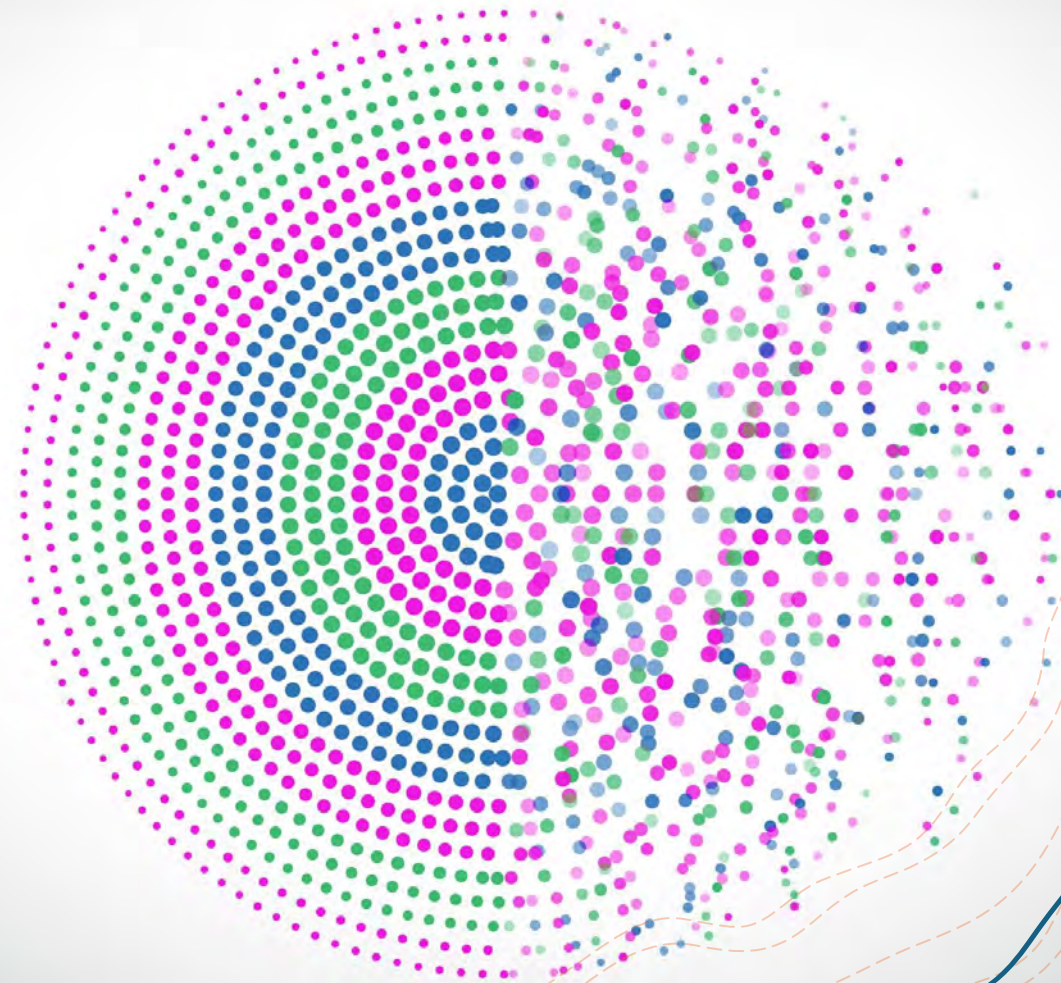




CALIFORNIA GEOGRAPHIC INFORMATION ASSOCIATION

# Integrating GIS and AI Technologies

Dr. Kostas Alexandridis, GISP  
Spatial Data Scientist

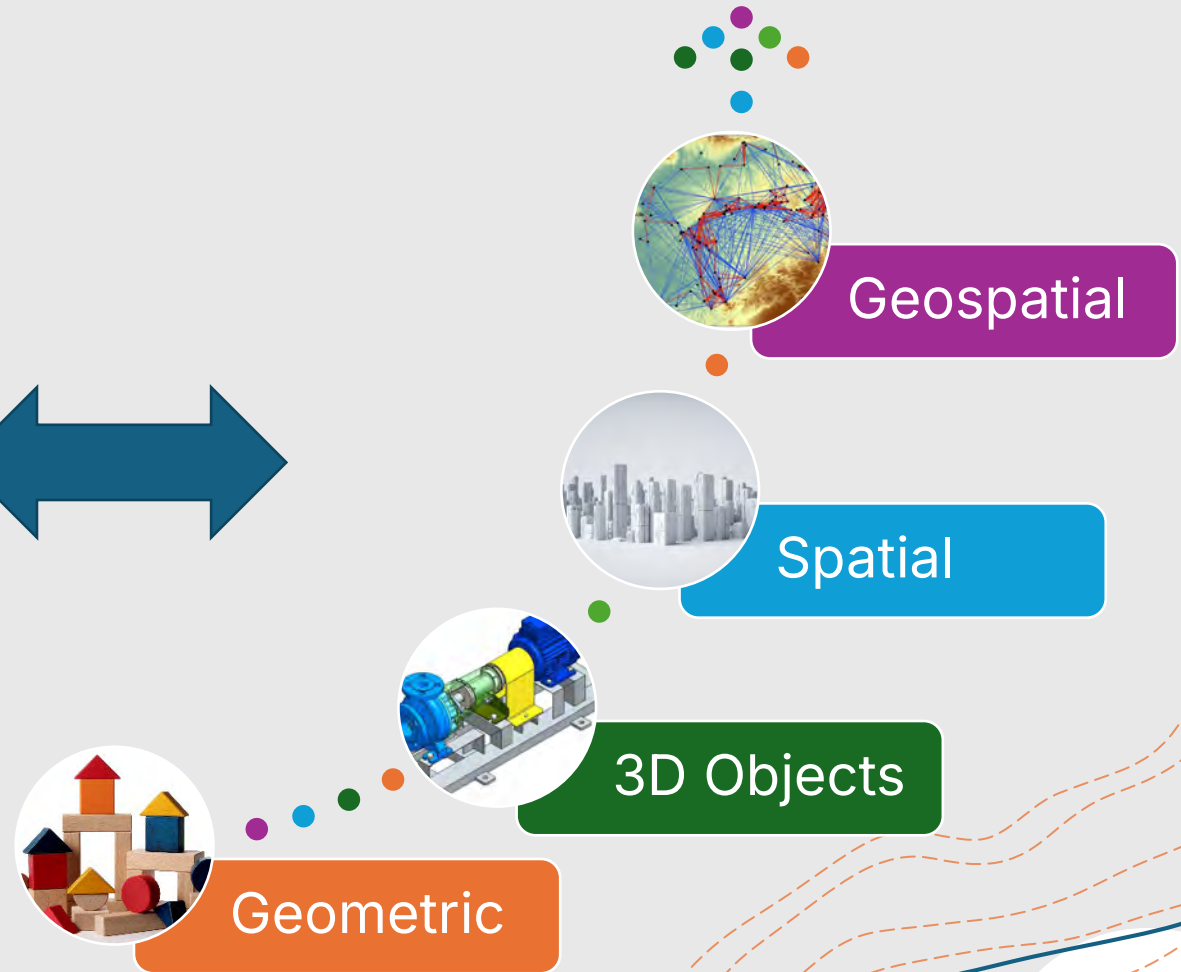


OC Public Works  
Geospatial Services



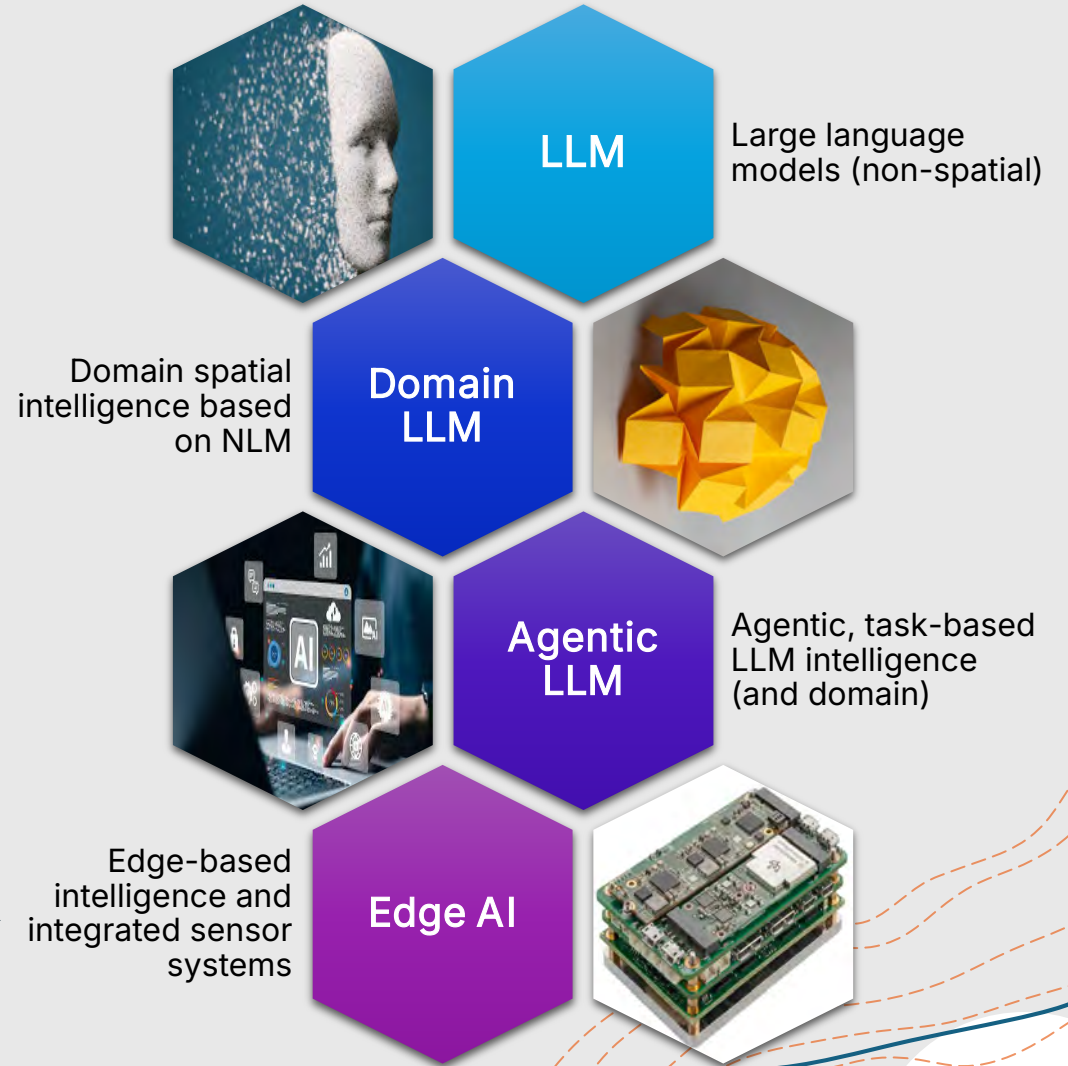
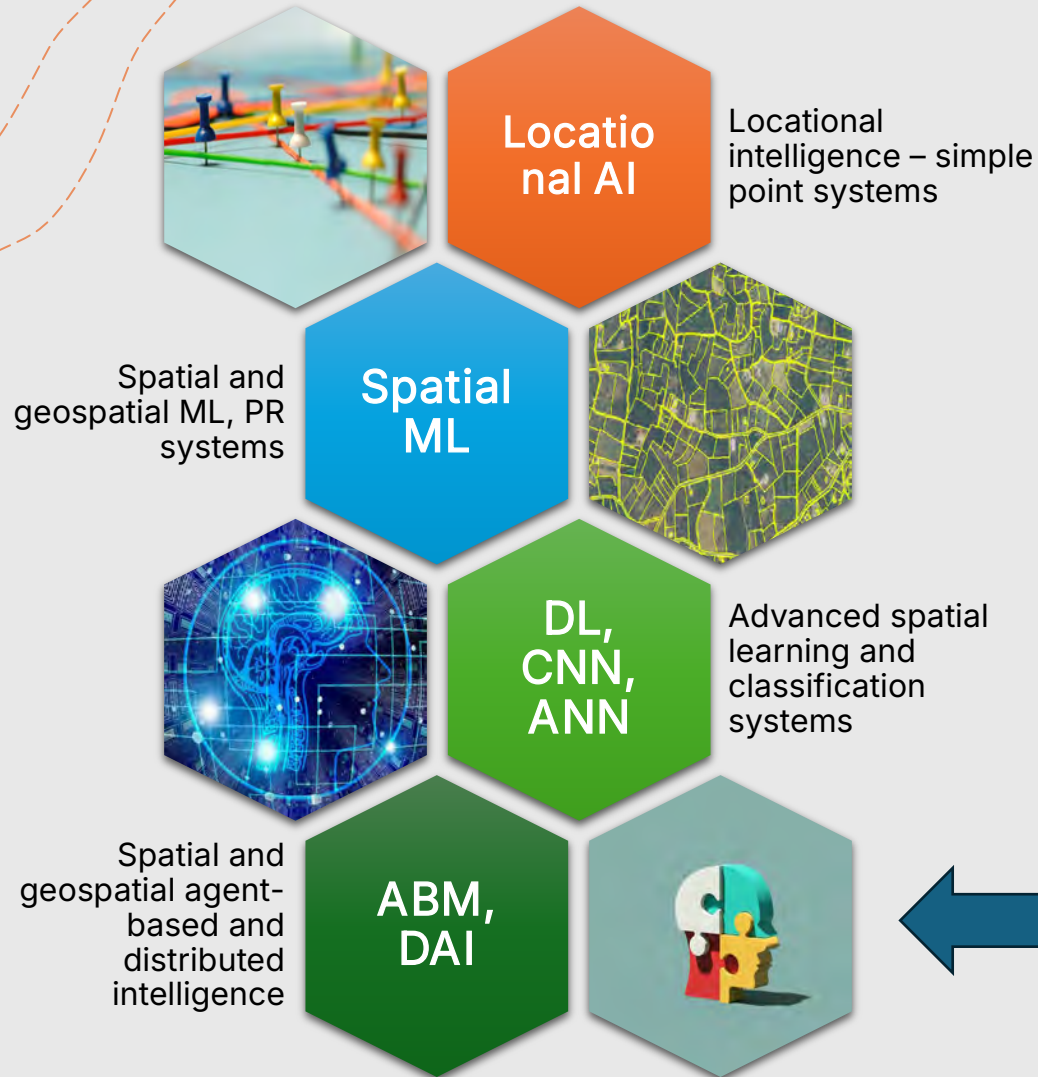


