

RESEARCH REVIEW 2019

Video Summarization and Search

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The goal of video summarization and search is to assist analysts by

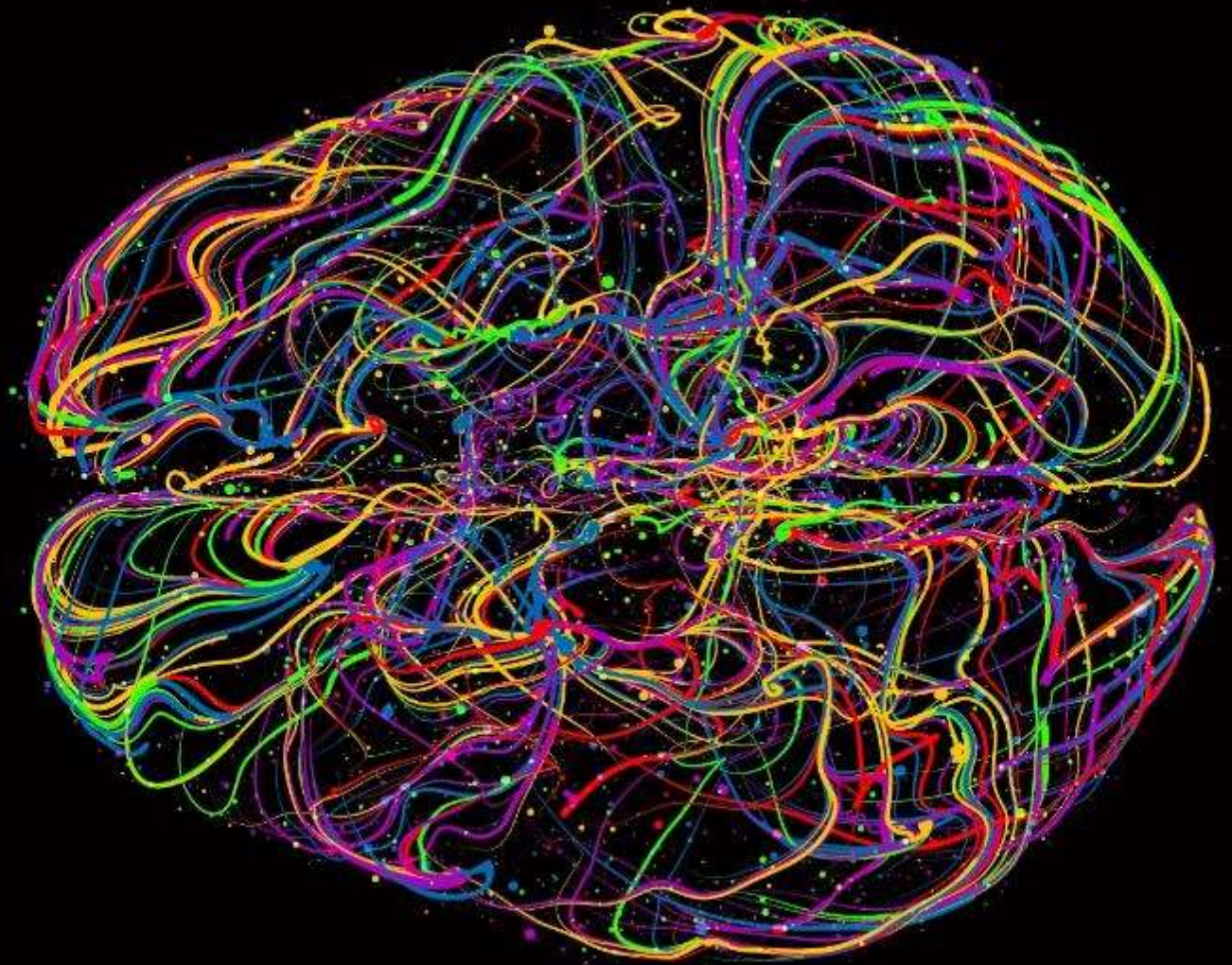
- increasing volume of data that can be analyzed
- providing insights into patterns of life that would be difficult to otherwise identify

Three core technologies to make video summarization and search possible in the DoD problem space:

- Domain adaptation to address limitations of *training data* to improve object identification
- Geometry-aware visual surveillance to improve *tracking* of moving objects
- Pattern-of-life analysis to *characterize* relationships and behaviors of those objects

Video Summarization and Search:
Domain Adaptation

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Dr. Rachel Brower-Sinning



Object Identification in the DoD Problem Space



Solving machine learning problems starts with having sufficient data

- DoD datasets have limitations:
 - May not reflect future mission environments
 - Often unlabeled
 - Few examples of the target object
- DoD datasets and public datasets are not good analogs:
 - Semantic differences
 - Perspective
 - Scale
 - Types of objects
 - Density of objects
 - Texture differences
 - Non-standard environments
 - Diverse objects

Image reference: *Vision Meets Drones: A Challenge*. Zhu, Pengfei; Wen, Longyin; Bian, Xiao; Haibin, Ling; and Hu, Qinghua. arXiv. 2018

