GeoAI: Vertical Use Cases using AI with ArcGIS

Omar Maher - Director, Artificial Intelligence

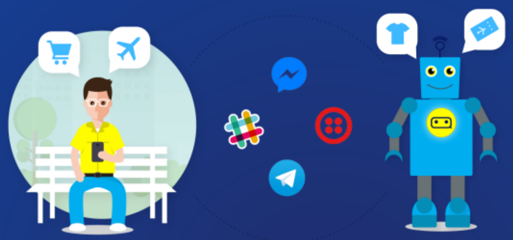
Joel McCune – Solution Engineer, Artificial Intelligence

AI is used today literally everywhere..

Autonomous Cars

Sentiment Analysis

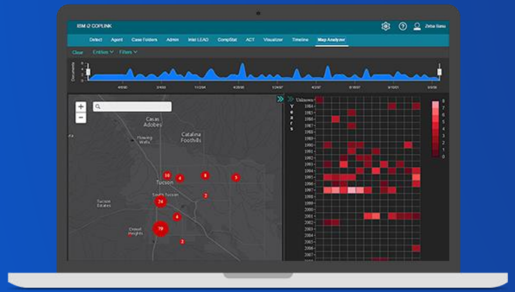
Chatbots



Robots

Advanced Video Analytics

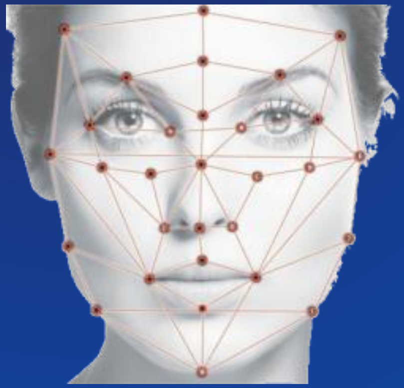
Crime Prediction



Predictive Maintenance

Cancer Detection

Facial Recognition



Personalized Marketing

Advanced Satellite Intelligence

Stock Market Prediction

1. AI > ML > DL

Artificial Intelligence

Reasoning

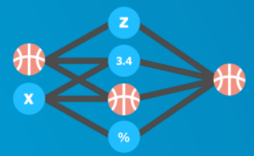
Knowledge Representation

Perception

NLP

Robotics

Machine Learning



Machine Learning

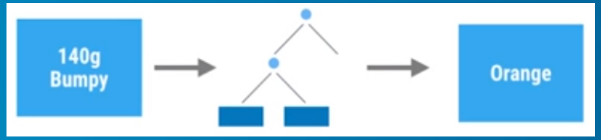
Supervised Learning

1. Training *features* *Labels*

Examples

Weight	Texture	Label
150g	Bumpy	Orange
170g	Bumpy	Orange
140g	Smooth	Apple
130g	Smooth	Apple
…	…	…

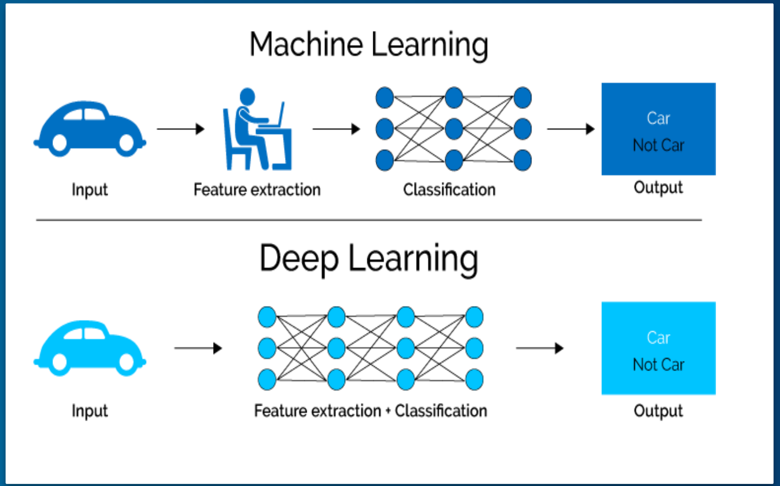
2. Predicting



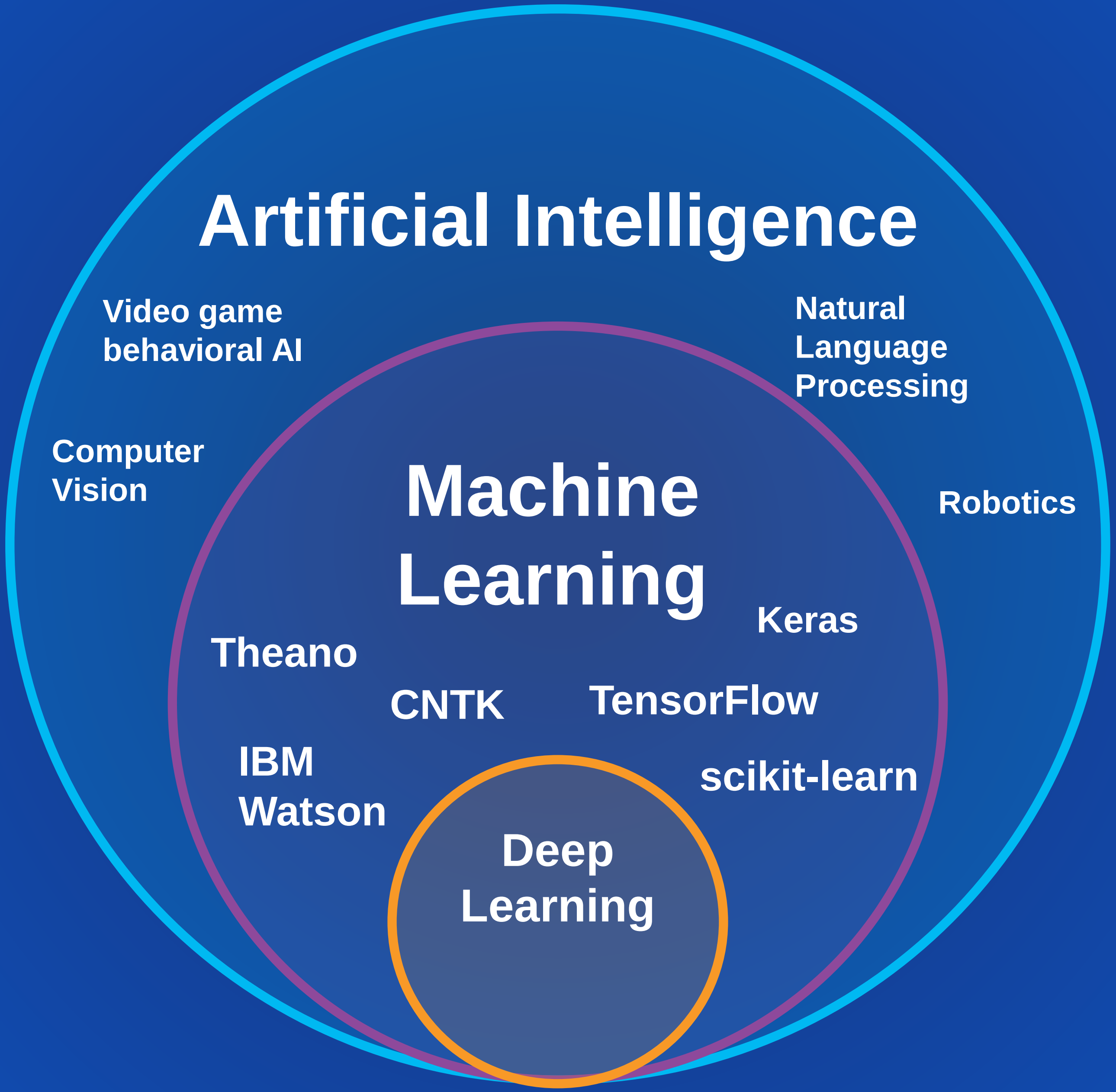
Unsupervised Learning
Reinforcement Learning

Deep Learning

Deep Supervised Learning

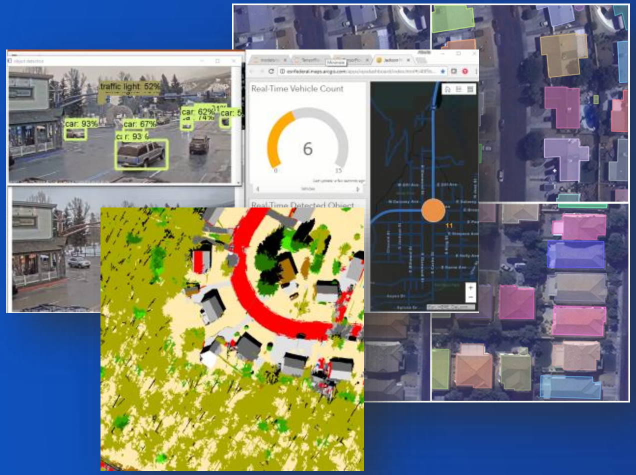


Dog


Artificial Intelligence
Video game behavioral AI
Natural Language Processing
Computer Vision
Robotics
Machine Learning
Keras
Theano
CNTK
TensorFlow
IBM Watson
scikit-learn
Deep Learning

How can **ArcGIS AI** Capabilities Help you today?

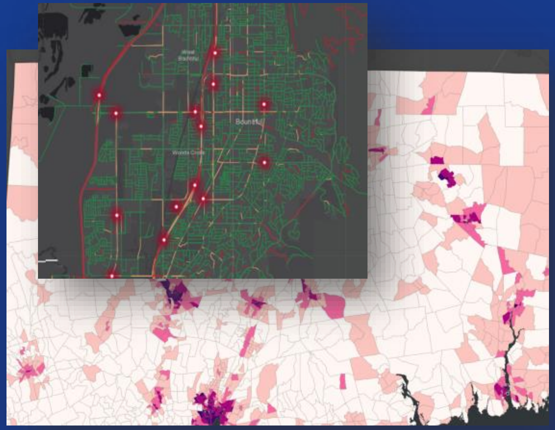
Object Detection



Detecting Objects from Imagery/Videos, Land Cover, Change Detection..

Buildings, Road Segments, Swimming Pools, Blight, Graffiti, Overgrowth, Road Signs, Vehicles from CCTVs, and more

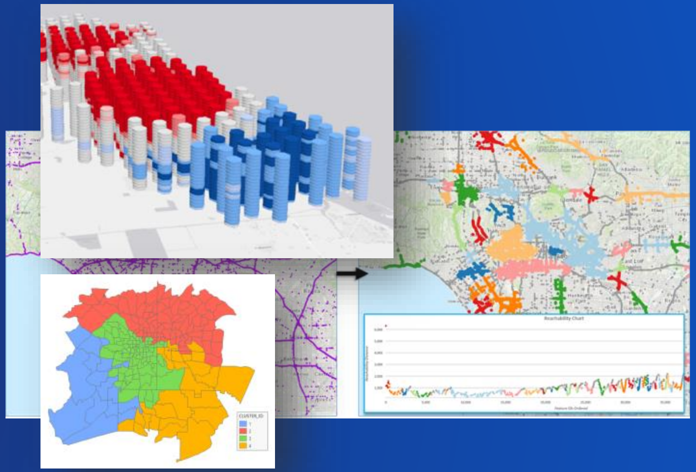
Prediction



Predicting Geospatial Events/Phenomena

Water Pipe Breaks, Asthma Rates, Diseases, Crimes, Crashes, Incidents, Fires, Congestion, 911 Calls,

Pattern Detection



Finding Statistically Significant Clusters & Patterns

Top Risky Segments, Emerging Hotspots of 911 Calls, Disease Clusters, and more

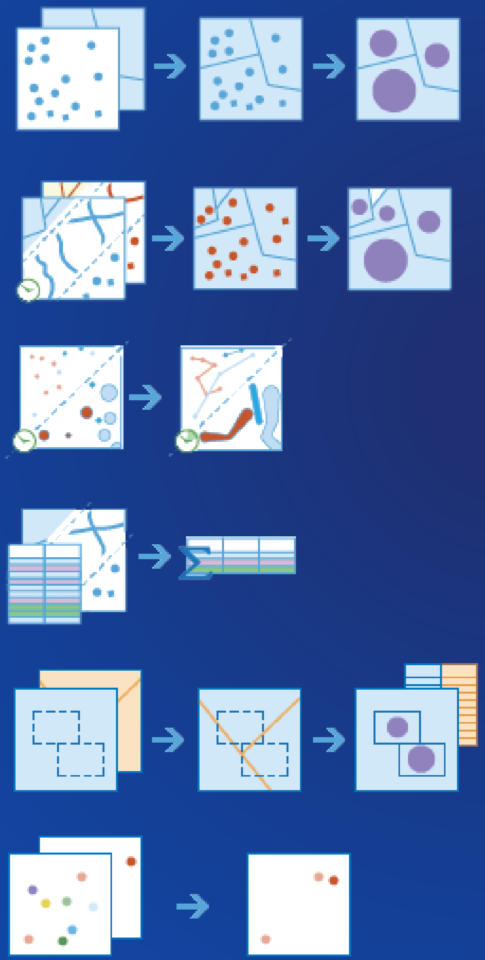
Machine Learning Tools in ArcGIS

Classification

- Maximum Likelihood Classification
- Random Trees
- Support Vector Machine

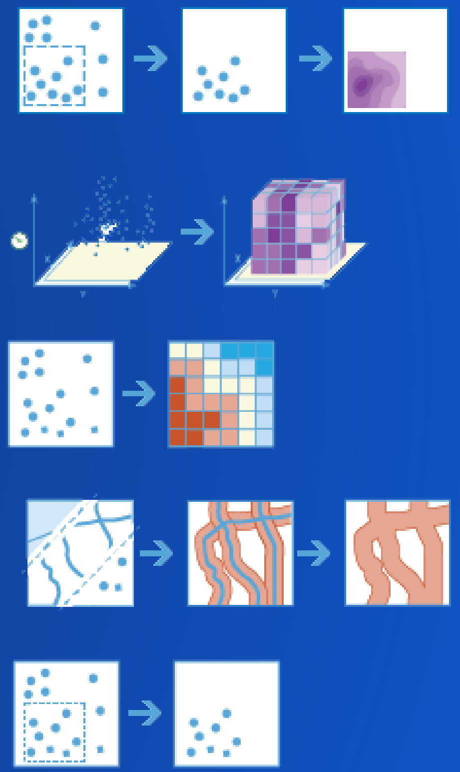
Clustering

- Spatially Constrained Multivariate Clustering
- Multivariate Clustering
- Density-based Clustering
- Image Segmentation
- Hot Spot Analysis
- Cluster and Outlier Analysis
- Space Time Pattern Mining