# Geospatial Composability

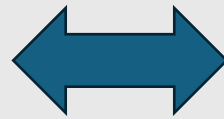


# Typology of GeoAI Methods

Big-Data-Driven



Language-Driven



# Methodology in Perspective

## Artificial Intelligence (AI)

Engineering of intelligent machines and programs



## Machine Learning (ML)

Ability to learn without being explicitly programmed



## Deep Learning (DL)

Algorithmic sets to model high-level of abstraction



# Data Challenges



TOO MUCH DATA



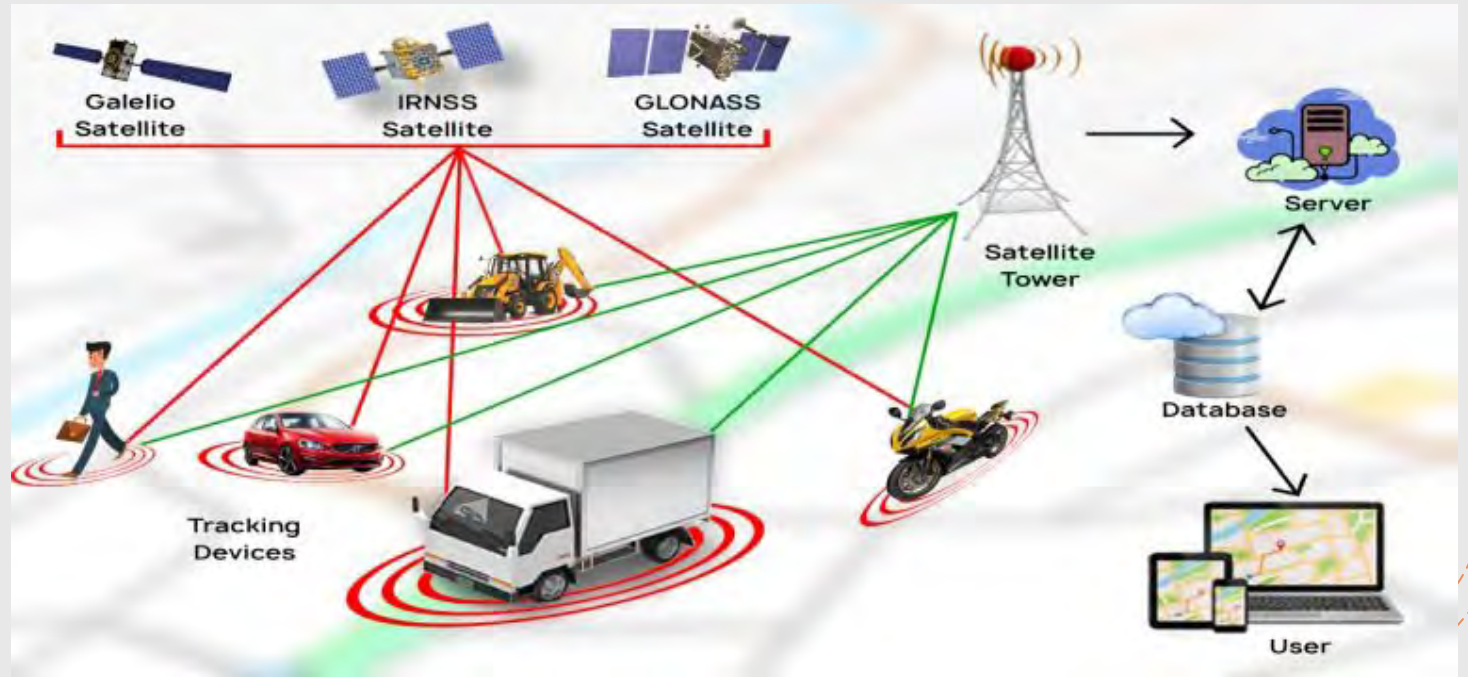
DATA SILOS



SINGLE SOURCE OF DATA

# Multi-Sensor Systems

- + Global Navigation Satellite System (GNSS)
- + Global Positioning System (GPS)
- + Uses satellites to Position on the Earth
- + Time and Orbit to Calculate Positioning
- + Data Use Cases:
  - + Precise Positioning (Dams, Post-Earthquake)
  - + Navigation Systems (your phone)

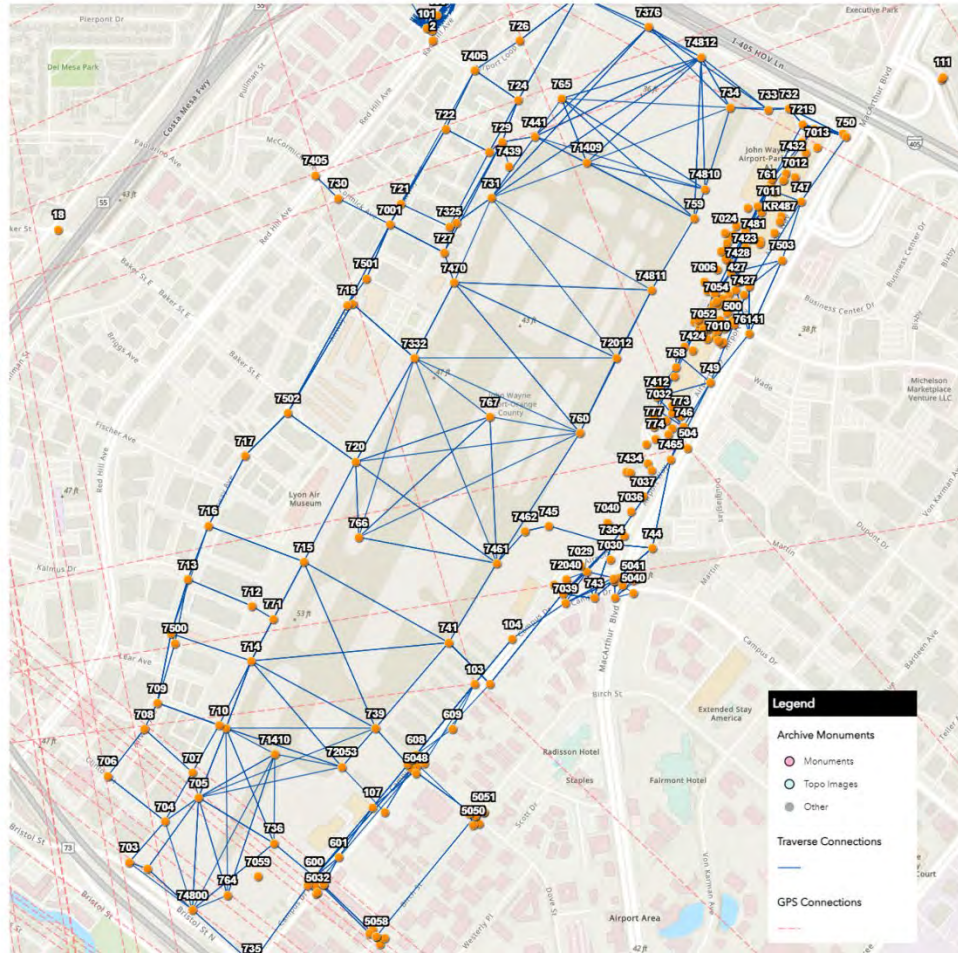


# Example: JWA Tied Geodetic Control

### Monument Examples



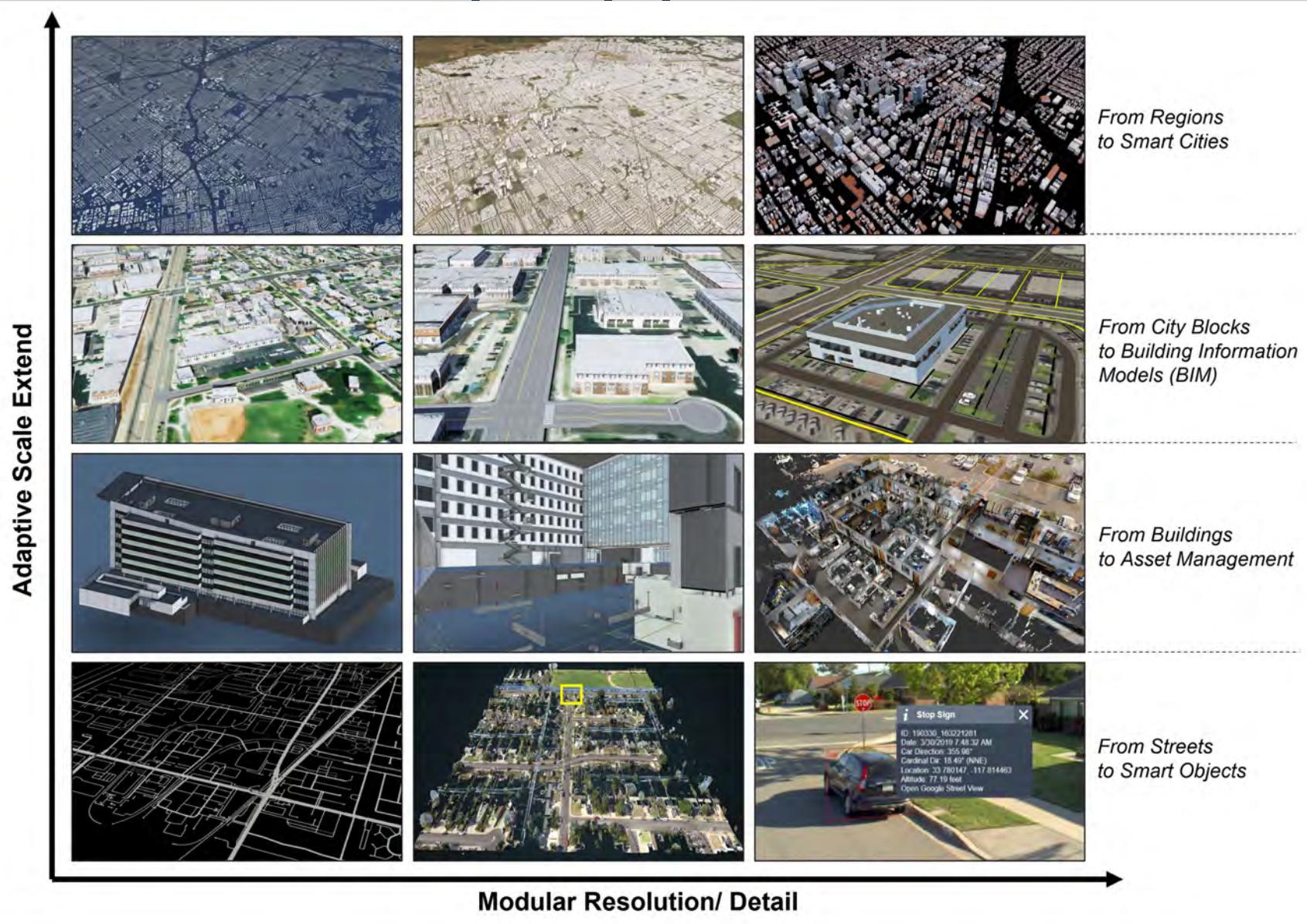
### JWA Monuments and Geodetic Control Network



