Neuro-Symbolic Reasoning for Assured Autonomy

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Outline

- Challenge: Assured and Trusted Collaborative Autonomy
- Sample of ATL assurance approaches
- Challenge Problems in Developing a Neuro-Symbolic OODA Loop
- Directions for future research

ATL Strategic Initiatives

Autonomy and Crewed-Uncrewed Teaming

- Human-Autonomy Collaborative Teams
- Cognitive Load Optimization
- Assurance and Trust

Neuro-Symbolic Reasoning

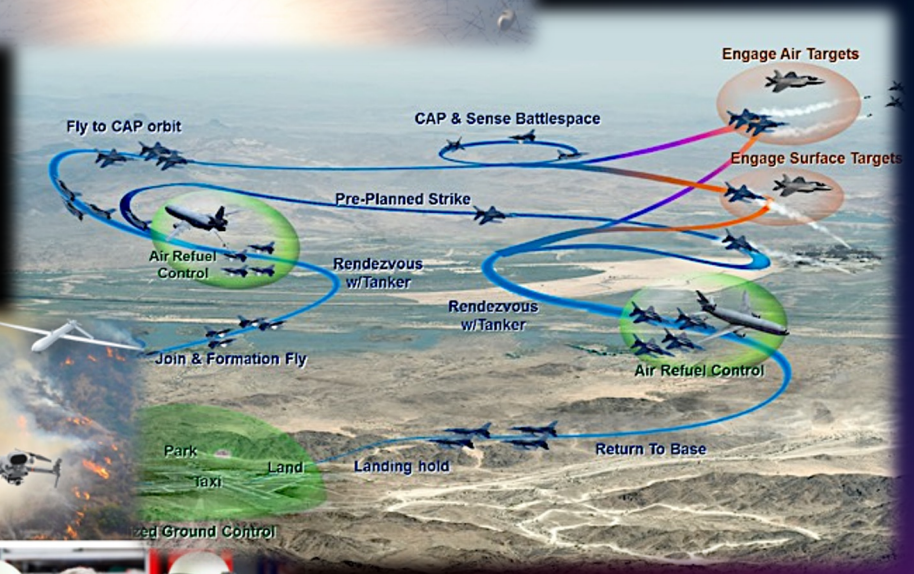
- Uncertainty and Ambiguity Management
- Causal Generative Models
- Lifelong Learning at the Edge