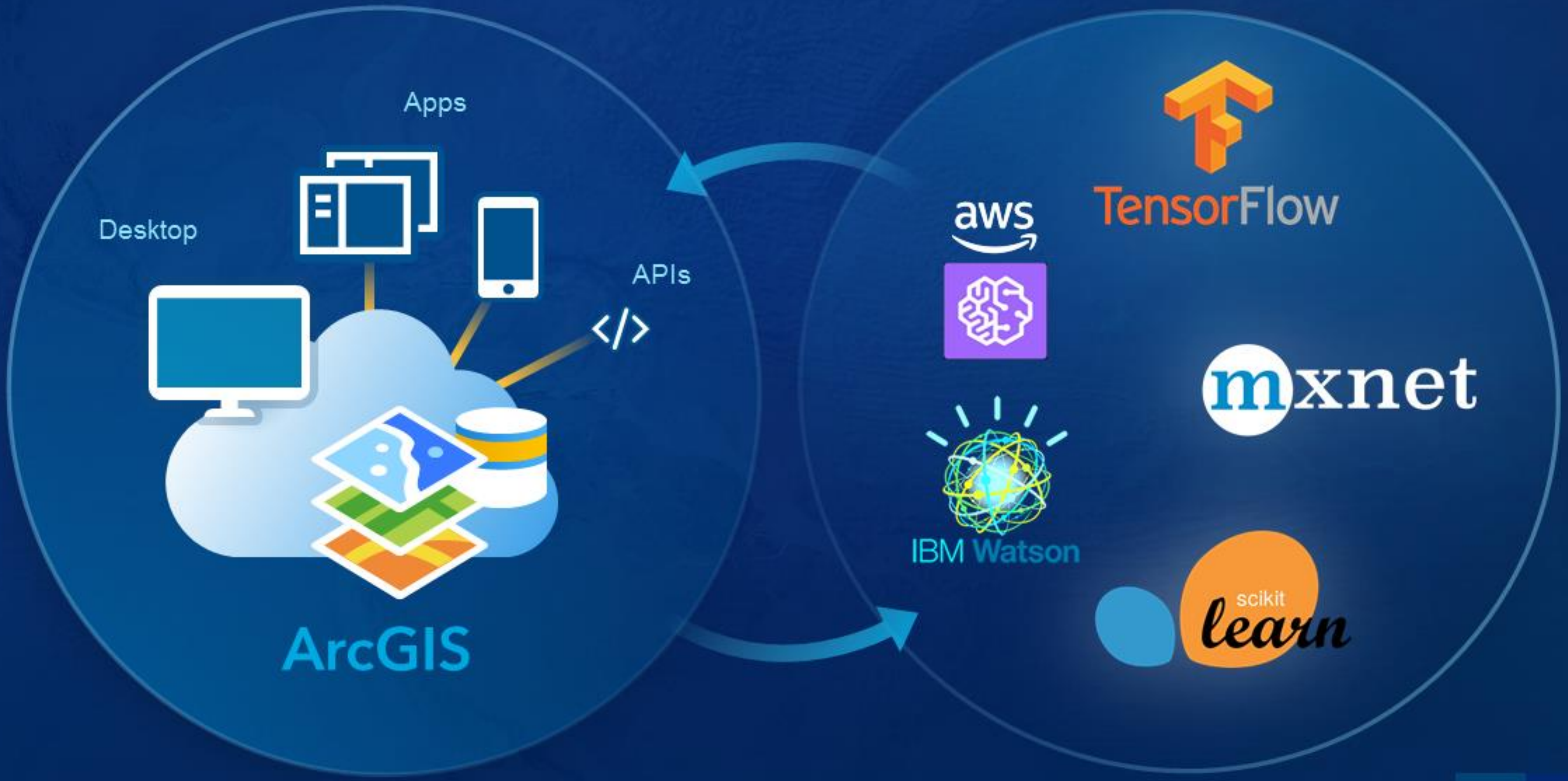


Prediction

- Empirical Bayesian Kriging
- Areal Interpolation
- EBK Regression Prediction
- Ordinary Least Squares Regression and Exploratory Regression
- Geographically Weighted Regression
- Forest Based Prediction



Machine Learning Integration with External Frameworks

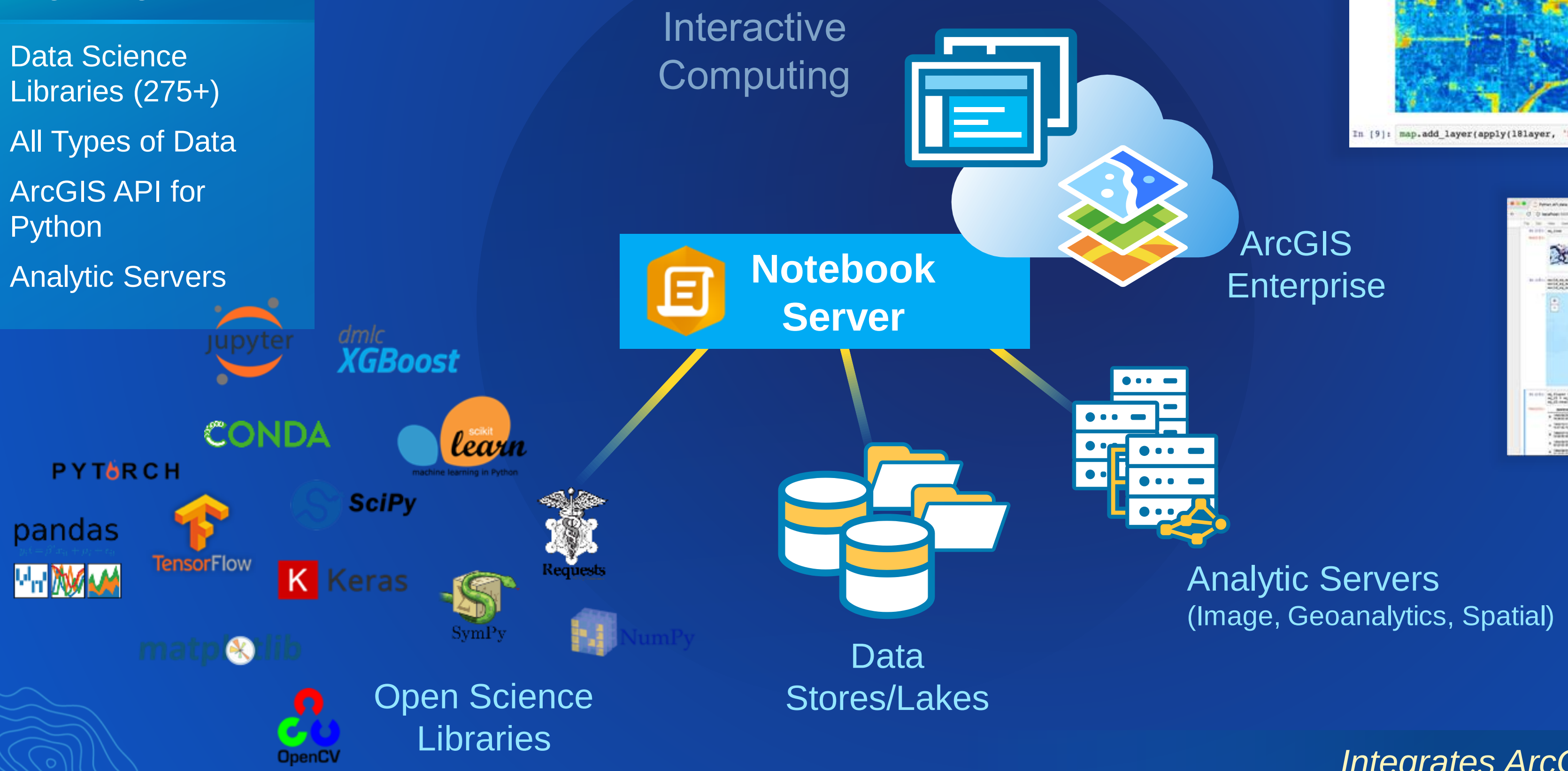


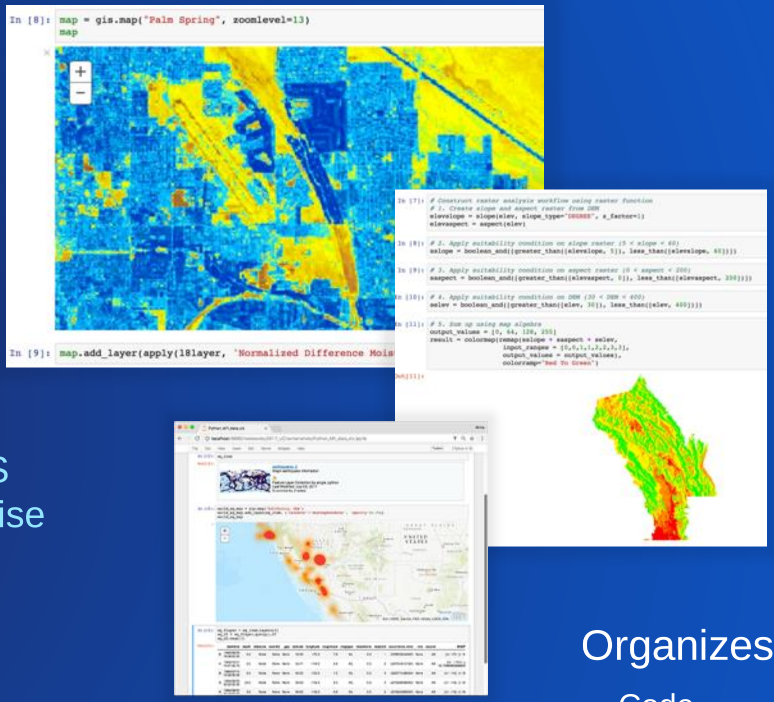
ArcGIS Notebooks | For Integration, Modeling, and Automation Scripting

Providing Notebooks as an Item . . .
and ArcPy Geoprocessing in a Server

Integrating

- Data Science Libraries (275+)
- All Types of Data
- ArcGIS API for Python
- Analytic Servers





Organizes

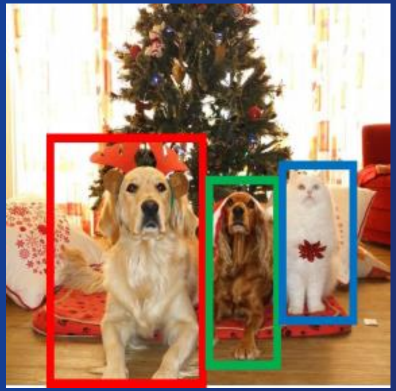
- Code
- Data
- Visualization
- Documentation

Integrates ArcGIS with the World of Data Science

Flavors of Deep Learning with Imagery

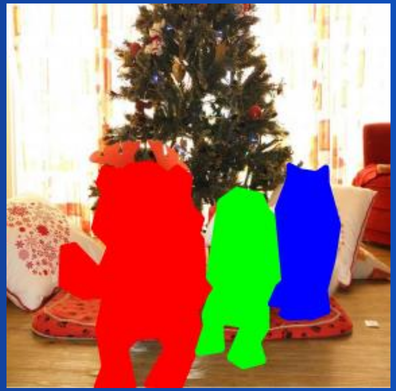
Image Classification

Object Detection



Semantic Segmentation

Instance Segmentation



AI for Disaster Response

Detect Damaged Buildings, Detect Damaged Roads, & Allocate Resources

The Unique Challenges of Coordinating Response

- Limited time and resources
- Need human analysis of large areas of imagery
- Multiple elements involved (detection, routing, monitoring)

We propose an AI augmented pipeline that provides an end-to-end solution

Detect damaged structures

An AI model runs on aerial imagery and outputs a feature class of damaged and undamaged structures

Detect damaged roads

An AI model runs on aerial imagery + road layer and outputs a feature class of damaged and undamaged roads

Optimal routing

ArcGIS Network Analyst consumes the damaged structures and blocked roads feature classes, and creates an optimal route from a base (fire station, shelter etc.) to all the damaged structures, accounting for blocked roadways

Situational Awareness

Utilizing the Esri Workforce mobile app, we can assign each responder a set of structures to inspect and use Operations Dashboard to monitor their progress and other key metrics

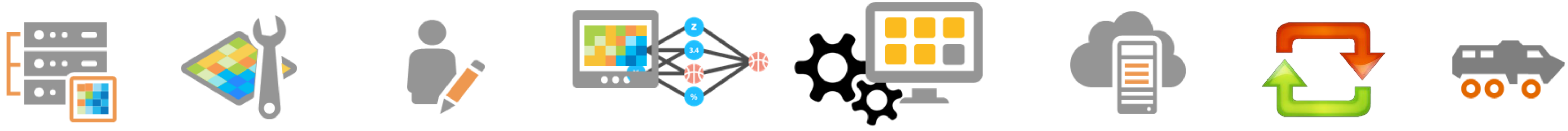
Demo

PACI: Nation wide Building Footprint Extraction

Previously: 5 People, 5 hours/day, 1 year

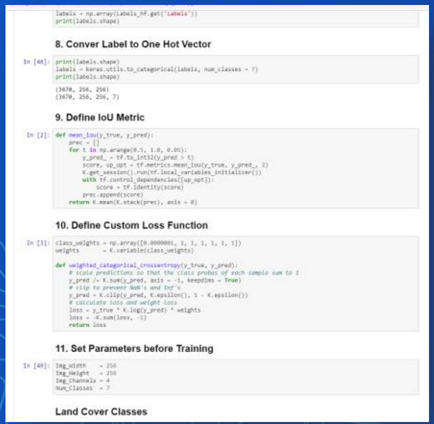
Now: 37,000 Buildings in 3 Minutes!

Beyond Detections: End to End AI Workflows with Imagery



Imagery Access | Imagery Prep | Training Data Prep | Train & Consume Models | Deploy Models to Production | Run Inference at SCALE | Feedback Loop | Take Action

Before ArcGIS.Learn



- Installing External DL Frameworks
- Dozens of lines of Code
- HARD!

After ArcGIS.Learn

- No Installation (Notebooks)
- 3-5 lines
- EASY

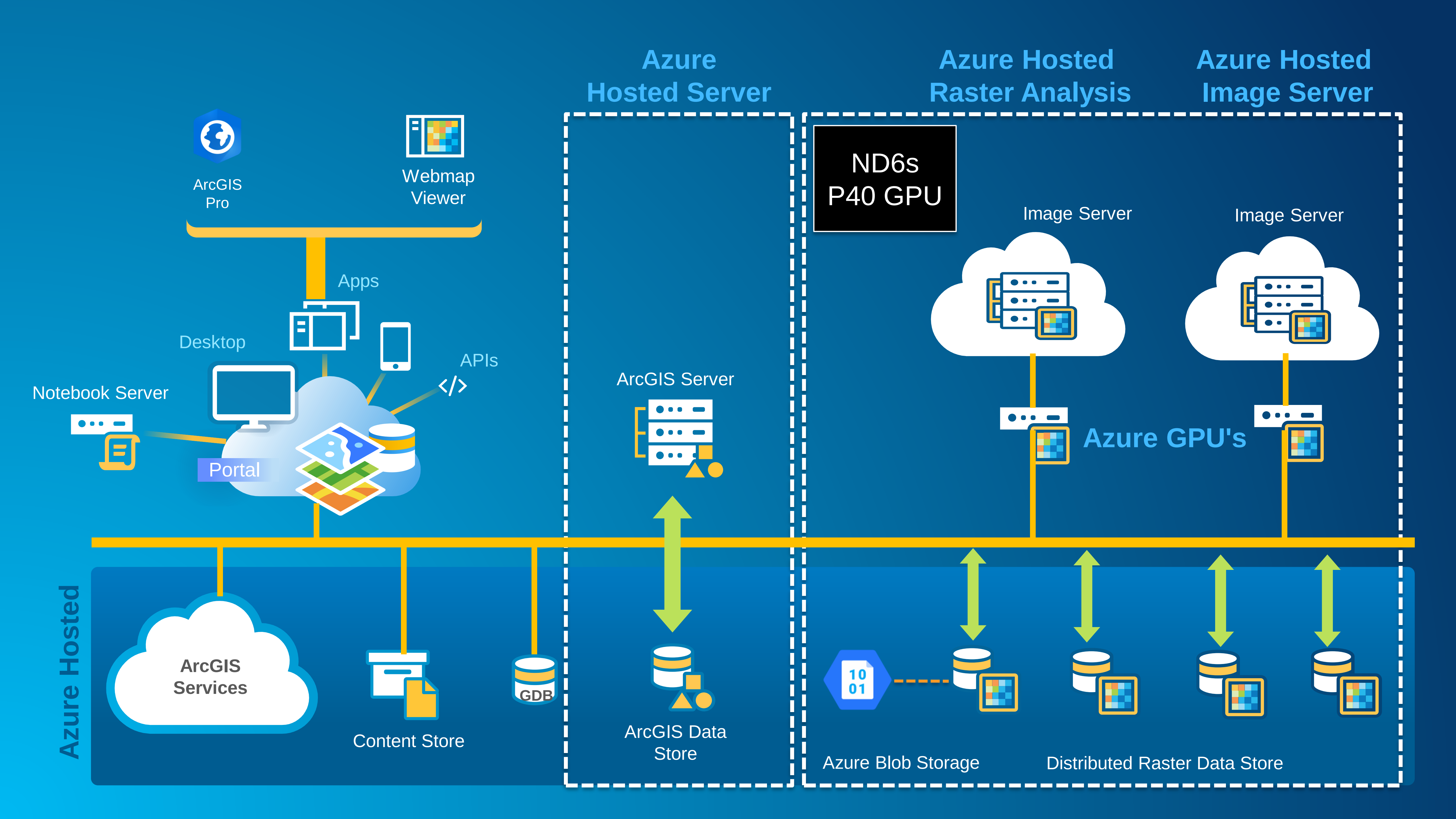
Train SingleShotDetector Model

```
from arcgis.learn import SingleShotDetector

ssd = SingleShotDetector(data, grids=[9], zooms=[1.0], ratios=[[1.0, 1.0]])
```

```
ssd.fit(10, lr=slice(1e-3, 1e-2))
```

