Demonstrating a Tactical Server Concept Leveraging Big Data, Deep Analytics, Machine Learning (ML), and Artificial Intelligence (AI) Algorithms

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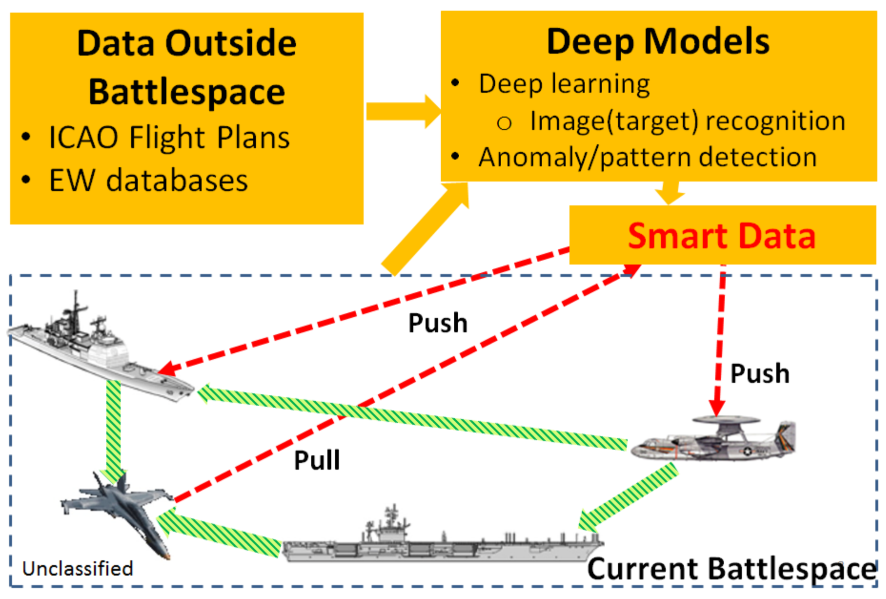
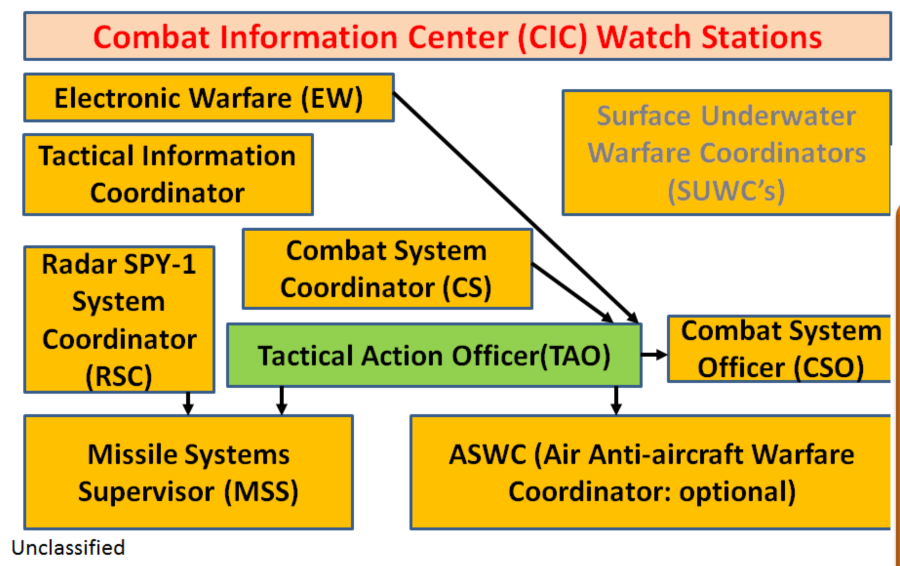
Big Picture and Challenges





Common Tactical Air Picture (CTAP)

- Collects, processes, and analyzes data from a vast network of sensors, platforms, and decision-makers
- Provides situational awareness to air warfare decision-makers

Combat Identification (CID)

- Locates and identifies critical airborne objects as friendly, hostile, or neutral with high precision

CID goals in general are to

- Increase fidelity
- Reduce cognitive burden
- Reduce latency

The demo shows the feasibility of applying ML/AI methods to accurately classify military aircraft or not.