Our Approach: Domain Adaptation

Use existing datasets to train a classifier for our new target domain

- Semantic information in the metadata of images is used to create a matched subset
 - Currently we only match on object density
- To match texture, we use CycleGAN
 - CycleGAN uses machine learning to transform a set of images to appear more similar to another set of images

Train Mask R-CNN classifiers using a combination of

- Original dataset
- Small set of target data
- Adapted dataset

Influence of Training Data on Object Identification

Poor Object Identification



- Using pretrained MSCOCO weights
- Fails to classify many objects, likely due to training on ground-level perspective
- Major problems with misclassifying building components as vehicles/personnel

Improved Object Identification

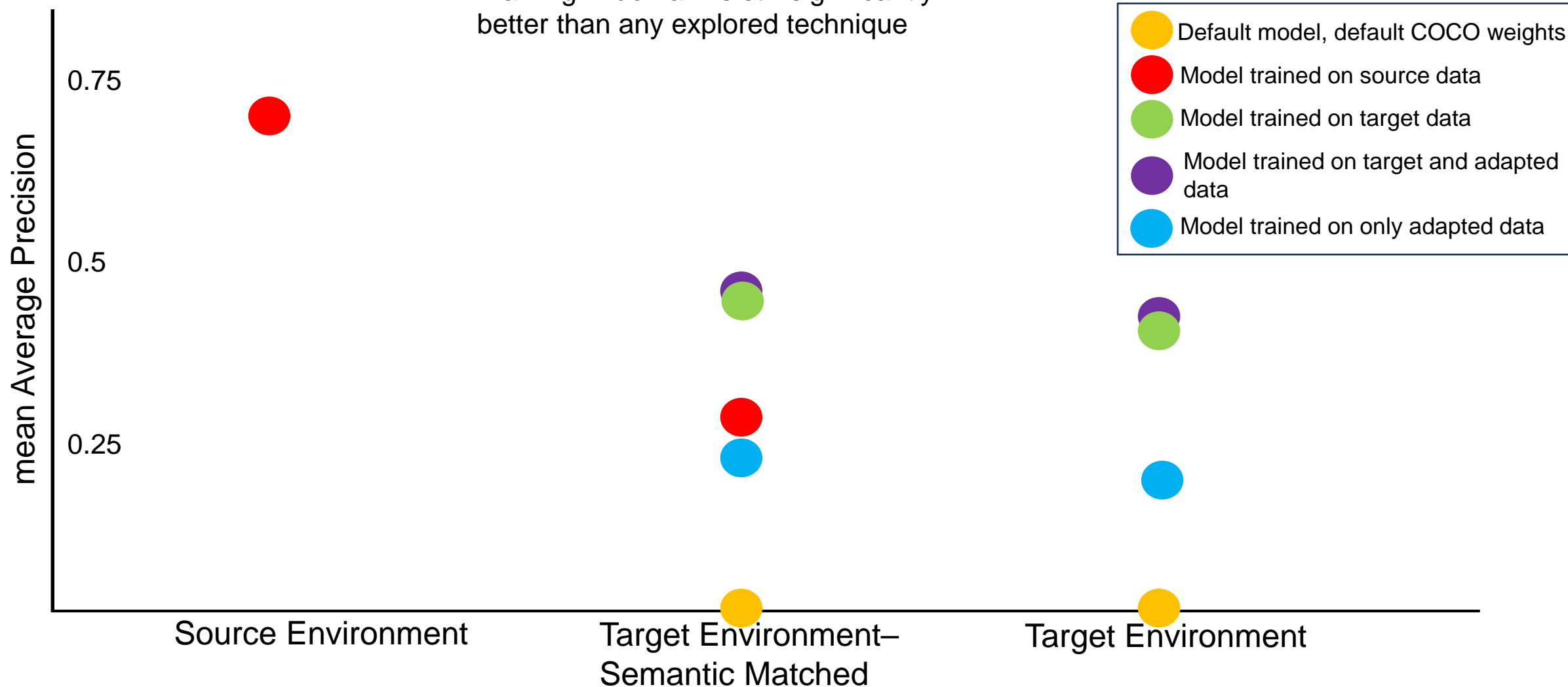


- Using a combination of adapted and target domain datasets for training
- Significantly more objects are correctly classified
- Minor problems with misclassifying building components as vehicles/personnel

Image reference: *Vision Meets Drones: A Challenge*. Zhu, Pengfei; Wen, Longyin; Bian, Xiao; Haibin, Ling; and Hu, Qinghua. arXiv. 2018

Results

- Poor performance with a pretrained model
- Incremental performance increases with adapted data
- Training in domain is still significantly better than any explored technique



