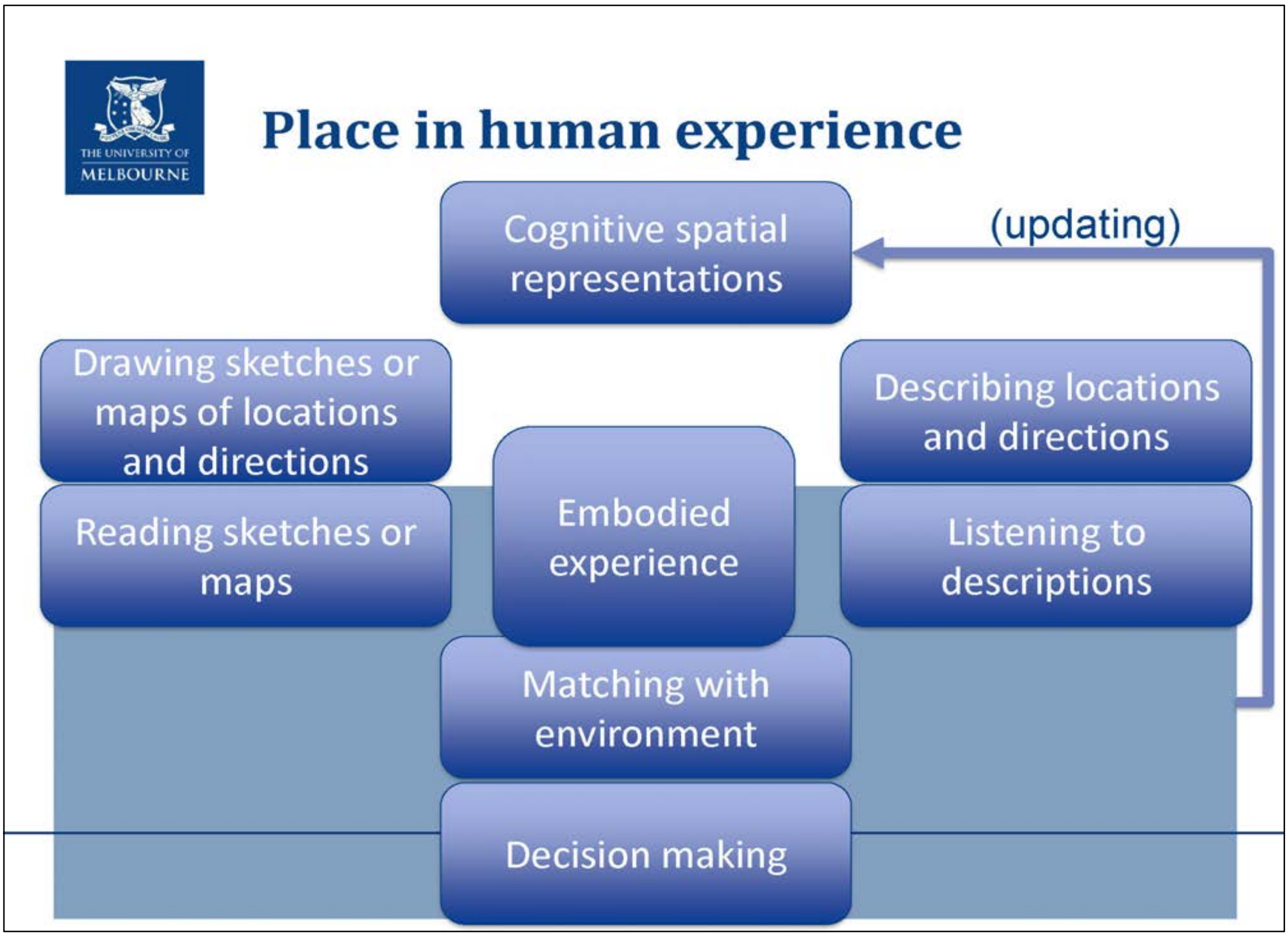
Place in human experience
Cognitive spatial representations
Drawing sketches or maps of locations and directions
Describing locations and directions
Reading sketches or maps
Embodied experience
Listening to descriptions
Matching with environment
Decision making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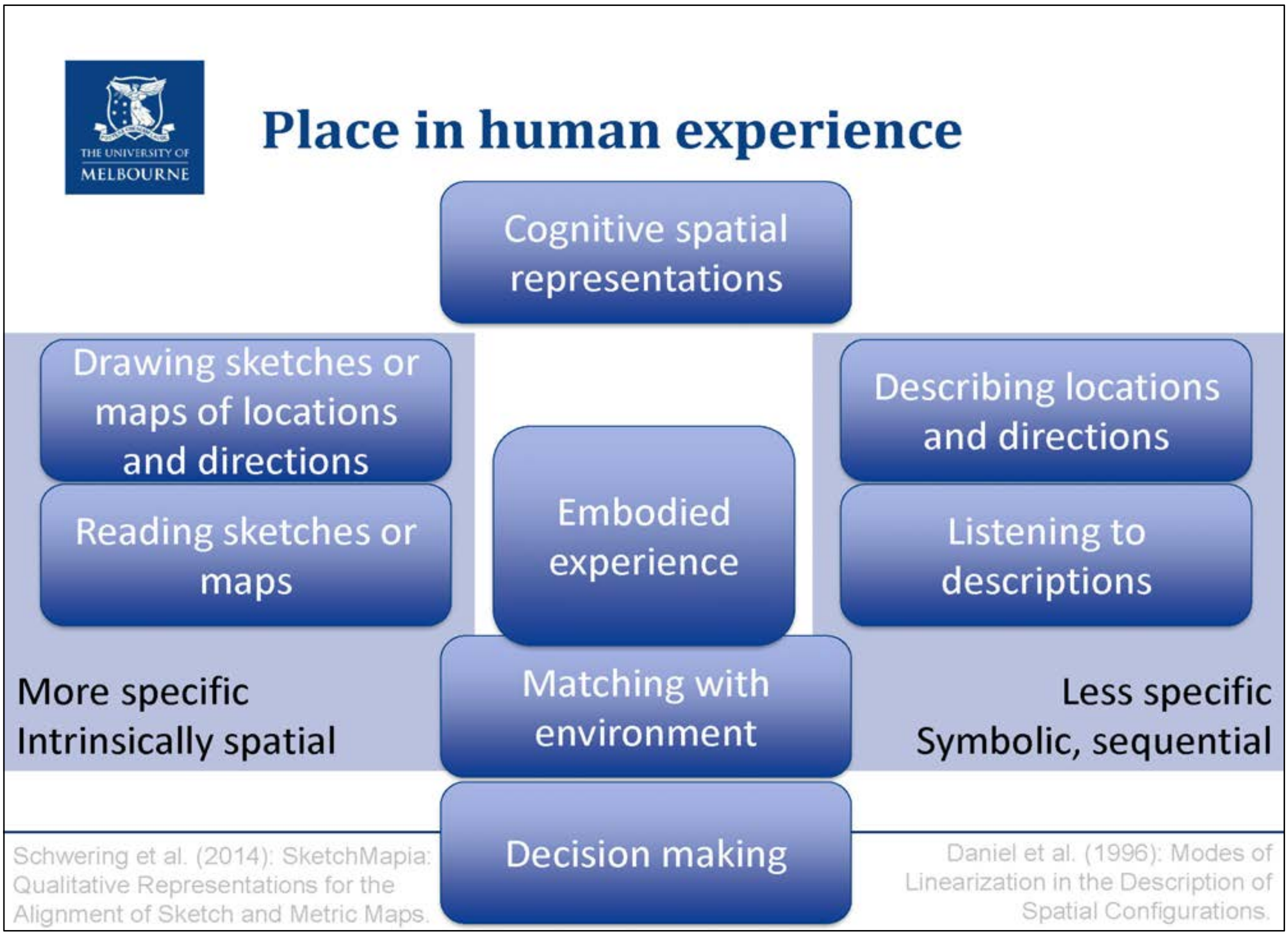
Place in human experience
Cognitive spatial representations
(updating)
Drawing sketches or maps of locations and directions
Describing locations and directions
Reading sketches or maps
Embodied experience
Listening to descriptions
Matching with environment
Decision making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Place in human experience
Cognitive spatial representations
Drawing sketches or maps of locations and directions
Describing locations and directions
Reading sketches or maps
Embodied experience
Listening to descriptions
More specific
Intrinsically spatial
Matching with environment
Less specific
Symbolic, sequential
Decision making
Schwering et al. (2014): SketchMapia: Qualitative Representations for the Alignment of Sketch and Metric Maps.
Daniel et al. (1996): Modes of Linearization in the Description of Spatial Configurations.

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Place-based GIS

Why it is needed

– To realize naïve geography in UX

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Place-based GIS

What it needs

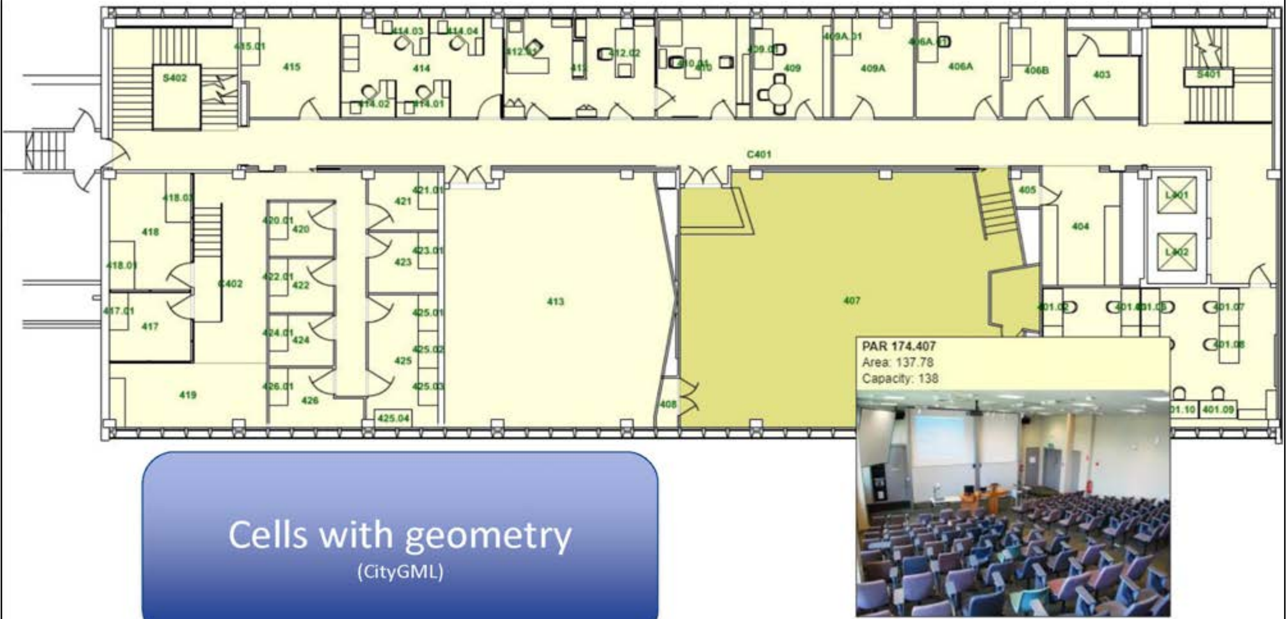
– Tools/theories for *capturing*, *managing*, *analysing* and *querying* place-based knowledge
– Atomic elements:
  - *places* and *relationships*
– Linking with space-based GIS:
  - geocoding places ↔ reverse geocoding

Place-based GIS

How it can be built

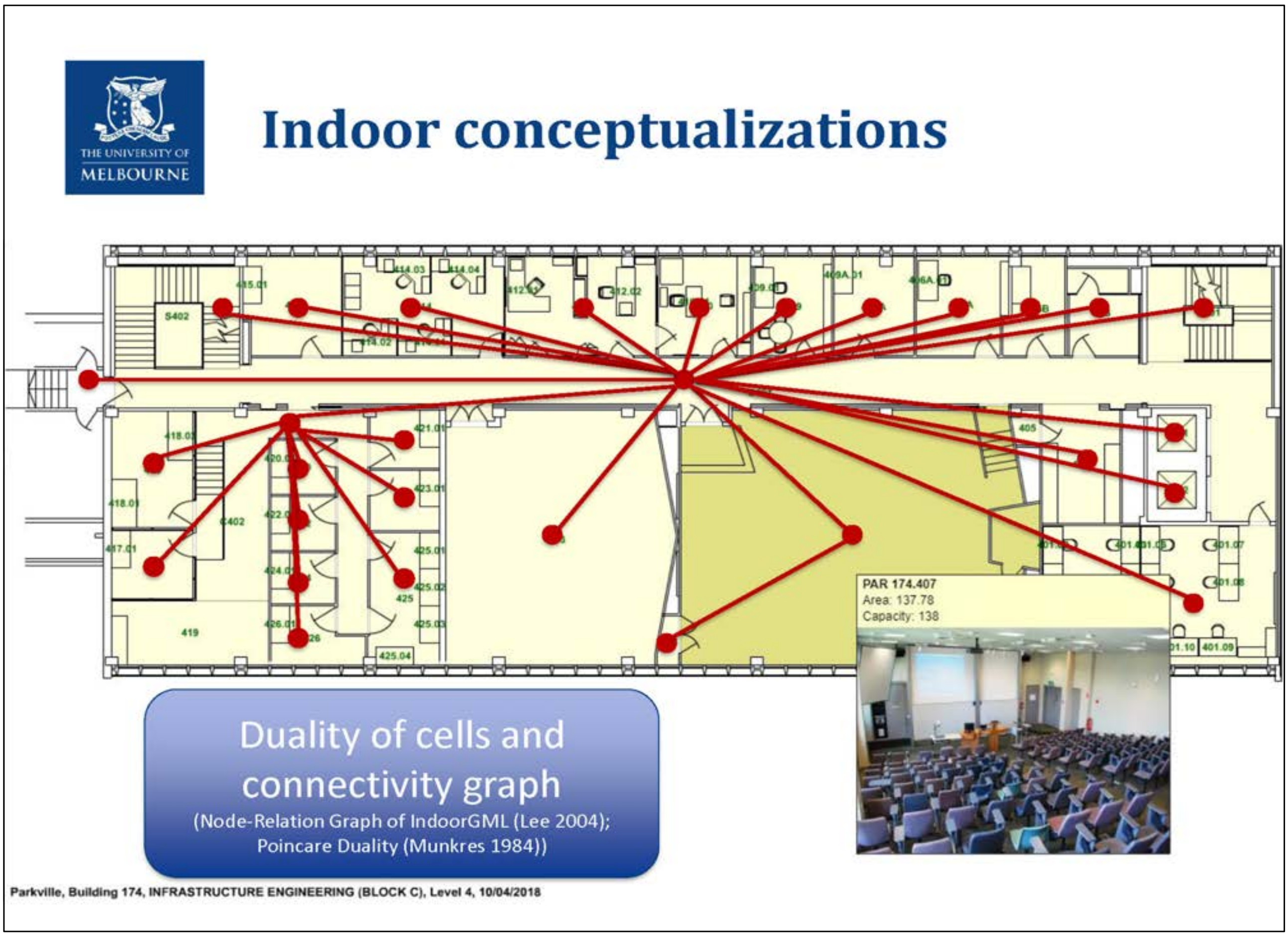
- Capturing
  - Place descriptions, route descriptions as source
  - Parsing and tagging (places, relations, context)
- Managing
  - Graph database, database query language (Cypher)
- Analysing / Querying
  - Network analysis. Geocoding. Reasoning.
  - Ontology of Q&A

Indoor conceptualizations



Cells with geometry
(CityGML)

Parkville, Building 174, INFRASTRUCTURE ENGINEERING (BLOCK C), Level 4, 10/04/2018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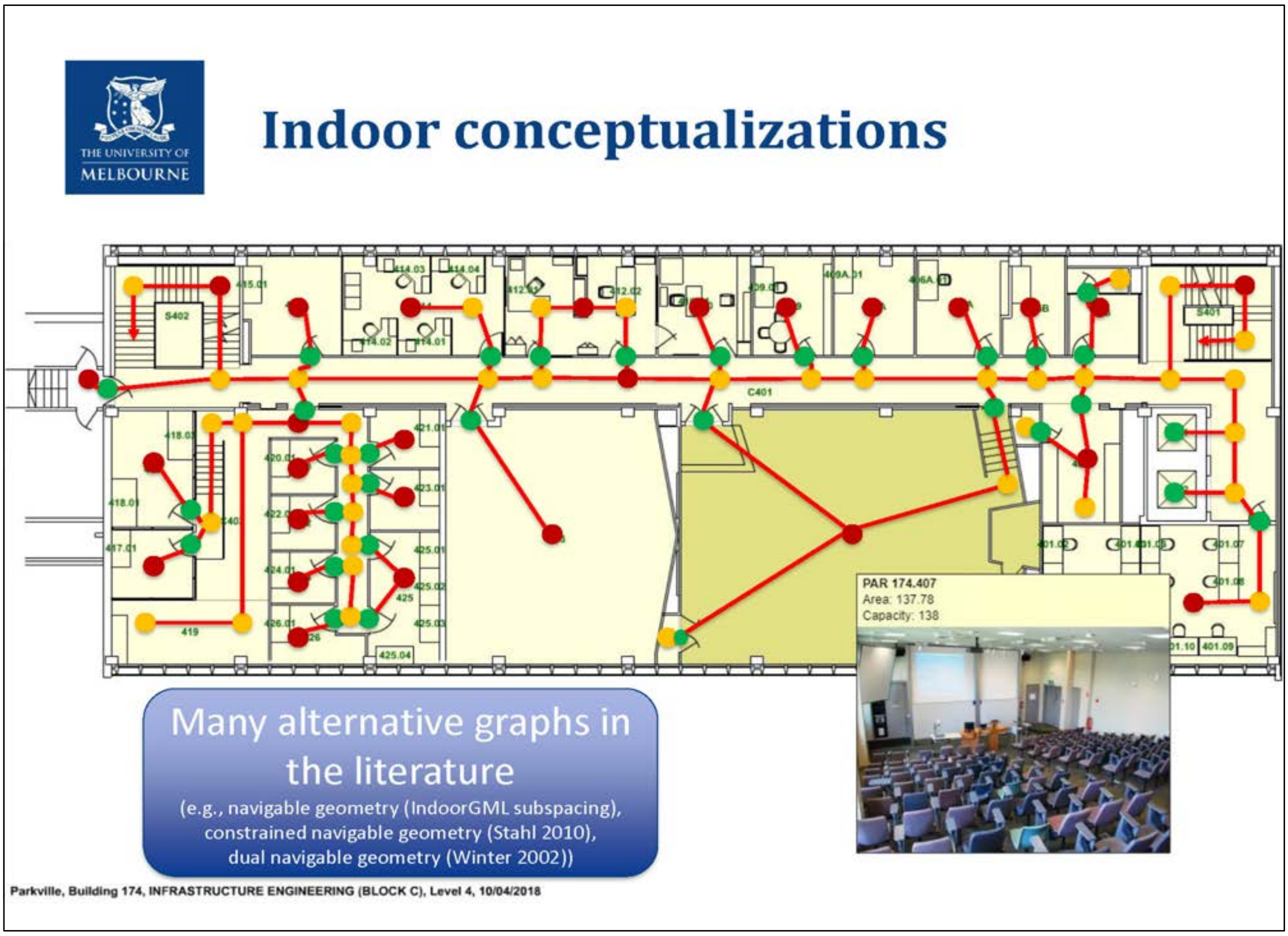
Indoor conceptualizations
PAR 174.407
Area: 137.78
Capacity: 138
Duality of cells and connectivity graph
(Node-Relation Graph of IndoorGML (Lee 2004);
Poincare Duality (Munkres 1984))
Parkville, Building 174, INFRASTRUCTURE ENGINEERING (BLOCK C), Level 4, 10/04/2018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Indoor conceptualizations
PAR 174.407
Area: 137.78
Capacity: 138
Many alternative graphs in the literature
(e.g., navigable geometry (IndoorGML subspacing),
constrained navigable geometry (Stahl 2010),
dual navigable geometry (Winter 2002))
Parkville, Building 174, INFRASTRUCTURE ENGINEERING (BLOCK C), Level 4, 10/04/2018

Indoor conceptualizations

- Levels of detail
  - indicate a hierarchical structure (Richter and Winter 2011; IndoorGML 2016)
  - chosen for task at hand

- Connectivity (topology)
  - has least detail
  - (roughly) matches granularity of indoor descriptions

A formulaic place description

My office is in Block B,
on the third floor,
opposite the kitchen.

- Configurational knowledge
- No instructions how to find it

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A formulaic **route** description

[For the office,]
enter the hallway,
take the lift to the third floor,
walk down the corridor.

- Sequential instructions how to find it
- No explicit configurational knowledge

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A **place** description ontology

Triplets of:

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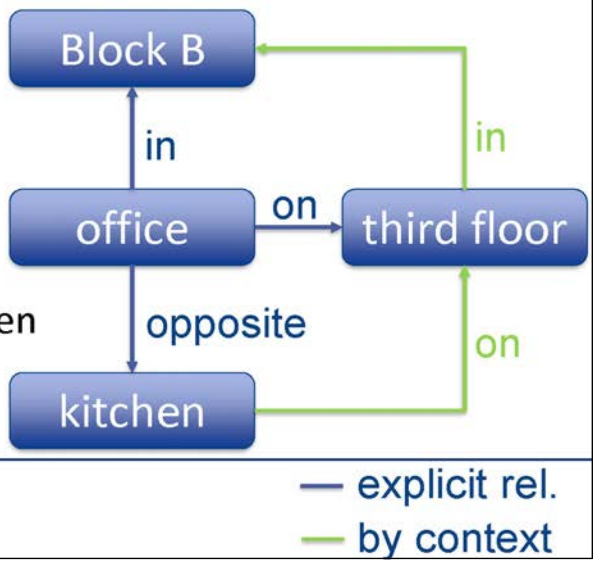
A place description ontology

My office is in Block B,
on the third floor,
opposite the kitchen.

- My office is in Block B
  - complete triplet
- Inferences:
  - [my office] is on the third floor
  - [my office] is opposite the kitchen



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A route description ontology

Triplet of:

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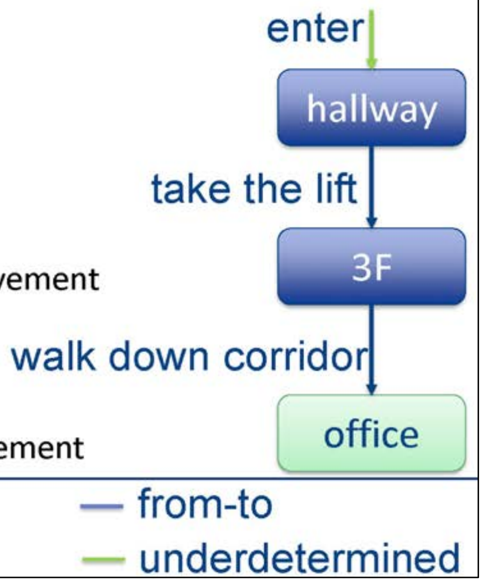
A route description ontology

Enter the hallway,
take the lift to the third floor,
walk down the corridor.

- Enter the hallway
  - no explicit origin
  - origin missing
- Take the lift to the third floor
  - no explicit origin
  - origin can be inferred from continuity of movement
- Walk down the corridor
  - no explicit origin, no explicit destination
  - both can be inferred from continuity of movement



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Observations

- Rarely a ‘pure’ place or route description
  (Winter et al. 2018, Krukar et al. 2018)

[*At the stairs*],
take the left corridor

  - ➢ Integrated graph ontology required
- Ontological conflicts between place and route graphs
  - ➢ Nodes (places): rest vs pass
  - ➢ Arcs: relations vs actions

Footer 36

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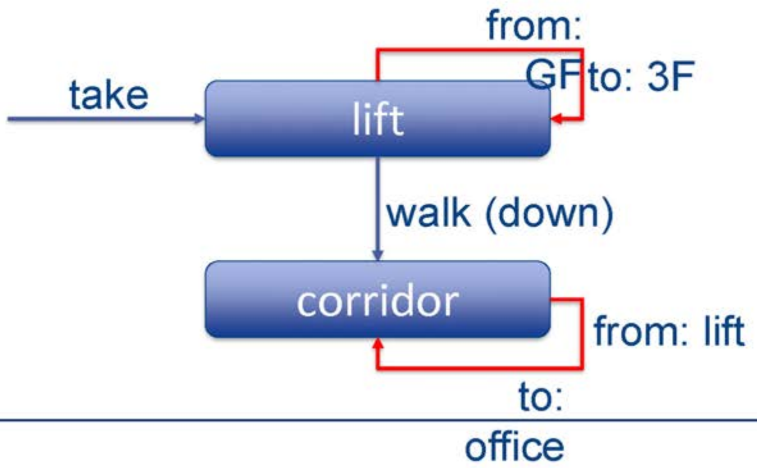
Nodes

- Extend passages by loops

Enter the hallway,
take the lift to the third floor,
walk down the corridor.



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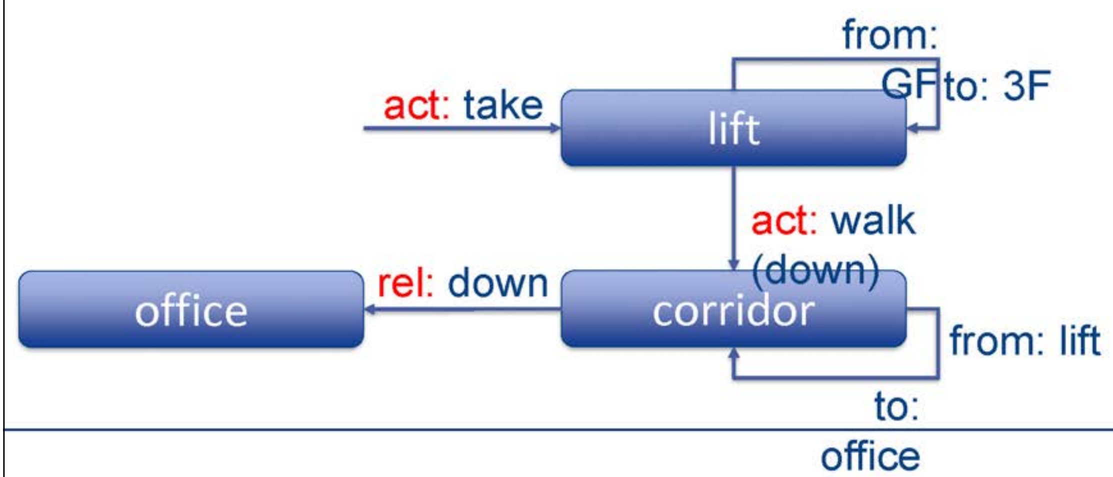
Arcs

- Introduce parameterized arcs

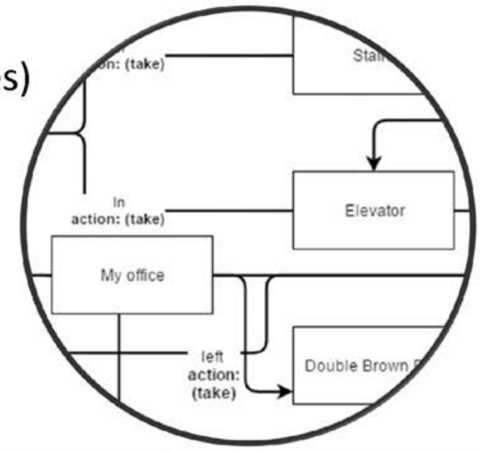
Enter the hallway,
take the lift to the third floor,
walk down the corridor.



Discussion & outlook

Conclusions

- Place can be formally captured
  - By core spatial concepts
  - From language
  - In graphs (w. parametrized edges)
- Tension between configurational and instructional structures
- AI required at any level



Thank you

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- Kim, J.; Vasardani, M.; Winter, S. (2017): **Similarity matching for integrating spatial information extracted from place descriptions**. *International Journal of Geographical Information Science*, 31 (1): 56-80.
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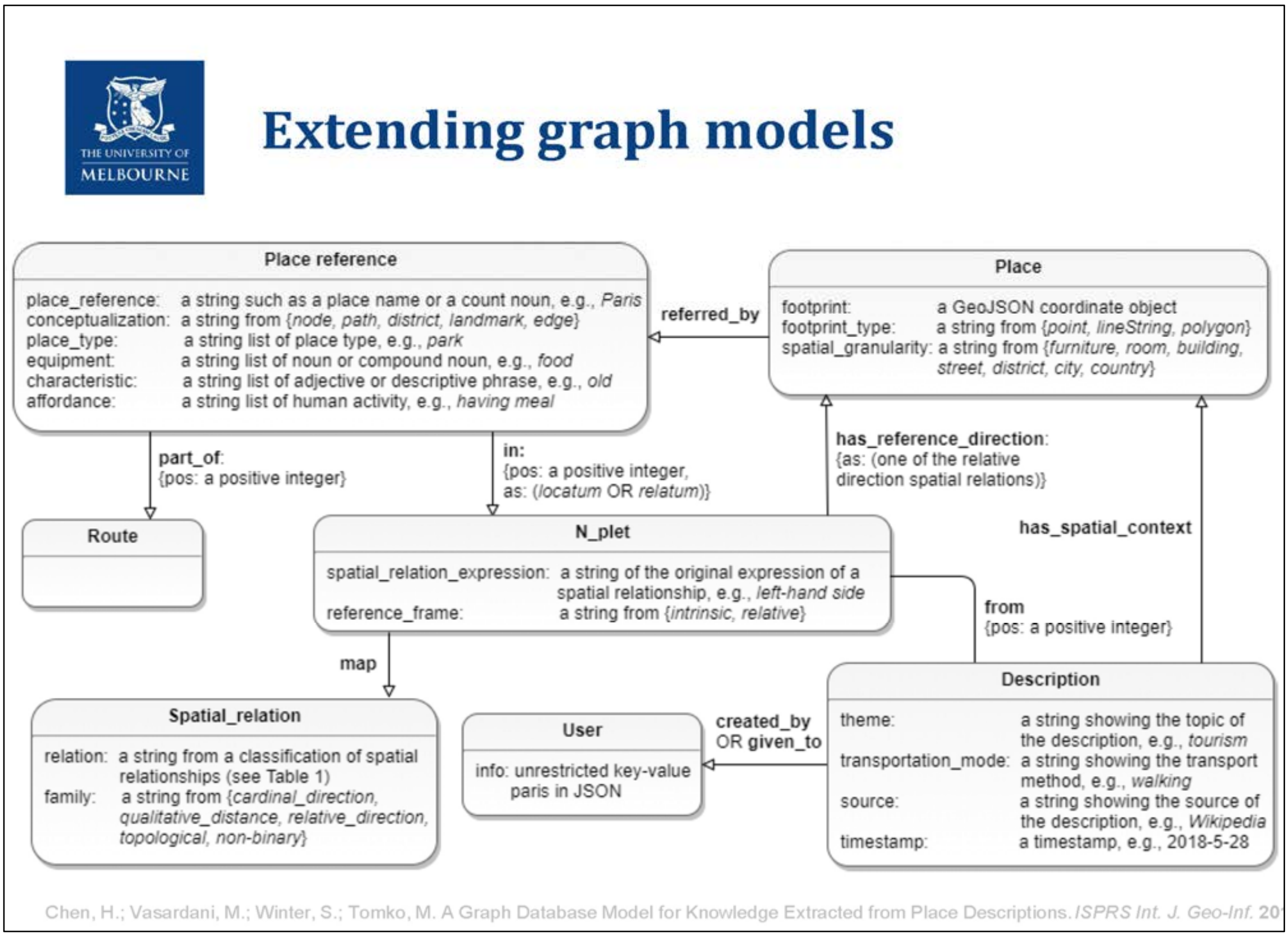
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Extending graph models
Place reference
place_reference: a string such as a place name or a count noun, e.g., Paris
conceptualization: a string from {node, path, district, landmark, edge}
place_type: a string list of place type, e.g., park
equipment: a string list of noun or compound noun, e.g., food
characteristic: a string list of adjective or descriptive phrase, e.g., old
affordance: a string list of human activity, e.g., having meal
referred_by
Place
footprint: a GeoJSON coordinate object
footprint_type: a string from {point, lineString, polygon}
spatial_granularity: a string from {furniture, room, building, street, district, city, country}
part_of:
{pos: a positive integer}
in:
{pos: a positive integer,
as: (locatum OR relatum)}
has_reference_direction:
{as: (one of the relative direction spatial relations)}
has_spatial_context
Route
N_plet
spatial_relation_expression: a string of the original expression of a spatial relationship, e.g., left-hand side
reference_frame: a string from {intrinsic, relative}
from
{pos: a positive integer}
map
Description
theme: a string showing the topic of the description, e.g., tourism
transportation_mode: a string showing the transport method, e.g., walking
source: a string showing the source of the description, e.g., Wikipedia
timestamp: a timestamp, e.g., 2018-5-28
Spatial_relation
relation: a string from a classification of spatial relationships (see Table 1)
family: a string from {cardinal_direction, qualitative_distance, relative_direction, topological, non-binary}
User
info: unrestricted key-value paris in JSON
created_by
OR given_to
Chen, H.; Vasardani, M.; Winter, S.; Tomko, M. A Graph Database Model for Knowledge Extracted from Place Descriptions. ISPRS Int. J. Geo-Inf. 20

New Approaches to Space-Time Analytics of Human Dynamics

May Yuan
Professor, The University of Texas at Dallas

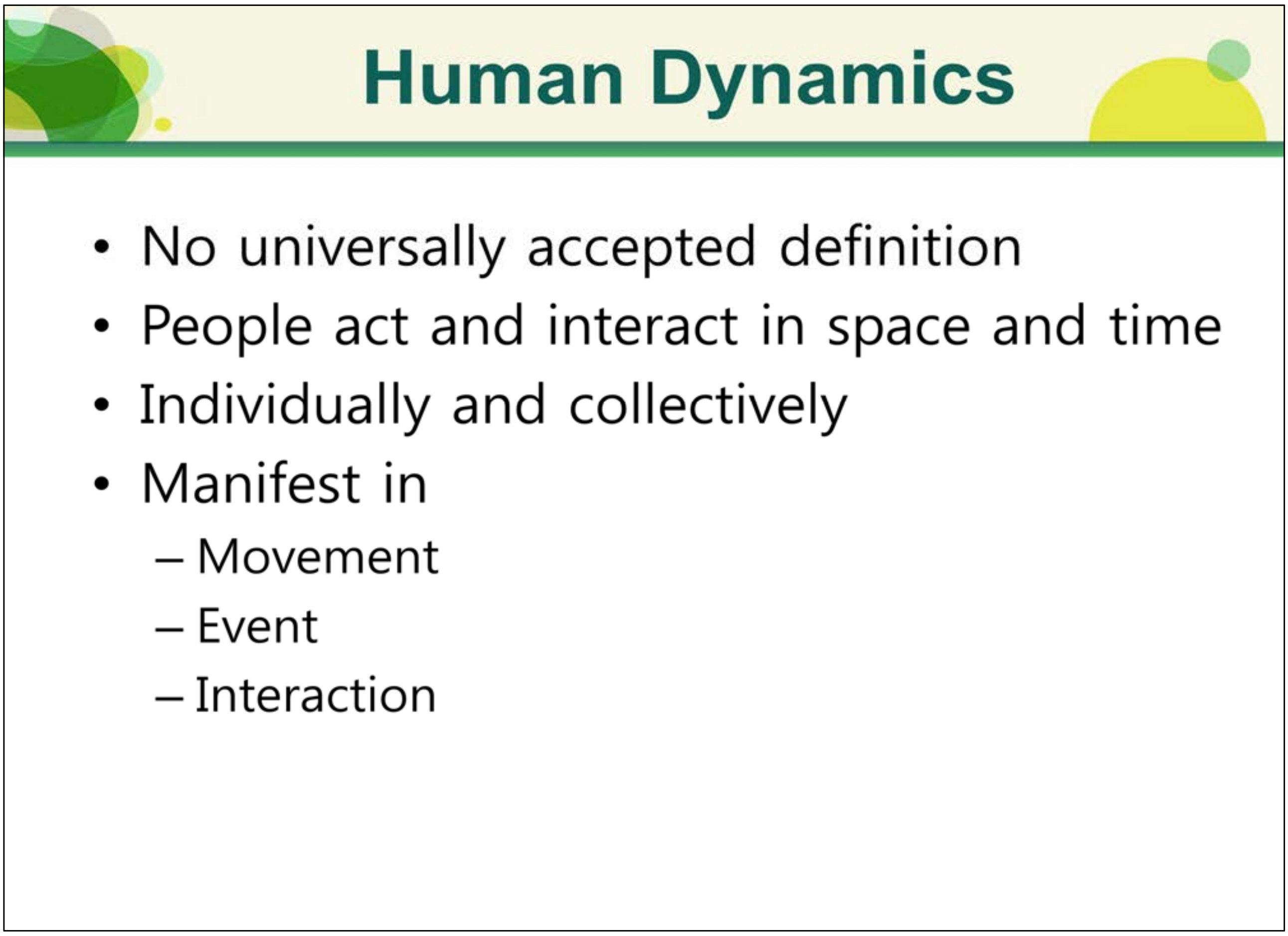
New Approaches to Space-Time Analytics of Human Dynamics

May Yuan
myuan@utdallas.edu
University of Texas at Dallas

Abstract

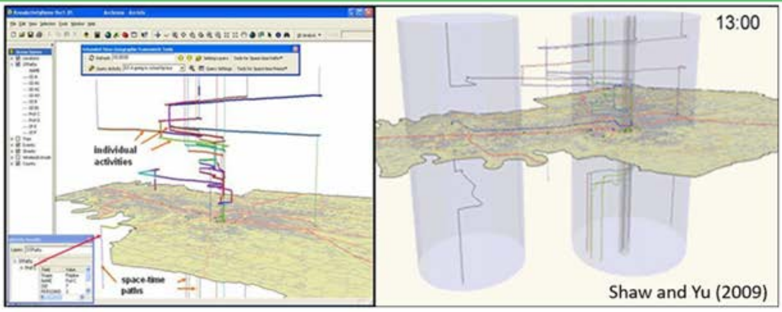
Human dynamics broadly include human activities and interactions in space and time. To-date, research on human dynamics in space and time is fueled by ambient data from social media, call detailed records, GPS devices, social internet of things, sensor networks, and various governmental open data source. Traditional GIS methods are inadequate to handle such massive, messy, and disaggregate space-time data. In this talk, I will present three new approaches to eliciting and analyzing patterns of human dynamics in space and time. I will focus on three conceptual constructs of human dynamics: movement, event, and interaction. For each construct, I will present new conceptual and computational bases with a case study. Specifically, I will use GPS trajectory data to understand movement patterns, use crime events to elicit criminogenic places, and use international trade data to uncover interaction trends. The most important objective is to distill how movement, event, and interaction vary in space and time. Machine learning methods play a key role in achieving the objective in these cases. While there are many published studies on movement analysis, event prediction, and interaction modeling, this talk will show how the new approaches to space-time analytics can reveal novel insights. With the cases, I wish to communicate the importance of developing new conceptual and computational approaches to understanding human dynamics and call for new space-time thinking beyond the current GIS framework.


KRIHS
2018 International Conference on Geospatial Information Science
New Approach to Space-Time Analytics of Human Dynamics
May Yuan, PhD (myuan@utdallas.edu)
University of Texas at Dallas

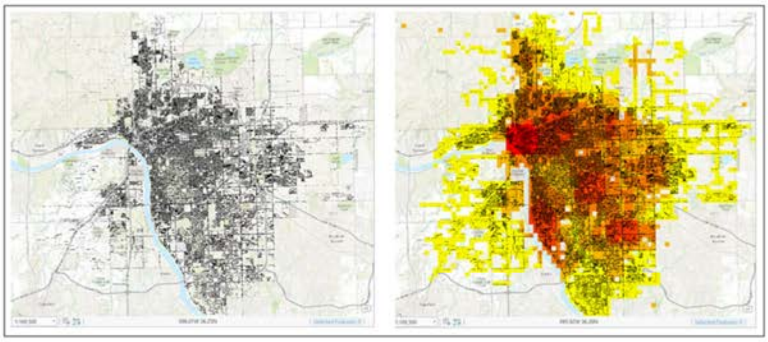

Human Dynamics
• No universally accepted definition
• People act and interact in space and time
• Individually and collectively
• Manifest in
– Movement
– Event
– Interaction

Conventional approaches

Examples



Movement



Event

http://geography.name/spatial-interaction/

Interactions

The Thesis

How we conceptualize space-time

thinking and questioning

↓ **influence**

How we construct GIS representation

element: themes, object, field, event, process
organization: structure and relationship

↓ **constrain**

What analysis we can do in GIS

Perspectives, interpretations, and understanding

From Movement to Patterns of Life

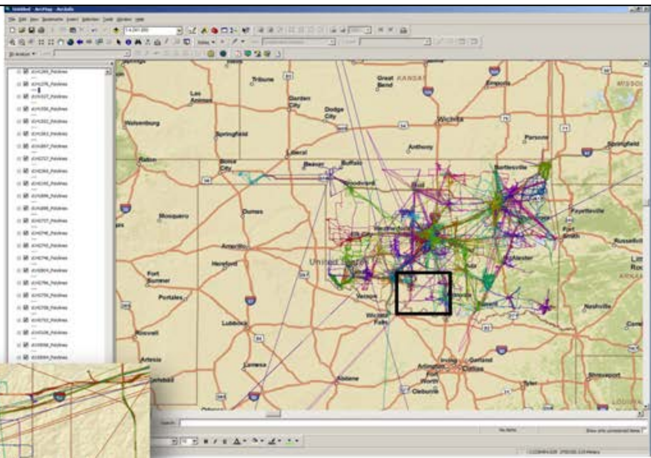
With Atsushi Nara

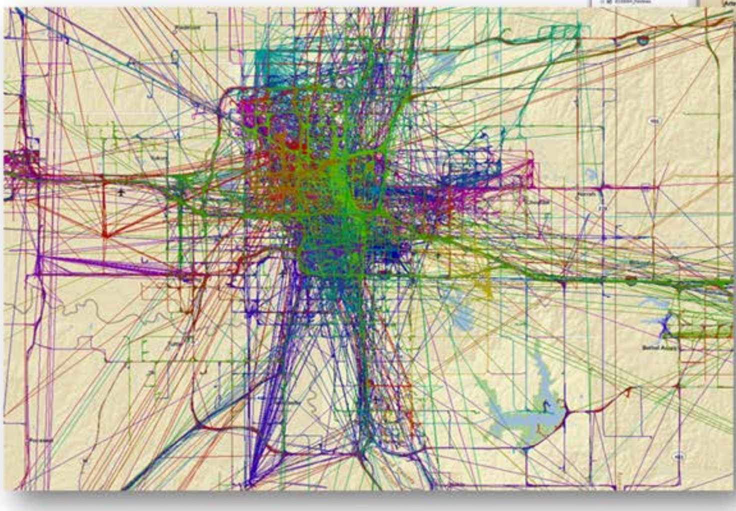
GPS Offender Monitoring Systems

- **Solve overcrowded prisons**
  - ➢ Release low-risk offenders
- **Reduce rising incarceration costs**
  - ➢ Average cost for GPS-based supervision is approximately $5 to $10
- **Reduce increasing incarceration and recidivism rates**
  - ➢ Deter negative behavior by monitoring

Daily ST Paths

- 23 months (2/23/2009 – 1/12/2011)
- 2871 GPS inmates

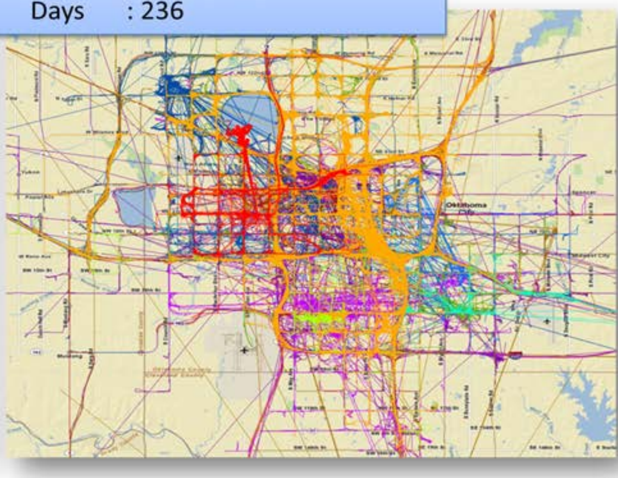




GPS sampling:
- Stay: every hour
- In Motion: every minute
- In Violation: every 15 sec
  - ➢ Exclusion zones (e.g., near school)
  - ➢ Inclusion zones (e.g., curfew)
  - ➢ Device oriented violations (e.g., no signal, battery low, tamper)

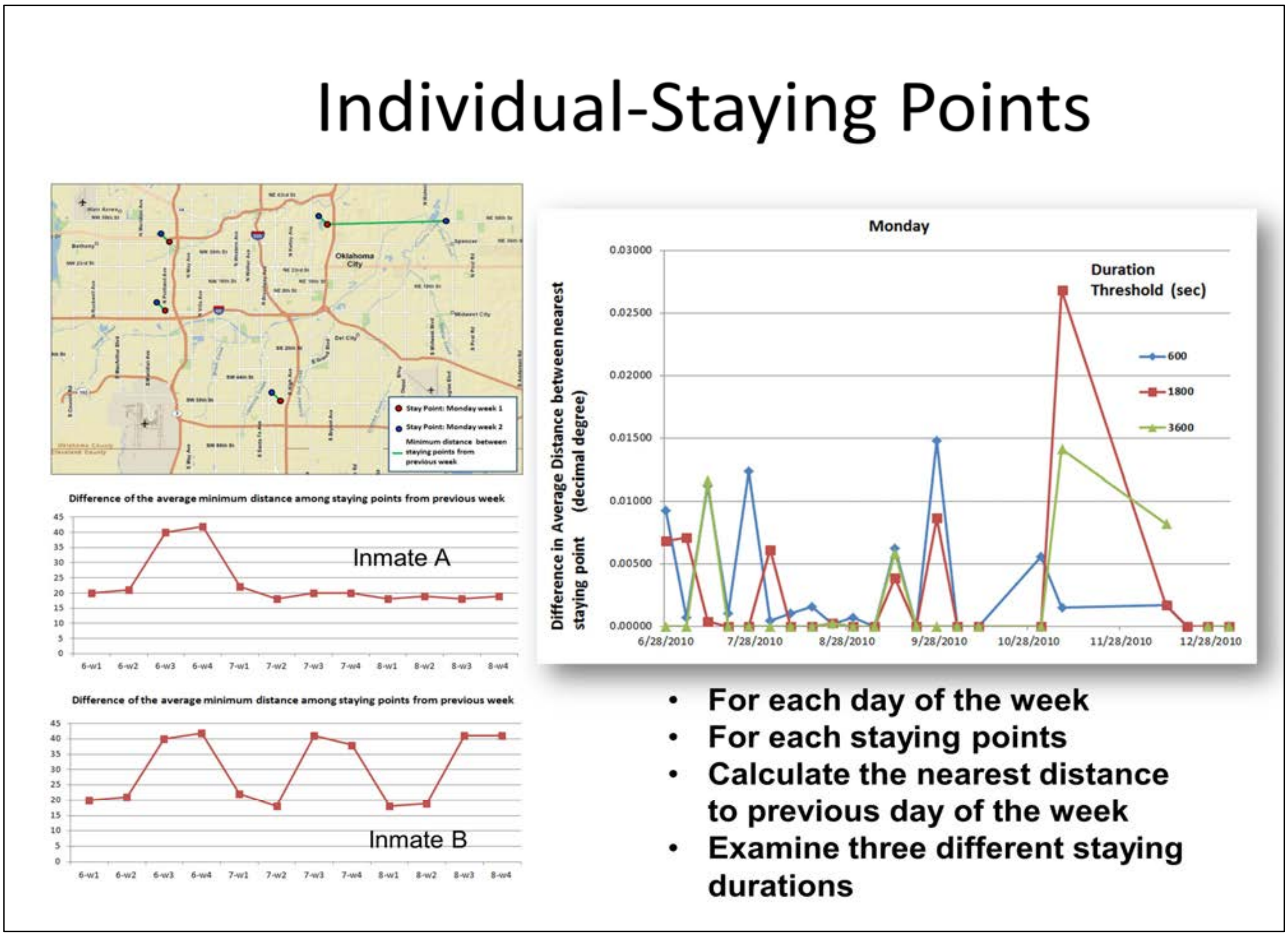
Individual inmate (d106954)
Sampling points: 128,235
Date From: 2009-03-26
Date To : 2009-10-26
Days : 215

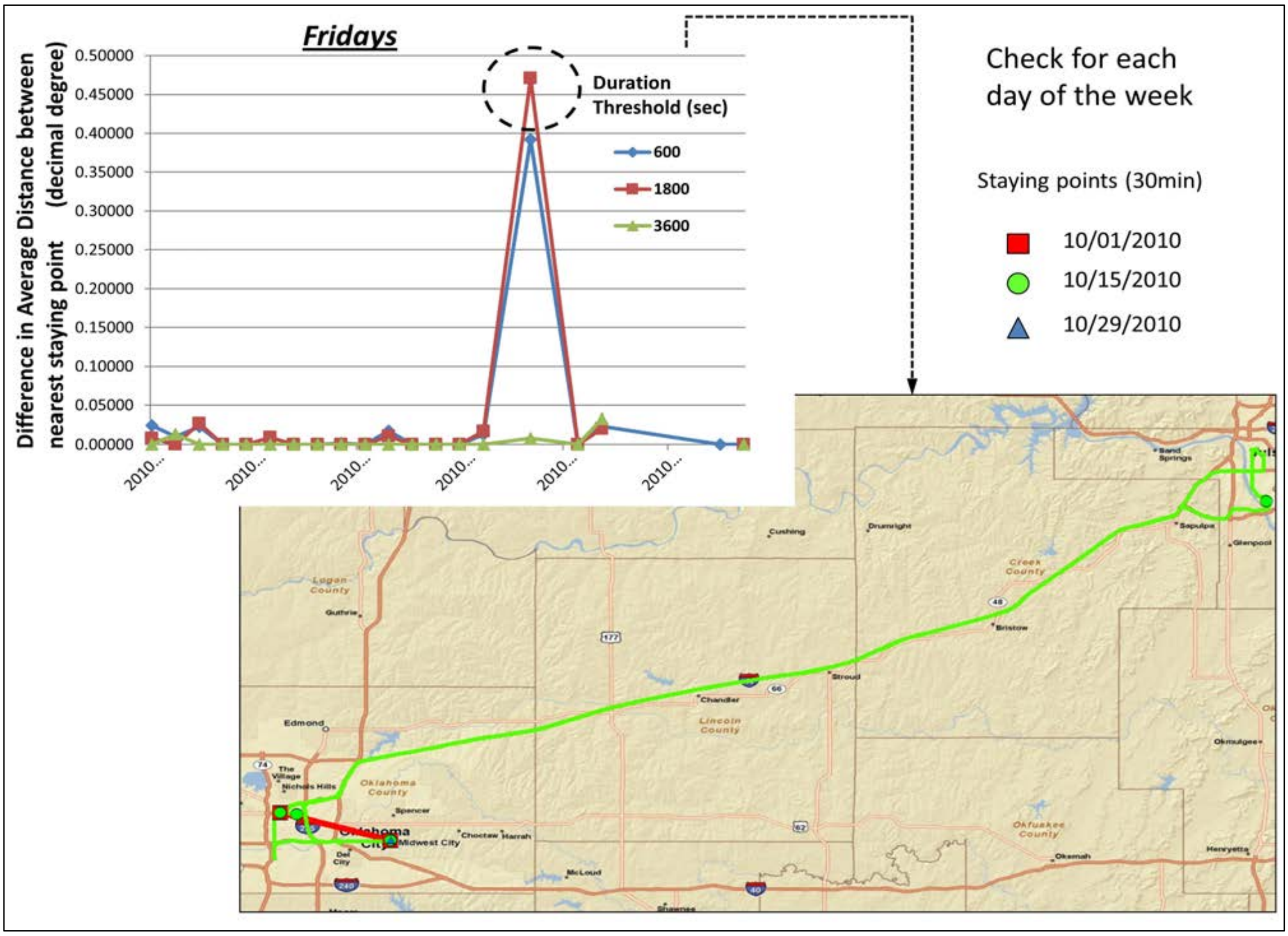
Multiple inmates (14)
Sampling points: 1,118,651
Date From: 2009-03-11
Date To : 2009-10-26
Days : 236



Individual GPS inmates
- Daily, weekly, and monthly patterns
- Automatic detection of violation
- Evolution of space-time tracking patterns
- Automatic detection of abnormal patterns

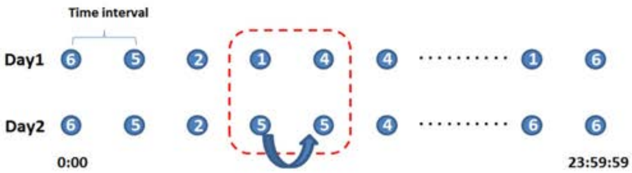
Multiple GPS inmates
- Automatic detection of possibility of meetings
- Automatic detection of potential social networks


Individual-Staying Points
Stay Point: Monday week 1
Stay Point: Monday week 2
Minimum distance between staying points from previous week
Difference of the average minimum distance among staying points from previous week
Inmate A
Difference of the average minimum distance among staying points from previous week
Inmate B
Monday
Difference in Average Distance between nearest staying point (decimal degree)
Duration Threshold (sec)
600
1800
3600
6/28/2010
7/28/2010
8/28/2010
9/28/2010
10/28/2010
11/28/2010
12/28/2010
For each day of the week
For each staying points
Calculate the nearest distance to previous day of the week
Examine three different staying durations


Fridays
Difference in Average Distance between nearest staying point (decimal degree)
Duration Threshold (sec)
600
1800
3600
Check for each day of the week
Staying points (30min)
10/01/2010
10/15/2010
10/29/2010

Individual – Paths

- Origin point
- Destination point
- Intermediate time-ordered points
- speed



Different numbers of observation points
- ➤ **Staying at one location or faster movement**
- ➤ **Repeat previous location**