Neuro-Symbolic Reasoning

- Scalable Reinforcement Learning
- Composable AI
- Generalizable AI

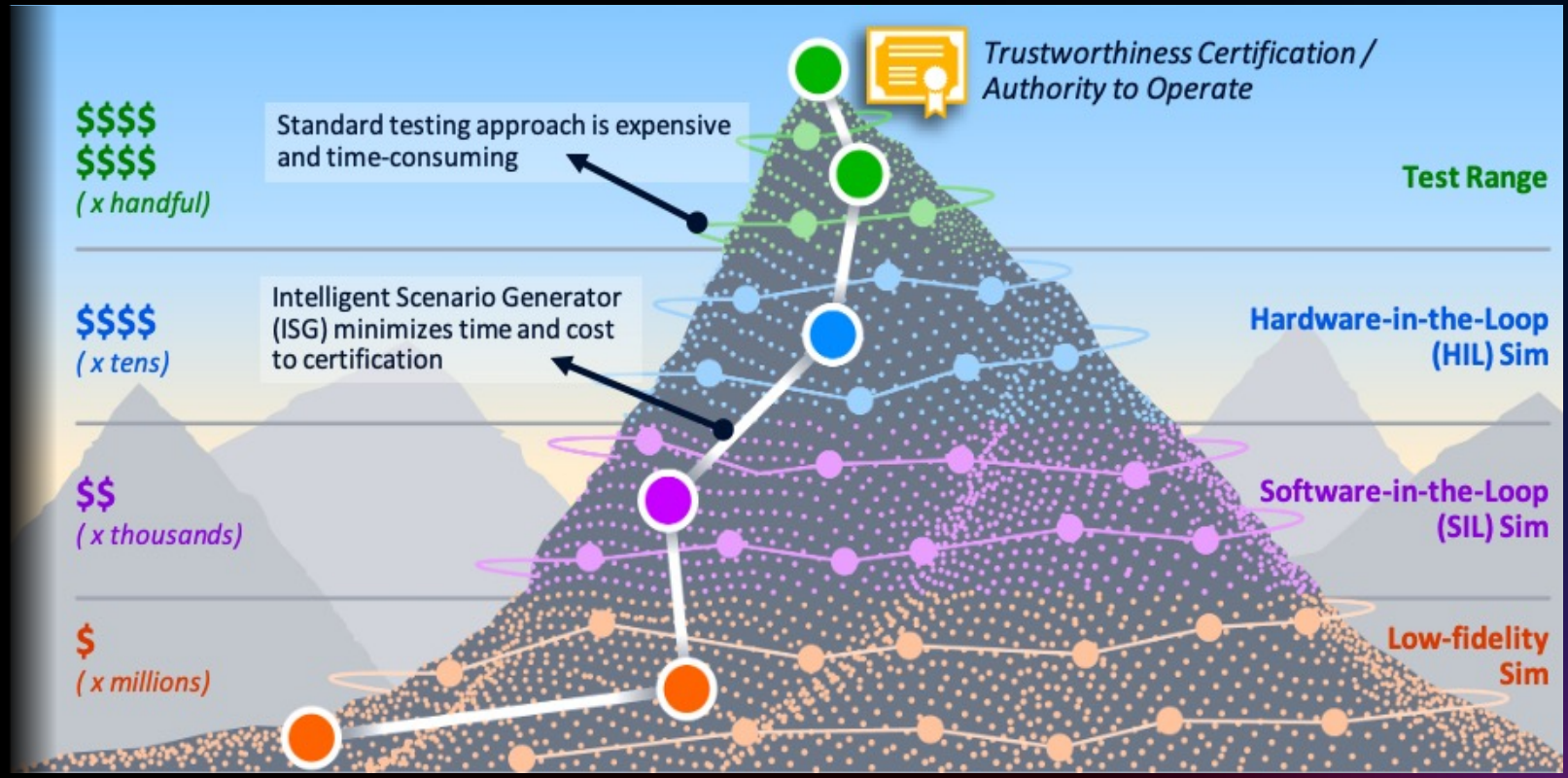
Challenge: Assured and Trusted Collaborative Autonomy

- Human-autonomy collaborative teams
- Multi-scale and multi-domain
- Scalability and composability
- Uncertain and ambiguous environments



ATL Assurance Research: Scenario Generation

- Defines ***what and how to test***
- Three categories of experiments:
  - Targeted discovery (“known unknowns”)
  - Exploratory discovery (“unknown unknowns”)
  - Evidence gathering (“justified confidence”)
- Technologies:
  - Ability to express and reason about scenarios as distributions
  - Generation of information-lucrative experiments
  - Architecture for scalability
  - Software-enabled Simulation-Emulation-Stimulation