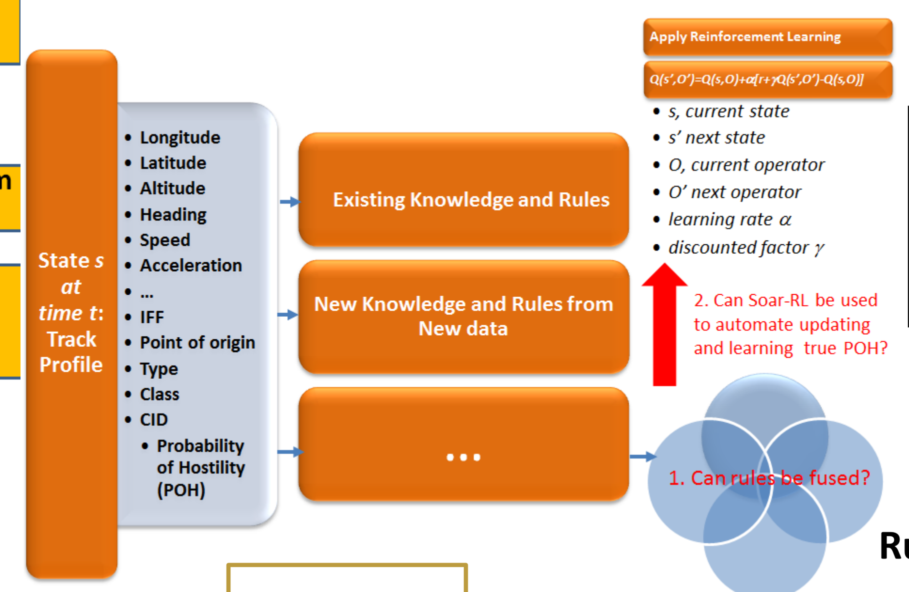
The data can be extended to include

- UAS patrol patterns
- Adversarial air tracks
- Surface tracks

ML/AI Algorithm: Combine Soar Reinforcement Learning (Soar-RL) with Lexical Link Analysis (LLA)

Soar: An open-source cognitive architecture and rule-based AI tool including reinforcement learning and long-term memory, developed by University of Michigan (Laird, 2012)

Lexical Link Analysis: Text/data mining method to discover initial correlations and rules



Soar-RL Rule Example

```
UM-101_Stealth_UAV-000> sp {classification-rl*likelihood-speed-3-HOSTILE
    (state <s> ^speed 3 ^name send-hello-response ^operator <op> +)
    (<op> ^classification HOSTILE ^name classify)
    -->
    (<s> ^operator <op> = 0.777644669166665)
}
```

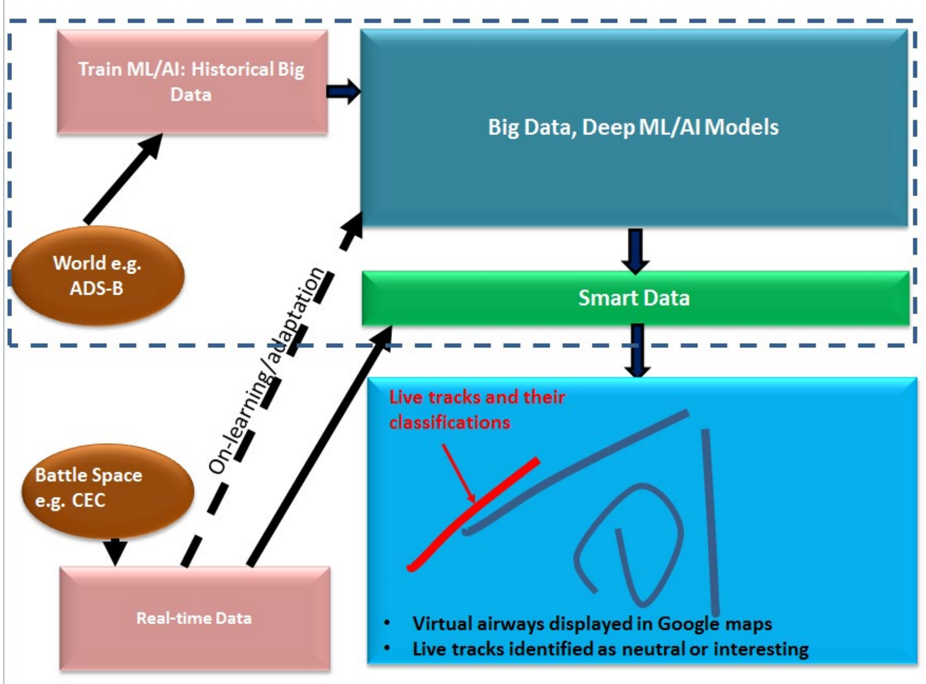
Rules preferences need to be trained and updated