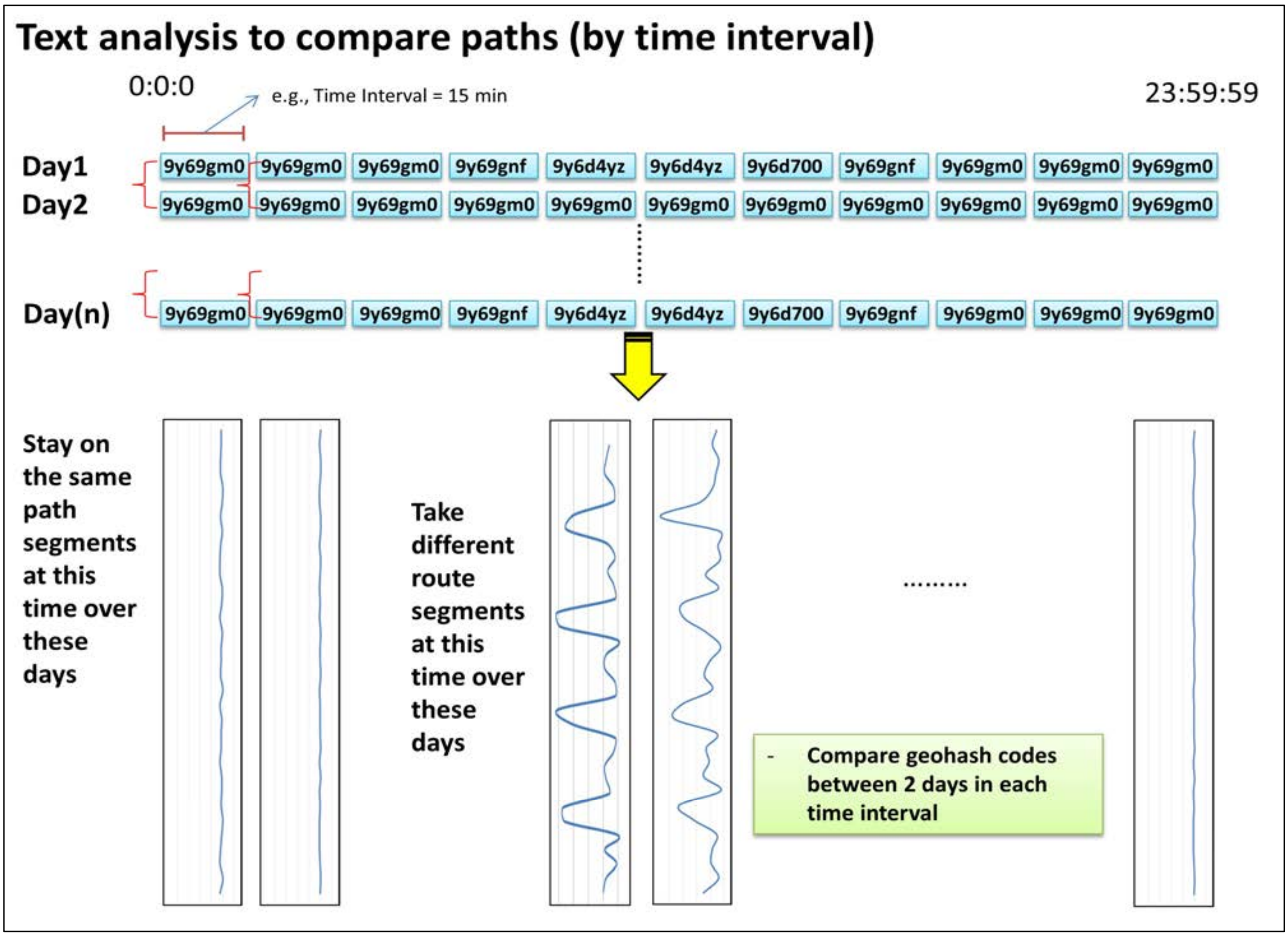
Geohash codes as location IDs

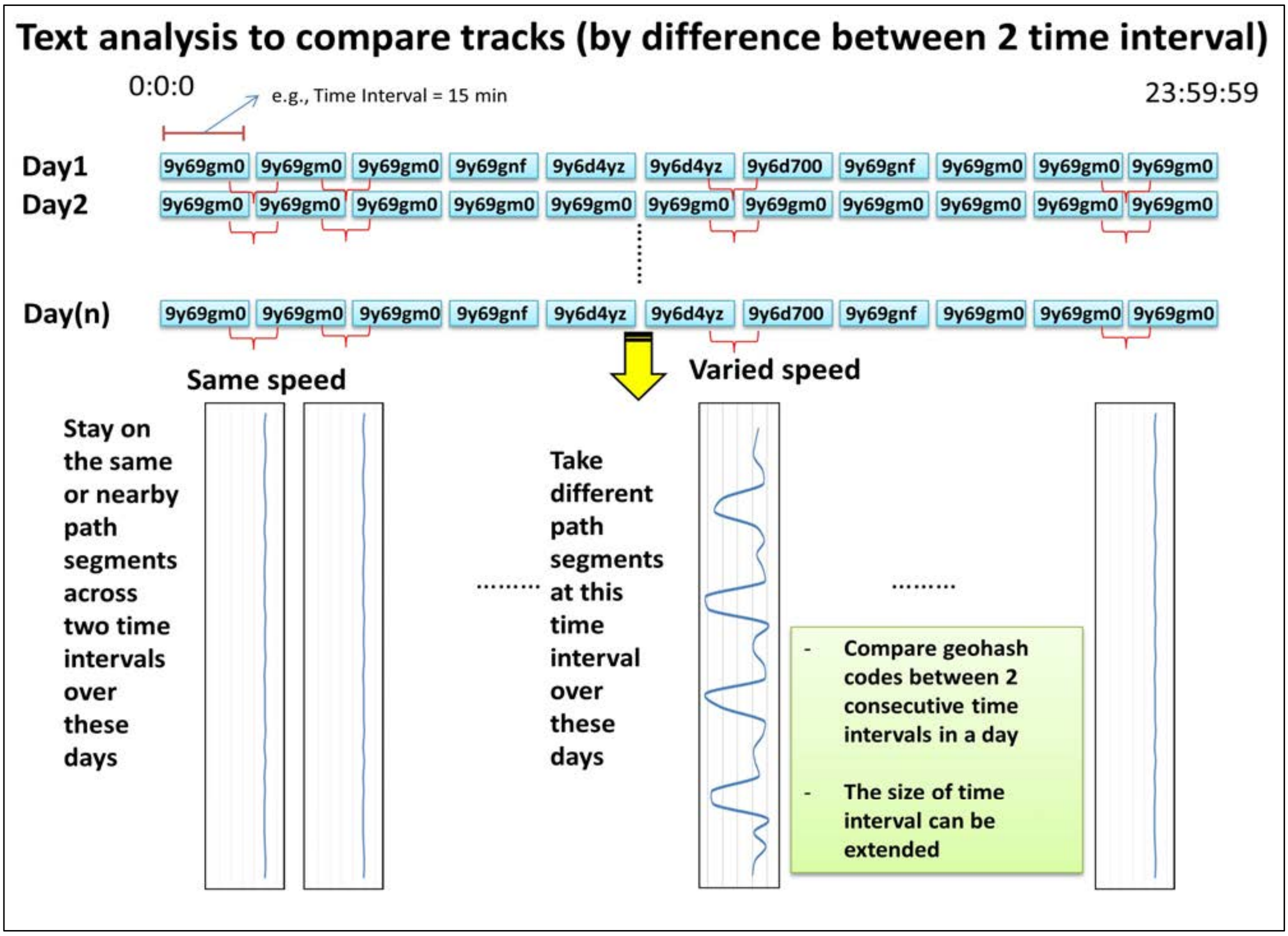
Level 2

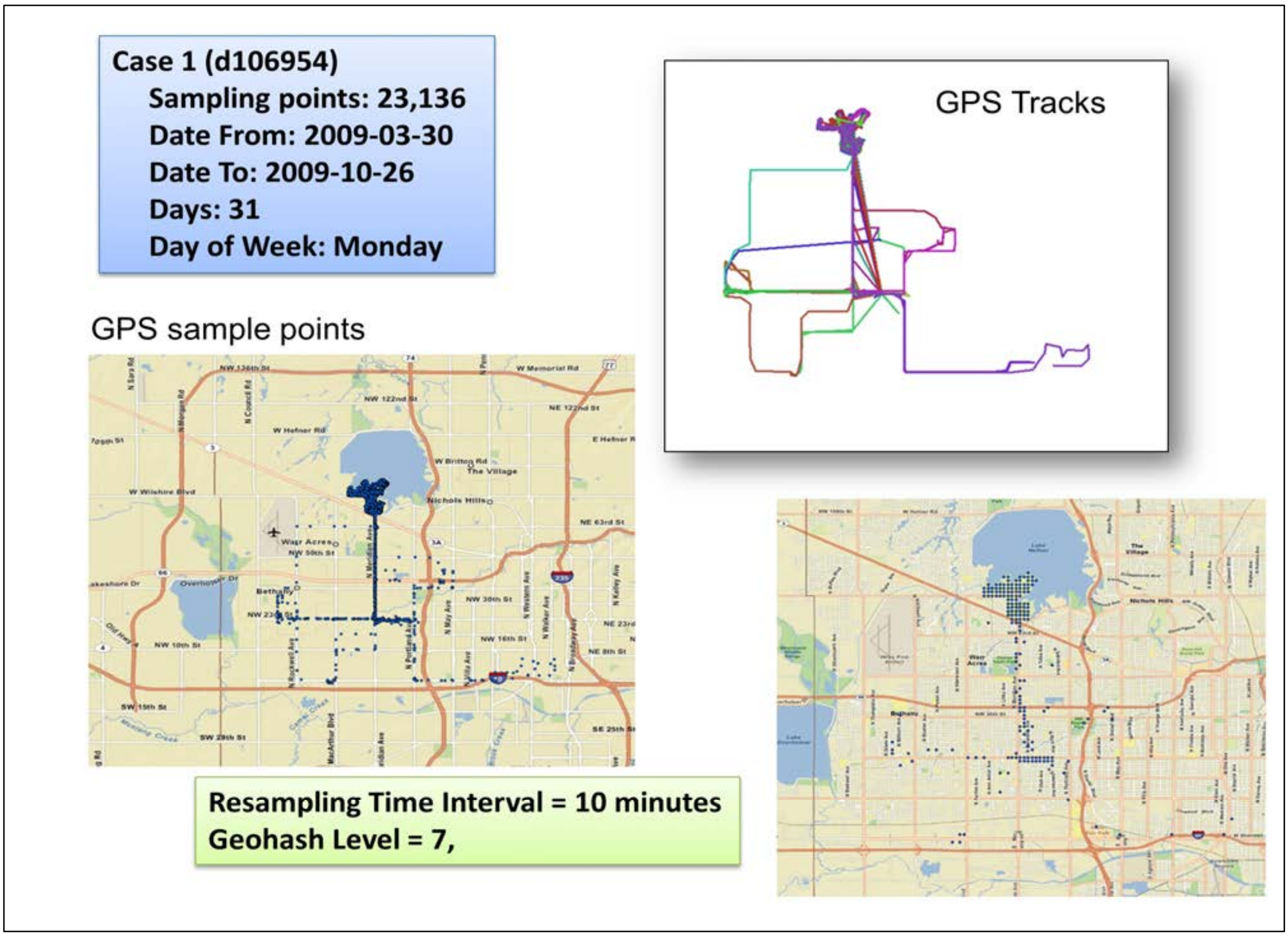
Level 4

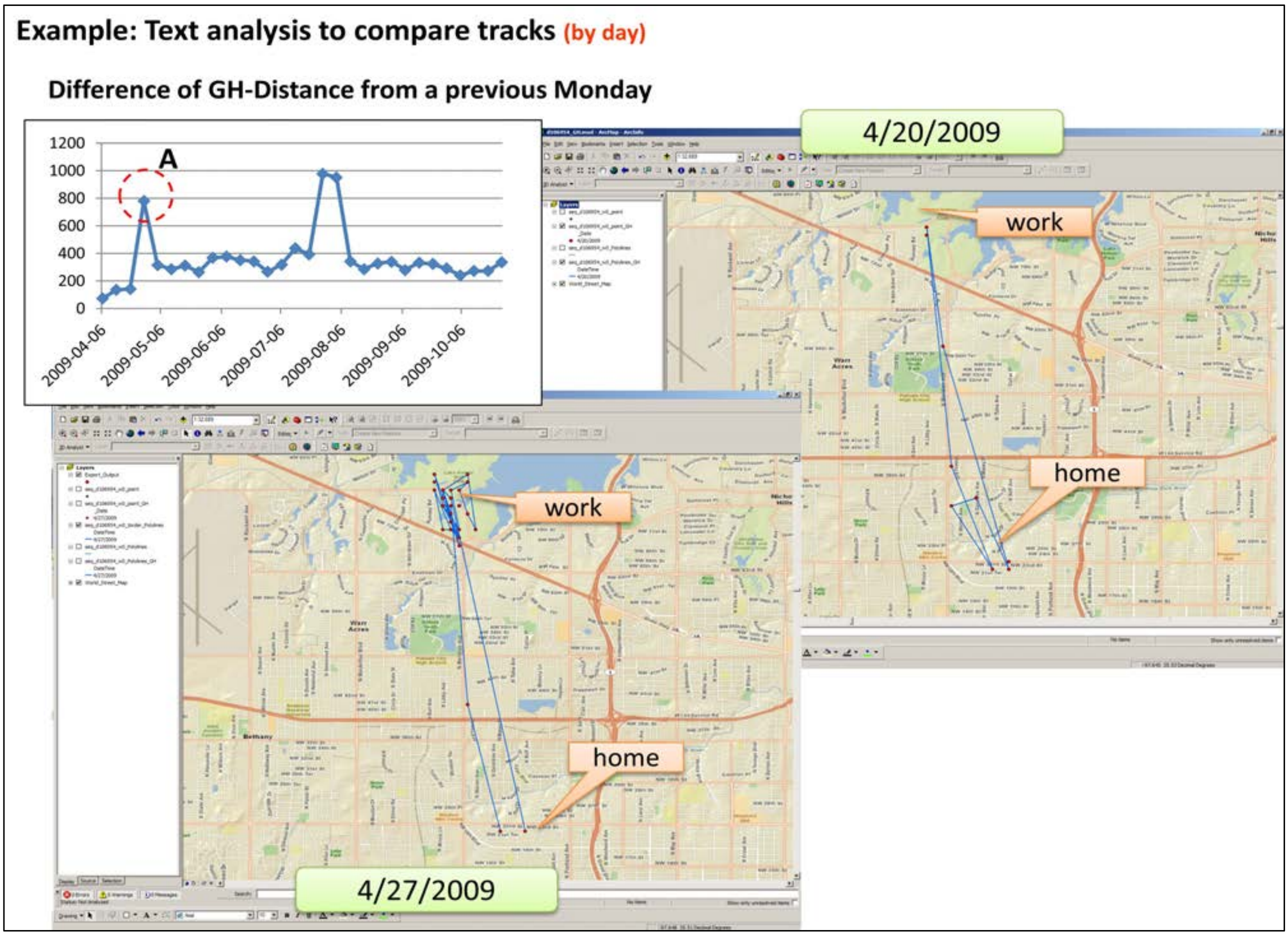
Level 7

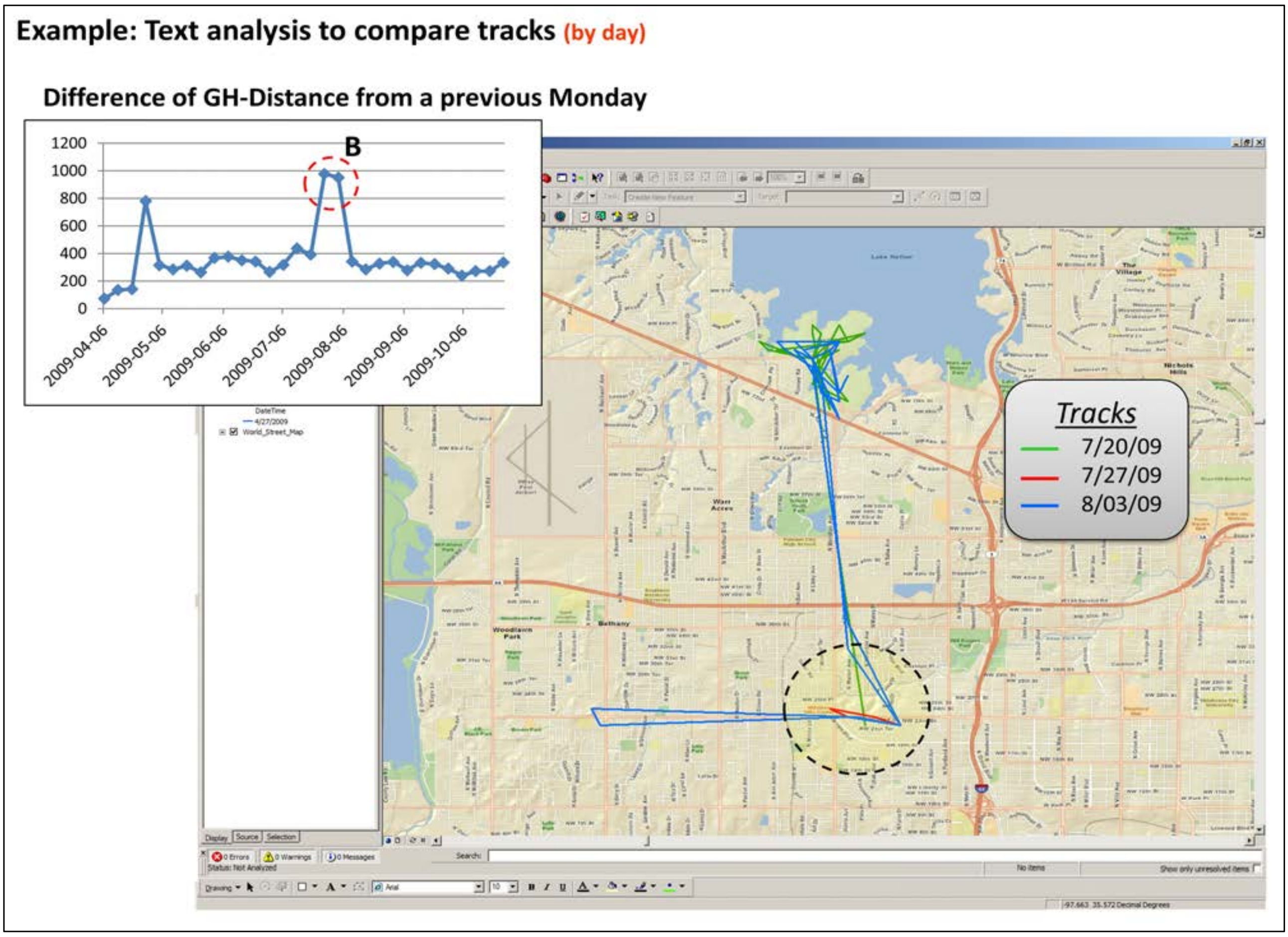
Level 8

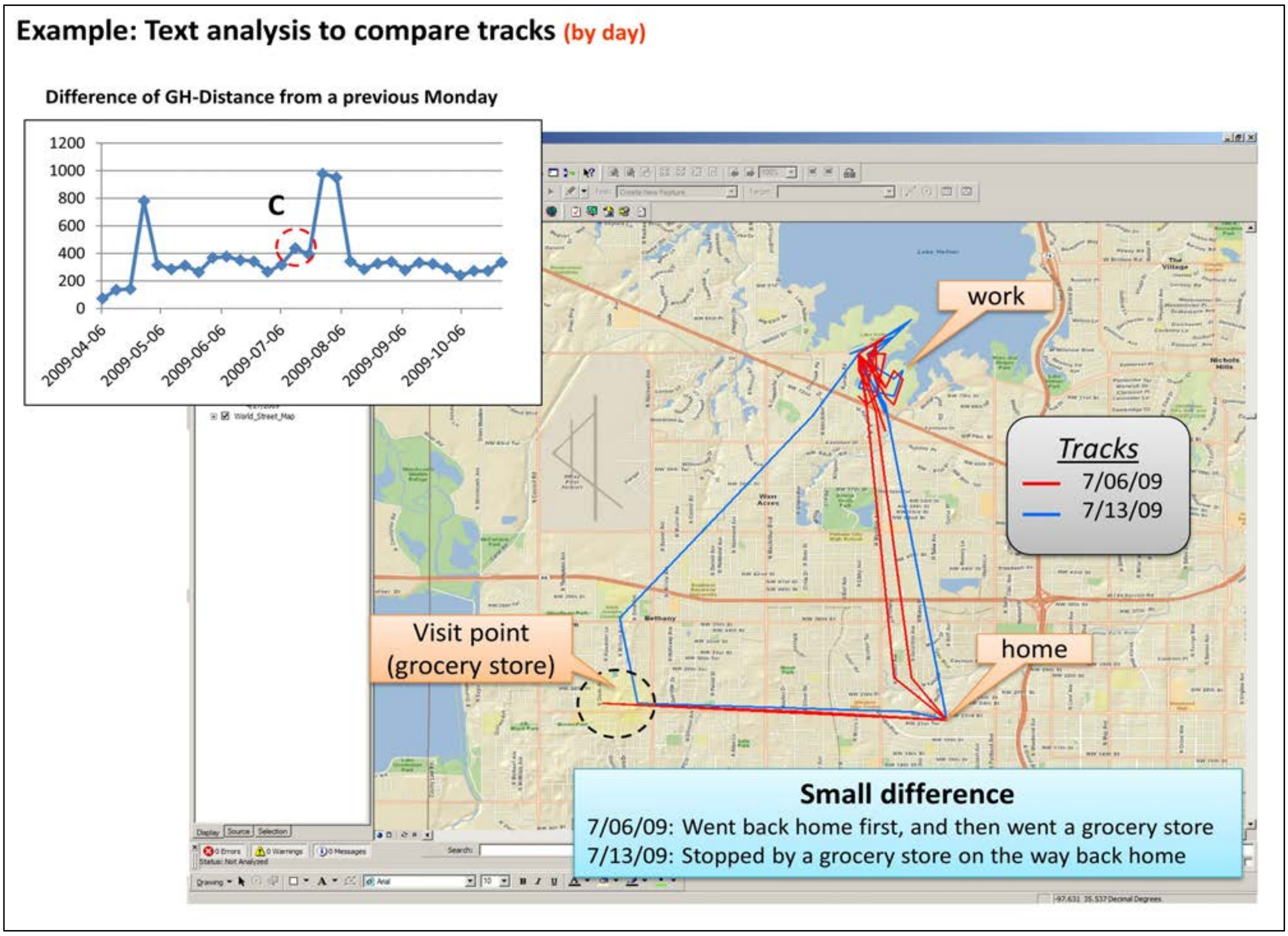

Text analysis to compare paths (by time interval)
0:0:0
e.g., Time Interval = 15 min
23:59:59
Day1 9y69gm0 9y69gm0 9y69gm0 9y69gnf 9y6d4yz 9y6d4yz 9y6d700 9y69gnf 9y69gm0 9y69gm0 9y69gm0
Day2 9y69gm0 9y69gm0 9y69gm0 9y69gm0 9y69gm0 9y69gm0 9y69gm0 9y69gm0 9y69gm0 9y69gm0 9y69gm0
Day(n) 9y69gm0 9y69gm0 9y69gm0 9y69gnf 9y6d4yz 9y6d4yz 9y6d700 9y69gnf 9y69gm0 9y69gm0 9y69gm0
Stay on the same path segments at this time over these days
Take different route segments at this time over these days
....
- Compare geohash codes between 2 days in each time interval

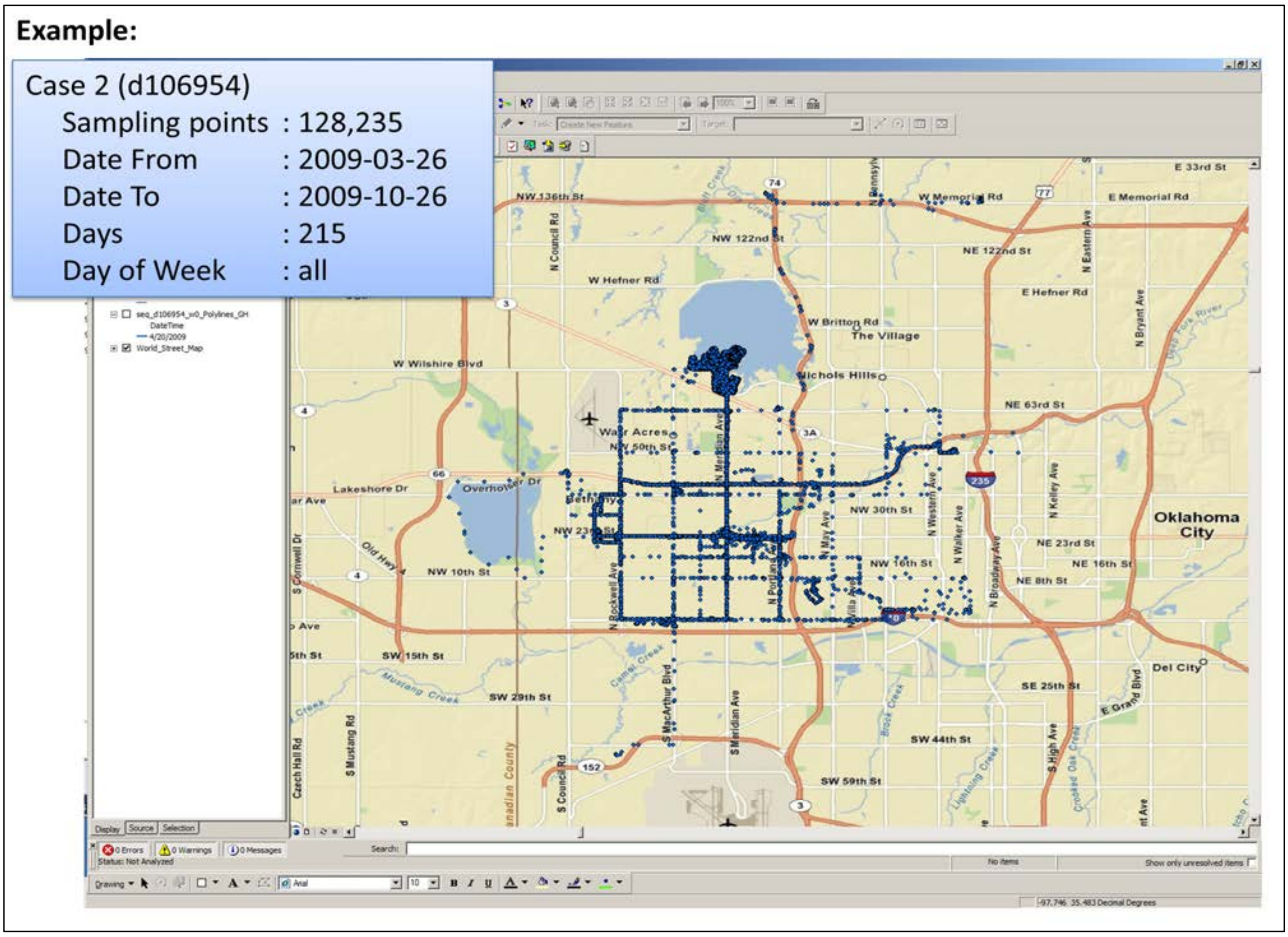

Text analysis to compare tracks (by difference between 2 time interval)
0:0:0
e.g., Time Interval = 15 min
23:59:59
Day1 9y69gm0 9y69gm0 9y69gm0 9y69gnf 9y6d4yz 9y6d4yz 9y6d700 9y69gnf 9y69gm0 9y69gm0 9y69gm0
Day2 9y69gm0 9y69gm0 9y69gm0 9y69gm0 9y69gm0 9y69gm0 9y69gm0 9y69gm0 9y69gm0 9y69gm0 9y69gm0
Day(n) 9y69gm0 9y69gm0 9y69gm0 9y69gnf 9y6d4yz 9y6d4yz 9y6d700 9y69gnf 9y69gm0 9y69gm0 9y69gm0
Same speed
Varied speed
Stay on the same or nearby path segments across two time intervals over these days
....
Take different path segments at this time interval over these days
....
- Compare geohash codes between 2 consecutive time intervals in a day
- The size of time interval can be extended

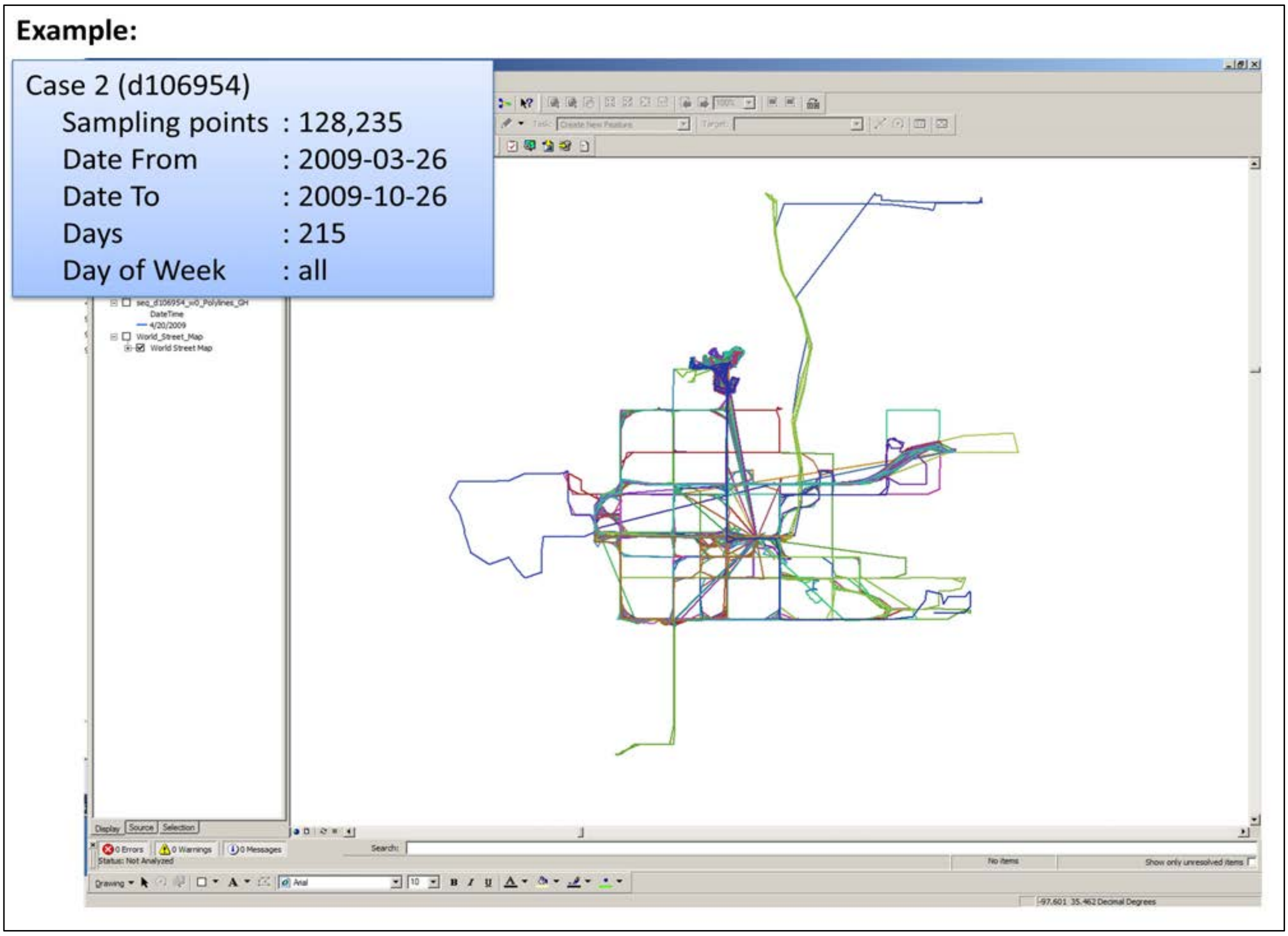

Case 1 (d106954)
Sampling points: 23,136
Date From: 2009-03-30
Date To: 2009-10-26
Days: 31
Day of Week: Monday
GPS Tracks
GPS sample points
Resampling Time Interval = 10 minutes
Geohash Level = 7,

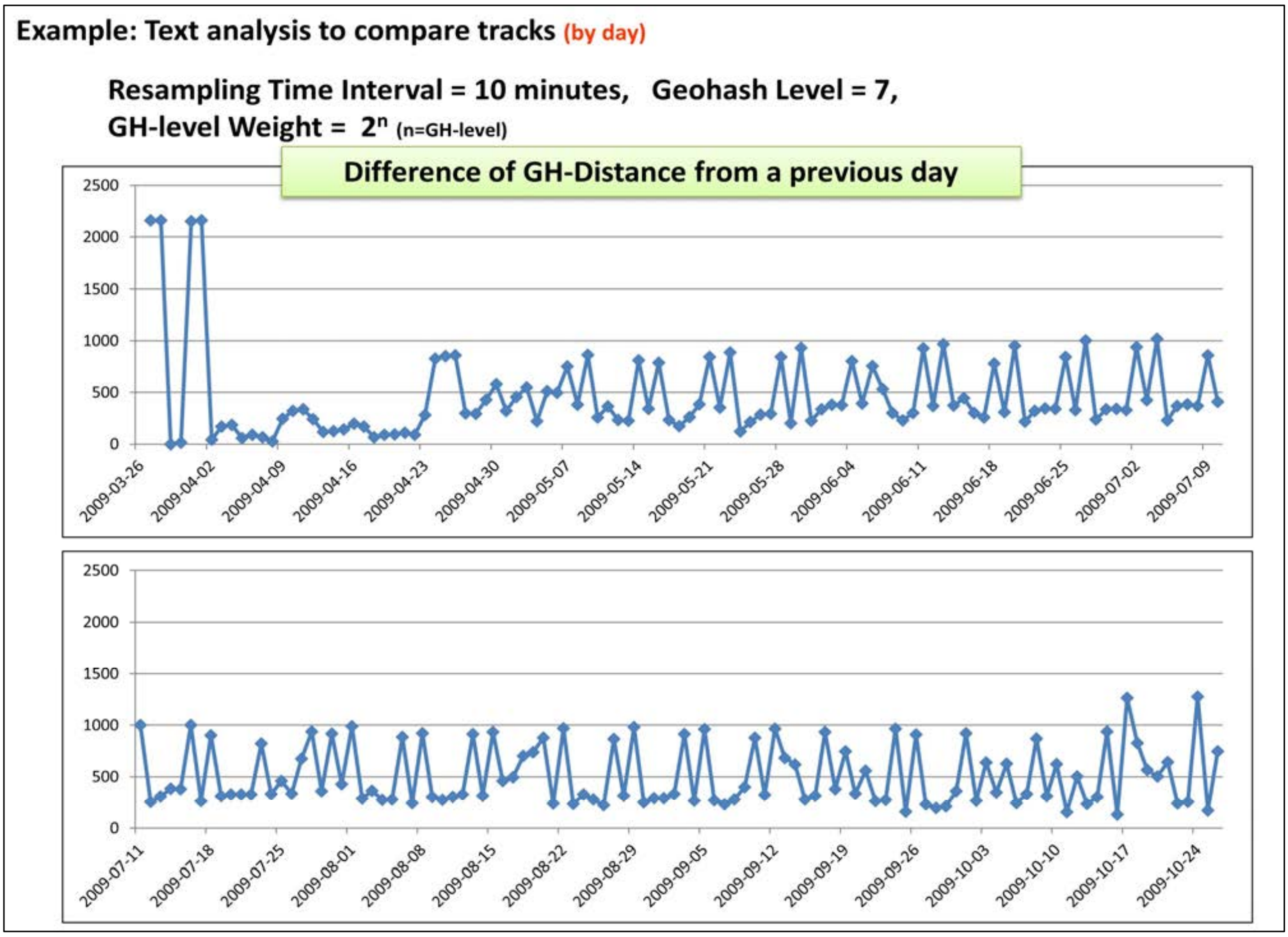

Example: Text analysis to compare tracks (by day)
Difference of GH-Distance from a previous Monday
1200
1000
800
600
400
200
0
A
2009-04-06
2009-05-06
2009-06-06
2009-07-06
2009-08-06
2009-09-06
2009-10-06
4/20/2009
work
home
work
home
4/27/2009

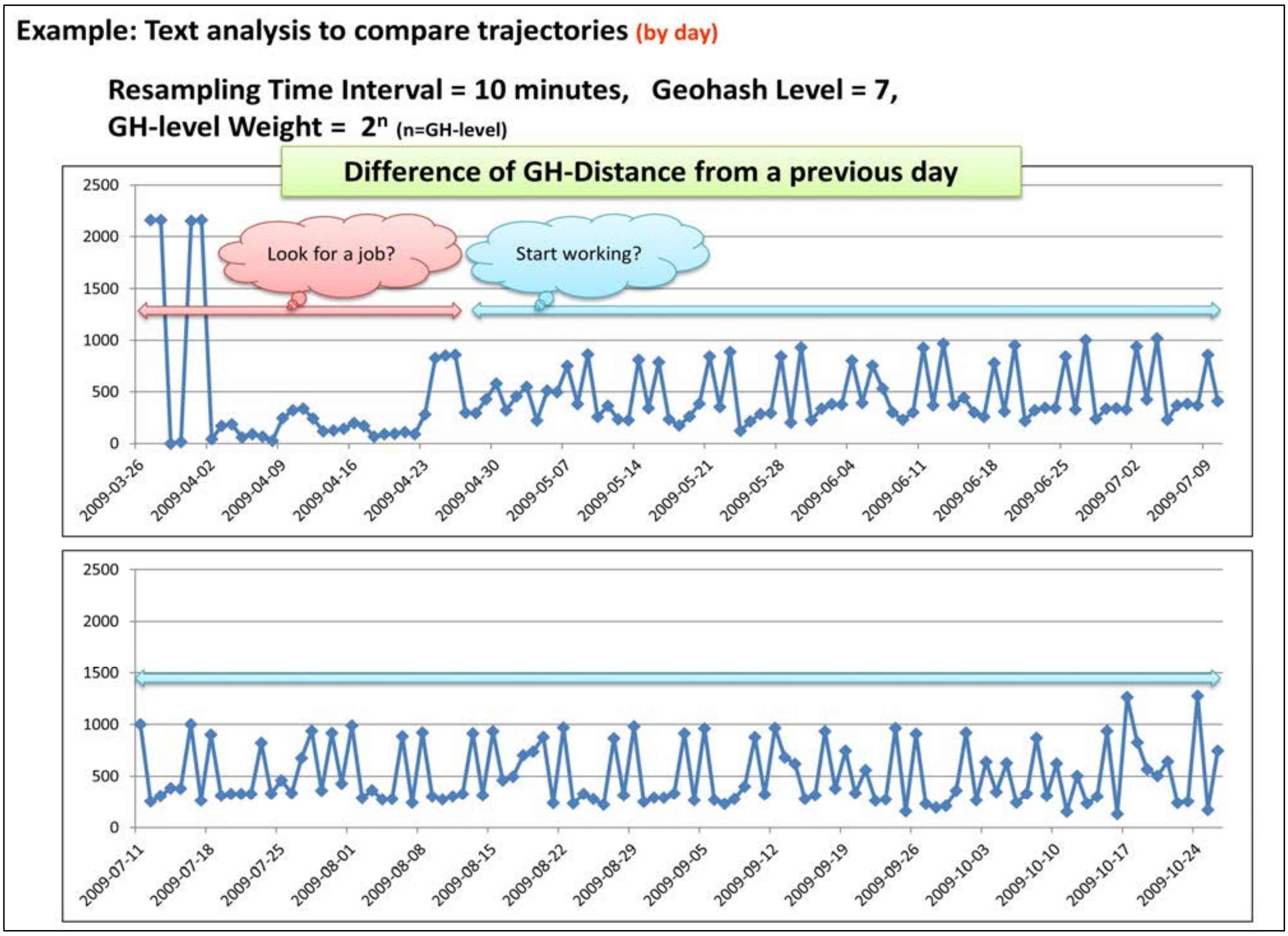

Example: Text analysis to compare tracks (by day)
Difference of GH-Distance from a previous Monday
1200
1000
800
600
400
200
0
2009-04-06
2009-05-06
2009-06-06
2009-07-06
2009-08-06
2009-09-06
2009-10-06
B
Tracks
7/20/09
7/27/09
8/03/09

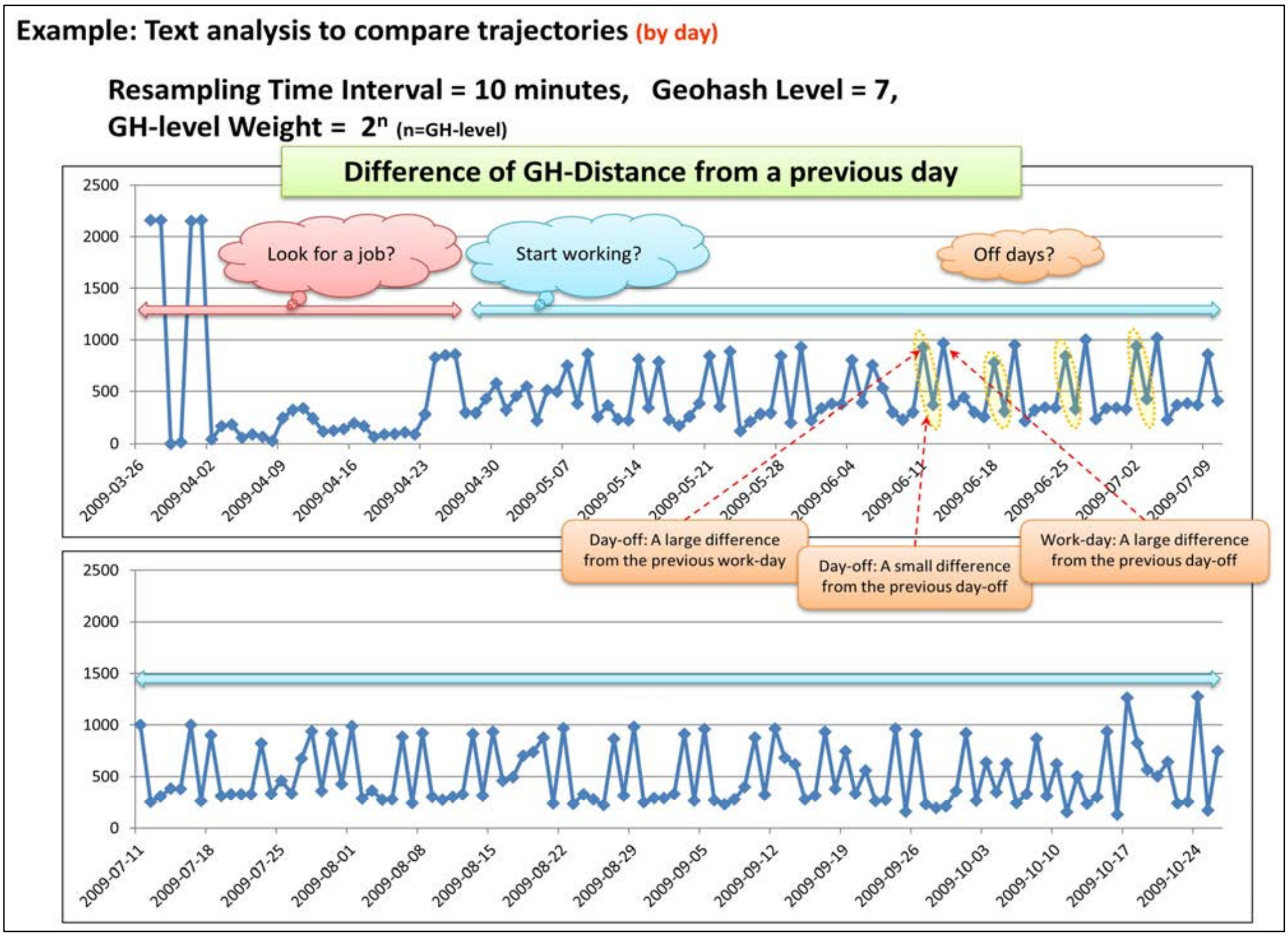

Example: Text analysis to compare tracks (by day)
Difference of GH-Distance from a previous Monday
1200
1000
800
600
400
200
0
2009-04-06
2009-05-06
2009-06-06
2009-07-06
2009-08-06
2009-09-06
2009-10-06
C
work
Tracks
7/06/09
7/13/09
Visit point
(grocery store)
home
Small difference
7/06/09: Went back home first, and then went a grocery store
7/13/09: Stopped by a grocery store on the way back home


Example:
Case 2 (d106954)
Sampling points : 128,235
Date From : 2009-03-26
Date To : 2009-10-26
Days : 215
Day of Week : all
W Wilshire Blvd
W Hefner Rd
W Britton Rd
The Village
Nichols Hills
NE 63rd St
Lakeshore Dr
NW 10th St
NW 30th St
NW 16th St
NE 23rd St
NE 8th St
SW 15th St
SW 29th St
SW 44th St
SW 59th St
SE 25th St
Del City
Oklahoma City
NW 122nd St
NE 122nd St
E Memorial Rd
W Memorial Rd
E 33rd St
S Mustang Rd
S Meridian Ave
S Council Rd
Czech Hall Rd


Example:
Case 2 (d106954)
Sampling points : 128,235
Date From : 2009-03-26
Date To : 2009-10-26
Days : 215
Day of Week : all


Example: Text analysis to compare tracks (by day)
Resampling Time Interval = 10 minutes, Geohash Level = 7,
GH-level Weight = 2^n (n=GH-level)
Difference of GH-Distance from a previous day
2500
2000
1500
1000
500
0
2009-03-26
2009-04-02
2009-04-09
2009-04-16
2009-04-23
2009-04-30
2009-05-07
2009-05-14
2009-05-21
2009-05-28
2009-06-04
2009-06-11
2009-06-18
2009-06-25
2009-07-02
2009-07-09
2009-07-11
2009-07-18
2009-07-25
2009-08-01
2009-08-08
2009-08-15
2009-08-22
2009-08-29
2009-09-05
2009-09-12
2009-09-19
2009-09-26
2009-10-03
2009-10-10
2009-10-17
2009-10-24


Example: Text analysis to compare trajectories (by day)
Resampling Time Interval = 10 minutes, Geohash Level = 7,
GH-level Weight = 2^n (n=GH-level)
Difference of GH-Distance from a previous day
Look for a job?
Start working?
2500
2000
1500
1000
500
0
2009-03-26
2009-04-02
2009-04-09
2009-04-16
2009-04-23
2009-04-30
2009-05-07
2009-05-14
2009-05-21
2009-05-28
2009-06-04
2009-06-11
2009-06-18
2009-06-25
2009-07-02
2009-07-09
2009-07-11
2009-07-18
2009-07-25
2009-08-01
2009-08-08
2009-08-15
2009-08-22
2009-08-29
2009-09-05
2009-09-12
2009-09-19
2009-09-26
2009-10-03
2009-10-10
2009-10-17
2009-10-24


Example: Text analysis to compare trajectories (by day)
Resampling Time Interval = 10 minutes, Geohash Level = 7,
GH-level Weight = 2n (n=GH-level)
Difference of GH-Distance from a previous day
Look for a job?
Start working?
Off days?
Day-off: A large difference from the previous work-day
Day-off: A small difference from the previous day-off
Work-day: A large difference from the previous day-off
2500
2000
1500
1000
500
0
2009-03-26
2009-04-02
2009-04-09
2009-04-16
2009-04-23
2009-04-30
2009-05-07
2009-05-14
2009-05-21
2009-05-28
2009-06-04
2009-06-11
2009-06-18
2009-06-25
2009-07-02
2009-07-09
2009-07-11
2009-07-18
2009-07-25
2009-08-01
2009-08-08
2009-08-15
2009-08-22
2009-08-29
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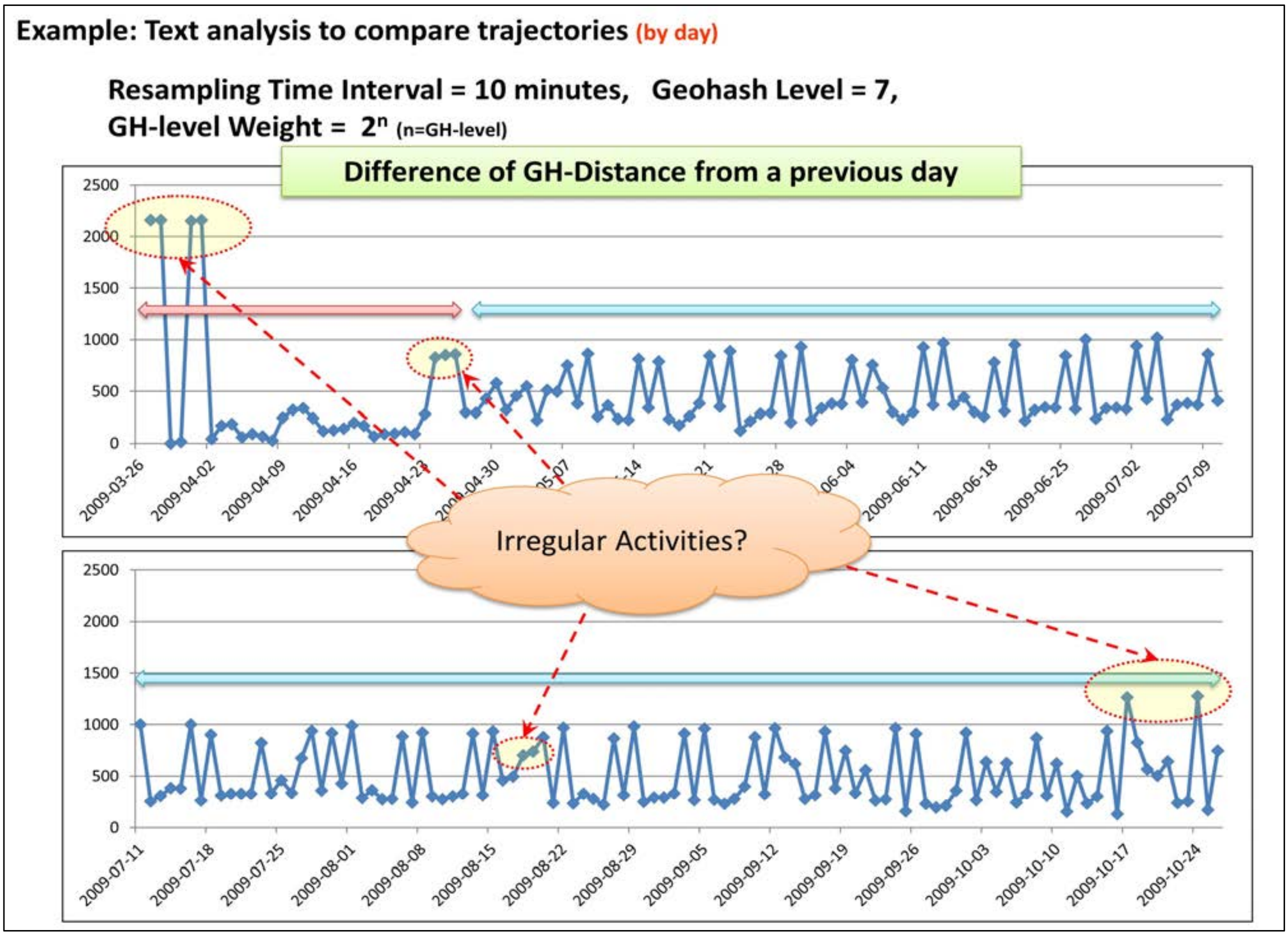
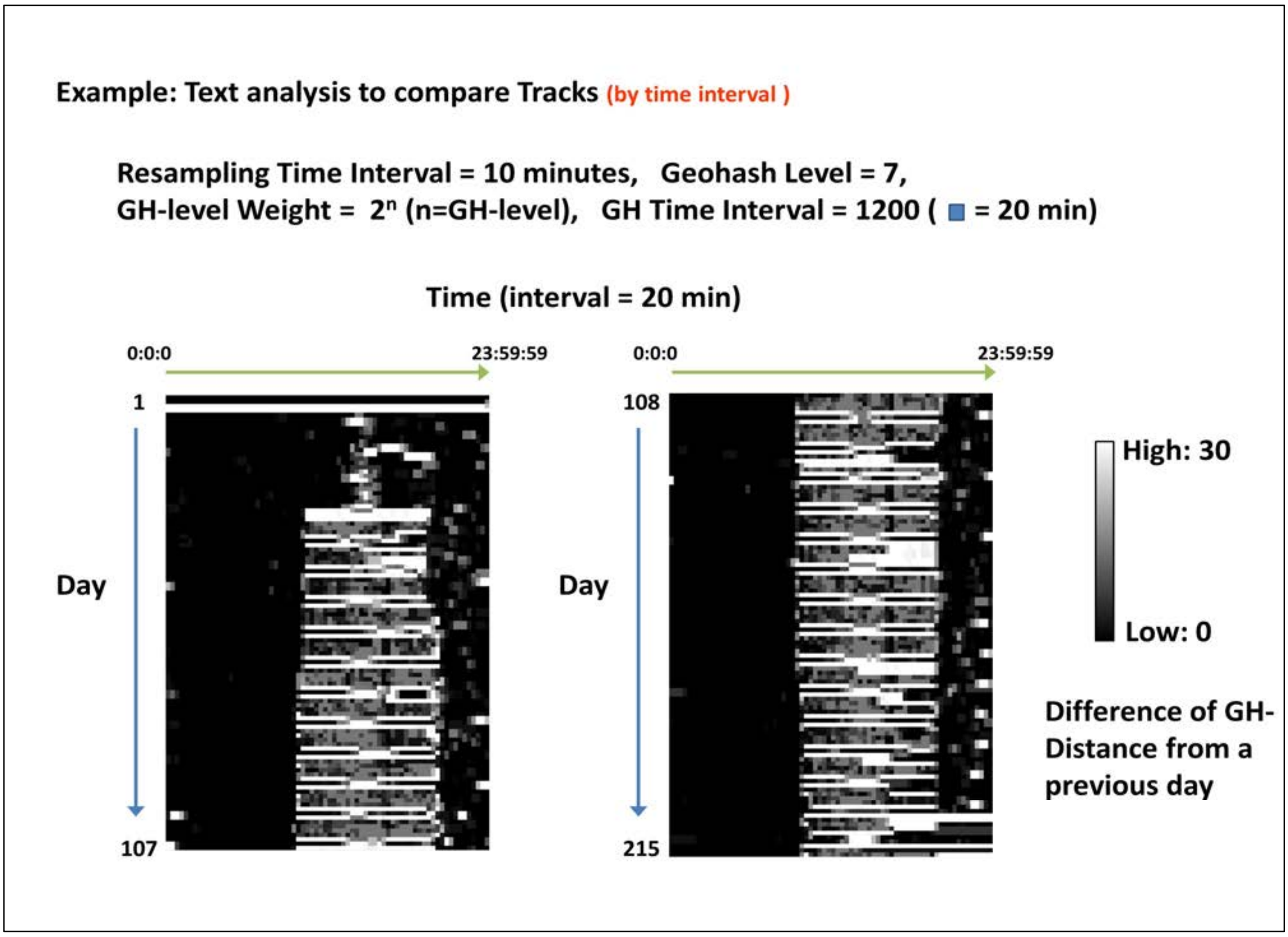
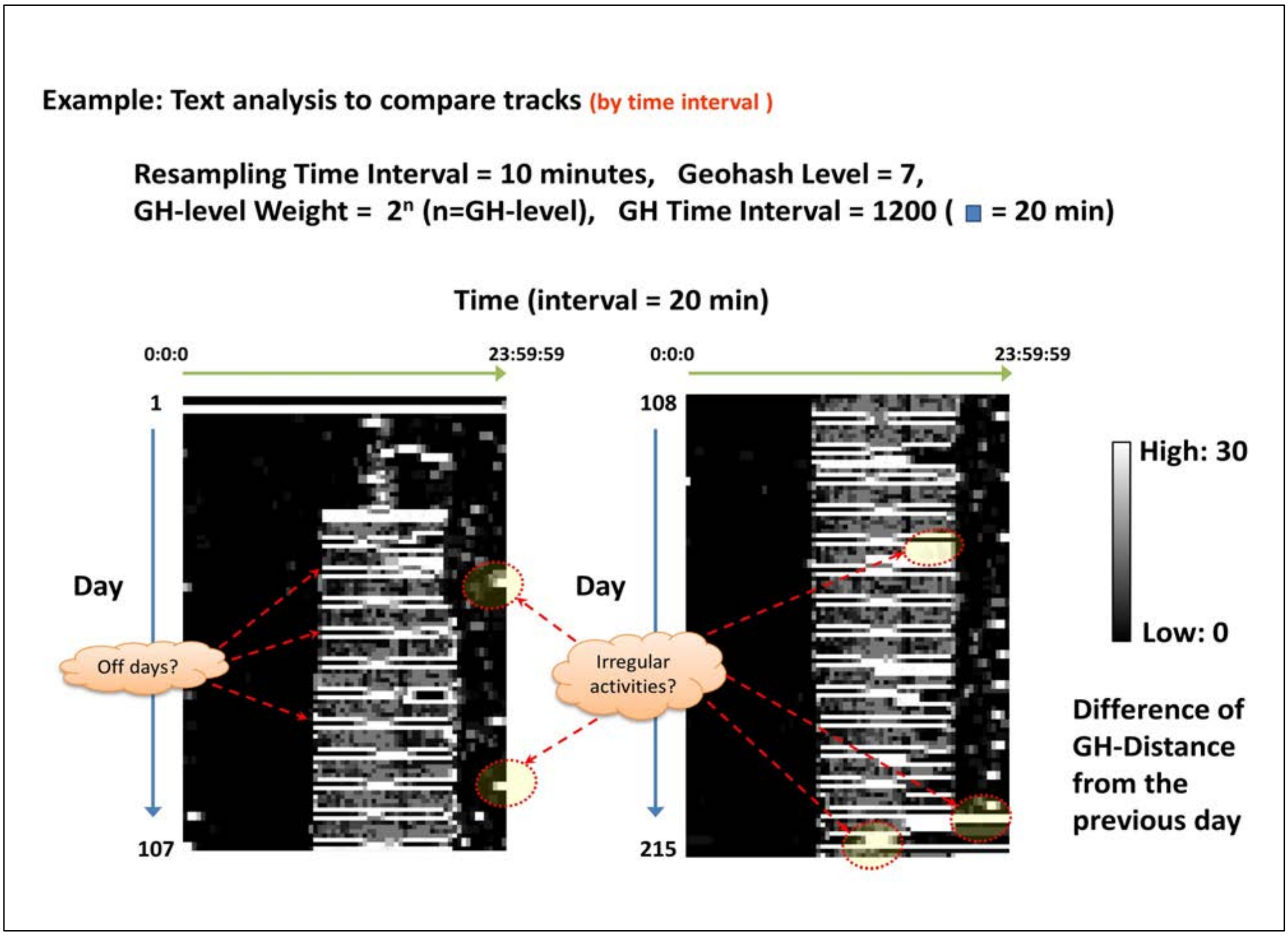
2009-10-10
2009-10-17
2009-10-24

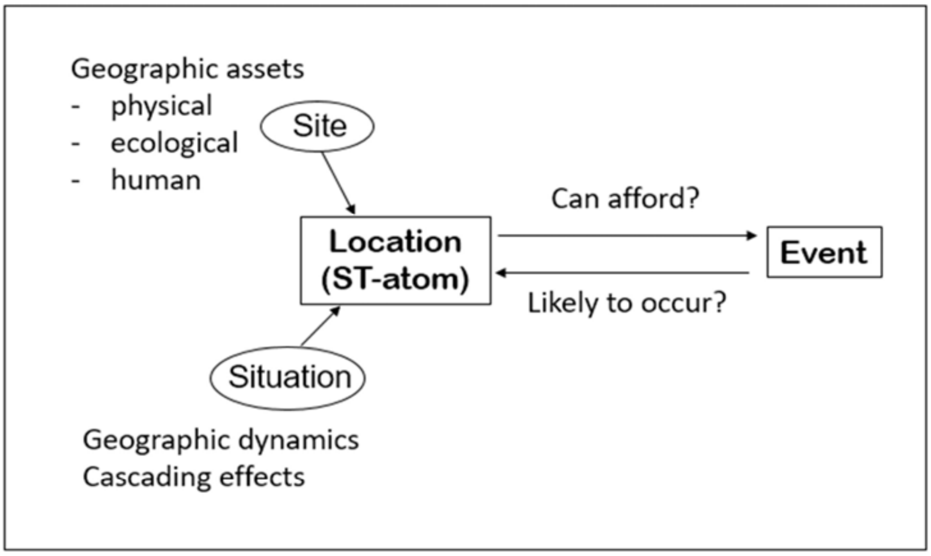

Example: Text analysis to compare trajectories (by day)
Resampling Time Interval = 10 minutes, Geohash Level = 7,
GH-level Weight = 2n (n=GH-level)
Difference of GH-Distance from a previous day
Irregular Activities?
2500
2000
1500
1000
500
0
2009-03-26
2009-04-02
2009-04-09
2009-04-16
2009-04-23
2009-06-04
2009-06-11
2009-06-18
2009-06-25
2009-07-02
2009-07-09
2009-07-11
2009-07-18
2009-07-25
2009-08-01
2009-08-08
2009-08-15
2009-08-22
2009-08-29
2009-09-05
2009-09-12
2009-09-19
2009-09-26
2009-10-03
2009-10-10
2009-10-17
2009-10-24

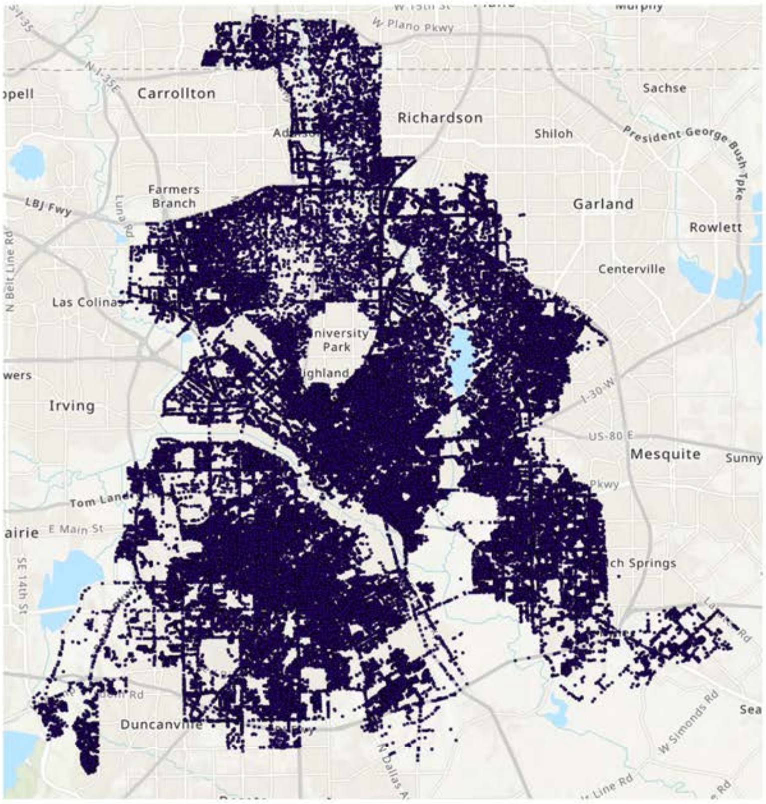

Example: Text analysis to compare Tracks (by time interval)
Resampling Time Interval = 10 minutes, Geohash Level = 7,
GH-level Weight = 2ⁿ (n=GH-level), GH Time Interval = 1200 (■ = 20 min)
Time (interval = 20 min)
0:0:0
23:59:59
1
Day
107
0:0:0
23:59:59
108
Day
215
High: 30
Low: 0
Difference of GH-Distance from a previous day


