

Summarizing and Searching Video: Patterns-of-Life Analysis

Introduction

Over the past five years, image recognition has improved dramatically thanks to new deep learning architectures. Coupled with systems such as the Navy's Minotaur System, it is now possible to start with a raw video feed and generate geo-located tracks of multiple human and non-human actors in real time. These tracks are themselves a new type of data which can be subjected to further downstream processing called Pattern-of-Life Analysis.

Pattern-of-Life (PoL) Analysis

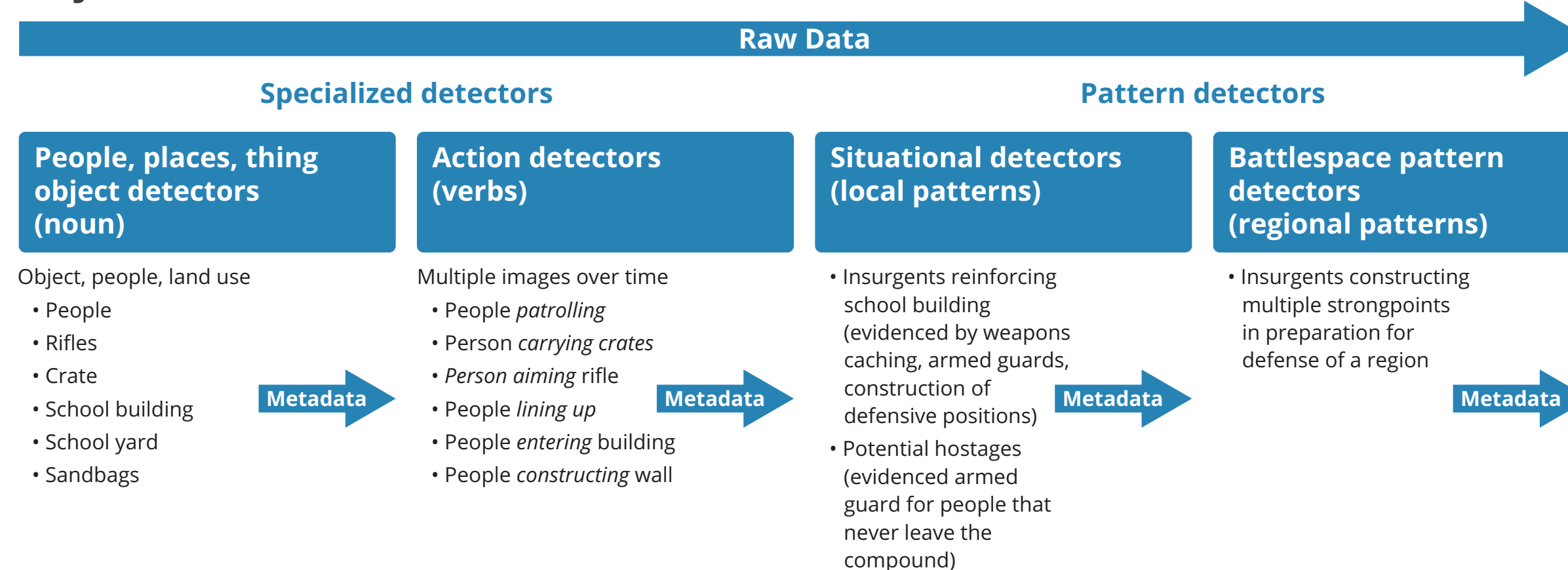
In PoL Analysis, we move from the "what is it?" question to the "what is it doing?" question. At the lowest levels, a PoL analyzer might take track data for a set of objects and either identify targeted types of behaviors (e.g., roadblock, insurgents planting an IED, patrol of a compound, etc), or report unusual or suspicious types of activity (i.e., anomaly detection). Higher-level PoL analyzers might further refine these analyses to identify situations (e.g., compound with high value target).

Methods

While much progress has been made, real-time tracking is still an emerging technology. Tracks can be lost, or registration errors can occur. In addition, it is very difficult to obtain ground truth for this type of data. For these reasons, we have chosen to use simulation to generate synthetic patterns to explore the possibilities of PoL analysis with perfect data. We use the SUMO traffic simulator and have explored both classification and anomaly detection tasks using this data.