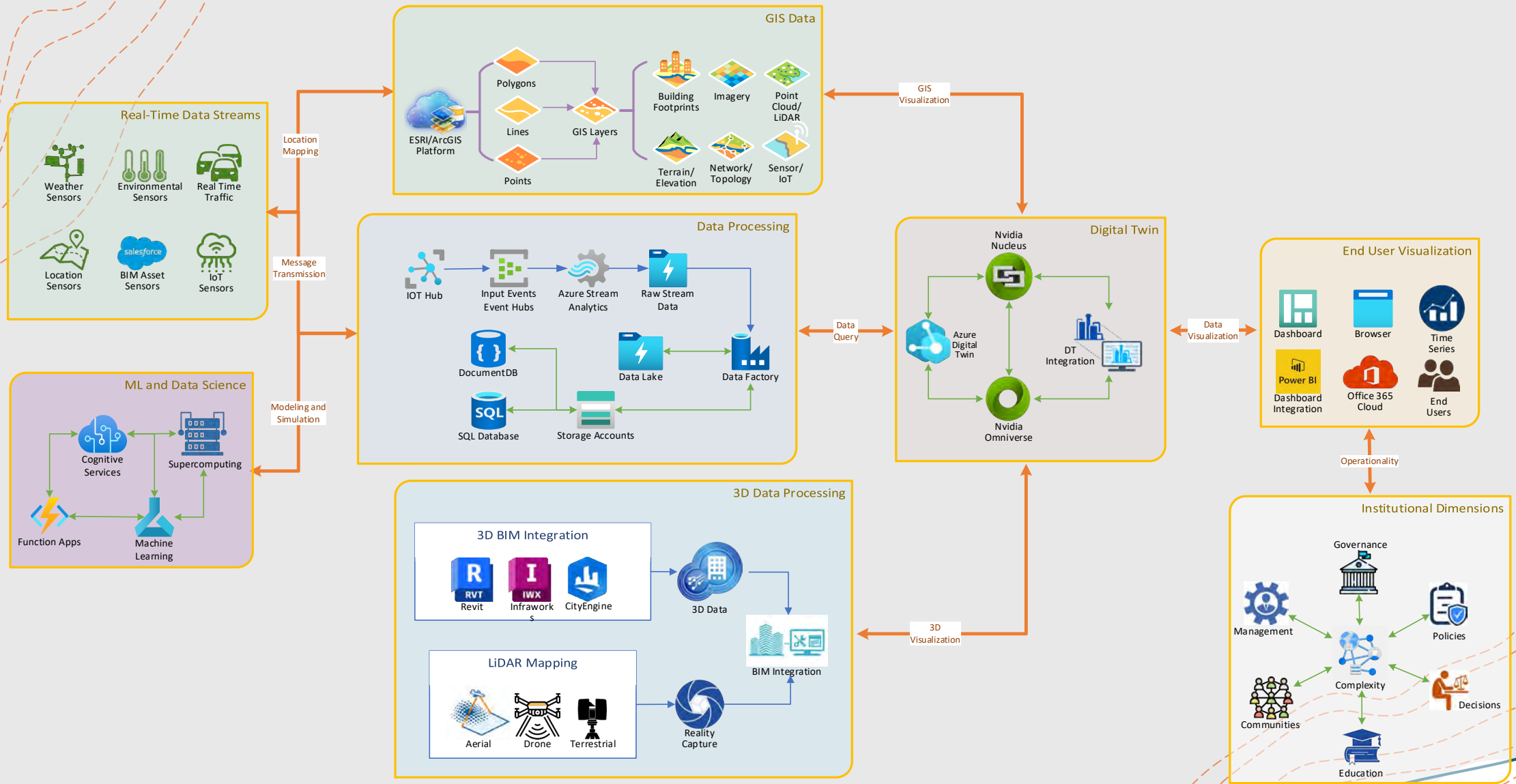
### Orange County GPS Real-Time Network



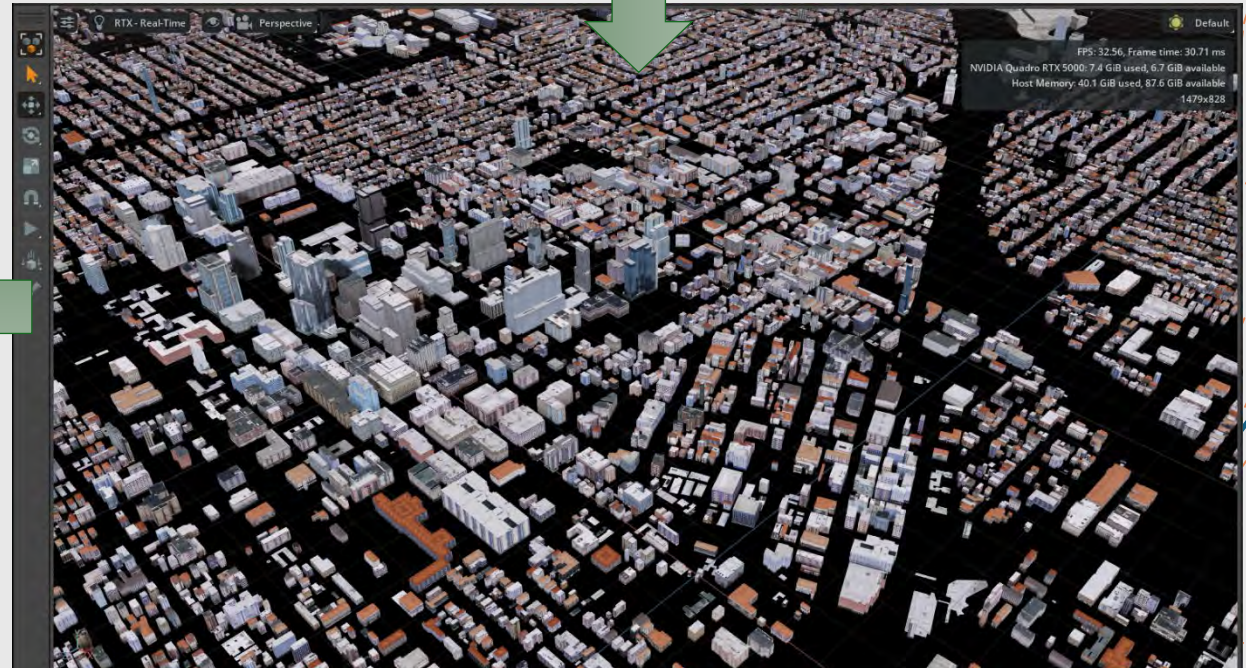
# Cross-Scalability Approach



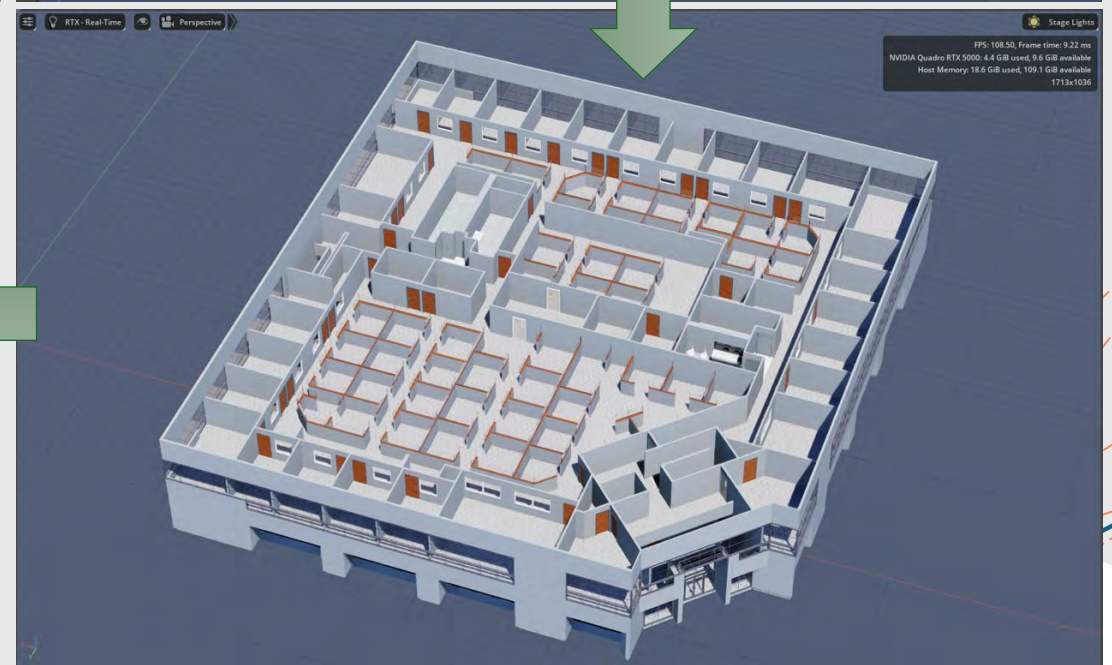
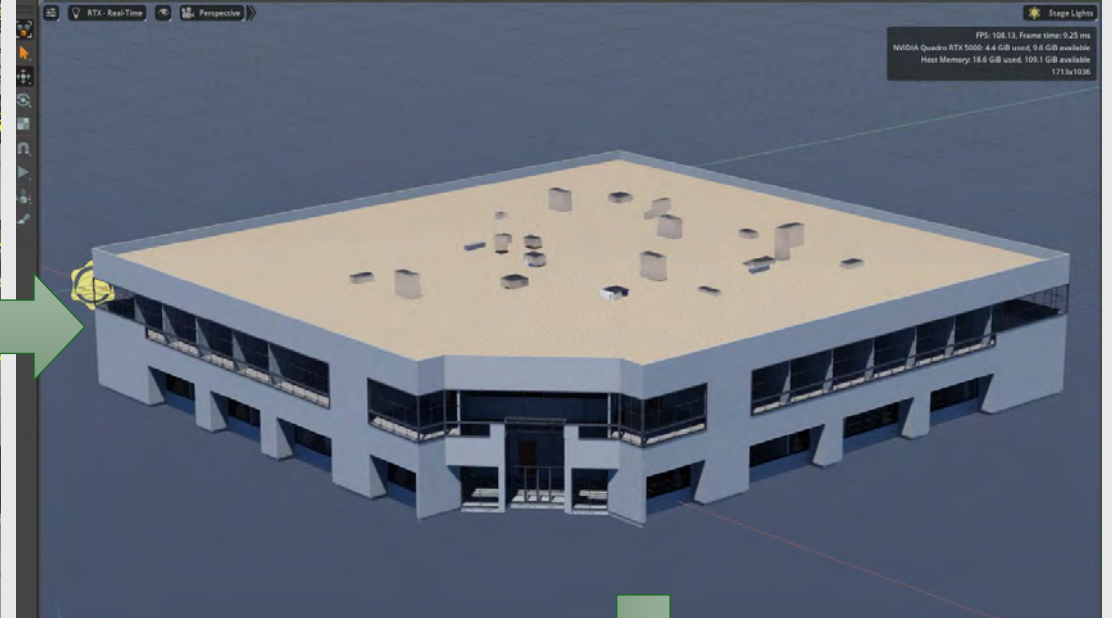
# Example Framework Overview

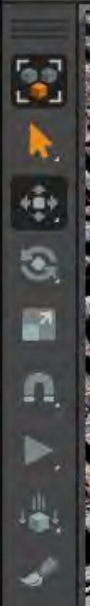


# Scalability, Robustness and Interoperability: From Cities to Buildings



# Scalability, Robustness and Interoperability: From Cities to Buildings





Default

FPS: 32.56, Frame time: 30.71 ms  
NVIDIA Quadro RTX 5000: 7.4 GiB used, 6.7 GiB available  
Host Memory: 40.1 GiB used, 87.6 GiB available  
1479x828



Stage Layer Render Settings

Search

Name	Type
way_1101791241_91b11f	Xform
way_1101791242_91b29	Xform
way_1101791243_91b34	Xform
way_1101791244_91b3f	Xform
way_1101791245_91b4a	Xform
way_1101791246_91b55	Xform
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way_1101793200_91b6b	Xform
way_1101793203_91b77	Xform
way_1101793204_91b87	Xform
way_1101807332_91b92	Xform
way_1101807336_91b9e	Xform
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way_1101816212_91bc1	Xform
way_1101816213_91bcf	Xform
way_1101816214_91bda	Xform
way_1101817289_91be5	Xform

Property

+ Add mesh

Prim Path /OCGlassell52/Terrain\_Imagery5/Terrain

Instanceable

▼ Transform

This prim has no transforms

+ Add Transforms

▼ Materials on selected models

Prim /OCGlassell52/Terrain\_Imagery5/Terrain

/OCGlassell52/Terrain\_Imager

Strength Weaker than Descendants

▼ Geometry

Bookmarks

Omniverse

9ea69715-b84f-49fc-af9a-79ae08fad7d0

Library

NVIDIA

assets

layers

OCGlassell52

OCGlassell52.usdc

Date Modified 11/18/

Created by kostas.alexandridis@oc

Modified by kostas.alexandridis@oc

File size

OCGlassell52.usdc

Date Modified 11/18/

Created by kostas.alexandridis@oc

Modified by kostas.alexandridis@oc

File size



Stage Layer Render Settings

Search

Name	Type
way_1101791241_91b1f1	Xform
way_1101791242_91b29	Xform
way_1101791243_91b34	Xform
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way_1101791245_91b4a	Xform
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way_1101791247_91b60	Xform
way_1101793200_91b6b	Xform
way_1101793203_91b77	Xform
way_1101793204_91b87	Xform
way_1101807332_91b92	Xform
way_1101807336_91b9e	Xform
way_1101816210_91baa	Xform
way_1101816211_91bb5	Xform
way_1101816212_91bc1	Xform
way_1101816213_91bcf	Xform
way_1101816214_91bda	Xform
way_1101817289_91be5	Xform

Property

**+** Add mesh

Prim Path /OCglassell52/Terrain\_Imagery5/Terrair

Instanceable

**▼** Transform

This prim has no transforms

**+** Add Transforms

**▼** Materials on selected models

Prim /OCglassell52/Terrain\_Imagery!

/OCglassell52/Terrain\_Imager

Strength Weaker than Descendants **▼**

**▼** Geometry

Bookmarks

Omniverse

9ea69715-b84f-49fc-af9a-79ae08fad7d0

Library

NVIDIA

assets layers OCglassell52

OCglassell52.usdc

Date Modified 11/18/

Created by kostas.alexandridis@ocj

Modified by kostas.alexandridis@ocj

File size

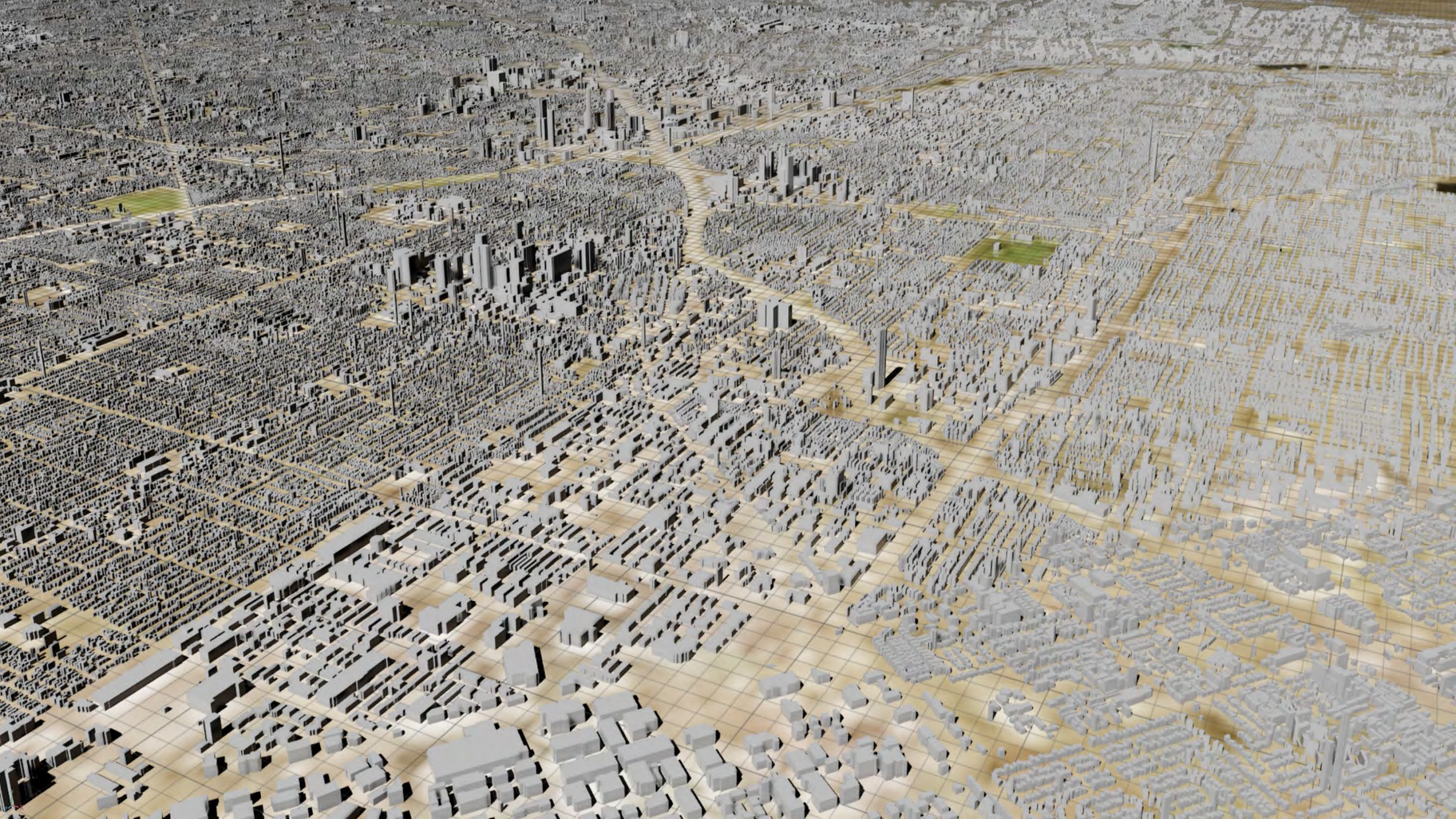
OCglassell52.usdc

Date Modified 11/18/

Created by kostas.alexandridis@ocj

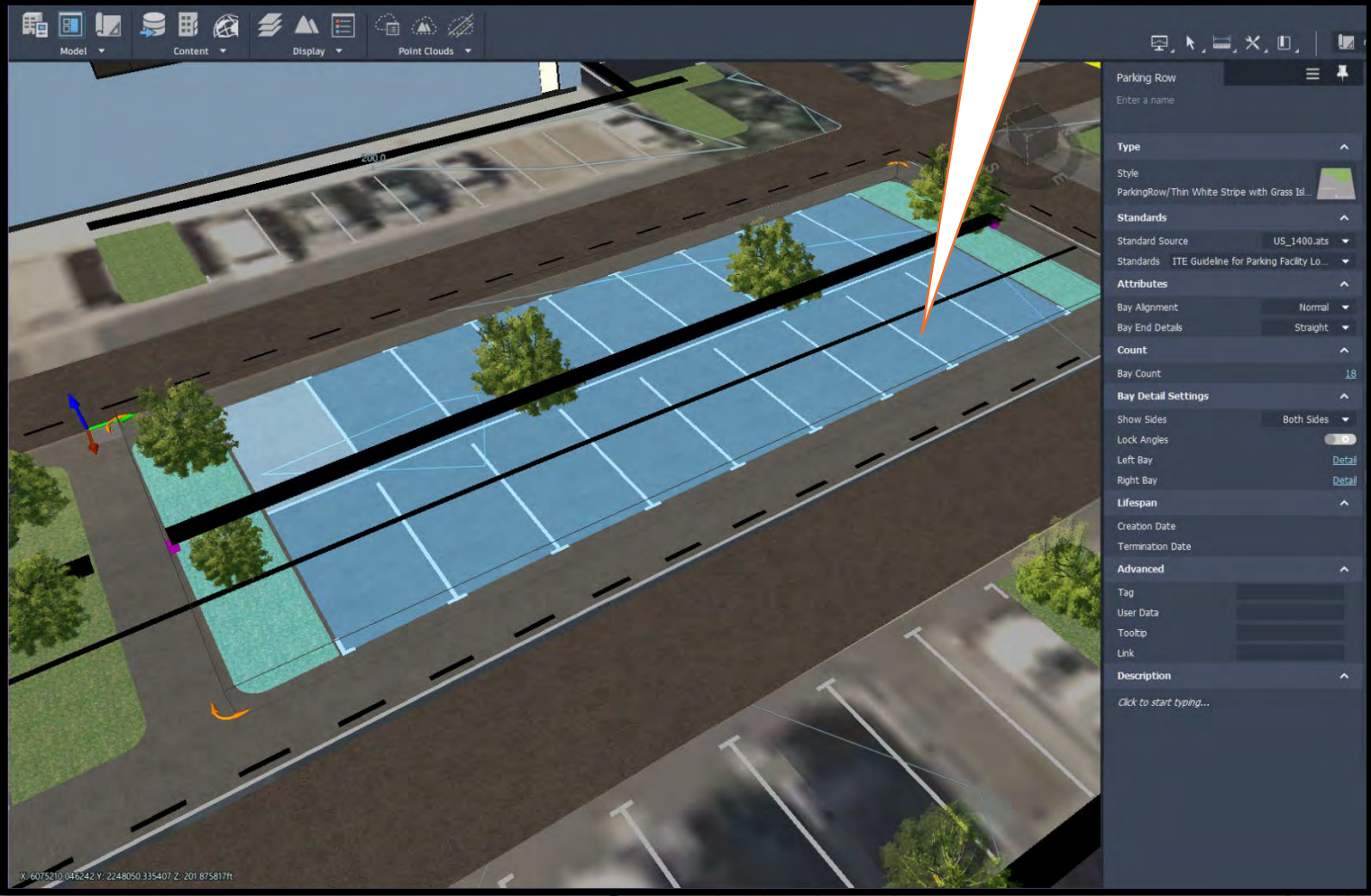
Modified by kostas.alexandridis@ocj

File size



# Digital 3D Object Generation from Reality Capture

Digital Object Recognition using GeoAI



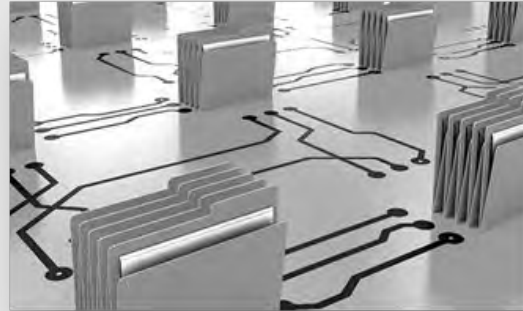
# Data-Centric Approach to AI Development