Example: Text analysis to compare tracks (by time interval)
Resampling Time Interval = 10 minutes, Geohash Level = 7,
GH-level Weight = 2ⁿ (n=GH-level), GH Time Interval = 1200 (■ = 20 min)
Time (interval = 20 min)
0:0:0
23:59:59
1
Day
Off days?
107
0:0:0
23:59:59
108
Day
Irregular activities?
215
High: 30
Low: 0
Difference of GH-Distance from the previous day

From Events to Places

Sunghwan Cho



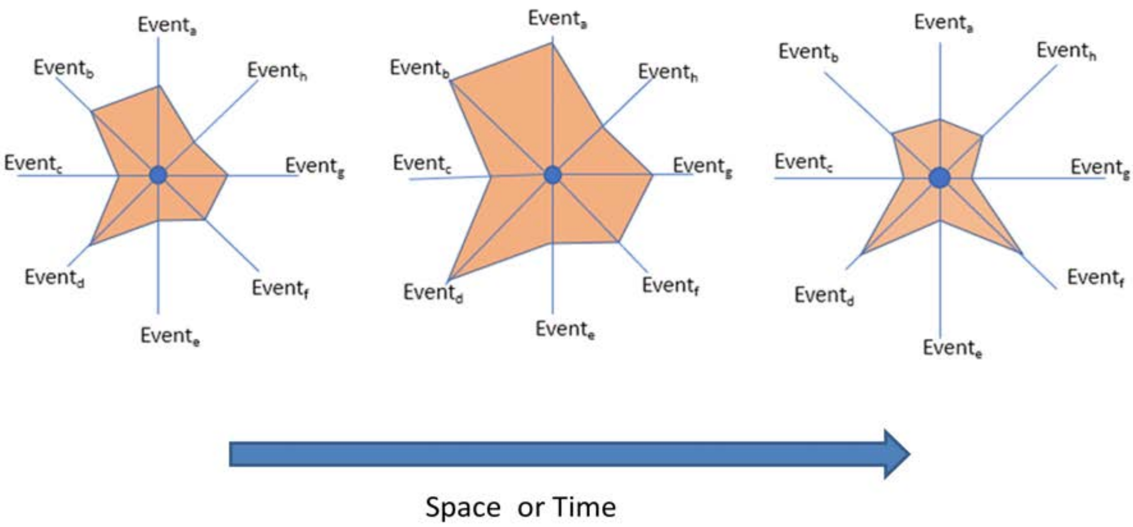


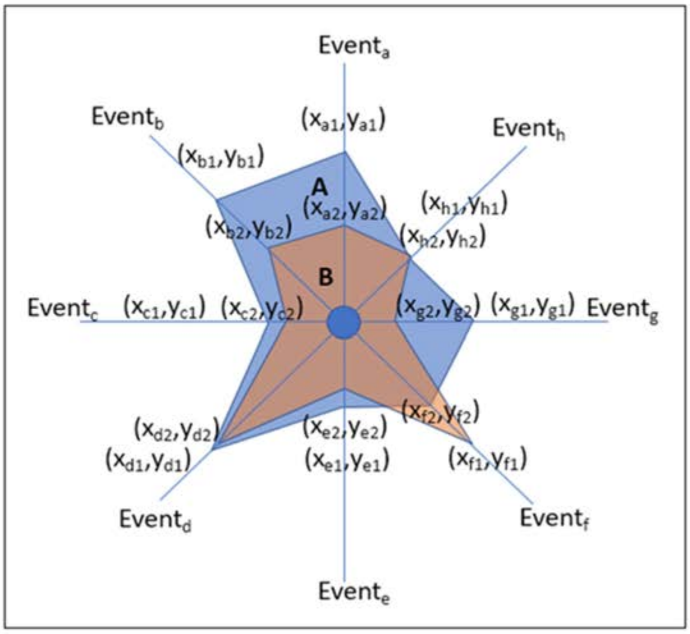
Dallas. Texas
Population: 1.4 millions

6/1/2014 to 3/29/2018
572,652 crime incidents

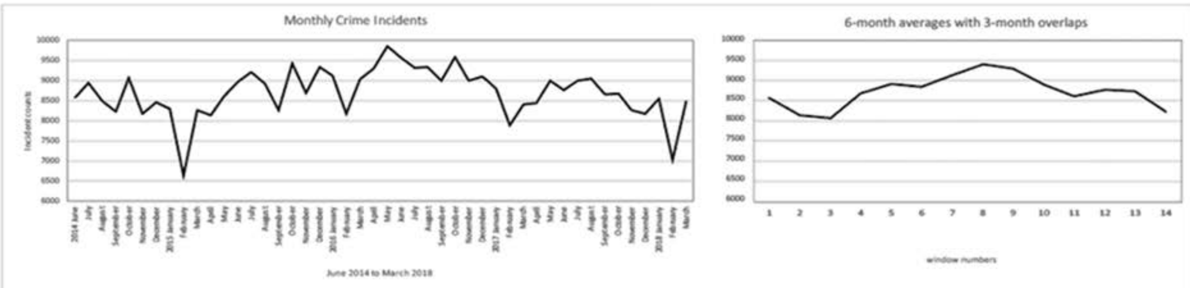
UCR	FREQUENCY	COUNT_UCR
Aggravated Assault	13765	13765
All Larceny	176328	176328
Burglary	75512	75512
Motor Vehicle Theft	13734	13734
Murder	703	703
Part II Crime	262920	262920
Robbery	29690	29690

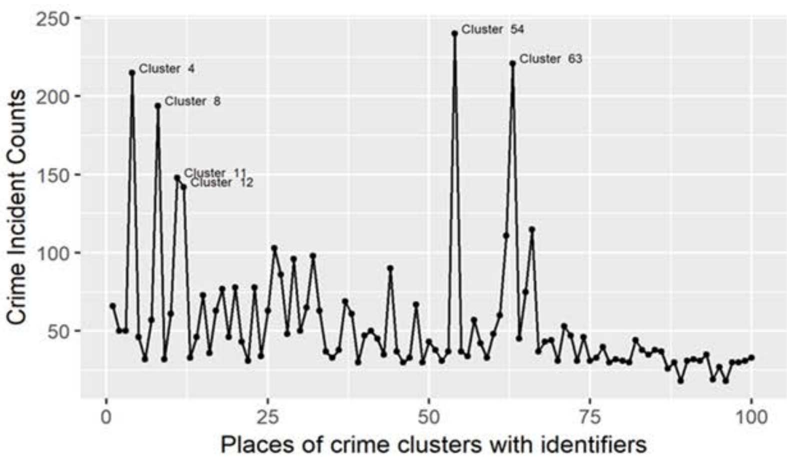
DBSCAN to identify
local clusters
100m
Min 30 events





$$Similarity = \frac{Area(A) \cap Area(B)}{Area(A) \cup Area(B)}$$

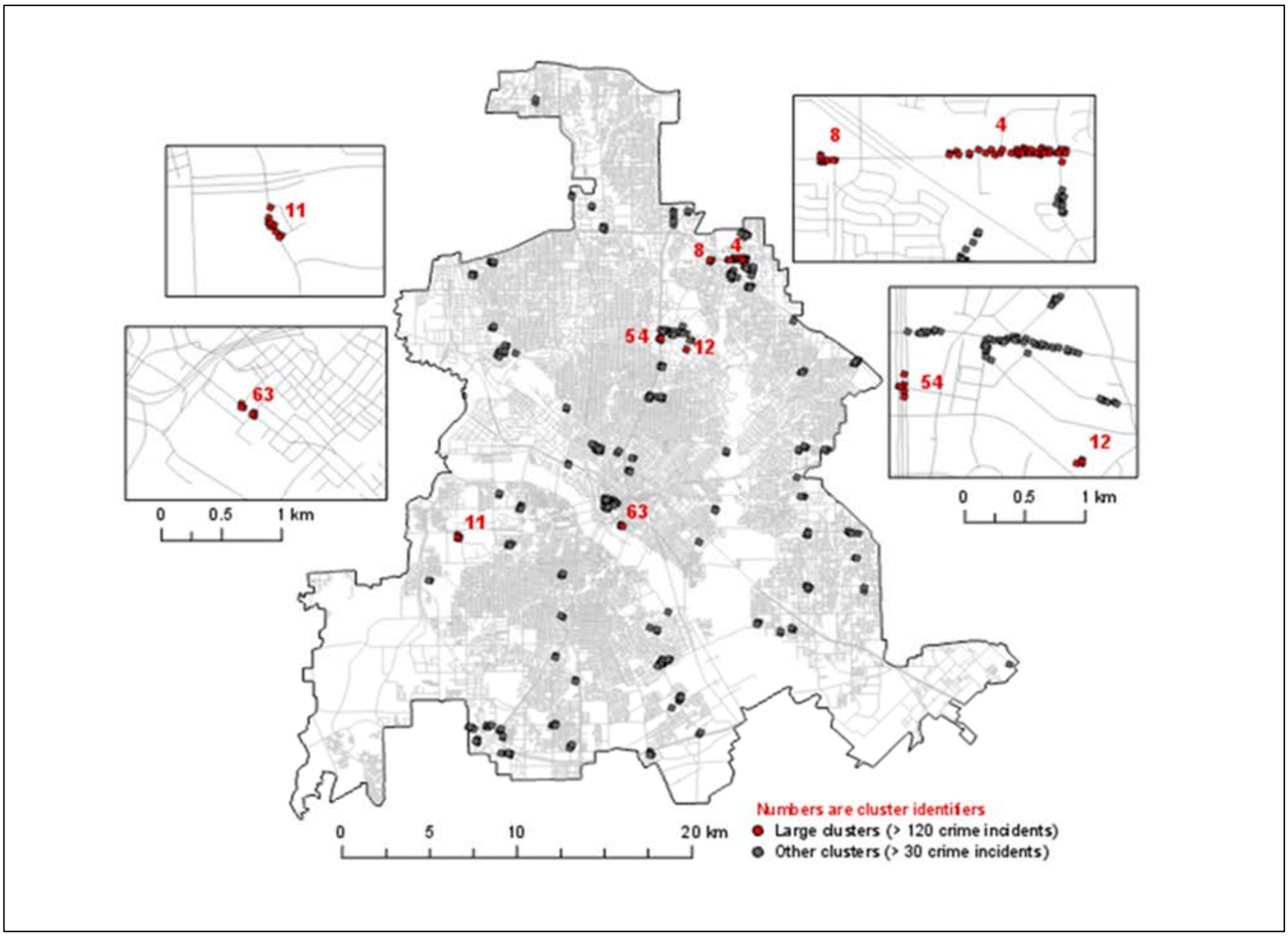




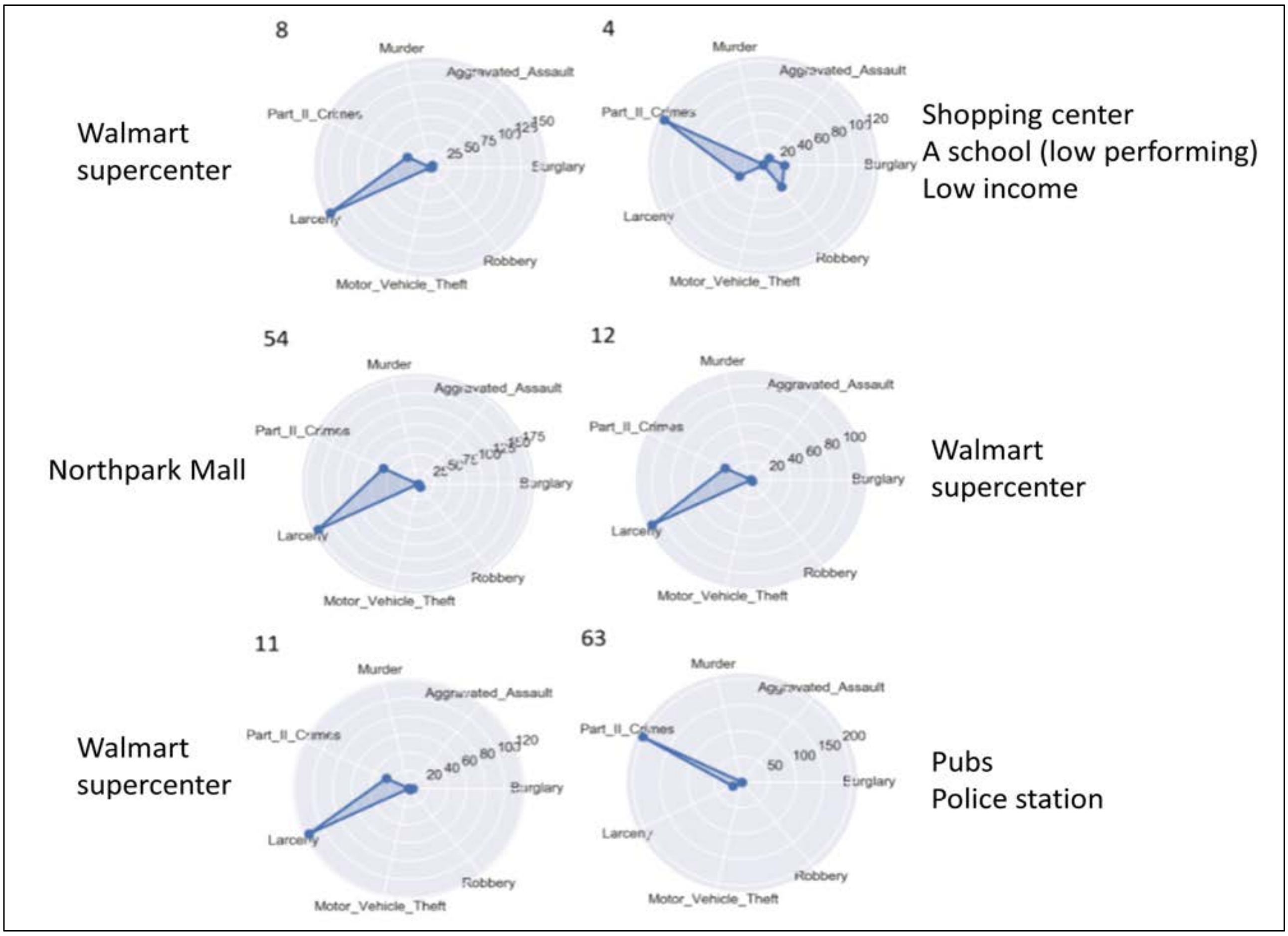
First time-window
1 June 2014 to
30 November 2014

One hundred (100) places contain 15% of the total crime incidents (5,544 out of 36,647 events).

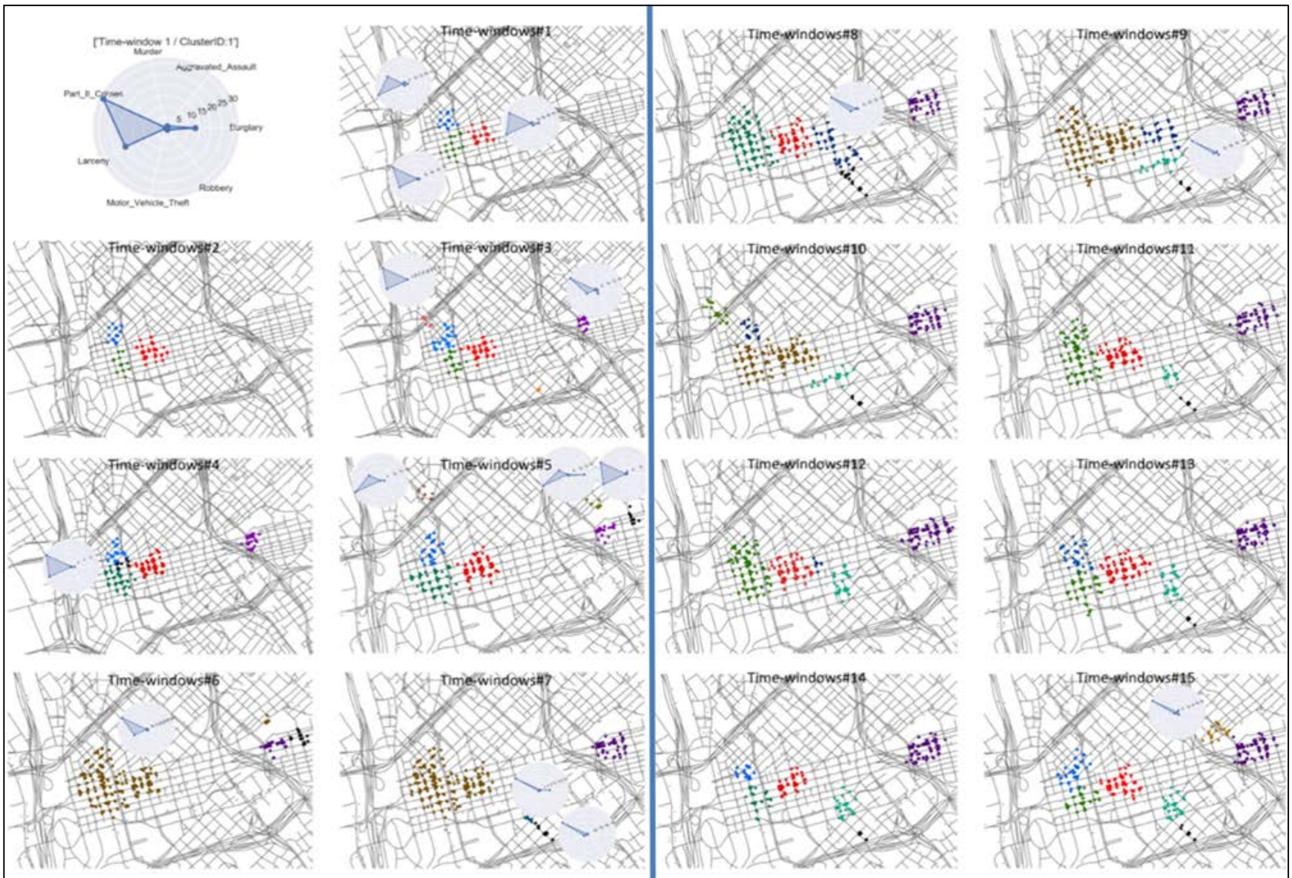
Six places experienced significantly more crime incidents than other places. Cluster identifiers were assigned arbitrarily.



8
4
11
54
12
63
0 0.5 1 km
0 5 10 20 km
Numbers are cluster identifiers
Large clusters (> 120 crime incidents)
Other clusters (> 30 crime incidents)



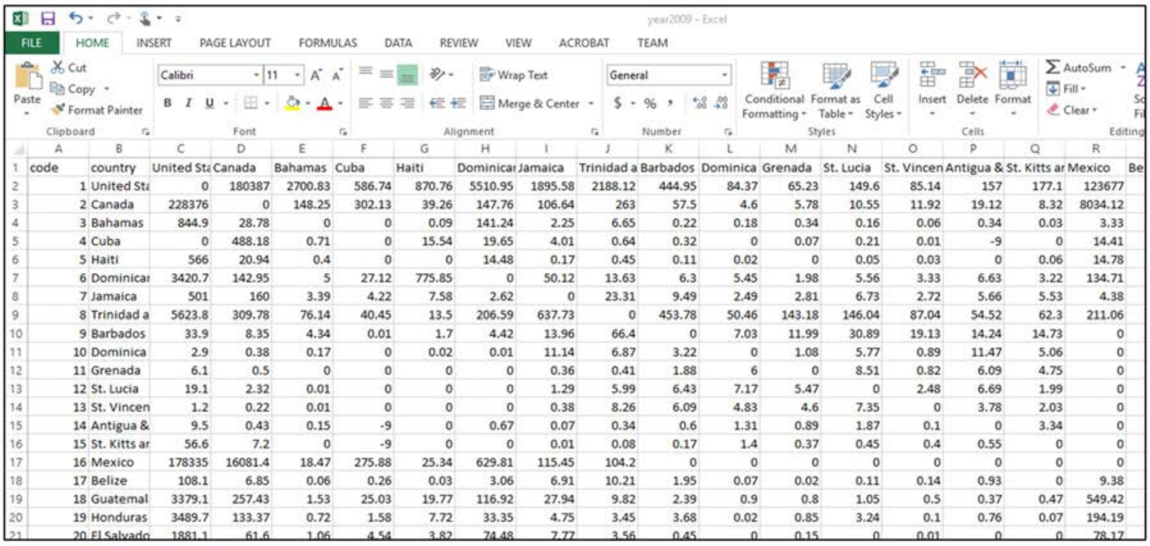
8
Walmart supercenter
4
Shopping center
A school (low performing)
Low income
54
Northpark Mall
12
Walmart supercenter
11
Walmart supercenter
63
Pubs
Police station
Murder
Aggravated_Assault
Burglary
Robbery
Motor_Vehicle_Theft
Larceny
Part_II_Crimes



International Trade: from bilateral interactions to trending trading patterns

With Wei Lou

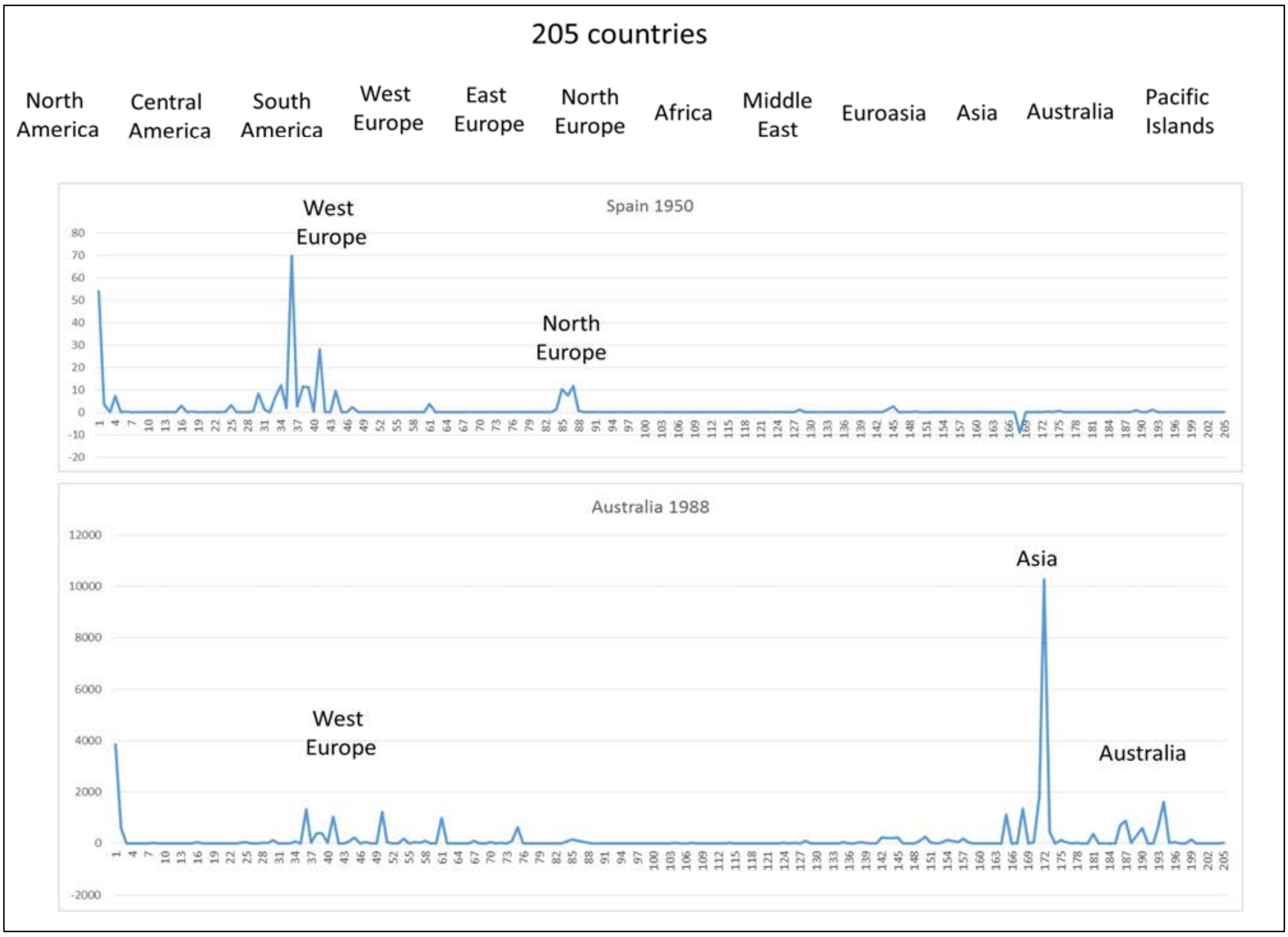
Barbieri, Katherine, Omar M. G. Keshk, and Brian Pollins. 2009. "TRADING DATA: Evaluating our Assumptions and Coding Rules." Conflict Management and Peace Science. 26(5): 471-491.

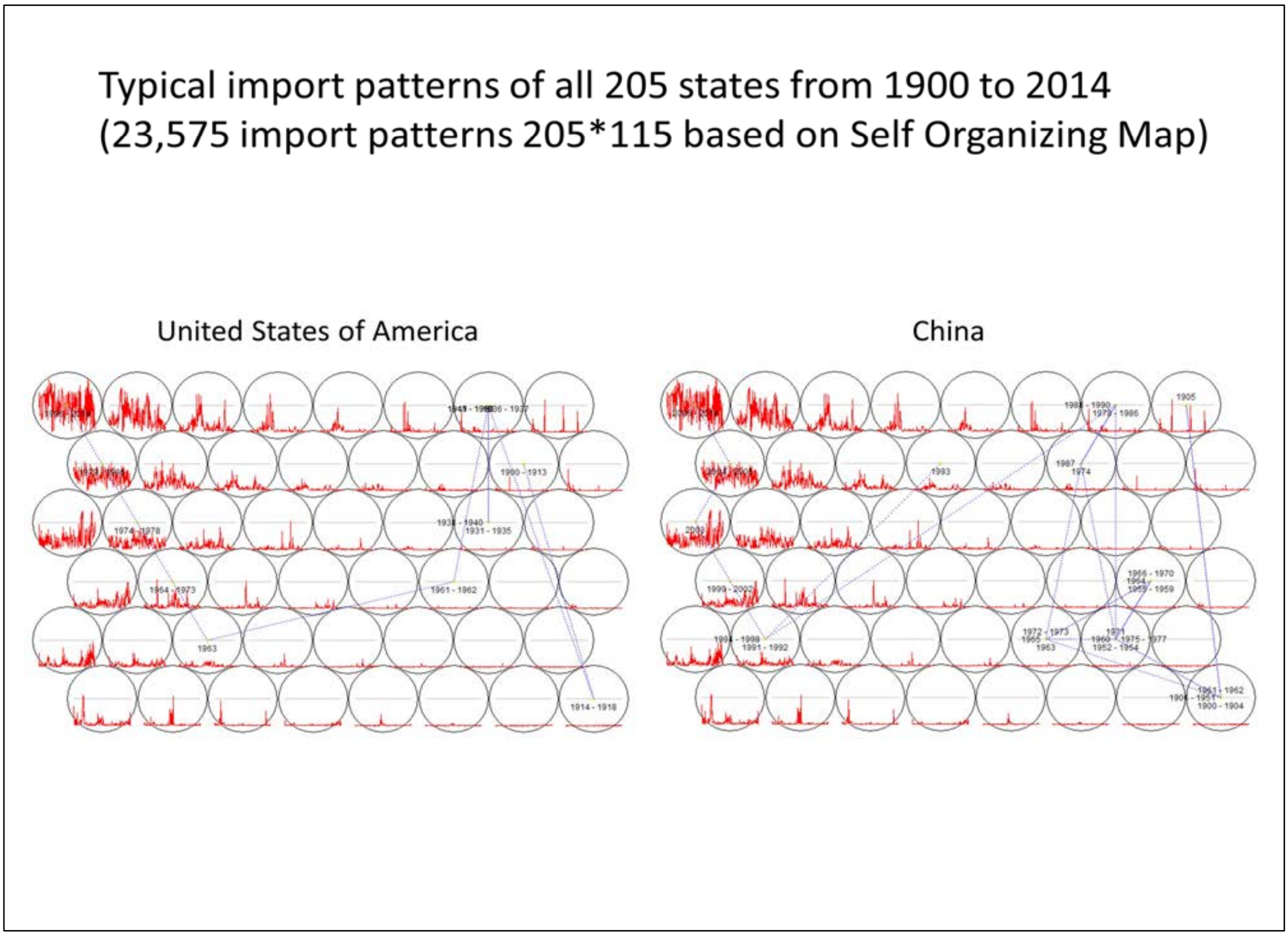


code	country	United Sta	Canada	Bahamas	Cuba	Haiti	Dominicar	Jamaica	Trinidad a	Barbados	Dominica	Grenada	St. Lucia	St. Vincen	Antigua &	St. Kitts ar	Mexico	Be
1	United Sta	0	180387	2700.83	586.74	870.76	5510.95	1895.58	2188.12	444.95	84.37	65.23	149.6	85.14	157	177.1	123677	
2	Canada	228376	0	148.25	302.13	39.26	147.76	106.64	263	57.5	4.6	5.78	10.55	11.92	19.12	8.32	8034.12	
3	Bahamas	844.9	28.78	0	0	0.09	141.24	2.25	6.65	0.22	0.18	0.34	0.16	0.06	0.34	0.03	3.33	
4	Cuba	0	488.18	0.71	0	15.54	19.65	4.01	0.64	0.32	0	0.07	0.21	0.01	-9	0	14.41	
5	Haiti	566	20.94	0.4	0	0	14.48	0.17	0.45	0.11	0.02	0	0.05	0.03	0	0.06	14.78	
6	Dominicar	3420.7	142.95	5	27.12	775.85	0	50.12	13.63	6.3	5.45	1.98	5.56	3.33	6.63	3.22	134.71	
7	Jamaica	501	160	3.39	4.22	7.58	2.62	0	23.31	9.49	2.49	2.81	6.73	2.72	5.66	5.53	4.38	
8	Trinidad a	5623.8	309.78	76.14	40.45	13.5	206.59	637.73	0	453.78	50.46	143.18	146.04	87.04	54.52	62.3	211.06	
9	Barbados	33.9	8.35	4.34	0.01	1.7	4.42	13.96	66.4	0	7.03	11.99	30.89	19.13	14.24	14.73	0	
10	Dominica	2.9	0.38	0.17	0	0.02	0.01	11.14	6.87	3.22	0	1.08	5.77	0.89	11.47	5.06	0	
11	Grenada	6.1	0.5	0	0	0	0	0.36	0.41	1.88	6	0	8.51	0.82	6.09	4.75	0	
12	St. Lucia	19.1	2.32	0.01	0	0	0	1.29	5.99	6.43	7.17	5.47	0	2.48	6.69	1.99	0	
13	St. Vincen	1.2	0.22	0.01	0	0	0	0.38	8.26	6.09	4.83	4.6	7.35	0	3.78	2.03	0	
14	Antigua &	9.5	0.43	0.15	-9	0	0.67	0.07	0.34	0.6	1.31	0.89	1.87	0.1	0	3.34	0	
15	St. Kitts ar	56.6	7.2	0	-9	0	0	0.01	0.08	0.17	1.4	0.37	0.45	0.4	0.55	0	0	
16	Mexico	178335	16081.4	18.47	275.88	25.34	629.81	115.45	104.2	0	0	0	0	0	0	0	0	
17	Belize	108.1	6.85	0.06	0.26	0.03	3.06	6.91	10.21	1.95	0.07	0.02	0.11	0.14	0.93	0	9.38	
18	Guatemal	3379.1	257.43	1.53	25.03	19.77	116.92	27.94	9.82	2.39	0.9	0.8	1.05	0.5	0.37	0.47	549.42	
19	Honduras	3489.7	133.37	0.72	1.58	7.72	33.35	4.75	3.45	3.68	0.02	0.85	3.24	0.1	0.76	0.07	194.19	
20	El Salvado	1881.1	61.6	1.06	4.54	3.82	74.48	7.77	3.56	0.45	0	0.15	0	0.01	0	0	78.17	

International bilateral trade data: 1870 to 2009 from the Correlates of War (COW) project. In 2009 US dollars for pairs of 205 sovereign states. Based on IMF data and other state reports when necessary. In case of country name changes, record the data based on state list with the COW state membership list.

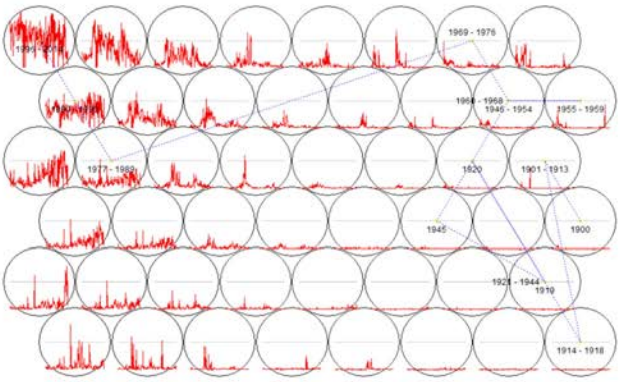
Instead of modeling spatial interactions of state pairs, can we seek how a state develops international trade patterns and in comparison with other states?


205 countries
North America
Central America
South America
West Europe
East Europe
North Europe
Africa
Middle East
Euroasia
Asia
Australia
Pacific Islands
Spain 1950
West Europe
North Europe
Australia 1988
Asia
West Europe
Australia

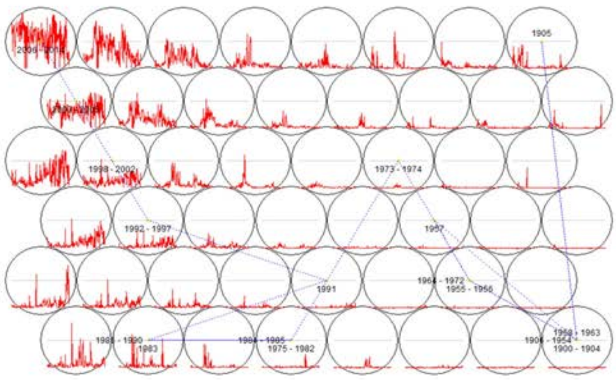

Typical import patterns of all 205 states from 1900 to 2014
(23,575 import patterns 205*115 based on Self Organizing Map)
United States of America
China

exports

United States of America



China



Concluding Remarks

Going beyond the conventional

What can movements, events, and interactions tell us about human dynamics in space and time?

New Business Models integrating Artificial Intelligence and Geospatial Information

Kyoung-Jun Lee
Professor, Kyung Hee University

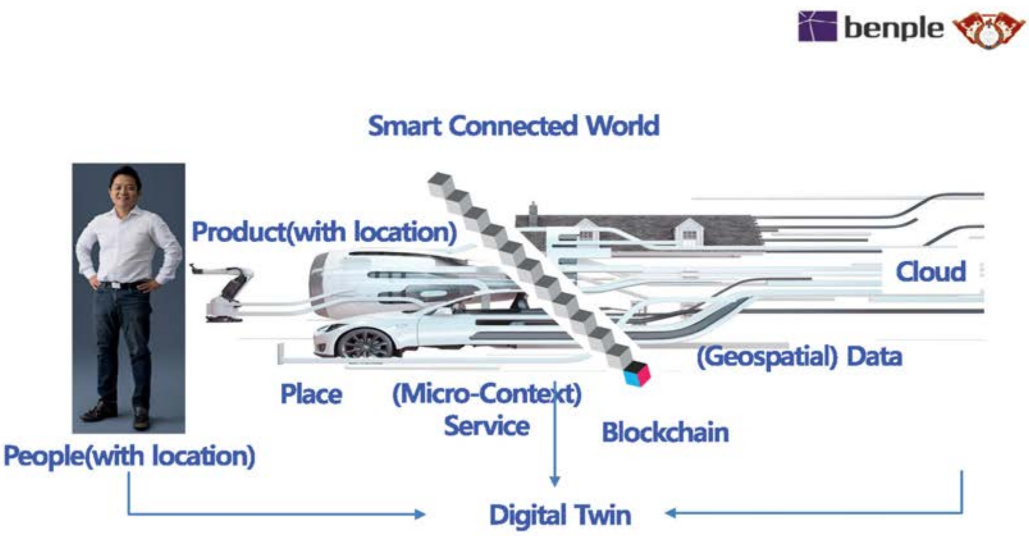
New Business Models integrating Artificial Intelligence and Geospatial Information

Kyoung Jun Lee
klee@khu.ac.kr, leekj@benple.com
Prof. of Kyung Hee University & CEO of Benple Inc.

KRIHS 2018 International Conference on Geospatial Information Science

New Business Models integrating Artificial Intelligence and Geospatial Information

Kyoung Jun Lee(klee@khu.ac.kr, leekj@benple.com)
Prof. of Kyung Hee University & CEO of Benple Inc.



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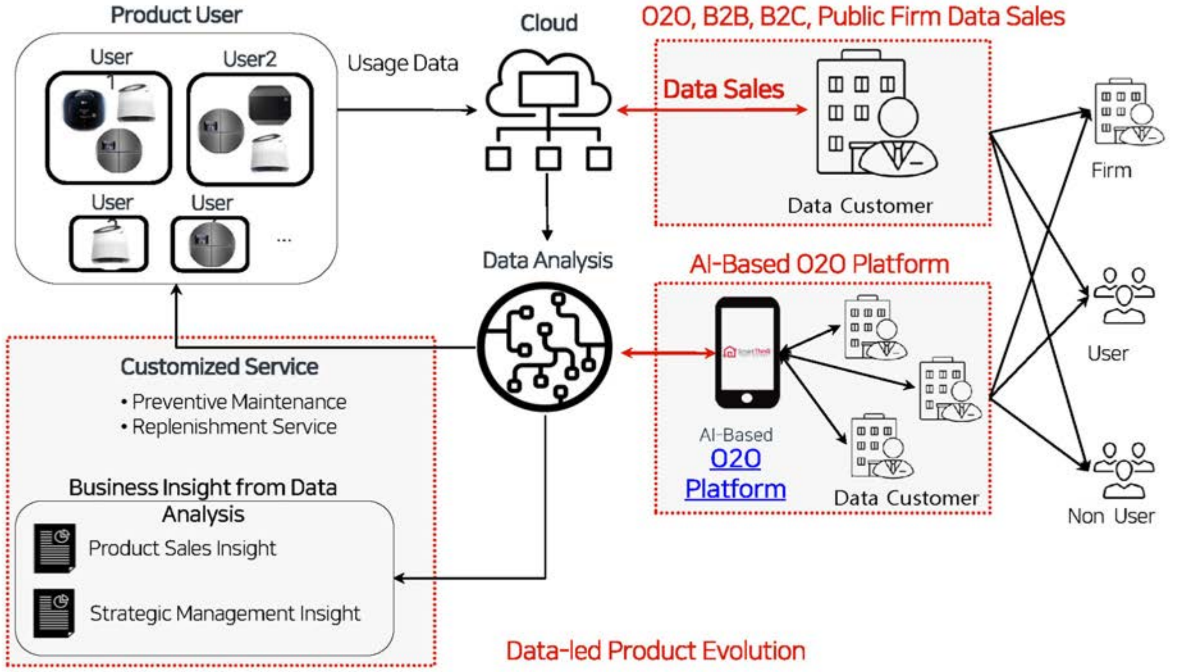
IoT-AI Mixed BM: Smart Connected Product + AI-Based Business Process



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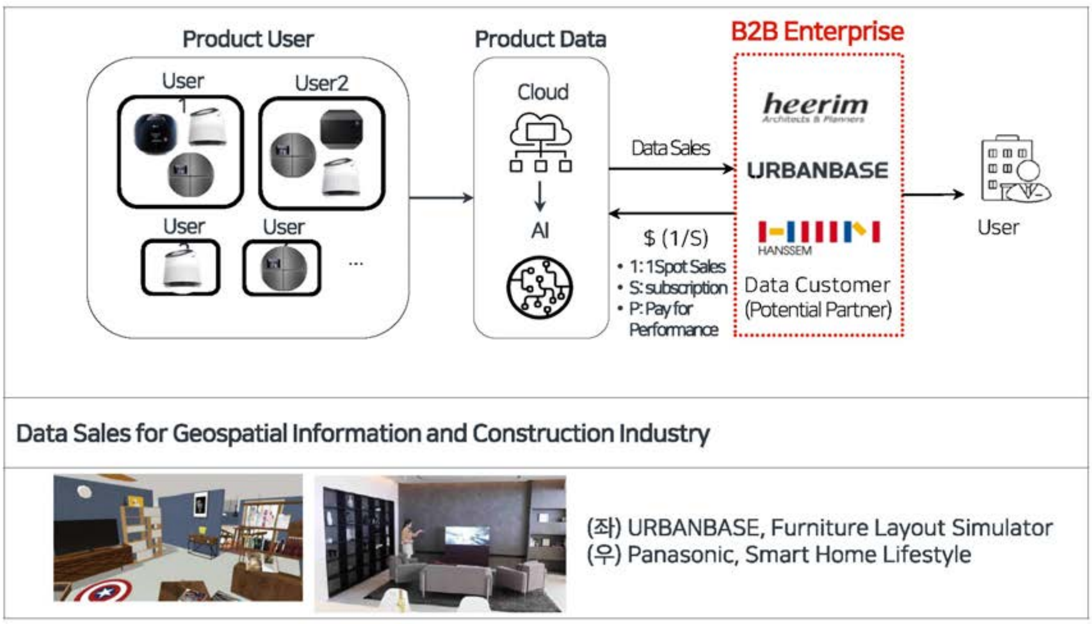
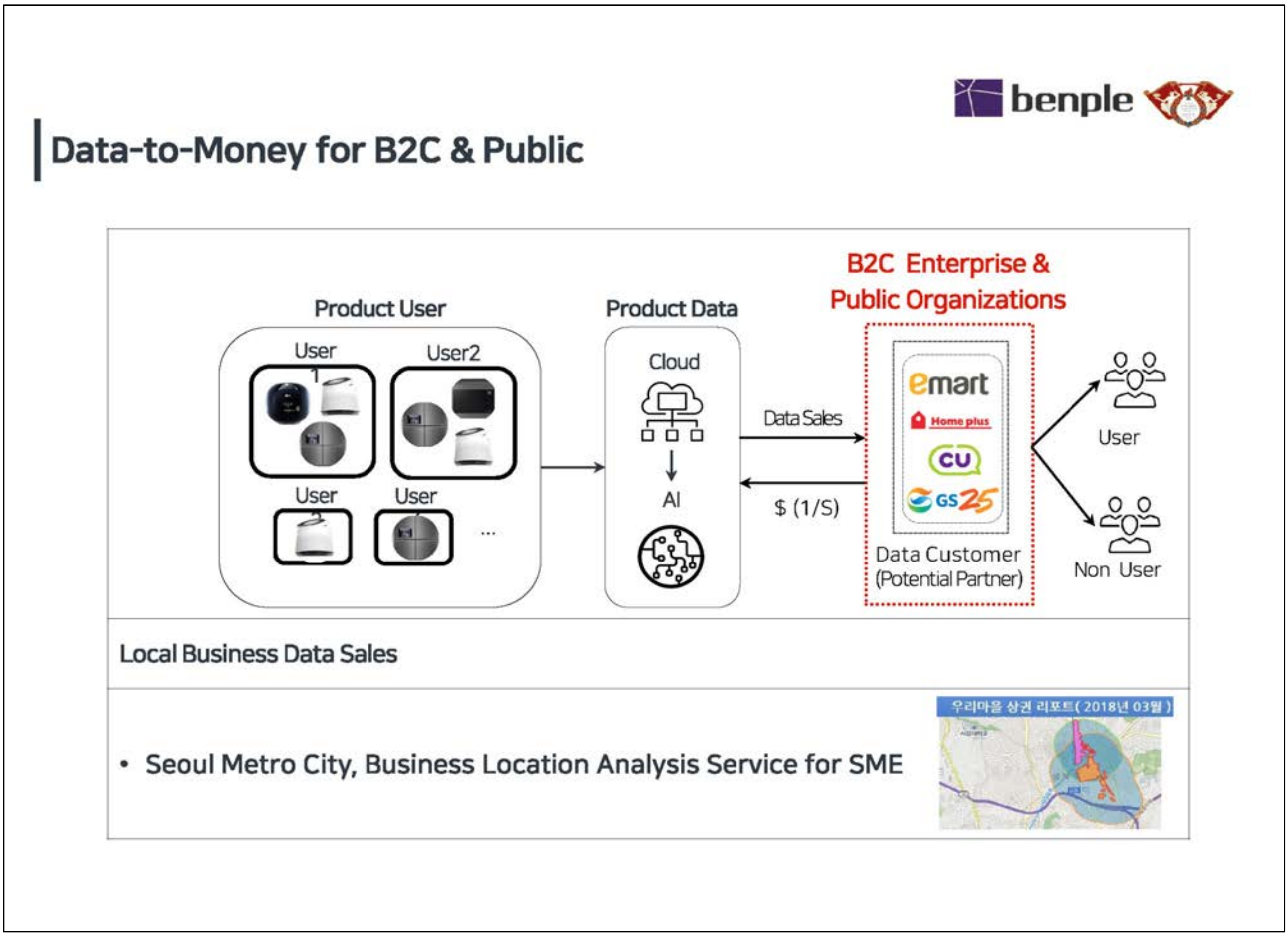
Data-to-Money for B2B Firms

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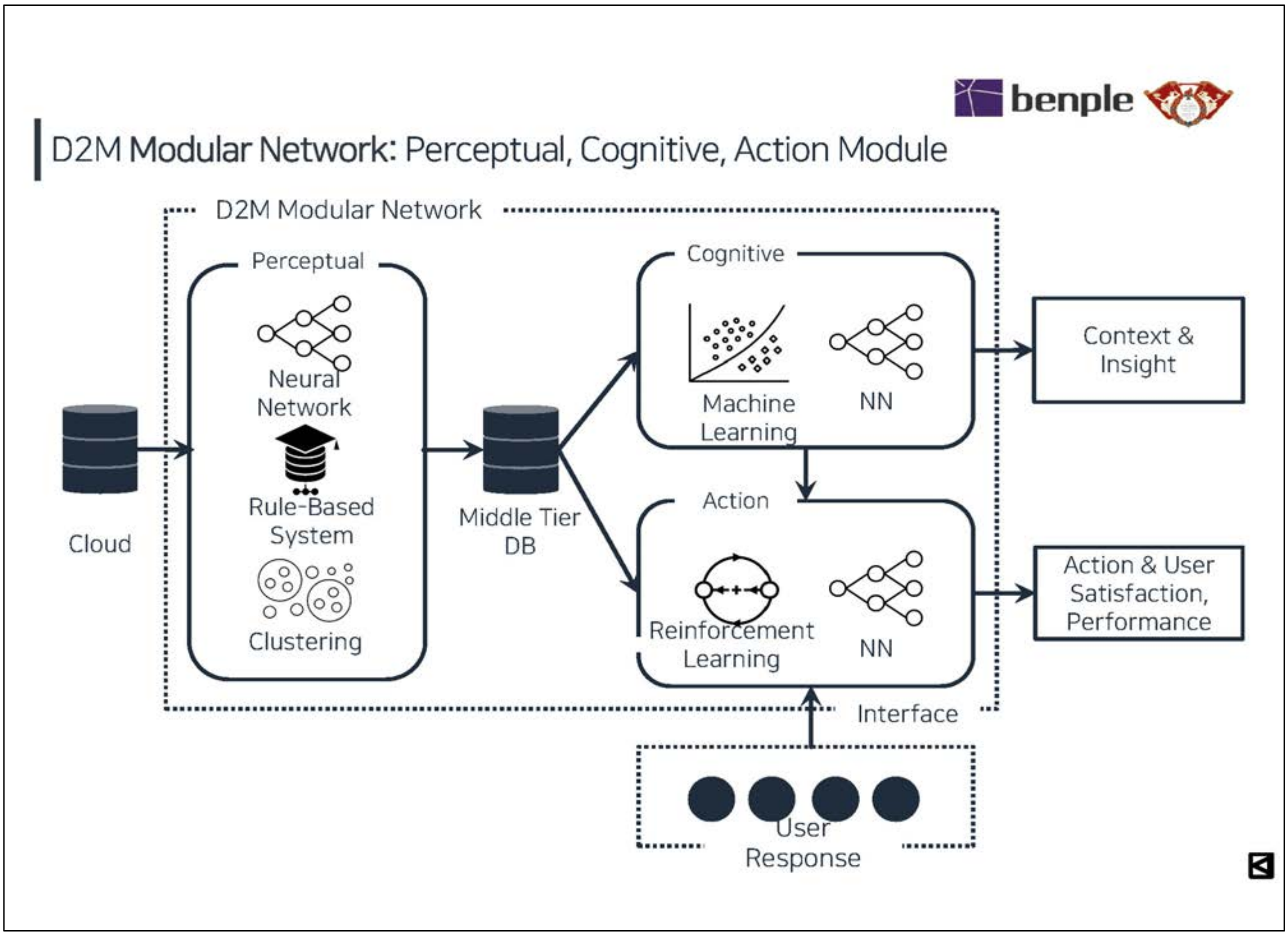
Data-to-Money for B2C & Public
B2C Enterprise &
Public Organizations
Product User
Product Data
User 1
User2
User
User
...
Cloud
AI
Data Sales
$ (1/S)
emart
Home plus
CU
GS25
Data Customer
(Potential Partner)
User
Non User
Local Business Data Sales
• Seoul Metro City, Business Location Analysis Service for SME
우리마을 상권 리포트(2018년 03월)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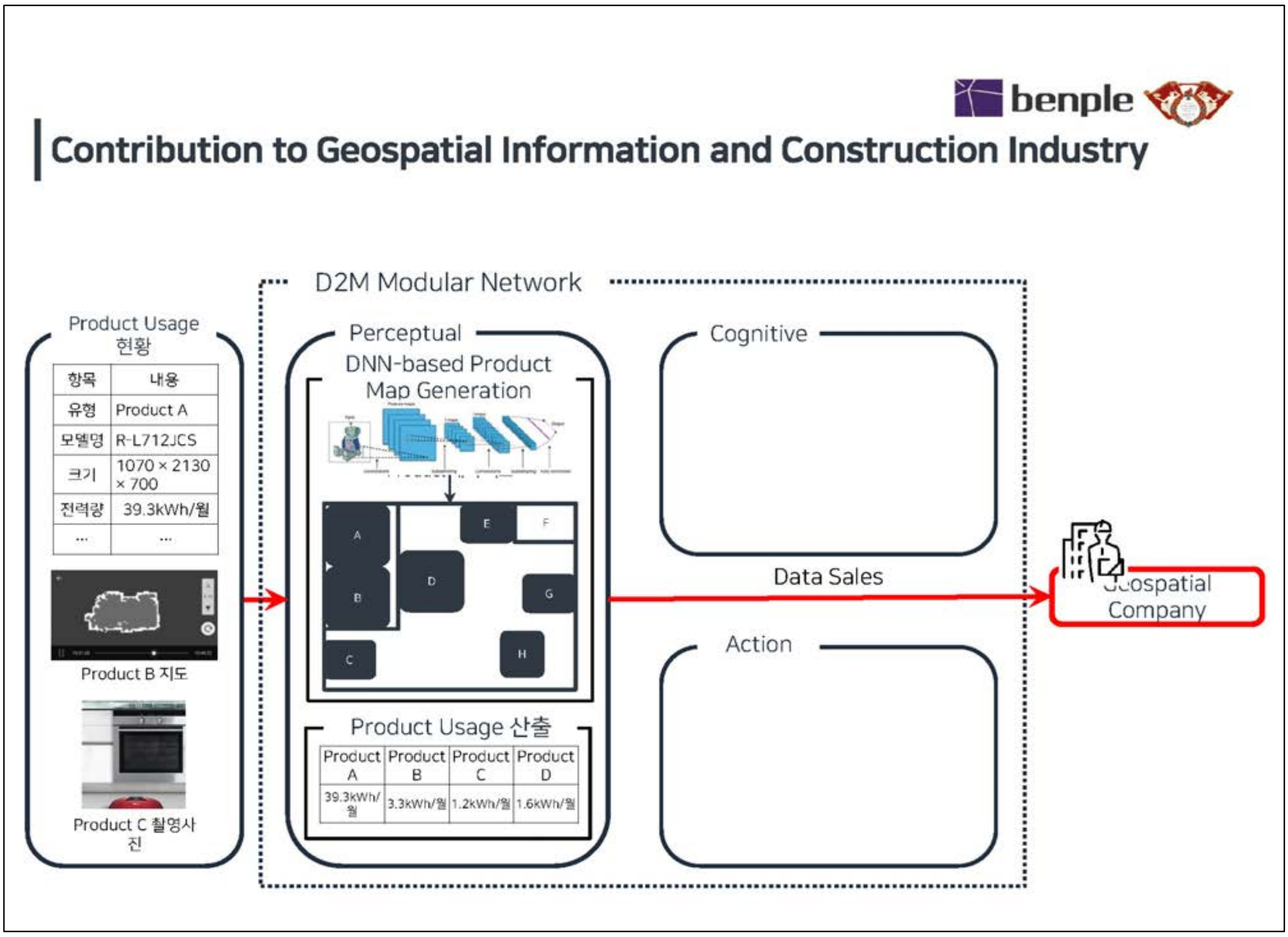
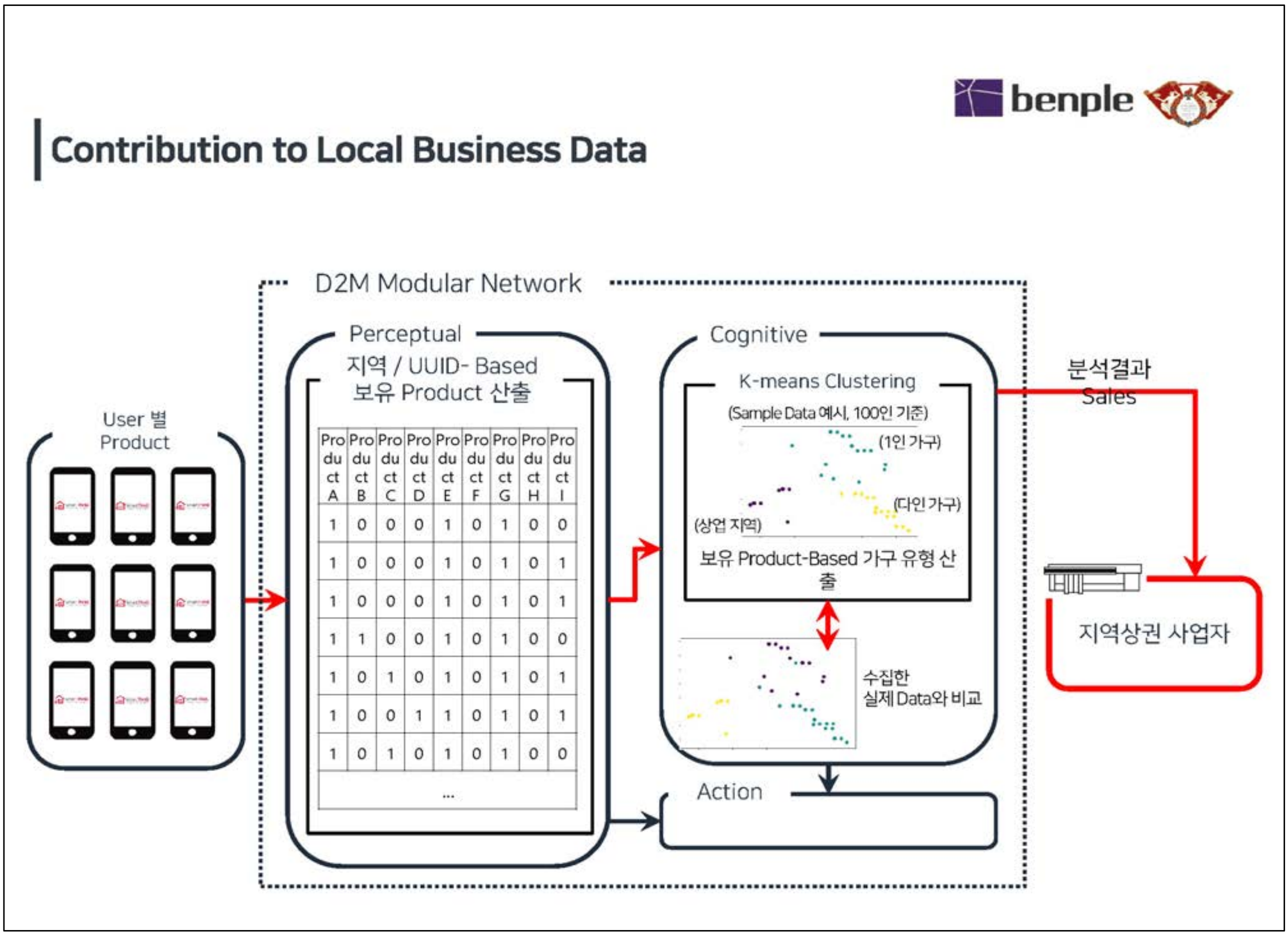
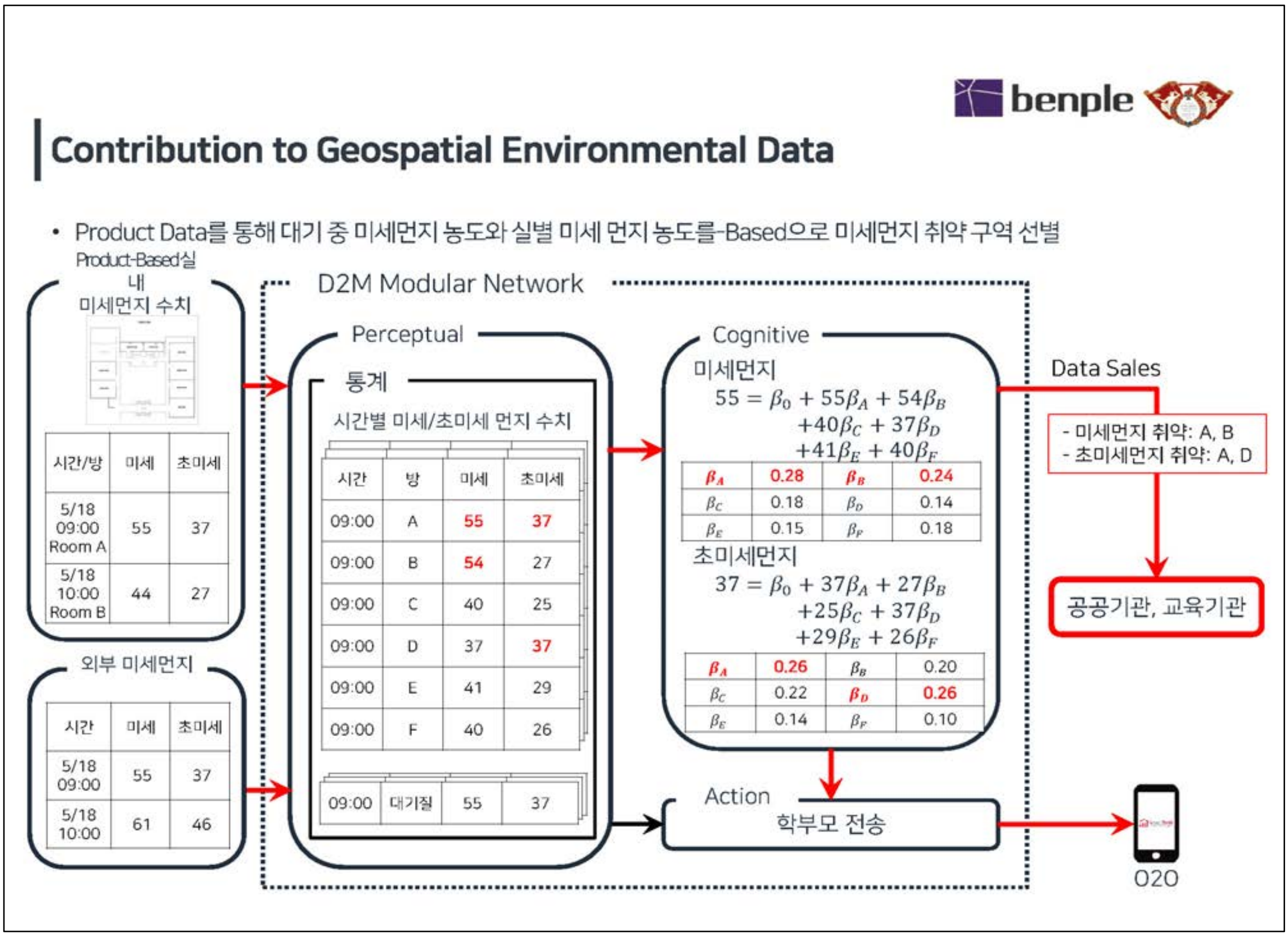
D2M Modular Network: Perceptual, Cognitive, Action Module
D2M Modular Network
Perceptual
Neural Network
Rule-Based System
Clustering
Cloud
Middle Tier DB
Cognitive
Machine Learning
NN
Action
Reinforcement Learning
NN
Context & Insight
Action & User Satisfaction, Performance
Interface
User Response


benple
Contribution to Geospatial Information and Construction Industry
D2M Modular Network
Product Usage
현황
항목 | 내용
유형 | Product A
모델명 | R-L712JCS
크기 | 1070 × 2130 × 700
전력량 | 39.3kWh/월
… | …
Product B 지도
Product C 촬영사진
Perceptual
DNN-based Product Map Generation
A
B
C
D
E
F
G
H
Product Usage 산출
Product A | Product B | Product C | Product D
39.3kWh/월 | 3.3kWh/월 | 1.2kWh/월 | 1.6kWh/월
Cognitive
Data Sales
Action
Geospatial Company


benple
Contribution to Local Business Data
D2M Modular Network
User 별 Product
Perceptual
지역 / UUID- Based
보유 Product 산출
Product A | Product B | Product C | Product D | Product E | Product F | Product G | Product H | Product I
1 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0
1 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1
1 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1
1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0
1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1
1 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 1
1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0
…
Cognitive
K-means Clustering
(Sample Data 예시, 100인 기준)
(1인 가구)
(다인 가구)
(상업 지역)
보유 Product-Based 가구 유형 산출
수집한 실제 Data와 비교
Action
분석결과 Sales
지역상권 사업자