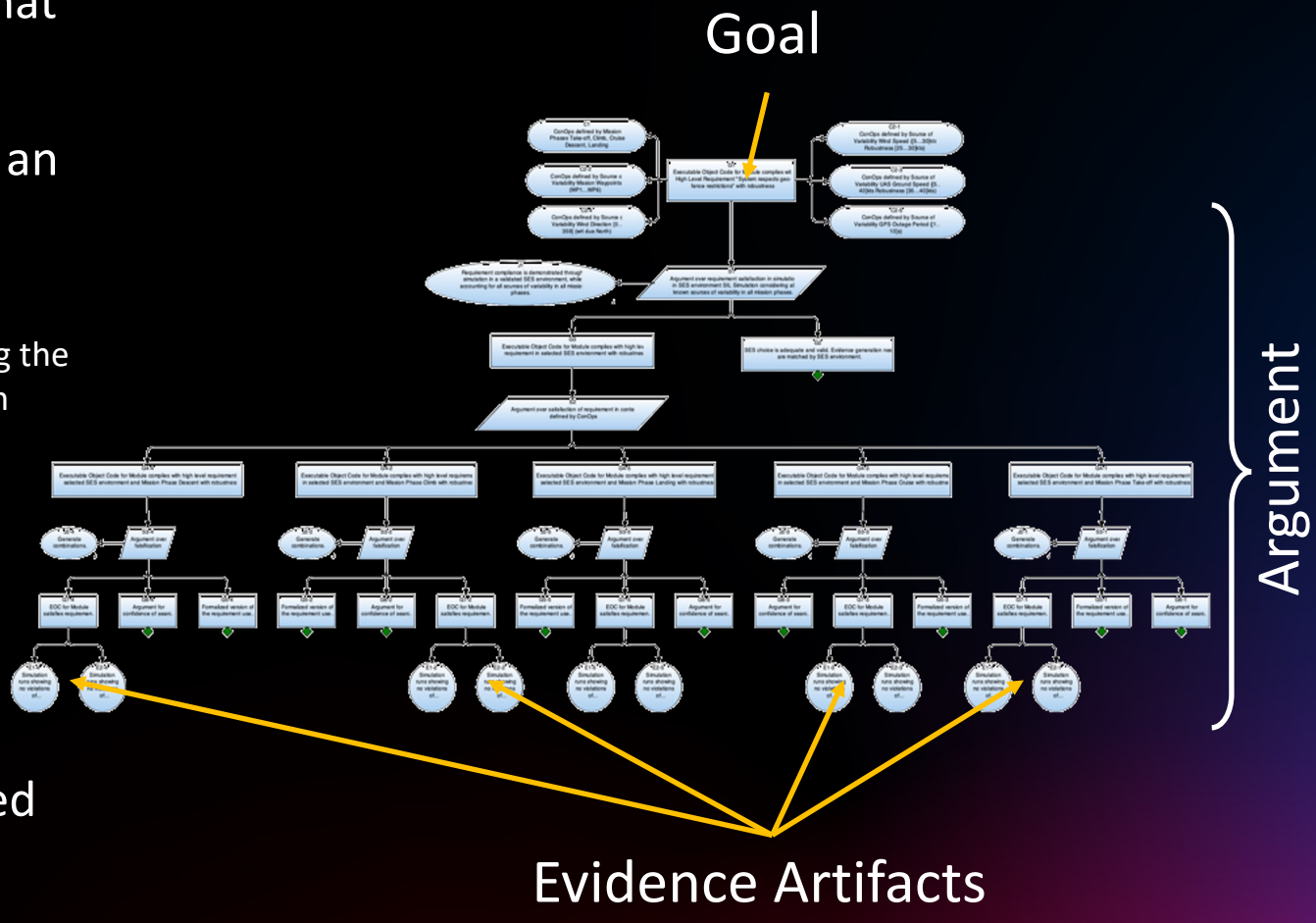


ATL Assurance Research: Assurance Cases

- A means of increasing well-founded confidence that a system will behave as intended
- An assurance case requires claims, evidence, and an argument linking evidence to claims:

  Evidence
  > Results of observing, analyzing, testing, simulating, and estimating the properties of a system that provide fundamental information from which the presence of some system property can be inferred

  High Level Argument
  > Explanation of how the available evidence can be reasonably interpreted as indicating acceptable operation, usually by demonstrating compliance with requirements, sufficient mitigation of hazards, avoidance of hazards, etc.