Scalable Deep Learning in the Cloud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Azure Hosted
Raster Analysis
Azure Hosted
Image Server
ArcGIS
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Webmap
Viewer
ND6s
P40 GPU
Image Server
Image Server
Apps
Desktop
APIs
Notebook Server
Portal
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Content Store
GDB
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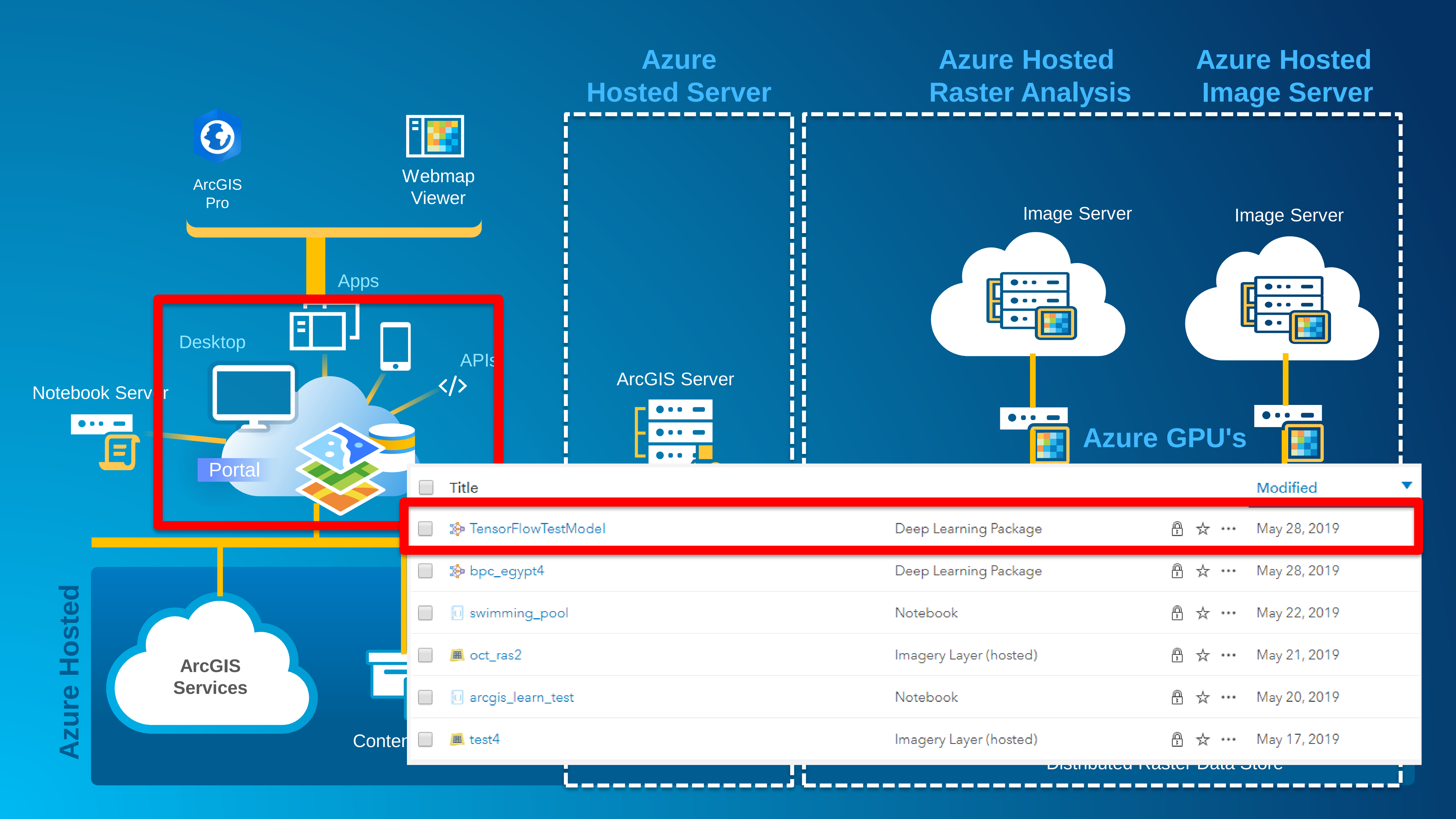
Azure Blob Storage
Distributed Raster Data Store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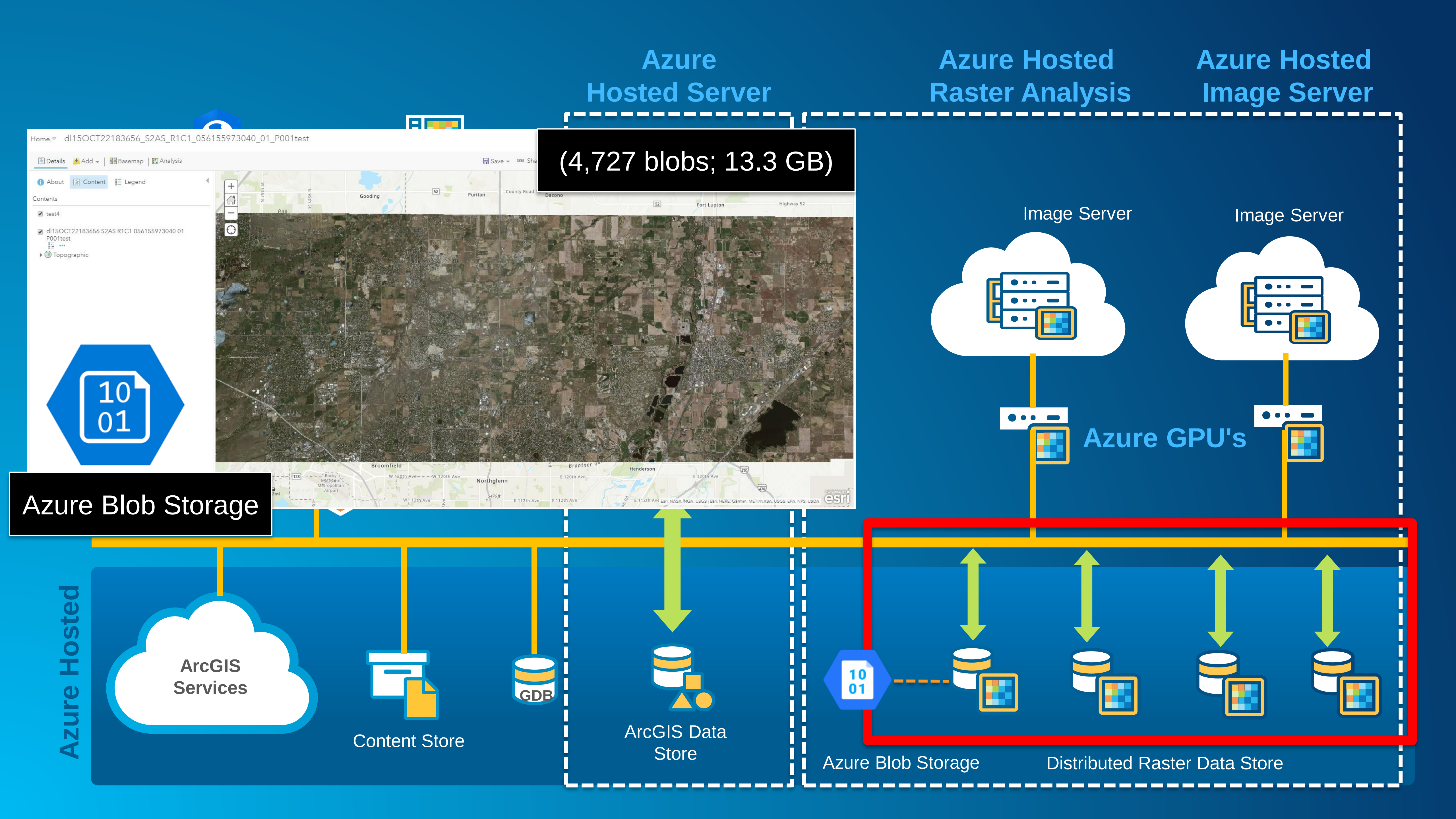
TensorFlowTestModel
Deep Learning Package
May 28, 2019
bpc_egypt4
Deep Learning Package
May 28, 2019
swimming_pool
Notebook
May 22, 2019
oct_ras2
Imagery Layer (hosted)
May 21, 2019
arcgis_learn_test
Notebook
May 20, 2019
test4
Imagery Layer (hosted)
May 17, 2019



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Azure Hosted
Raster Analysis
Azure Hosted
Image Server
(4,727 blobs; 13.3 GB)
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Details
Add
Basemap
Analysis
Save
About
Content
Legend
Contents
test4
Topographic
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Azure Hosted
ArcGIS
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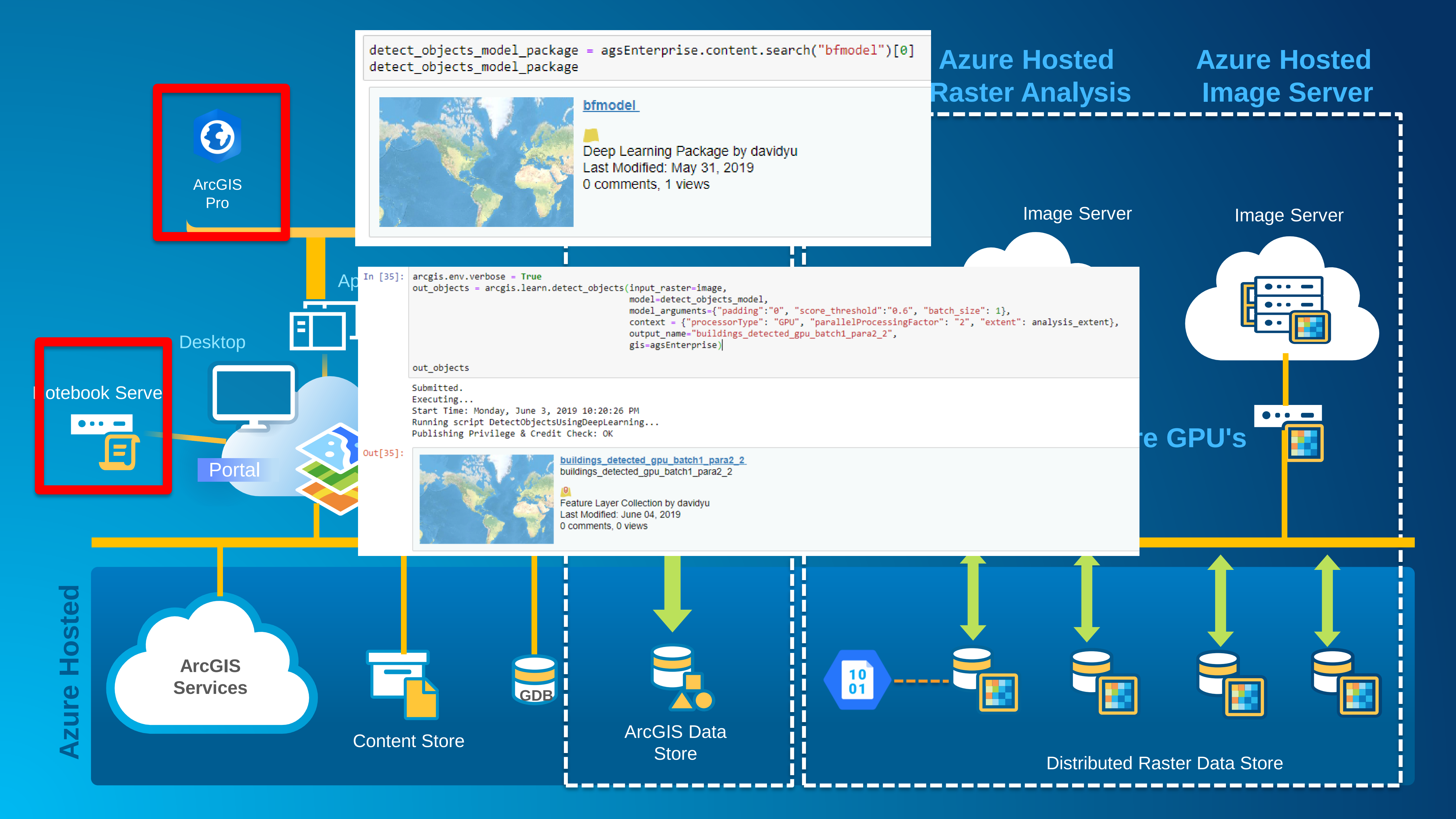
Azure Blob Storage
Distributed Raster Data Store



