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Bayesian Networks for Interpretable and Extensible Multi-Sensor Fusion

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Presentation Overview

- Problem Statement
- Review Relevant Background information
  - Review Air Defense Regime
  - Past usage of Bayesian networks and Interpretable ML
- Introduce Bayesian network prototype
- Review 5 Test Cases and Results
- Key Takeaways and Future Work

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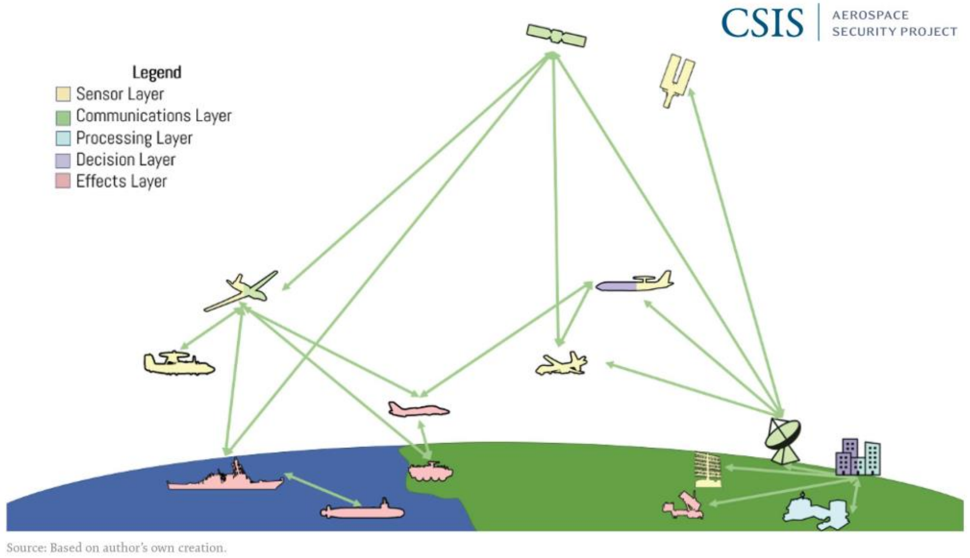
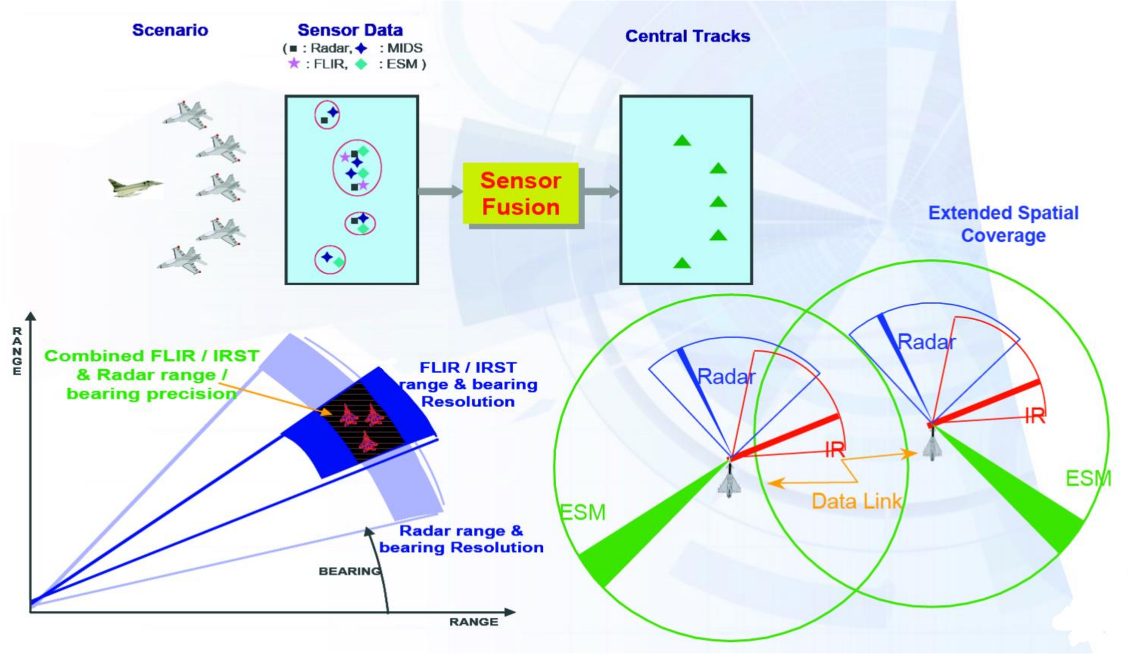
Problem Statement