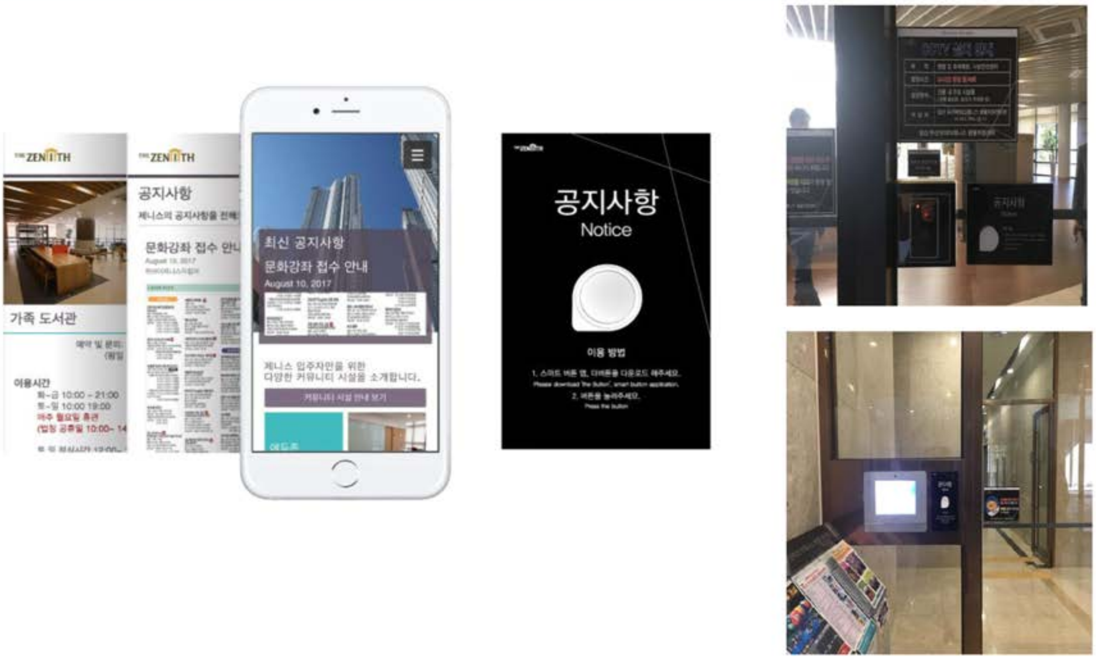

benple
Contribution to Geospatial Environmental Data
• Product Data를 통해 대기 중 미세먼지 농도와 실별 미세 먼지 농도를-Based으로 미세먼지 취약 구역 선별
Product-Based실 내 미세먼지 수치
시간/방 | 미세 | 초미세
5/18 09:00 Room A | 55 | 37
5/18 10:00 Room B | 44 | 27
외부 미세먼지
시간 | 미세 | 초미세
5/18 09:00 | 55 | 37
5/18 10:00 | 61 | 46
D2M Modular Network
Perceptual
통계
시간별 미세/초미세 먼지 수치
시간 | 방 | 미세 | 초미세
09:00 | A | 55 | 37
09:00 | B | 54 | 27
09:00 | C | 40 | 25
09:00 | D | 37 | 37
09:00 | E | 41 | 29
09:00 | F | 40 | 26
09:00 | 대기질 | 55 | 37
Cognitive
미세먼지
$55 = \beta_0 + 55\beta_A + 54\beta_B + 40\beta_C + 37\beta_D + 41\beta_E + 40\beta_F$
β_A 0.28 β_B 0.24
β_C 0.18 β_D 0.14
β_E 0.15 β_F 0.18
초미세먼지
$37 = \beta_0 + 37\beta_A + 27\beta_B + 25\beta_C + 37\beta_D + 29\beta_E + 26\beta_F$
β_A 0.26 β_B 0.20
β_C 0.22 β_D 0.26
β_E 0.14 β_F 0.10
Action
학부모 전송
Data Sales
- 미세먼지 취약: A, B
- 초미세먼지 취약: A, D
공공기관, 교육기관
O2O

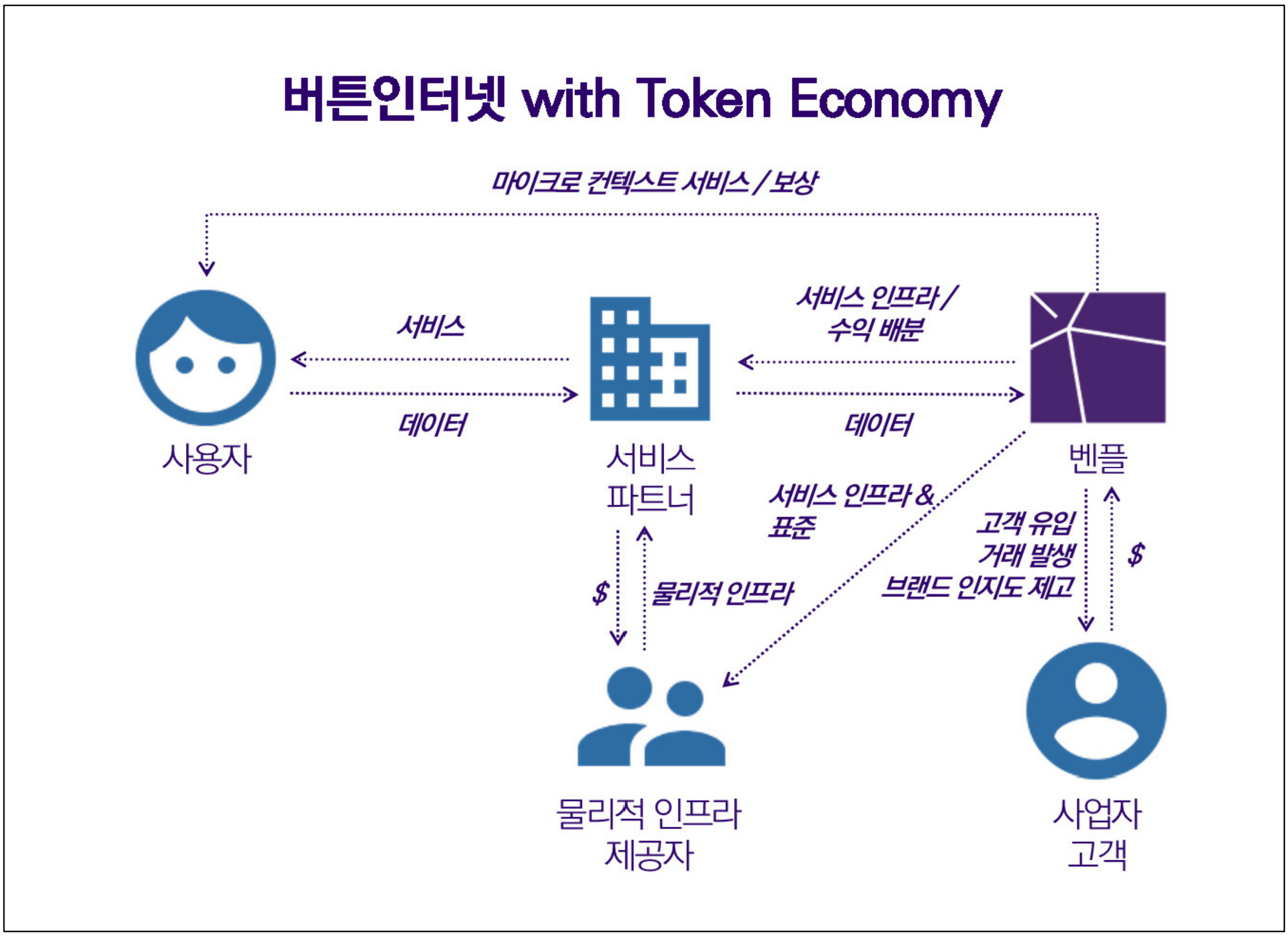

Smart Untact Case:
Samsung Digital Plaza
benple
디지털프라자
SAMSUNG
스마트 체험 가이드
버튼을 눌러주세요
이용 방법
581만원
국내 최대용량
김치냉장고
노트북9 Always

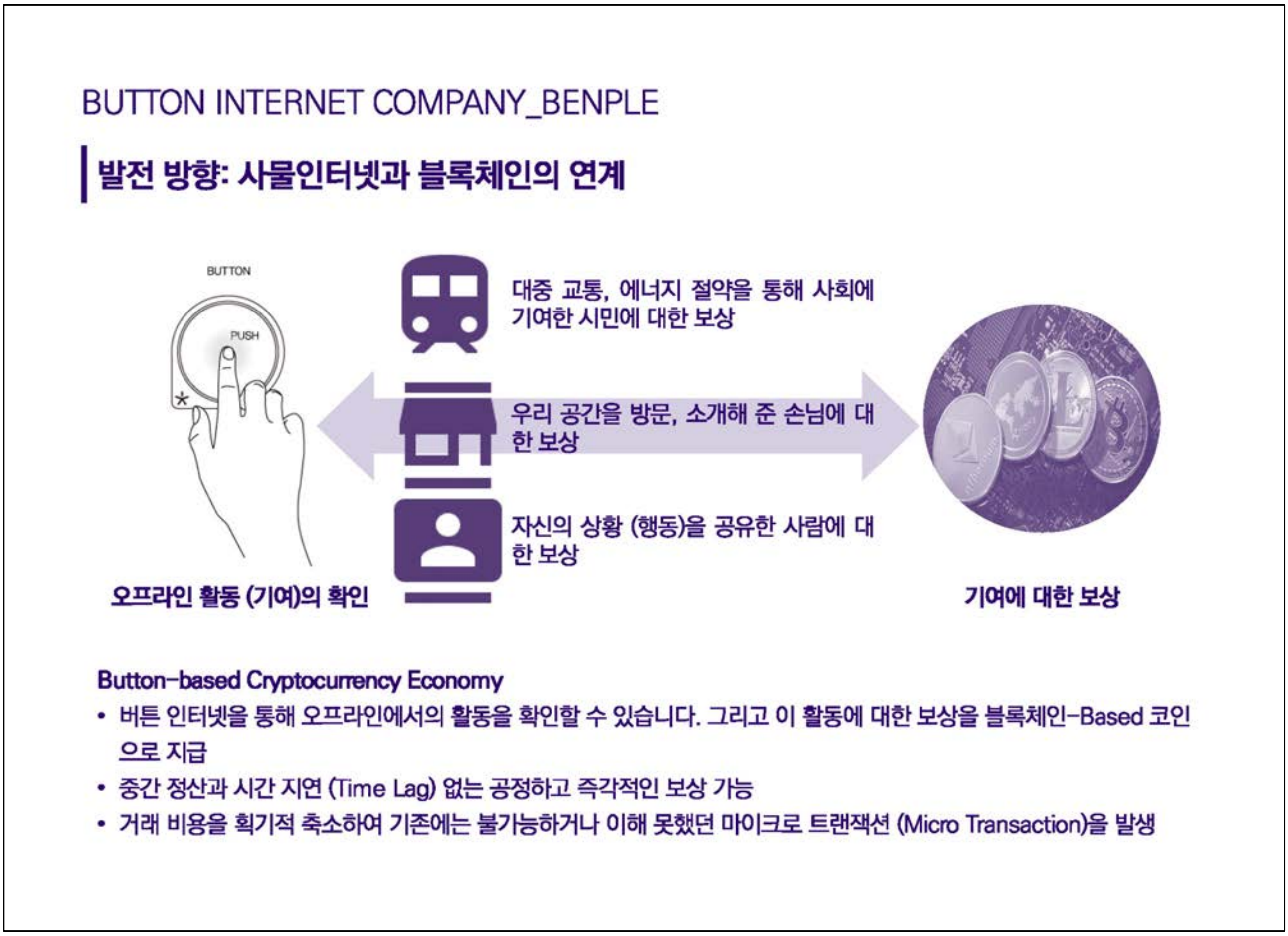
Retail as an Exhibition + O2O Marketing + Customer Retention

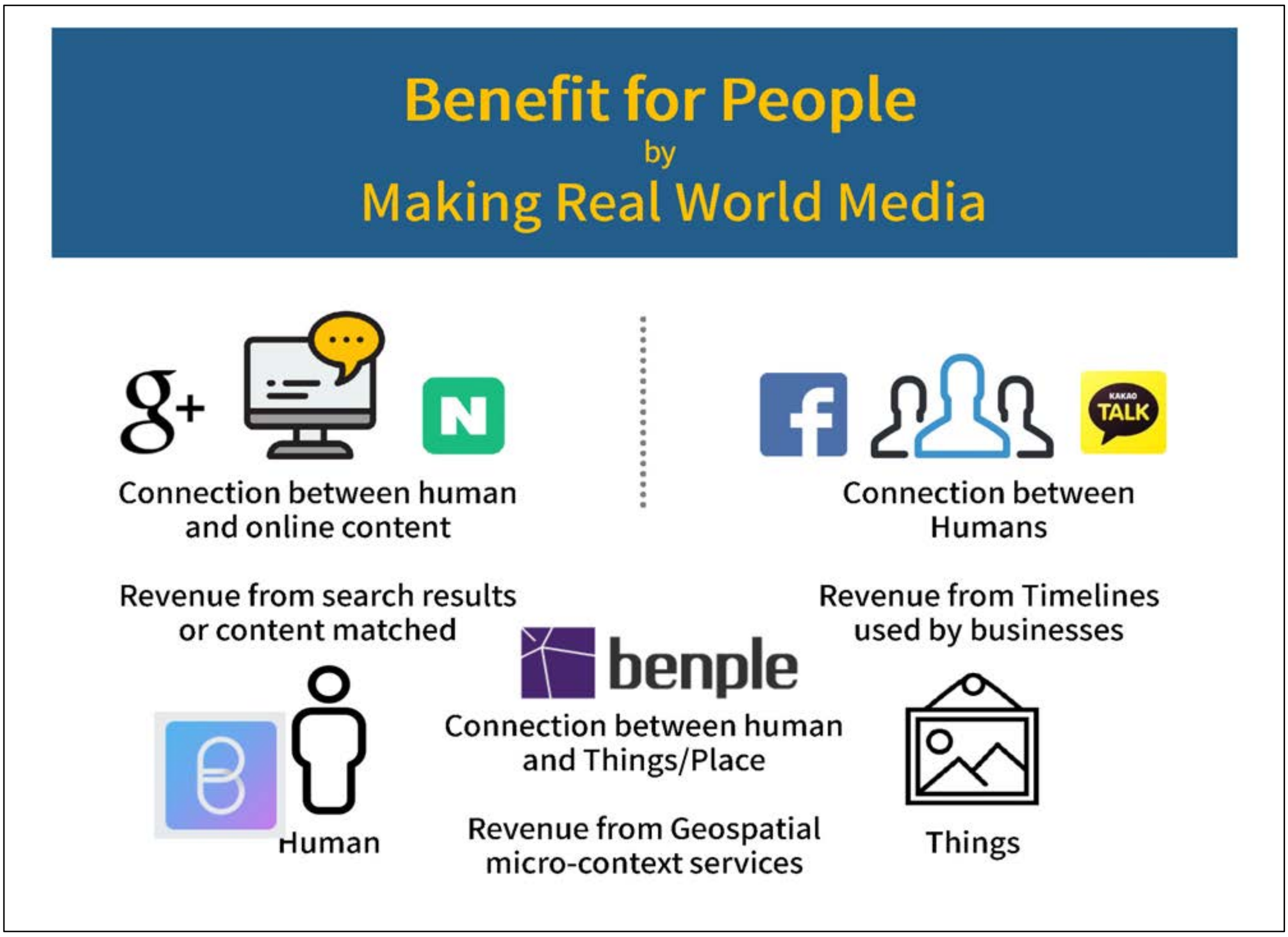
스마트 리테일 Service: LG U+

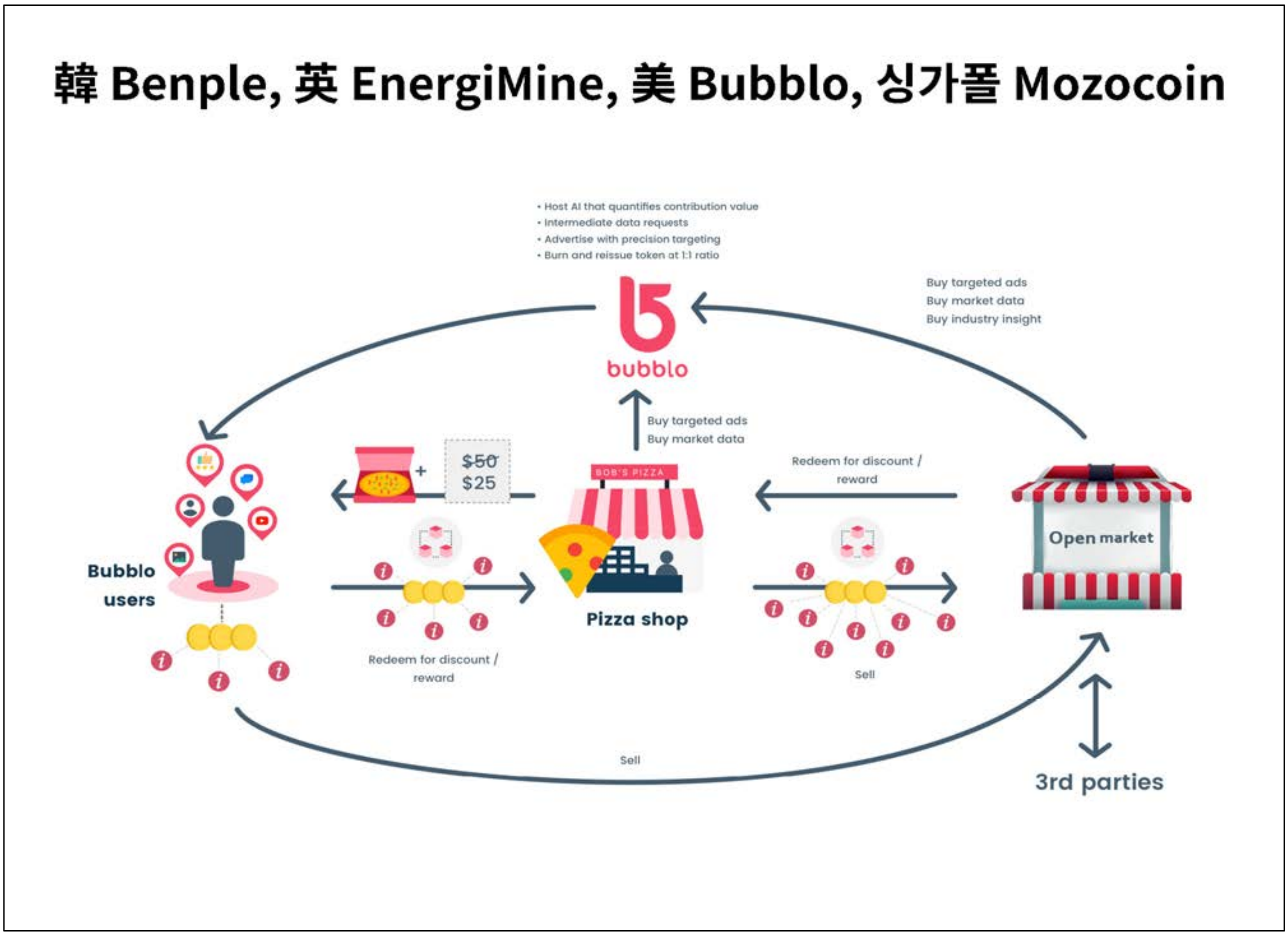
Residence Service as Exhibition + Community + Target Advertising




버튼인터넷 with Token Economy
마이크로 컨텍스트 서비스 / 보상
서비스
데이터
서비스 인프라 / 수익 배분
데이터
사용자
서비스 파트너
벤플
서비스 인프라 & 표준
고객 유입
거래 발생
브랜드 인지도 제고
$
$
물리적 인프라
물리적 인프라 제공자
사업자 고객


BUTTON INTERNET COMPANY_BENPLE
발전 방향: 사물인터넷과 블록체인의 연계
BUTTON
PUSH
대중 교통, 에너지 절약을 통해 사회에 기여한 시민에 대한 보상
우리 공간을 방문, 소개해 준 손님에 대한 보상
자신의 상황 (행동)을 공유한 사람에 대한 보상
오프라인 활동 (기여)의 확인
기여에 대한 보상
Button-based Cryptocurrency Economy
• 버튼 인터넷을 통해 오프라인에서의 활동을 확인할 수 있습니다. 그리고 이 활동에 대한 보상을 블록체인-Based 코인으로 지급
• 중간 정산과 시간 지연 (Time Lag) 없는 공정하고 즉각적인 보상 가능
• 거래 비용을 획기적 축소하여 기존에는 불가능하거나 이해 못했던 마이크로 트랜잭션 (Micro Transaction)을 발생


Benefit for People
by
Making Real World Media
Connection between human and online content
Revenue from search results or content matched
KAKAO TALK
Connection between Humans
Revenue from Timelines used by businesses
benple
Connection between human and Things/Place
Revenue from Geospatial micro-context services
Human
Things


韓 Benple, 英 EnergiMine, 美 Bubblo, 싱가폴 Mozocoin
• Host AI that quantifies contribution value
• Intermediate data requests
• Advertise with precision targeting
• Burn and reissue token at 1:1 ratio
Buy targeted ads
Buy market data
Buy industry insight
bubblo
Buy targeted ads
Buy market data
$50
$25
BOB'S PIZZA
Redeem for discount / reward
Open market
Bubblo users
Pizza shop
Redeem for discount / reward
Sell
Sell
3rd parties

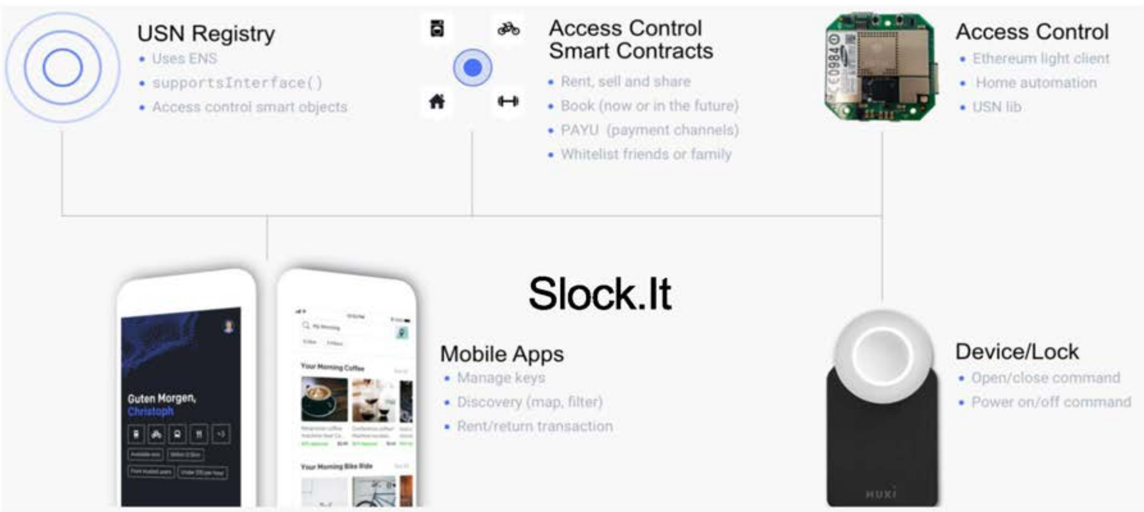
Disrupt Foot Traffic in Shopping Malls across Asia

Through Mozo tokens, NOT loyalty points

https://mozocoin.io

Decentralized B&B vs. AirBnB

- An open source infrastructure. Blockchain applications modules can be deployed.
- Open platform making it easy for 3rd parties including manufacturer, small or large, to onboard any object to the USN, without having to 'ask permission'.



Smart Connected City

Beyond Human Pay

Smart Connected Products and Geospatial Data

- Smart Connected Products generate vast amount of new geospatial data.
- The analysis of geospatial data will be done by AI rather than by humans.
- Geospatial information business should cooperate with the smart connected product companies and platforms
- Serendipitous services will emerge from the integration of AI and geospatial information.
- New platform business in 4IR will emerge from the new services fulfilling new demand through the new stream of geospatial data.
- The new business will be realized through the support of edge computing based AI, cloud-based AI, and possibly token economy systems and incentive engineering.

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2018 ICGIS (International Conference on Geospatial Information Science)


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2018 International Conference on Geospatial Information Science
THANK YOU

Session 2: New and Smart Geospatial Information Industries with AI

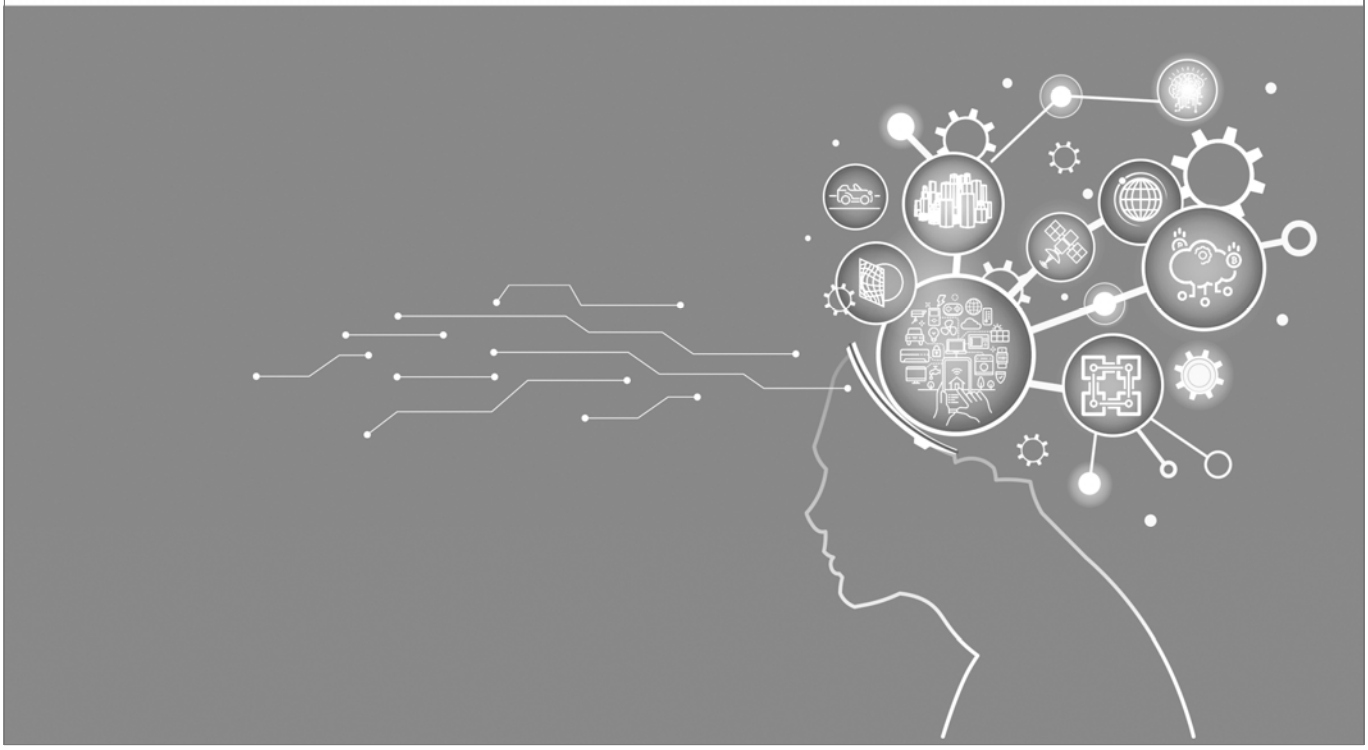
Keynote Speech 2
Geo AI for Smart New Industries
- *Brett Dixon,* General Manager, Asia Pacific at ESRI

AI for Smart Mobility
- *Seung-Il You,* Head of Datalab, Kakao Mobility

Geospatial Information and Machine Learning Application in Japan
- *Yoshiki Ogawa,* Project Researcher, The University of Tokyo

Cloud-powered Machine Learnings on Geospatial Services - From the Earth to Your Home
- *Channy Yun,* Tech Evangelist, Amazon Web Service Korea

A Deep Learning Approach for Simulating Urban Development
- *Donghan Kim,* Research Fellow, KRIHS



Keynote Speech 2

Geo AI for Smart New Industries

Brett Dixon
General Manager, Asia Pacific at ESRI

Geo AI for Smart New Industries

Brett Dixon
BDixon@esri.com
General Manager for Asia Pacific, Esri

Memo

Memo

AI for Smart Mobility

Seung-Il You
Head of Datalab, Kakao Mobility

AI for Smart Mobility

Seung Il You
sean.you@kakaomobility.com
Kakao Mobility Datalab.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AI for smart mobility
Seungil You (sean.you@kakaomobility.com)
KakaoMobility
Head of Datalab

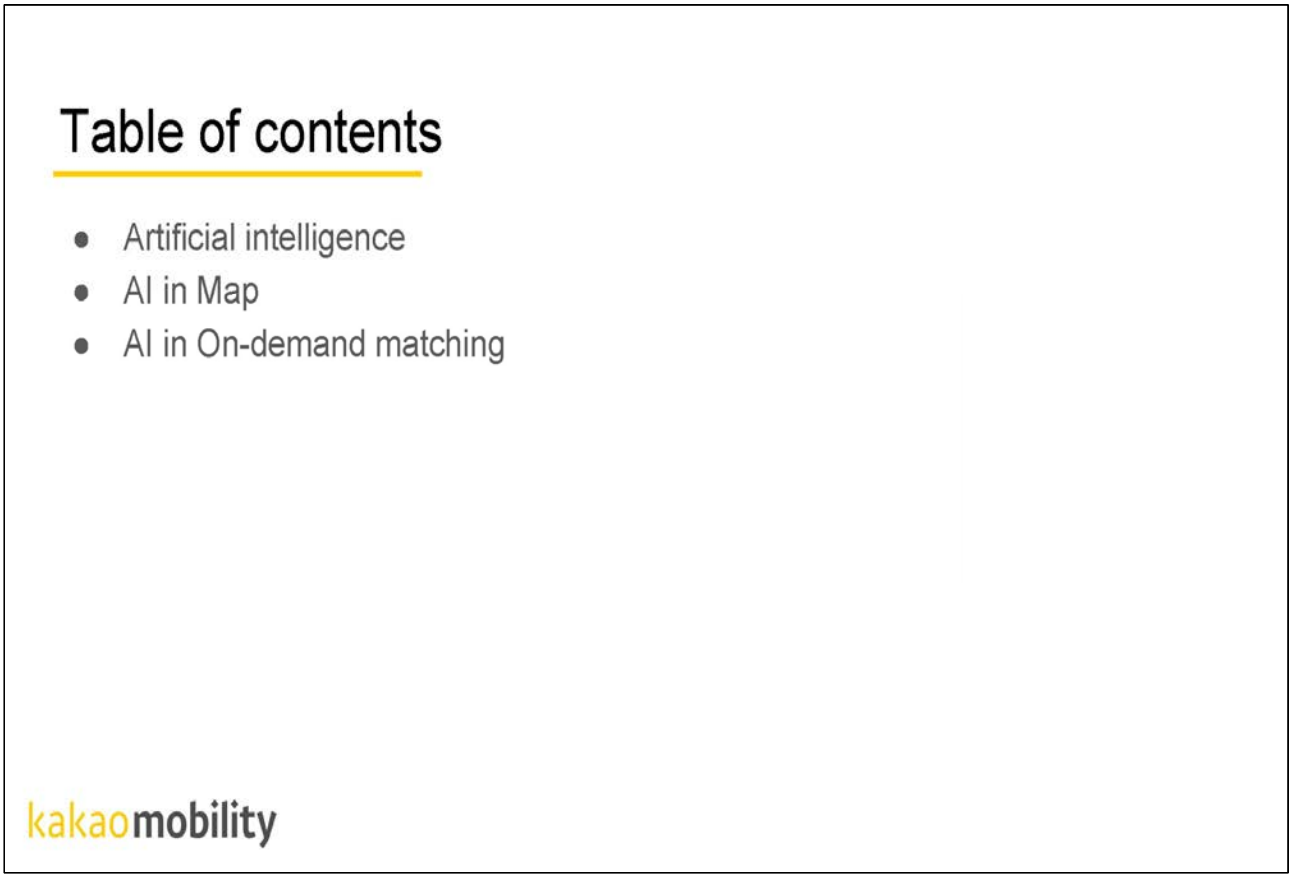
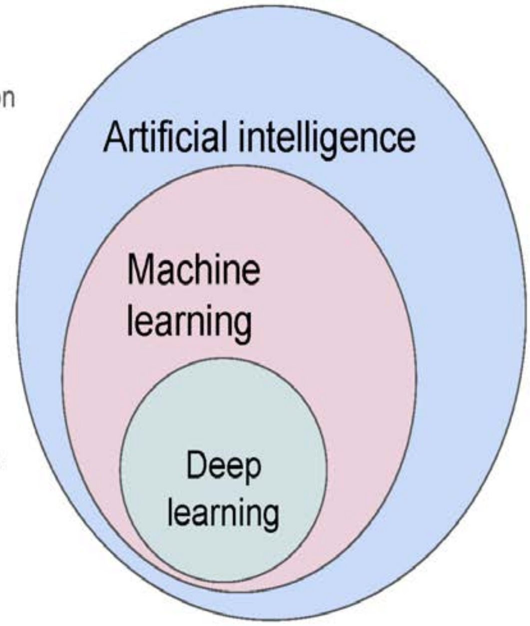


Table of contents
Artificial intelligence
AI in Map
AI in On-demand matching
kakaomobility

Artificial intelligence

- Artificial intelligence
  - A system that can make a prediction and decision
  - Route planning, logistics planning, etc
- Machine learning
  - A scalable approach to build an AI system
  - Use data to learn a pattern
  - ARIMA, SVM, Boosted tree, etc
- Deep learning
  - A scalable approach to build an ML system
  - Excels at perception tasks, e.g., computer vision



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Smart mobility

Traffic forecasting

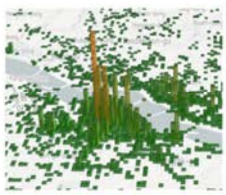
ETA prediction

AI Dispatch

AI Pricing

Positioning

Map Matching



Demand prediction

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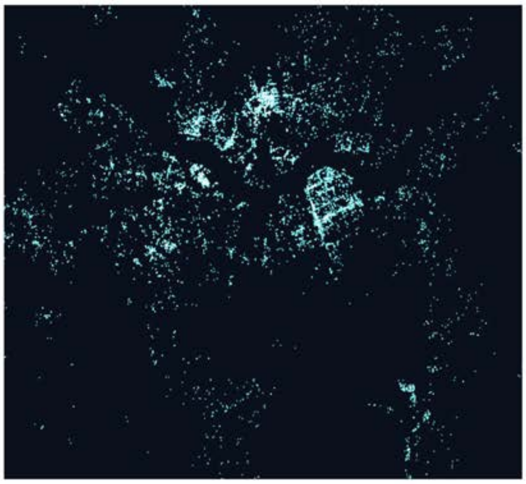
Spatiotemporal information and AI

- Geo + Time information is a key
- Existing statistical approach
  - STARIMA, DTWarp, etc.
- Deep learning approach rises
  - CNN + LSTM
  - Graph CNN, etc.



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AI in Map

- Map is a core to smart mobility.
- Utilizing geospatial information is critical for faster and better map related services
- On-going research areas
  - Traffic forecasting
  - Routing
  - Map matching

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Traffic forecasting

Historical data:

Aggregated speed of each link (road)

Question:

How do we predict a future traffic speed?

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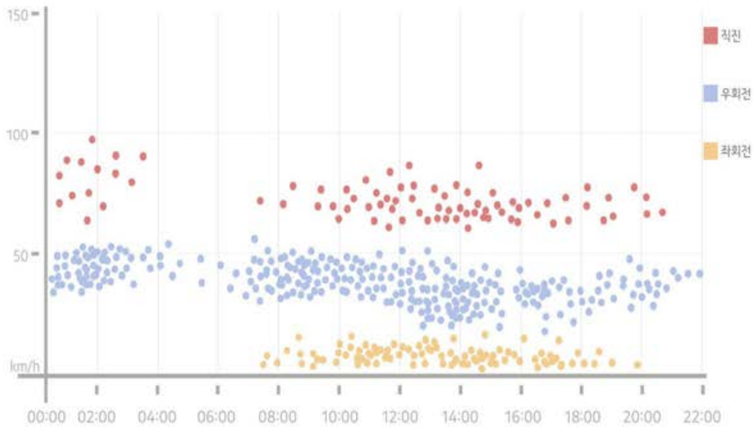
Data representation



[그림 5] 회전에 의한 속도 패턴

source: [카카오AI리포트] 카카오내비 예측의 정확성 그리고 AI, https://brunch.co.kr/@kakao-it/193

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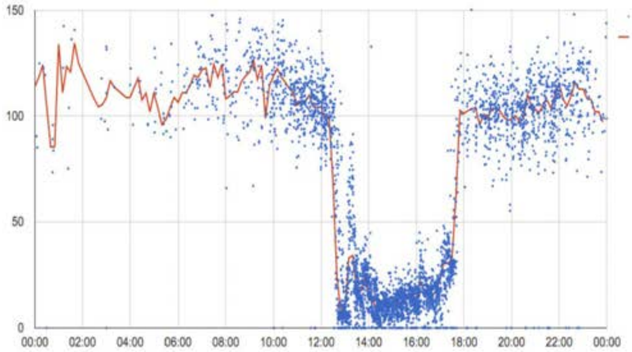
Time series approach

- Utilizing a temporal pattern
- How about geospatial information?



source: [카카오AI리포트] 카카오내비 예측의 정확성 그리고 AI, https://brunch.co.kr/@kakao-it/193

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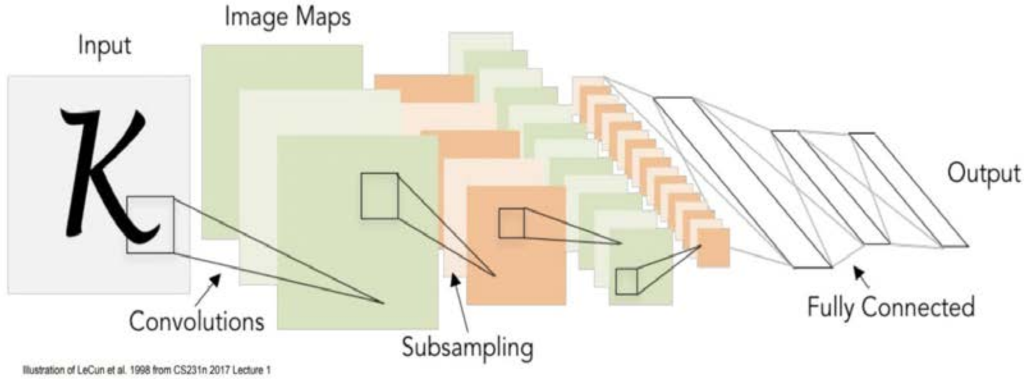
Convolutional Neural Networks

CNN is great for images.



source: http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture5.pdf

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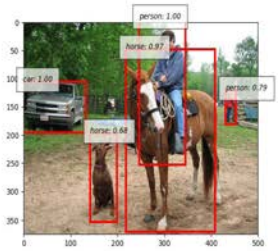
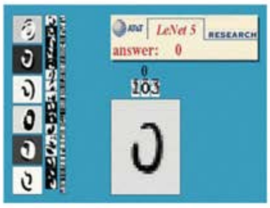
Convolutional Neural Networks



Object detection

Image generation



Digit recognition

Many more..

source: https://github.com/tkarras/progressive_growing_of_gans
source: https://chainercv.readthedocs.io/en/stable/tutorial/detection.html
source: http://yann.lecun.com/exdb/lenet/

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Traffic forecasting with CNN

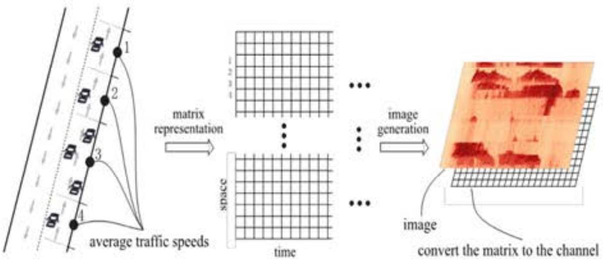

Figure 1. An illustration of the traffic-to-image conversion on a network.

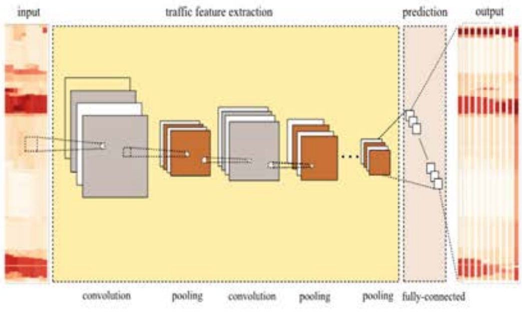

Figure 2. Deep learning architecture of CNN in the context of transportation.

source: Ma, Xiaolei, et al. "Learning traffic as images: a deep convolutional neural network for large-scale transportation network speed prediction." *Sensors* 17.4 (2017)

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Traffic forecasting with CNN

Capturing spatial dependency is a key!

Table 3. Prediction performance (MSE) of the CNN and other algorithms.

Study Network	Model	MSE of Different Models (on Test Datasets)			
		Task 1	Task 2	Task 3	Task 4
Network 1	CNN	**22.825 ***	**24.345 ***	**30.593 ***	**31.424 ***
	OLS	27.047	31.273	41.334	48.107
	KNN	51.700	55.708	60.256	64.132
	RF	35.092	35.431	40.476	40.638
	ANN	67.764	52.339	58.797	57.225
	SAE	60.751	69.082	65.292	68.326
	RNN	33.408	36.833	40.551	39.038
	LSTM NN	37.759	33.218	42.909	42.865
Network 2	CNN	**27.163 ***	**28.479 ***	**37.987 ***	**38.816 ***
	OLS	33.741	41.657	50.123	62.282
	KNN	69.965	74.863	79.367	83.881
	RF	48.603	48.946	52.676	53.067
	ANN	124.937	147.489	133.299	168.136
	SAE	85.079	94.982	82.271	99.020
	RNN	48.877	47.470	52.577	52.114
	LSTM NN	43.304	45.657	50.928	48.345

Note: * indicates the best result.

Table 4. Prediction performance (accuracy) of the CNN and other algorithms.

Study Network	Model	Accuracy Score of Different Models (on Test Datasets)			
		Task 1	Task 2	Task 3	Task 4
Network 1	CNN	**0.939 ***	**0.942 ***	**0.925 ***	**0.928 ***
	OLS	0.935	0.929	0.915	0.909
	KNN	0.901	0.897	0.893	0.890
	RF	0.917	0.917	0.910	0.910
	ANN	0.869	0.876	0.852	0.865
	SAE	0.867	0.870	0.866	0.866
	RNN	0.908	0.913	0.898	0.900
	LSTM NN	0.910	0.908	0.901	0.905
Network 2	CNN	**0.938 ***	**0.936 ***	**0.920 ***	**0.922 ***
	OLS	0.929	0.920	0.907	0.897
	KNN	0.886	0.884	0.879	0.876
	RF	0.898	0.898	0.893	0.892
	ANN	0.794	0.867	0.823	0.832
	SAE	0.846	0.835	0.848	0.825
	RNN	0.901	0.900	0.896	0.896
	LSTM NN	0.903	0.907	0.901	0.895

Note: * indicates the best result.

source: Ma, Xiaolei, et al. "Learning traffic as images: a deep convolutional neural network for large-scale transportation network speed prediction." *Sensors* 17.4 (2017)

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Routing

Data:

Road link structure

Starting and end point

Question:

How to route?

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Routing

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Routing

A classic computer science problem!

Dijkstra algorithm

A star algorithm

Contraction hierarchies

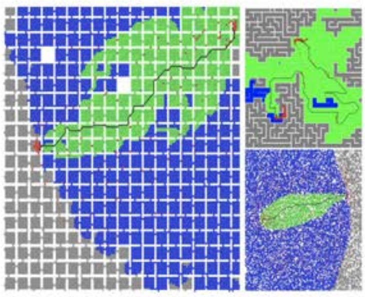

Fig. 4. Examples for rooms, mazes and random graphs. Nodes expanded by Dijkstra blue, by A* green and by the CH-Dijkstra red.

source: https://en.wikipedia.org/wiki/Dijkstra%27s_algorithm
source: https://en.wikipedia.org/wiki/A*_search_algorithm
source: Storandt, Sabine. "Contraction hierarchies on grid graphs." *Annual Conference on Artificial Intelligence*. Springer, Berlin, Heidelberg, 2013.

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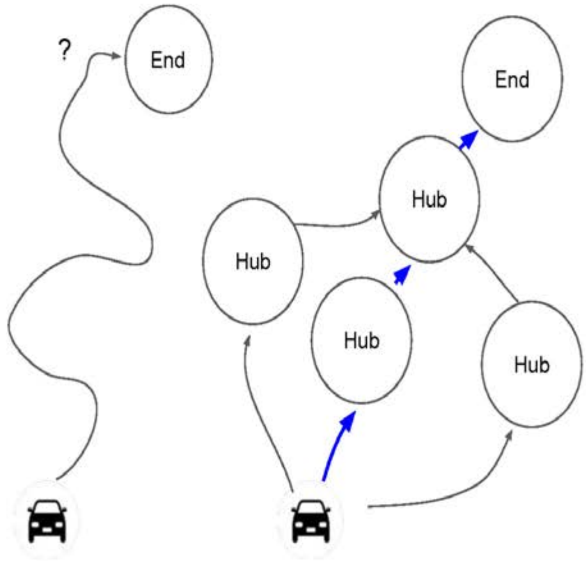
Hub algorithm

Construct hubs to accelerate the computation time

Q) How to select the right hub?

A) Still in progress.. Spatial information is the key!



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Map matching

Data points:

GPS measurements (red dots) are noisy and sparse.

Question:

Can we map it to the actual link (road)?

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Map matching

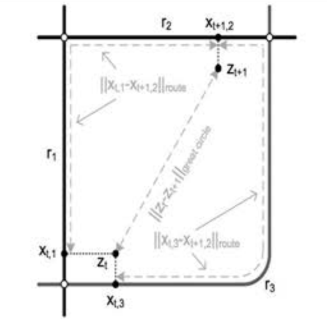

Figure 4: This shows an example of our notation. There are three road segments, r_1, r_2, and r_3, and two measured points, z_t and z_{t+1}. The first measured point, z_t, has candidate road matches at $x_{t,1}$ and $x_{t,3}$. Each match candidate results in a route to $x_{t+1,2}$, which is a match candidate for the second measured point, z_{t+1}. These two routes have their own lengths, as does the great circle path between the two measured points. Our data shows that the route distance and great circle distance are closer together for correct matches than for incorrect matches.

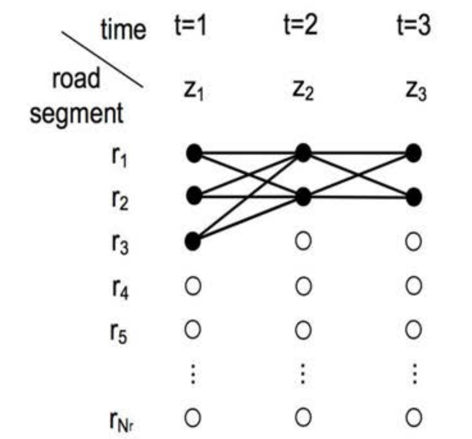

Figure 3: For each measurement z_t, the HMM considers all the road segments r_i as well as all the transitions between the road segments.

source: Hidden Markov Map Matching Through Noise and Sparseness, Paul Newson and John Krumm, ACM SIGSPATIAL GIS 2009

Map recap

1. Traffic forecasting
   - Deep learning rises
2. Routing
   - Faster algorithms with geospatial index
3. Map matching
   - From noisy measurements to the accurate geospatial information

AI in on-demand matching

- Our platform provides on-demand matching services (like Uber and Didi)
- Matching on-demand request is hard because of geological and time constraints
- On-going research
  - Demand prediction
  - AI matching

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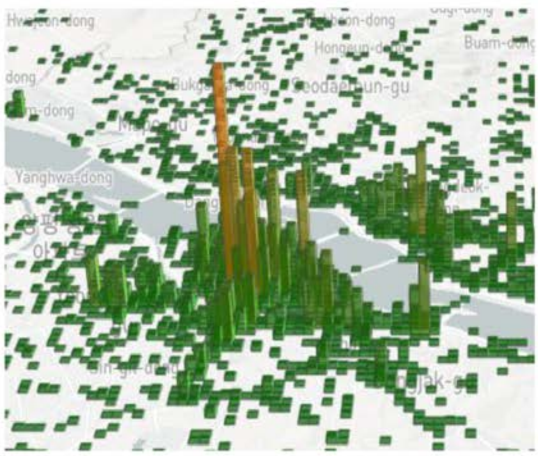
Demand prediction

Historical data:

Aggregated taxi demand at each location

Question:

Can we predict a future taxi demand?



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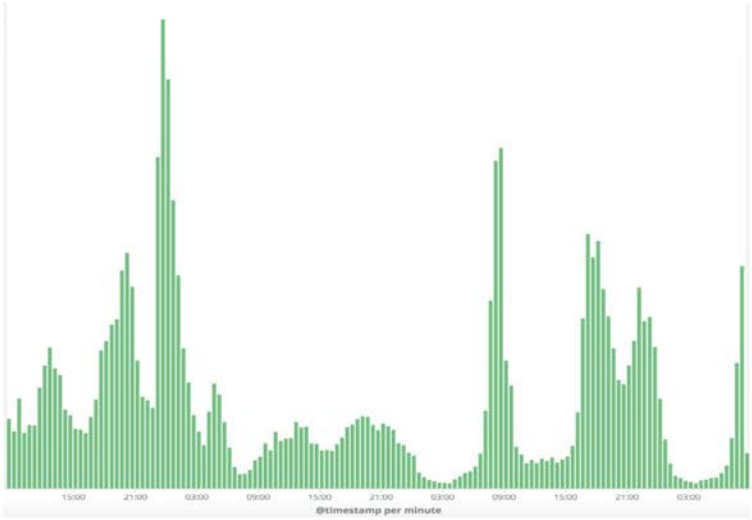
Data representation

In each region, we have historical time series of demand requests.



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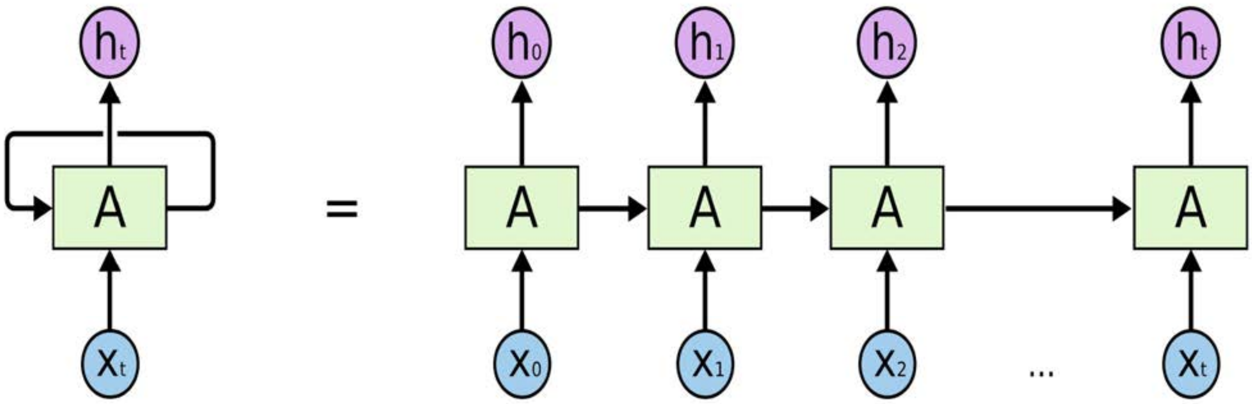
Deep learning: Recurrent network

- Good for sequential data (e.g., time-series)
- Not for spatial data..



source: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

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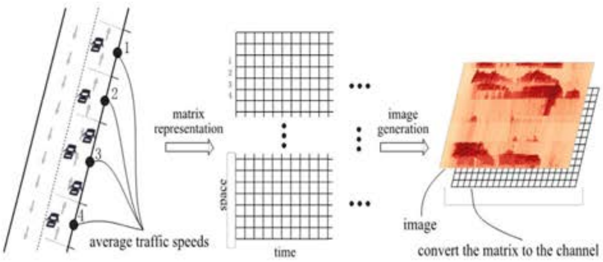
Traffic forecasting with CNN

- CNN can capture spatial pattern.