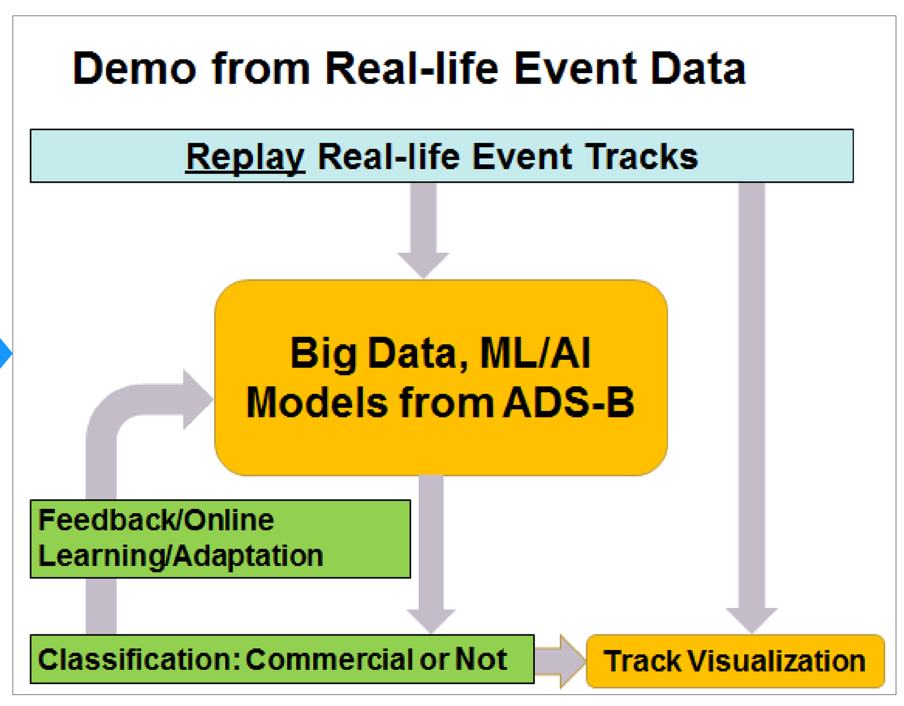
As shown in Equation (1),Soar-RL is implemented in a typical RL implementation involving a recursive formula that is widely accepted in the RL research and literature. Since we only consider an on-policy setting or SARSA, $Q(s_{t+1}, a) = 0$ in Equation (1). Therefore, $Q(s_{t+1}, a_{t+1})$ is updated continuously for each time point and immediate reward r.

$$Q(s_{t+1}, a_{t+1}) = Q(s_t, a_t) + \alpha[r + \gamma \max_{a \in A} Q(s_{t+1}, a) - Q(s_t, a_t)] \qquad (1)$$

(https://soar.eecs.umich.edu/downloads/Documentation/SoarManual.pdf: page 145)

Tactical Server Concept





Open Source ADS-B Data

- ADS-B supports separation assurance and traffic flow management (FAA Order 8200.45); broadcasts and self-reports ID and location
- ICAO uses ADS-B–enabled Mode-S devices