Future Directions

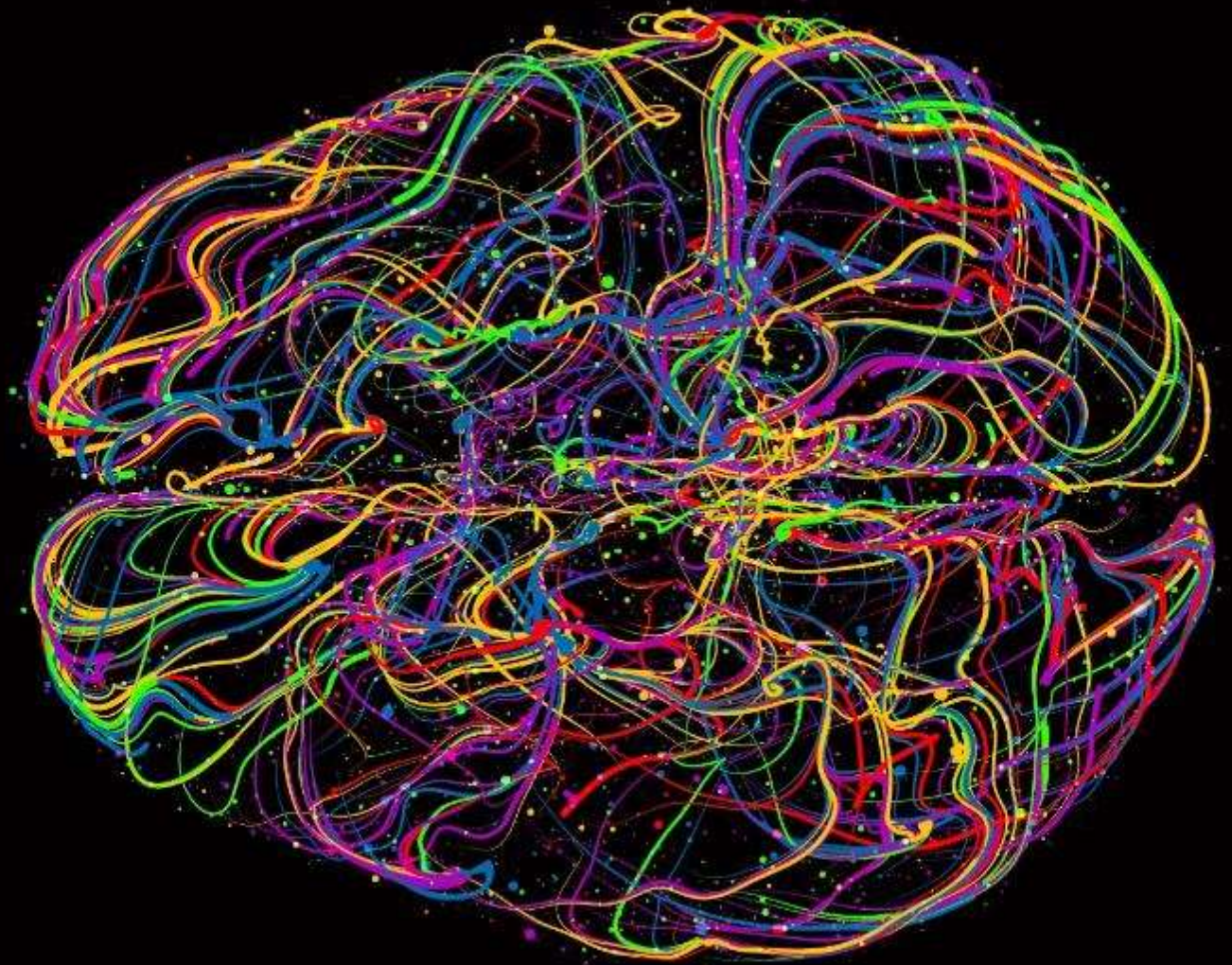
Current results may be improved by additional matching of target and source image semantics:

- We match only on object density. We will be extending this to include other image features such as perspective and scale.
- After improved semantic matching, can addition of supplemental data increase performance or act as a substitute for target data?

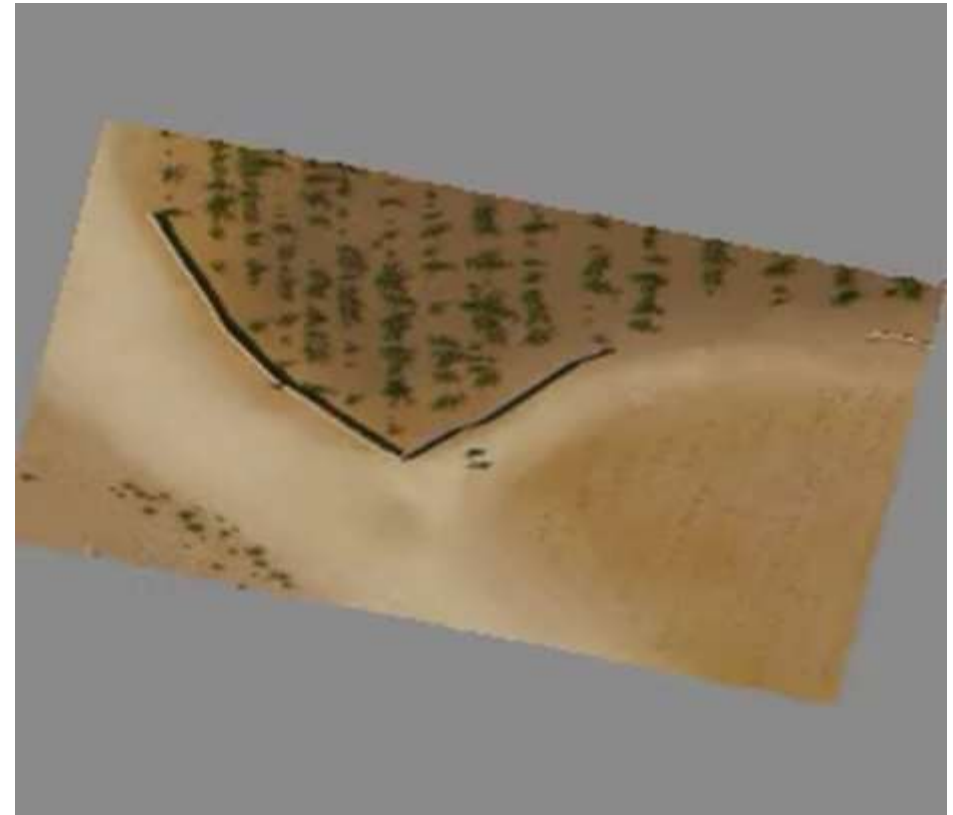
Exploration of feature statistics indicated that automatic determination of object identification quality may be possible.