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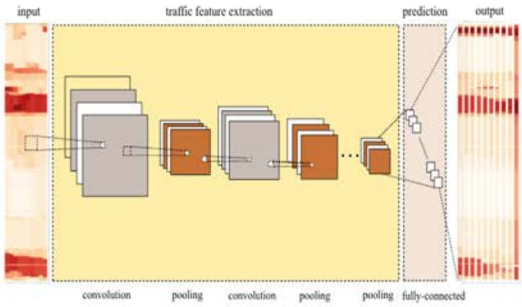

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source: Ma, Xiaolei, et al. "Learning traffic as images: a deep convolutional neural network for large-scale transportation network speed prediction." *Sensors* 17.4 (2017)

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CNN + LSTM?

source: https://knowyourmeme.com/photos/538731-why-not-both-why-dont-we-have-both

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Taxi demand prediction with CNN + LSTM

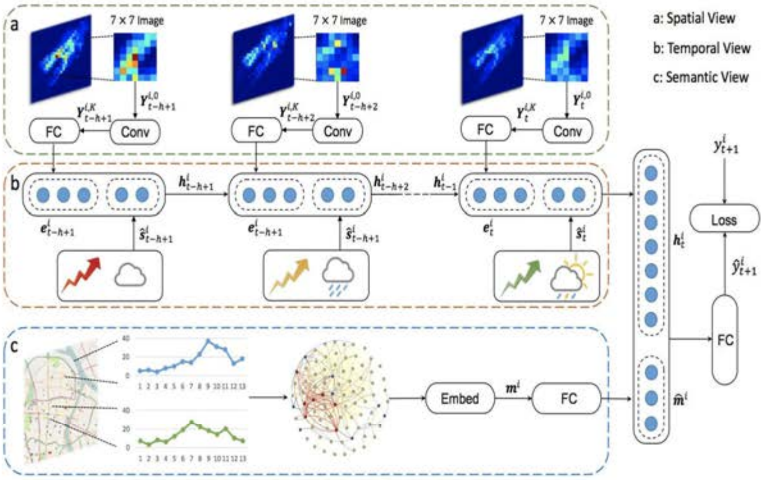

Table 1: Comparison with Different Baselines

Method	MAPE	RMSE
Historical average	0.2513	12.167
ARIMA	0.2215	11.932
Ordinary least square regression	0.2063	10.234
Ridge regression	0.2061	10.224
Lasso	0.2091	10.327
Multiple layer perceptron	0.1840	10.609
XGBoost	0.1953	10.012
ST-ResNet	0.1971	10.298
DMVST-Net	**0.1616**	**9.642**

source: Deep Multi-View Spatial-Temporal Network for Taxi Demand Prediction, H. Yao et. al, AAAI, 2018

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Taxi demand prediction (in preparation)

Maptile source: Mapbox, Mapdata source: Open street map

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AI dispatch

- "Fast and convenient ride"
- Driver - Rider matching

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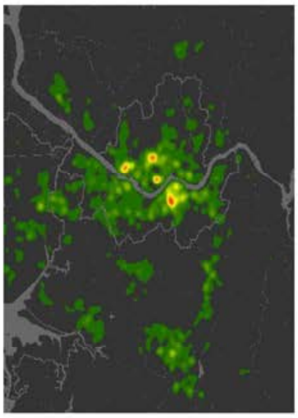
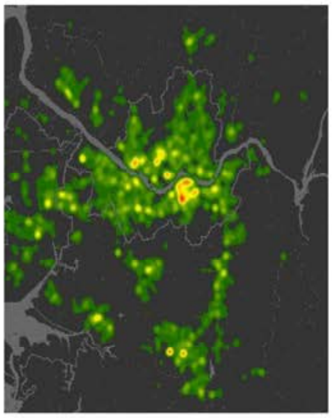
Mobility demands in NYC vs Seoul

Pickups



Drop offs



source: Todd W. Schneider's blog

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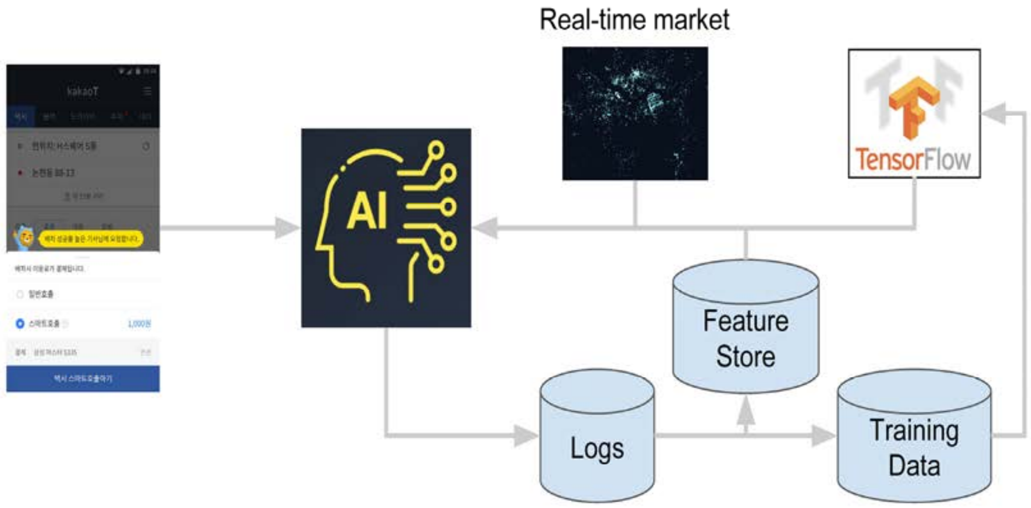
AI dispatch



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AI for smart mobility

Our AI systems **connect people** and help our users to **explore the world**.

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Geospatial Information and Machine Learning Application in Japan

Yoshiki Ogawa
Project Researcher, The University of Tokyo

Geo spatial information and machine learning application in Japan

Yoshiki Ogawa
ogawa@csis.u-tokyo.ac.jp
Institute of Industrial Science, The University of Tokyo

Abstract

Recent years have accumulated a dramatic growth of geo spatial data (e.g., smart phone GPS and CDRs, satellite images, building data, vehicle-mounted smartphone images, business transaction data, and tweets). Geo spatial data contain all kinds of information about the real world and human behavior and urban model, thus offering great opportunities for analyzing and mining vast amounts of GIS data ("big geo data") to support Local government and citizens tasks and optimize decision making in many kinds of application. However, raw accumulated Geospatial data cannot yet accurately understand real world; as such, involving machine learning in the loop of interactive data mining is essential. In this talk, I will present the application of Geo-spatial data and machine learning, an interactive data analysis tool for estimate people flow and disaster damage to enable us to perform intelligent information analysis in decision making support framework. Geospatial data and AI would allow us to see and estimate useful hidden information buried in large amounts of accumulated data that would otherwise be unknown to us. As examples of data mining, I will present some general AI algorithms that we have recently used for joint analysis of geospatial information data to discover availability of new application for geo spatial science in Japan.


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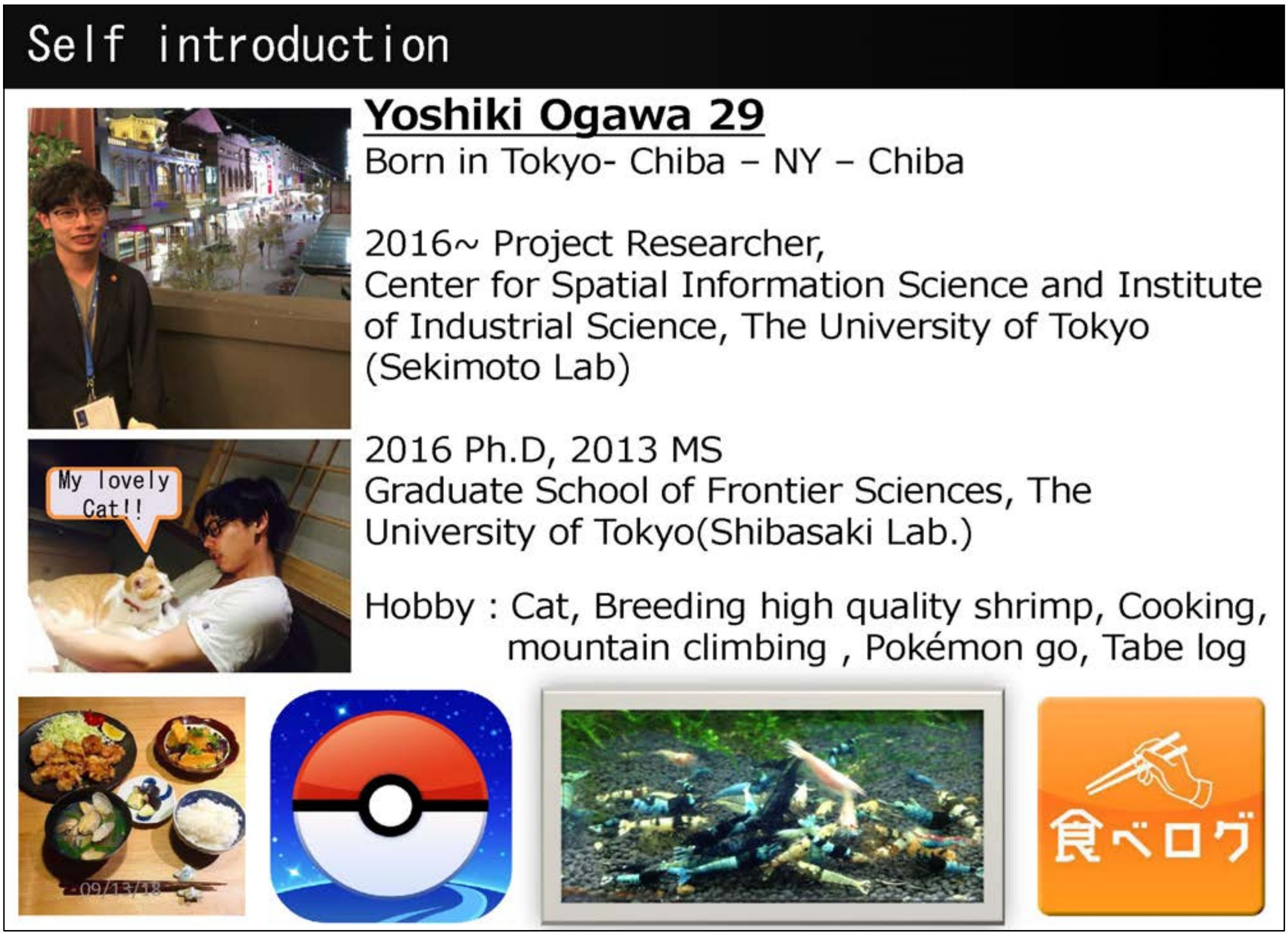
2018 International Conference on Geospatial Information Science
Geo spatial information and machine learning application in Japan
Yoshiki Ogawa, PhD(yoshiki.ogawa1220@gmail.com
Center for Spatial Information Science Institute of Industrial Science
The University of Tokyo


Self introduction
Yoshiki Ogawa 29
Born in Tokyo- Chiba – NY – Chiba
2016~ Project Researcher,
Center for Spatial Information Science and Institute of Industrial Science, The University of Tokyo (Sekimoto Lab)
2016 Ph.D, 2013 MS
Graduate School of Frontier Sciences, The University of Tokyo(Shibasaki Lab.)
Hobby : Cat, Breeding high quality shrimp, Cooking, mountain climbing , Pokémon go, Tabe log
My lovely Cat!!
食べログ

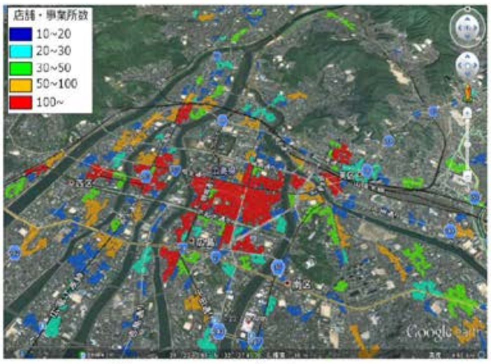
Today's Agenda

1. Geo big data in Japan
2. AI for road damage detection
3. AI for disaster management

09/13/18

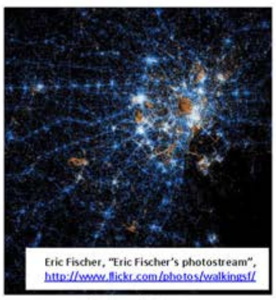
Geo big data in Japan

Residential map

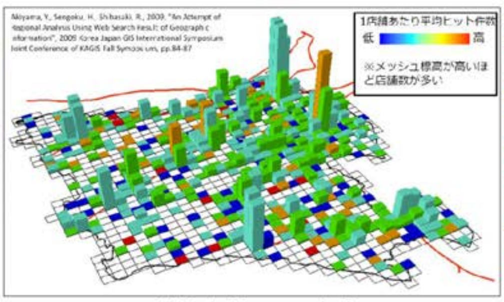


Commercial area

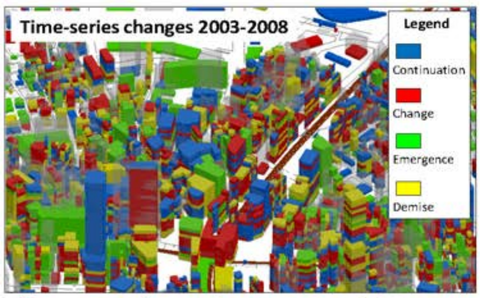
Business transaction



Twitter

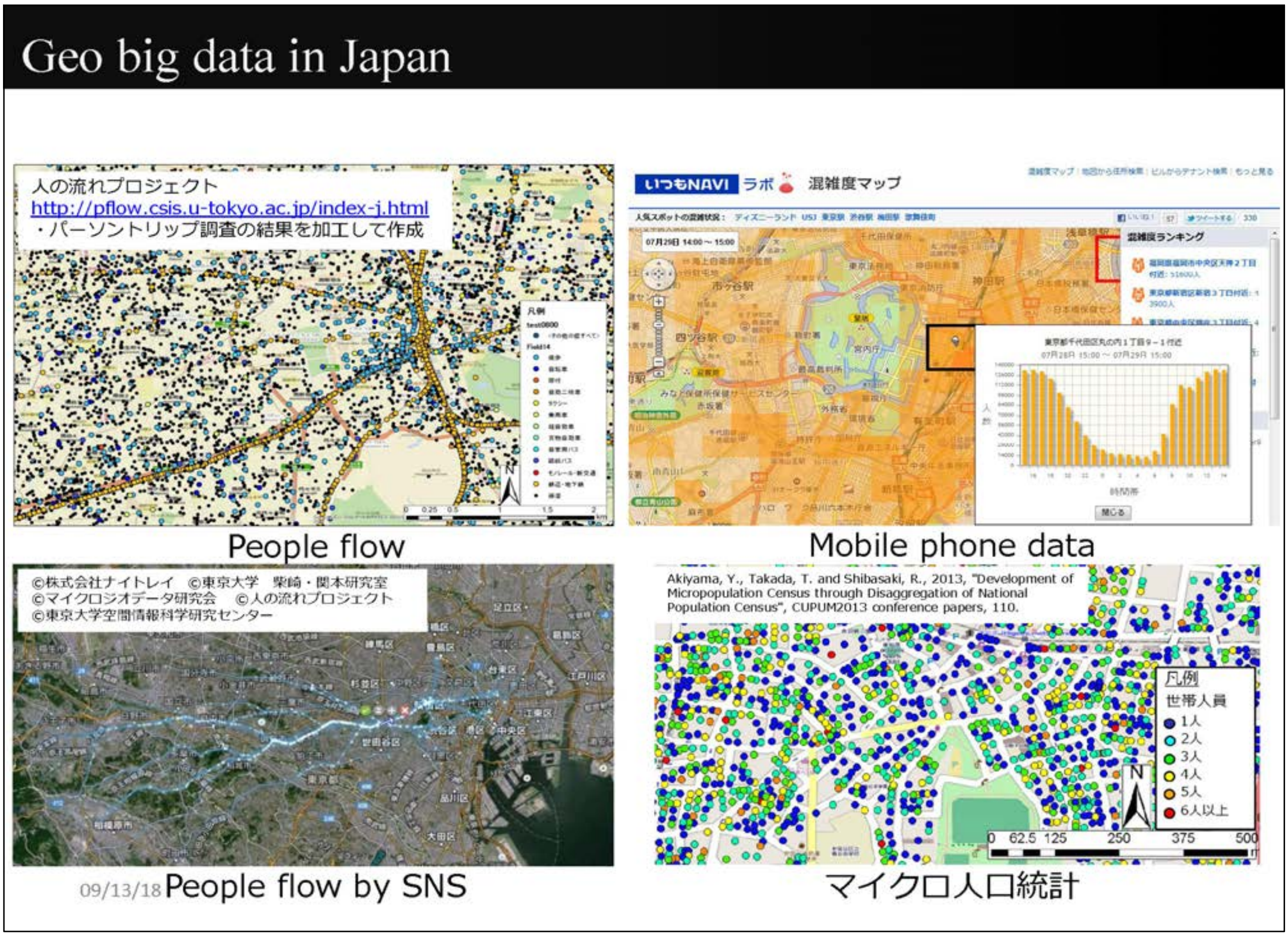


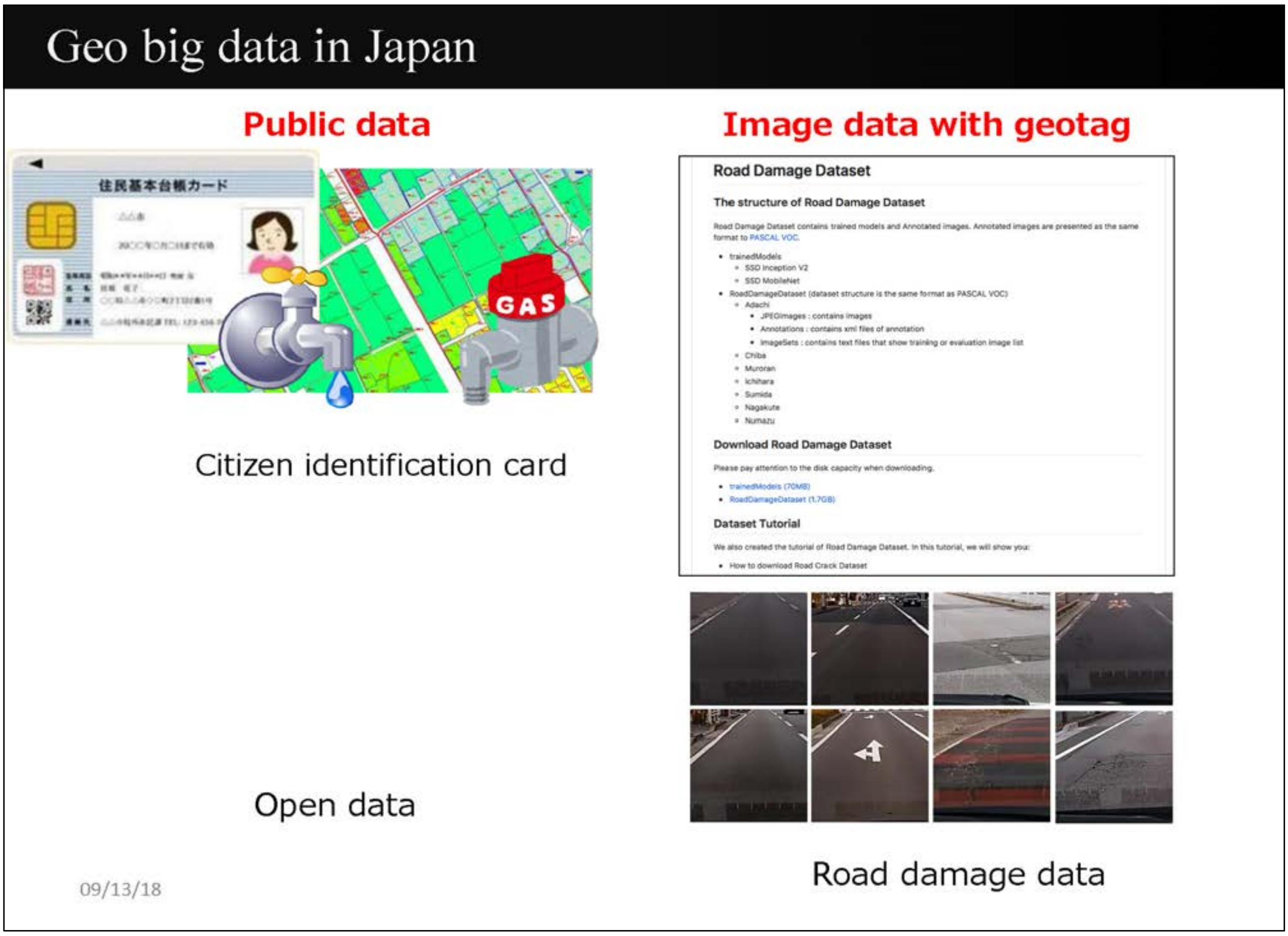
Web(google)

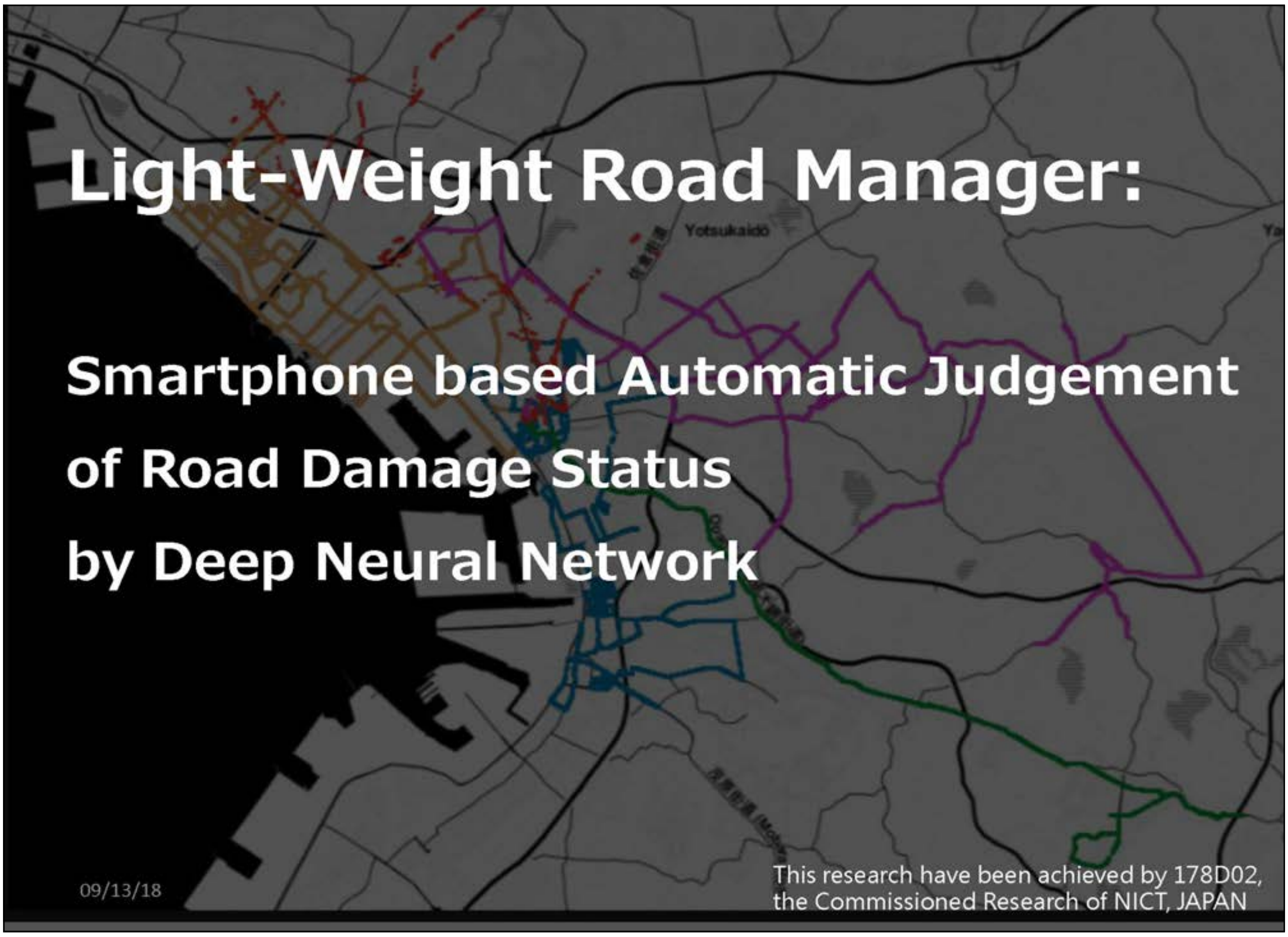


Time series changes of Stores

09/13/18


Geo big data in Japan
人の流れプロジェクト
http://pflow.csis.u-tokyo.ac.jp/index-j.html
・パーソントリップ調査の結果を加工して作成
People flow
いつもNAVI ラボ 混雑度マップ
Mobile phone data
©株式会社ナイトレイ ©東京大学 柴崎・関本研究室
©マイクロジオデータ研究会 ©人の流れプロジェクト
©東京大学空間情報科学研究センター
09/13/18
People flow by SNS
Akiyama, Y., Takada, T. and Shibasaki, R., 2013, "Development of Micropopulation Census through Disaggregation of National Population Census", CUPUM2013 conference papers, 110.
凡例
世帯人員
1人
2人
3人
4人
5人
6人以上
マイクロ人口統計


Geo big data in Japan
Public data
住民基本台帳カード
GAS
Citizen identification card
Open data
09/13/18
Image data with geotag
Road Damage Dataset
The structure of Road Damage Dataset
Road Damage Dataset contains trained models and Annotated images. Annotated images are presented as the same format to PASCAL VOC.
trainedModels
SSD Inception V2
SSD MobileNet
RoadDamageDataset (dataset structure is the same format as PASCAL VOC)
Adachi
JPEGImages : contains images
Annotations : contains xml files of annotation
ImageSets : contains text files that show training or evaluation image list
Chiba
Muroran
Ichihara
Sumida
Nagakute
Numazu
Download Road Damage Dataset
Please pay attention to the disk capacity when downloading.
trainedModels (70MB)
RoadDamageDataset (1.7GB)
Dataset Tutorial
We also created the tutorial of Road Damage Dataset. In this tutorial, we will show you:
How to download Road Crack Dataset
Road damage data



Summary

What I did

- Made Smartphone app that can judge road damage status
- Proposed how to use this app in the whole system

Method

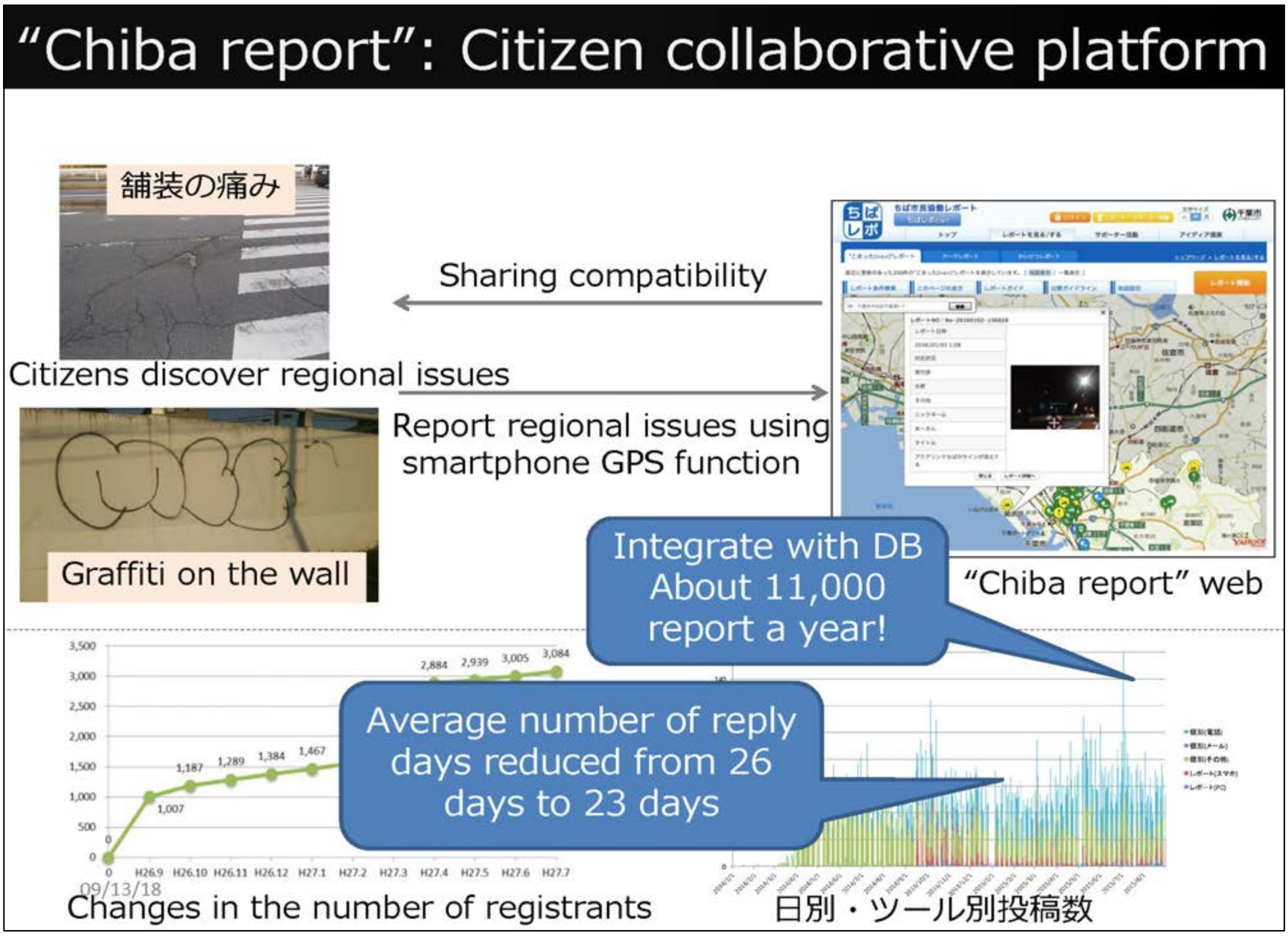
Image processing by Deep Neural Network Model

Result

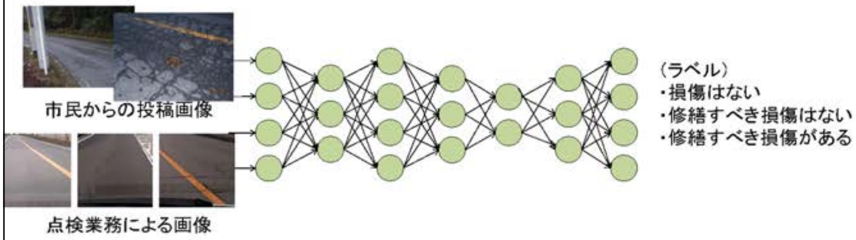
By only taking a photo of the road,
with more than 90% accuracy only in 1 second,
Road Damage Status Judgement!!

09/13/18


Background
Possibility of Citizens Reports
◆ Infrastructure maintenance
● Lack of Experts
● Expensive Cost
◆ ICT
● Open Government
● Incident Reporting System
Citizens can report local problems
■ Chiba Report
■ FixMyStreet
■ 311 Chicago
Etc…
09/13/18


"Chiba report": Citizen collaborative platform
舗装の痛み
Sharing compatibility
Citizens discover regional issues
Report regional issues using smartphone GPS function
Graffiti on the wall
Integrate with DB
About 11,000
report a year!
"Chiba report" web
Average number of reply days reduced from 26 days to 23 days
3,500
3,000
2,500
2,000
1,500
1,000
500
0
2,884
2,939
3,005
3,084
1,187
1,289
1,384
1,467
1,007
H26.9 H26.10 H26.11 H26.12 H27.1 H27.2 H27.3 H27.4 H27.5 H27.6 H27.7
09/13/18
Changes in the number of registrants
日別・ツール別投稿数

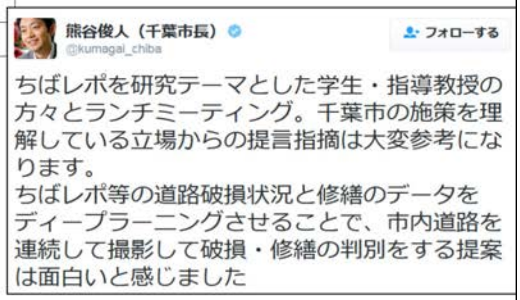
Introducing AI to reduce the burden on site



Iter=10000		正解			class precision
		(0)	(1)	(2)	
予測	(0)	480	11	1	98%
	(1)	15	441	25	92%
	(2)	5	48	474	90%
class recall		96%	88%	95%	ACCURACY=93%

(0):損傷はない
(1):修繕すべき損傷はない
(2):修繕すべき損傷がある

千葉市との共同研究成果（2016年3月）

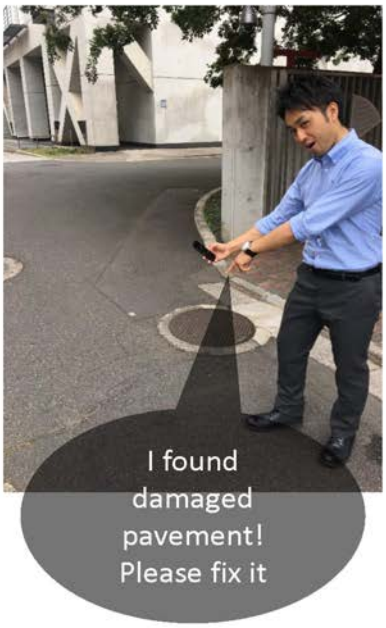

熊谷俊人（千葉市長）
@kumagai_chiba
フォローする

ちばレポを研究テーマとした学生・指導教授の方々とランチミーティング。千葉市の施策を理解している立場からの提言指摘は大変参考になります。
ちばレポ等の道路破損状況と修繕のデータをディープラーニングさせることで、市内道路を連続して撮影して破損・修繕の判別をする提案は面白いと感じました

09/13/18

Background

Citizen reports & Sharing information



Chiba Report System (Chiba repo) homepage

09/13/18

Background

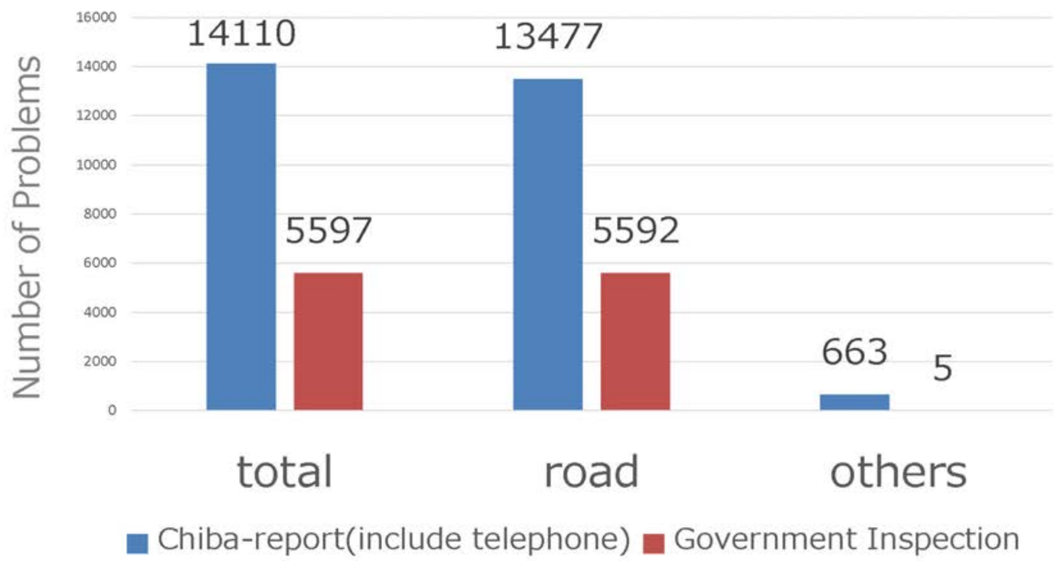
Examples of incident report system

System	Since	Initiated by	Area
Chiba Report (Chiba-repo)	August 2014	Public sector	Chiba City
Cambridge iReport	December 2011	Public sector	Cambridge, MA
City sourced	September 2009	Start-up	Location independent
Standard open311 Specification	June 2009	Consortium/ Public	Location independent
SFC	September 2008	Start-up	Location independent
Ushahidi	January 2008	Start-up/ NPO	Location independent
FixMyStreet	February 2007	NPO	UK, Japan
NYC311 online	March 2003	Public sector	New York City

09/13/18

Purpose

Citizen Reports vs Government Inspection



The period of **Sep 2014 - Aug 2015**

09/13/18

Proposed System

Light-Weight Road Manager

Smartphone application that can judge road damaged status by only taking a photo of the road!

- Citizens can judge road damage status as an expert!
- Communal Awareness between Citizens and Government

Decrease minor reports from Citizens!

09/13/18

Proposed System

Light-Weight Road Manager

This model can classify input images (especially road surface)

① Smooth

② Damaged & No Need to Repair

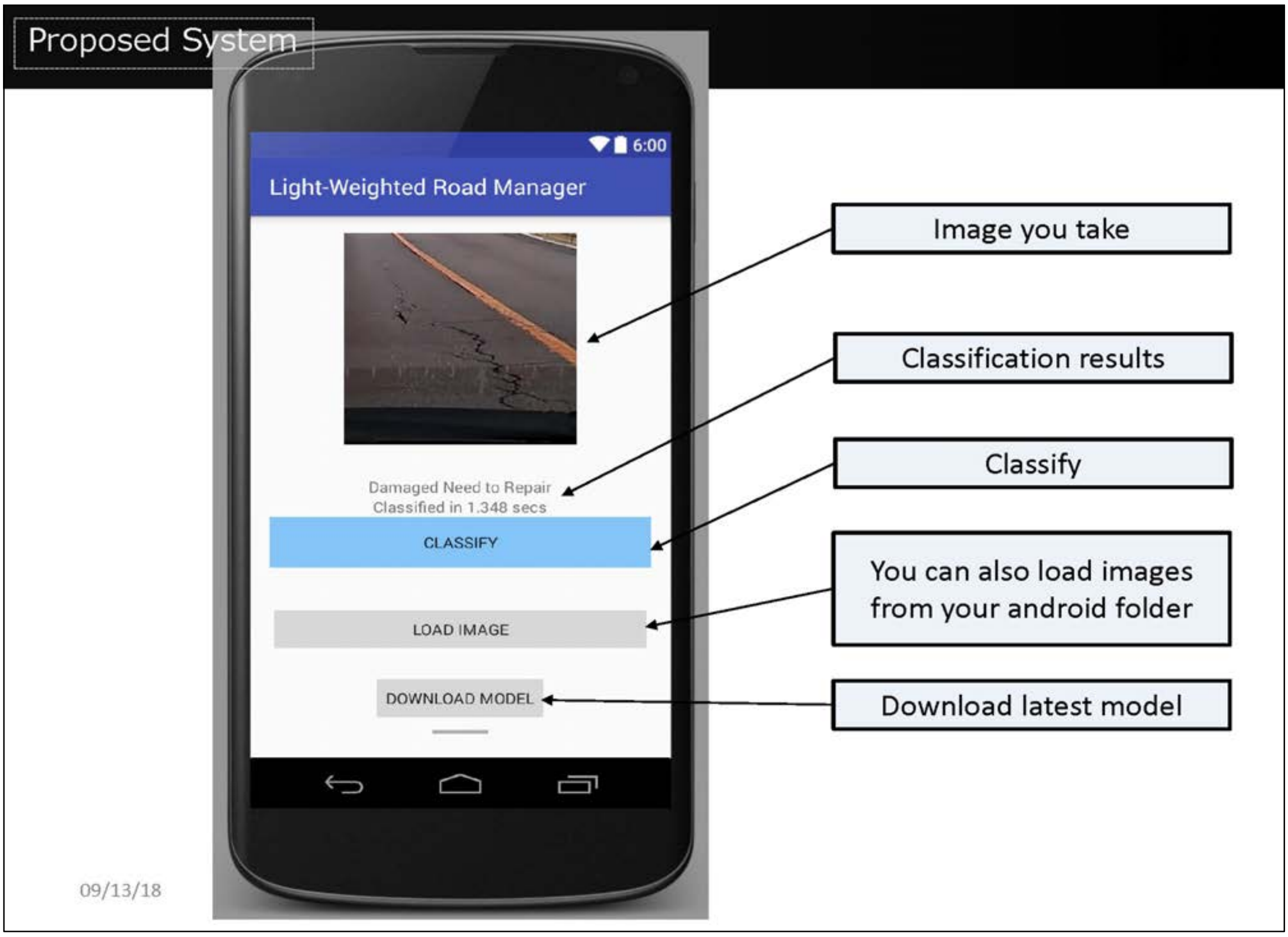
③ Damaged & Need to Repair

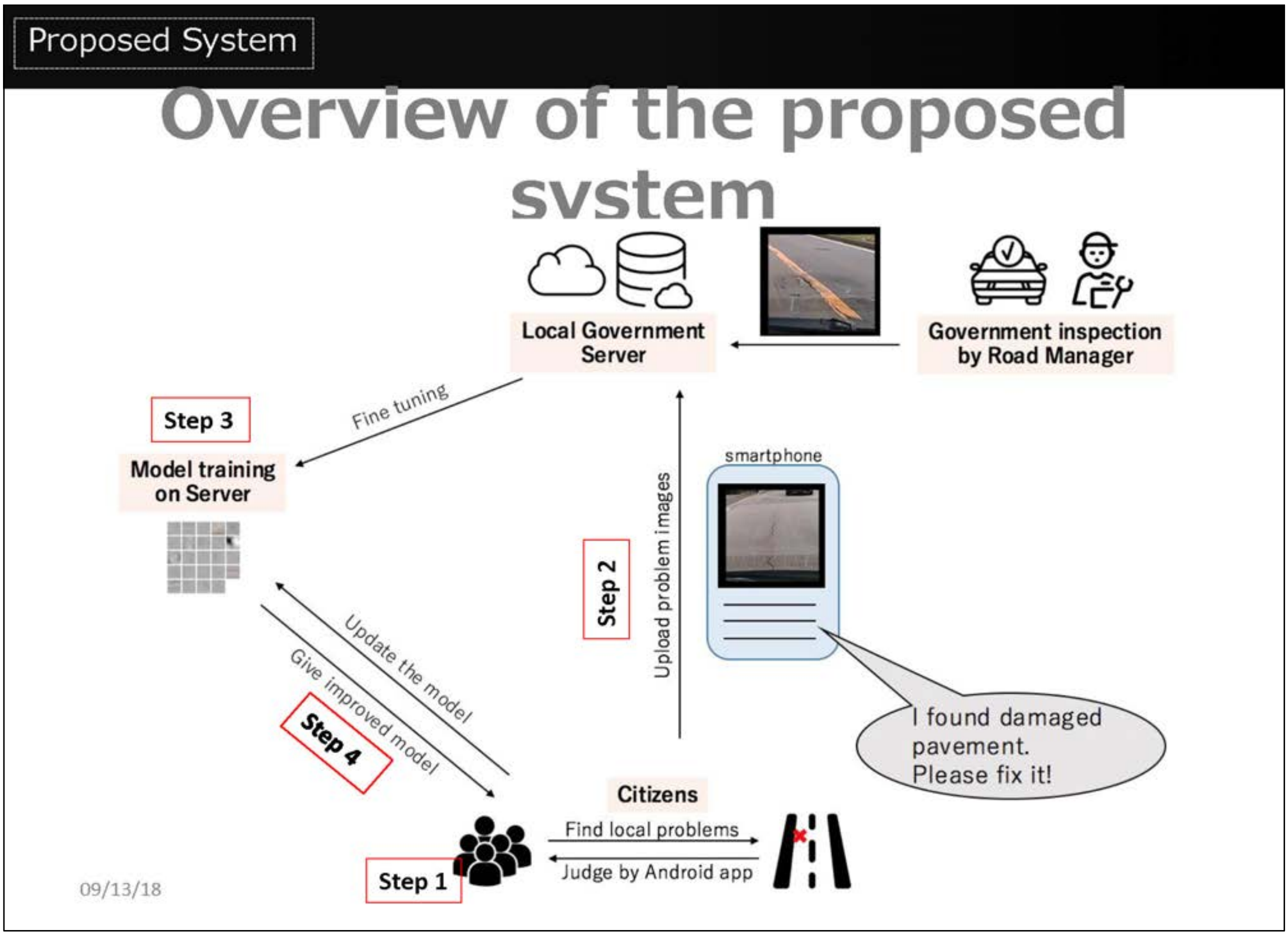
①Smooth

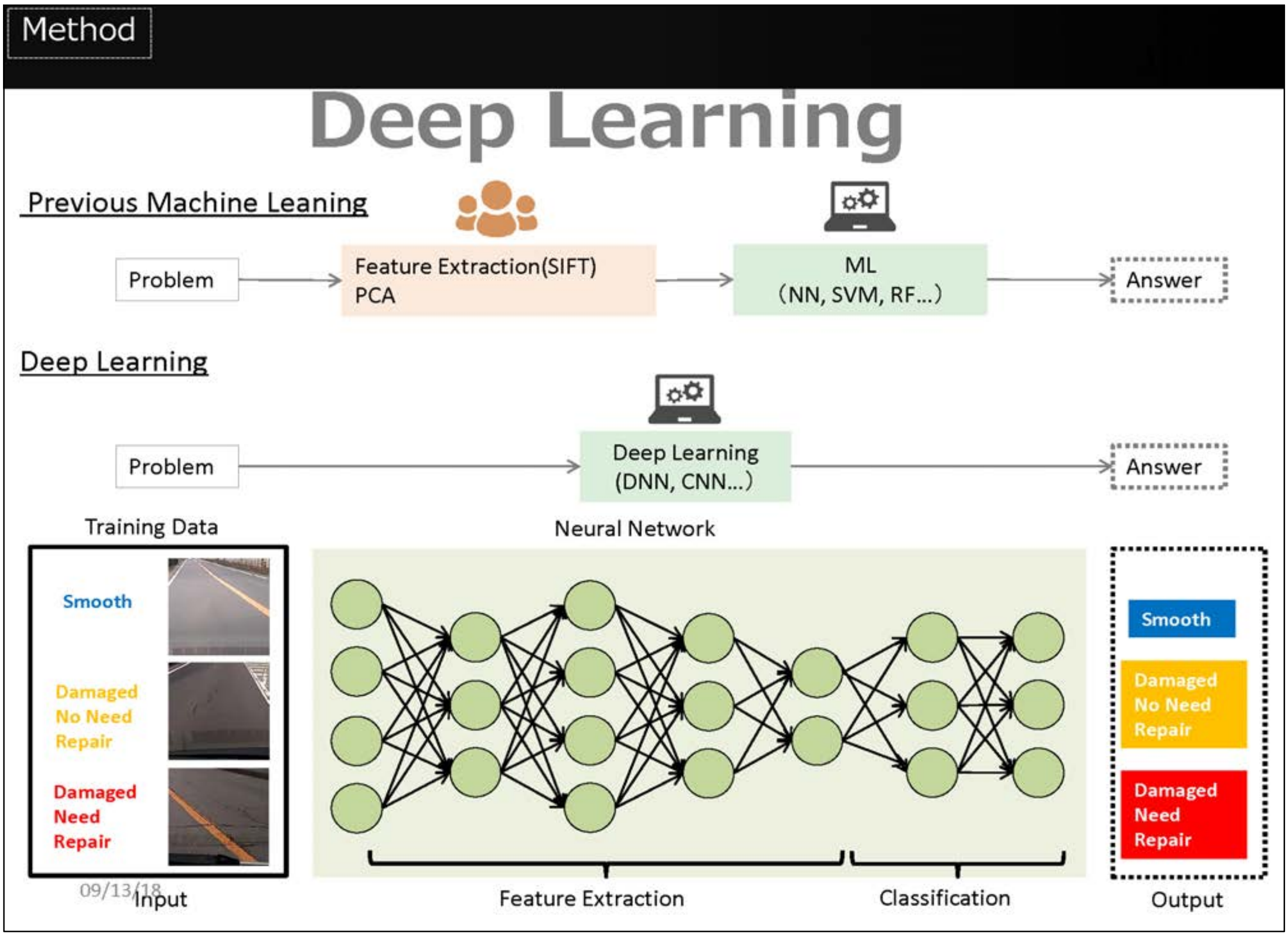
②No Need Repair

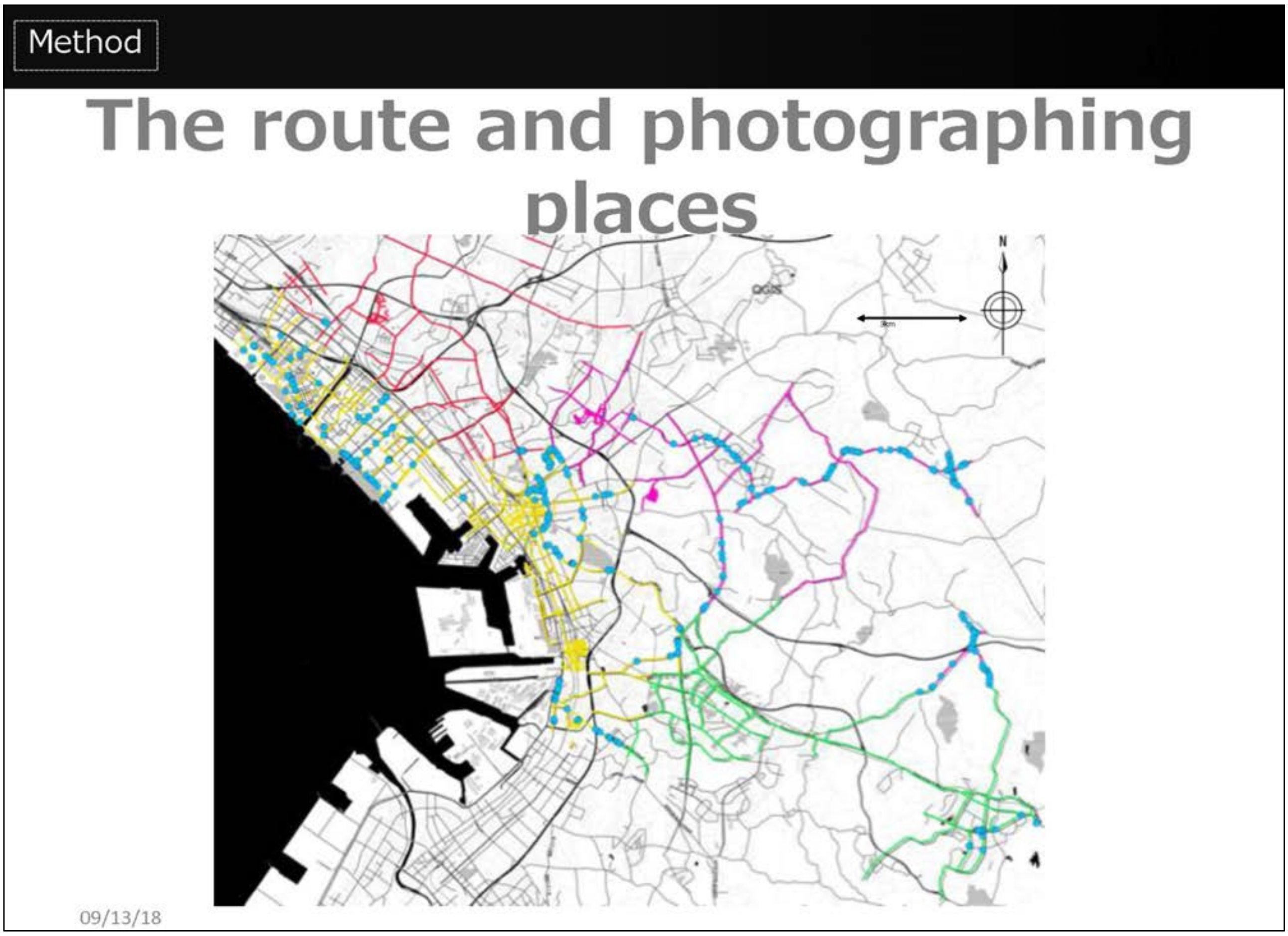
③Need Repair

09/13/18


Proposed System
6:00
Light-Weighted Road Manager
Damaged Need to Repair
Classified in 1.348 secs
CLASSIFY
LOAD IMAGE
DOWNLOAD MODEL
Image you take
Classification results
Classify
You can also load images from your android folder
Download latest model
09/13/18

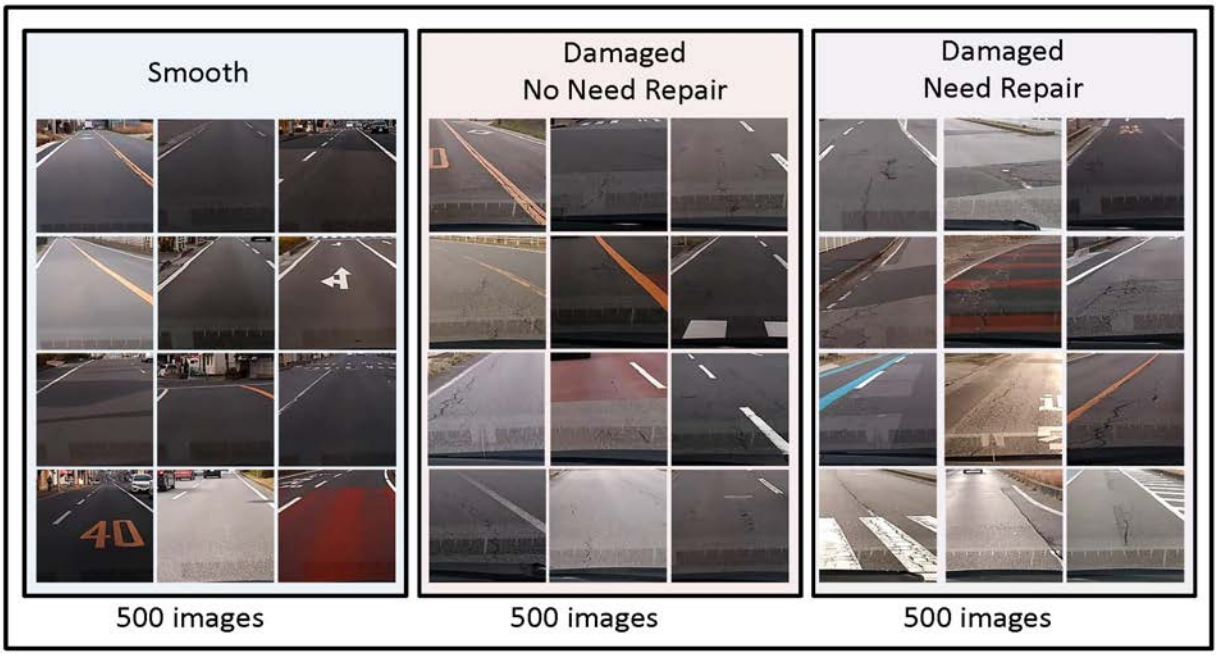

Proposed System
Overview of the proposed system
Local Government Server
Government inspection by Road Manager
Fine tuning
Step 3
Model training on Server
smartphone
Step 2
Upload problem images
Update the model
Give improved model
Step 4
I found damaged pavement. Please fix it!
Citizens
Find local problems
Judge by Android app
Step 1
09/13/18


Method
Deep Learning
Previous Machine Leaning
Problem
Feature Extraction(SIFT)
PCA
ML
(NN, SVM, RF...)
Answer
Deep Learning
Problem
Deep Learning
(DNN, CNN...)
Answer
Training Data
Neural Network
Smooth
Damaged
No Need
Repair
Damaged
Need
Repair
Smooth
Damaged
No Need
Repair
Damaged
Need
Repair
09/13/18
Input
Feature Extraction
Classification
Output


Method
The route and photographing places
N
09/13/18

Method

Training data set



09/13/18

Result

The number of neurons ↓
Total parameter ↓
The size of model ↓

CNN arch

	layer1	layer2	layer3	layer4	layer5	layer6	layer7	layer8		
	11×11×3	5×5×96	3×3×256	3×3×384	3×3×384	9216×1×1	4096×1×1	4096×1×1		
	C1 P1 N1	C2 P2 N2	C3	C4	C5 P5	FC6	FC7	FC8	Total parameter	Model size
①	96	256	384	384	256	4096	4096	3	58.3 million	227.5MB
②	48	128	192	192	128	2048	2048	3	14.6 million	56.9MB
③	24	64	96	96	64	1024	1024	3	3.7 million	14.3MB
④	24	64	96	96	64	512	512	3	1.9 million	6.4MB
⑤	12	32	48	48	32	512	512	3	0.9 million	3.6MB

$\underbrace{\text{layer1–layer5}}_{\lambda}$ $\underbrace{\text{layer6–layer7}}_{\mu}$

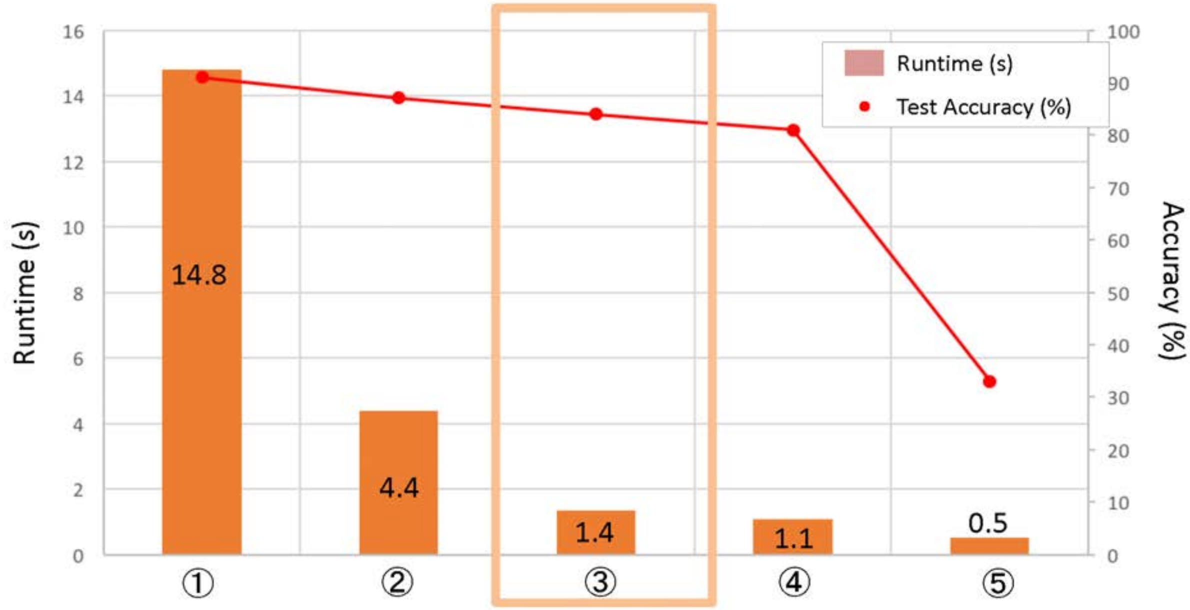
Convolutional layer | Local Response Normalization | Max Pooling layer | Fully Connected layer

The number of filters with dimensions mentioned above it

09/13/18

Result

Runtime & Accuracy on Android



09/13/18

Result

Confusion Matrix (Model3)

Model3			Actual: Smooth	Actual: Damaged – No Need Repair	Actual: Damaged – Need Repair	Precision
Prediction	Smooth		395	8	3	97.3%
Prediction	Damaged	No Need Repair	90	414	38	76.4%
Prediction	Damaged	Need Repair	15	78	459	83.2%
Recall			79.0%	82.8%	91.8%	Overall Accuracy 84.5%

09/13/18

Expansion of the Targeted Area

We expand the targeted area this year!
5 local government join us!