**DATA  
AGGREGATION**



**DATA  
VALIDATION**

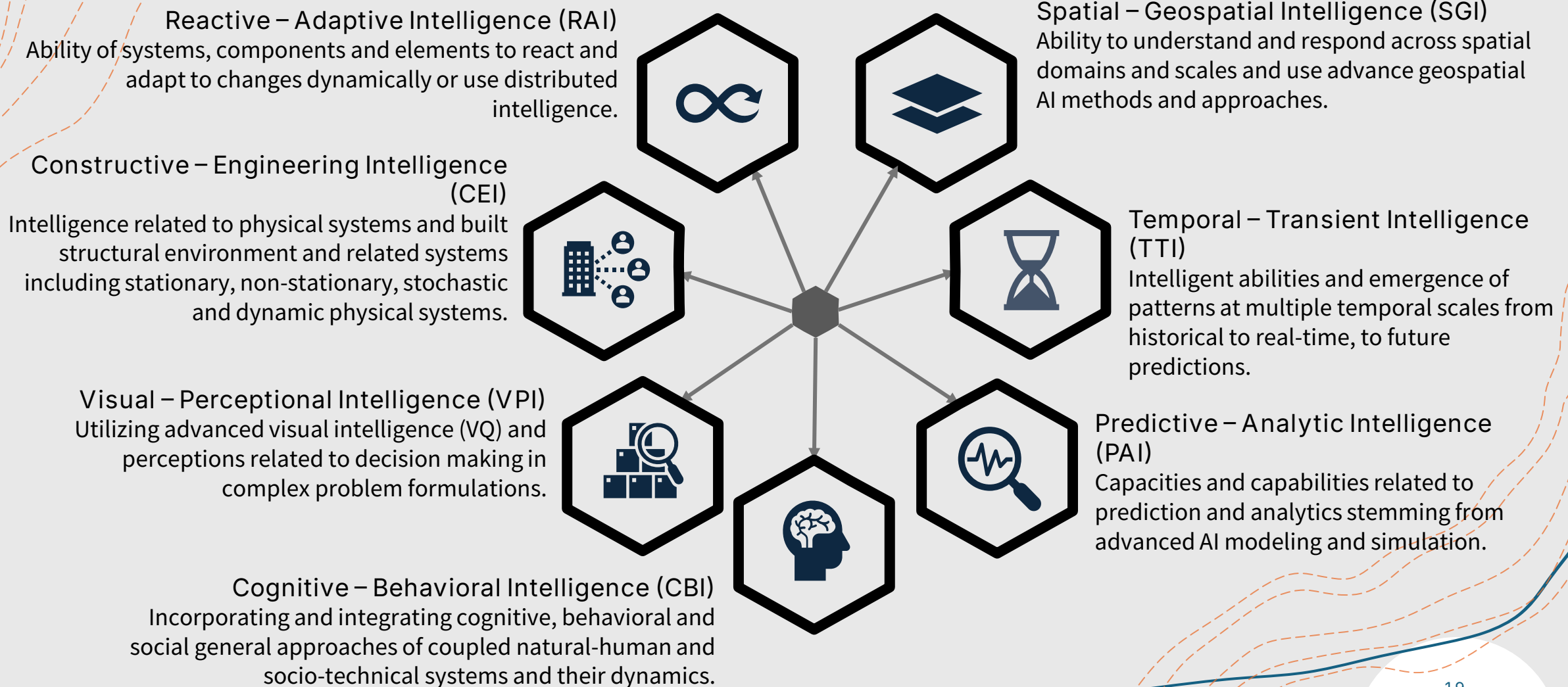


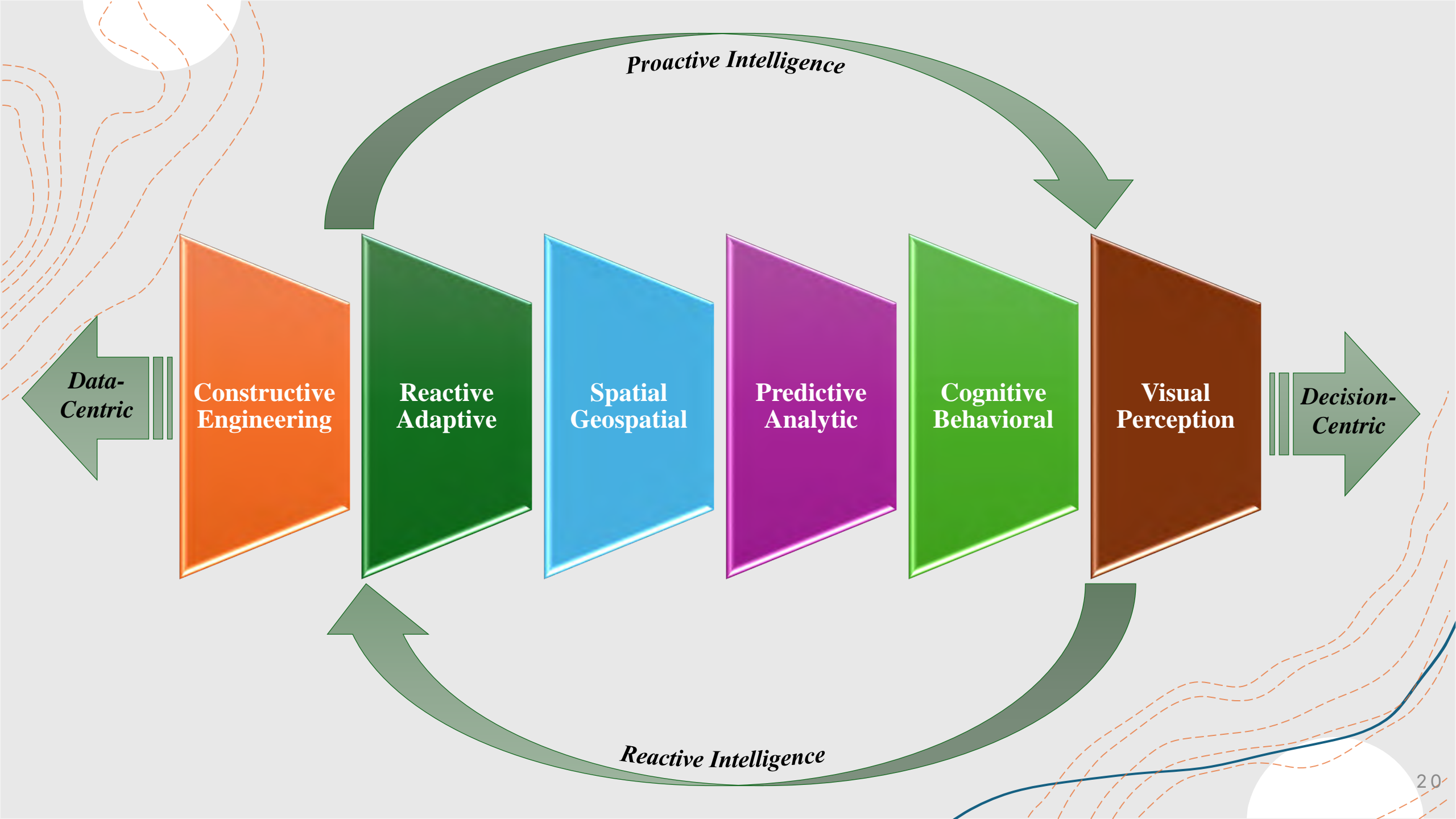
**DATA  
STANDARDIZATION**



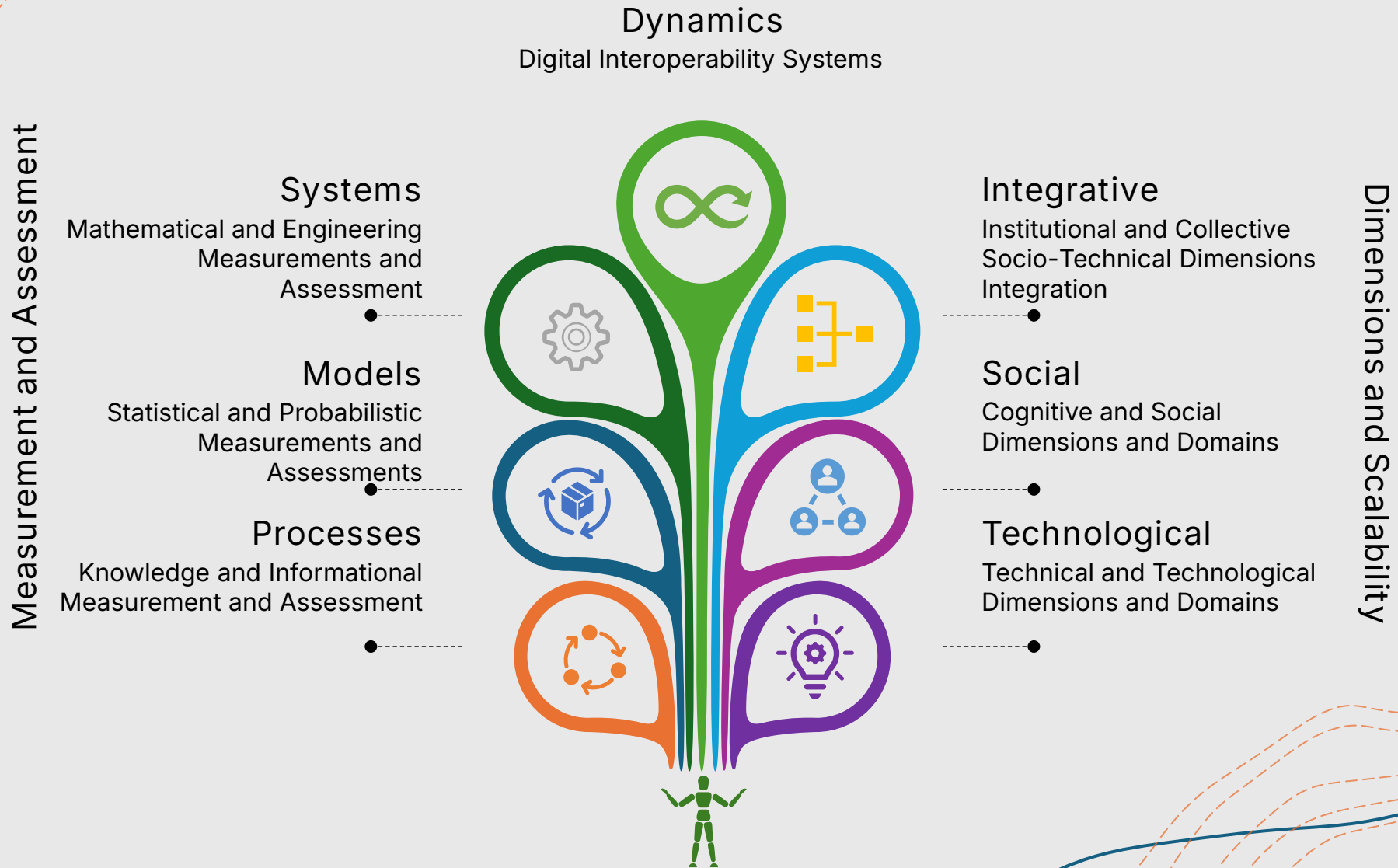
**DATA  
PIPELINES**

# Intelligent Digital Transformation Approach





# Digital transformations in complex integrated systems context



# GeoAI framework's points of interest

- + Full automation of workflows
- + Achieving near real-time results
- + Towards an augmented reality approach to high-resolution visualizations
- + Real-world production experience and implementation of big-data structures (terra-data workflows)
- + Successful partnering of government and public/community benefits with private/commercial sector (AI & cloud processing)

# GeoAI framework's points of interest

- + Intelligent management and operational processing of critical urban public infrastructure and resources.
- + Preparing and embracing digital transformation and digital innovation technologies in service of communities and citizens.
- + High-value, data-centric and scientific approach to County's geospatial service provisioning.
- + Reducing uncertainty and subjective interpretations for decision-making
- + Implementing knowledge economies of scale

# GeoAI framework's points of interest

- + Utilizing highly-valued skills and competencies
- + Reducing labor costs whilst producing added-value services for the citizens and the community at large (public benefits)
- + Adopting innovation, creative thinking and cutting-edge technologies at the core of the Orange County's geospatial services public service
- + Promoting learning, teaching and outreach for training the next generation of employees and collaborators

# Technology trends

- + More likely than not **real-time, real-world, and reality-like-visualization** are dominating the future developments.
- + **Cross-disciplinary**, ability to cross professional boundaries and skills are key.
- + What can you do to **stand out** of the crowd? How can your skills and training set you apart from others?
- + Adopt a **continuous learning** and skill-development attitude.
- + Learn to work and thrive in **group environments** and collective work settings.
- + **Embrace complexity** and cutting-edge technology. Do not settle with what you already know and feel comfortable with.
- + **Challenge yourselves** and others around you. Think outside the box.

# Big Data and Open Science

- + Technological push towards **big data**.
- + Need for integrated solutions tackling pressing issues with **real impact** for our societies.
- + Movement towards **open-data, open-source, open-science**.
  - + **Fusion and synergism** between science proliferation and technology.
  - + **Managing the complex** – embracing complexity, understanding