Video Summarization and Search:
**Geometry-Aware Visual
Surveillance**

Adam Harley
Professor Katerina Fragkiadaki



Egomotion-Stabilized Perception



Using the relative camera motion information from the drone

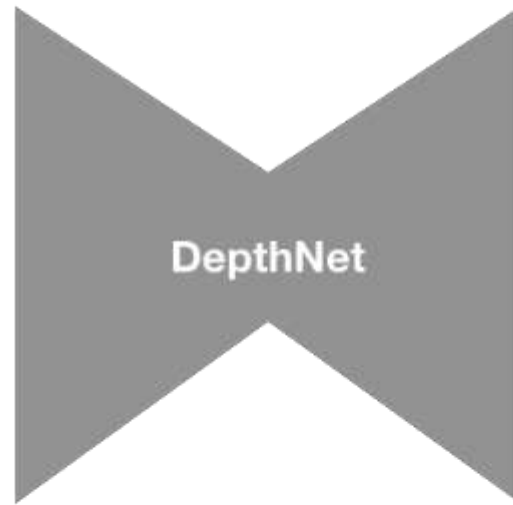
- Learn a depth map of the scene
- Use this depth map to project pixels from a virtual overhead camera

Learning Depth from Telemetry

Estimate of
ground plane,
from camera pose



RGB image



Metric per-pixel depth



Tracking Model: Template Matching in the Stabilized Map

Frame t



Encoder-Decoder

Featuremap 0

shared weights

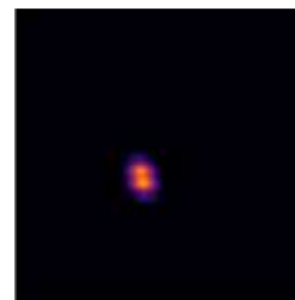
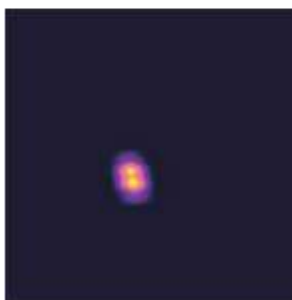
Frame t+1



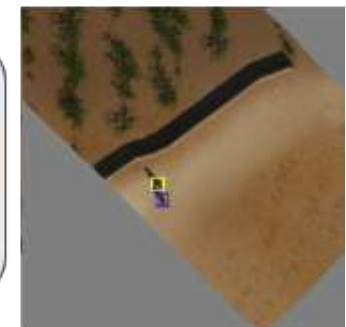
Encoder-Decoder

Featuremap 1

Cross correl.