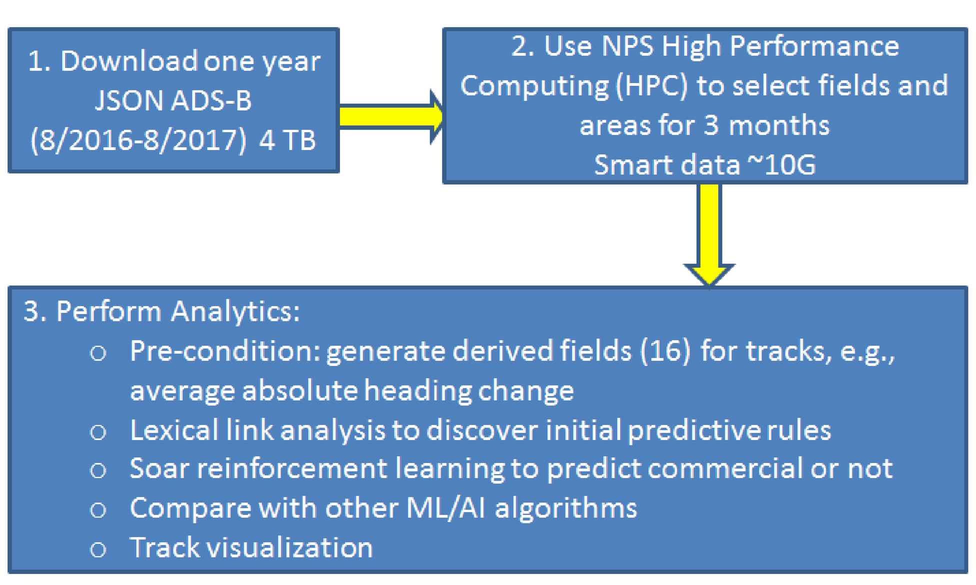


Table 1: 3-month ADS-B Data Divided into 7 Data Sets

Name	Month of Data
Data set 7_1	July, 2016,Train
Data set 7_0	July, 2016,Test
Data set 7_2	July, 2016,Test
Data set 8_0	August, 2016,Test
Data set 8_1	August, 2016,Test
Data set 6_0	June, 2016,Test
Data set 6_1	June, 2016,Test