# Stage 1: Crop original photosphere (8000 × 8000) to a functional area (1000 × 8000)

Width: 8000 pixels

Hight: 4000 pixels



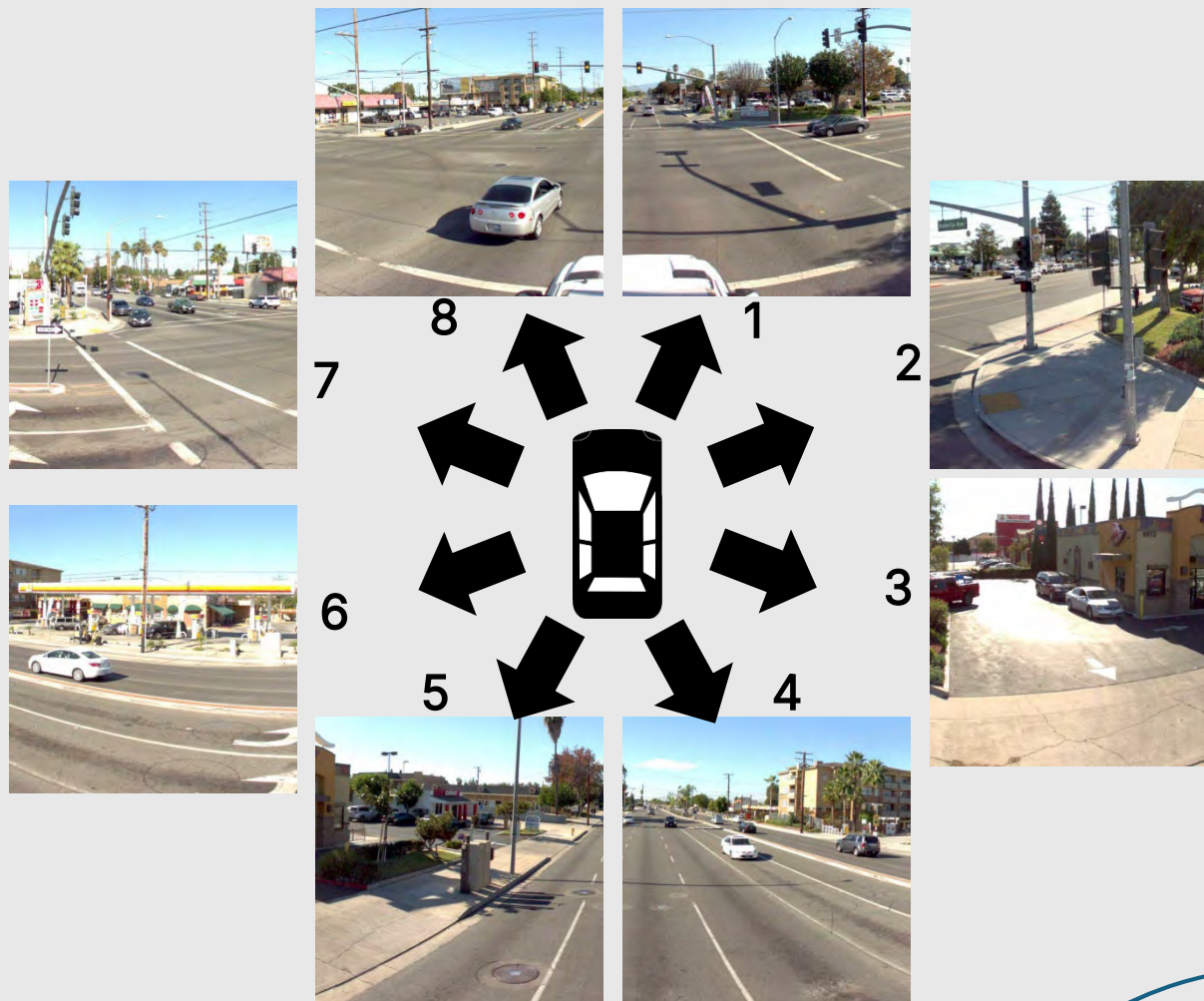
Cropped: 1000 pixels

# Photosphere 360° image segmentation





**Stage 2:**  
Separate  
functional area  
into 8 cardinal  
directions  
(1000×1000)  
pixels each

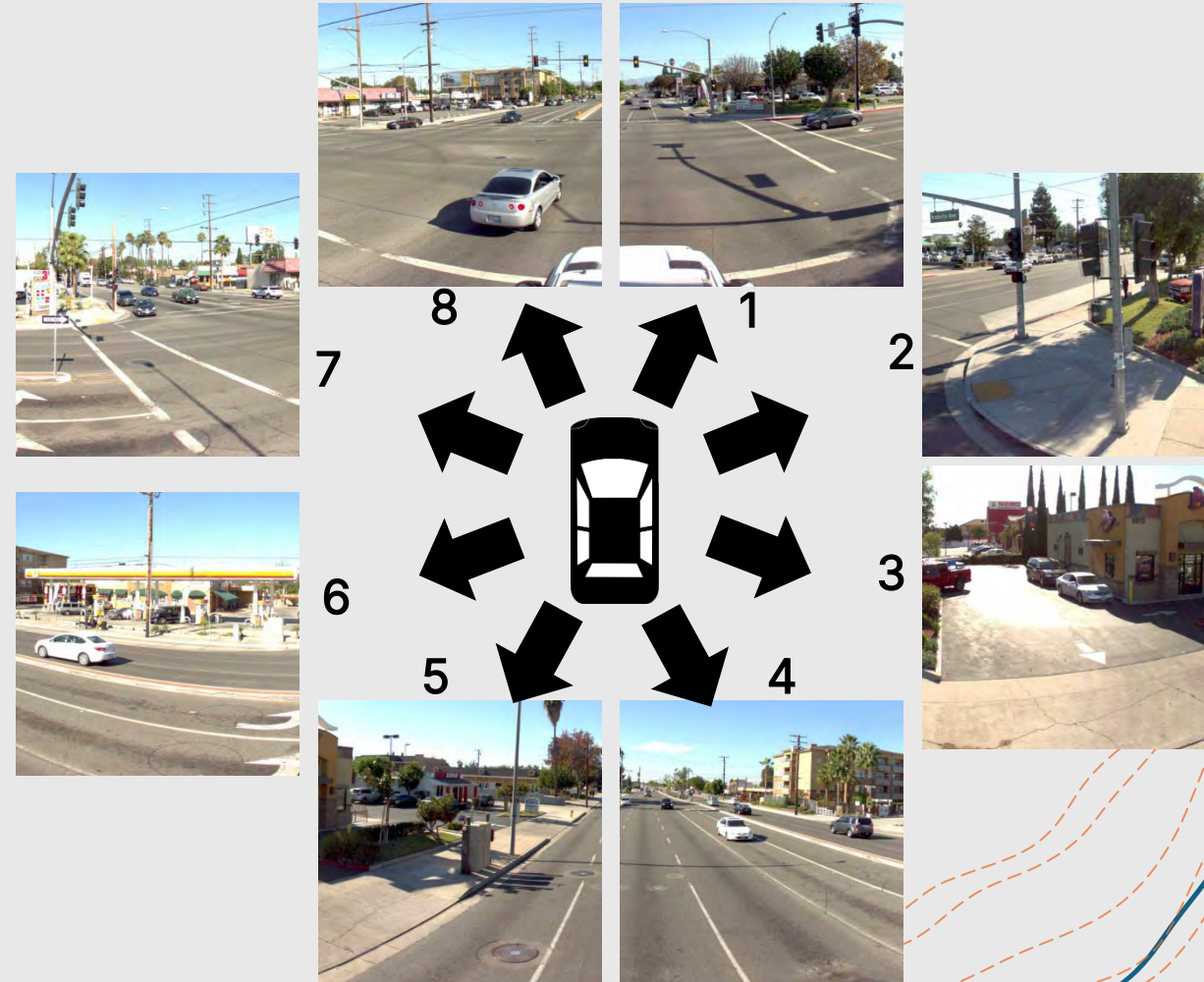


**Stage 3:**  
Perform  
analysis of  
each cardinal  
images using  
Azure  
Cognitive  
Services  
Computer  
Vision API

# Directional angle detection

## Notes:

- If we know driving directions, then we know cardinal direction of images. E.g., if vehicle travels N:
  - Dir 1 = NNE ( $0^\circ - 45^\circ$ )
  - Dir 2 = ENE ( $45^\circ - 90^\circ$ )
  - Dir 3 = ESE ( $90^\circ - 135^\circ$ )
  - Dir 4 = SSE ( $135^\circ - 180^\circ$ )
  - Dir 5 = SSW ( $180^\circ - 225^\circ$ )
  - Dir 6 = WSW ( $225^\circ - 270^\circ$ )
  - Dir 7 = WNW ( $270^\circ - 315^\circ$ )
  - Dir 8 = NNW ( $315^\circ - 360^\circ$ )
- Each pixel is  $0.045^\circ$  ( $360^\circ/8000$  pixels)
- Cropping original photosphere images reduces noise and helps pinpoint objects more accurately.
- Splitting image into cardinal directions helps object and pattern recognition.



# Directional position corrections

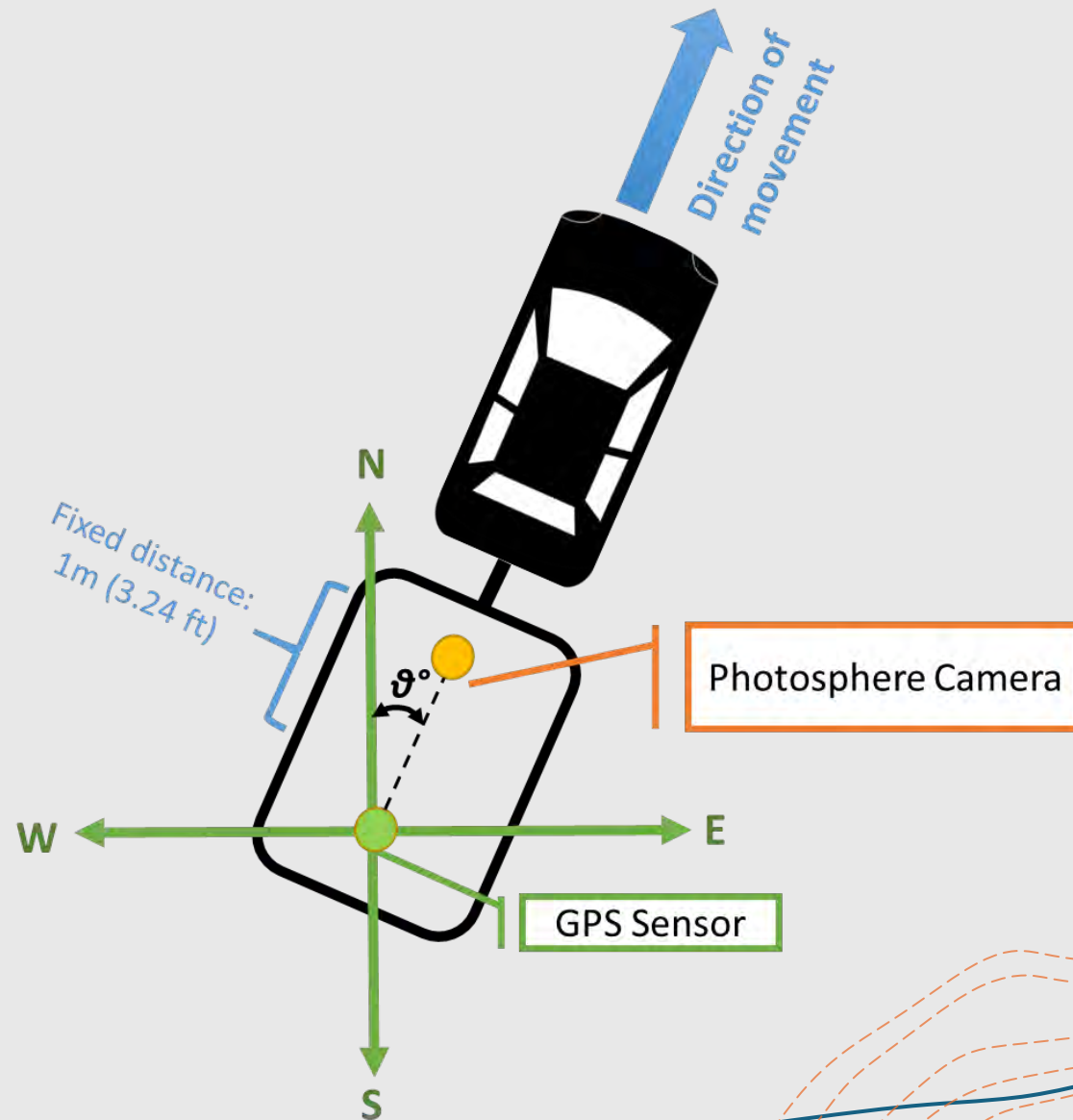
**Direction ( $\theta$ ):**

**inverse tangent function expressed in degrees:**

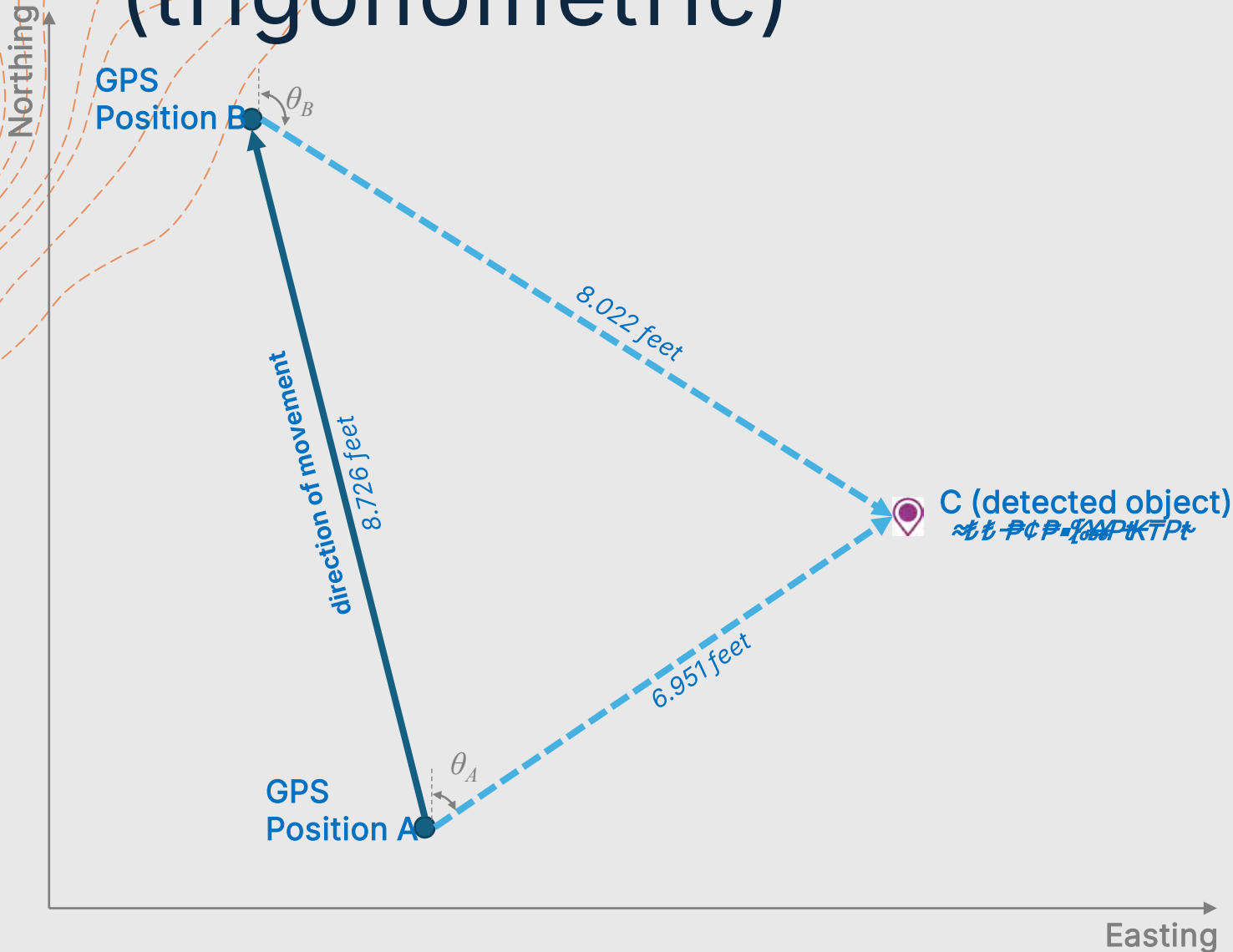
$$\theta = \text{degrees}(\arctan(\text{Easting}, \text{Northing})) - 180^\circ$$

if  $\theta < 0$ :

$$\theta' = (\theta + 360^\circ) \% 360$$



# Detected object position algorithm (trigonometric)



From directions to slopes:

$$\mu_A = \tan(\theta_A) = \frac{y_A - y_C}{x_A - x_C}$$

$$\mu_B = \tan(\theta_B) = \frac{y_B - y_C}{x_B - x_C}$$

Calculated object coordinates :

$$x_C = \frac{y_B - y_A + \mu_A x_A - \mu_B x_B}{\mu_A - \mu_B}$$

$$y_C = y_A - \mu_A (x_A - x_C)$$

# ML Vision Detection Methods

+ML methods:

Google Cloud  
Vision

Azure Cognitive  
Services  
Computer Vision

Image  
Annotator  
Client:

- label detection
- object localization (multiple)

Analyze  
Visual  
Features:

- Categories
- Tags
- Description
- Image Type
- Color
- Objects (multiple)



# AI can be trained to detect any visible object

- + As ML and AI tools improve, the number of features and the accuracy with which we can detect them will improve
- + Can expand AI to look for cracks in pavement/potholes
- + Manholes, signs, other road assets
- + Real Time processing of 360 photos