- Modern Air Defense is a complex, high-stakes problem facing a myriad of advanced threats
- Legacy and Next-Generation systems need to be integrated cohesively – wide variety of available sensing units across domains need to be fused together [6,7]
- Data streams are typically fused at different levels to perform three core task stages [8]:
    - Detection, Tracking, Classification
- Then, higher level tasks can be performed [8]:
    - Intent Classification, Situational Awareness, Impact Assessment
- Joint Target Tracking, Classification, and Intent (JTCI) Framework performs each stage **simultaneously** [8]
- Current generation, neural network-based AI solves some problems, but suffers from various limitations
- Some defense specific issues include [2,3]:
    - High volume of data, lacking labeled data
    - High compute costs (not-edge compliant)
    - Lack of explainable and interpretable outputs



Example Diagram of Sensor Systems and Communication Channels [4]



Example Sensor Fusion in Air Defense Regime [9]

Bayesian Network: Key Motifs

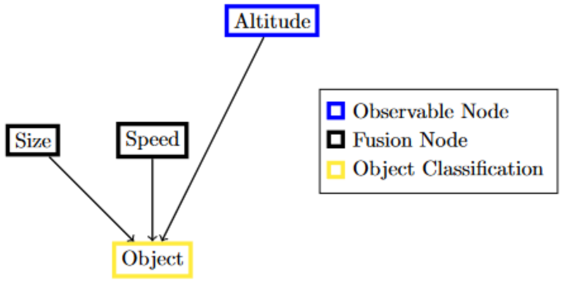


Figure 2. Object Classification input nodes and states.

- Objects:
  - Missiles
  - Fighter Jets
  - Bombers
  - UAVs
- CPDs developed by intuition on characteristics of each platform

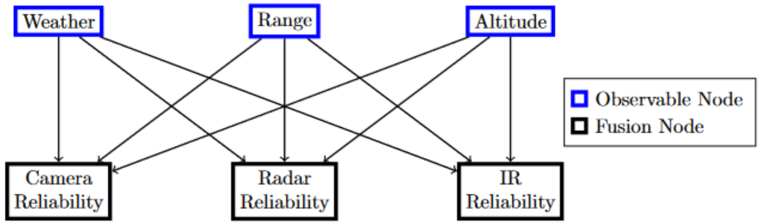


Figure 4. Sensor Reliability input nodes and states.

- Conditioned by:
  - Weather: Clear, Inclement
  - Range: Far, Medium, Near
  - Altitude: High, Medium Low
- CPDs populated by intuition, but could easily use empirical or operator supplied information

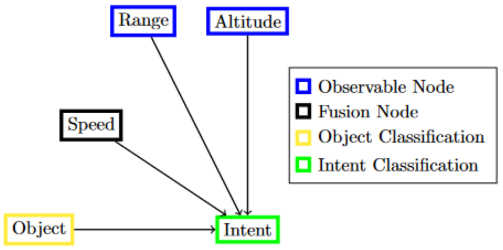


Figure 1. Intent input nodes and states.

- Intents:
  - Travel/cruise mode
  - Attack mode
  - Evasive/neutralized mode
- CPDs developed by heuristic-backed routine to distribute probabilistic mass according to intuitive rule base

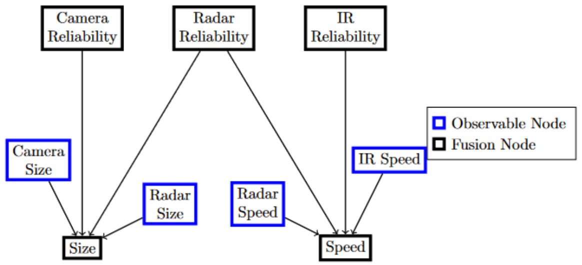


Figure 3. Size and Speed input nodes and states.

- Size:
  - Large
  - Medium
  - Small
- Speed:
  - Fast
  - Medium
  - Slow
- CPDs developed by intuition of characteristics for each object