detect_objects_model_package = agsEnterprise.content.search("bfmodel")[0]
detect_objects_model_package
bfmodel
Deep Learning Package by davidyu
Last Modified: May 31, 2019
0 comments, 1 views
Azure Hosted
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In [35]:
arcgis.env.verbose = True
out_objects = arcgis.learn.detect_objects(input_raster=image,
model=detect_objects_model,
model_arguments={"padding":"0", "score_threshold":"0.6", "batch_size": 1},
context = {"processorType": "GPU", "parallelProcessingFactor": "2", "extent": analysis_extent},
output_name="buildings_detected_gpu_batch1_para2_2",
gis=agsEnterprise)
out_objects
Submitted.
Executing...
Start Time: Monday, June 3, 2019 10:20:26 PM
Running script DetectObjectsUsingDeepLearning...
Publishing Privilege & Credit Check: OK
Out[35]:
buildings_detected_gpu_batch1_para2_2
buildings_detected_gpu_batch1_para2_2
Feature Layer Collection by davidyu
Last Modified: June 04, 2019
0 comments, 0 views
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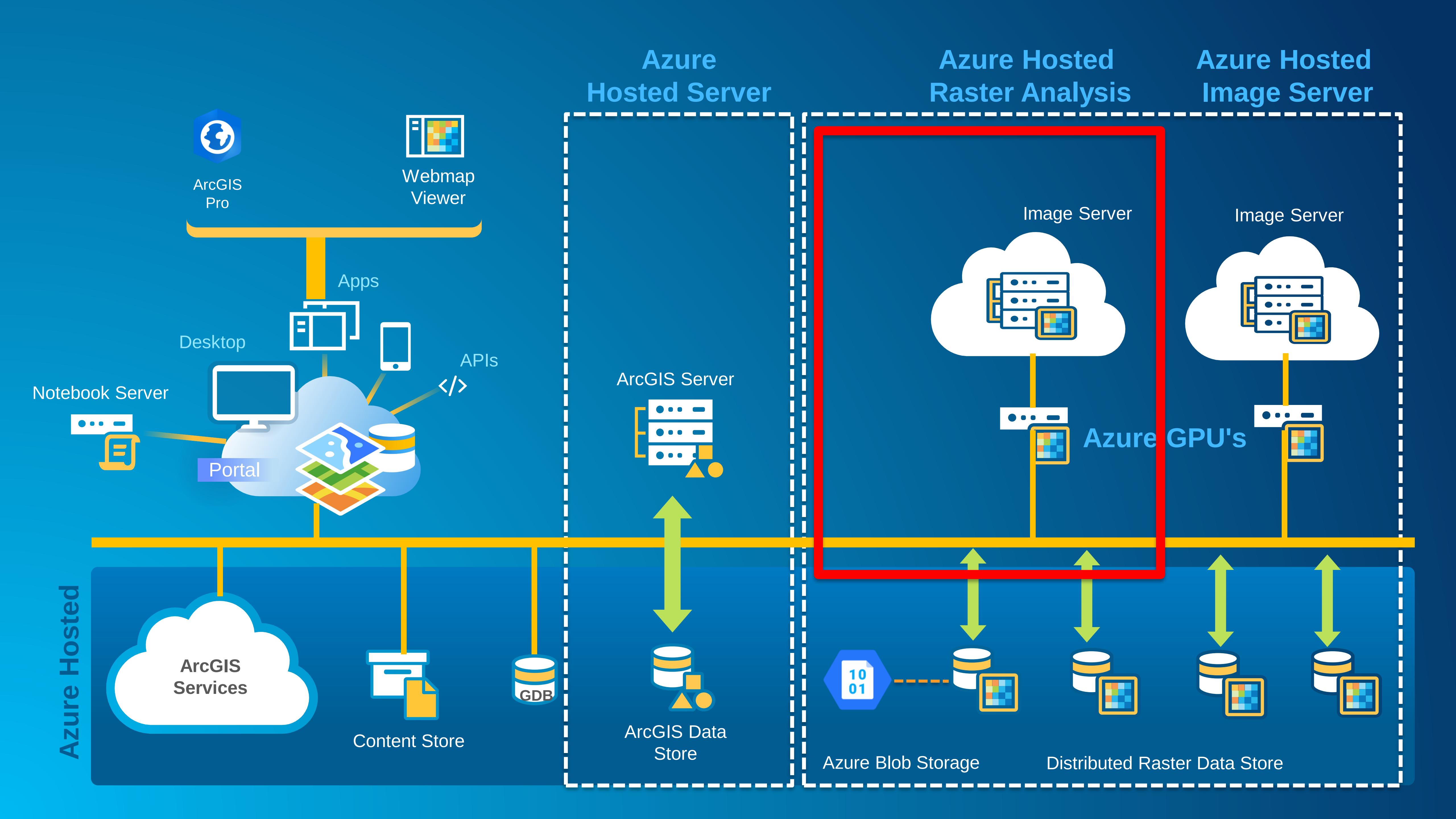
Distributed Raster Data Store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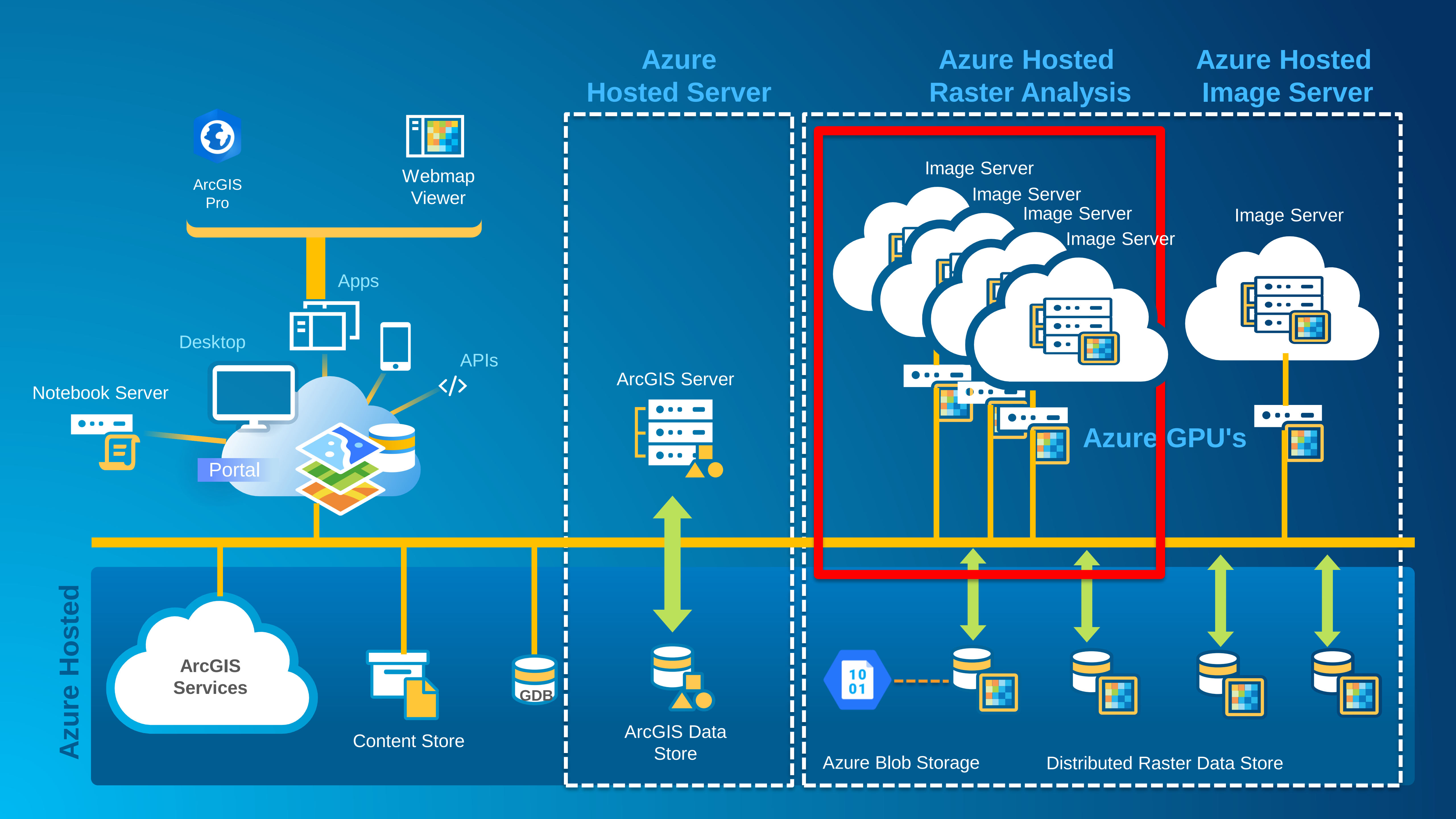
Azure Blob Storage
Distributed Raster Data Store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Raster Analysis
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Image Server
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Pro
Webmap
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Apps
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Notebook Server
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Image Server
Azure GPU's
Azure Hosted
ArcGIS
Services
Content Store
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ArcGIS Data
Store
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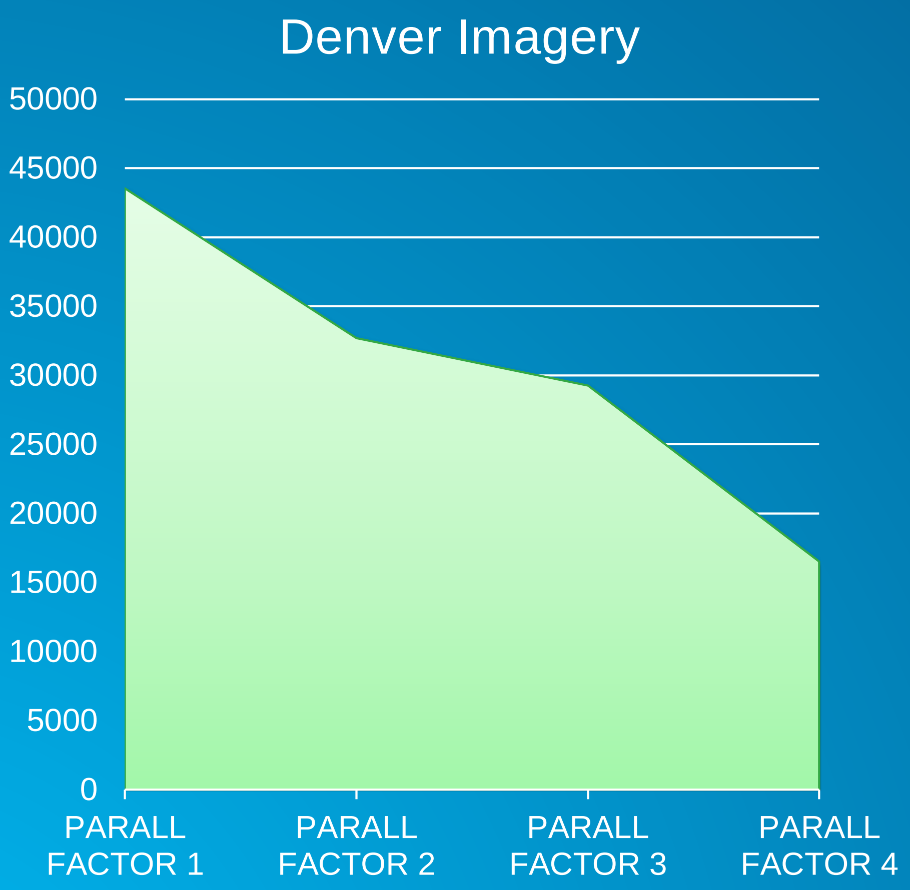
Azure Blob Storage
Distributed Raster Data Store

Benchmarks


Denver Imagery
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45000
40000
35000
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15000
10000
5000
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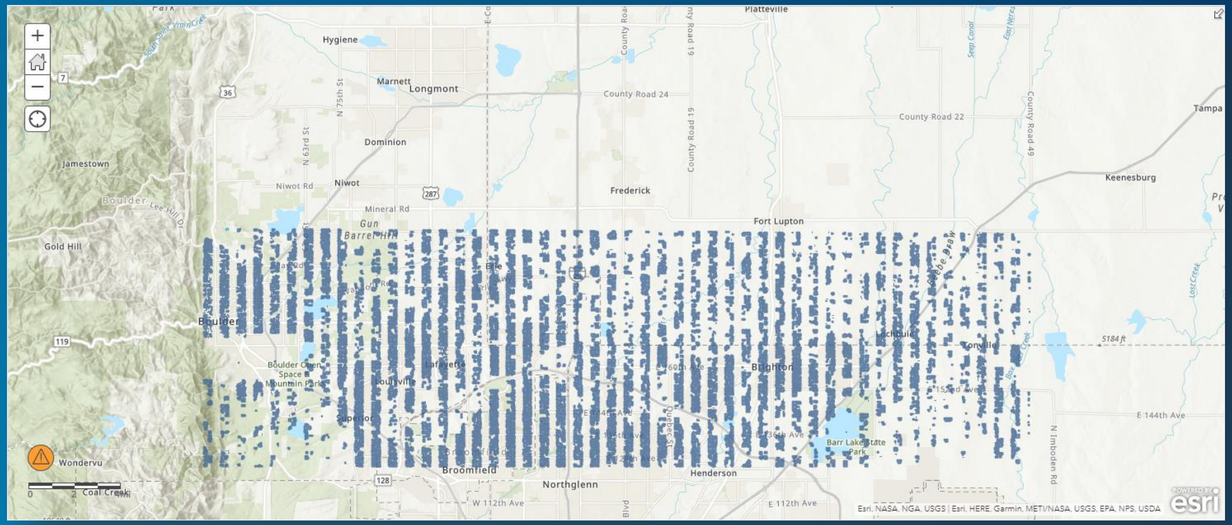
PARALL FACTOR 1
PARALL FACTOR 2
PARALL FACTOR 3
PARALL FACTOR 4


Hygiene
Marnett
Longmont
Dominion
Jamestown
Niwot
Frederick
Fort Lupton
Keenesburg
Platteville
Tampa
Gold Hill
Broomfield
Northglenn
Henderson
Wondervu
County Road 24
County Road 22
esri

Faster Inferencing using Distributed Raster Analytics

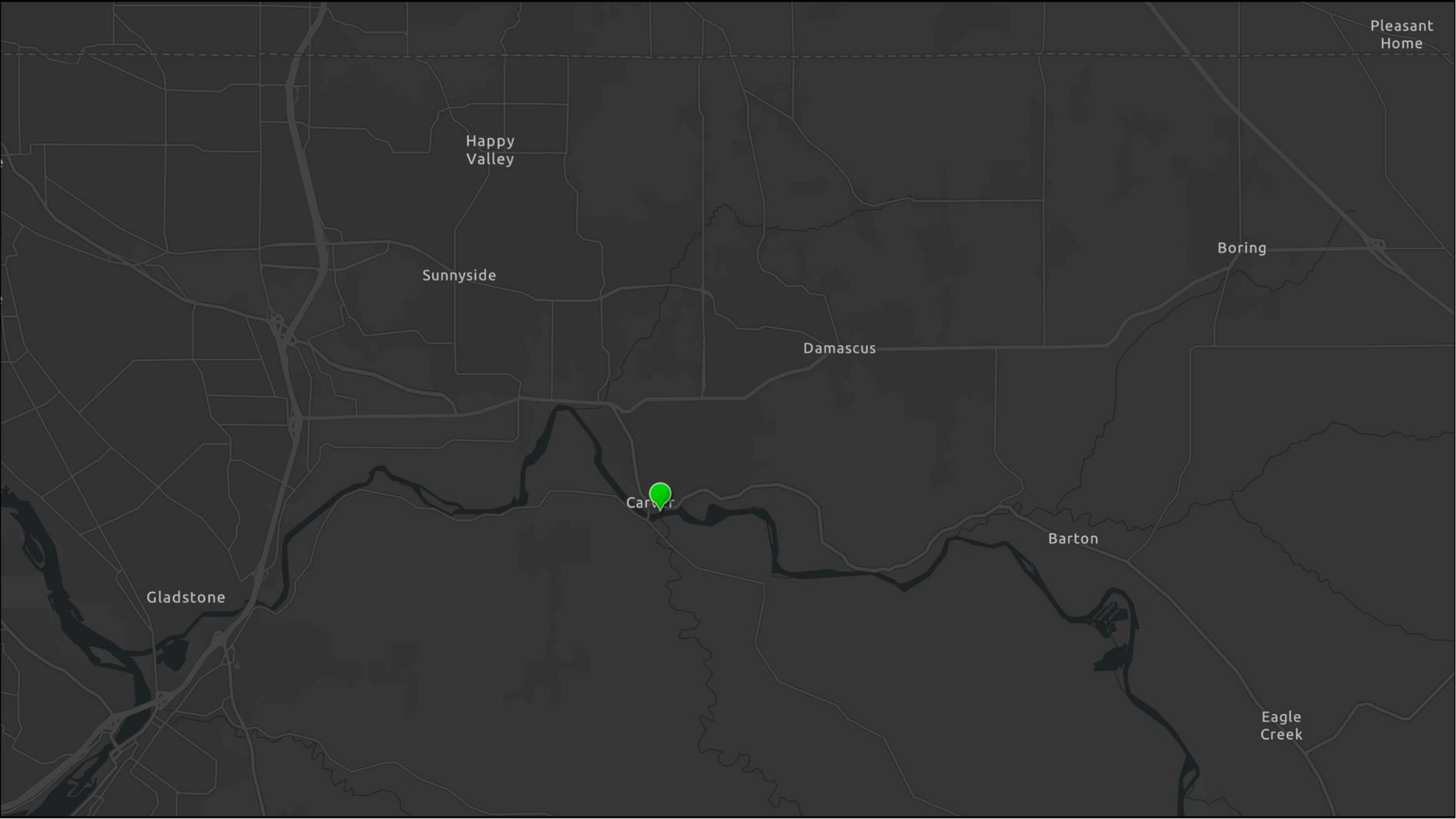
- 60,000 buildings
- Building Footprint Detection
- 1 Machine 1 GPU: 4.5 Hours
- 4 Image Servers with 4 GPUs: **20 Minutes (13X Faster)**