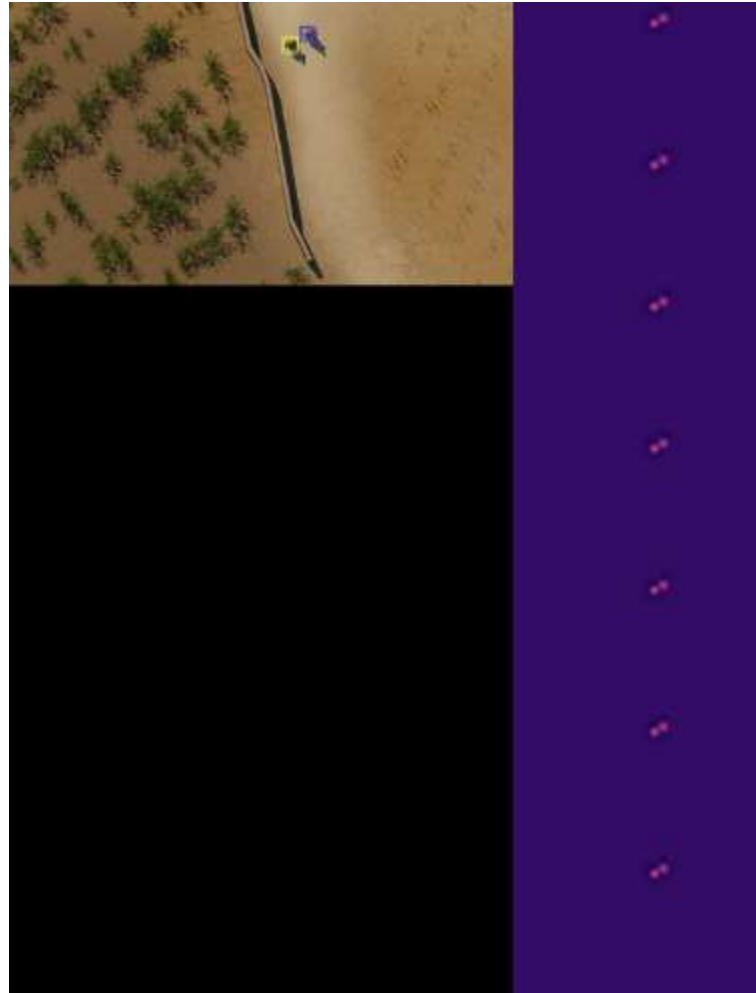


greedy matching



Tracking Visualization

Unstabilized



Stabilized

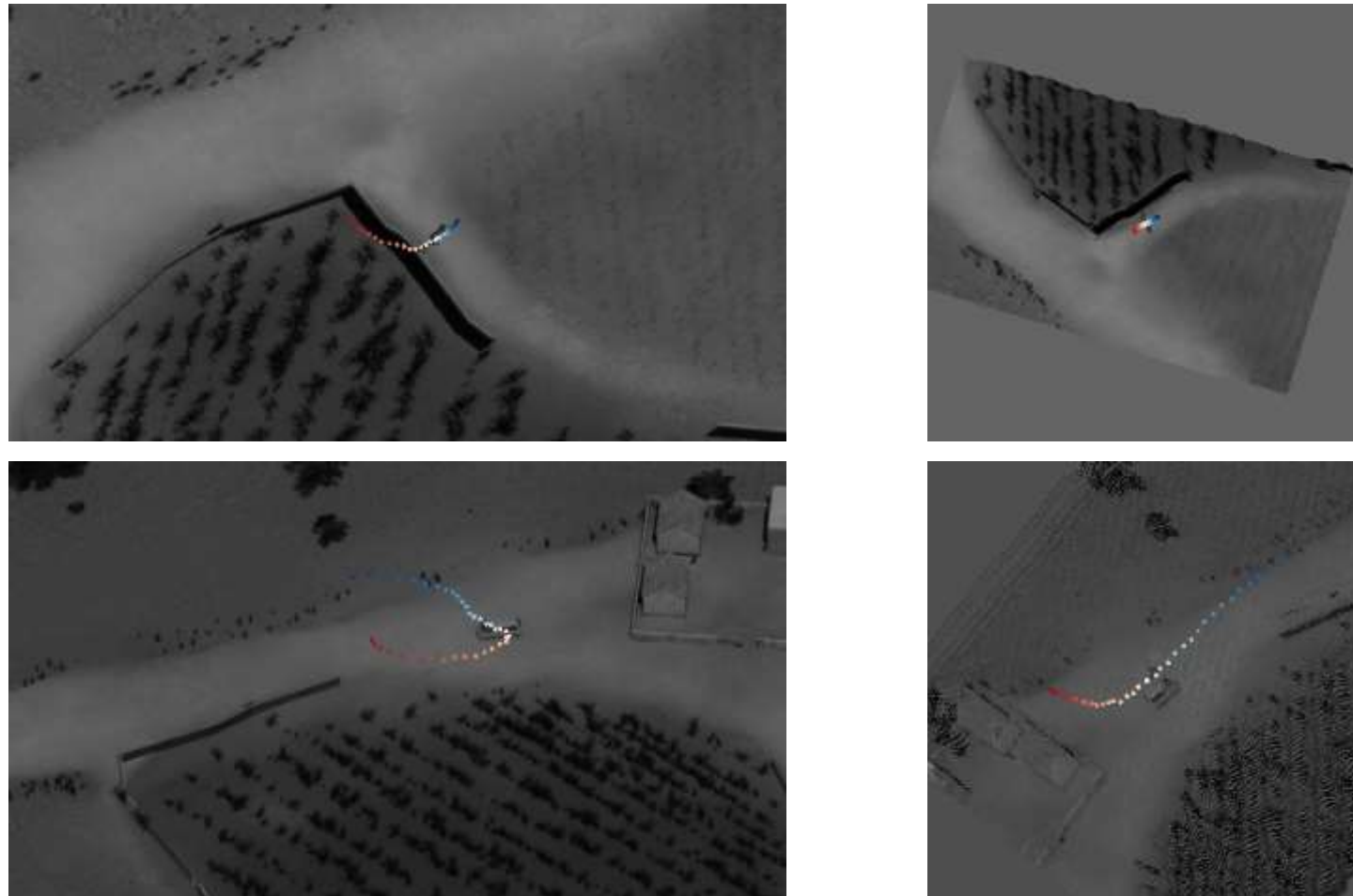


Stabilization Helps

Method	Mean IOU
Unstabilized	0.5185
Unstabilized+DataAug	0.5567
Unstabilized+DataAug+Hungarian	0.6240
Unstabilized+DataAug+Hungarian+VelocityPrior	0.6428
Stabilized+DataAug+Hungarian+VelocityPrior	0.7958