Assembled Bayesian Network

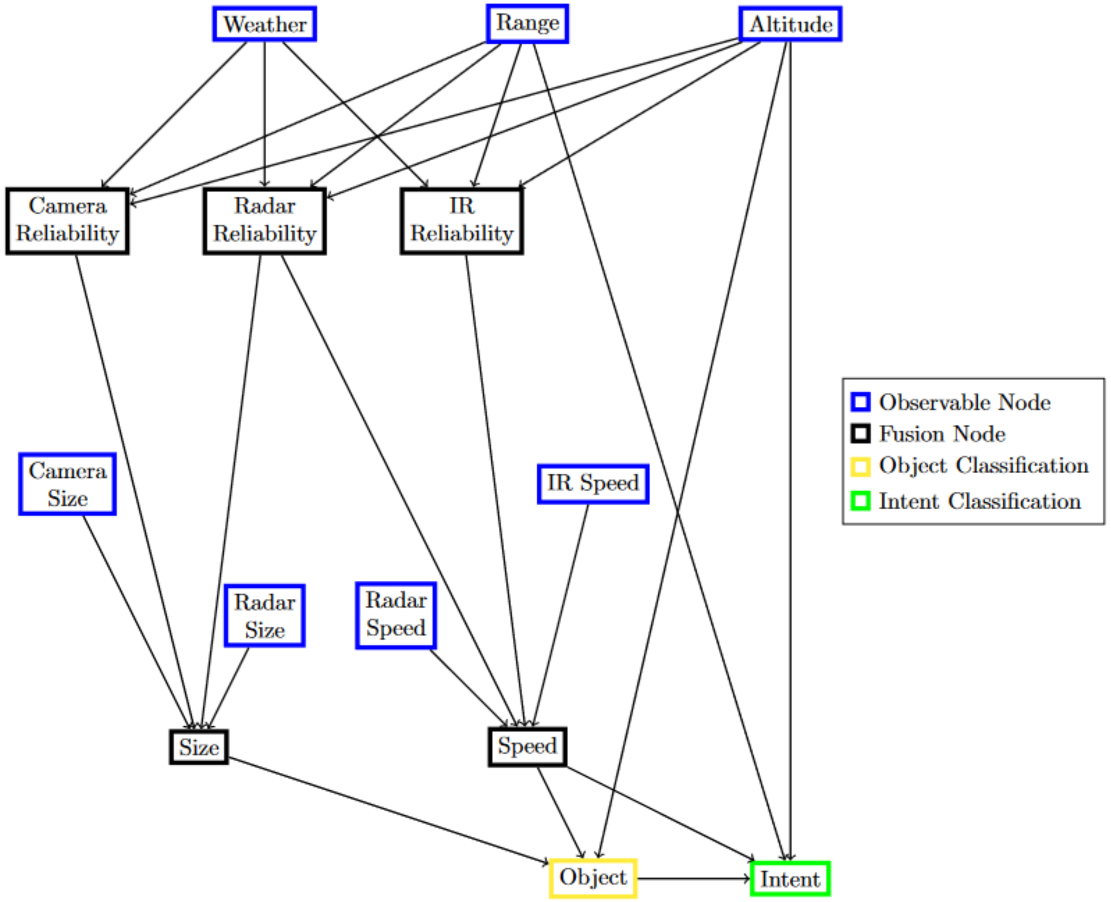


Figure 5. Full Bayesian Network architecture.

- Simple Layout
- Easy to extend behind abstract Fusion Node interfaces
- All CPDs can be populated empirically, through heuristics, or by human

- Exercise through several Test Cases:
  1. Network Baselining
  2. Network Verification
  3. Disagreement of Observables
  4. Network Sensitivity to Offline Sensors
  5. Extensibility of Network

Test Case 1: Network Baselining

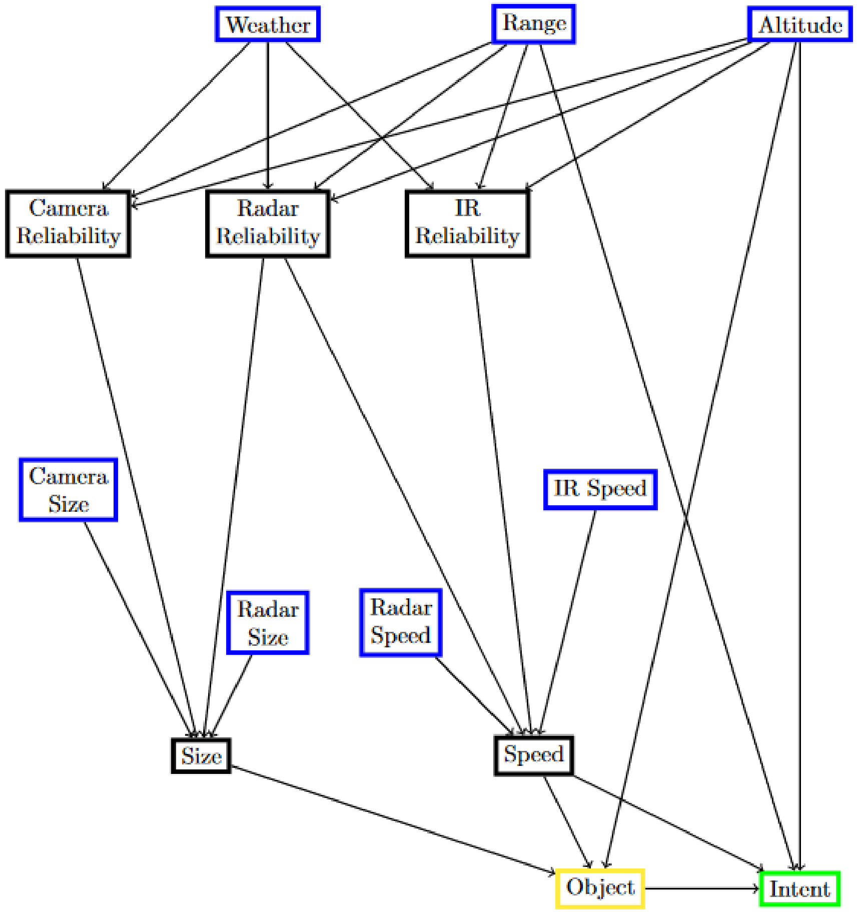


Table 1. Results when no Observations present

Observations	
Conditions	none
Range	none
Altitude	none
Size - Camera	none
Size - Radar	none
Speed - Radar	none
Speed - IR	none