Retail Trade Area Prediction

Predicting Top Areas for Targeted Marketing Spend

Retail

- Trade Area
  - Forecasting
  - Marketing
  - Merchandising
  - New Site Selection
  - Existing Location Closures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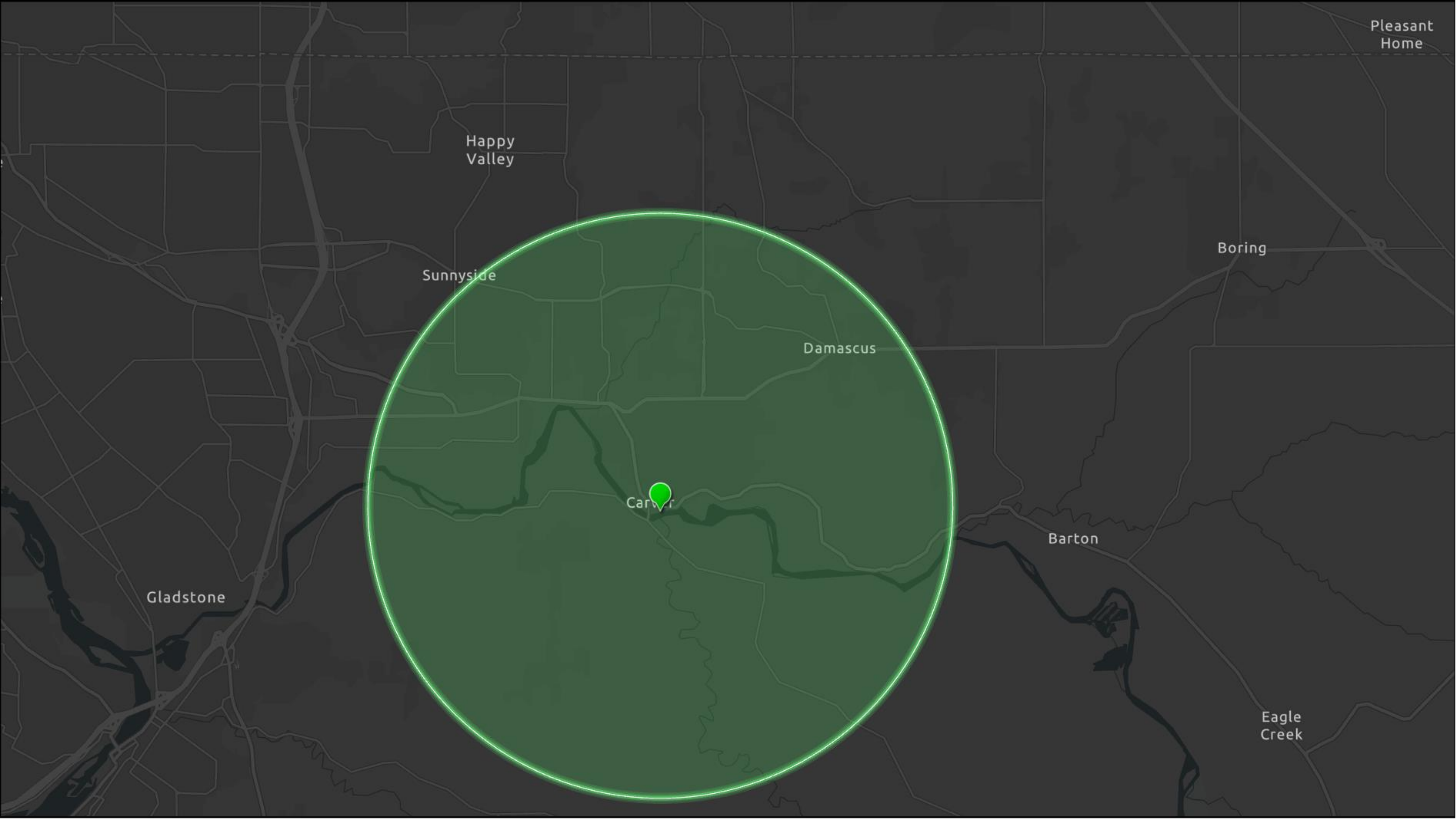
Happy Valley
Sunnyside
Boring
Damascus
Barton
Gladstone
Eagle Creek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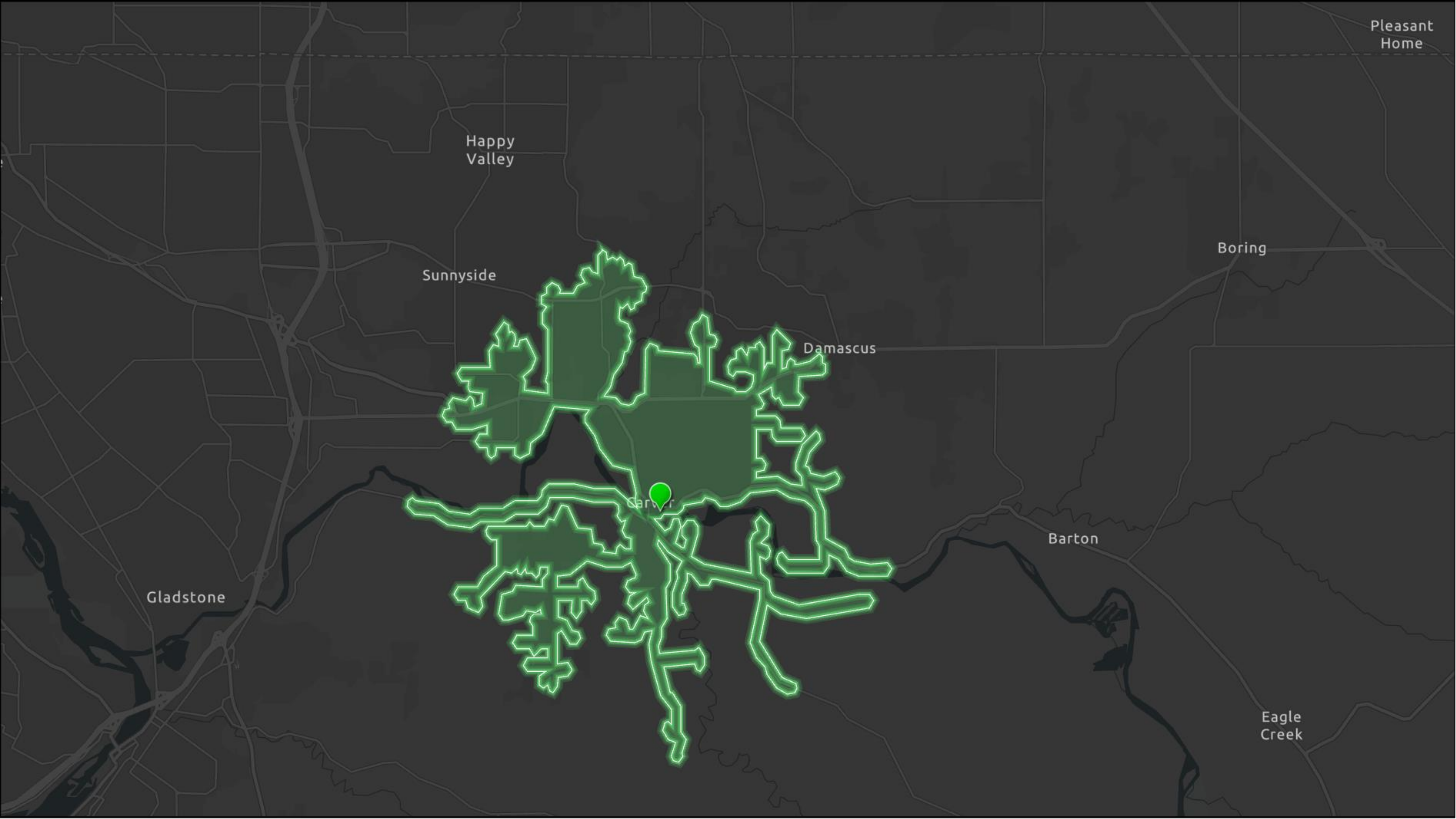
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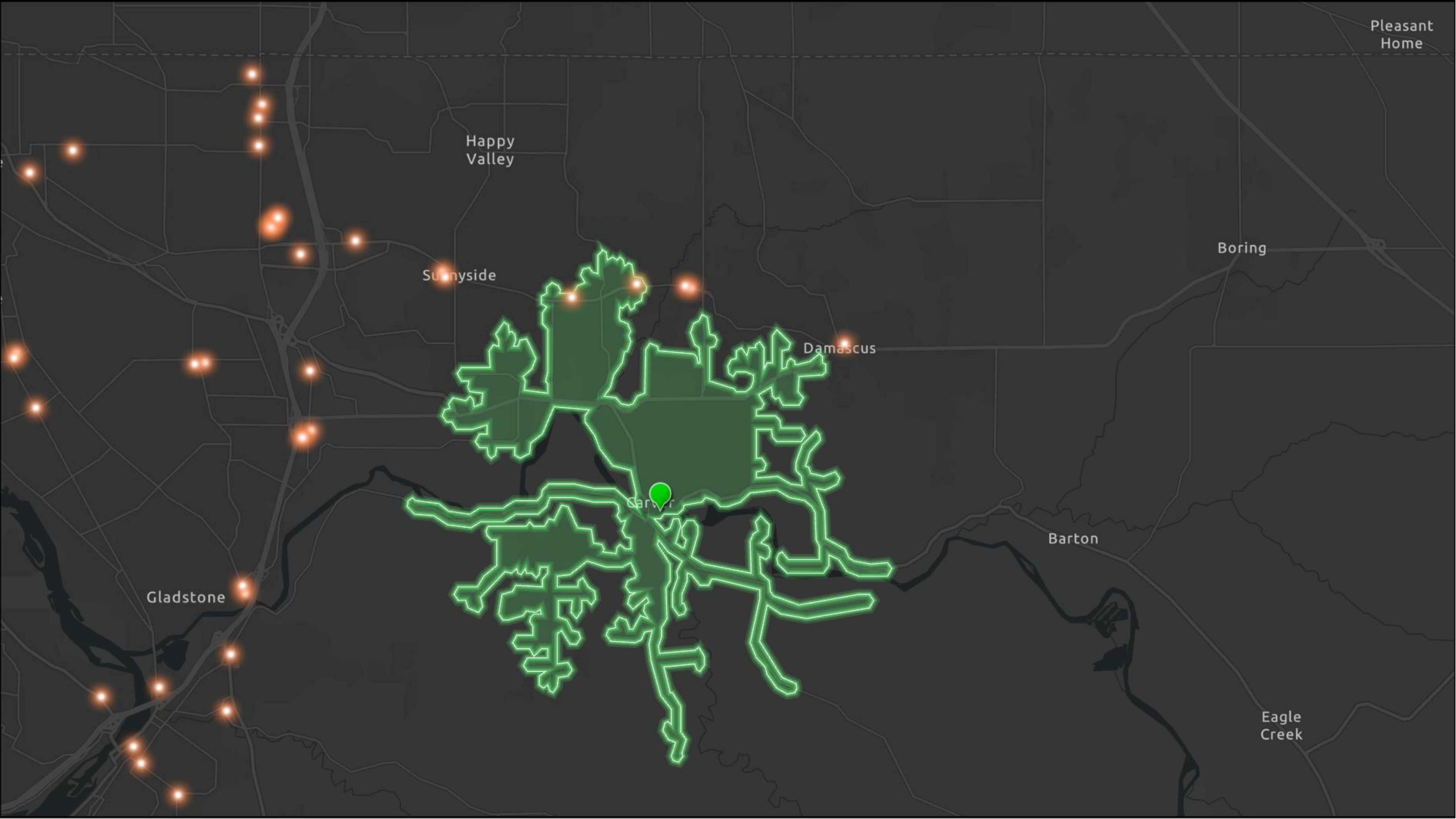
Pleasant Home
Happy Valley
Boring
Sunnyside
Damascus
Carver
Barton
Gladstone
Eagle Creek

Customer Centric

- Forecast Patronage by Geography for *Every* Location
- Factors Considered
  - Nearest Locations – currently using closest four
    - Competition
    - Cannibalization
  - Demographics – over 1,200 factors
  - Brand Loyalty or Aversion – if only one location, grouped together as ”INDEPENDENT”


Pleasant Home
Happy Valley
Boring
Sunnyside
Damascus
Carver
Barton
Gladstone
Eagle Creek


Pleasant
Home
Happy
Valley
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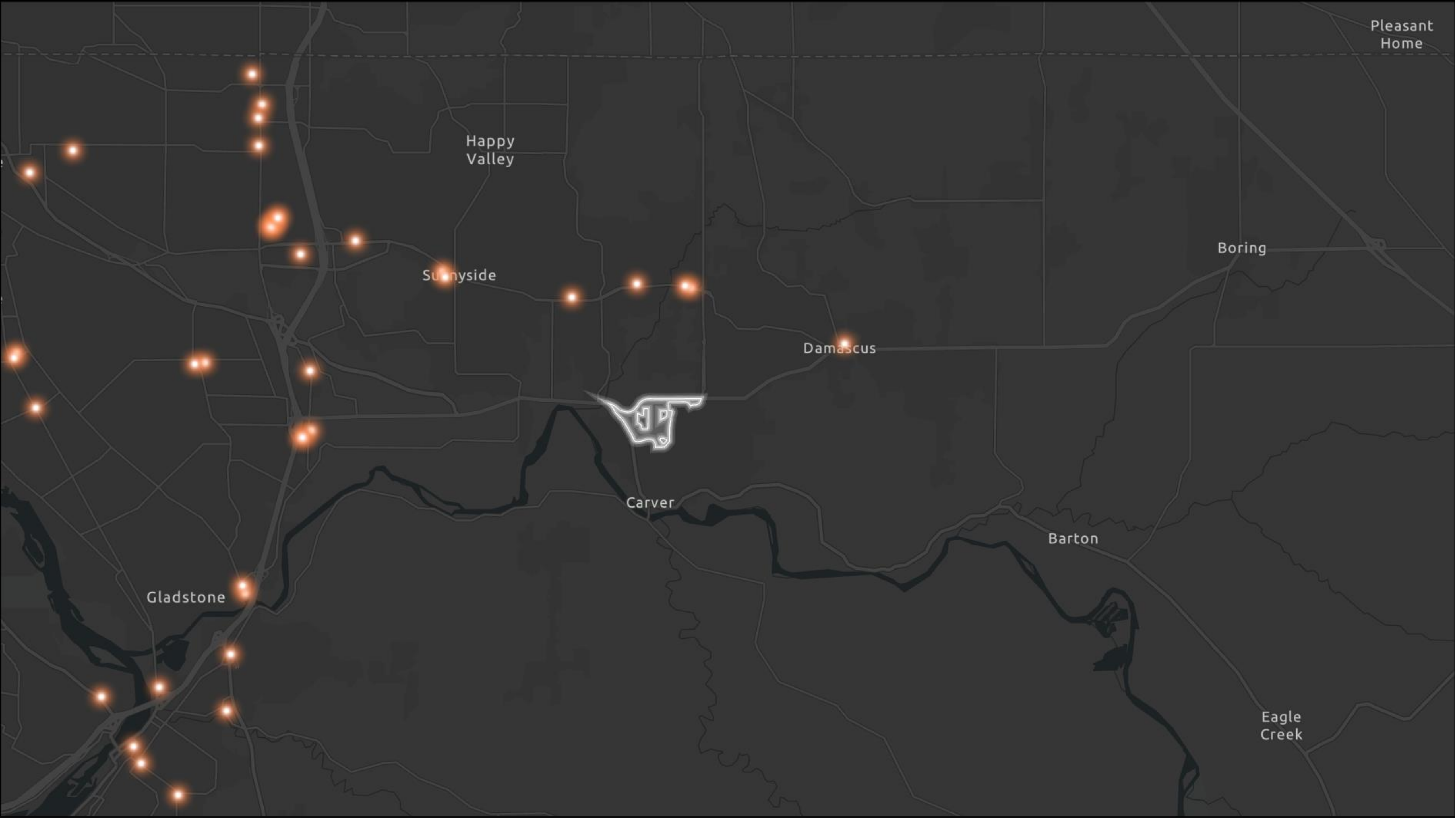
Carver
Barton
Gladstone
Eagle
Creek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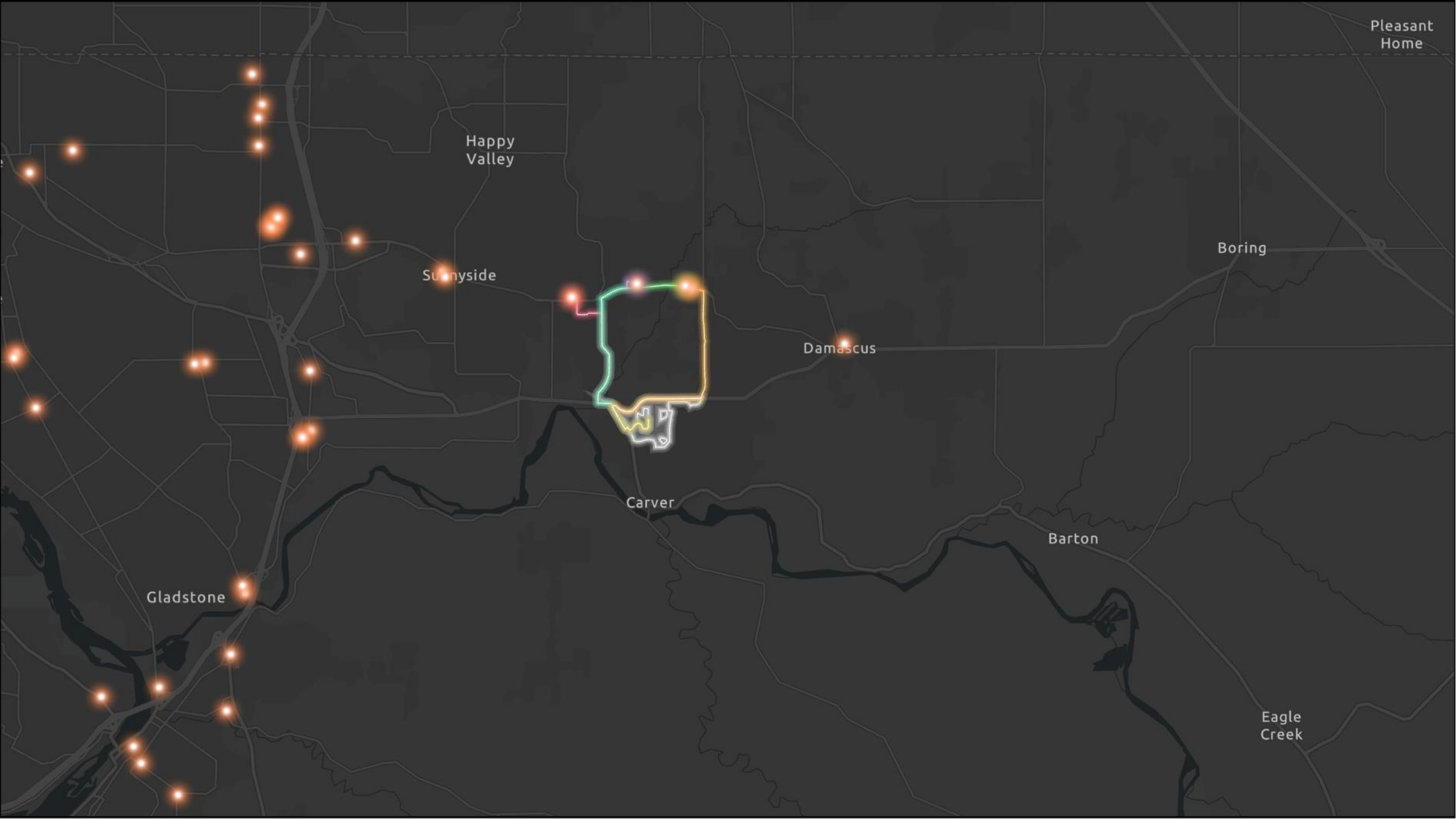
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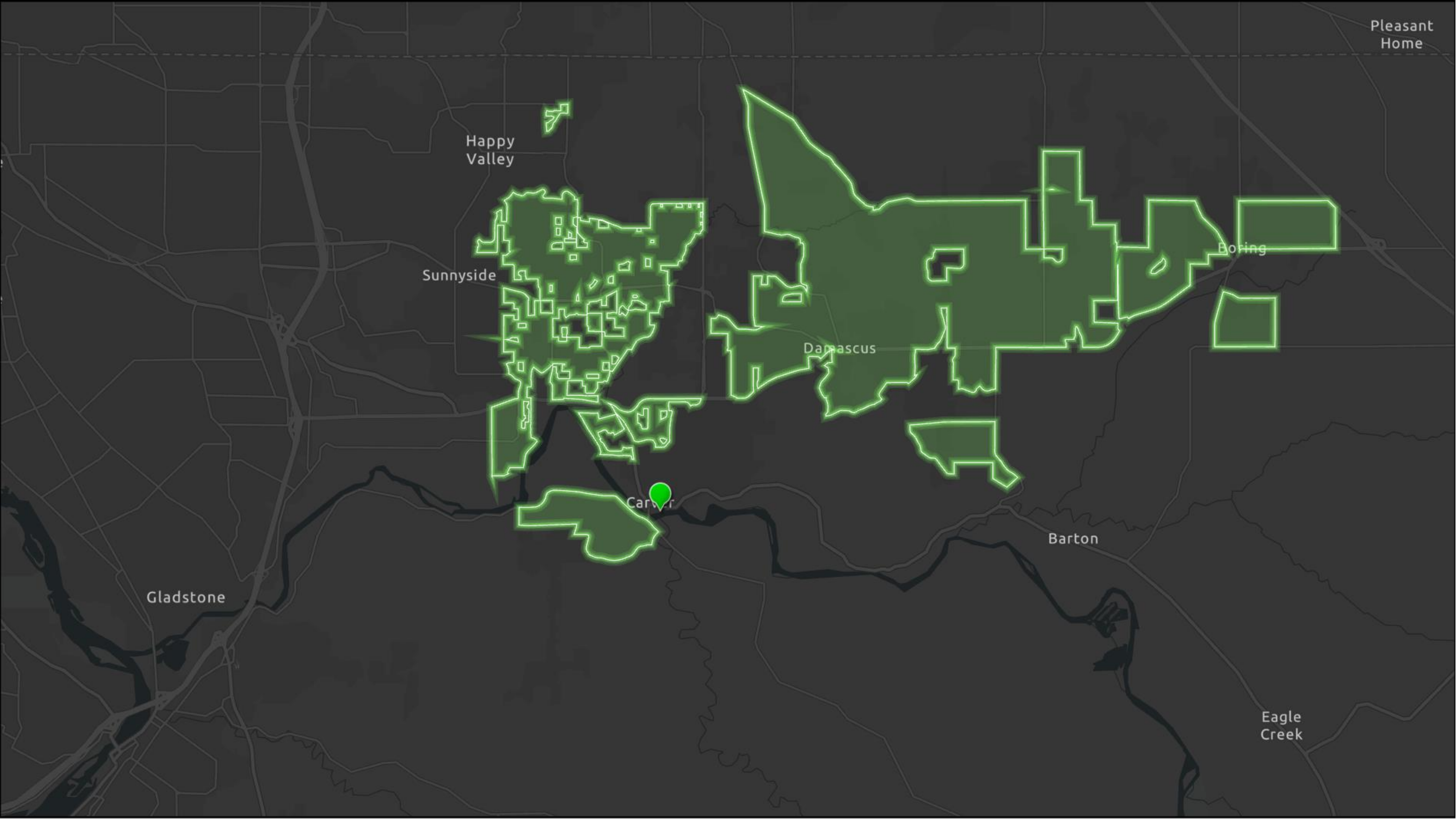
Pleasant Home
Happy Valley
Sunnyside
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Boring
Barton
Gladstone
Eagle Creek