Stabilization gives >10% boost

Trajectory Forecasting is Possible Only in Stabilized Space



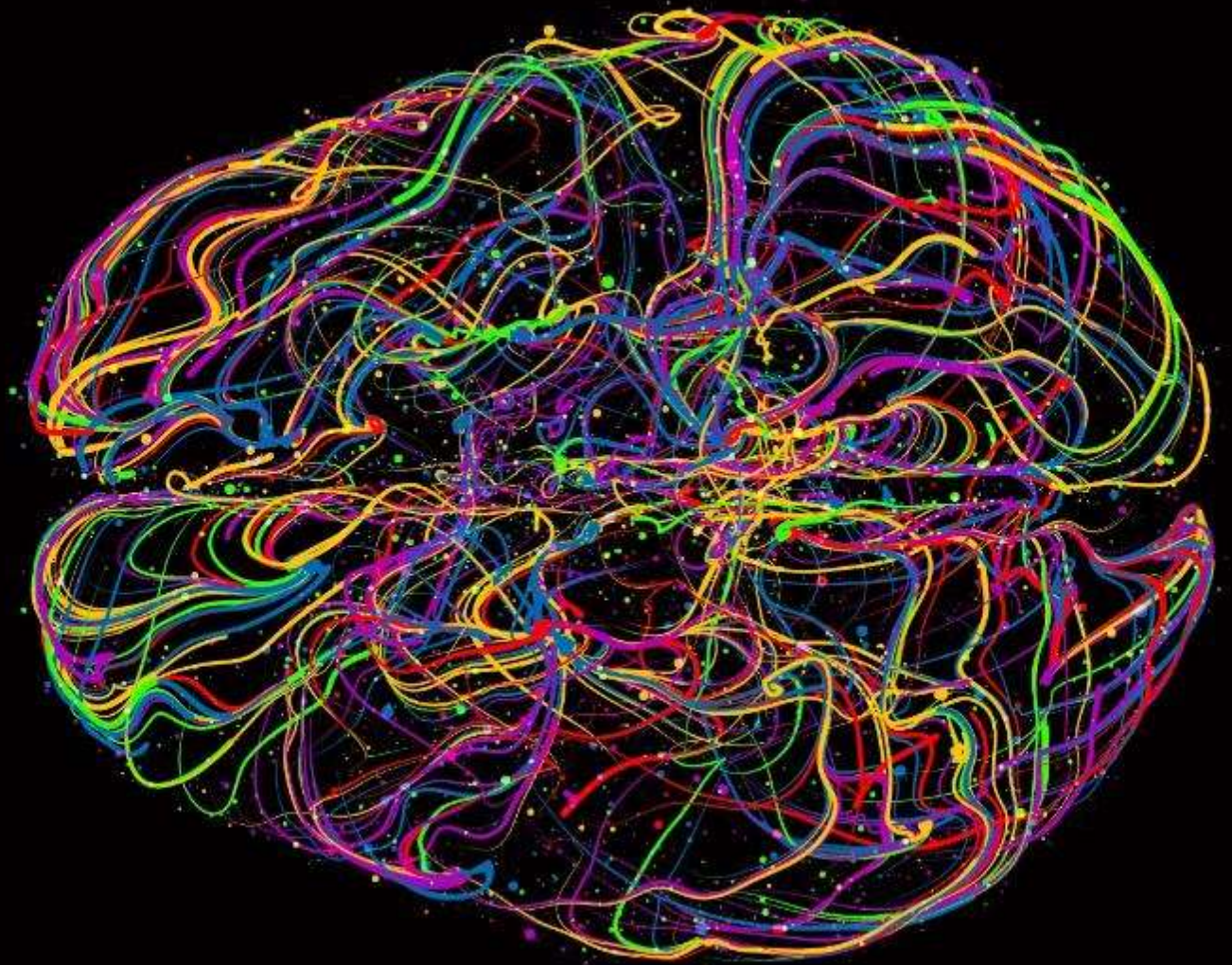
Past

Present

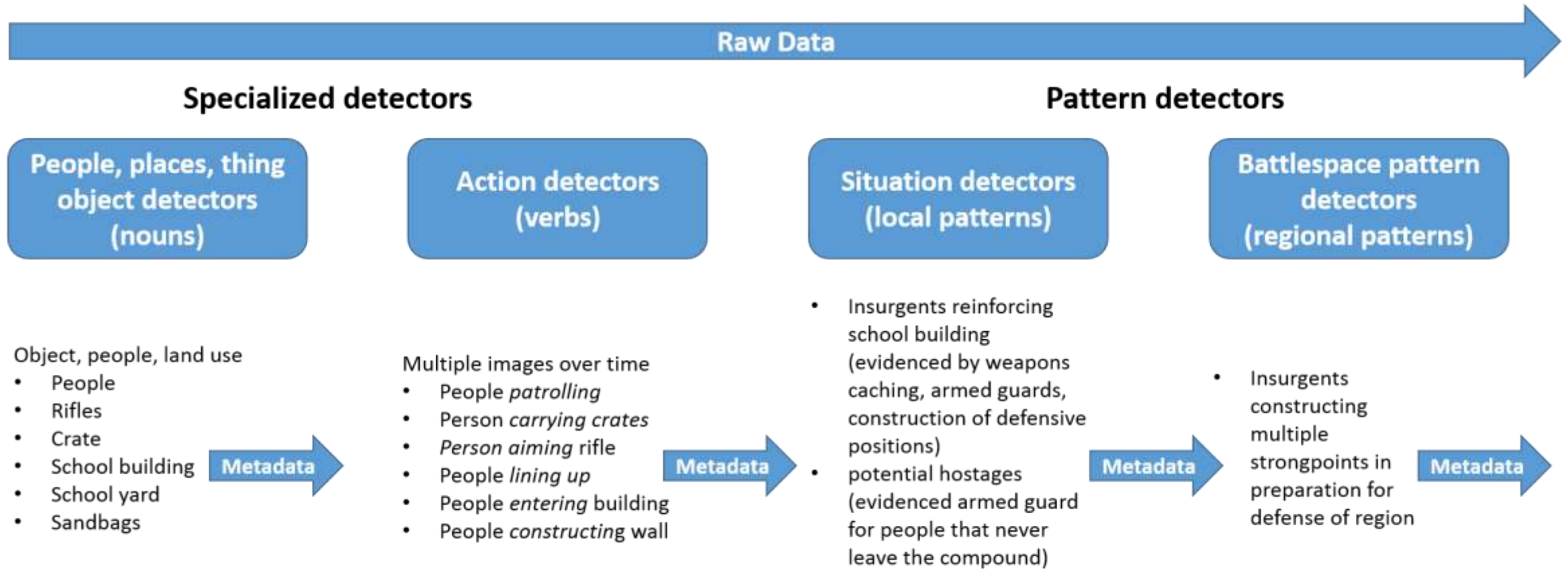
Future

Video Summarization and Search:
Pattern-of-Life Analysis

Dr. Jeffery Hansen



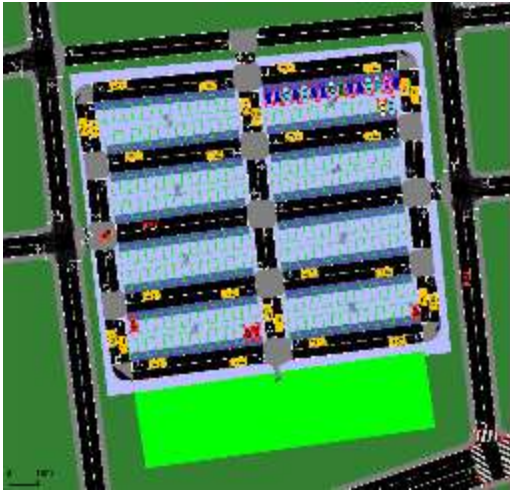
Pattern-of-Life Analysis: Hierarchy of Detectors