Node	Class	Probability
Object	missile	0.257
	fighter	0.257
	bomber	0.239
	uav	0.246
Intent	cruise	0.439
	attack	0.296
	evade/neut	0.265

Object	Intent	Probability
Missile	attack	0.111
	cruise	0.088
	evade	0.058
Fighter	cruise	0.112
	attack	0.073
	evade	0.073
Bomber	cruise	0.106
	attack	0.066
	evade	0.067
UAV	cruise	0.111
	attack	0.068
	evade	0.067

- Effectively **equal likelihood** of Objects
- **Cruise** is highest Intent
- Missile in Attack is **only** per-object case where Attack is highest

Test Case 2: Network Verification

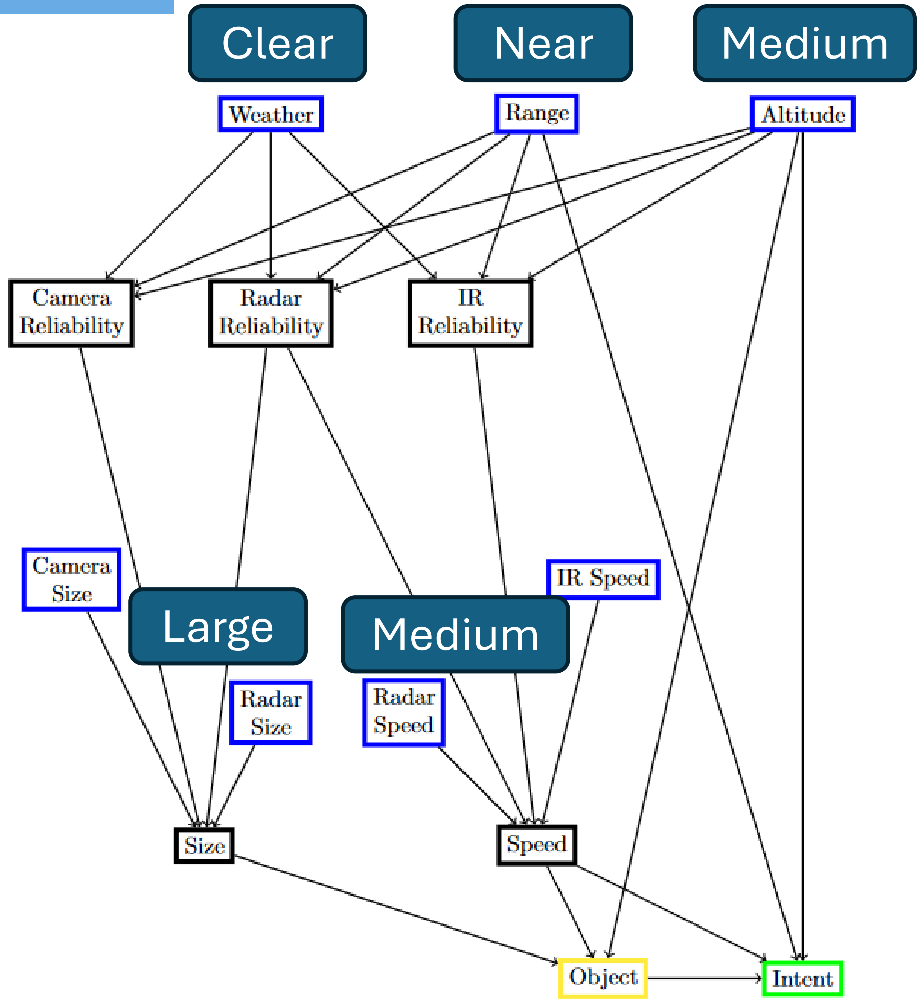


Table 2. Test Case 2 Observations and Results

Observations	
Conditions	clear
Range	near
Altitude	medium
Size - Camera	large
Size - Radar	large
Speed - Radar	medium
Speed - IR	medium

Node	Class	Probability
Object	missile	0.203
	fighter	0.203
	bomber	0.348
	uav	0.245
Intent	cruise	0.233
	attack	0.466
	evade/neut	0.301

Object	Intent	Probability
bomber	attack	0.201
uav	attack	0.100
fighter	attack	0.091
uav	evade	0.084
bomber	evade	0.079
missile	attack	0.075
missile	evade	0.070
bomber	cruise	0.068
fighter	evade	0.067
uav	cruise	0.061
missile	cruise	0.058
fighter	cruise	0.045

- Define characteristics of Bomber in Attack – all sensors agree
- As expected, **Bomber in Attack** is highest Object-Intent Pair

- **Easy to interpret results:**
  - Bomber receives **35% of probabilistic mass** (10.9% abs increase, 145% relative increase)
  - Bomber in Attack **2x of next class,** receiving **20% more probabilistic mass** (13.5% abs increase, 304.5% relative increase)