LifeMode Group: Family Landscapes

Soccer Moms

4A

Households: 3,541,300

Average Household Size: 2.97

Median Age: 37.0

Median Household Income: $90,500

WHO ARE WE?

Soccer Moms is an affluent, family-oriented market with a country flavor. Residents are partial to new housing away from the bustle of the city but close enough to commute to professional job centers. Life in this suburban wilderness offsets the hectic pace of two working parents with growing children. They favor time-saving devices, like banking online or housekeeping services, and family-oriented pursuits.

OUR NEIGHBORHOOD

- *Soccer Moms* residents prefer the suburban periphery of metropolitan areas.
- Predominantly single family, homes are in newer neighborhoods, 34% built in the 1990s (Index 236), 31% built since 2000.
- Owner-occupied homes have high rate of mortgages at 68% (Index 164), and low rate vacancy at 4%.
- Median home value is $257,400.

SOCIOECONOMIC TRAITS

- Education: 40.5% college graduates; more than 72% with some college education.
- Low unemployment at 3.8%; high labor force participation rate at 71%; 2 out of 3 households include 2+ workers (Index 124).
- Connected, with a host of wireless devices from iPods to tablets—anything that enables convenience, like banking, paying bills, or even shopping online.
- Well insured and invested in a range of

Progress

- *Halo Forecasting*
  - Much Easier to Predict
  - Effect of Physical Location on Online Sales in Surrounding Area
- In-Store Binary Classification – Nonstandard Trade Areas

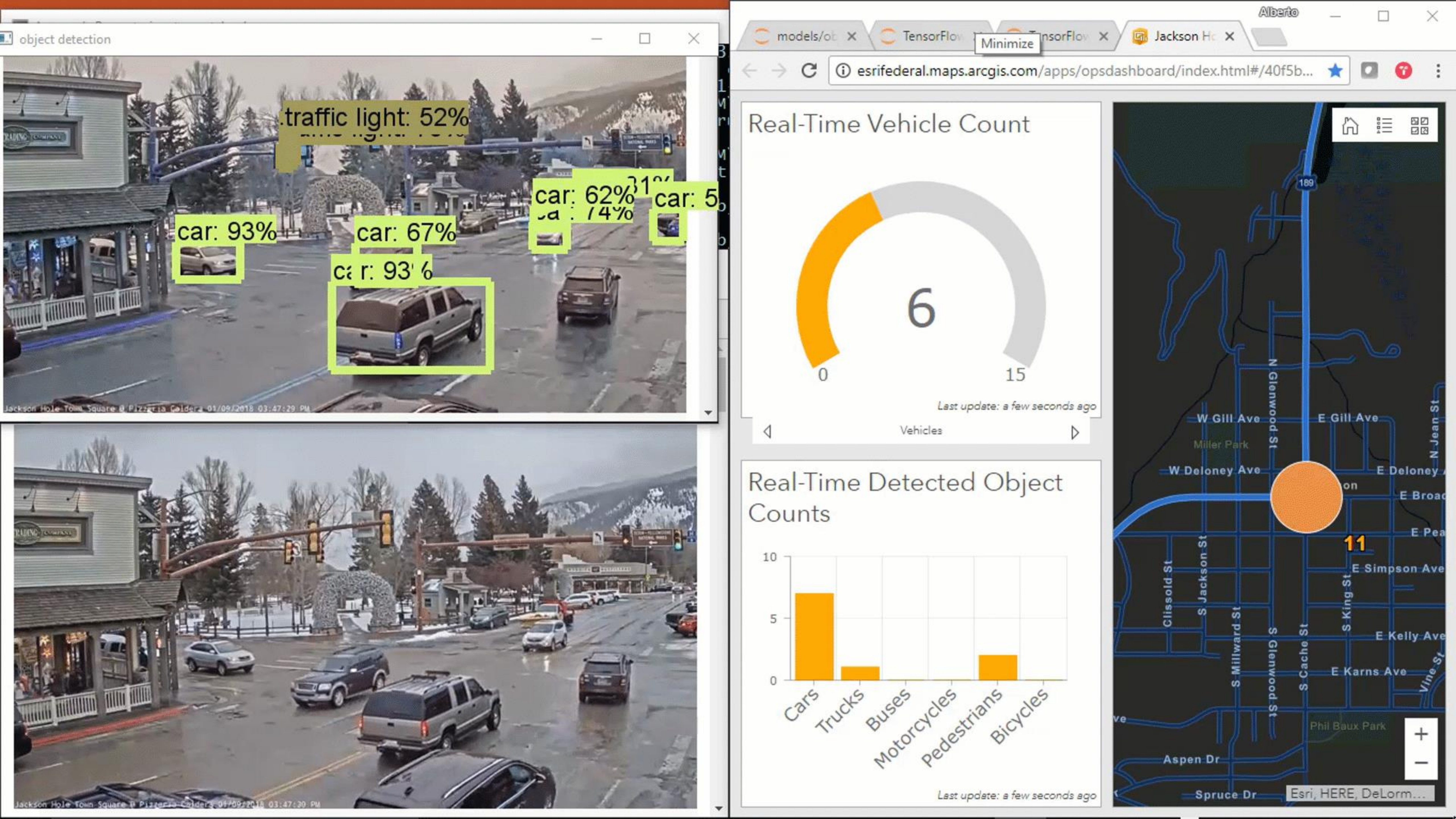
Next Steps

- Additional Factors
  - “On the Way to Work”
    - Right Side of the Road
  - Proximity to nearest competitor by destination
- Quantitative Prediction by Geography

Demo

Object Detection from CCTVs

Traffic Analysis & Anomaly Detection


object detection
traffic light: 52%
car: 62%
car: 5
car: 93%
car: 67%
car: 93%
models/ob
TensorFlow
Minimize
Jackson H
esrifederal.maps.arcgis.com/apps/opsdashboard/index.html#/40f5b...
Alberto
Real-Time Vehicle Count
6
0
15
Last update: a few seconds ago
Vehicles
Real-Time Detected Object Counts
10
5
0
Cars
Trucks
Buses
Motorcycles
Pedestrians
Bicycles
Last update: a few seconds ago
189
W Gill Ave
E Gill Ave
Miller Park
N Glenwood St
W Deloney Ave
E Deloney
E Broad
E Pea
11
E Simpson Ave
E Kelly Ave
E Karns Ave
Clissold St
S Jackson St
S Millward St
S Glenwood St
S Cache St
S King St
N Jean St
Phil Baux Park
Aspen Dr
Spruce Dr
Esri, HERE, DeLorm...

DDOT Traffic Camera Net ×

esrifederal.maps.arcgis.com/apps/opsdashboard/index.html#/d2fc32e1974540939e6a1bf9cac331c4

Activity Detection in Washington D.C. Machine Learning and ArcGIS

Constitution Ave @ 15th St
Last Detection: 5/28/2018, 2:43 PM

4 Cars Detected
8 Pedestrians Detected
0 Buses Detected
0 Trucks Detected

12th St @ Constitution Ave
Last Detection: 5/28/2018, 2:42 PM

1 Cars Detected
7 Pedestrians Detected
0 Buses Detected
0 Trucks Detected

Constitution Ave @ 17th St
Last Detection: 5/28/2018, 2:43 PM

3 Cars Detected
6 Pedestrians Detected
0 Buses Detected
0 Trucks Detected

15th St @ New York Ave & Pennsylvania Ave
Last Detection: 5/28/2018, 2:44 PM

6 Cars Detected
6 Pedestrians Detected
0 Buses Detected
1 Trucks Detected

Independence Ave @ 7th St
Last Detection: 5/28/2018, 2:41 PM

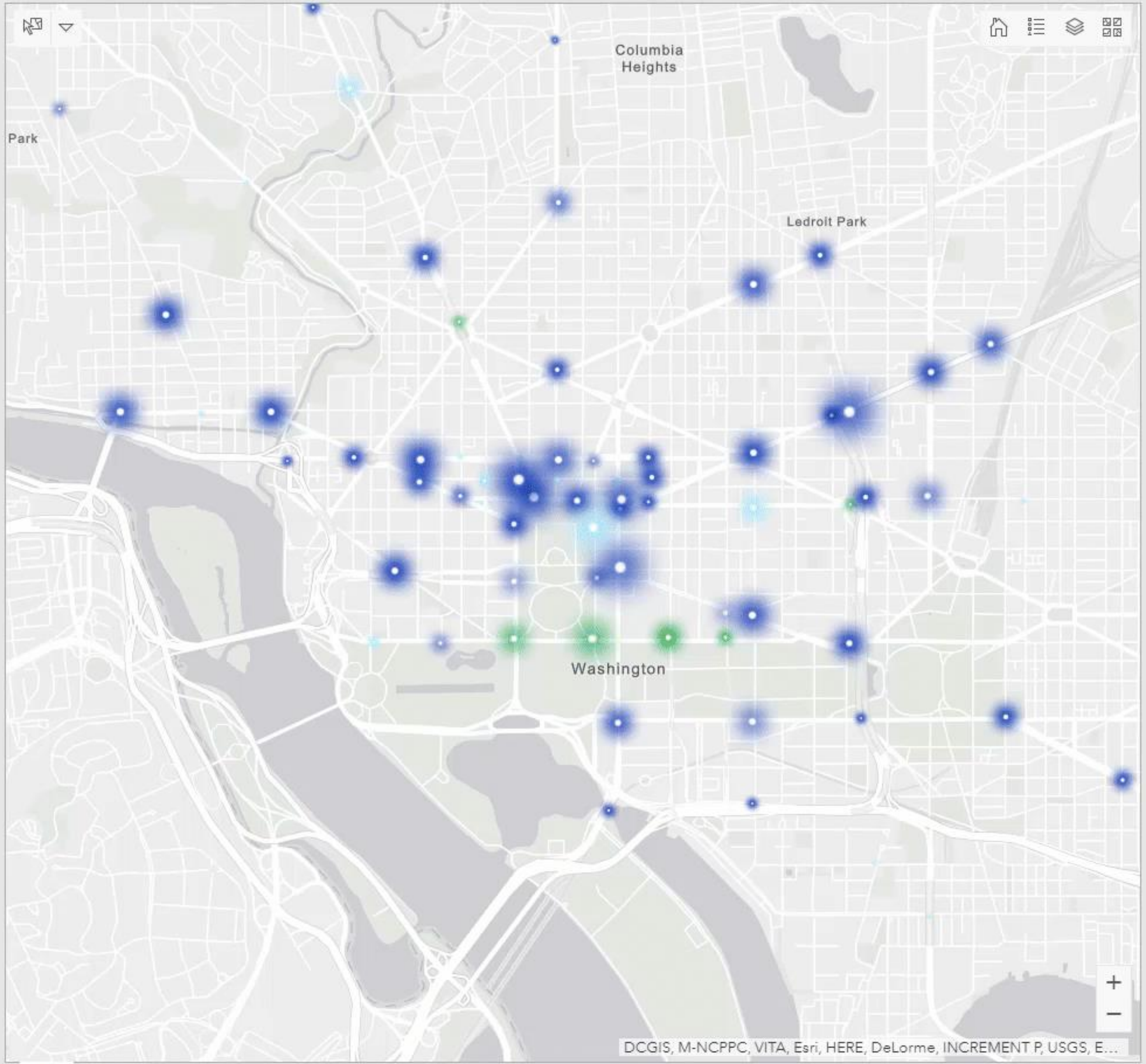
6 Cars Detected
4 Pedestrians Detected
0 Buses Detected
0 Trucks Detected