And more...

09/13/18

World's first road damage image release

- 全自治体の総走行時間 ：300時間
- 総撮影枚数 ：163,664枚
- 損傷候補画像（深層学習による） ：37,282枚
- 損傷候補画像（学生による目視チェックによる） ：30,188枚
- 上の損傷候補画像から分類をチェックし公開した画像数 ：10,000枚
- 分類別に傷画像があった画像数（重複あり） ：9,053枚
- 分類済み教師画像は、損傷位置のbndbox座標含め2018年1月に公開。
  https://github.com/sekilab/RoadDamageDetector

	D00 車輪走行部	D01 施工ジョイント部	D10 間隔が均等	D11 施工ジョイント部	D20 車輪走行部	D21 舗装面全域	D30 わだち掘れ	D40 段差・ポットホール・剥離	D43 横断歩道のかすれ	D44 白線のかすれ	difficult	TOTAL	総撮影枚数	損傷候補画像（学生）
室蘭市	734	1241	106	437	822	876	25	497	73	893	69	5773	62,620	20,713
沼津市	627	1425	234	656	558	415	24	556	180	1304	14	5993	25,032	4,081
足立区	501	1072	169	439	96	27	44	88	246	1034	12	3728	25,015	1,717
墨田区	140	675	21	172	29	14	18	75	239	589	3	1975	23,926	1,300
千葉市	189	230	6	20	32	3	2	13	115	333	1	944	13,291	496
市原市	146	108	19	15	48	20	6	12	24	197	2	597	2,460	258
長久手市	470	898	175	382	225	222	38	165	118	1092	6	3791	11,320	1,623
合計	2807	5649	730	2121	1810	1577	157	1406	995	5442	107	22,801	163,664	30,188

H. Maeda, Y. Sekimoto, T. Seto, T. Kashiyama, H. Omata, Road Damage Detection and Classification Using Deep Neural Networks with Smartphone Images, Computer-Aided Civil and Infrastructure Engineering, 2018 (Accepted)

09/13/18

26

World's first road damage image release

各自治体の皆様にご協力いただいて収集した道路損傷データを公開しました
（世界初！）（https://github.com/sekilab/RoadDamageDetector）

Road Damage Dataset

The structure of Road Damage Dataset

Road Damage Dataset contains trained models and Annotated images. Annotated images are presented as the same format to PASCAL VOC.

- trainedModels
  - SSD Inception V2
  - SSD MobileNet
- RoadDamageDataset (dataset structure is the same format as PASCAL VOC)
  - Adachi
    - JPEGImages : contains images
    - Annotations : contains xml files of annotation
    - ImageSets : contains text files that show training or evaluation image list
  - Chiba
  - Muroran
  - Ichihara
  - Sumida
  - Nagakute
  - Numazu

Download Road Damage Dataset

Please pay attention to the disk capacity when downloading.

- trainedModels (70MB)
- RoadDamageDataset (1.7GB)

Dataset Tutorial

We also created the tutorial of Road Damage Dataset. In this tutorial, we will show you:

- How to download Road Crack Dataset
- The structure of the Dataset
- The statistical information of the dataset
- How to use trained models.

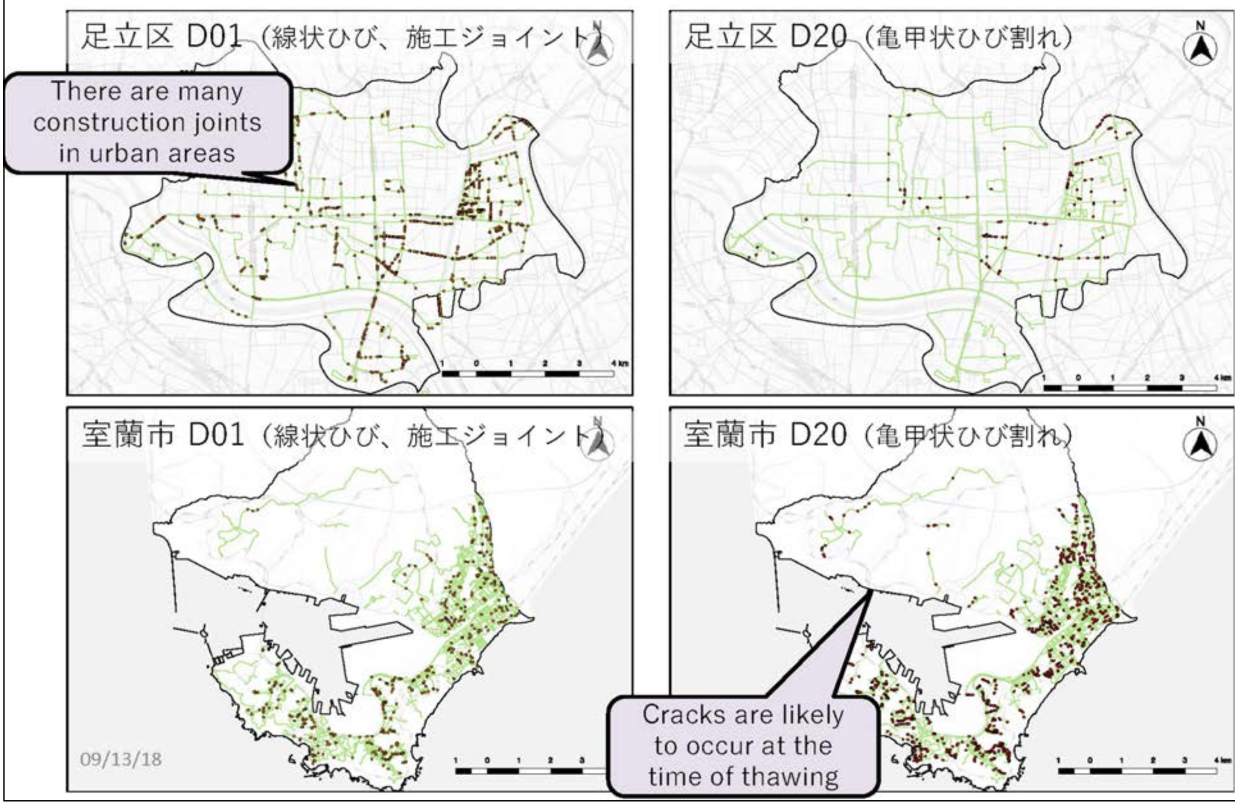
Please check RoadDamageDatasetTutorial.ipynb.

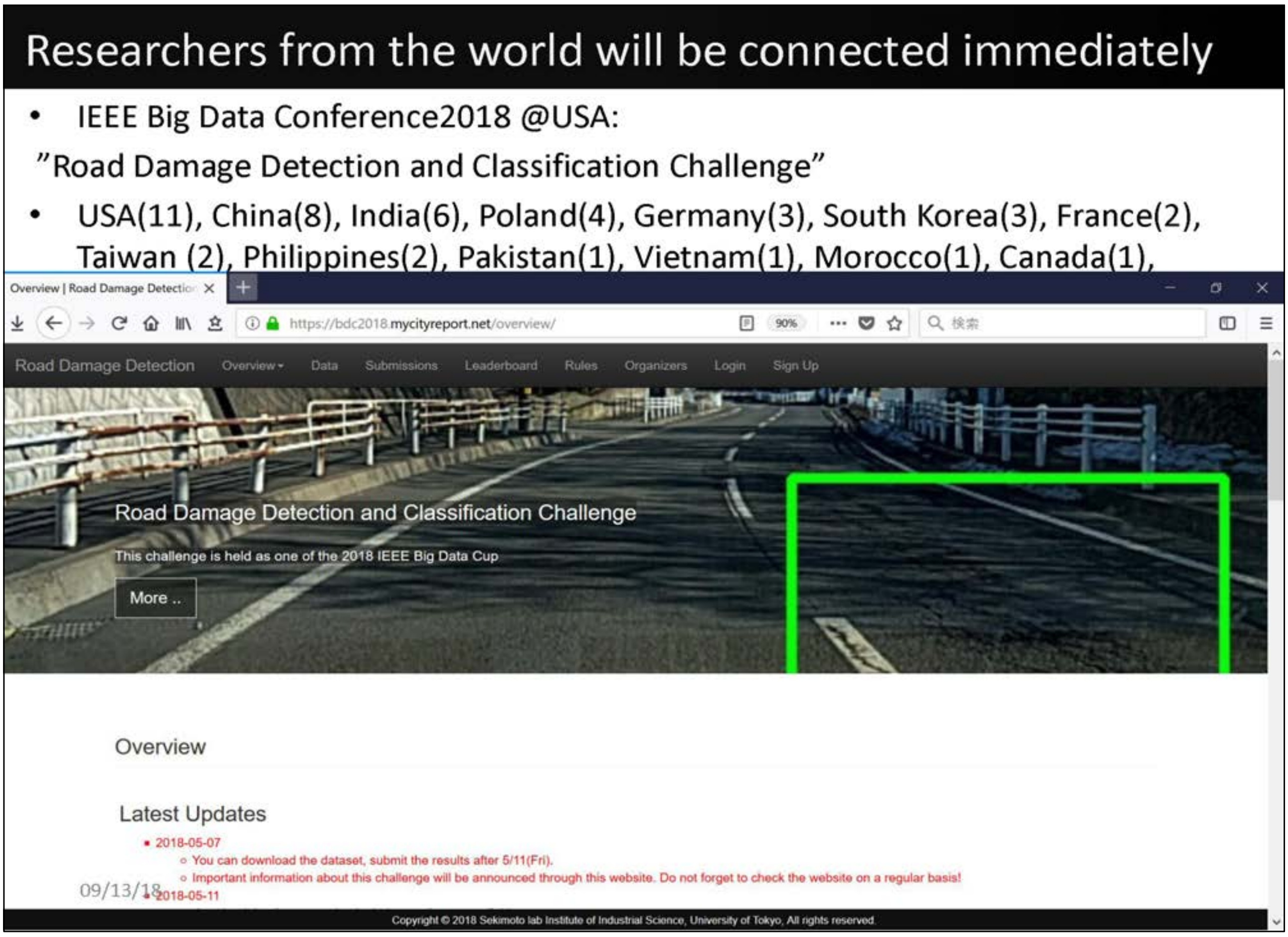
Privacy matters

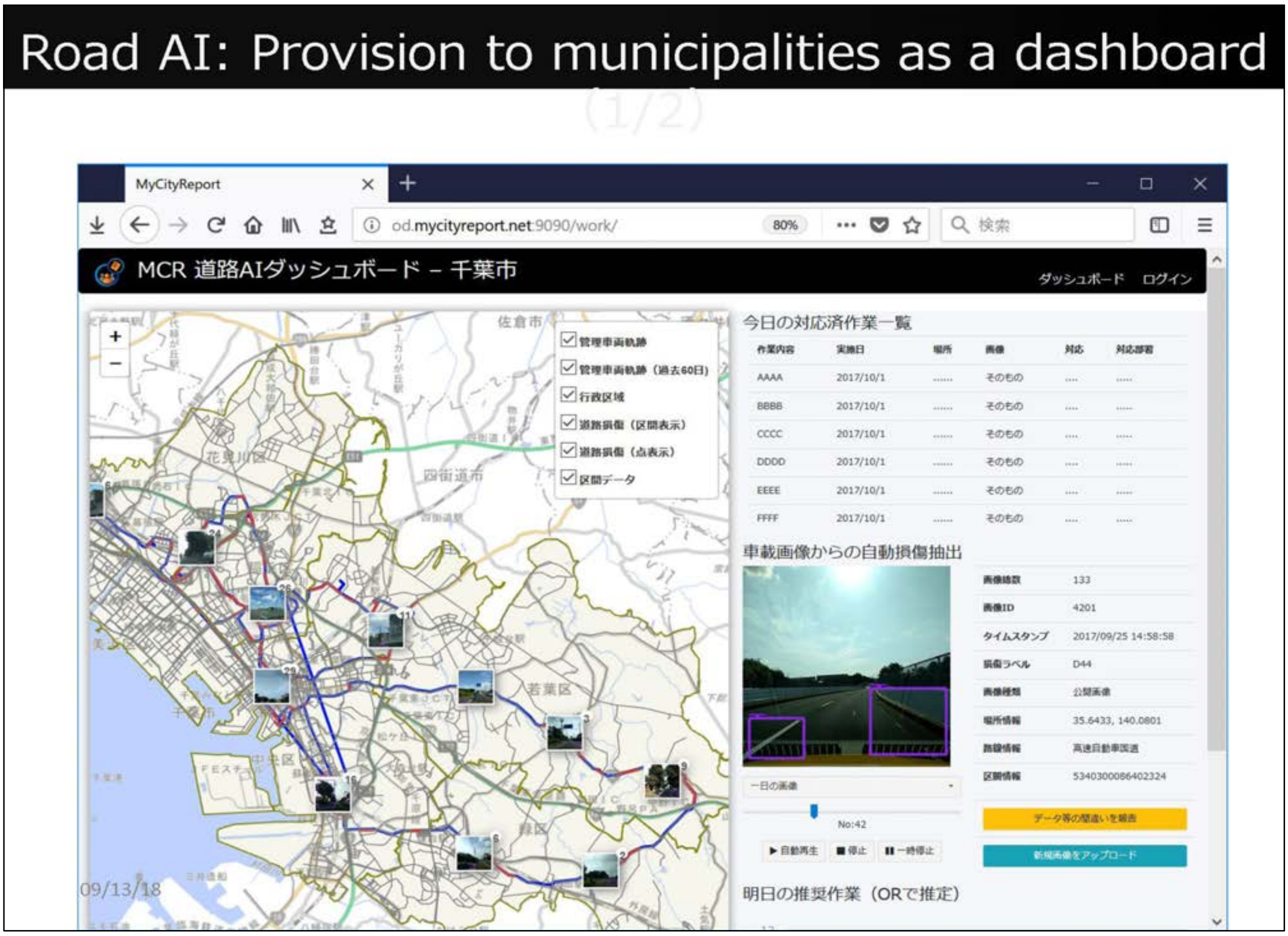
09/13/18

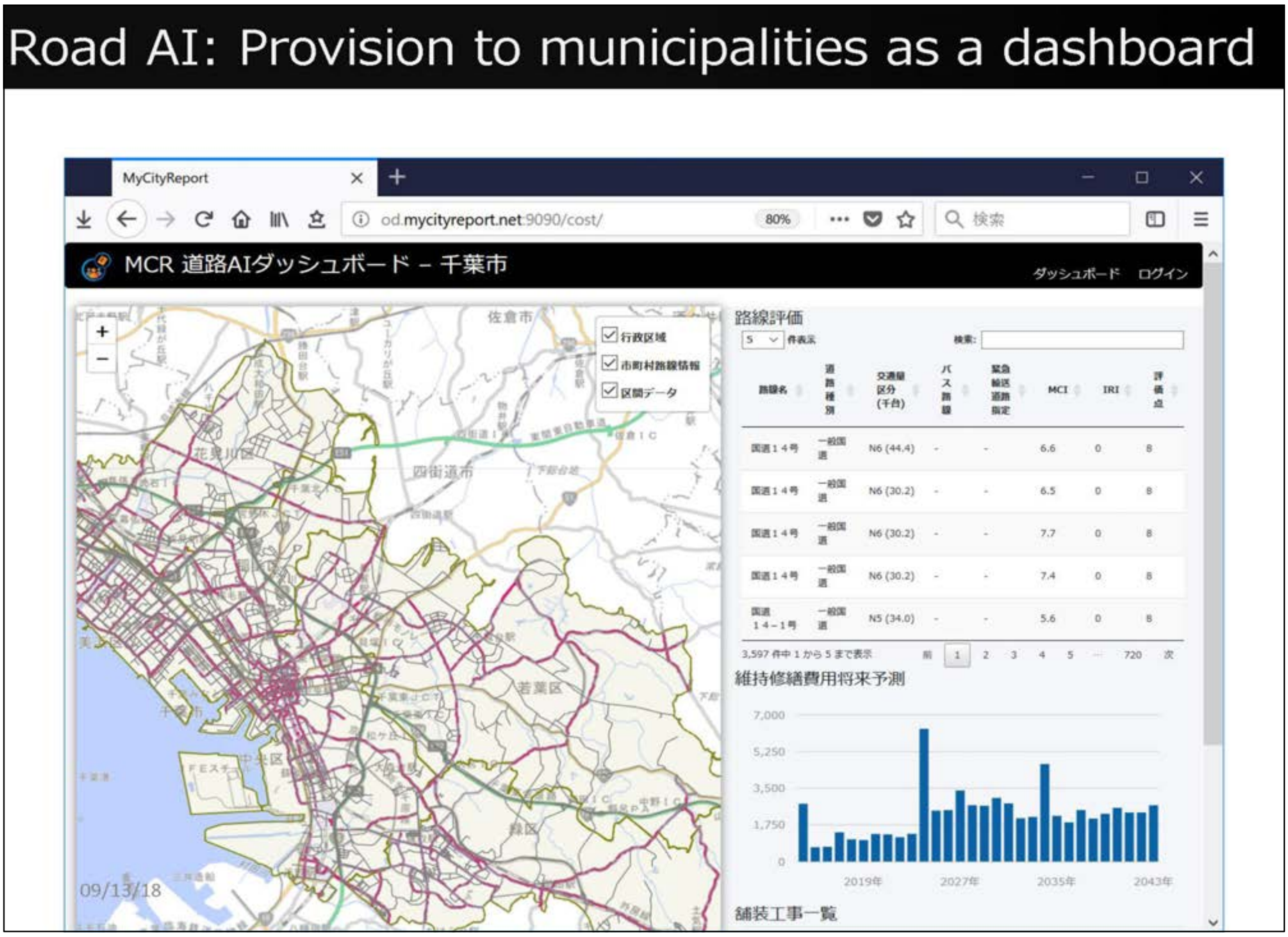
※プライバシー保護のため、人の顔、
車のナンバープレートにモザイクをかけています。

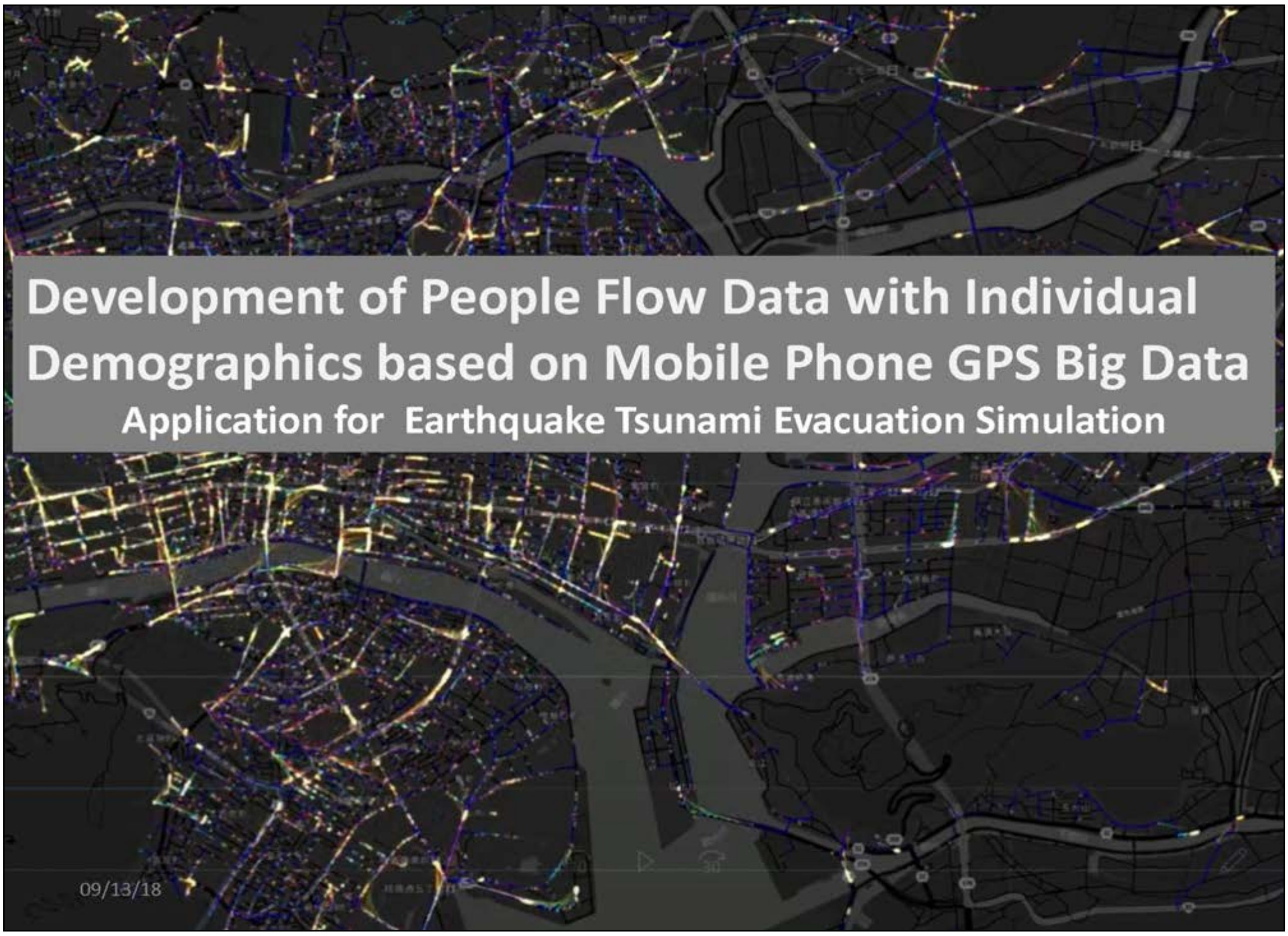
Distribution of damaged parts in each local government

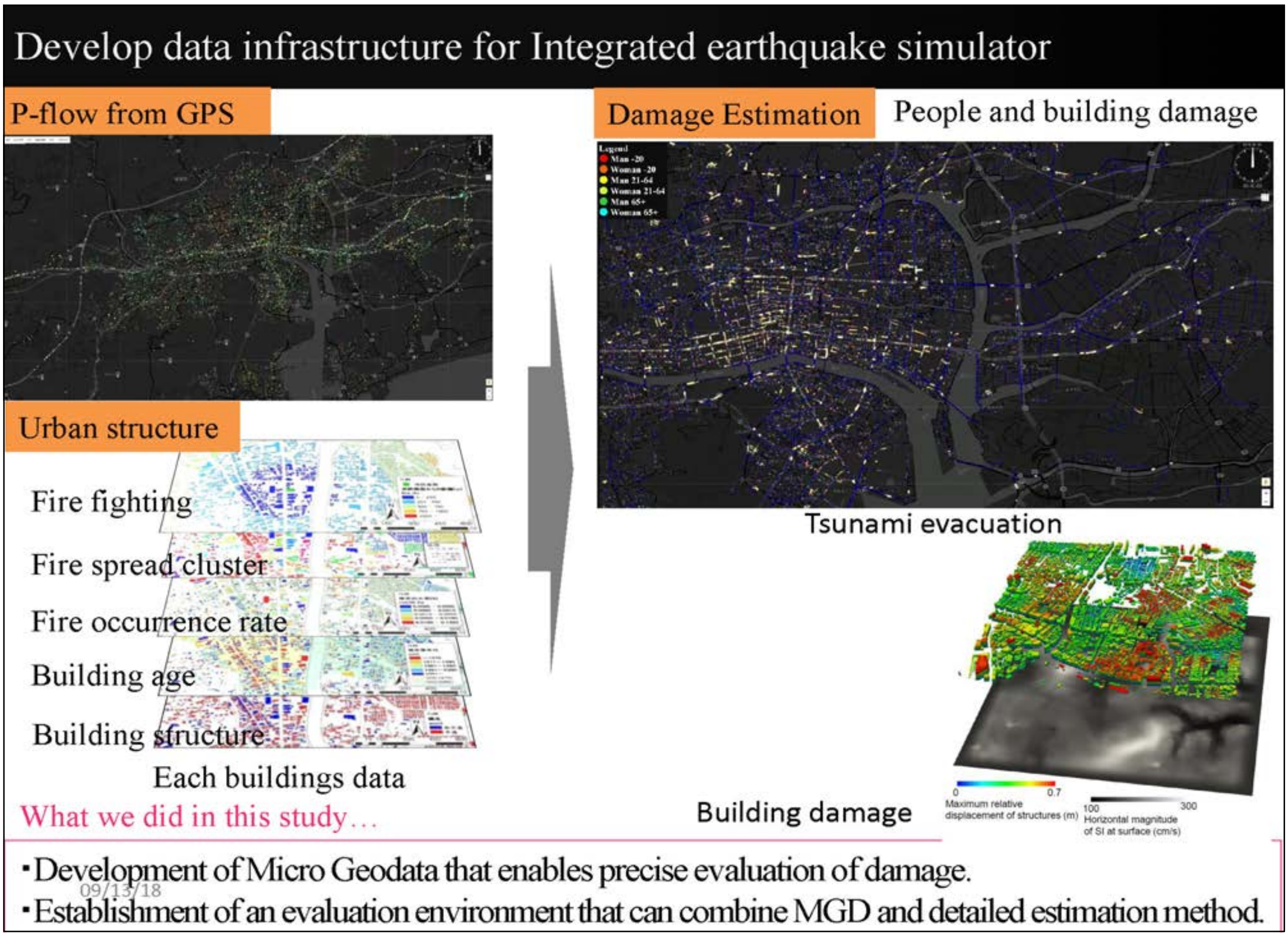


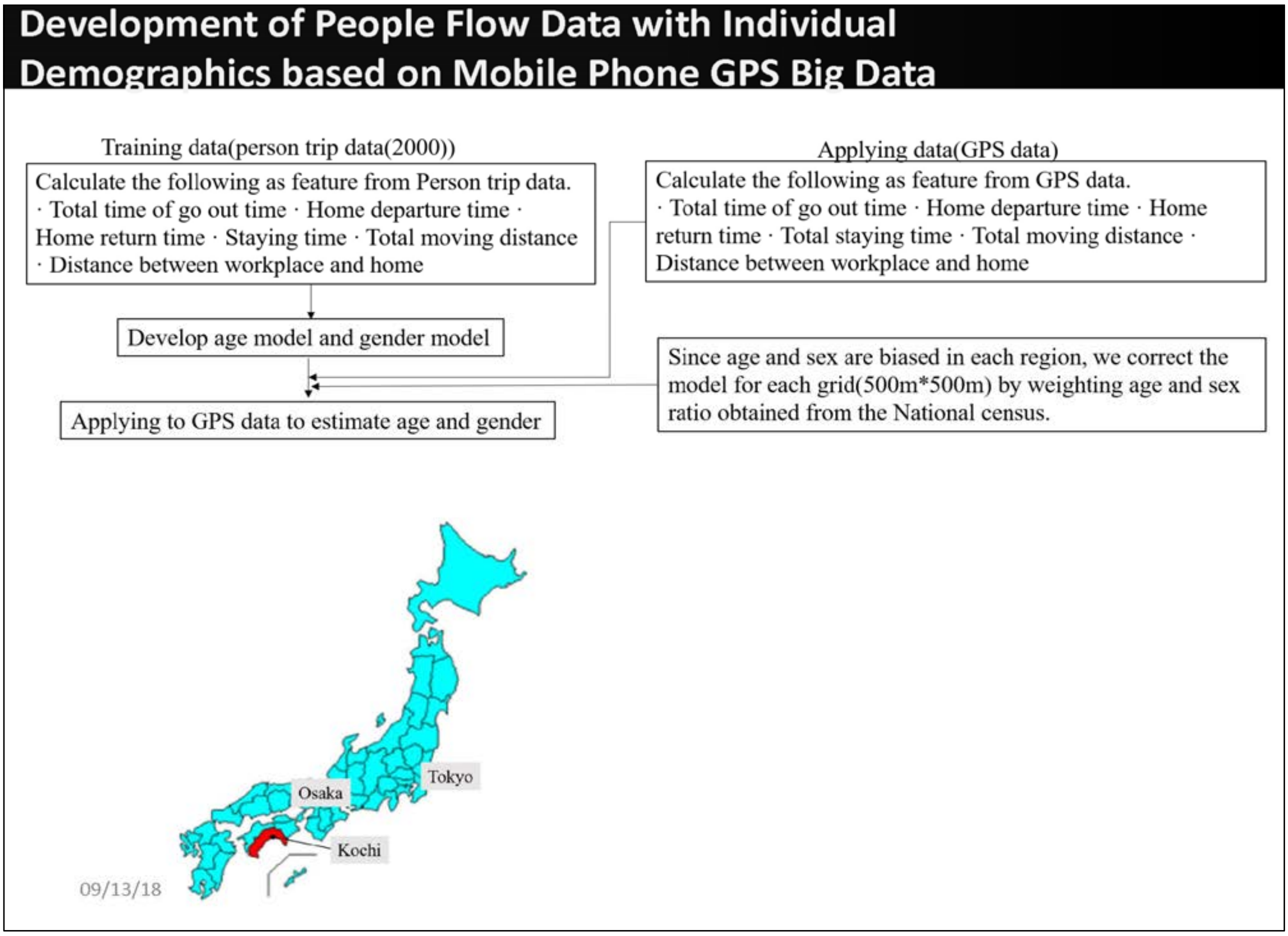

Researchers from the world will be connected immediately
• IEEE Big Data Conference2018 @USA:
"Road Damage Detection and Classification Challenge"
• USA(11), China(8), India(6), Poland(4), Germany(3), South Korea(3), France(2), Taiwan (2), Philippines(2), Pakistan(1), Vietnam(1), Morocco(1), Canada(1),
Overview | Road Damage Detection
https://bdc2018.mycityreport.net/overview/
Road Damage Detection
Overview
Data
Submissions
Leaderboard
Rules
Organizers
Login
Sign Up
Road Damage Detection and Classification Challenge
This challenge is held as one of the 2018 IEEE Big Data Cup
More ..
Overview
Latest Updates
2018-05-07
You can download the dataset, submit the results after 5/11(Fri).
Important information about this challenge will be announced through this website. Do not forget to check the website on a regular basis!
2018-05-11
09/13/18
Copyright © 2018 Sekimoto lab Institute of Industrial Science, University of Tokyo, All rights reserved.


Road AI: Provision to municipalities as a dashboard
MyCityReport
od.mycityreport.net:9090/work/
MCR 道路AIダッシュボード – 千葉市
ダッシュボード
ログイン
今日の対応済作業一覧
車載画像からの自動損傷抽出
明日の推奨作業（ORで推定）
09/13/18


Road AI: Provision to municipalities as a dashboard
MyCityReport
od.mycityreport.net:9090/cost/
MCR 道路AIダッシュボード – 千葉市
ダッシュボード ログイン
行政区域
市町村路線情報
区間データ
路線評価
維持修繕費用将来予測
7,000
5,250
3,500
1,750
0
2019年
2027年
2035年
2043年
舗装工事一覧
09/13/18


Development of People Flow Data with Individual Demographics based on Mobile Phone GPS Big Data
Application for Earthquake Tsunami Evacuation Simulation
09/13/18


Develop data infrastructure for Integrated earthquake simulator
P-flow from GPS
Damage Estimation
People and building damage
Urban structure
Fire fighting
Fire spread cluster
Fire occurrence rate
Building age
Building structure
Each buildings data
Tsunami evacuation
Building damage
What we did in this study…
・Development of Micro Geodata that enables precise evaluation of damage.
・Establishment of an evaluation environment that can combine MGD and detailed estimation method.
09/13/18


Development of People Flow Data with Individual Demographics based on Mobile Phone GPS Big Data
Training data(person trip data(2000))
Calculate the following as feature from Person trip data. · Total time of go out time · Home departure time · Home return time · Staying time · Total moving distance · Distance between workplace and home
Develop age model and gender model
Applying to GPS data to estimate age and gender
Applying data(GPS data)
Calculate the following as feature from GPS data. · Total time of go out time · Home departure time · Home return time · Total staying time · Total moving distance · Distance between workplace and home
Since age and sex are biased in each region, we correct the model for each grid(500m*500m) by weighting age and sex ratio obtained from the National census.
Tokyo
Osaka
Kochi
09/13/18

Validation

N fold cross validation(N=10)

Accuracy	Multi Logit	Lasso SVM	RF	Lasso Logit
Gender	62.2%	**64.4%**	63.4%	63.5%
Age	59.8%	**66.6%**	62.4%	59.8%

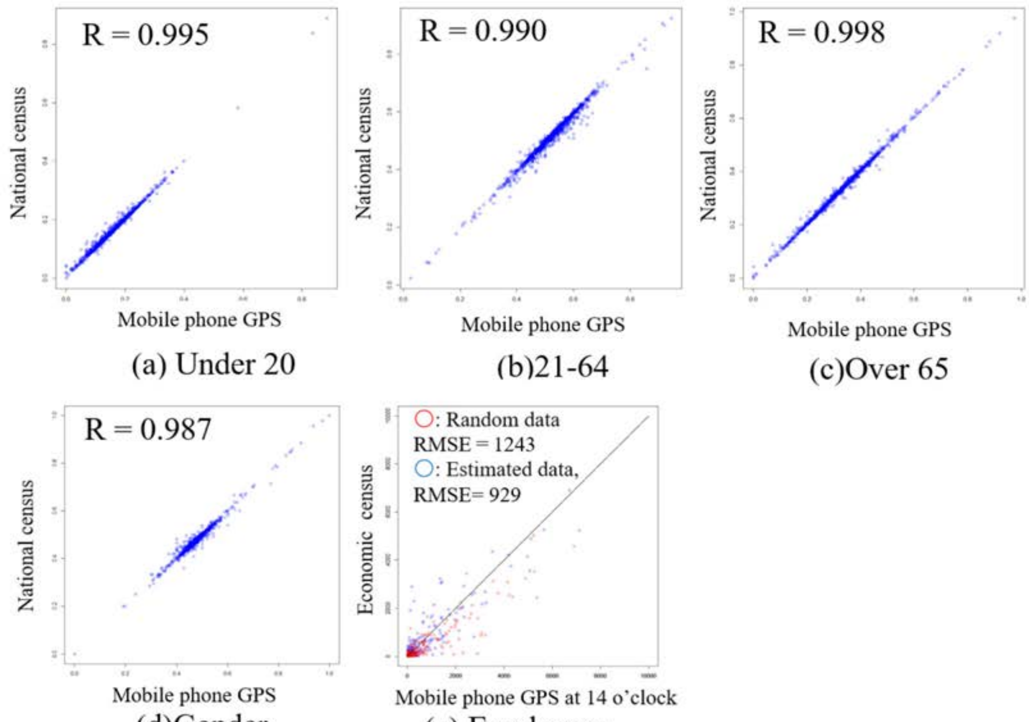
Error Matrix of Age estimation(Lasso SVM)

		Predict data			
		Under 20	21-65	65 over	User's accuracy
Classified data	Under 20	589	835	66	0.395
	21-65	183	3798	767	0.799
	65 over	77	929	1173	0.538
	Producer accuracy	0.694	0.683	0.585	**Over all: 0.660**

Error Matrix of gender estimation(Lasso SVM)

		Predict data		
		Man	Woman	User's accuracy
Classified data	Man	1803	2056	0.467
	Woman	1072	3486	0.765
		0.627	0.629	**Over all: 0.628**

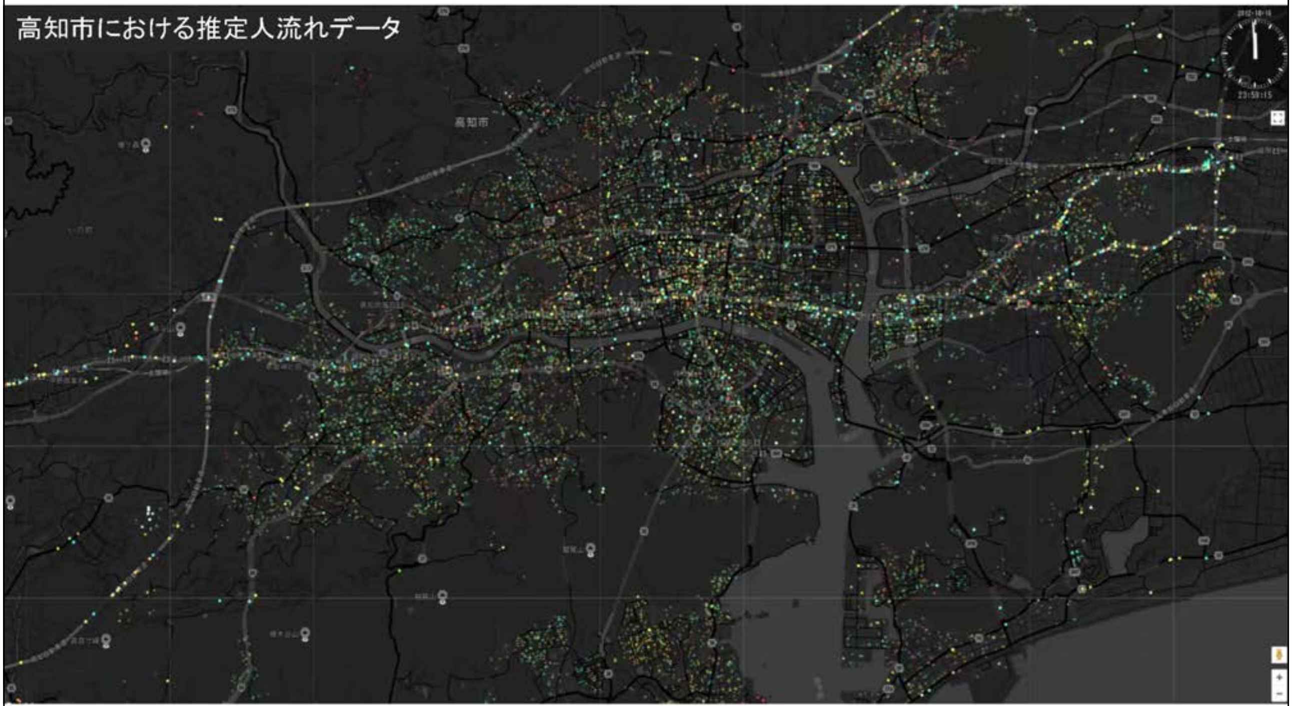
09/13/18



(a) Under 20 (b)21-64 (c)Over 65

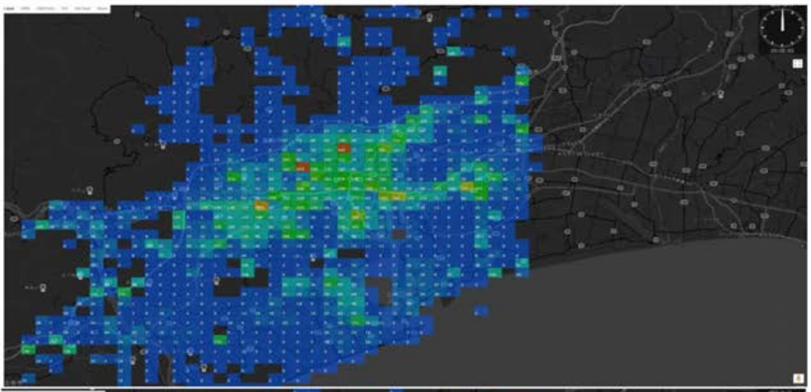
(d)Gender (e) Employees

09/13/18

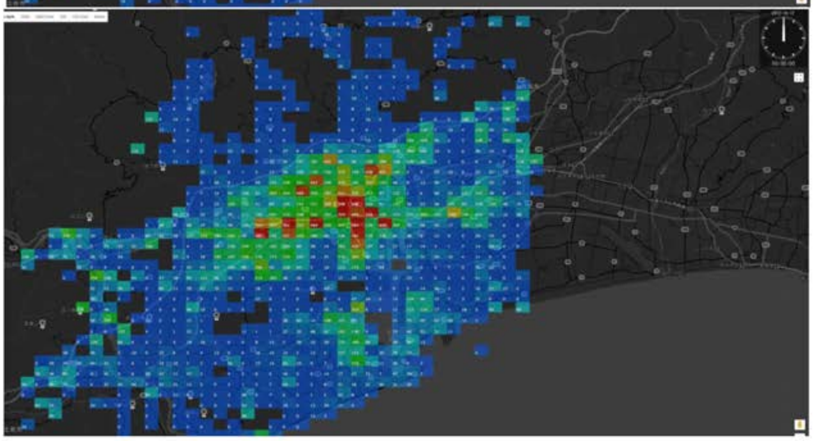


09/13/18

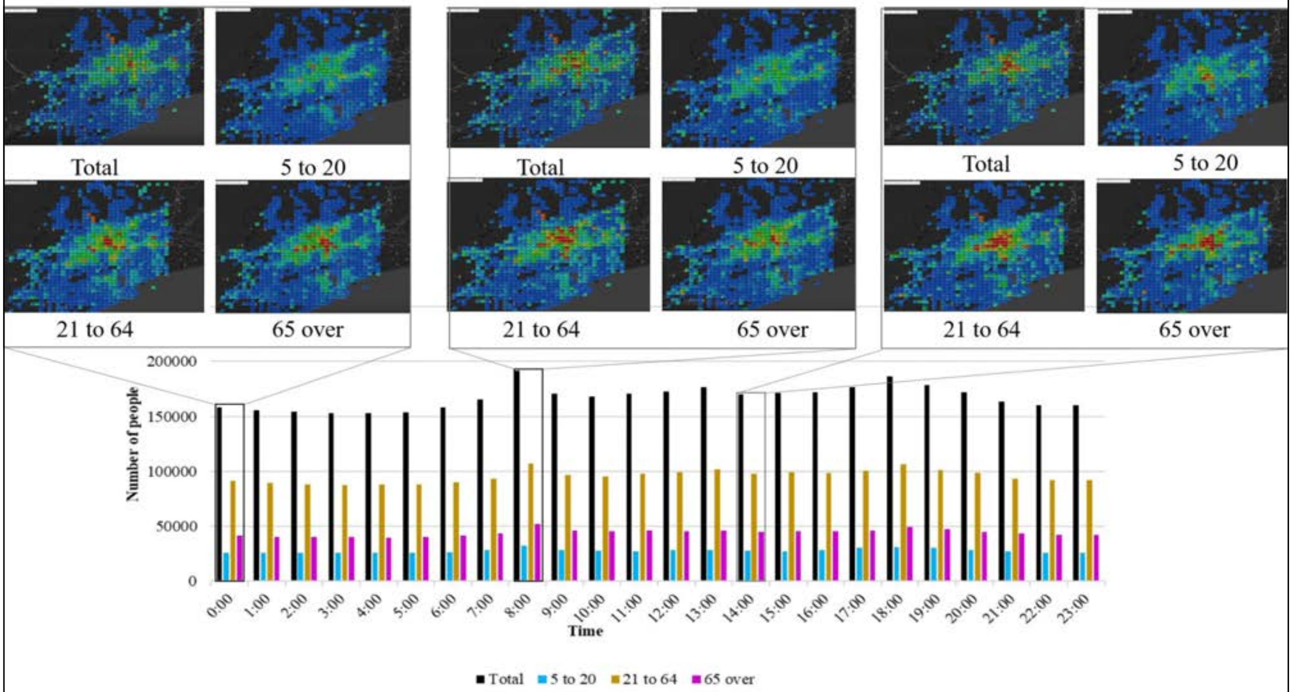
5-20



21-64

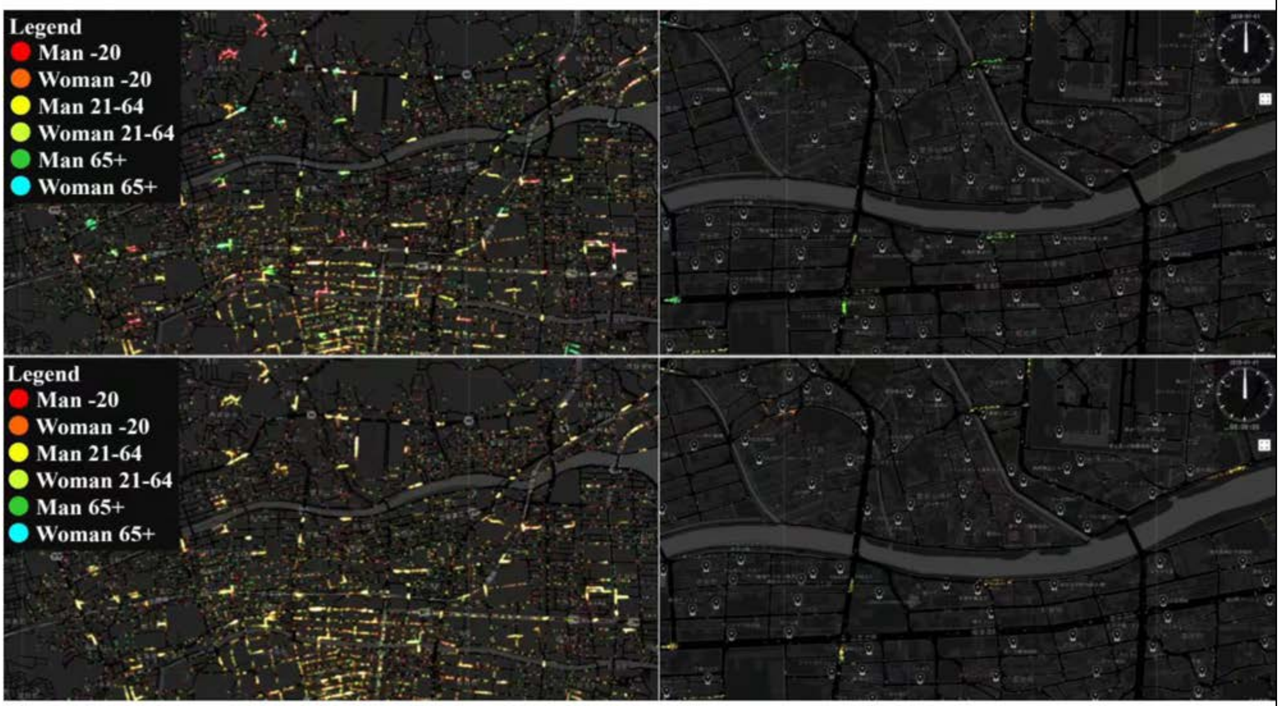


09/13/18

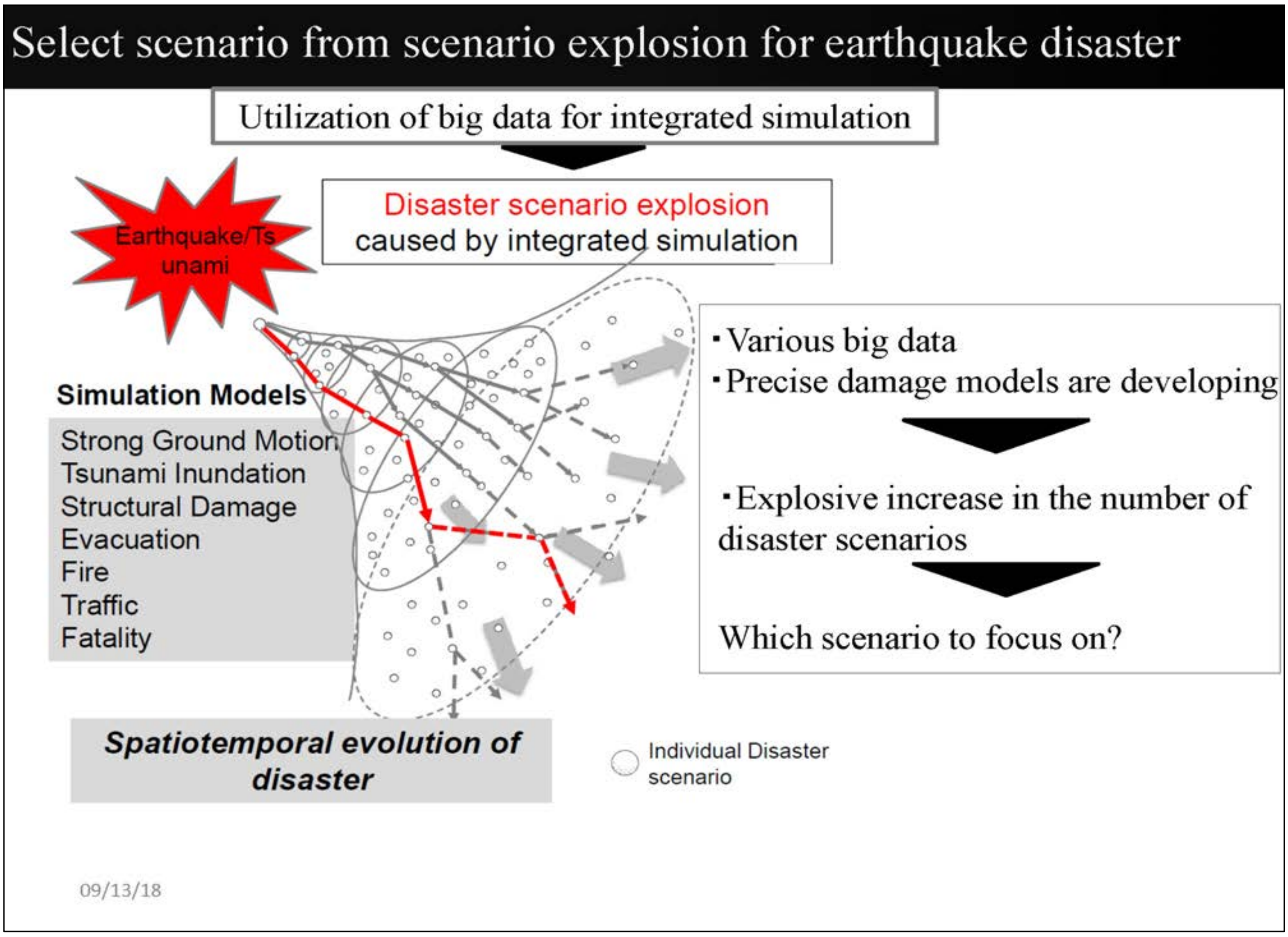


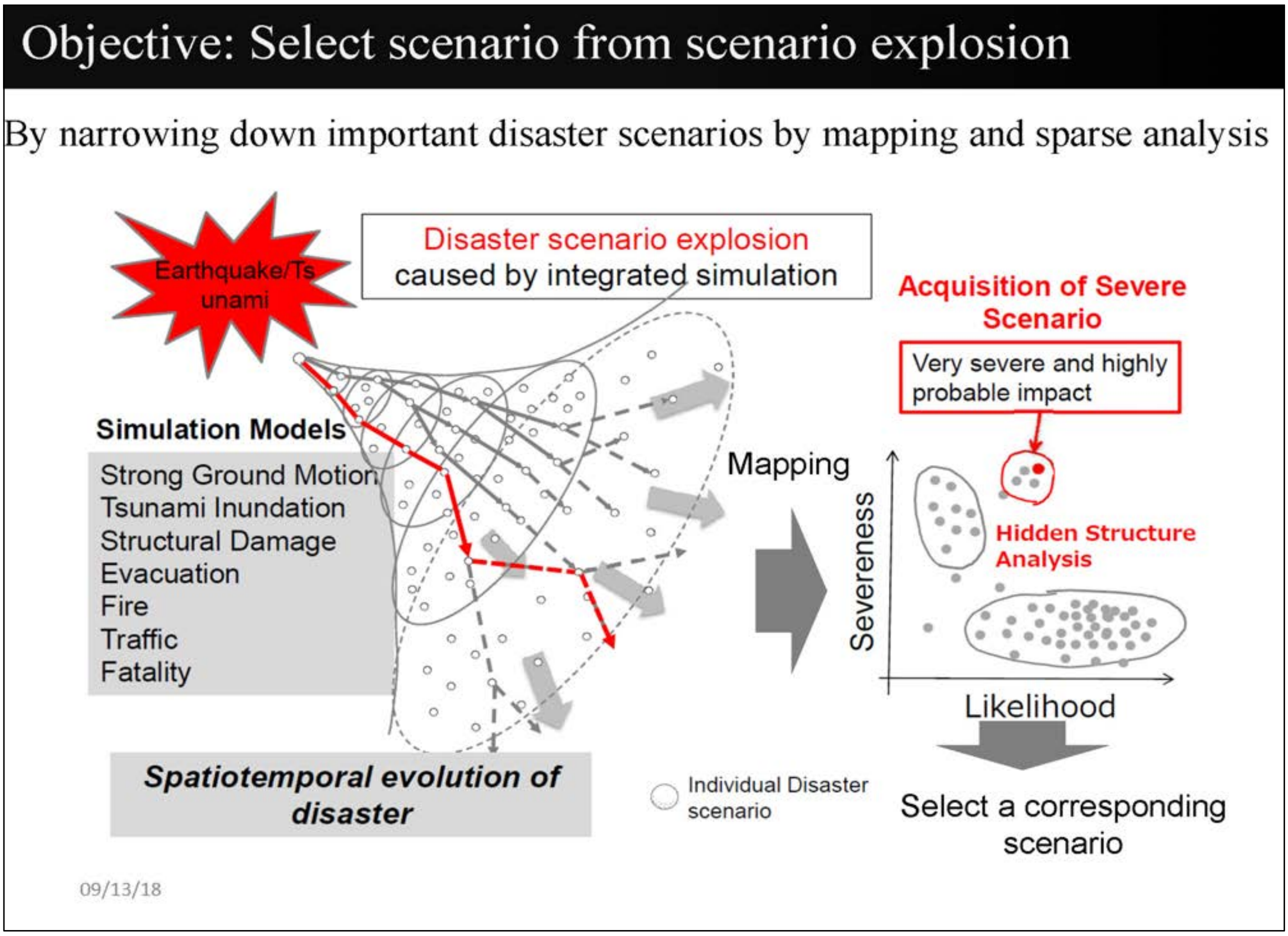
09/13/18

Tsunami evacuation simulation



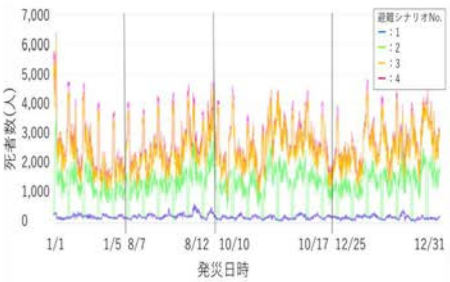
09/13/18

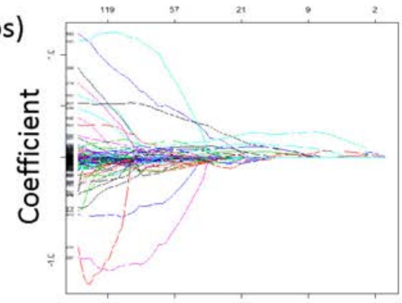

Select scenario from scenario explosion for earthquake disaster
Utilization of big data for integrated simulation
Earthquake/Tsunami
Disaster scenario explosion
caused by integrated simulation
Simulation Models
Strong Ground Motion
Tsunami Inundation
Structural Damage
Evacuation
Fire
Traffic
Fatality
・Various big data
・Precise damage models are developing
・Explosive increase in the number of disaster scenarios
Which scenario to focus on?
Spatiotemporal evolution of disaster
Individual Disaster scenario
09/13/18


Objective: Select scenario from scenario explosion
By narrowing down important disaster scenarios by mapping and sparse analysis
Earthquake/Tsunami
Disaster scenario explosion
caused by integrated simulation
Simulation Models
Strong Ground Motion
Tsunami Inundation
Structural Damage
Evacuation
Fire
Traffic
Fatality
Mapping
Acquisition of Severe Scenario
Very severe and highly probable impact
Severeness
Hidden Structure Analysis
Likelihood
Select a corresponding scenario
Spatiotemporal evolution of disaster
Individual Disaster scenario
09/13/18

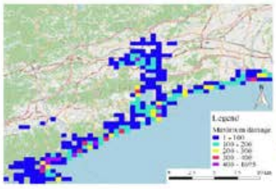
Extracting significant scenario for earthquake disaster

Damage estimation(40,000 scenarios)





Number of scenarios



Maximum damage in each mesh from 40000scenarios

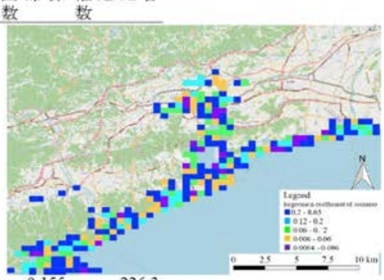
Applying Lasso

Extract 2035 scenarios which match with maximum damage in each mesh

Selecting model and scenario

Confidential

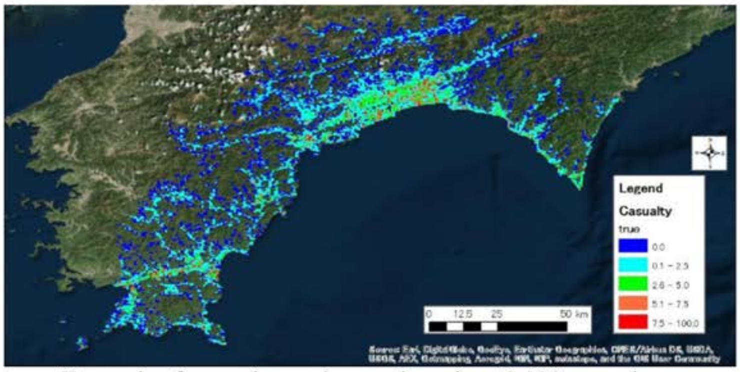
地震確率	避難シナリオ	発災日時	回帰係数	推定死者数
2%	3	8/12, 8:30		
2%	2	12/30, 8:15		
2%	4	12/27, 0:45		
[illegible]	4	12/29, 3:45		
2%	1	1/1, 15:15		
2%	4	1/2, 4:15		
2%	2	1/3, 6:45		
2%	2	8/12, 7:00		
2%	1	1/2, 4:15		
2%	4	12/25, 10:45		
2%	2	1/3, 8:30		
2%	2	1/5, 10:15		
2%	1	1/5, 10:15	0.155	236.3
2%	4	1/4, 9:45	0.154	2117.4
2%	4	1/5, 10:00	0.152	2211.5
2%	2	10/14, 13:15	0.128	1562.8