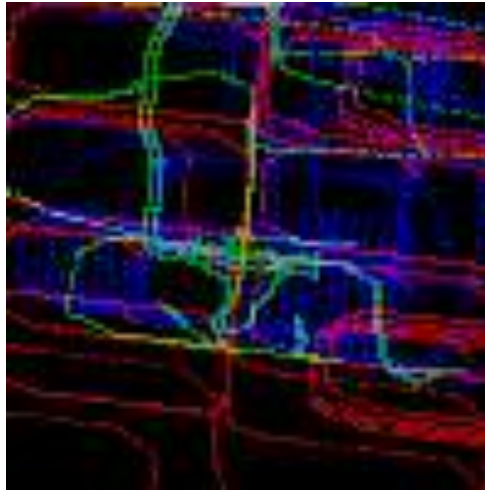
Metadata: Minimally *who-what-when-where*, but augmented by post-detector analysis producing additional metadata

Pattern-of-Life Analysis: “Mall Parking Lot” Experiment

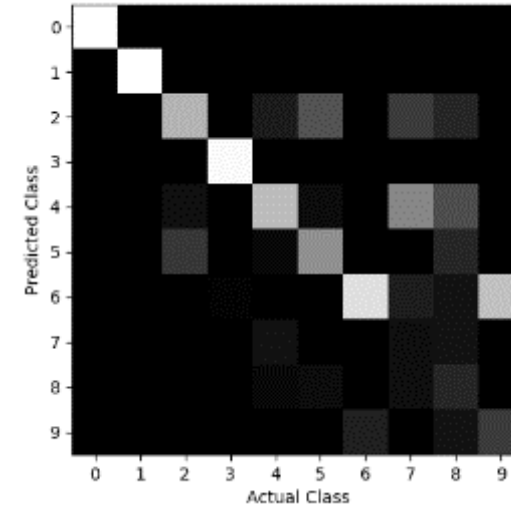
We have conducted initial experiments on a “Mall Parking Lot” example for using machine learning techniques to analyze patterns of life.