- Claims with no supporting evidence are unfounded
- Evidence without claims is unexplained
- Argument-based approaches: UL4600 “Standard for Safety for the Evaluation of Autonomous Vehicles and Other Products”

Neuro-Symbolic Reasoning: Motivation

Challenges addressed

- Scalability and composability
- Human-autonomy collaborative teams

Deep Neural Networks

- Large training data sets required
- Difficult to incorporate physics, human expert knowledge
- Limited applicability outside of learning data sets
- Susceptible to adversarial attacks
- Simulation-based Reinforcement Learning not scalable
- Limited composability
- Limited explainability
- **Limited verification approaches**

E. Cohen, Y.Y. Elboher, C. Barrett, and G. Katz, Tighter Abstract Queries in Neural Network Verification, EPiC Series in Computing , Vol. 94, 2023.

H. Hanspaal, A. Lomuscio, Efficient Verification of Neural Networks LVM-based Specifications, Proceedings of the 36th IEEE CVPR23.

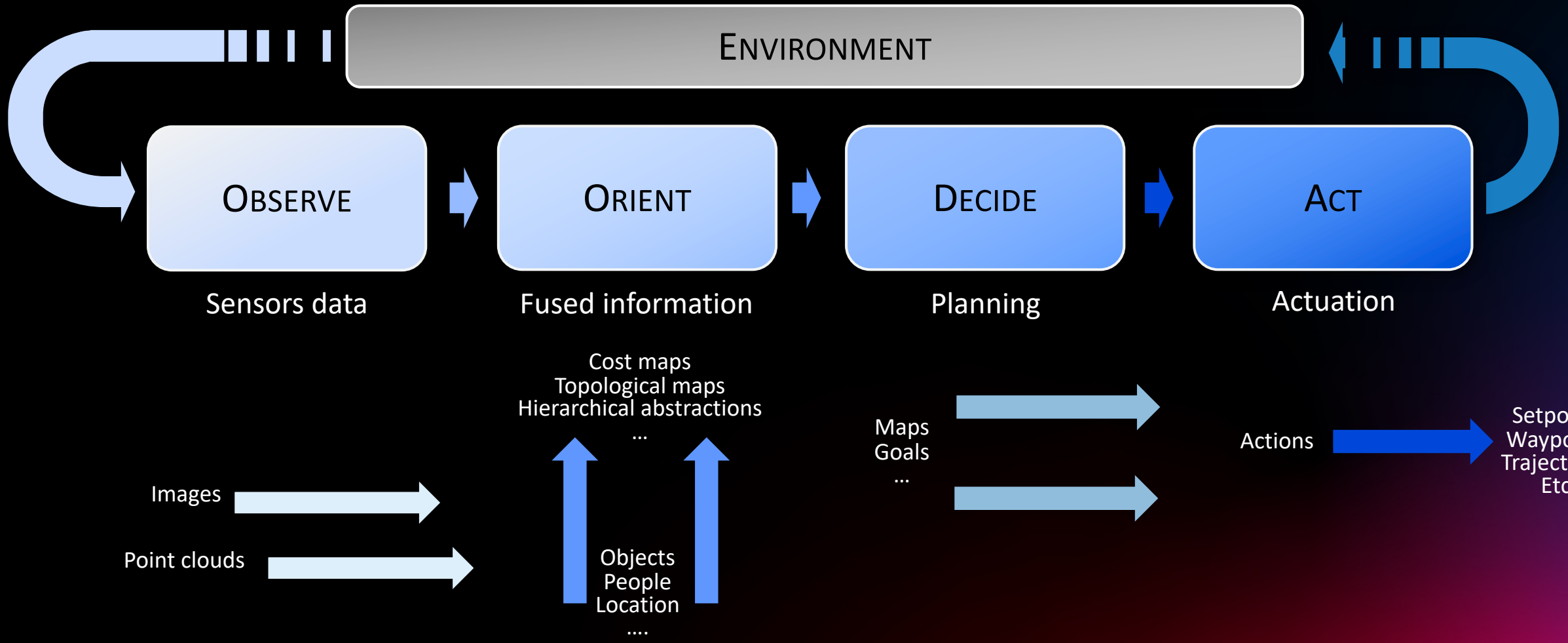
Neuro-Symbolic Reasoning

- Reduces data requirements by orders of magnitude
- Enables capturing domain knowledge
- Extends applicability (knowledge captured in symbolic layers)
- Reduces susceptibility (contextual reasoning)
- Accelerates Reinforcement Learning (symbolic abstractions)
- Builds-in composability
- Enables explainability and human dialog
- Enables formal verification (symbolic layers)
- Reduces verification effort (sub-symbolic layers)