# GeoAI: Deep Learning Convolutional ANN Model

+ Network Configuration

+ Network Topology

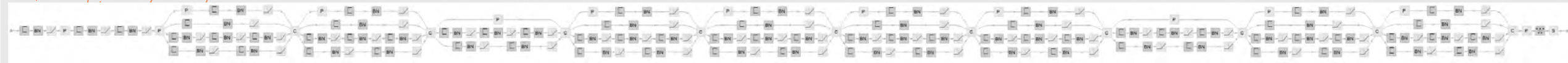
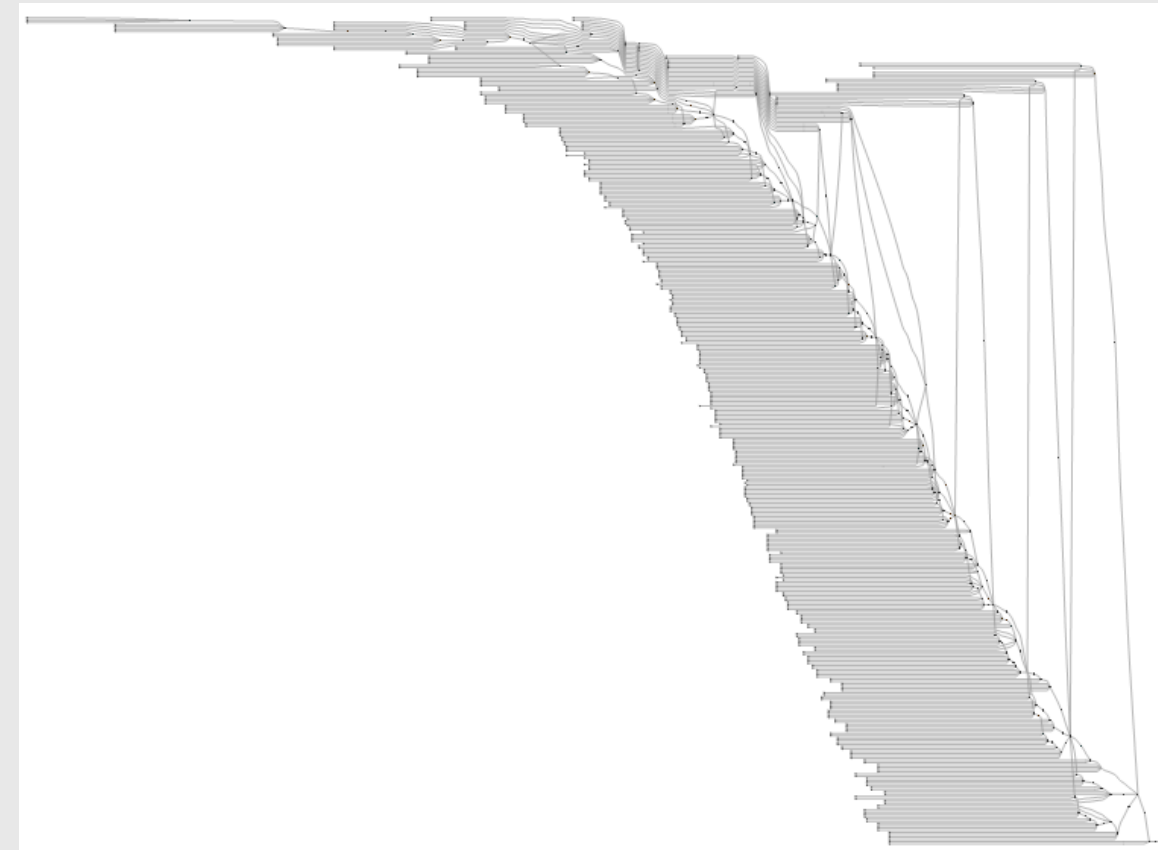



		image
	Input	array (size: 3 × 224 × 224)
conv_1	ConvolutionLayer	array (size: 64 × 112 × 112)
bn_1	BatchNormalizationLayer	array (size: 64 × 112 × 112)
relu_1	Ramp	array (size: 64 × 112 × 112)
pool_1	PoolingLayer	array (size: 64 × 55 × 55)
conv_2_red	ConvolutionLayer	array (size: 64 × 55 × 55)
bn_2_red	BatchNormalizationLayer	array (size: 64 × 55 × 55)
relu_2_red	Ramp	array (size: 64 × 55 × 55)
conv_2	ConvolutionLayer	array (size: 192 × 55 × 55)
bn_2	BatchNormalizationLayer	array (size: 192 × 55 × 55)
relu_2	Ramp	array (size: 192 × 55 × 55)
pool_2	PoolingLayer	array (size: 192 × 27 × 27)
3a	NetGraph (23 nodes)	array (size: 256 × 27 × 27)
3b	NetGraph (23 nodes)	array (size: 320 × 27 × 27)
3c	NetGraph (17 nodes)	array (size: 576 × 14 × 14)
4a	NetGraph (23 nodes)	array (size: 576 × 14 × 14)
4b	NetGraph (23 nodes)	array (size: 576 × 14 × 14)
4c	NetGraph (23 nodes)	array (size: 608 × 14 × 14)
4d	NetGraph (23 nodes)	array (size: 608 × 14 × 14)
4e	NetGraph (17 nodes)	array (size: 1056 × 7 × 7)
5a	NetGraph (23 nodes)	array (size: 1024 × 7 × 7)
5b	NetGraph (23 nodes)	array (size: 1024 × 7 × 7)
global_pool	PoolingLayer	array (size: 1024 × 1 × 1)
linear	LinearLayer	vector (size: 4315)
softmax	SoftmaxLayer	vector (size: 4315)
	Output	class



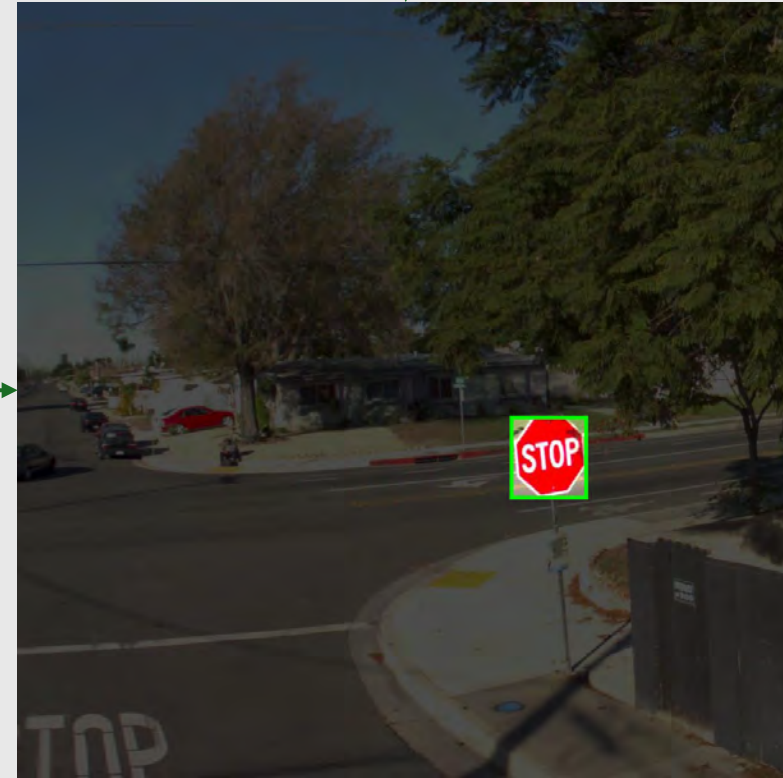
# Example: Stop Sign detections

Image	Concept	BoundingBox	Probability
	stop sign	Rectangle[ { 635.781, 362.607 }, { 732.331, 466.488 } ]	0.846811



*tagged and labeled*

Alternative  
display output  
configurations



*Focused with darkened background*

# Multiple object type detections




Image	Concept	BoundingBox	Probability
	stop sign	Rectangle [ [635.781, 362.607], [732.331, 466.488] ]	0.846811






Image	Concept	BoundingBox	Probability
	person	Rectangle [ [372.419, 60.3142], [455.796, 215.575] ]	0.713712
	automobile	Rectangle [ [480.086, 339.012], [650.738, 390.345] ]	0.600908
	automobile	Rectangle [ [640.382, 326.726], [785.321, 383.847] ]	0.523947

Image	Concept	BoundingBox	Probability
	automobile	Rectangle [ [379.327, 205.512], [570.379, 337.324] ]	0.594767

Missing | NotRecognized

Image	Concept	BoundingBox	Probability
	automobile	Rectangle [ [245.991, 288.577], [465.887, 365.635] ]	0.727035
	automobile	Rectangle [ [958.4, 384.183], [1000, 428.596] ]	0.557257

# Multiple object type detections



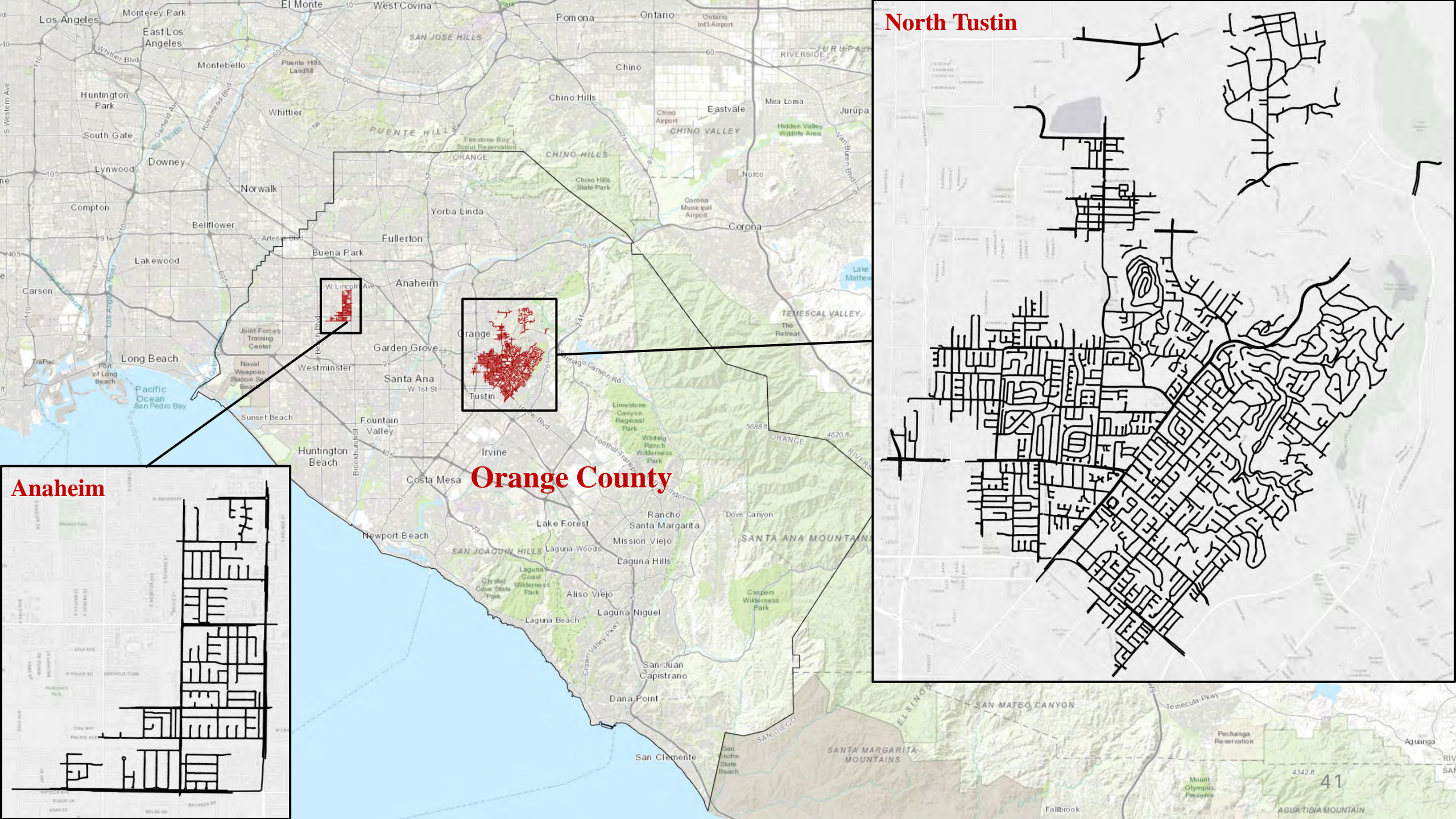
# Photosphere Sensor configurations

- + Sensor measurements approximately 10 feet apart (speed invariant).



# Example Application





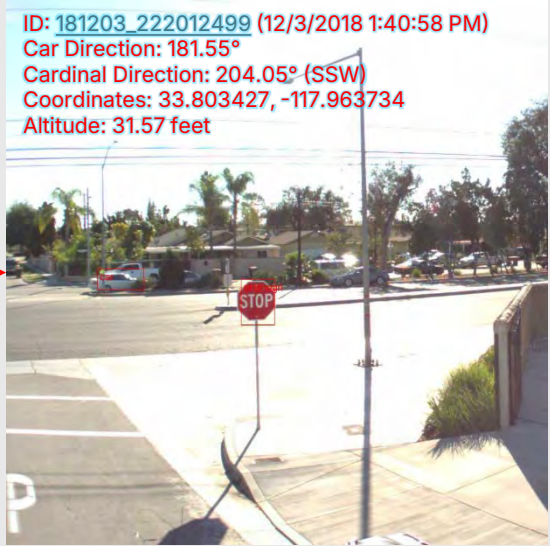
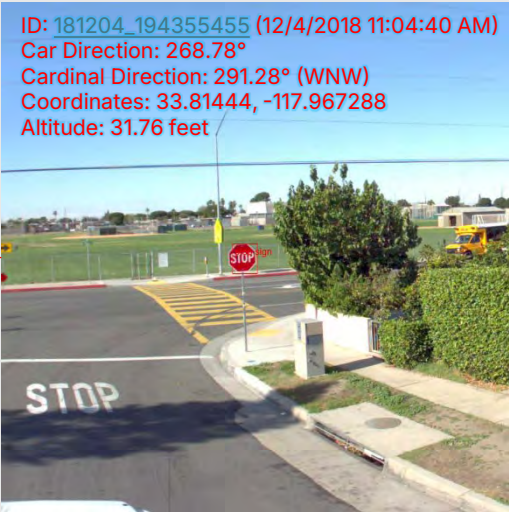
**North Tustin**

**Orange County**

**Anaheim**

41

# Anaheim Stop Signs

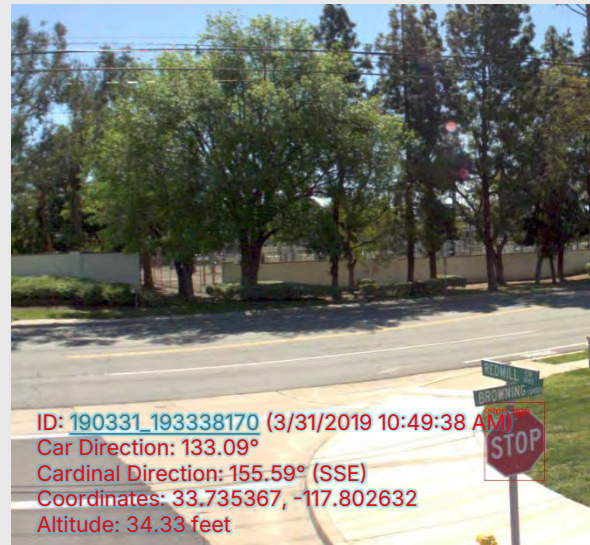
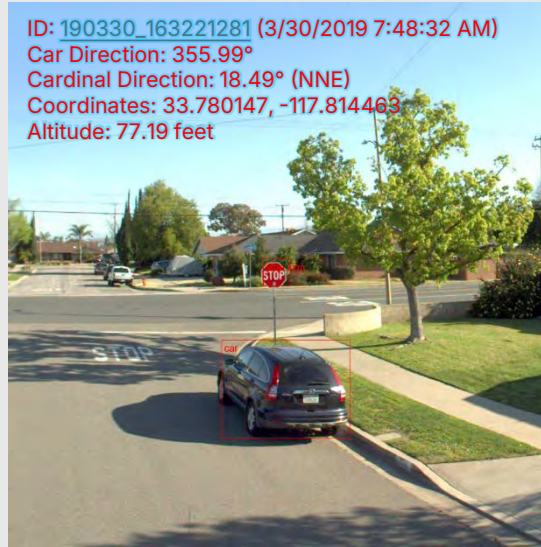