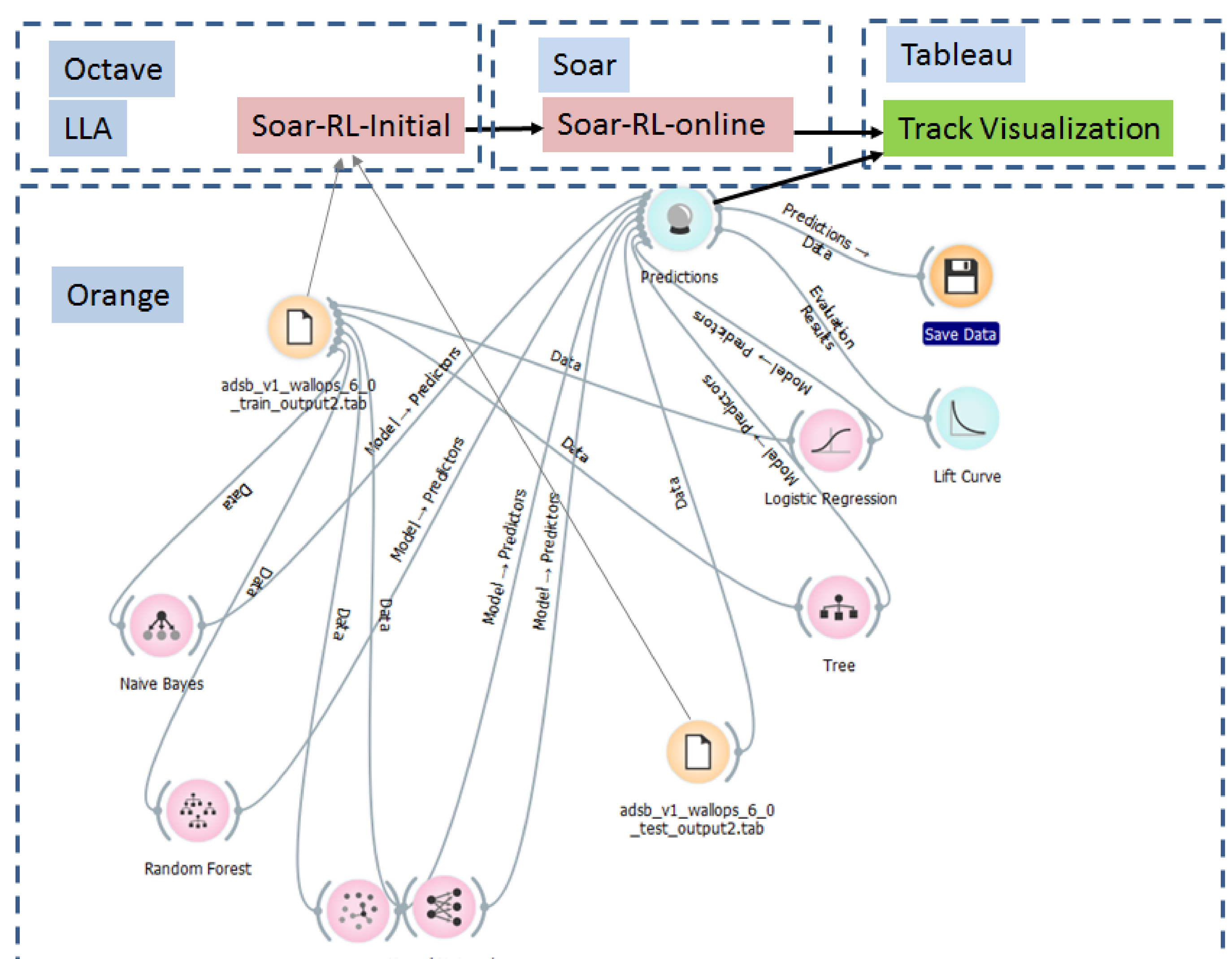
Goal: Identify Commercial Flights Using Kinematic Attributes

- Demo Data : Data set 6_0 (adsb_v1_wallops_6_0)
  - train on (1.3M tracks)
    - 2016-06-10
    - 2016-06-11
    - 2016-06-12
    - 2016-06-13
  - test on (340,000 tracks)
    - 2016-06-14

For each track, compute kinematics features:

- Average altitude up to time *t*
- Average altitude change up to time *t*
- Average absolute altitude change up to time *t*
- Average speed up to time *t*
- Average speed change up to time *t*
- Average absolute speed change up to time *t*
- Average heading change up to time *t*
- Average absolute heading change up to time *t*
- Total altitude change up to time *t*
- Total altitude absolute change up to time *t*
- Total heading change up to time *t*
- Total absolute heading change up to time *t*
- Total speed change to up to time *t*
- Total absolute speed change up to time *t*
- Total track duration up to time *t*