Test Case 3: Disagreement of Observables

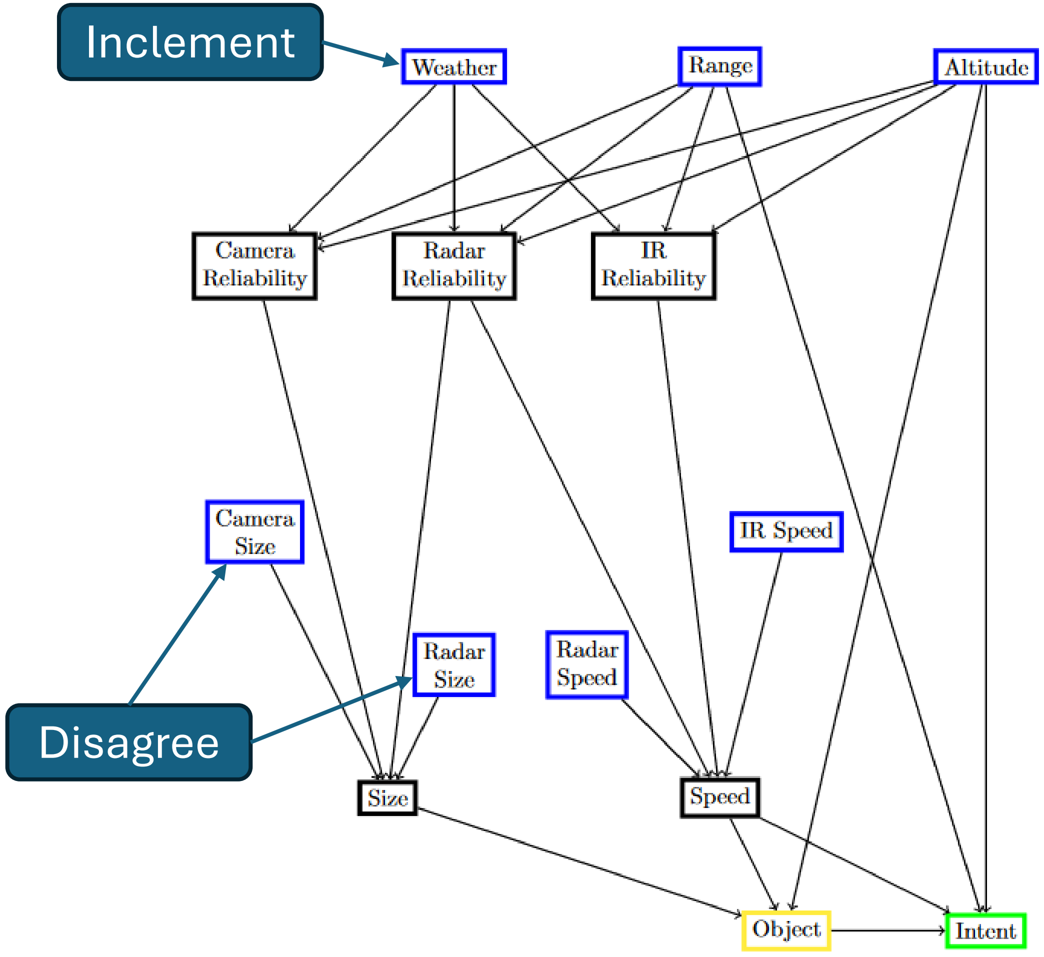


Table 3. Test Case 3 Observations and Results

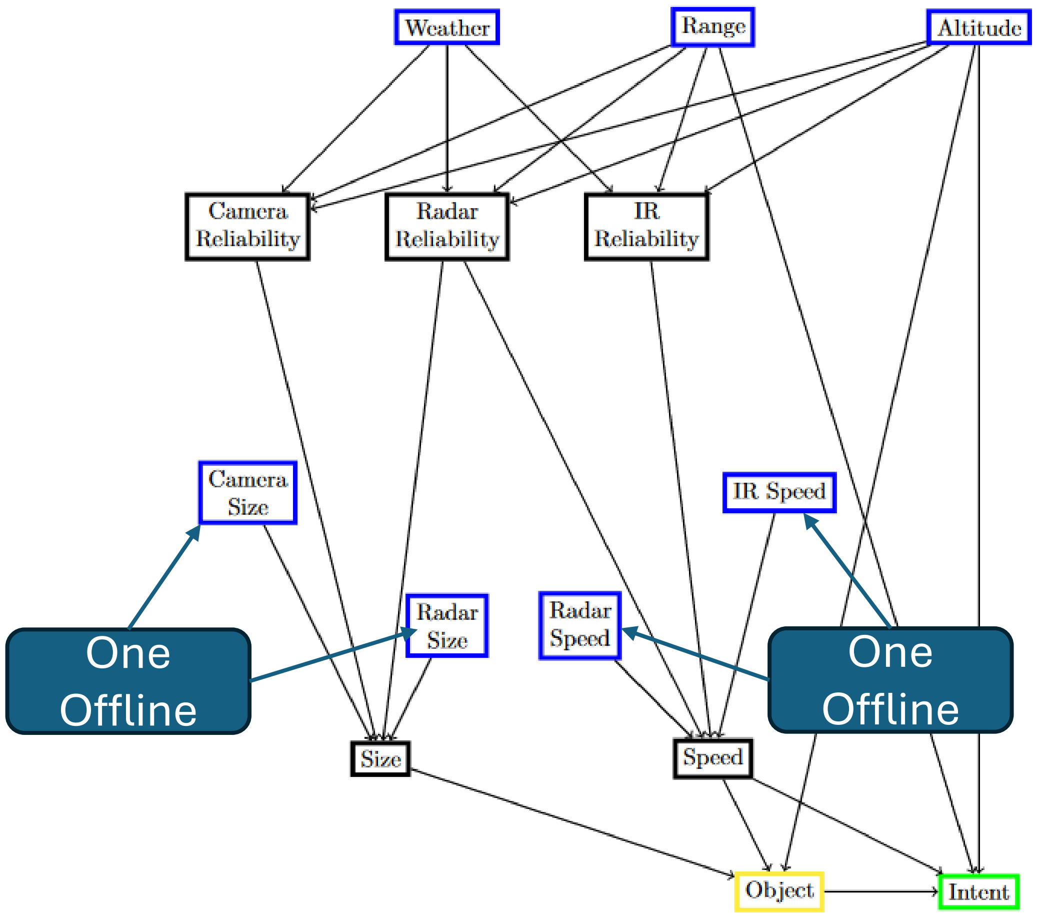
Observations	
Conditions	inclement
Range	near
Altitude	medium
Size - Camera	large
Size - Radar	small
Speed - Radar	medium
Speed - IR	medium

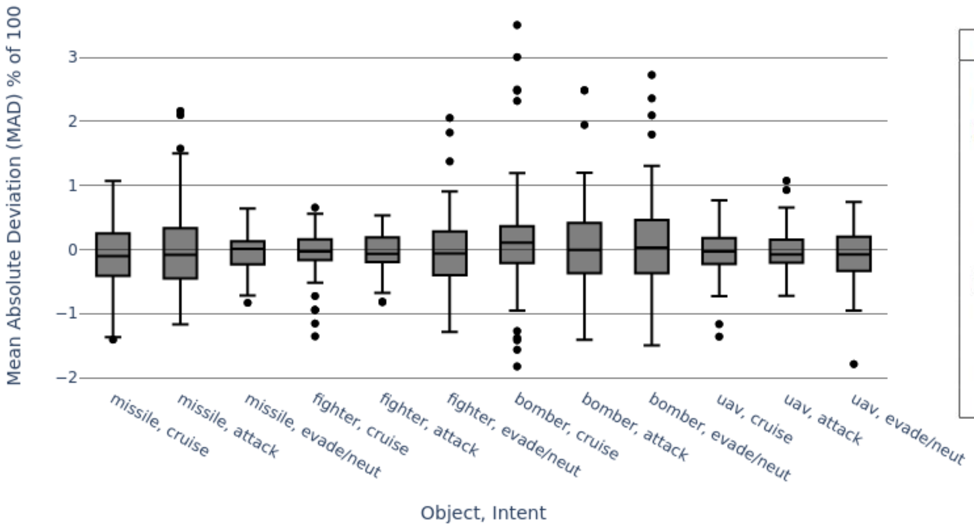
Node	Class	Probability
Object	missile	0.234
	fighter	0.234
	bomber	0.261
	uav	0.271
Intent	cruise	0.235
	attack	0.452
	evade/neut	0.313

Object	Intent	Probability
bomber	attack	0.149
uav	attack	0.111
fighter	attack	0.105
uav	evade	0.093
missile	attack	0.087
missile	evade	0.082
fighter	evade	0.078
uav	cruise	0.067
missile	cruise	0.065
bomber	evade	0.060
fighter	cruise	0.052
bomber	cruise	0.051

- **Size sensors disagree** (Radar mis-reading)
- Bomber is **not** the highest likelihood Object
- Attack is highest Intent
- Object-Intent pair is Bomber in Attack, at 1.3x probabilistic mass over UAV in Attack
- **Network reasonings through disagreement**

Test Case 4: Sensitivity to Offline Sensors





Object, Intent	MAD	STD
bomber, cruise	0.626	0.810
bomber, evade	0.623	0.598
bomber, attack	0.571	0.542
missile, attack	0.552	0.507
fighter, evade	0.458	0.429
missile, cruise	0.413	0.342
UAV, evade	0.341	0.298
bomber, attack	0.304	0.244
fighter, cruise	0.287	0.293
UAV, cruise	0.287	0.265
fighter, attack	0.260	0.195
missile, evade	0.623	0.598

- Two tests for each Fusion Node:
  - Size: Radar online, Camera offline (and vice versa)
  - Speed: Radar online, IR offline (and vice versa)
- Run against every combination of Weather, Range, Altitude values
- **Network is very stable**:
  - Maximum Mean Absolute Difference (MAD) is 0.625 (of 100)
  - In 8 of 12 object-intent pairs, less than 1% probabilistic mass shift, aka **99% consistency of predictions** as long as one producer for each fusion node is producing observables