As image recognition and tracking algorithms improve, new types of data will emerge, enabling the design of higher order detectors.

Object Identification

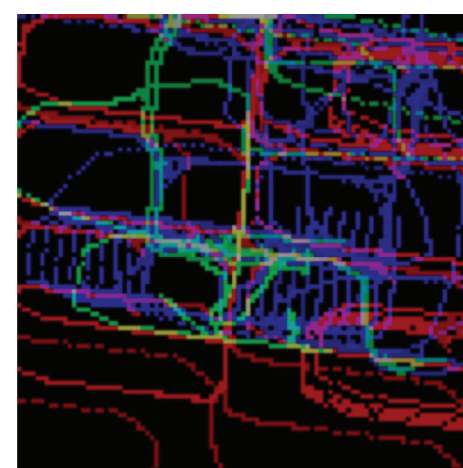


Metadata: Minimally who-what-when-where, but augmented by post-detector analysis producing additional metadata

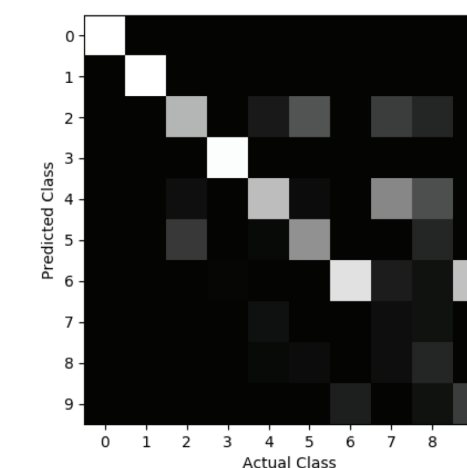
We demonstrate our PoL Analysis techniques using a "Shopping Plaza Parking Lot" example in which we analyze simulated spatiotemporal tracks to identify specific types of activity.



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.



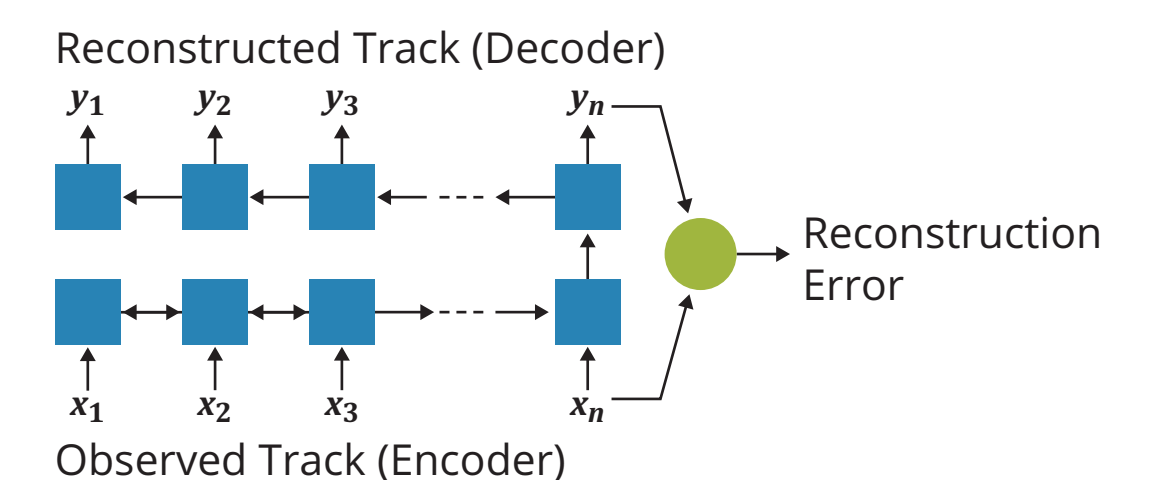
Using a CNN classifier, we correctly identified the track type with 86% accuracy out of 10 possible classes.

Anomaly Detection

In another experiment, we simulated 950 "best-path" vehicle trips into which we injected one with an unusual "ZigZag" path.



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



Of the 950 tracks, our injected "ZigZag" track consistently scored in the top 5 in terms of reconstruction error demonstrating the ability to identify anomalous behaviors.