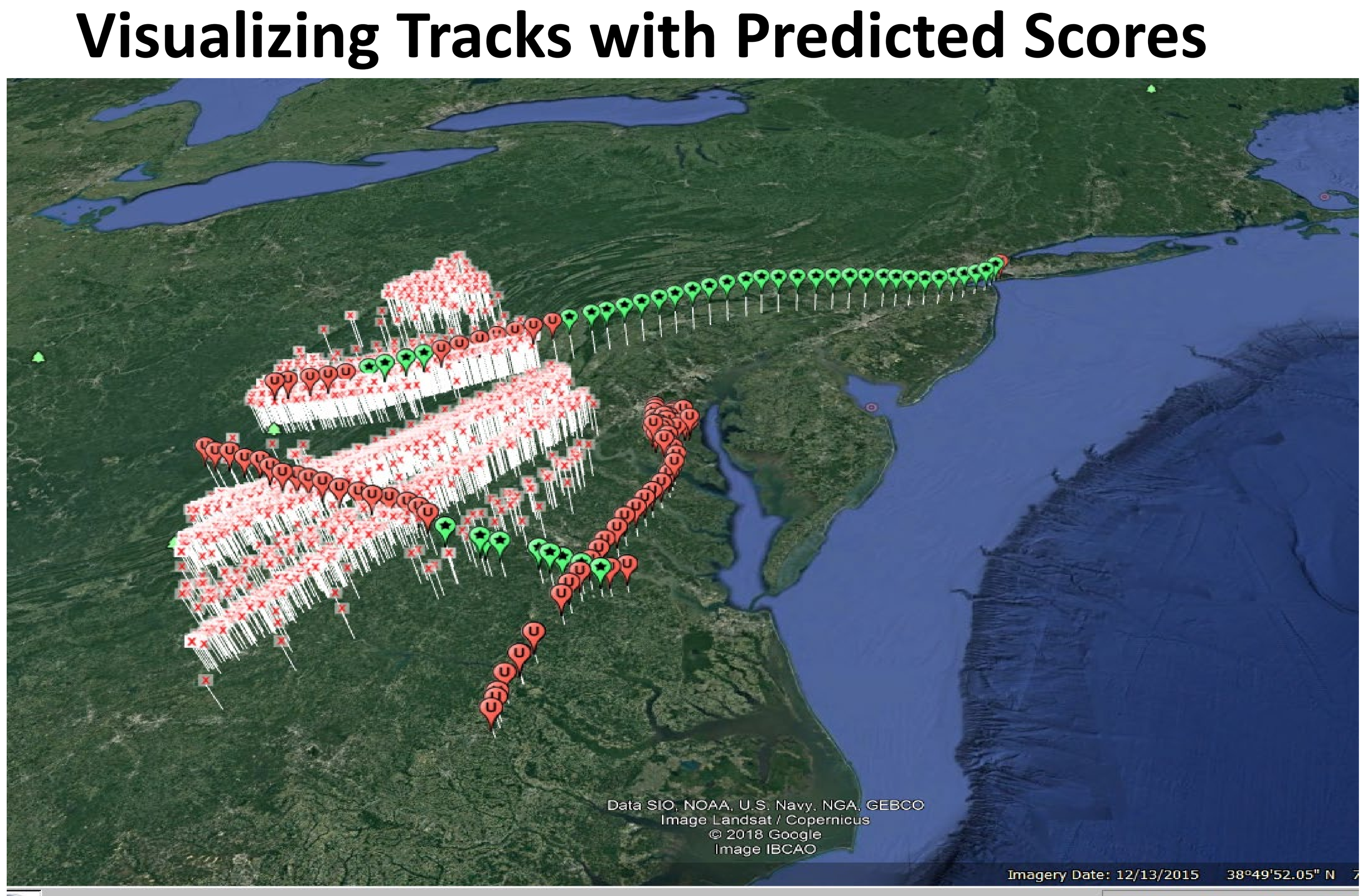
Comparing Soar-RL with Other Methods: All ML/AI Methods/Tools Used



Results: % of Commercial Flights Ranked by Predicted Scores

	Top 50% of Test Tracks (170,000) (Predicted commercial)	Bottom 50% of Test Tracks	Tracks as whole (Average)
Tree	99.32%	96.71%	
Naïve Bayes	99.03%	97.02%	
Random Forest	99.27%	96.77%	
kNN	99.32%	96.71%	
Neural Network	99.44%	96.59%	
Soar-RL	99.23%	96.81%	
			98%

Visualizing Tracks with Predicted Scores



Conclusion and Future Work

- Big data, deep analytics, and ML/AI algorithms are important for implementing a Tactical Server for CTAP and CID for classifying and predicting intent of airborne objects
- The Soar-RL/LLA methodology produces predictive results similar to other ML/AI methods but possesses the following advantages:
  - It uses rule-based reinforcement learning and so more easily incorporates new knowledge discovered from big data into its existing knowledge
  - It is an online training method, so the learning can be adapted in a new environment
- Future work
  - Class and type recognition need more data sources such as ICAO, FAA, ELINT (e.g., RF)
  - Pattern of life needs unsupervised learning and planning algorithms

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