# North Tustin Stop Signs

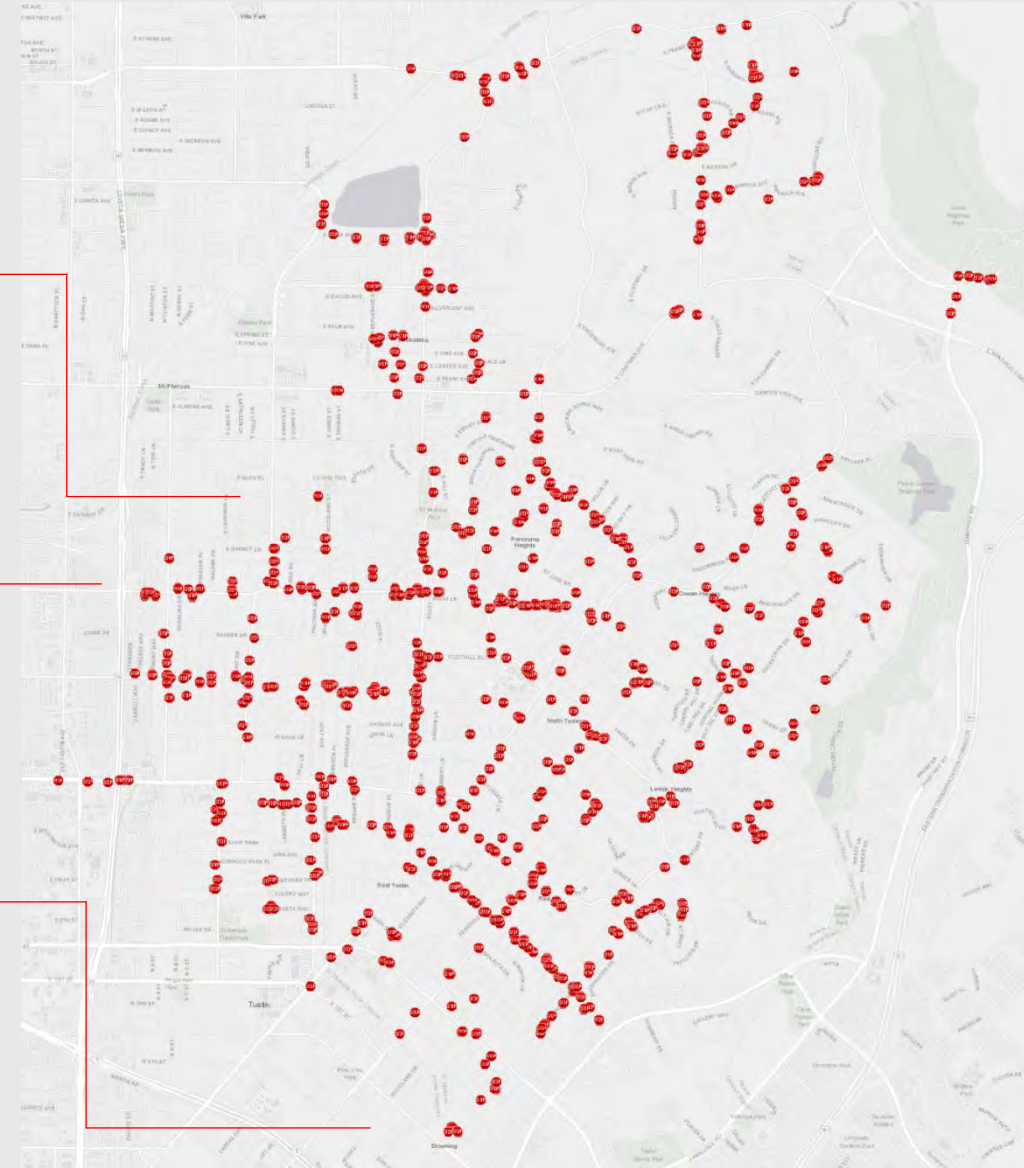
ID: [190329\\_222712056](#) (3/29/2019 7:43:47 AM)  
Car Direction: 180.01°  
Cardinal Direction: 202.51° (SSW)  
Coordinates: 33.773525, -117.826199  
Altitude: 68.21 feet



ID: [190330\\_163221281](#) (3/30/2019 7:48:32 AM)  
Car Direction: 355.99°  
Cardinal Direction: 18.49° (NNE)  
Coordinates: 33.780147, -117.814463  
Altitude: 77.19 feet



ID: [190331\\_193338170](#) (3/31/2019 10:49:38 AM)  
Car Direction: 133.09°  
Cardinal Direction: 155.59° (SSE)  
Coordinates: 33.735367, -117.802632  
Altitude: 34.33 feet



# Traffic Incidents and Aggregation

SWITRS Incidents (2012-2025)  
Crash Reports by Time  
Aggregated by City  
and Unincorporated Area

Parameters:  
- Time Step: 1 Month  
- Aggregated by City and Area  
(Raw Date and Time of Incident)

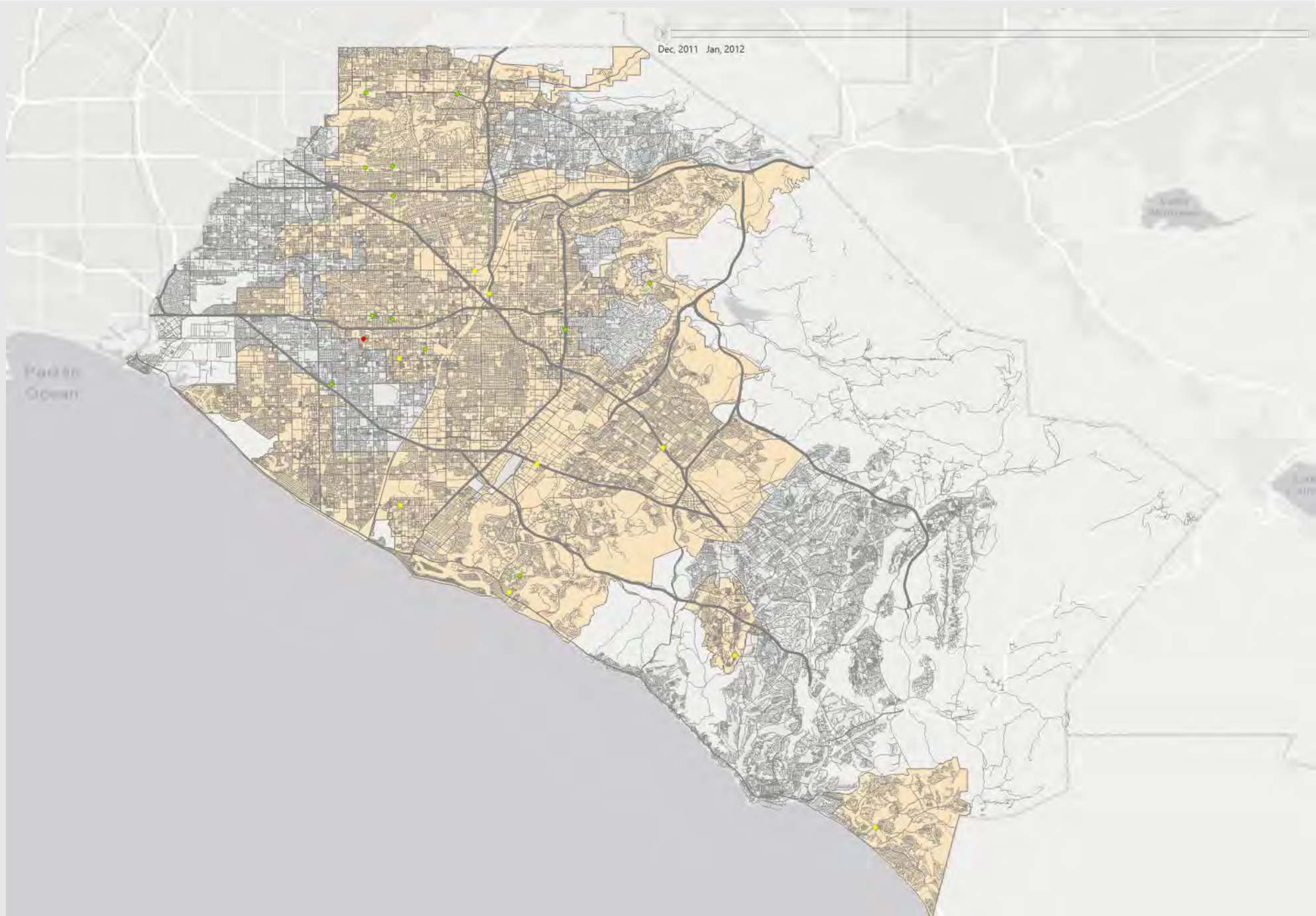
[Web App](#)

**Collision Severity**

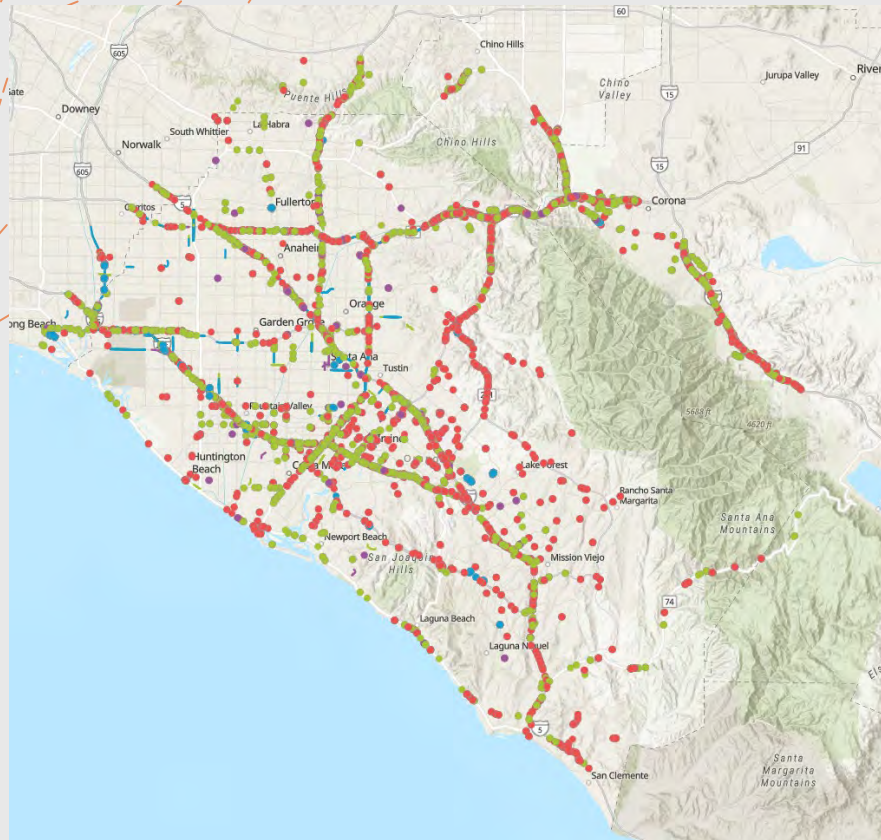
- Fatal
- Injury (Severe)
- Injury (Other Visible)
- Injury (Complaint of Pain)
- Property Damage Only (PDO)

**SWITRS: Total Incidents**

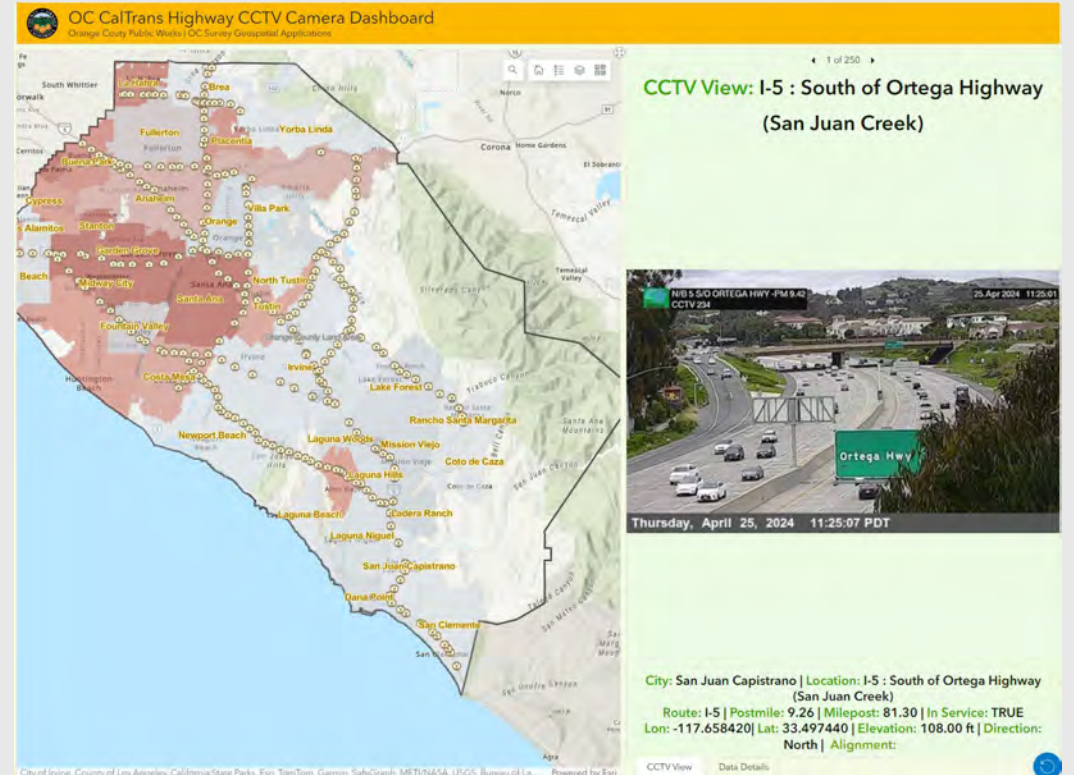
164 - 259	Primary
103 - 163	Secondary
50 - 102	Local
20 - 49	
1 - 19	