A. Speranzon, C.H. Debrunner, D. Rosenbluth, M. Castillo-Effen, A.R. Nowicki, K. Alcedo and A. Banaszuk, Challenge Problems in Developing a Neuro-Symbolic OODA Loop, NeSy 2023, 17th International Workshop on Neural-Symbolic Learning and Reasoning

Observe, Orient, Decide and Act (OODA) Loop

Typical architecture of an autonomous system includes:



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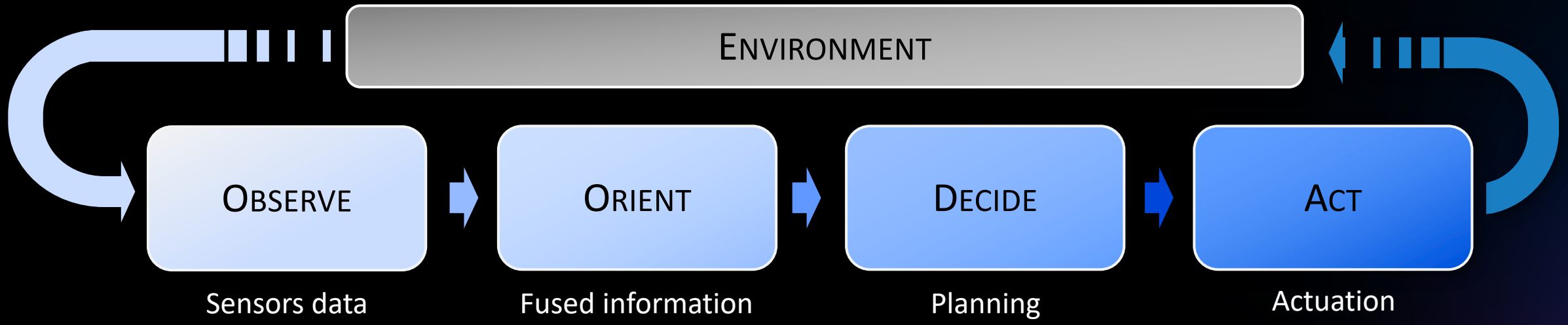
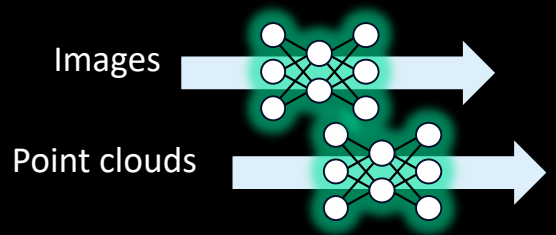
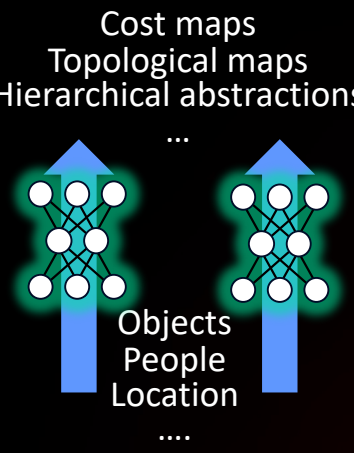
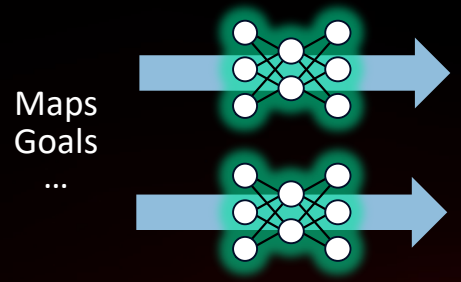
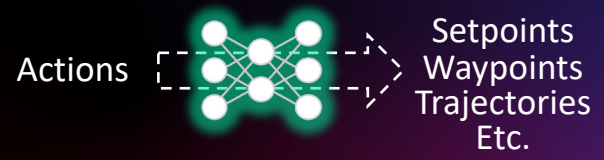