7th St @ H St
Last Detection: 5/28/2018, 2:42 PM

4 Cars Detected
4 Pedestrians Detected
0 Buses Detected
0 Trucks Detected

Last update: a few seconds ago

All | Cars | Pedestrians | Buses | Trucks | Time



Map | Details

Detected Cars
361
in 69 Scanned Locations
Last update: a few seconds ago

Detected Pedestrians
75
in 69 Scanned Locations
Last update: a few seconds ago

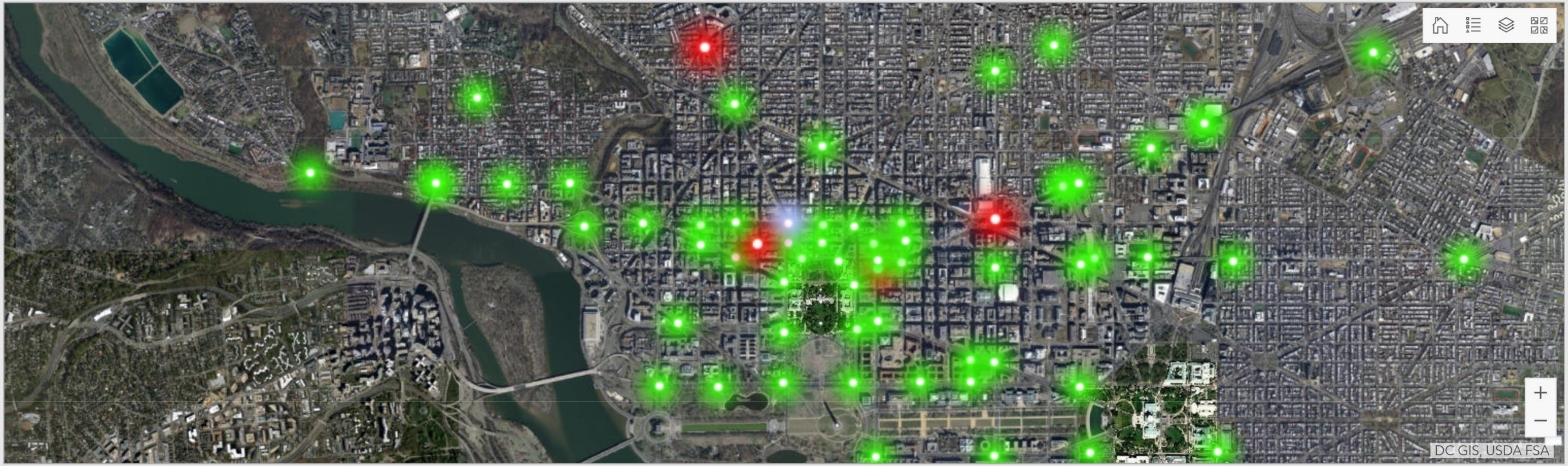
Detected Buses
4
in 69 Scanned Locations
Last update: a few seconds ago

Detected Trucks
13
in 69 Scanned Locations
Last update: a few seconds ago

Ops Dashboard | DDOT Traffic Ca

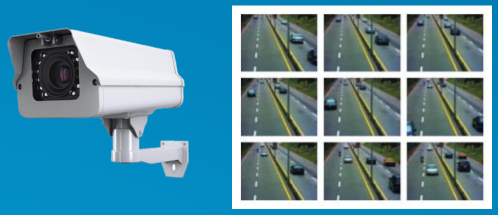
Not secure esrifederal.maps.arcgis.com/apps/opsdashboard/index.html#/4049c00f127b44b0a66dd77c9ea87171

Monitoring and Abnormal Activity Alerts - Washington D.C. Machine Learning and ArcGIS



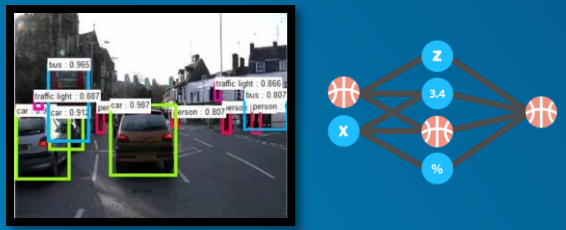
Car Trends Above Normal	Ped. Trends Above Normal	Bus Trends Above Normal	Truck Trends Above Normal
7	10	2	4
From 65 observed locations	From 65 observed locations	From 65 observed locations	From 65 observed locations
Last update: a few seconds ago	*Last update: a few seconds ago*	*Last update: a few seconds ago*	*Last update: a few seconds ago*

How it works



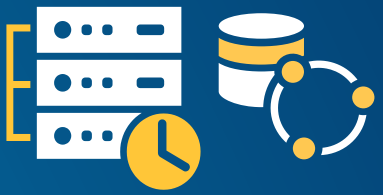
1. Decoding Feeds to Frames

Using OpenCV or available APIs



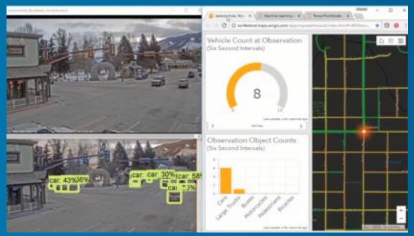
2. Deep Learning Detects Objects

A trained DL Model detects Objects/Incidents of Interest



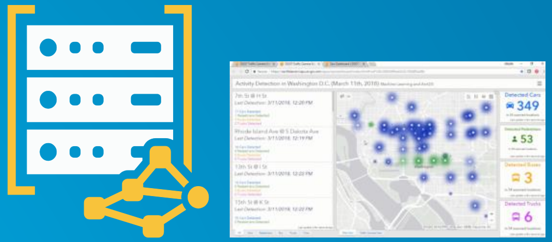
3. Real-Time Processing & Storage

Detected Objects passed as Streams to GeoEvent for Real-time Processing, BDS used for Storage & Replay



4. Visualization & Real-time Analytics

Operations Dashboard is used to Visualize Real-Time Traffic Patterns & Analytics



4. Historical Analysis & Anomaly Detection

Analyze Patterns back in time w/ Replay capability, and Spot Anomalies. Leverage GeoAnalytics for Faster Processing

Demo

Object Tracking & Path Tracing


9: On Lot
7: Parked
54: On Lot
41: On Lot
11: Parked
21: Parked
5: Parked
8: On Lot
6: Parked
Parked
17: Stopped
16: Stopped
12: Stopped
23: Stopped
13: Stopped
14: Stopped
69: Stopped
33: Stopped
36: Stopped
10: Stopped
60: Stopped
66: Stopped
37: Stopped
55: Stopped
2: Stopped
3: Stopped
24: Stopped
1: Stopped
28: Stopped
4: Stopped
19: Stopped
52: Stopped
38: Stopped
57: Stopped
71: Stopped
47: Stopped
30: Stopped
26: Stopped
81: 74: Stopped

Workflow

S1

Build and run vehicle detection model

S1

Reference model detections against designated areas (parking lot, drive-thru etc.)

* Very early model prototype video

S1

Vehicle ID	Time	Location	On Property	Type
1	2007-04-05T14:30	Parking	0:10:23	Sedan
2	2007-04-05T14:30	Entrance	0:00:01	Other
3	2007-04-05T14:30	Drive-thru	0:04	Pickup
1	2007-04-05T14:31	Parking	0:10:24	Sedan
2	2007-04-05T14:31	Drive-thru	0:00:02	Other
3	2007-04-05T14:31	Drive-thru	0:04:01	PIckup
1	2007-04-05T14:32	Parking	0:10:25	Sedan
2	2007-04-05T14:32	Drive-thru	0:00:03	Other
3	2007-04-05T14:32	Window	0:04:02	Pickup

Build vector dataset of vehicle movements

S2

Build model to detect key metrics (like drive-offs) and place results into dashboard

* example based on similar project

Static & Dynamic Heatmaps

Road Feature Detection & Geotagging

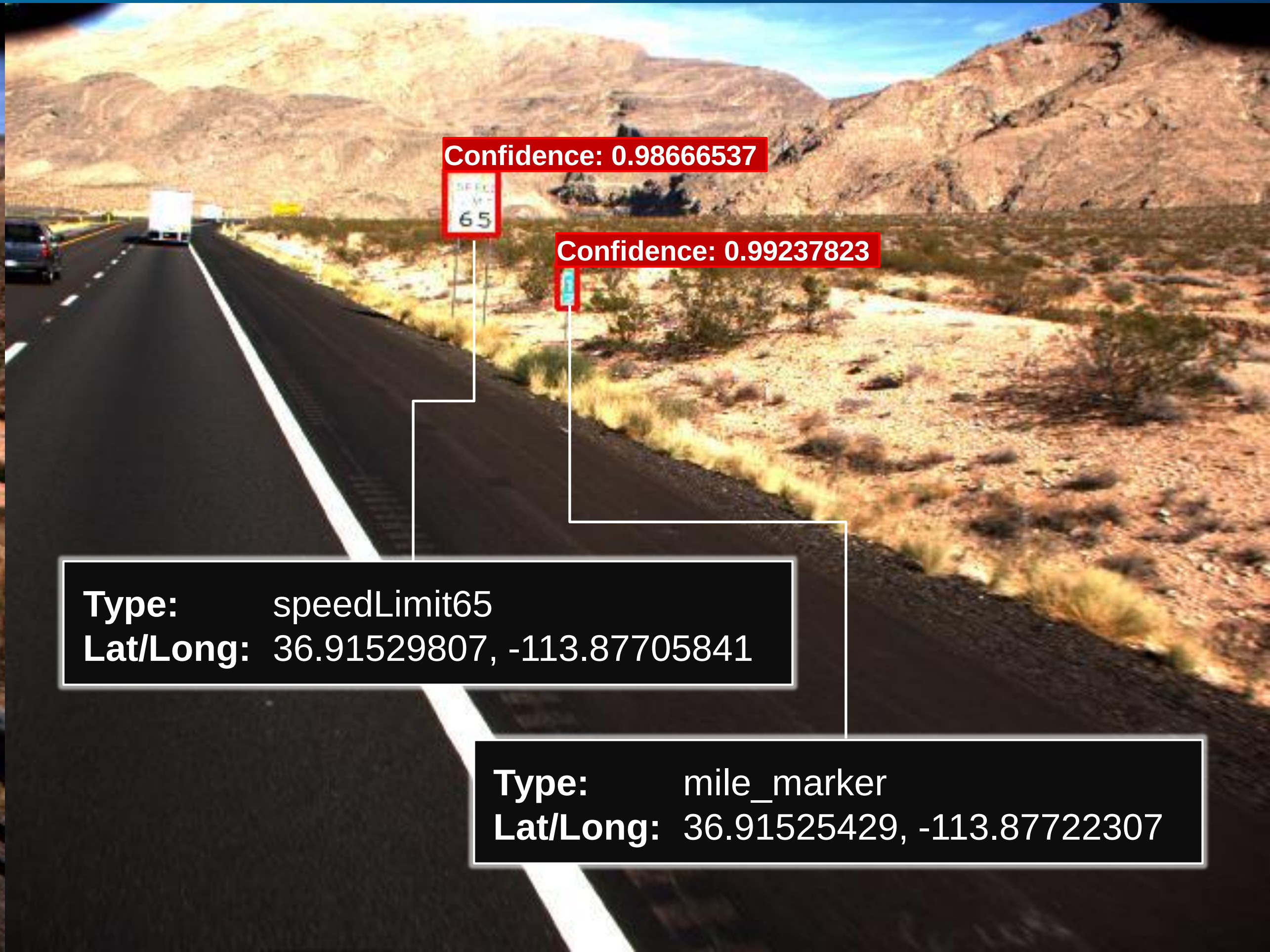
Detecting Road Signs, Detecting Text, Inferring Sign Location

Road Features

- Road signs
- Guard rails
- Curbs
- Road cracks
- Pavement markings
- Other road features

Detection Sample

https://arcg.is/0O1veL



Project Architecture / Tech Stack

Demo

Road Cracks Detection

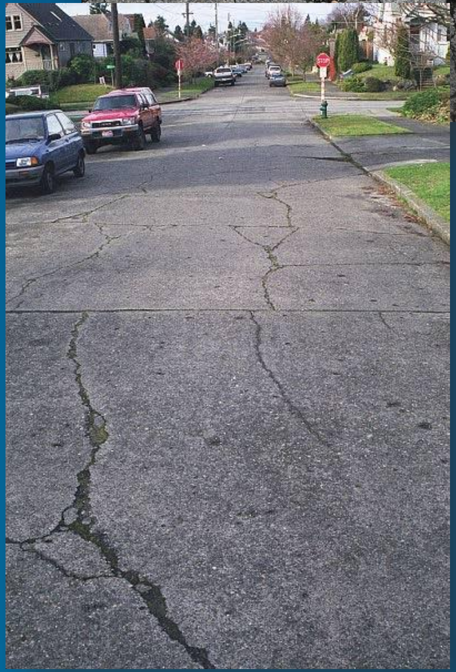
Discover and Quantify Road Cracks, Prioritize Work Orders, & Improve Operations

Training a Deep Learning model to detect different types of Road Cracks

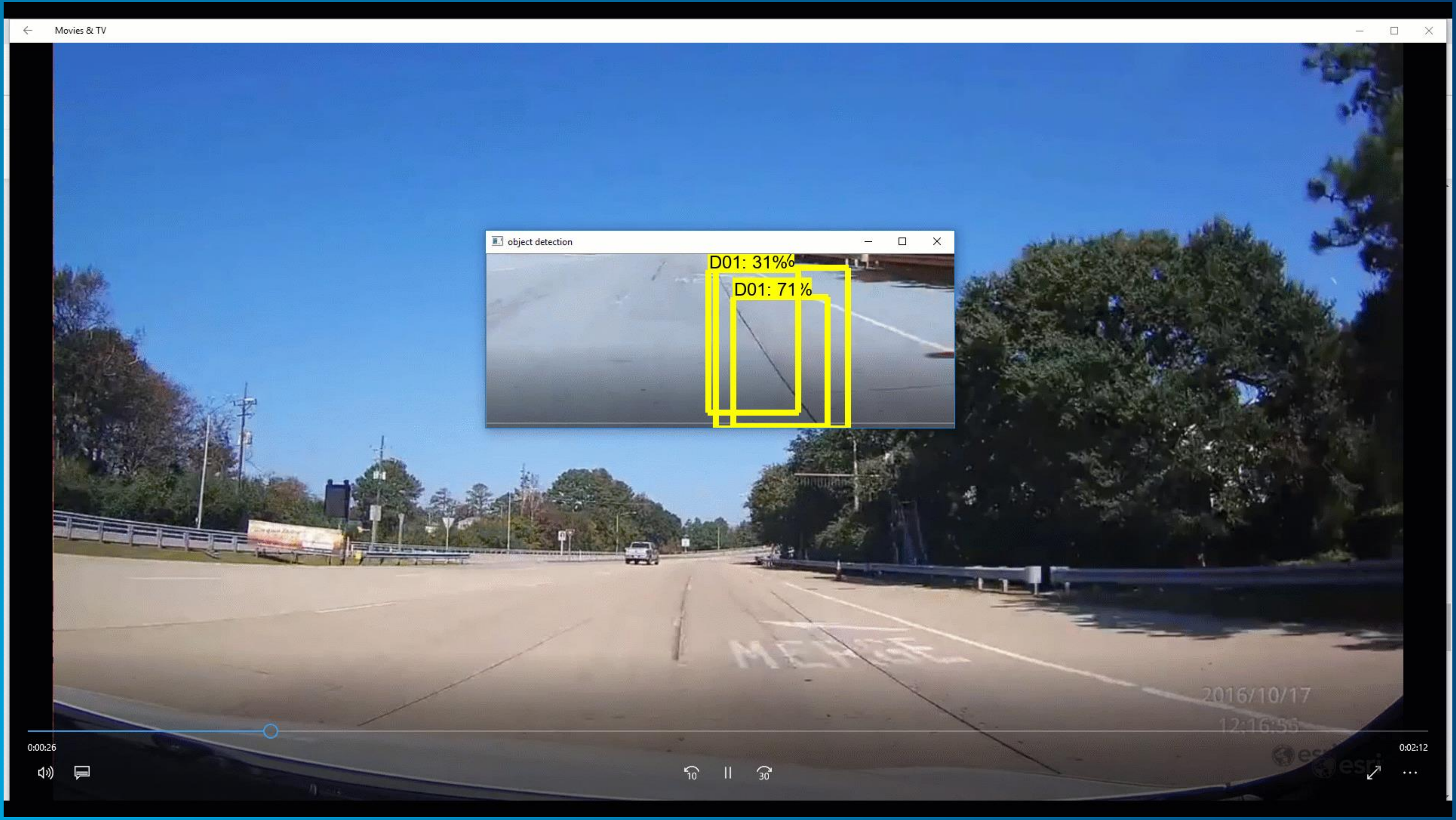
Table 1: Road damage types in our dataset and their definitions.