SUMO traffic simulator used to simulate vehicles and pedestrians including customers, employees, carpoolers, and “drug dealers.”

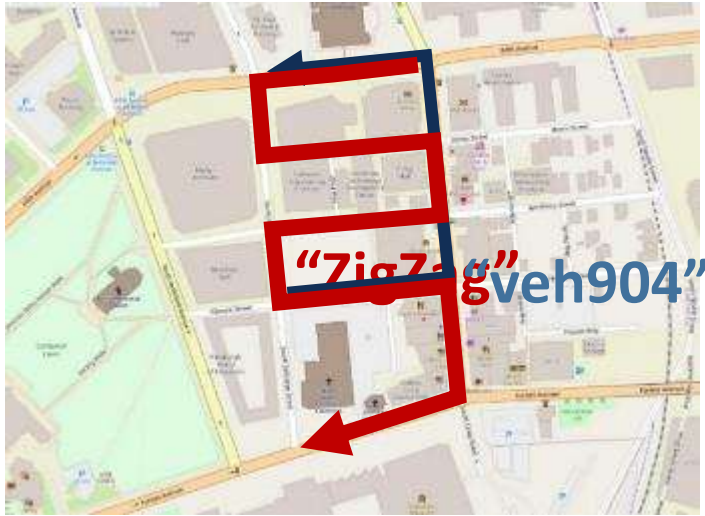


For each track, an ego-centric patch is generated characterizing the movement of that vehicle or pedestrian and its relationship to other vehicles, pedestrians, and fixed reference points.

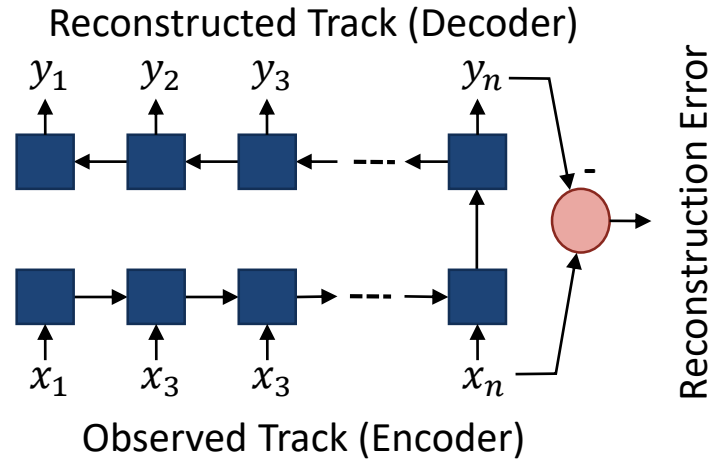


Using a CNN classifier, we correctly identified the track type with 86% accuracy out of 10 possible classes.

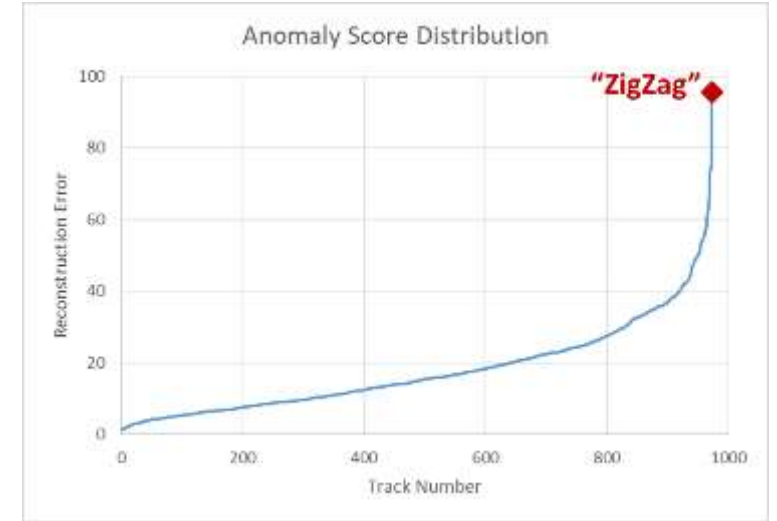
Pattern-of-Life Analysis: Anomaly Detection



In another experiment, we simulated 950 “best-path” vehicle trips into which we injected one with an unusual “zig zag” path.



We used an LSTM autoencoder to learn typical track behavior and compute a “reconstruction error” representing the degree to which a track is considered “unusual.”



Of the 950 tracks, our injected “zig-zag” track consistently scored in the top 5 in terms of reconstruction error demonstrating the ability to identify anomalous behaviors.

Increased training data for improved object identification,
improved object tracking,
and characterization of patterns of life

Enables the analyst to effectively **process more data and identify more complex patterns**