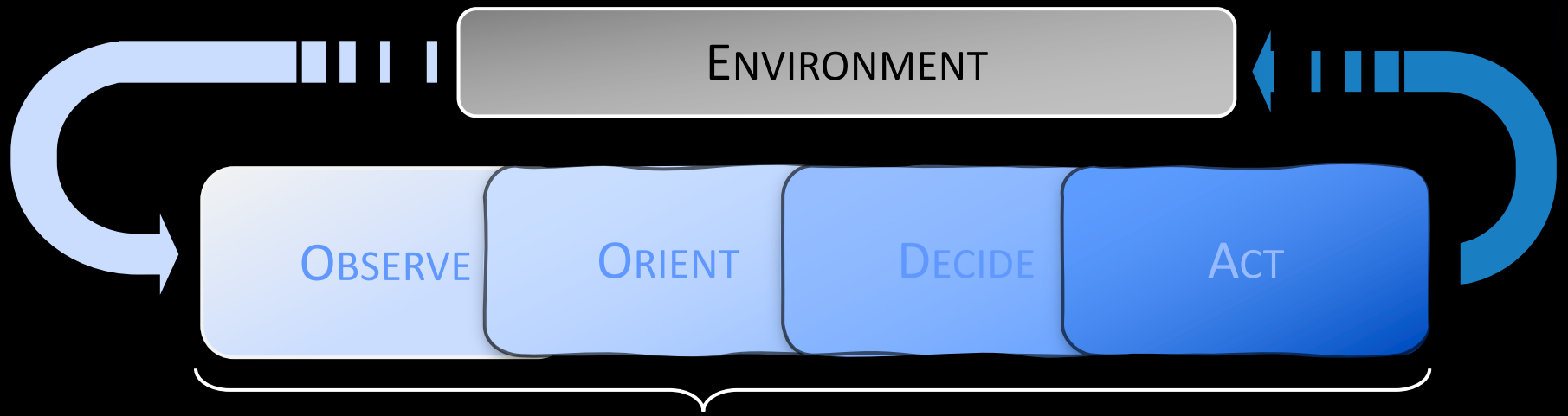


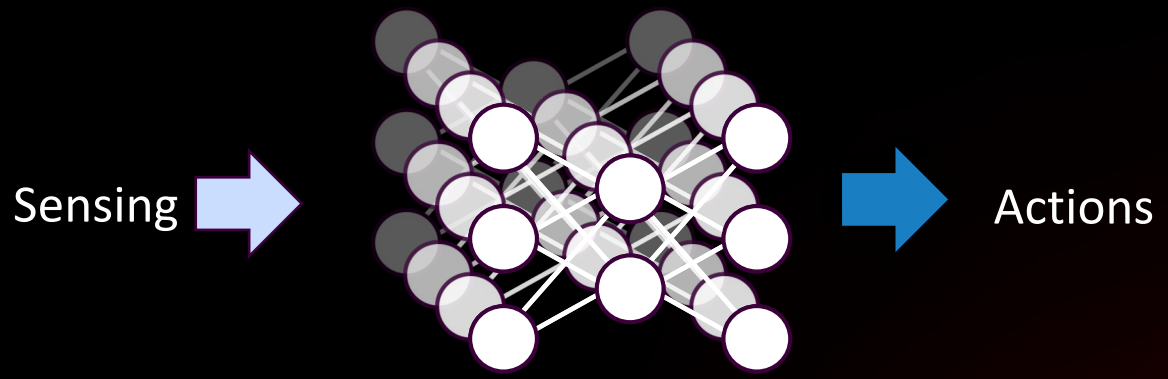


Deep Networks perform many *key processing steps* within the subfunctions of OODA loop