# Other Traffic Data

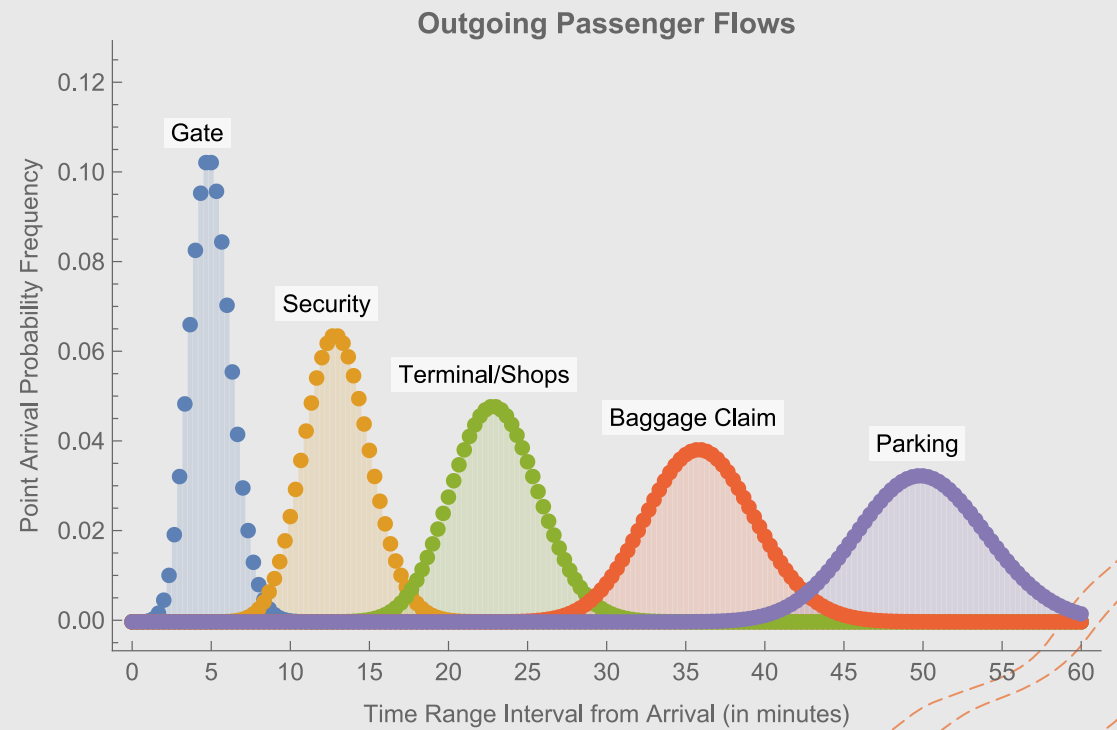
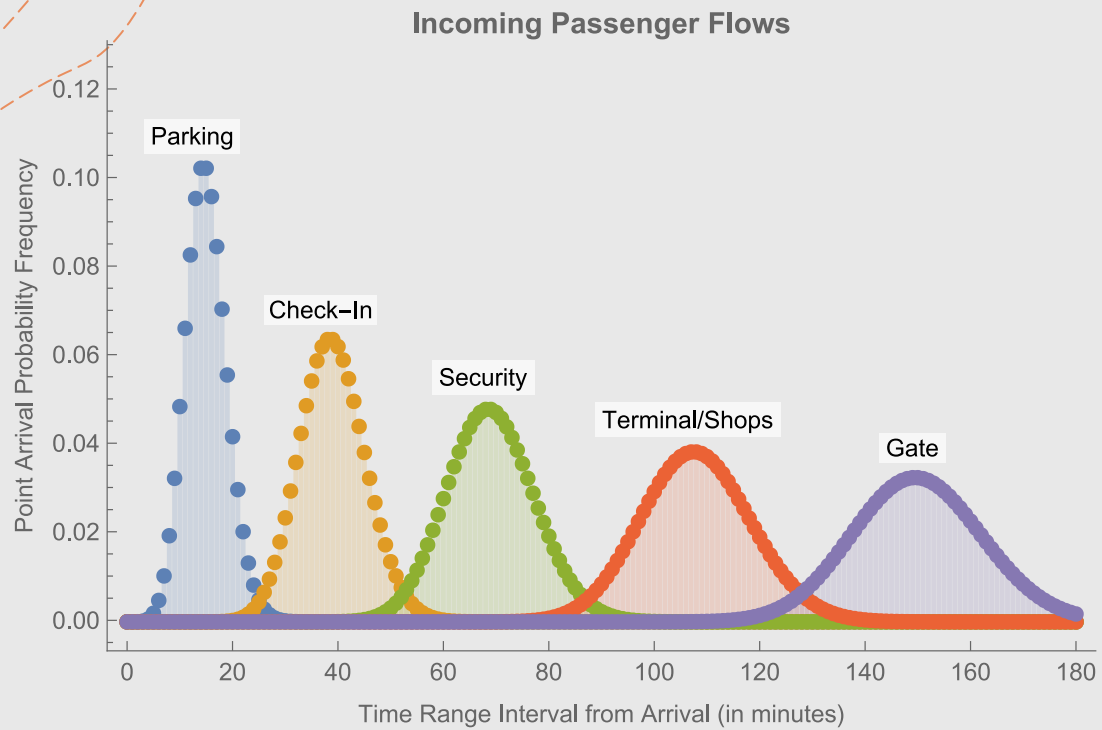


OC Waze Partnership Data

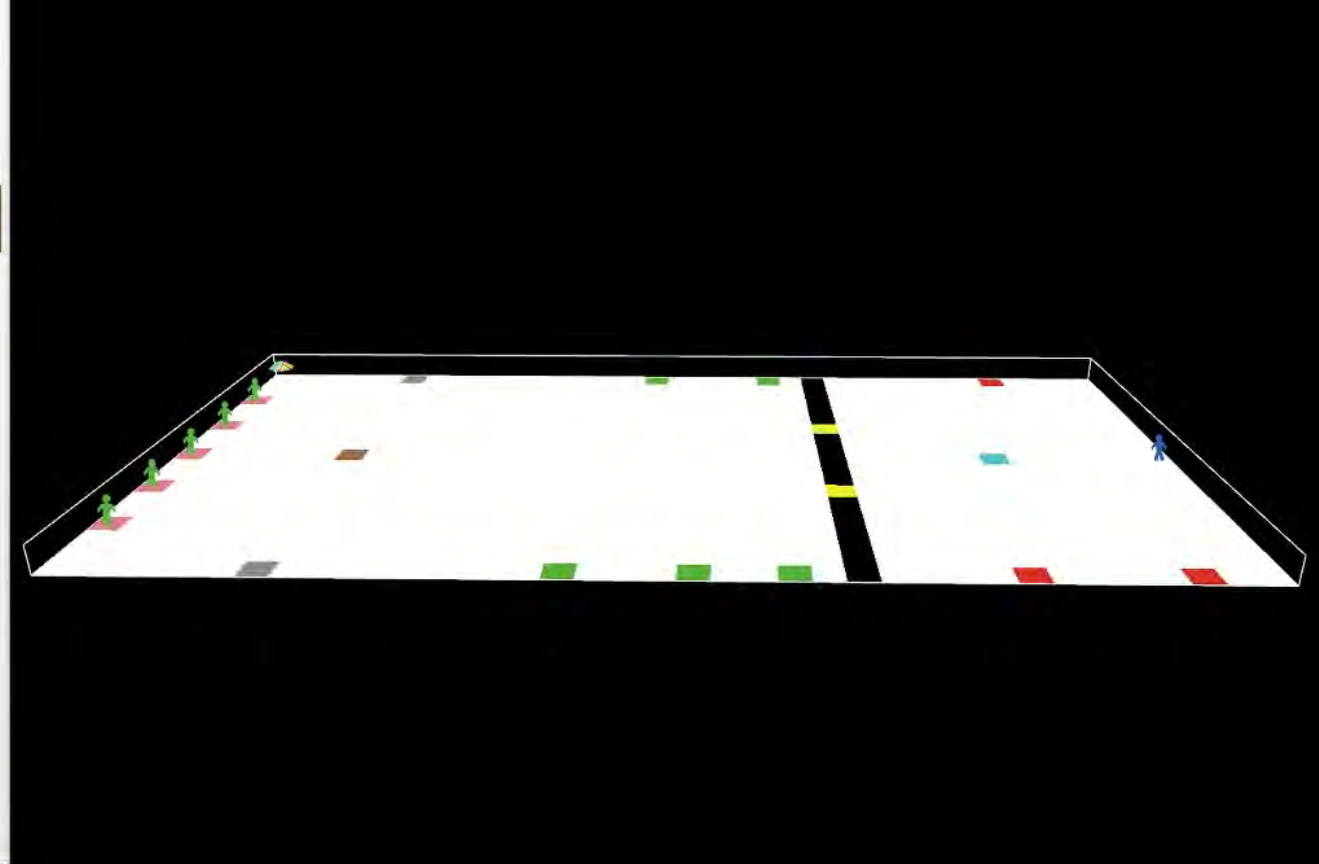
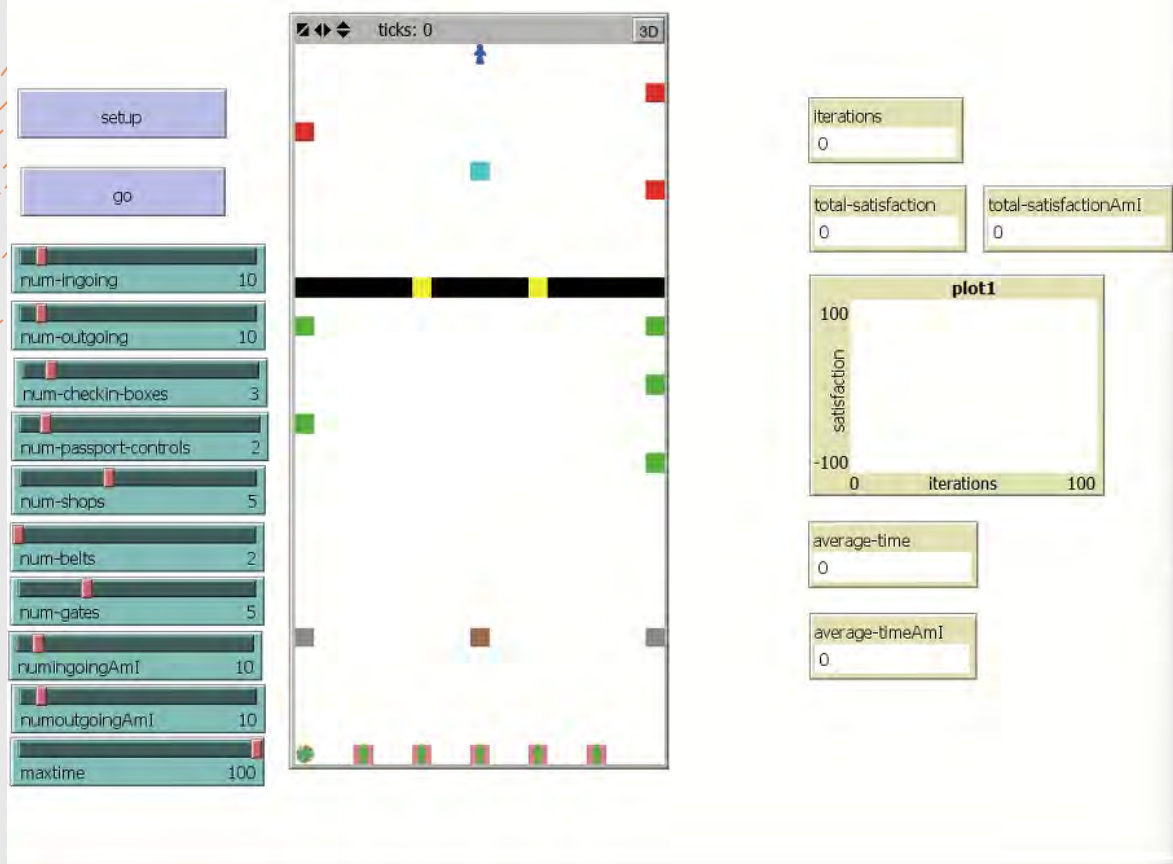


Real-Time Camera Dashboards

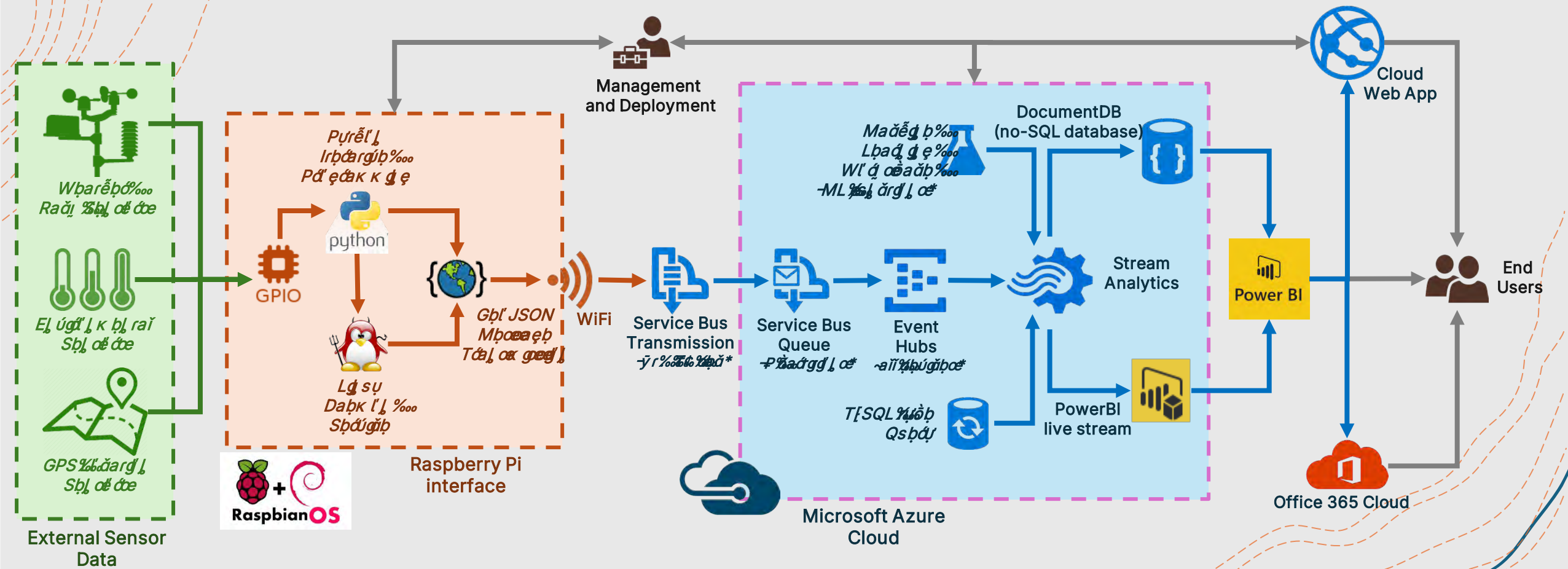
# Smart Airport DT: Example passenger arrival distributions



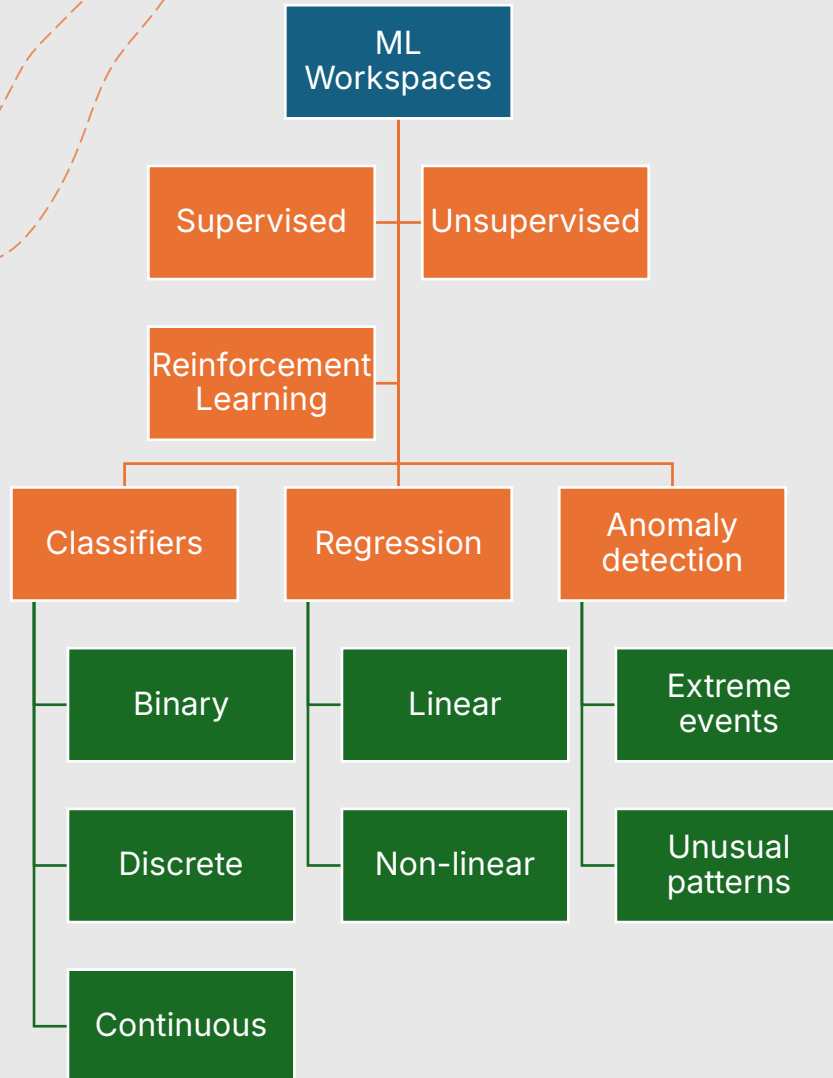
# Smart Airport Agent-Based Modeling



# Integrated IoT development



# Big Data Machine Learning



## + Example Algorithms:

### + Neural Networks

- + Averaged perceptron
- + Support Vector Machines

### + Bayesian (probabilistic)

- + Naïve Bayes
- + Bayes Point Machines

### + Regression-based

- + Linear
- + Logistic
- + Random Forests

### + Tree/Search-based

- + Decision trees
- + Boosted trees
- + PCA-based

# Machine Learning Experiments

**Example:**  
Spatial  
Boundary  
Prediction using  
2-layer ANN  
Classifier