Test Case 5: Extensibility

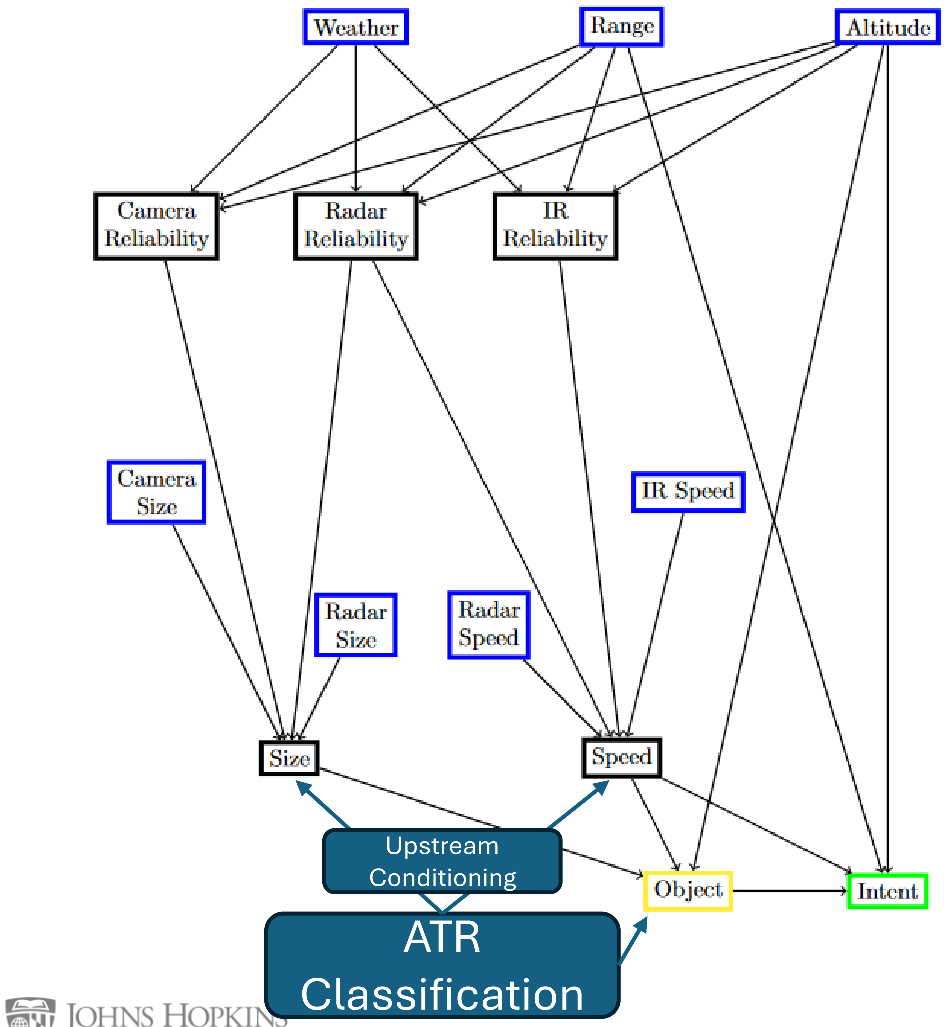


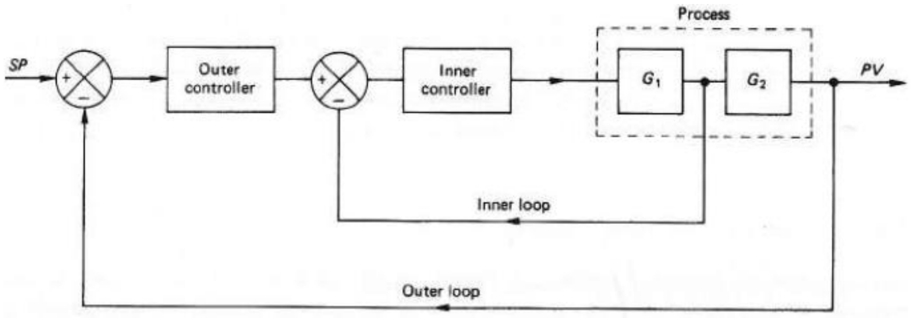
Table 5. Observations and inferred Size and Intent when integrating ATR Object observations

Observations		Inferred Size Value, by Object from ATR				Inferred Intent			
Conditions	clear	Object	Large	Med	Small	Object	Cruise	Attack	Evade
Range	near	uav	0.197	0.428	0.374	missile	0.532	0.442	0.025
Altitude	medium	bomber	0.311	0.441	0.247	fighter	0.515	0.333	0.152
Speed - Radar	medium	fighter	0.187	0.426	0.387	bomber	0.435	0.535	0.030
Speed - IR	medium	missile	0.187	0.426	0.387	uav	0.403	0.349	0.248