Damage Type			Detail	Class Name
Crack	Linear Crack	Longitudinal	Wheel mark part	D00
			Construction joint part	D01
		Lateral	Equal interval	D10
			Construction joint part	D11
	Alligator Crack		Partial pavement, overall pavement	D20
Other Corruption			Rutting, bump, pothole, separation	D40
			Cross walk blur	D43
			White line blur	D44

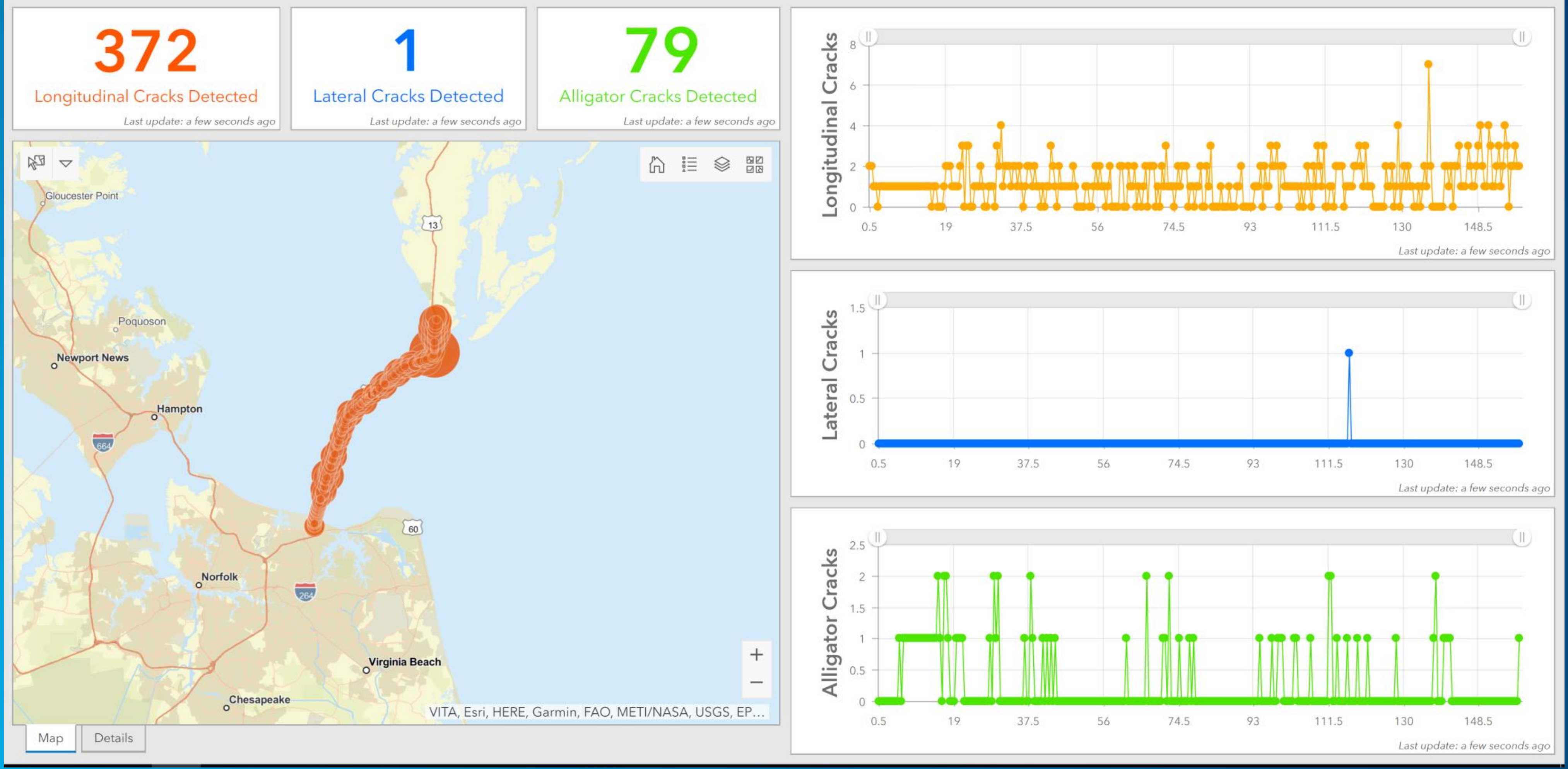
Source: Road Maintenance and Repair Guidebook 2013 JRA (2013) in Japan.
Note: In reality, rutting, bump, pothole, and separation are different types of road damage, but it was difficult to distinguish these four types using images. Therefore, they were classified as one class, viz., D40.



Real-Time Detection of Cracks (Video)



Visualizing Areas with Highest amount of Cracks



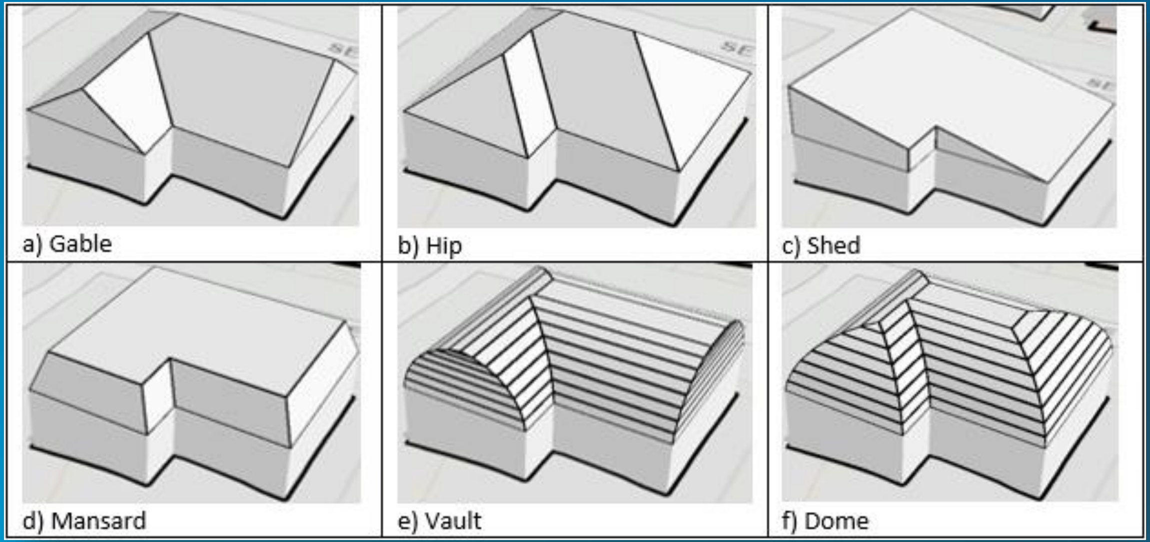
Telecom Advanced Analytics

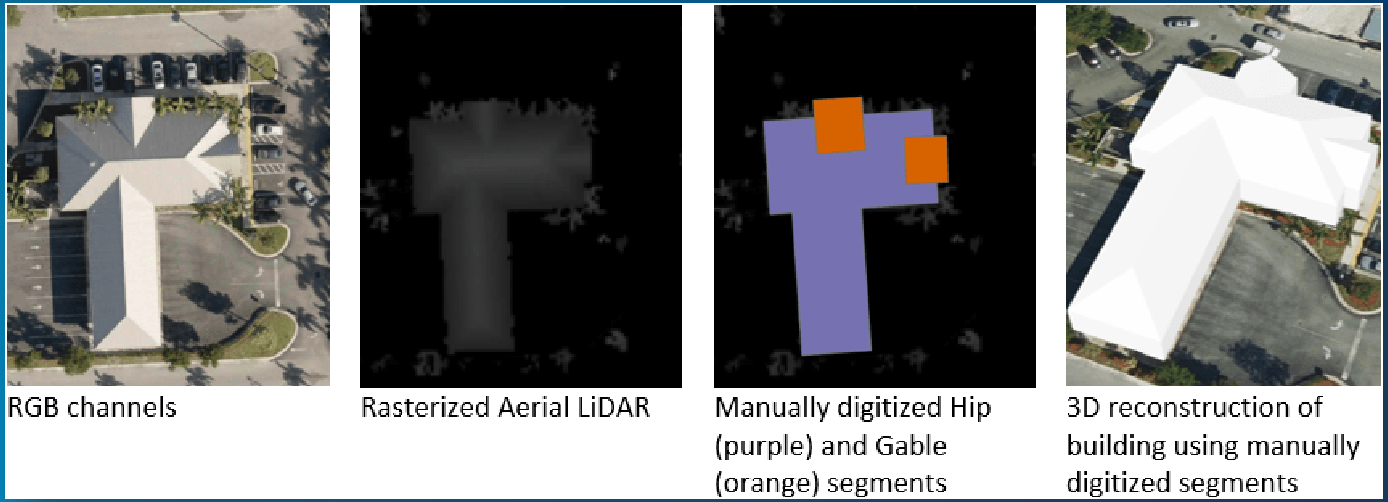
Clustering & Deep Learning to find Top Areas to Deploy Network Resoruces

3D Reconstruction from LiDar

Detect Buildings, Roof Type, Height, and More!

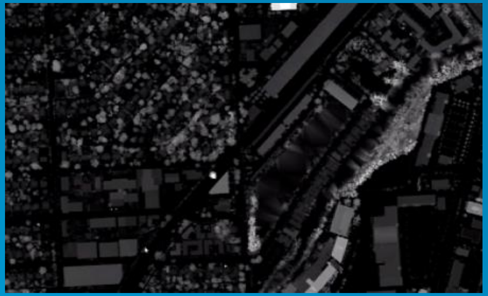
Complex Roof Types



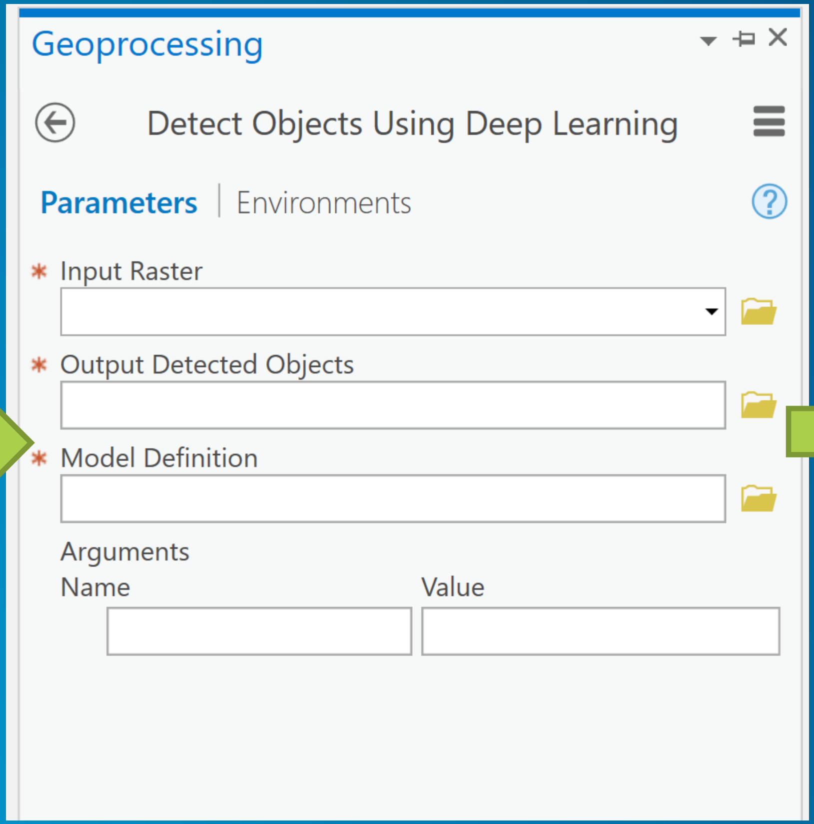


Inference through Detect Objects tool in Pro 2.3

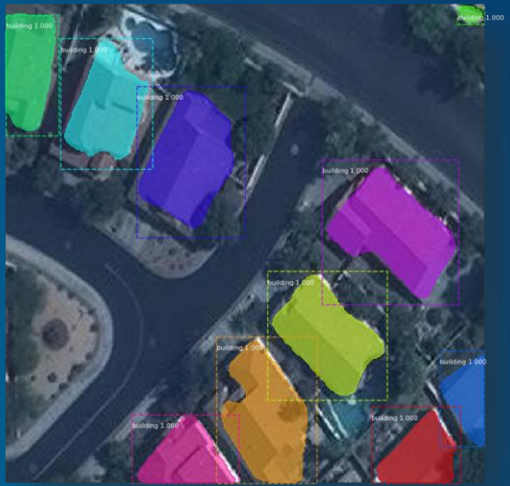
Aerial Lidar



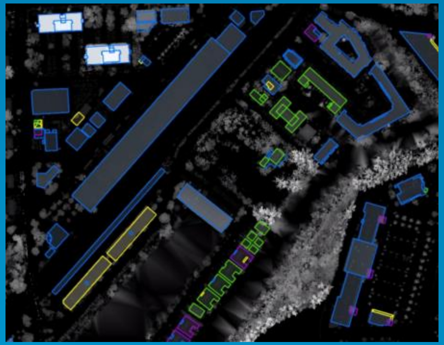
Trained Model



Output:
Building Footprints & Roof Type



Workflow

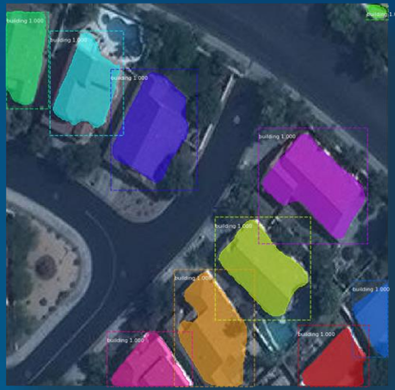


Labelled Lidar or Aerial Imagery

Export Training Data for Deep Learning tool

Train Model using Mask RCNN

Raster Function Runs Model w/ New Imagery



Output: Detected Buildings
+ Roof Type, Footage, Height and # Floors (if we have Lidar)

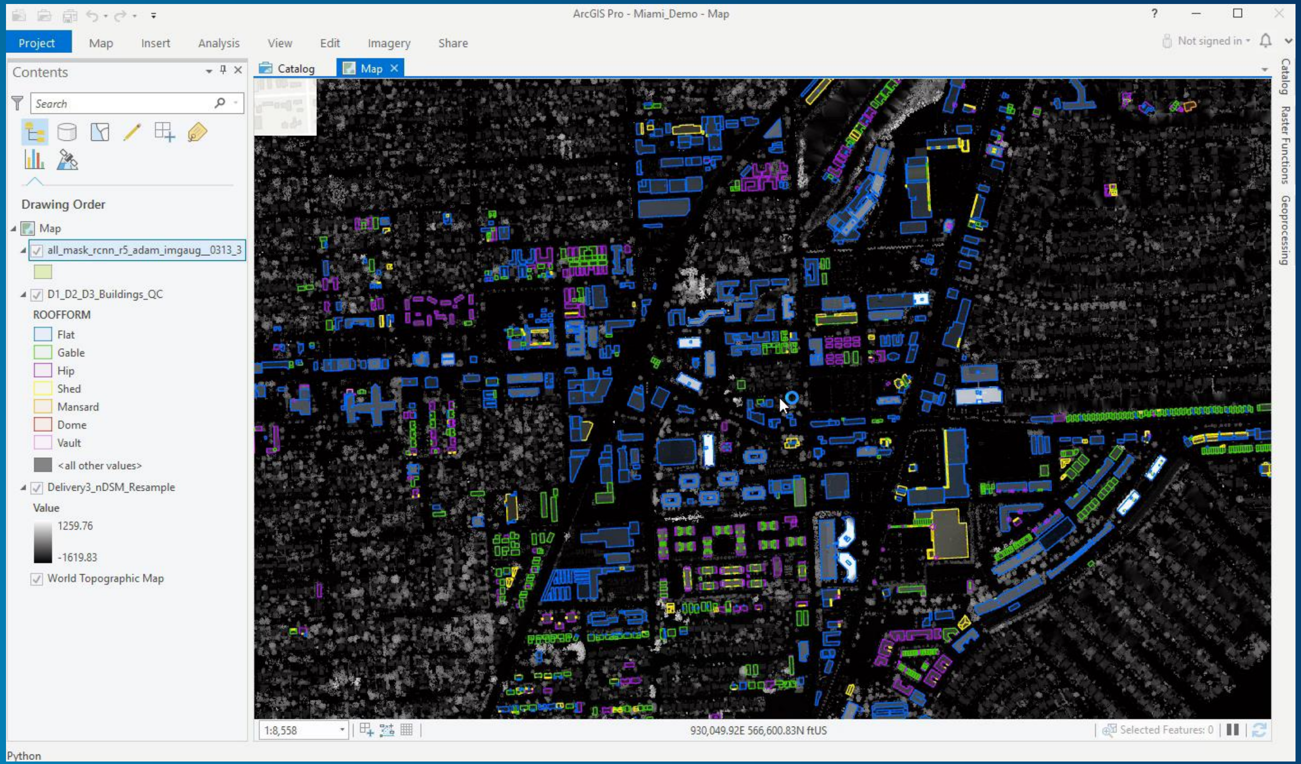
Regularize Building Footprint (GP)

Buildings Converted to 3D

Automated Buildings Detection using Deep Learning

1. Labelled Lidar or Aerial Imagery

2. Detected Buildings



3. 3D Buildings w/ Roof Types

Demo

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THE SCIENCE OF WHERE