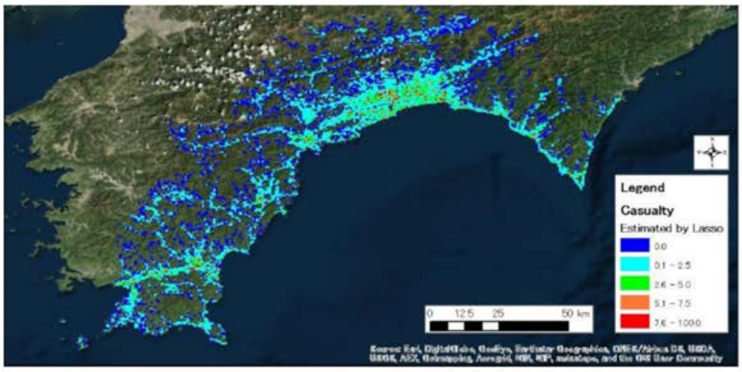
09/13/18

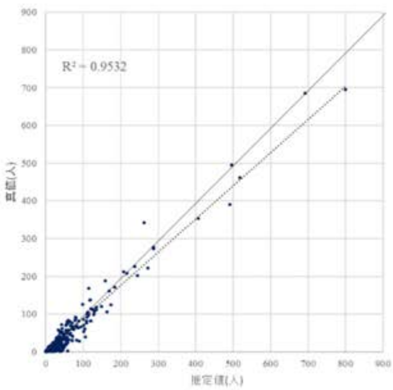
Validation

Confidential



True value for maximum damage by using 10,000 scenarios





09/13/18

Lasso model estimation by using selected scenarios （Maximum damage）

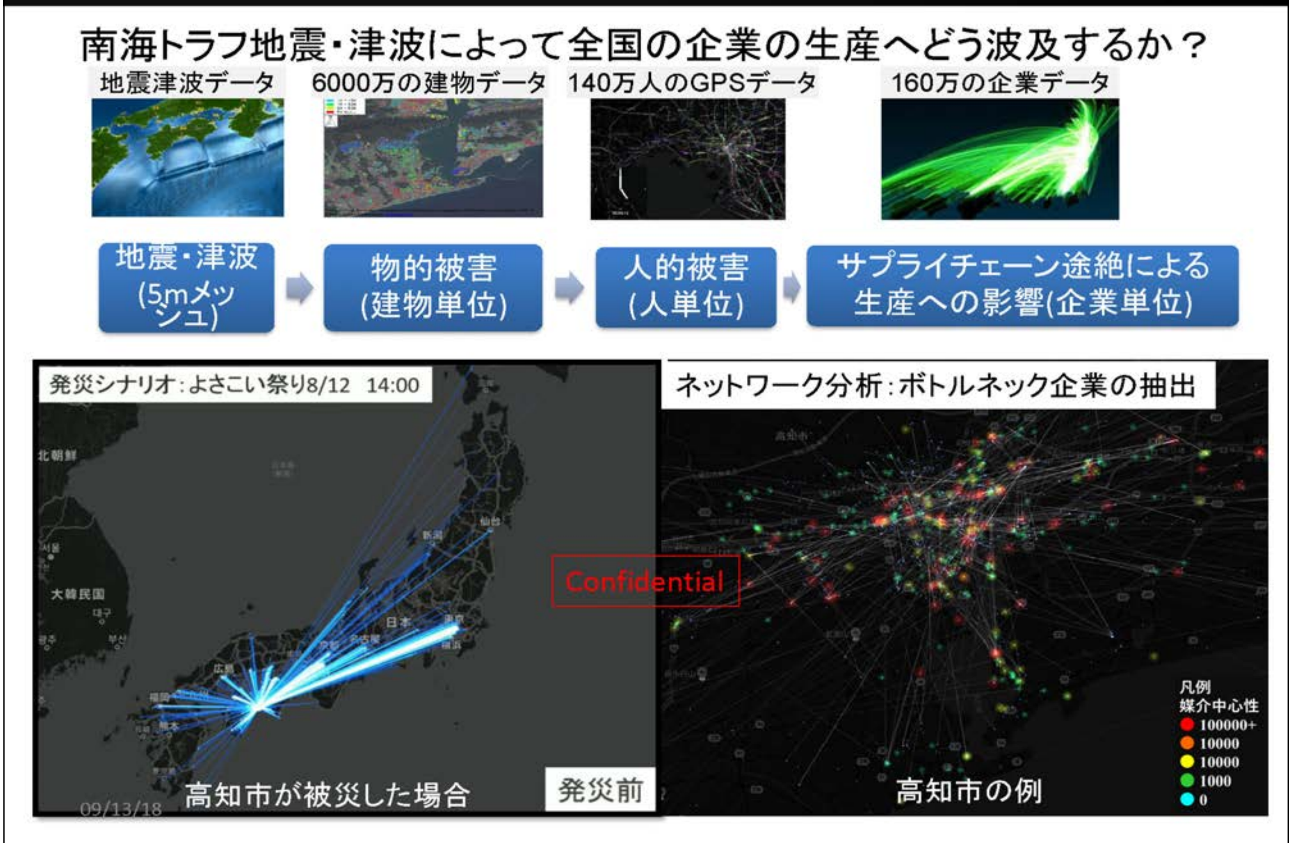
モデルと真値の比較

Estimate supply chain network disruptions due to earthquake Tsunami

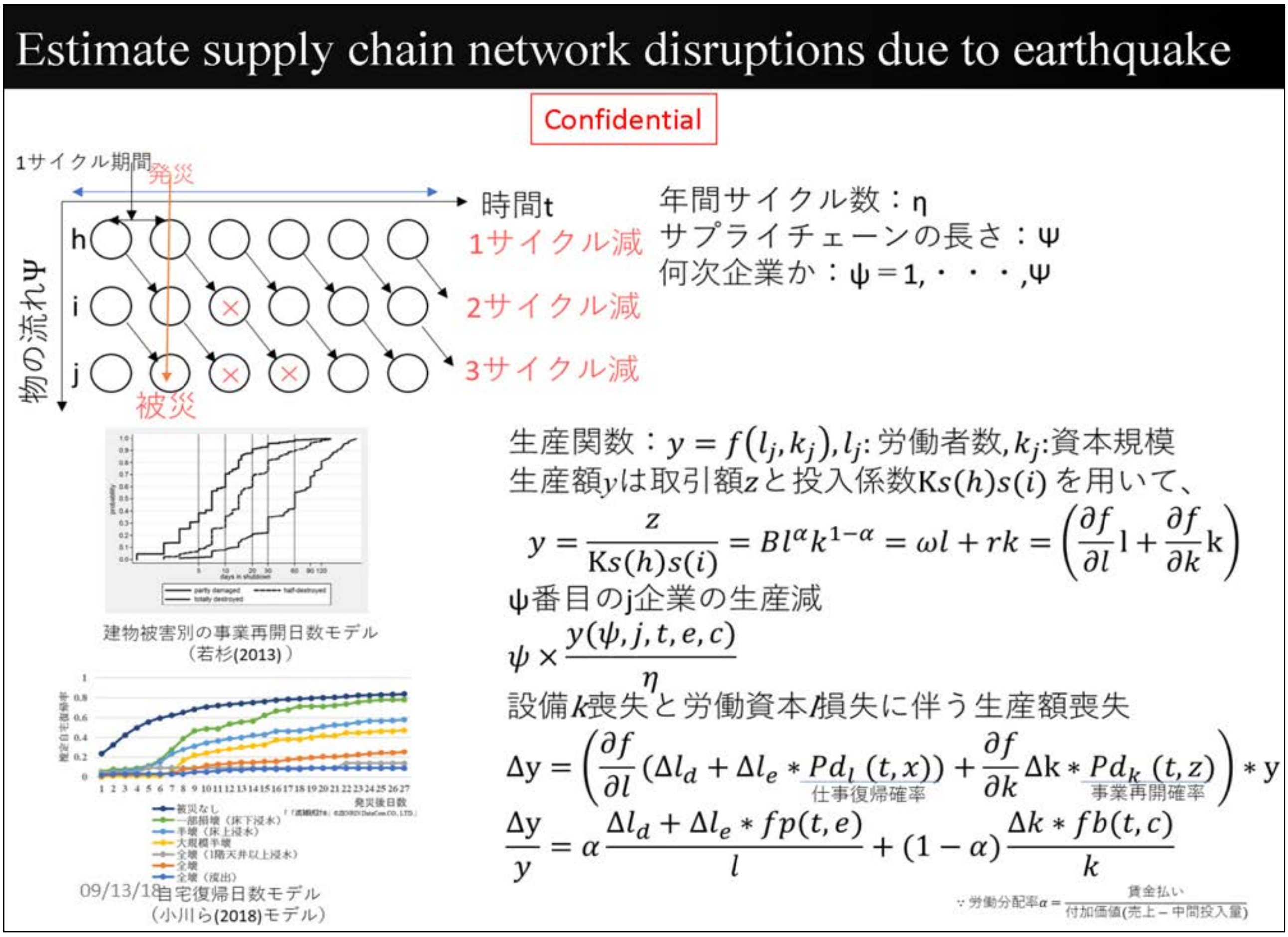
Confidential

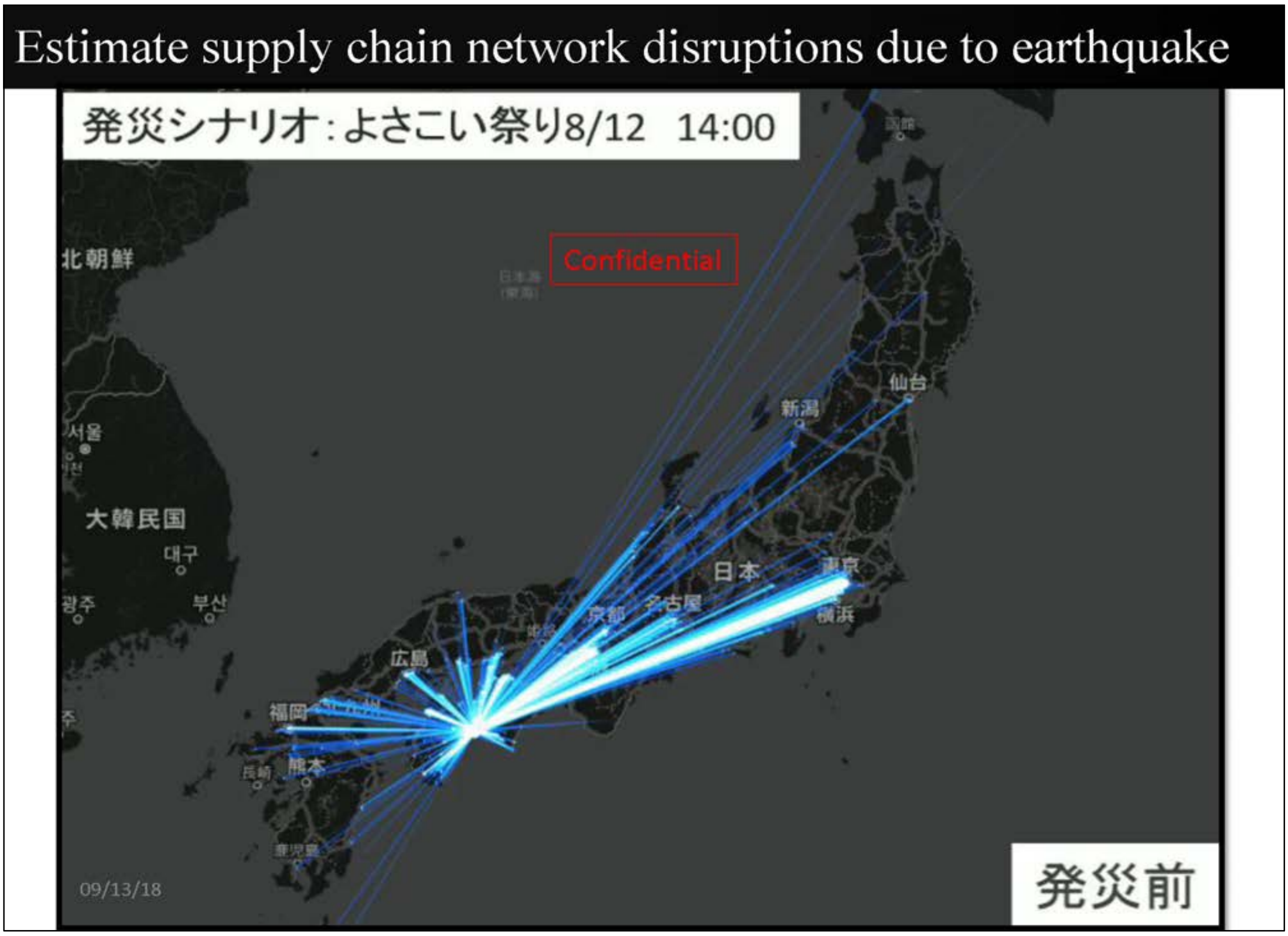
09/13/18

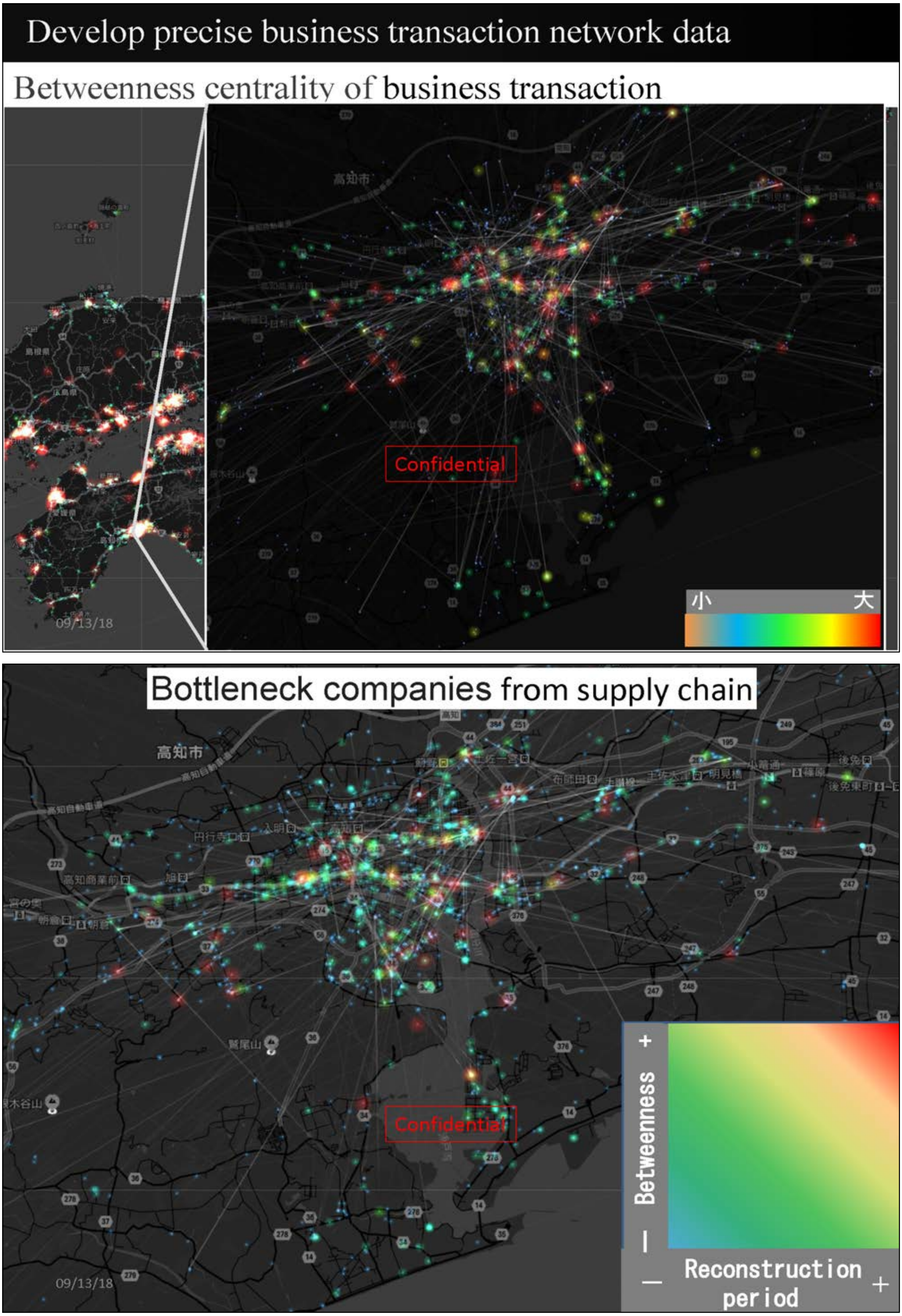
Estimate supply chain network disruptions due to earthquake



09/13/18


Estimate supply chain network disruptions due to earthquake
Confidential
1サイクル期間
発災
時間t
h
i
j
物の流れΨ
被災
1サイクル減
2サイクル減
3サイクル減
年間サイクル数：η
サプライチェーンの長さ：Ψ
何次企業か：ψ＝1,・・・,Ψ
生産関数：$y=f(l_j,k_j), l_j$: 労働者数, k_j:資本規模
生産額yは取引額zと投入係数$Ks(h)s(i)$を用いて、
$y=\frac{z}{Ks(h)s(i)}=Bl^{\alpha}k^{1-\alpha}=\omega l+rk=\left(\frac{\partial f}{\partial l}l+\frac{\partial f}{\partial k}k\right)$
ψ番目のj企業の生産減
$\psi\times\frac{y(\psi,j,t,e,c)}{\eta}$
設備k喪失と労働資本l損失に伴う生産額喪失
$\Delta y=\left(\frac{\partial f}{\partial l}(\Delta l_d+\Delta l_e*\underbrace{Pd_l(t,x)}_{仕事復帰確率})+\frac{\partial f}{\partial k}\Delta k*\underbrace{Pd_k(t,z)}_{事業再開確率}\right)*y$
$\frac{\Delta y}{y}=\alpha\frac{\Delta l_d+\Delta l_e*fp(t,e)}{l}+(1-\alpha)\frac{\Delta k*fb(t,c)}{k}$
∵労働分配率$\alpha=\frac{賃金払い}{付加価値(売上-中間投入量)}$
建物被害別の事業再開日数モデル
(若杉(2013))
被災なし
一部損壊（床下浸水）
半壊（床上浸水）
大規模半壊
全壊（1階天井以上浸水）
全壊
全壊（流出）
発災後日数
09/13/18
自宅復帰日数モデル
(小川ら(2018)モデル)


Estimate supply chain network disruptions due to earthquake
発災シナリオ：よさこい祭り8/12　14:00
Confidential
北朝鮮
서울
大韓民国
대구
광주
부산
仙台
新潟
日本
東京
横浜
名古屋
京都
広島
福岡
熊本
長崎
鹿児島
09/13/18
発災前


Develop precise business transaction network data
Betweenness centrality of business transaction
高知市
Confidential
小
大
09/13/18
Bottleneck companies from supply chain
高知市
Confidential
Betweenness
+
−
Reconstruction period
−
+
09/13/18


KRIHS
2018 International Conference on Geospatial Information Science
THANK YOU

Cloud-powered Machine Learnings on Geospatial Services - From the Earth to Your Home

Channy Yun
Tech Evangelist, Amazon Web Service Korea

Cloud-powered Machine Learnings on Geospatial Services - From the Earth to Your Home

Channy Yun
channyun@amazon.com
Amazon Web Services Korea

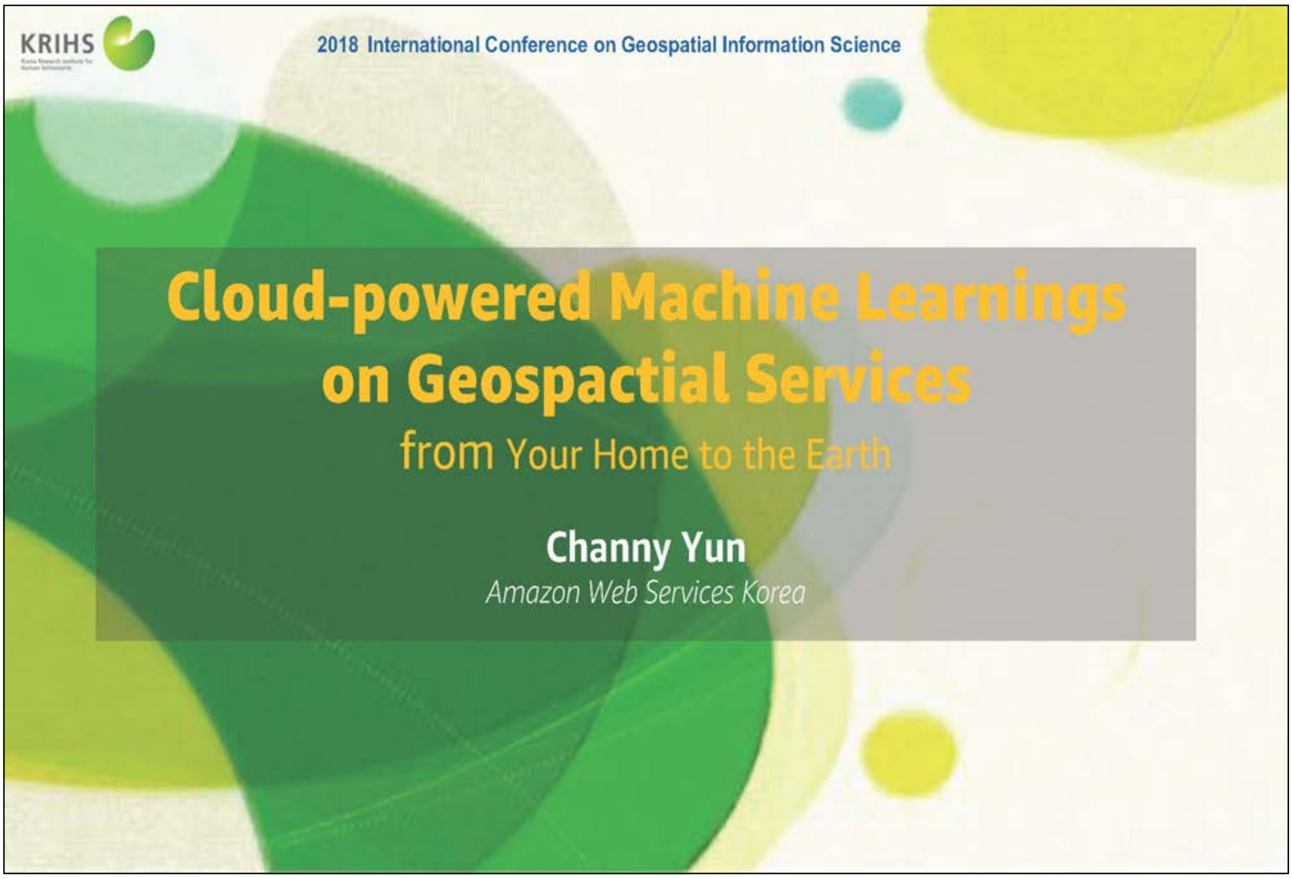
Abstract

Modern machine learning (ML) with problem-solving algorithms and its open source software libraries allows us to approach geospatial applications that were beyond reach a few years ago. They need to scale massive amounts of geospatial data for both training and prediction steps, and the increasing availability of cloud computing services and affordable graphics processing units (GPUs) eases accessibility to supercomputing capacity. Amazon SageMaker is a fully managed service that enables developers and data scientists to quickly and easily build, train, and deploy ML models at any scale, which it removes the barriers that typically slow down developers who want to use ML. By using Amazon SageMaker, DigitalGlobe's cache rate improved by more than a factor of two, often being around 83% and sometimes trending to 90% cache hit. This allowed them to also cut their cloud storage cost in half by better utilizing their S3 optimized cache and retrieving less from their 100+ PB Archive. Also, it enables the Geospatial Big Data platform called GBDX, a horizontally scalable compute environment for analyzing satellite imagery. SpaceNet, Development Seed and EOS are using ML to make a corpus of high-resolution satellite imagery and labeled training data and unlock fully automated ML pipeline from human-in-the-loop initial processing passes.

Amazon has expanded ML to solve specific spatial problems such as identifying inventory defects in Amazon's warehouses by harnessing computer vision and deep learning based on robotics' location predictions of delivery packaging, Amazon Prime Air — a delivery system to safely get packages to customers in 30 minutes within a 10-mile radius of a fulfillment center by GPS-navigated drones with sensing environments and self-driving avoid technologies. Recently Amazon Go introduces "Just Walk Out" technology that enables shoppers to purchase goods without the need for lines or checkout in an offline store based on computer vision by an array

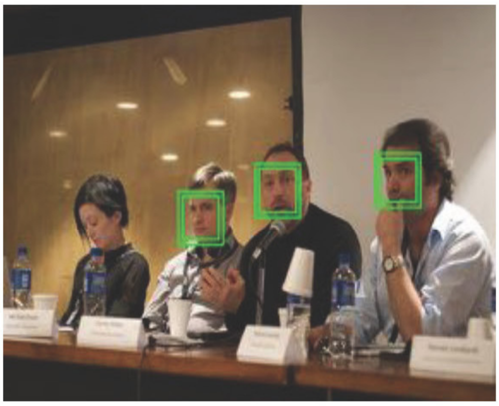
of fusion sensors, cameras and image recognition with deep learning algorithms. Amazon Alexa has powered innovations of home intelligence - virtual assistant features by voice recognition in many devices including Amazon Echo. It is expected to expand new applications that combine a variety of spatial information and artificial intelligence in logistics centers, shops, and home.

Modern GIS research is characterized by data-driven ML tools to solve challenging open research questions which often required to extract spatial semantics, spatial object relationships, tags associated with objects embedded in geographical coordinates. Earth on AWS initiatives - https://aws.amazon.com/earth are available for anyone to conduct research using Earth Observation data on AWS. Students, educators, and researchers can build planetary-scale applications in the cloud with open geospatial data.


KRIHS
2018 International Conference on Geospatial Information Science
Cloud-powered Machine Learnings
on Geospactial Services
from Your Home to the Earth
Channy Yun
Amazon Web Services Korea


CONTENTS
1. Deep Learning and Cloud Computing
2. Amazon SageMaker - Fully Managed DL Service
3. Case Study - ML on Geospacial Services
• Digital Globe
• Development Seed
• SpaceNet
4. Geospatial AI nearby You - Amazon Cases
• Amazon Fullfillment, PrimeAir, Go and Alexa
5. Earth on AWS and Research Credits Program
2

From Machine Learning to Deep Learning



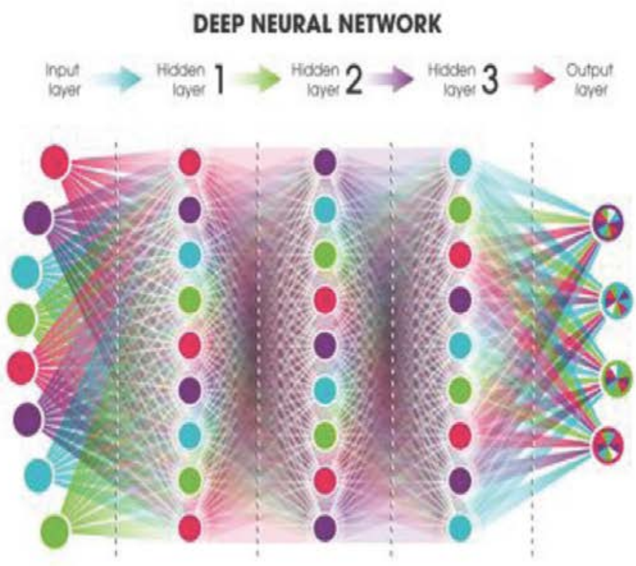
이미지 패턴 분석

음성 인식 및
자연어 처리

자율 주행 자동차

3

Deep Learning이란?

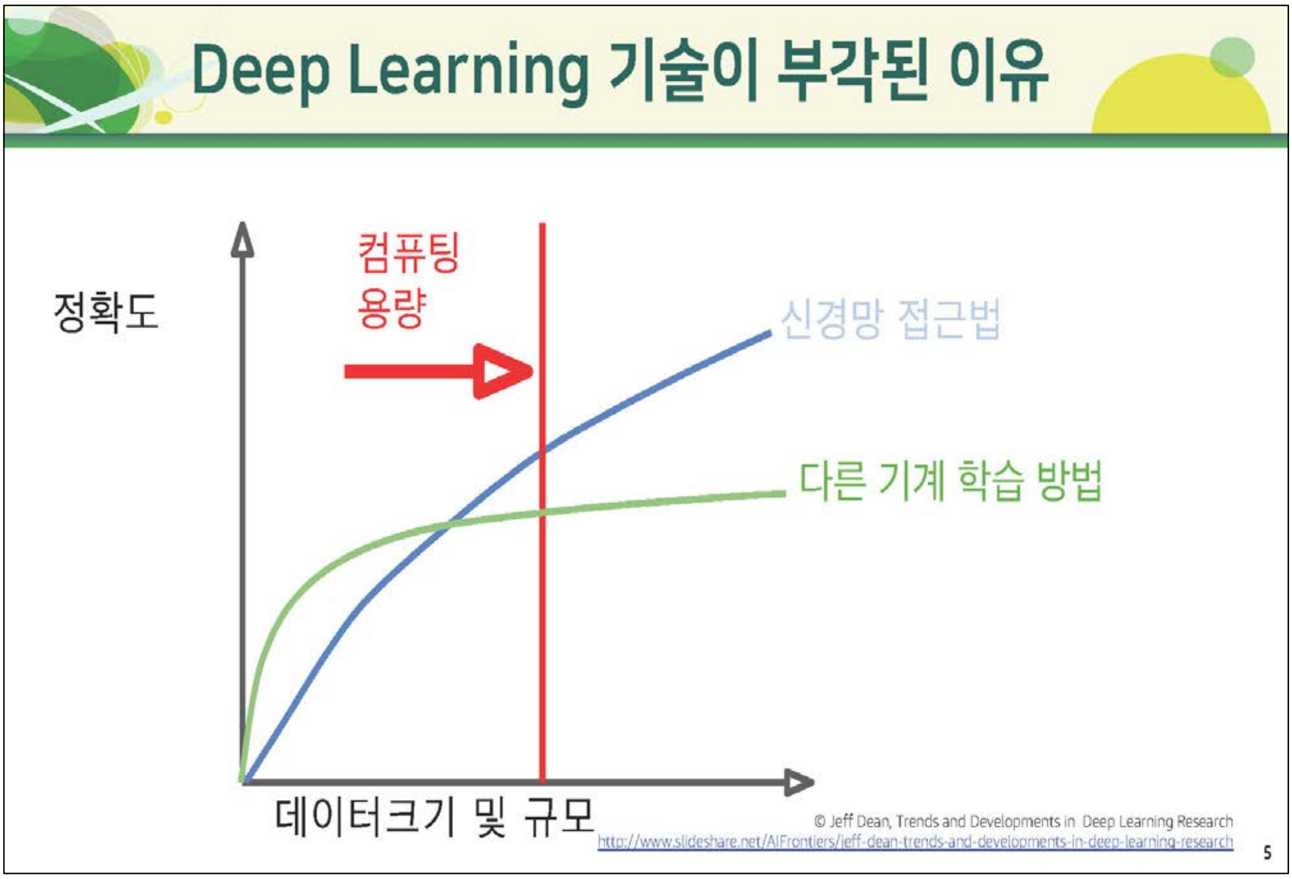


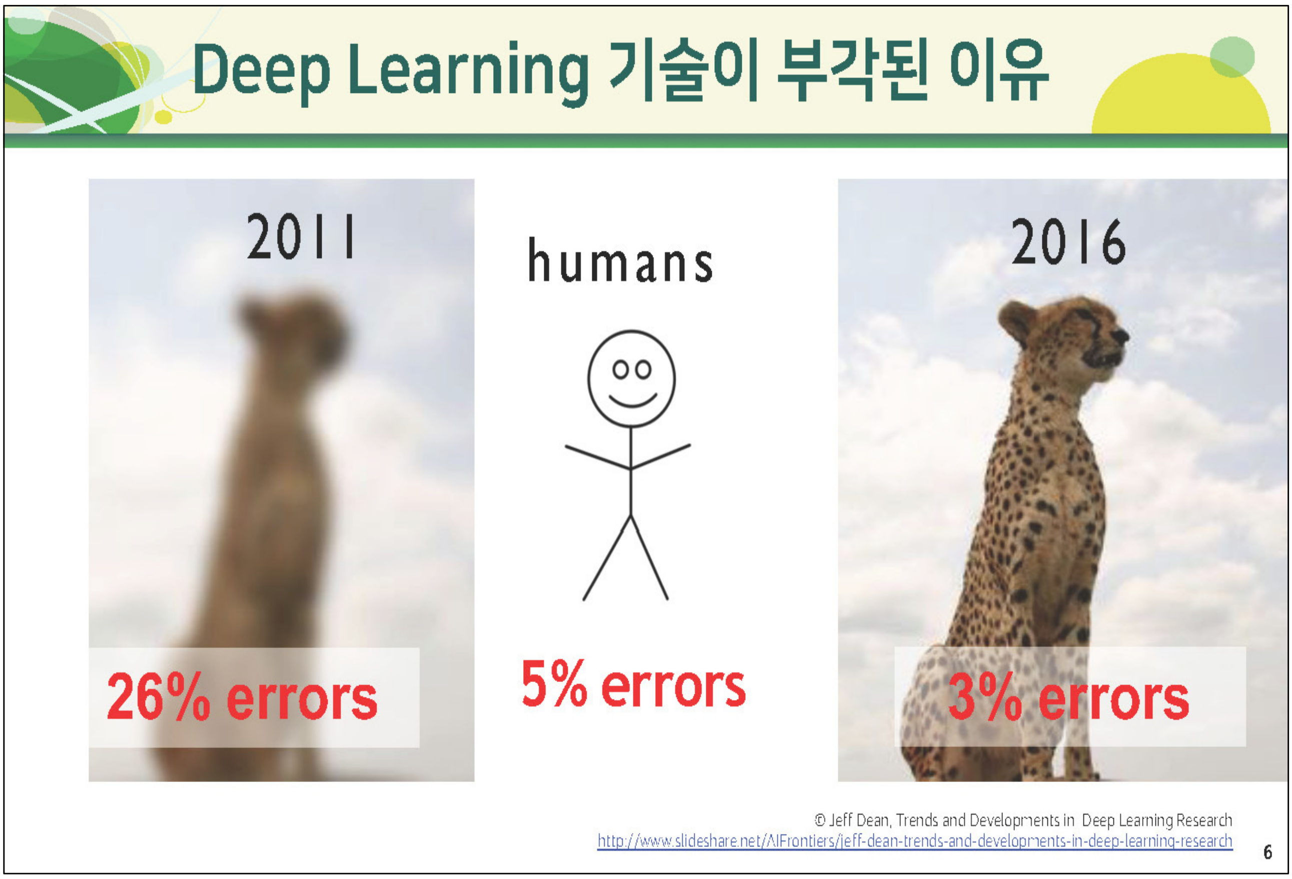
neuralnetworksanddeeplearning.com · Michael Nielsen, Yoshua Bengio, Ian Goodfellow, and Aaron Courville, 2016

딥러닝은 컴퓨터들이 인간의 두뇌와 비슷한 모양의 대형 인공 신경망을 형성하는 일종의 기계 학습 방법

고도화된 학습 알고리즘과 대용량 데이터를 공급함으로써, "사고"하는 능력과 처리하는 데이터를 "학습"하는 능력을 지속적으로 개선한다. "Deep"이란 시간이 지나면서 축적되는 신경망의 여러 층을 의미하며, 신경망의 깊이가 깊어질수록 성능이 향상된다.

4


Deep Learning 기술이 부각된 이유
정확도
컴퓨팅
용량
신경망 접근법
다른 기계 학습 방법
데이터크기 및 규모
© Jeff Dean, Trends and Developments in Deep Learning Research
http://www.slideshare.net/AIFrontiers/jeff-dean-trends-and-developments-in-deep-learning-research
5


Deep Learning 기술이 부각된 이유
2011
humans
2016
26% errors
5% errors
3% errors
© Jeff Dean, Trends and Developments in Deep Learning Research
http://www.slideshare.net/AIFrontiers/jeff-dean-trends-and-developments-in-deep-learning-research
6

Deep Learning은 어렵지 않다!

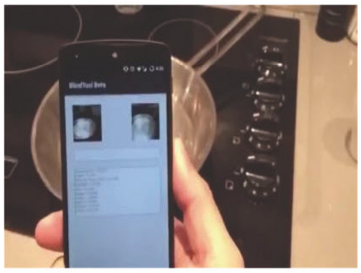
Deep Drone: Object Detection and Tracking for Smart Drones on Embedded System

https://web.stanford.edu/class/cs231a/prev_projects_2016/deep-drone-object__2_.pdf

MXNetJS in Web Browser Web Applications

https://github.com/dmlc/mxnet.js/

BlindTool by Joseph Paul Cohen on Nexus 4 Mobile Application



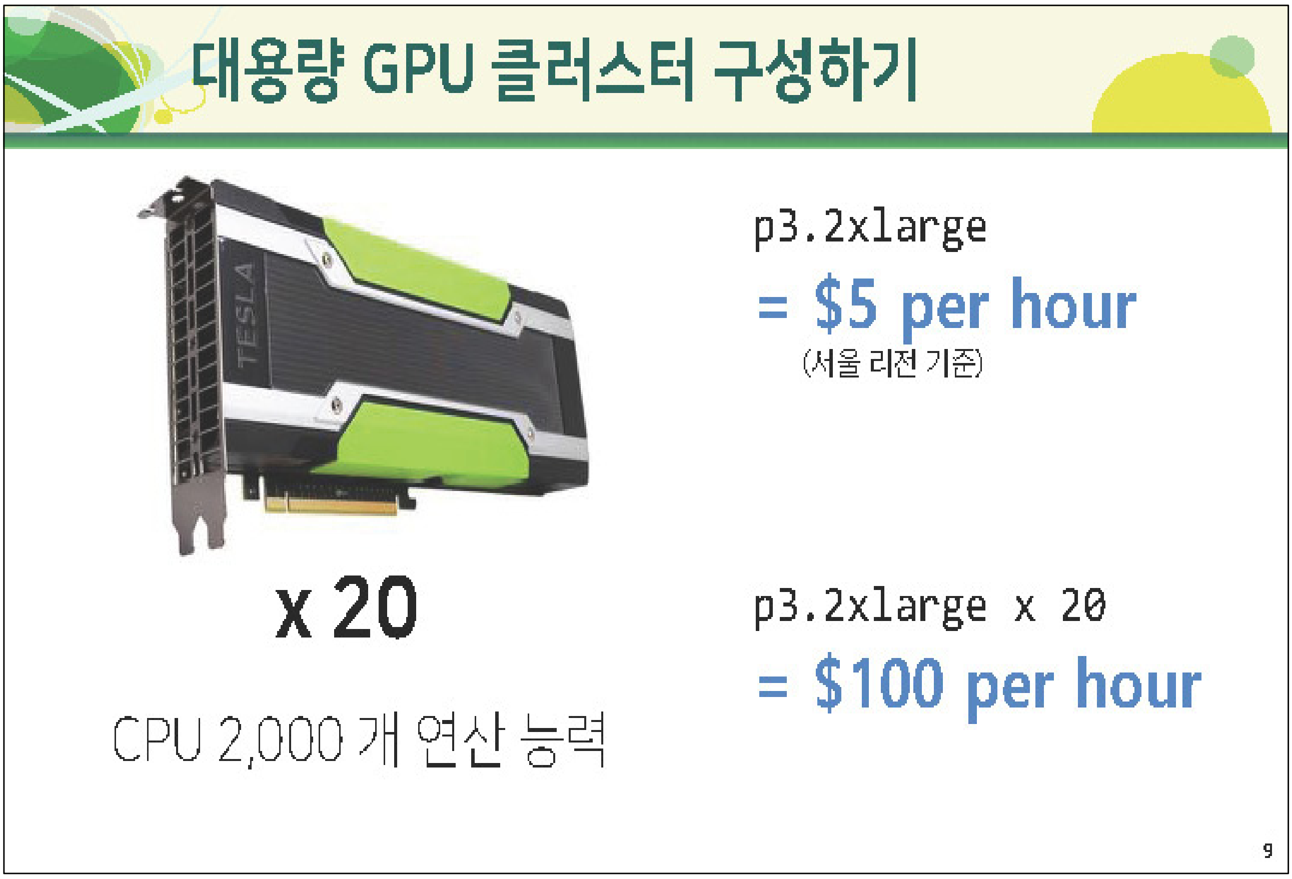
http://josephpcohen.com/w/blindtool-helping-the-blind-see/

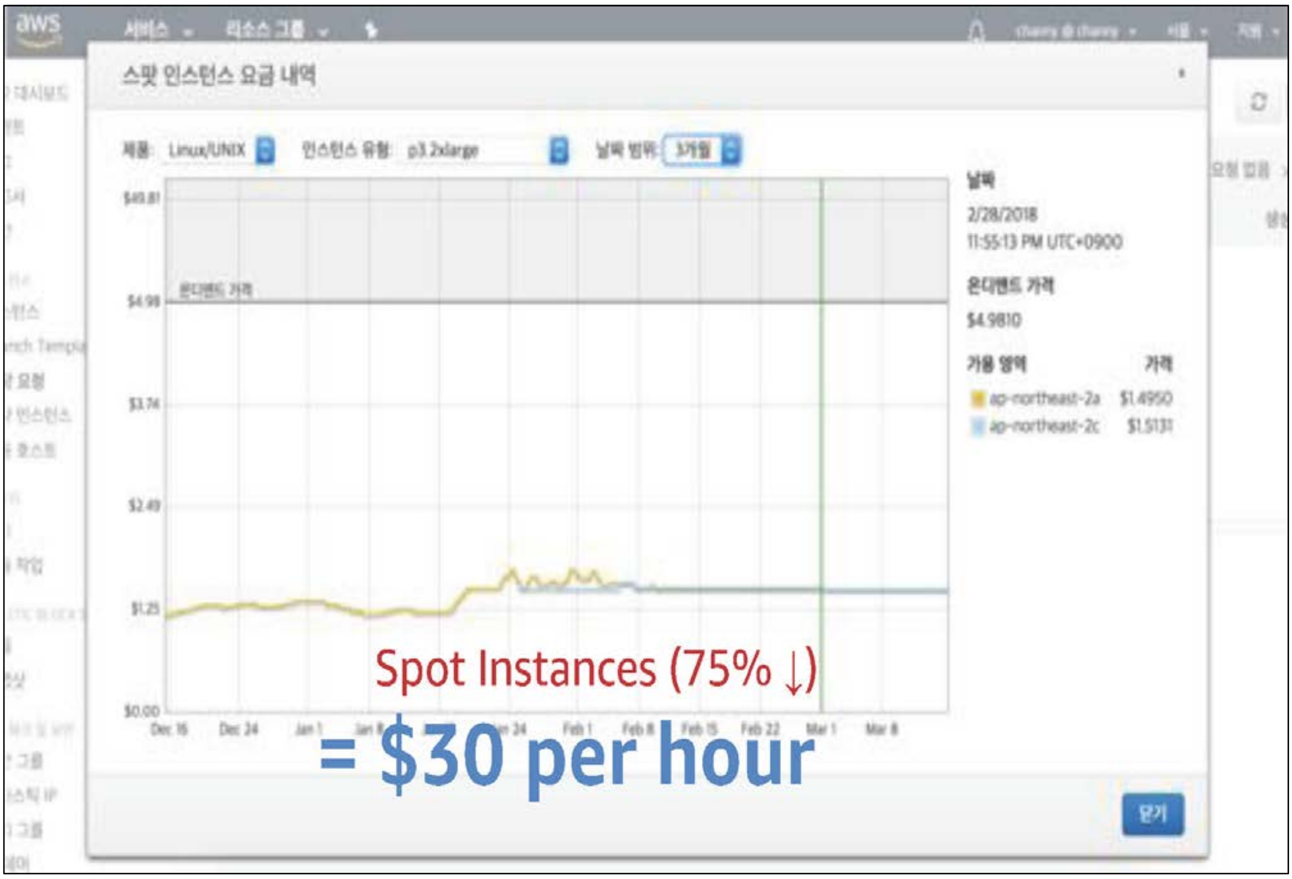
7

Cloud-based Deep Learning

Amazon EC2 Instances	High-performance GPU (G3/P3), CPU (C5) Instances
Deep Learning Framework	Nvidia/CUDA, TensorFlow, PyTourch, MXNet, Keras
Amazon SageMaker	Fully-managed Deep Learning Service

8

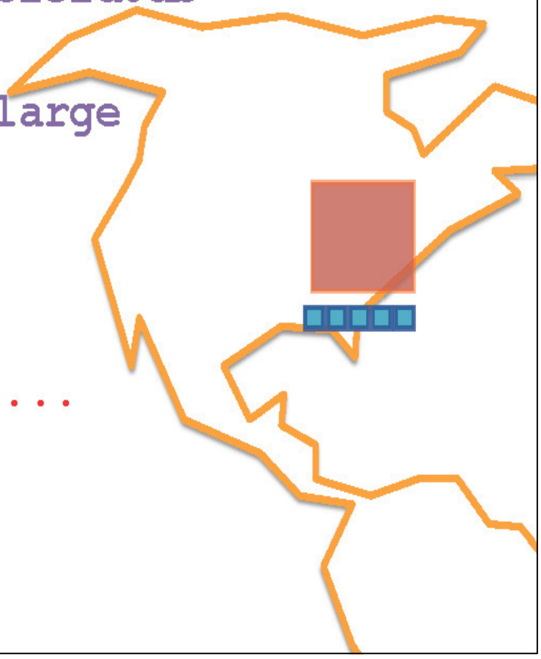

대용량 GPU 클러스터 구성하기
TESLA
x 20
CPU 2,000 개 연산 능력
p3.2xlarge
= $5 per hour
(서울 리전 기준)
p3.2xlarge x 20
= $100 per hour
9


aws
스팟 인스턴스 요금 내역
제품: Linux/UNIX
인스턴스 유형: p3.2xlarge
날짜 범위: 3개월
온디맨드 가격
날짜
2/28/2018
11:55:13 PM UTC+0900
온디맨드 가격
$4.9810
가용 영역
가격
ap-northeast-2a $1.4950
ap-northeast-2c $1.5131
Spot Instances (75% ↓)
= $30 per hour
닫기

대용량 GPU 클러스터 구성하기

```
$aws ec2-run-instances ami-b232d0db
      --instance-count 20
      --instance-type p3.2xlarge
      --region us-east-1

$aws ec2-stop-instances
      i-10a64379 i-10a64280 ...
```



TensorFlow on AWS

> "In analyzing the experiences of researchers supporting more than 388unique projects, Nucleus found that **88 percent of cloud-based TensorFlow projects are running on Amazon Web Services.**

https://nucleusresearch.com/research/single/guidebook-tensorflow-aws/

NUCLEUS RESEARCH

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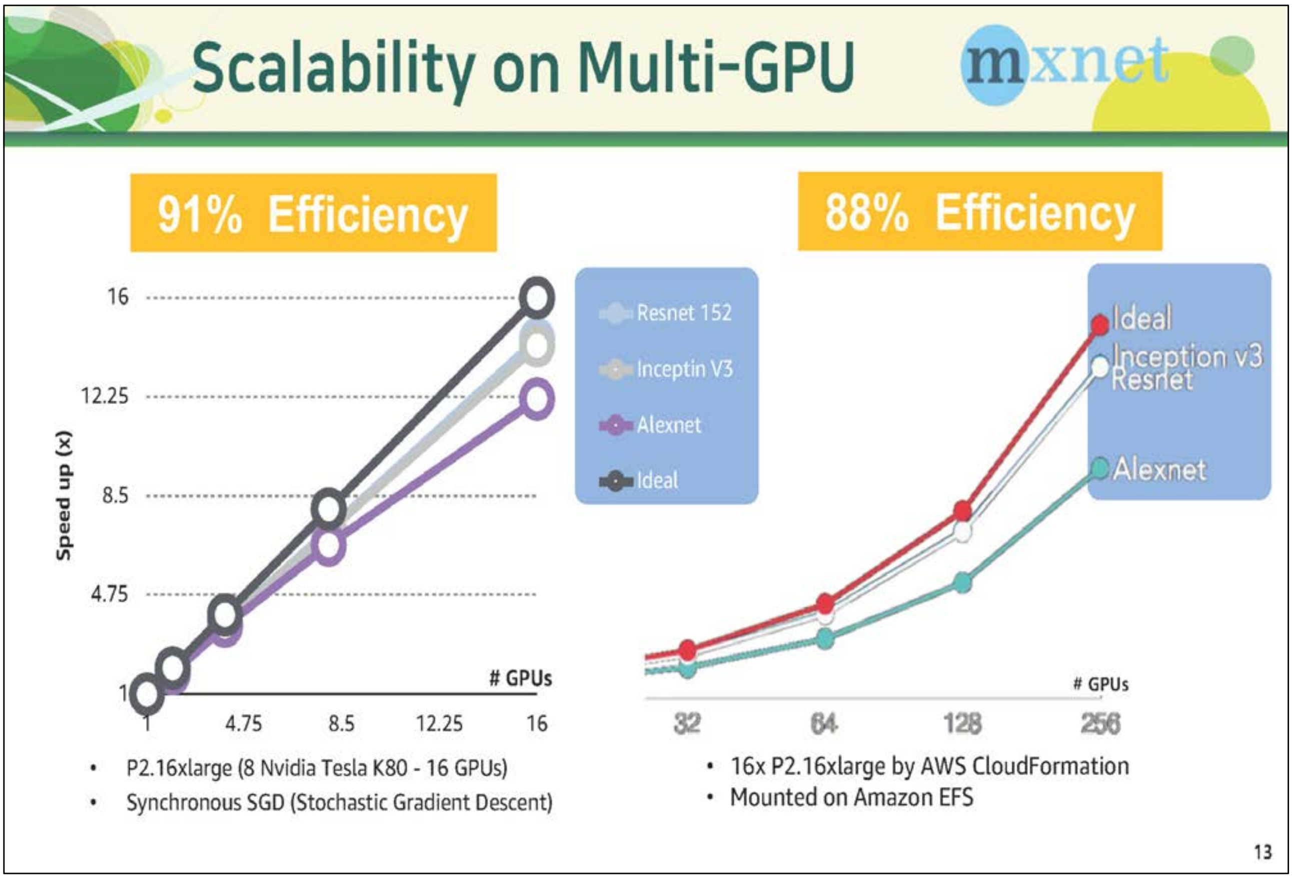
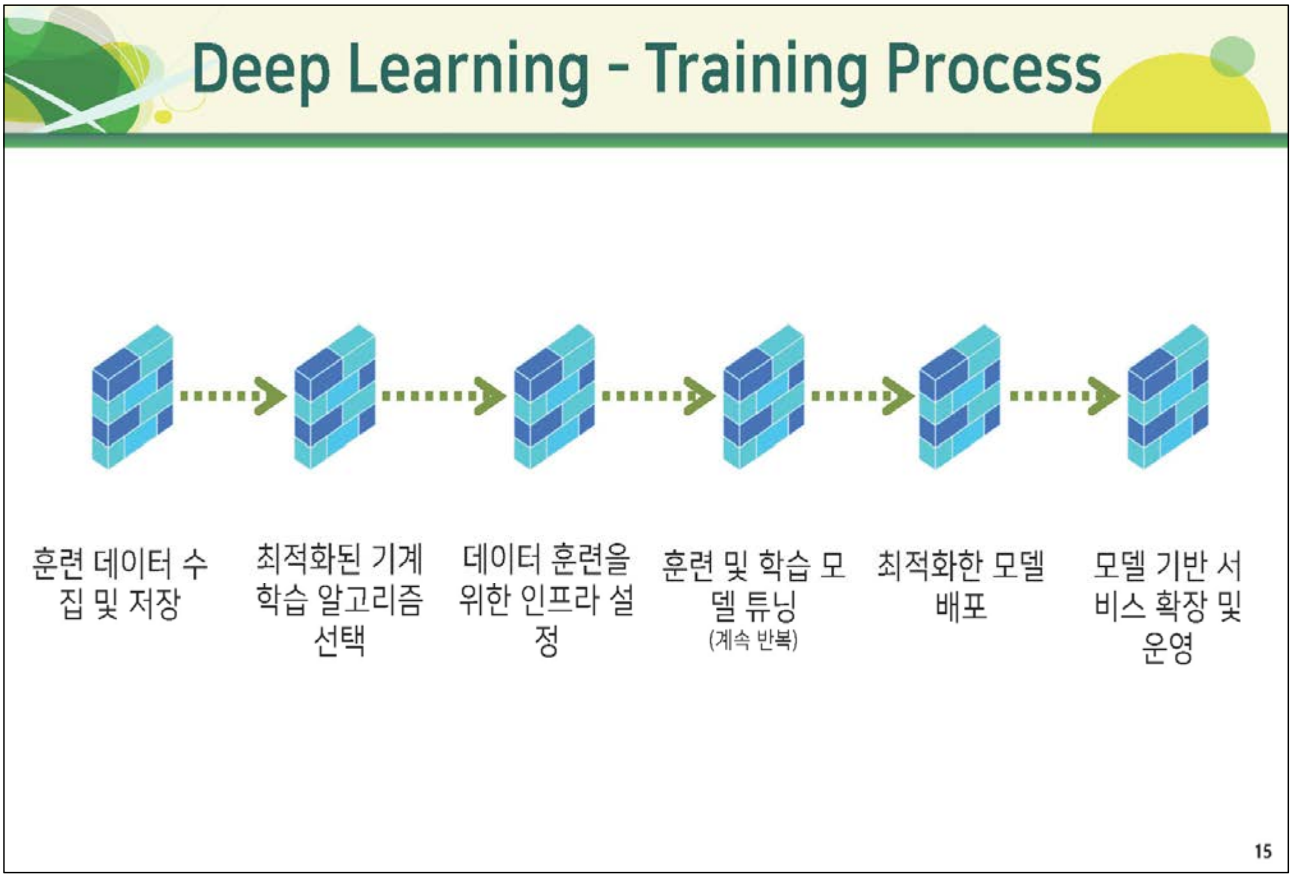
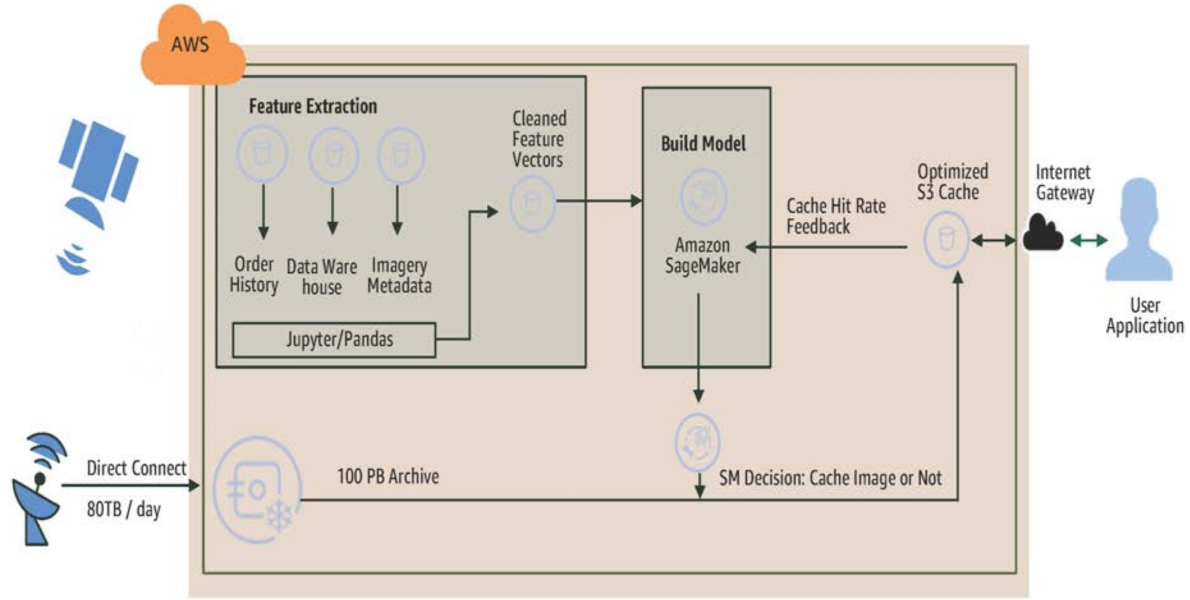

Scalability on Multi-GPU
mxnet
91% Efficiency
88% Efficiency
Speed up (x)
16
12.25
8.5
4.75
1
GPUs
1
4.75
8.5
12.25
16
Resnet 152
Inceptin V3
Alexnet
Ideal
Ideal
Inception v3
Resnet
Alexnet
GPUs
32
64
128
256
• P2.16xlarge (8 Nvidia Tesla K80 - 16 GPUs)
• Synchronous SGD (Stochastic Gradient Descent)
• 16x P2.16xlarge by AWS CloudFormation
• Mounted on Amazon EFS
13


Deep Learning - Training Process
훈련 데이터 수
집 및 저장
최적화된 기계
학습 알고리즘
선택
데이터 훈련을
위한 인프라 설
정
훈련 및 학습 모
델 튜닝
(계속 반복)
최적화한 모델
배포
모델 기반 서
비스 확장 및
운영
15


Amazon SageMaker
손쉬운 기계 학습 모델 생성, 훈련 및 서비스 배포 완전 관리 서비스
Jupyter Notebook 기반 서비스
고성능 알고리즘 미리 제공
원클릭 데이터 훈련
Hyper-parameter 최적화
원클릭 모델 배포
완전 관리 및 자동 스케일링
모델 생성
모델 훈련
모델 배포
https://aws.amazon.com/ko/sageamker
16


Digital Globe - 대용량 위성 이미지 제공
UBER
Where to?
mapbox
Cache hit rate dropped by nearly 2x
70 % ▶ 40%
Cache hit percentage
180 day cache
Daily access
Month 1 | Month 2 | Month 3
18

Digital Globe - 대용량 위성 이미지 제공



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DigitalGlobe - 위성 사진 분석 서비스

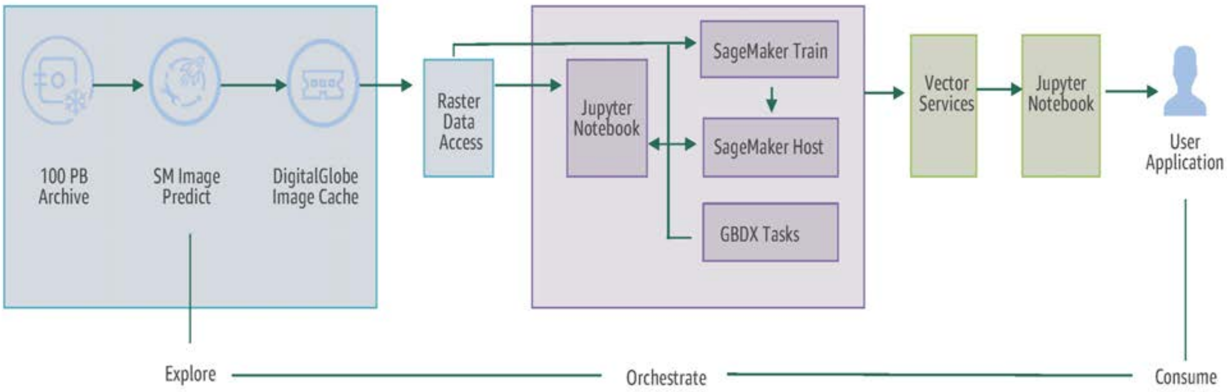
"We plan to use Amazon SageMaker to train models against **petabytes of Earth observation imagery datasets** using hosted Jupyter notebooks, so DigitalGlobe's Geospatial Big Data Platform (GBDX) users can just push a button, create a model, and deploy it all within one scalable distributed environment at scale."