- Can **easily add and remove** observable producers behind **abstract interfaces**
  - Can insert Object detectors (such as Automatic Target Recognition (ATR) systems)
  - Can insert new Size, Speed sensors
- “Known” values from new producers' condition **both** downstream and upstream nodes, **reducing uncertainty of entire network**

Key Takeaways & Future Research

- Bayesian networks are:
  - Intuitive to **interpret** and understand
  - Capable of **reasoning** through inconsistent sensor readings
  - **Consistent** and operationally **robust** and against subsystems going offline
  - Easy to **extend** to add new sensors and classifiers
  - Can coexist with other neural network-based black box models
- Highly useful for performing last-mile reasoning over information produced by a variety of systems



Example Cascading Control Loop containing Outer and Inner loops [14]

- In this work, only explored inference at point in time assuming all observables available
- In real world, sensor readings come at different frequencies
- Following Control Theory: higher frequency observables should be used to update priors of lower frequency “outer” loops, and when “outer” loops complete, supply that information as priors to the faster “inner” loops

Questions?

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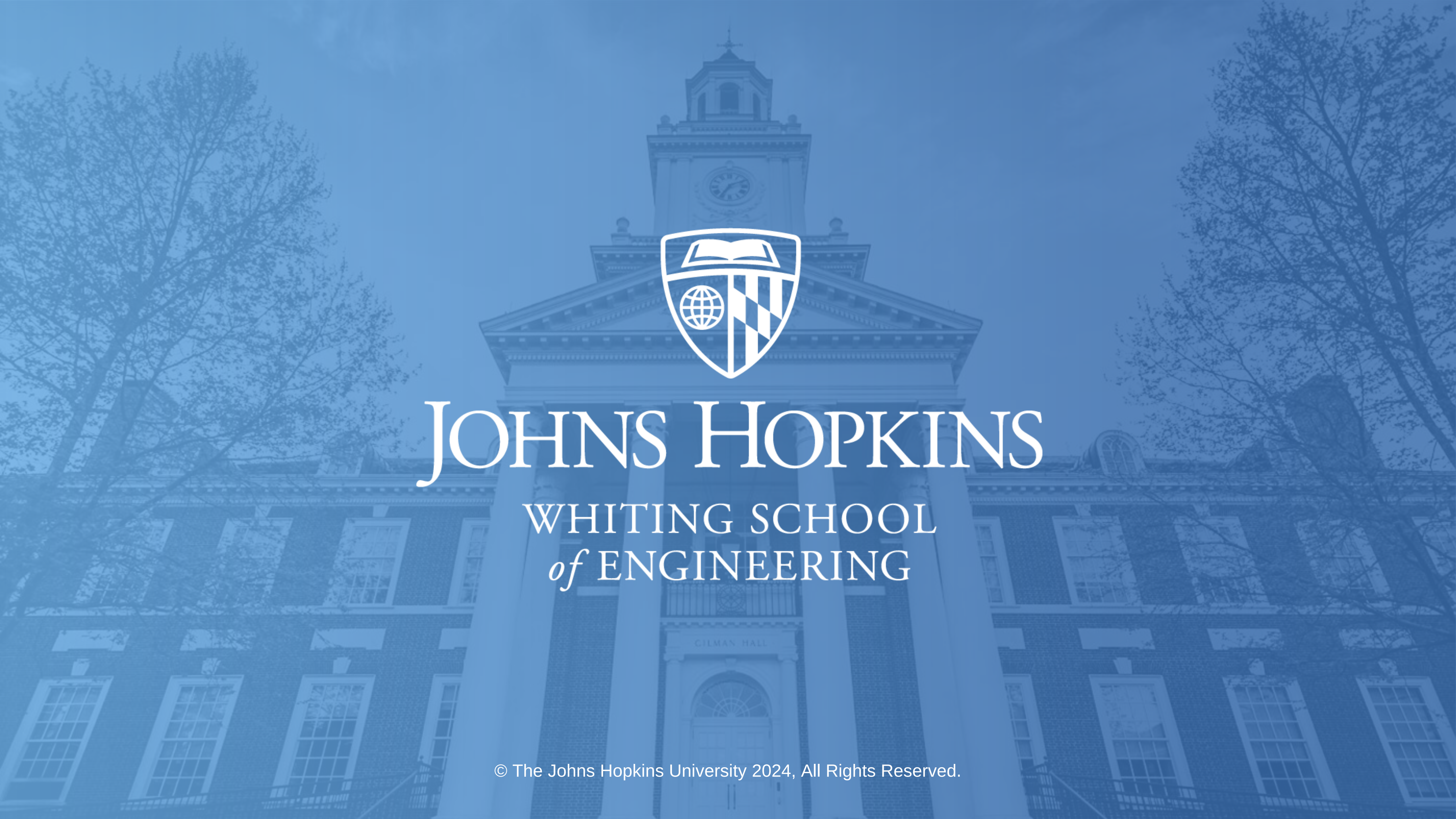

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