- Dr. Walter Scott, CTO of Maxar Technologies and founder of DigitalGlobe

20

DigitalGlobe - 위성 사진 분석 서비스

Real-time random access to all the pixels in DigitalGlobe's Archive



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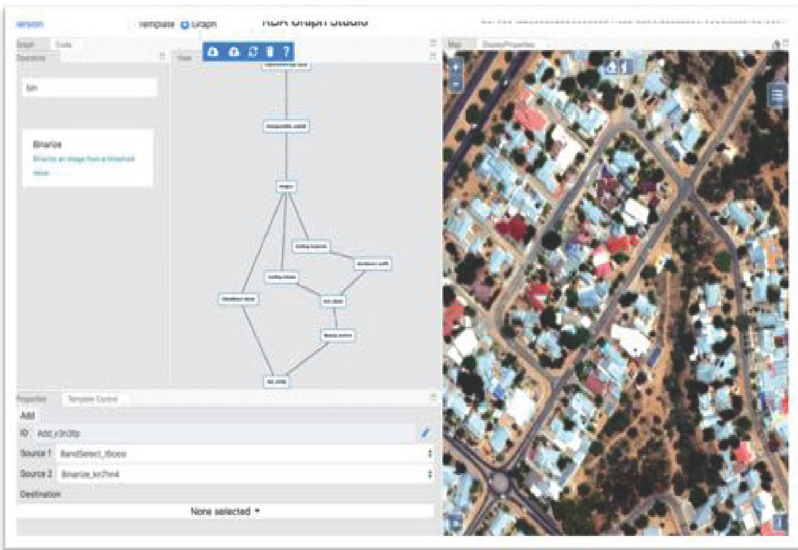
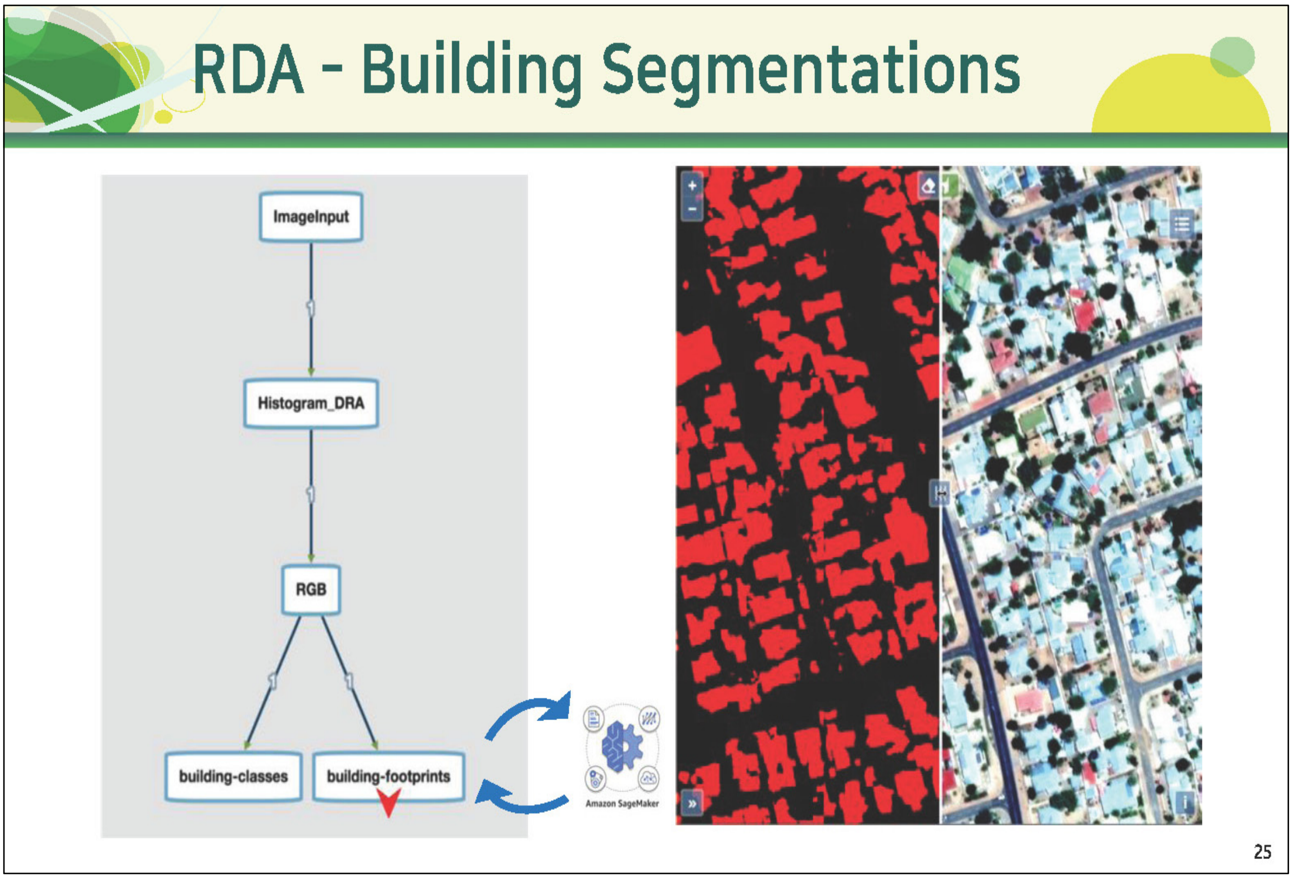
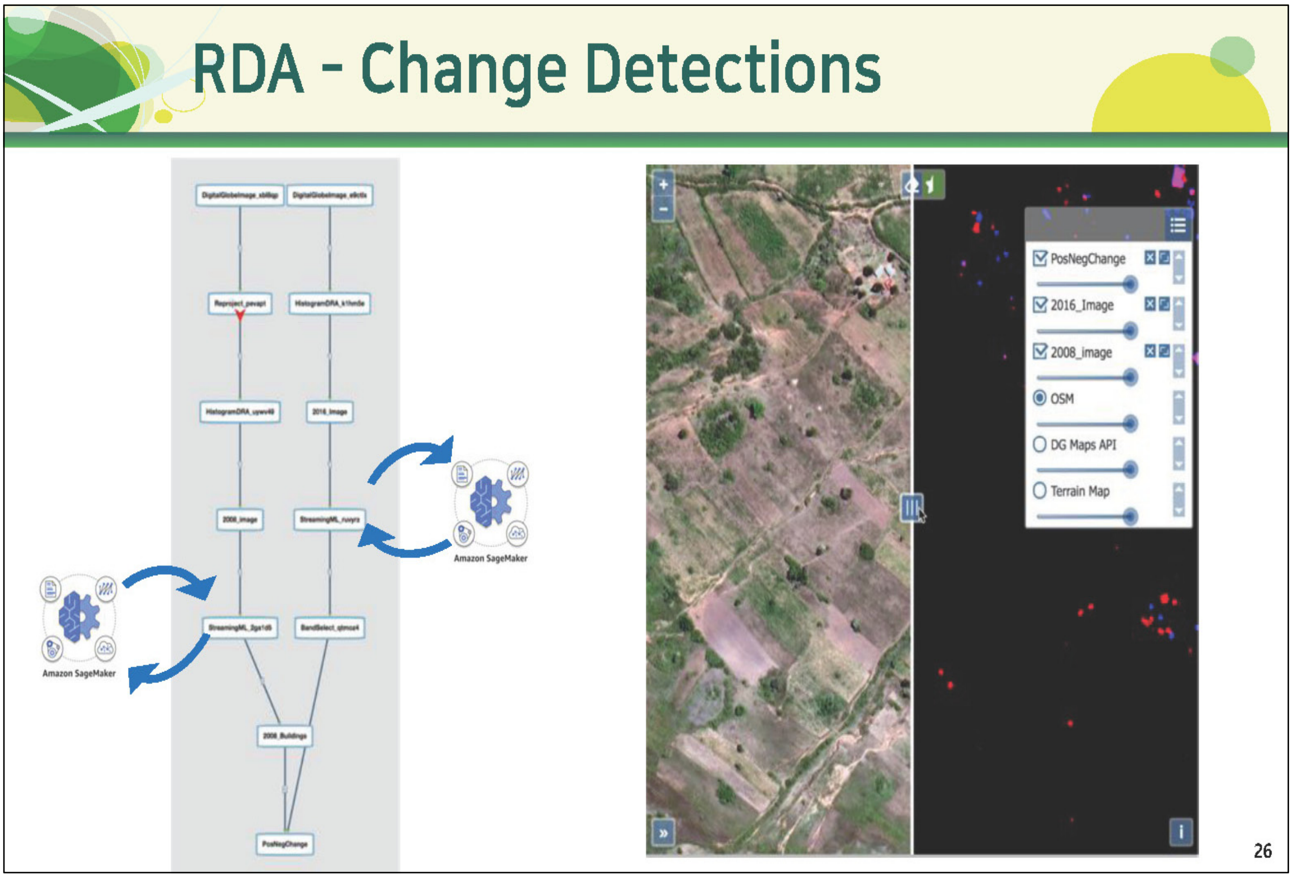
Raster Data Access (RDA) Service

- Any pixels, any way you want them
- REST API
- User defined Graphs
- 100s of operators
- Python API
- Gdal Driver



24


RDA - Building Segmentations
ImageInput
Histogram_DRA
RGB
building-classes
building-footprints
Amazon SageMaker
25


RDA - Change Detections
Amazon SageMaker
Amazon SageMaker
PosNegChange
2016_Image
2008_image
OSM
DG Maps API
Terrain Map
26

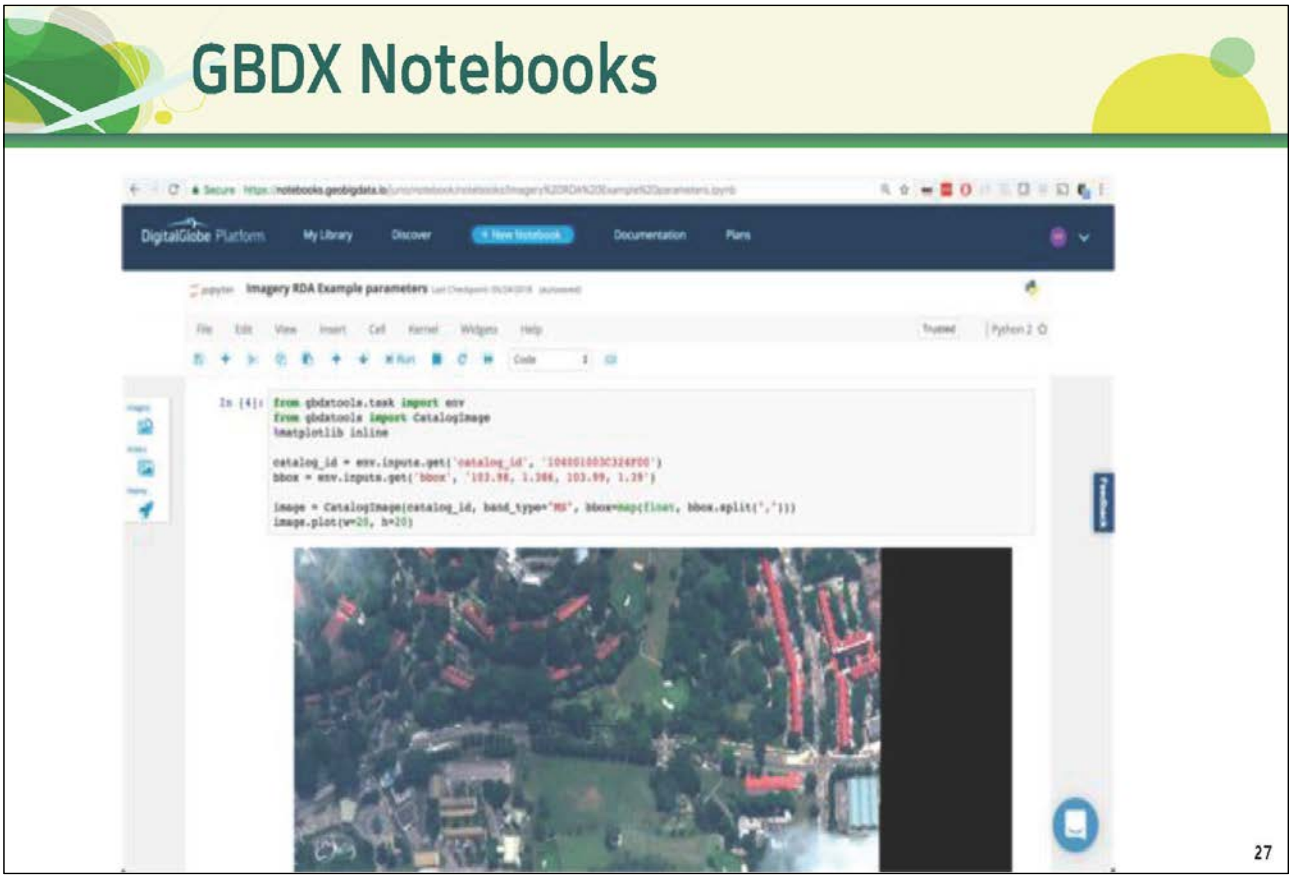

GBDX Notebooks
DigitalGlobe Platform
My Library
Discover
Documentation
Plans
27

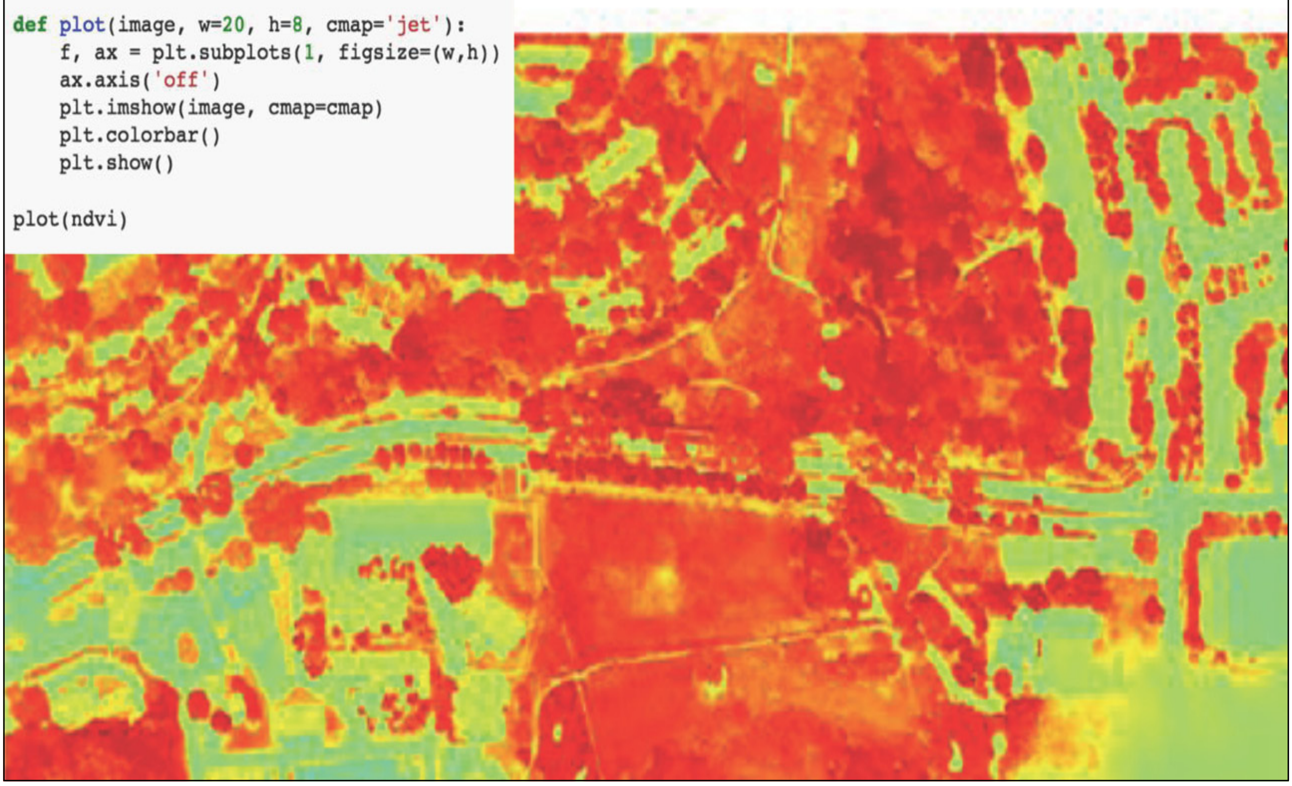

image = CatalogImage(catalog_id, band_type="MS", bbox=map(float, bbox.split(",")))
image.plot(w=20, h=20)

```
image = CatalogImage(catalog_id, band_type="PANSHARP", acomp=True, bbox=map(float, bbox.split
image.plot(w=20, h=20)
```

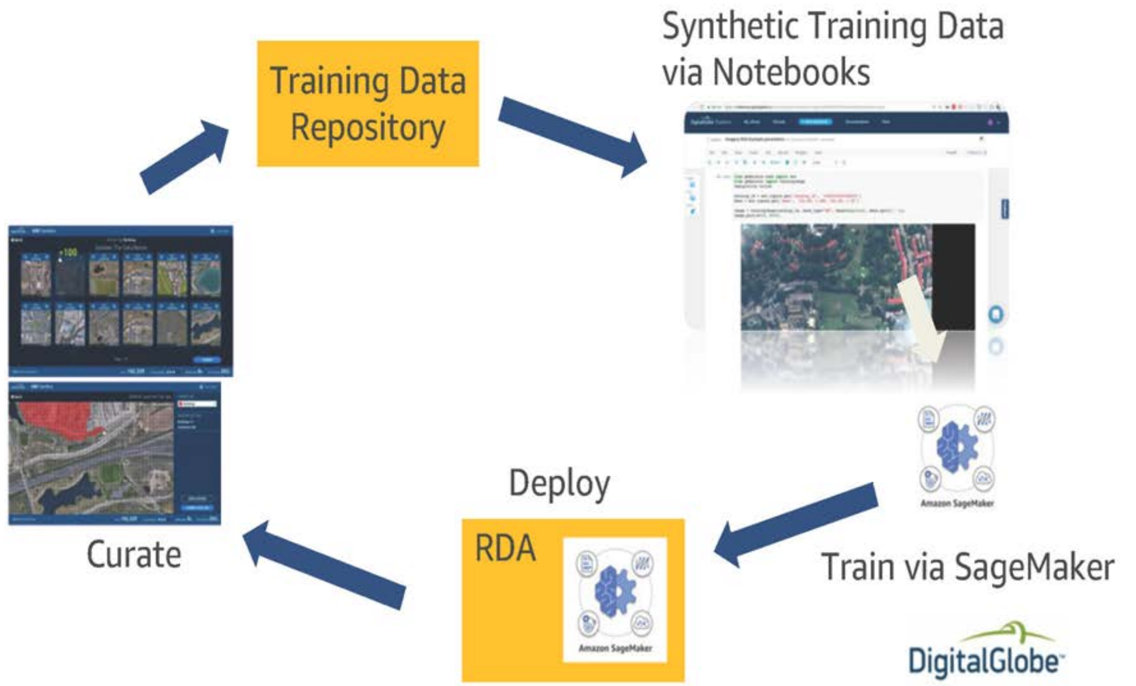
```
import matplotlib.pyplot as plt
%matplotlib inline

def plot(image, w=20, h=8, cmap='jet'):
    f, ax = plt.subplots(1, figsize=(w,h))
    ax.axis('off')
    plt.imshow(image, cmap=cmap)
    plt.colorbar()
    plt.show()

plot(ndvi)
```



RDA Service - What's Next



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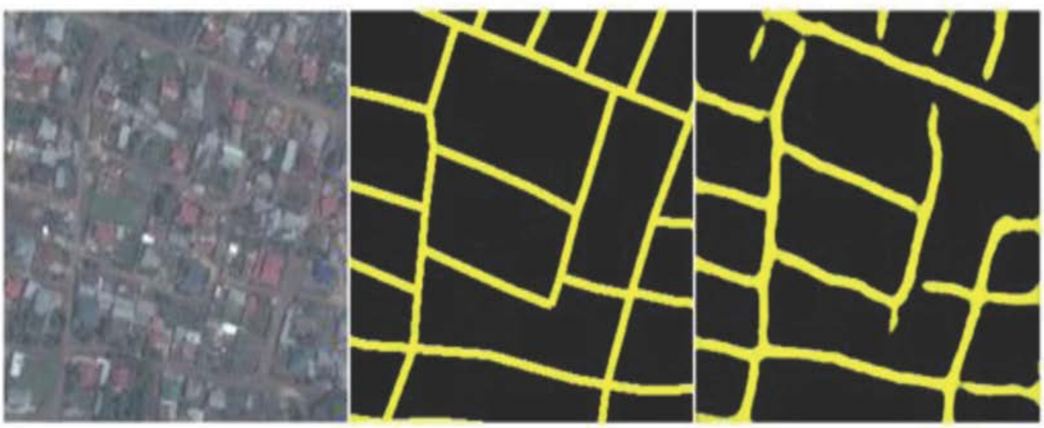
SkyNet

Skynet quickly analyze massive amounts of satellite imagery using machine learning and open data based on AWS EC2 g2 instance and set it up with nvidia-docker.



https://github.com/developmentseed/skynet-train

developmentSEED

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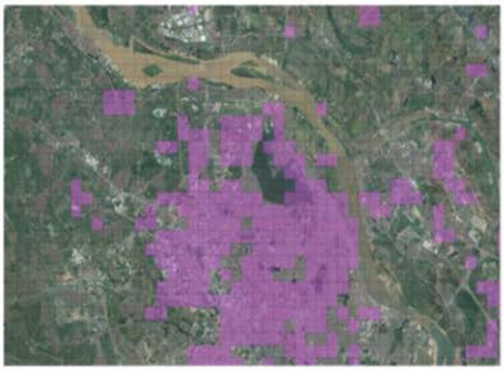
Label Maker

Label Maker is to help in extracting insight from satellite imagery that creates training data for most popular ML frameworks, including Keras, Tensor Flow, and MXNet.



Creating a building classifier in Vietnam using MXNet and SageMaker

https://github.com/developmentseed/label-maker/blob/master/examples/walkthrough-classification-mxnet-sagemaker.md

developmentSEED 33

SpaceNet Challenges

The SpaceNet Dataset is an open repository of over 5,700+ km^2 of satellite imagery across 5 cities, 520,000+ vectors, and a series of challenges to accelerate geospatial machine learning.

Automated Mapping Challenge: Building Extraction Rounds 1 & 2 Nov. 2016 – Jun. 2017

Automated Mapping Challenge: Road Network Extraction Nov 2017 – Feb 2018

High Revisit Challenge: Off-Nadir Object Detection Launching Spring 2018

SpaceNet cosmiQ works radiant SOLUTIONS NVIDIA 34

SpaceNet Challenge Examples

AOI 2 Vegas: Image 1014 | AOI 3 Paris: Image 1729 | AOI 5 Khartoum: Image 991

https://spacenetchallenge.github.io/

SpaceNet cosmiQ works radiant SOLUTIONS NVIDIA 35

Geospatial AI nearby You

amazon PrimeAir | amazon go | amazon alexa

Fulfillment automation and inventory mana gement

Automobile Delivery Drones

No checkout Store Expriences

Voice driven in teractions

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Amazon Fulfillment Center

- 물류센터 KIVA 로봇 도입
  - 이동 경로 계산 및 최적화 등에 머신 러닝 기법 활용
  - 물류 순환 속도: 60~75분 ▶ 15분
  - 재고 공간: 50% ↑
  - 운영비용: 약 20% ↓

- 미국 내 13개 물류 센터에 15,000개 로봇 시범 도입 (2014)

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Amazon PrimeAir - 드론 배송

- 자율 비행을 통한 상품 배송
  - 주문 부터 배송까지 완전 자율 경로 산정 및 배송 처리
  - 머신 러닝을 통한 GPS 비행 시뮬레이션 진행

- 영국 (2016) 및 미국 (2017)에서 실험 배송 진행 중

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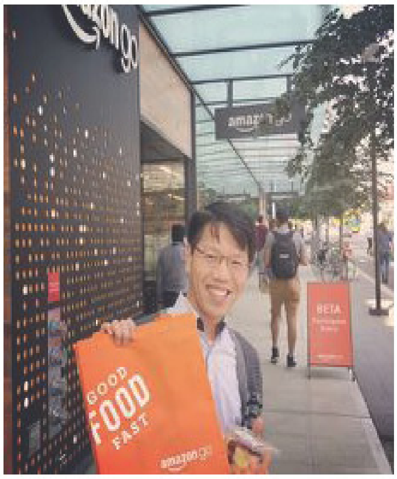
Amazon Go - 오프라인 쇼핑 경험 혁신

- Just Walk-Out
  - 계산대 없이 편리한 쇼핑 경험을 주기 위한 기술
  - 컴퓨터 비전, 센서 융합 및 딥러닝 알고리즘 활용
- 시애틀 시범 매장 베타 운영 (2017) 시작 후, 일반 공개 완료 (2018.1)



https://www.amazon.com/b?node=16008589011

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Amazon Alexa 기반 음성 인식 서비스

- 음성 인식을 기반한 가정용 비서 기기, Amazon Echo 최초 출시
- 장난감, 가전, 모바일 기기 등 수 천만대의 Alexa 탑재 기기 출시
- 다양한 음성 비서 서비스 산업 생태계 확대

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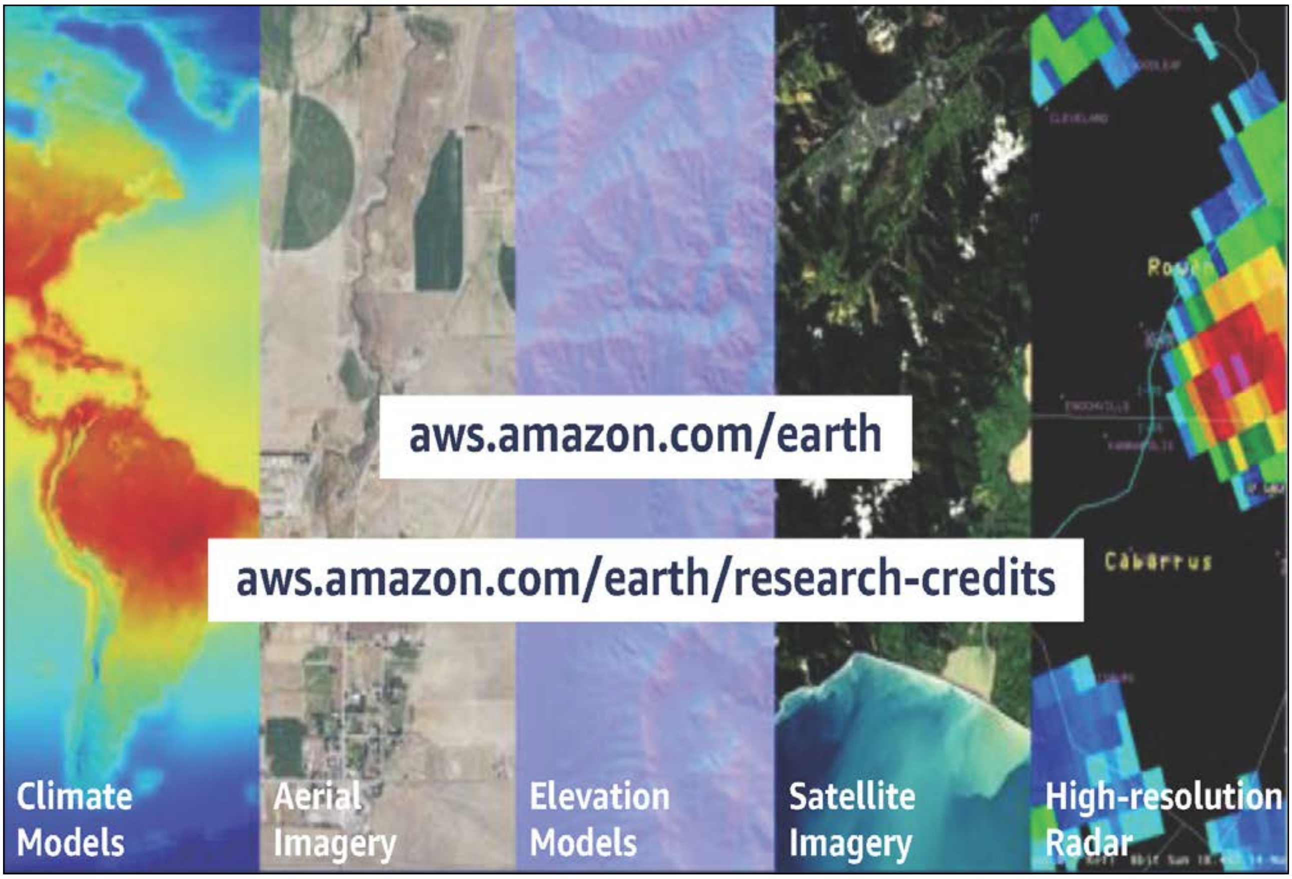
aws.amazon.com/earth
aws.amazon.com/earth/research-credits
Climate Models
Aerial Imagery
Elevation Models
Satellite Imagery
High-resolution Radar


특별 선물 - 딥러닝을 공부하시는 분들께!
AWS Only
Amazon SageMaker
$300 Credits
http://bit.ly/awskr-ml-credits
1. 위의 URL에 신청하시면, 1-2주일 이내에 크레딧 코드 발급 방법을 메일로 전해 드립니다.
2. 전달 받은 크레딧 코드는 Amazon SageMaker 요금에만 적용되며, 실습 시 사용하는 타 클라우드 리소스에 대한 요금이 부과될 수도 있습니다. (예: Amazon S3, 데이터 전송 요금 등)
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References

1. https://www.slideshare.net/AmazonWebServices/machine-learning-with-earth-observation-imagery
2. https://www.slideshare.net/AmazonWebServices/altime-machine-learning-on-satellite-imagery-how-digitalglobe-uses-amazon-sagemaker-to-massively-scaleup-information-extraction-from-satellite-imagery
3. https://www.slideshare.net/AmazonWebServices/data-boulders-from-space-how-digitalglobe-uses-aws-to-manage-data
4. http://geospatial.blogs.com/geospatial/2018/04/deep-learning-enables-automated-extraction-of-building-footprints-and-road-networks-from-satellite-imagery.html
5. https://aws.amazon.com/blogs/publicsector/how-digitalglobe-uses-amazon-sagemaker-to-manage-machine-learning-at-scale/
6. http://blog.digitalglobe.com/developers/gbdx-notebooks-and-amazon-sagemaker-for-systematic-mining-of-geospatial-data/

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2018 International Conference on Geospatial Information Science

THANK YOU

윤석찬

아마존웹서비스코리아, 테크에반젤리스트

channyun@amazon.com

http://bit.ly/awskr-feedback

@channyun

A Deep Learning Approach for Simulating Urban Development

Donghan Kim
Research Fellow, KRIHS

A Deep Learning Approach for Simulating Urban Development

Donhan Kim
dhkim@krihs.re.kr
KRIHS(Korea Research Institute for Human Settlements).


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2018 International Conference on Geospatial Information Science
A Deep Learning Approach for Simulating Urban Development
Donghan Kim, PhD (dhkim@krihs.re.kr)
Korea Research Institute for Human Settlements (KRIHS)

Contents

Introduction

Background

- Artificial Intelligence(AI) is expected to augment or replace human intelligence.
  - "AlphaGo shock" in Korea.
- Indeed, AI is not a brand new invention, and application of AI in social science and urban modelling field is nothing new either.
- However, we may wonder whether recently re-invented or re-enforced AI algorithm(such as deep learning) can better support human life.

Research Goals

- To develop a urban growth simulation model by using a deep learning algorithm
- To understand usability of artificial intelligence for decision support and urban planning

Acknowledgement

- This work is a part of an ongoing research project at the Korea Research Institute for Human Settlements(KRIHS)

"Improvement of Urban Planning System in Korea"

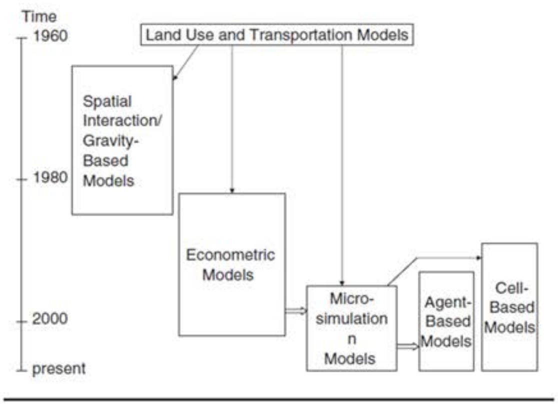
- 2018. 1. 1 - 12. 31
- Aims to suggest new directions and policy measures
  - Prediction of urban growth and development for scientific urban planning policy

Principal Investigator: Dr. Yong-Woo Lee

Concept of Urban Model

Trend of Urban Modelling

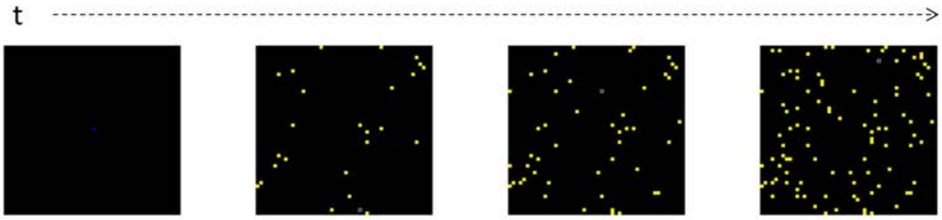
- Firstly appeared in the late 1950's and early 1960's
- Many different types of urban models over 50 years
  - Similar purpose but heterogeneous theories and methods
  - From static and aggregated to dynamic and disaggregated model



Source: Iacono, Levinson, and El-Geneidy(2008)

Spatially Explicit and Dynamic Model

- Cellular automata model, Agent based model

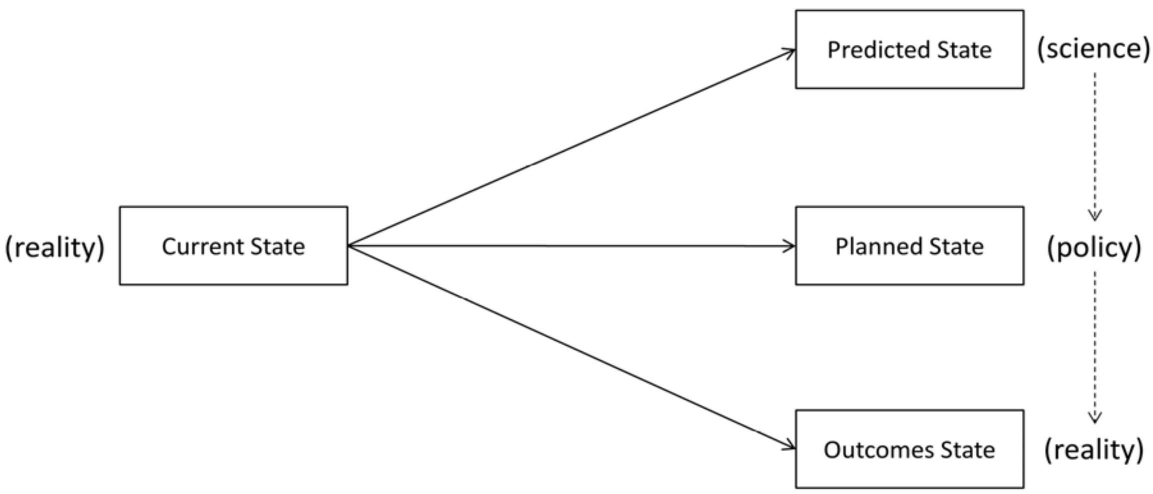


Random Urban Growth

Mono-centric Urban Growth

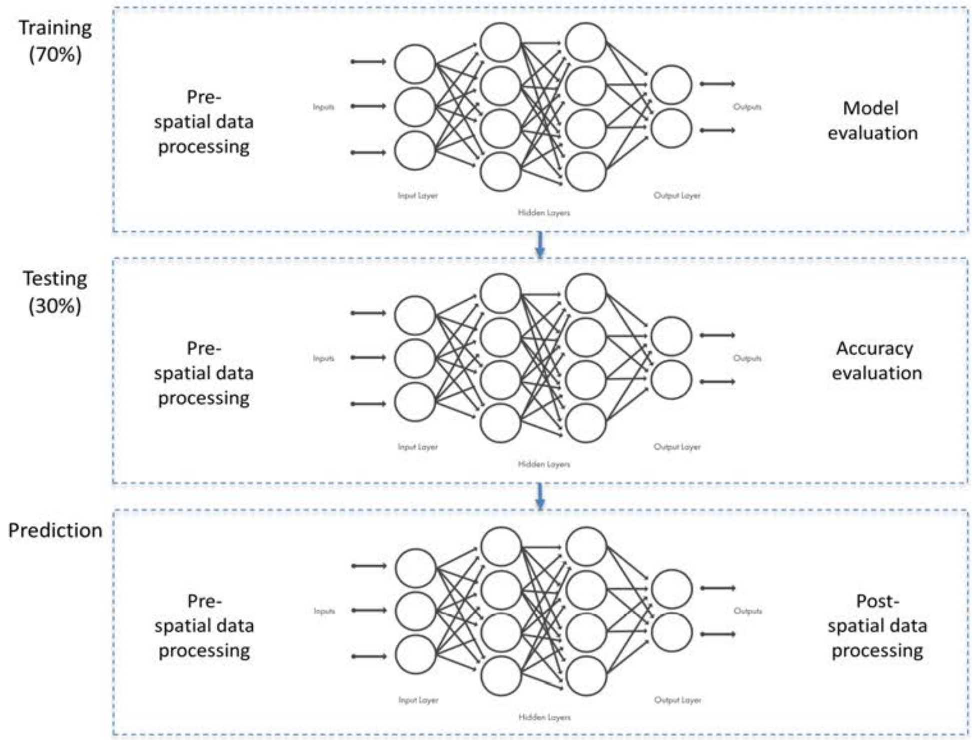
Value of Urban Model

- Scientific knowledge for urban planning

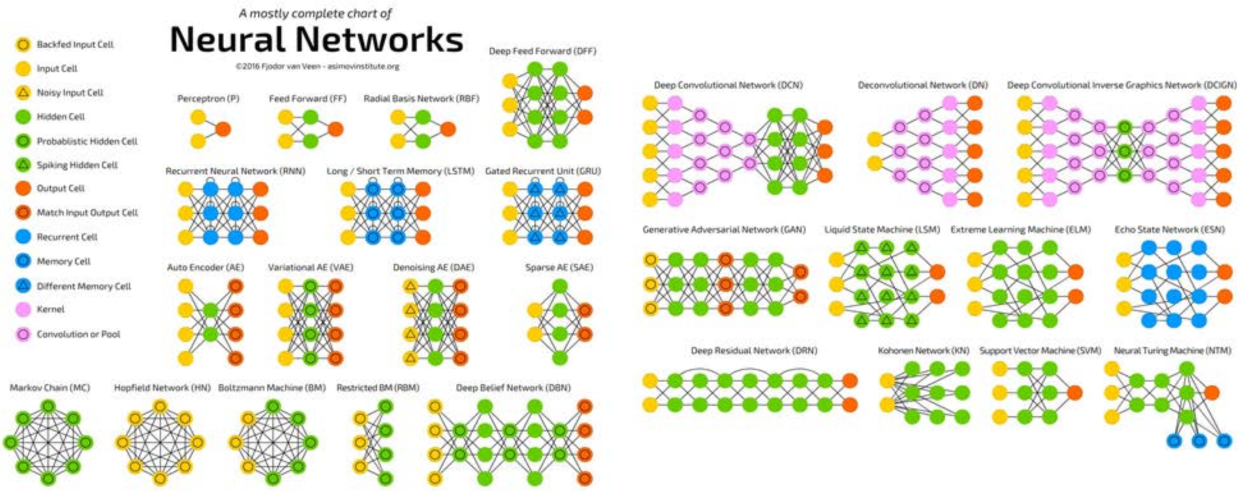


A Deep Learning Based Urban Simulation Model: Model Structure

Model Structure



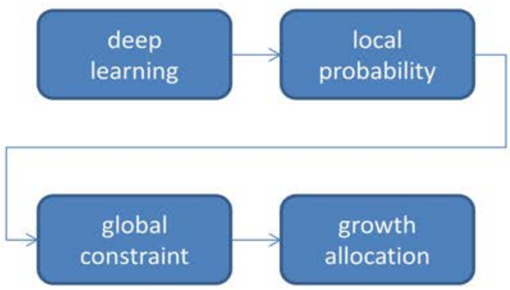
Which Network?



http://www.asimovinstitute.org/neural-network-zoo/

Model Run

- Dynamic growth
  - Iterative implementation of "deep learning-probability calculation-constraint application-growth allocation"
- Multi level structure
  - Micro level probability by endogenous model
  - Global level constraint by exogenous model



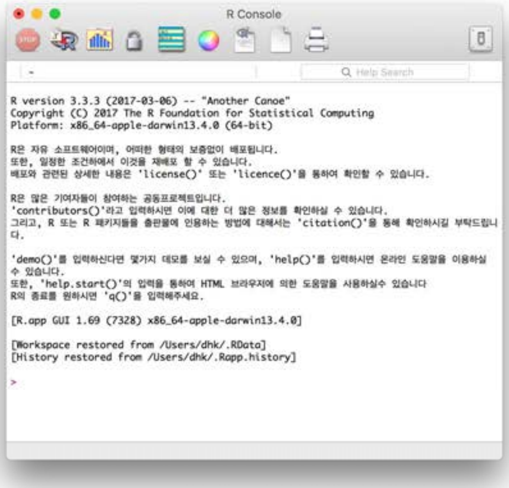
A Deep Learning Based Urban Simulation Model: Technological Framework

Tensorflow

- Open source software of deep learning and artificial intellegence
- Developed by Google Brain Team and firstly released in 2015
- https://www.tensorflow.org

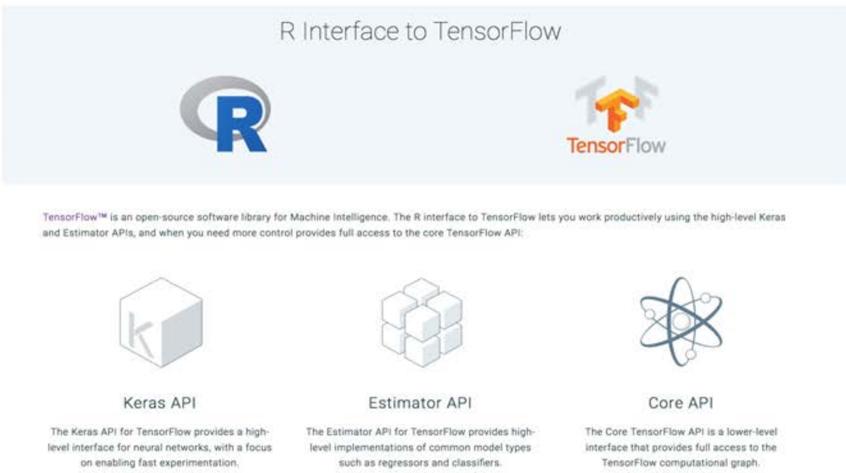
R

- One of the most popular open source statistical software
- Firstly developed by Ross Ihaka and Robert Gentleman
- http://www.r-project.org



Integration and Model Development

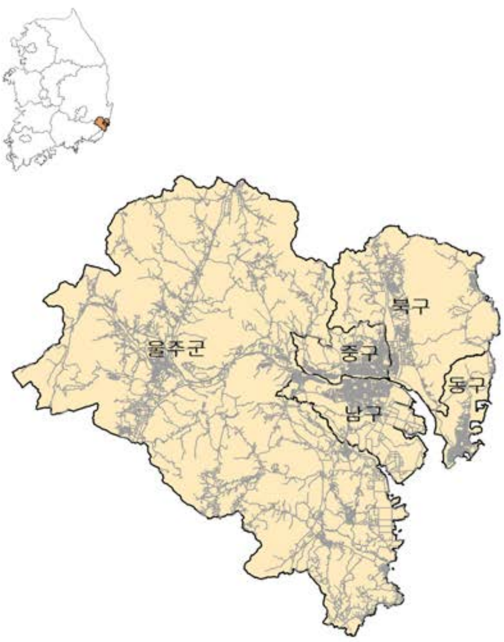
- Use and import of TensorFlow libraries in R
  - TensorFlow
  - R



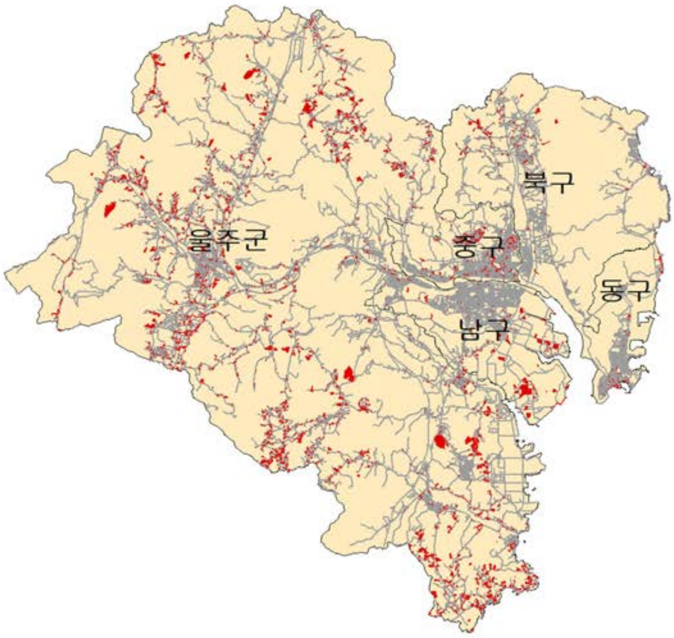
Experimental Case Study

Study Area

- Ulsan Metropolitan City
  - The largest industrial city and the richest city in Korea (GRDP per capita o $65,000 in 2017)
  - 1.2 million people
  - Lack of available land in the city area
  - Sprawling development in urban fringe areas and open spaces



New Urban Development

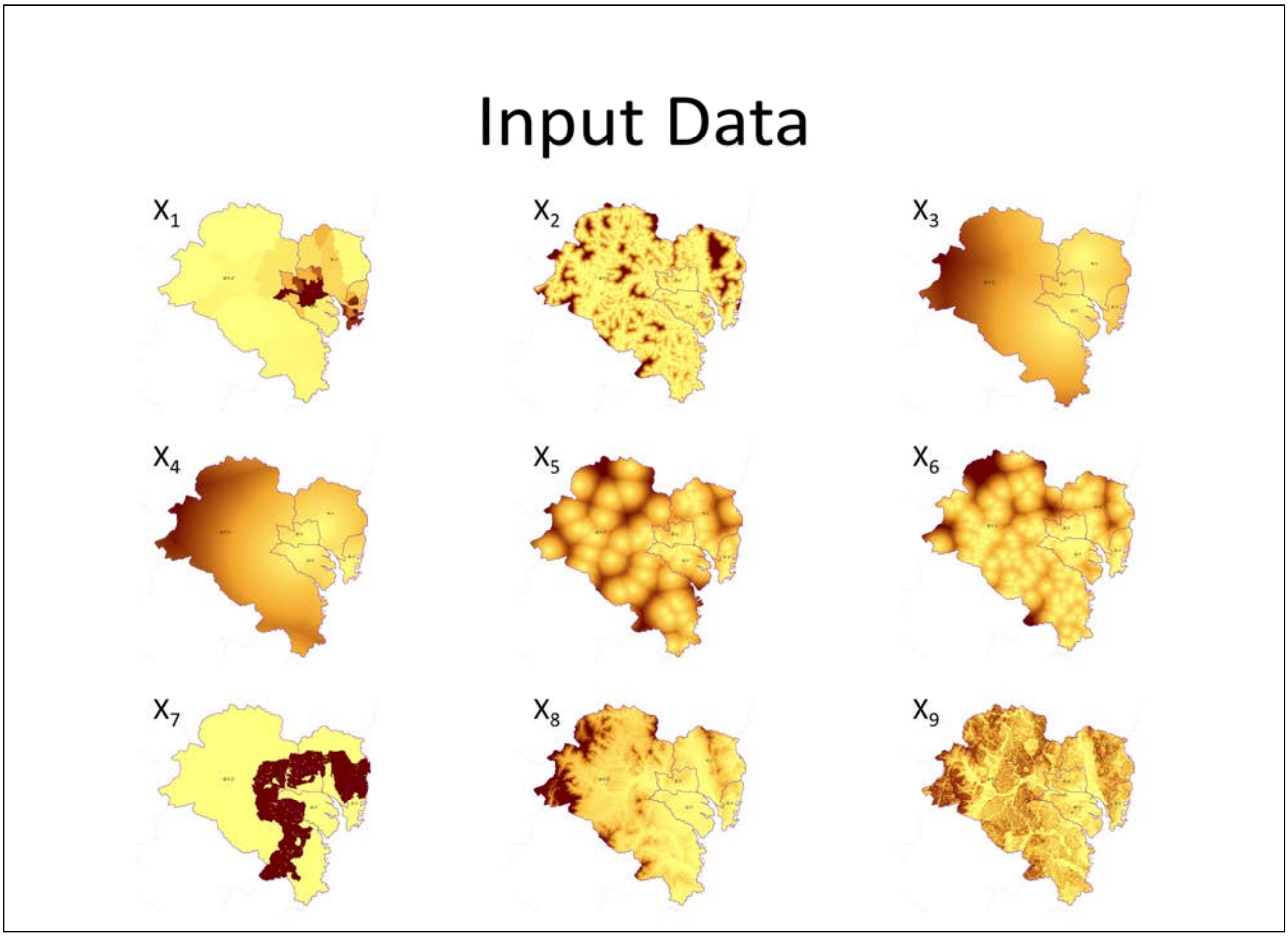


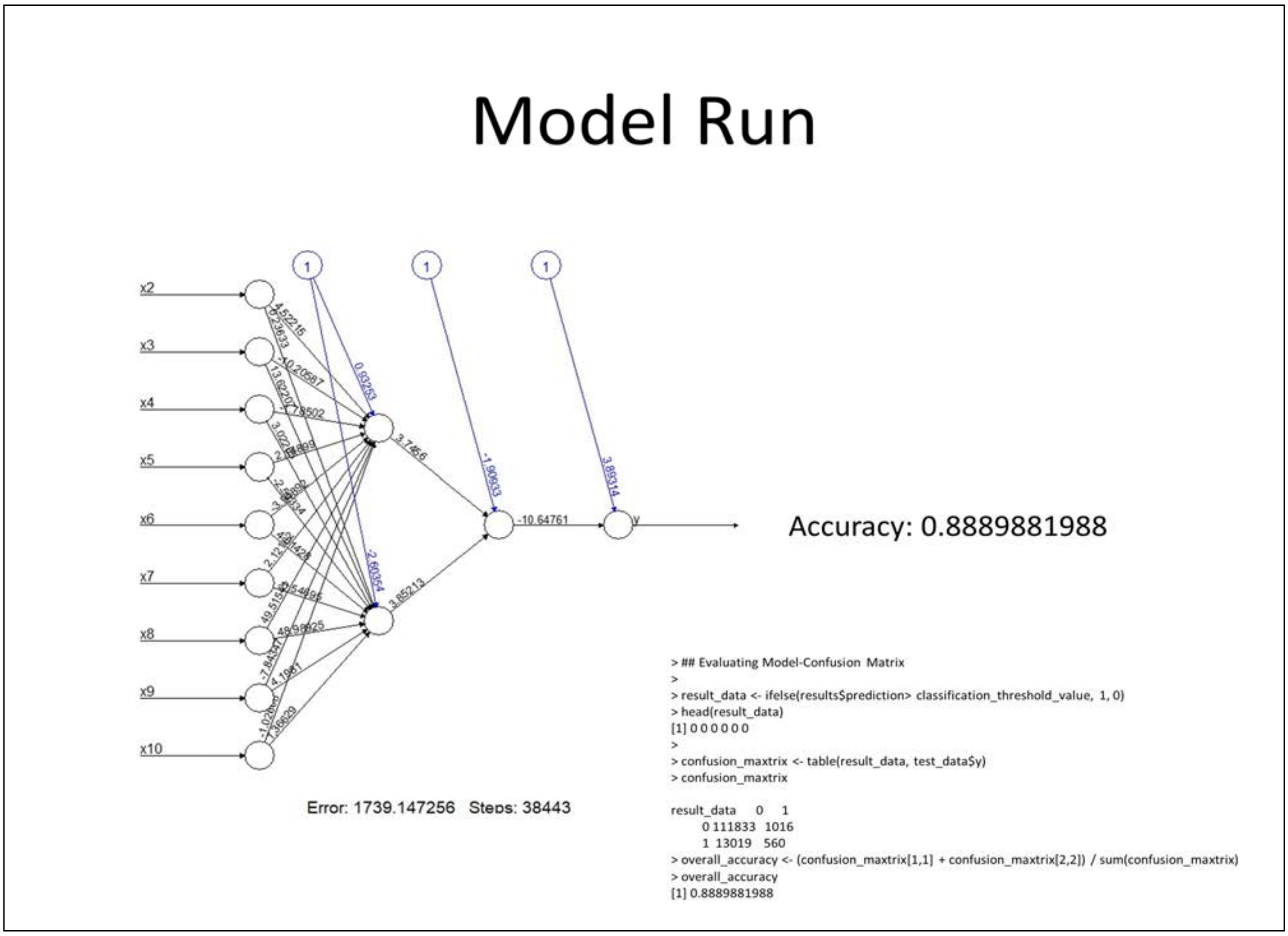
- Planning permission between 2010-2016
- About 5,000 individual cases
- Took place un urban fringe area

Input Data

- Initial variables were chosen based on literature review (subject to further expansion)
- Maps and statistical data of 2015 onwards
- Tessellated into 50m*50m grid cells

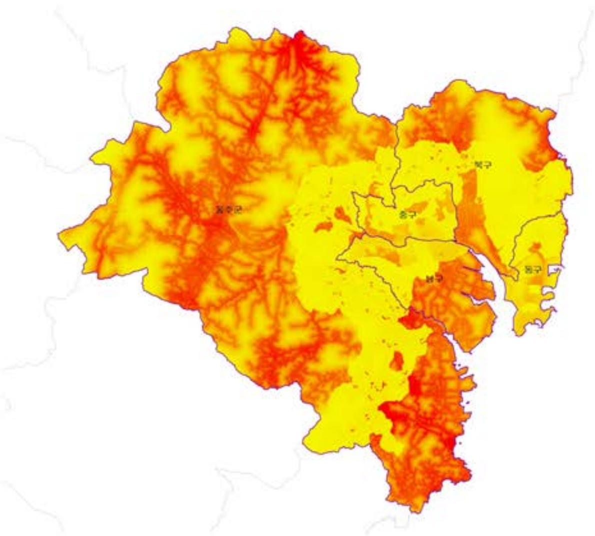
Variable	Description	Type
Dependent		
Y	0 – non urban, 1-urban	Dichotomous
Independent		
X_1	Population density (block, person/ha)	Continuous
X_2	Distance to the nearest road (m)	Continuous
X_3	Distance to the nearest railway station (m)	Continuous
X_4	Distance to CBD (m)	Continuous
X_5	Distance to the nearest primary school (m)	Continuous
X_6	Distance to the nearest retail shop (m)	Continuous
X_7	Development Control (Greenbelt)	Dichotomous
X_8	Elevation (m)	Continuous
X_9	Slope (degree)	Continuous


Input Data
X1
X2
X3
X4
X5
X6
X7
X8
X9


Model Run
x2
x3
x4
x5
x6
x7
x8
x9
x10
1
1
1
y
Accuracy: 0.8889881988
Error: 1739.147256 Steps: 38443
> ## Evaluating Model-Confusion Matrix
>
> result_data <- ifelse(results$prediction> classification_threshold_value, 1, 0)
> head(result_data)
[1] 0 0 0 0 0 0
>
> confusion_maxtrix <- table(result_data, test_data$y)
> confusion_maxtrix
result_data 0 1
0 111833 1016
1 13019 560
> overall_accuracy <- (confusion_maxtrix[1,1] + confusion_maxtrix[2,2]) / sum(confusion_maxtrix)
> overall_accuracy
[1] 0.8889881988

Probability of Urban Development

- Calculation of probability by using coefficients of the model
- Similar to the result of spatial logistic regression modelling
  - Static and stochastic at the moment



Inconclusion and Future Works

Implication

- Deep learning algorithms and AI technologies provide a new opportunity for modelling spatial and temporal dynamics of urban systems
- Thanks to open source libraries, application of deep learning algorithm and AI technology is possible without a large scale investment and development

Limitation

- In general, deep learning algorithms require a greater amount of data to improve model accuracy, which could result in “data hungriness” in model building.
- It is difficult to understand the relationship among variables and/or neurons, which could result in “black box” in decision making.
- There is no clear way to determine a best fit network structure, which could result in “ad-hoc model building”.

Future Works

- More trial and Errors
  - Data : different input data sets
  - Algorithm : different neural networks

- Integration with other modelling methods
  - Deep learning and agent based modelling
  - Macro or regional models for the external constraints

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Thank you!

Questions and comments.

dhkim@krihs.re.kr