A “Different” Observe, Orient, Decide and Act (OODA) Loop

One can conceive decision loops where representations are (mostly) *hidden* within the layers of DNNs:

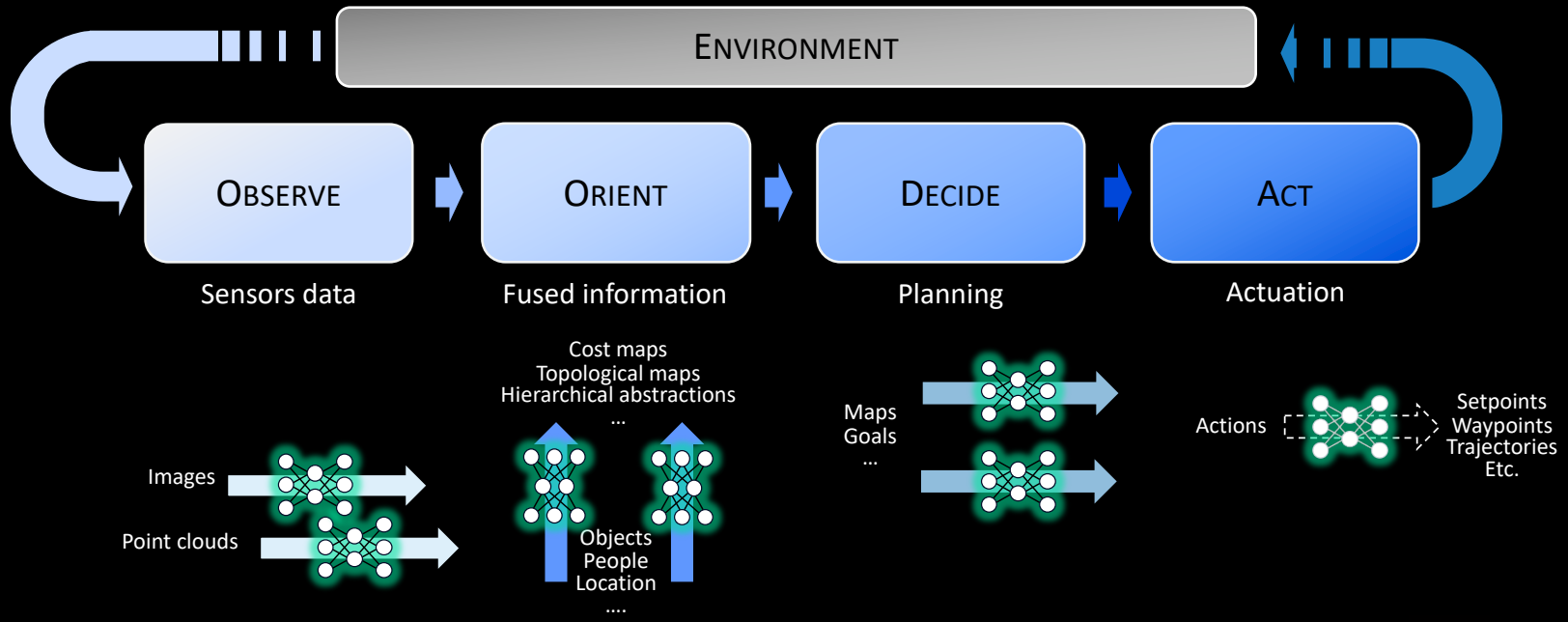




However:

- Difficult to verify and validate especially in safety critical settings
- Data may not be sufficient and/or available
- Simulations too slow to be run and/or too complex/costly to be built
- Difficult to provide operators interpretable insights on what led to certain decisions

Observe, Orient, Decide and Act (OODA) Loop in This Talk



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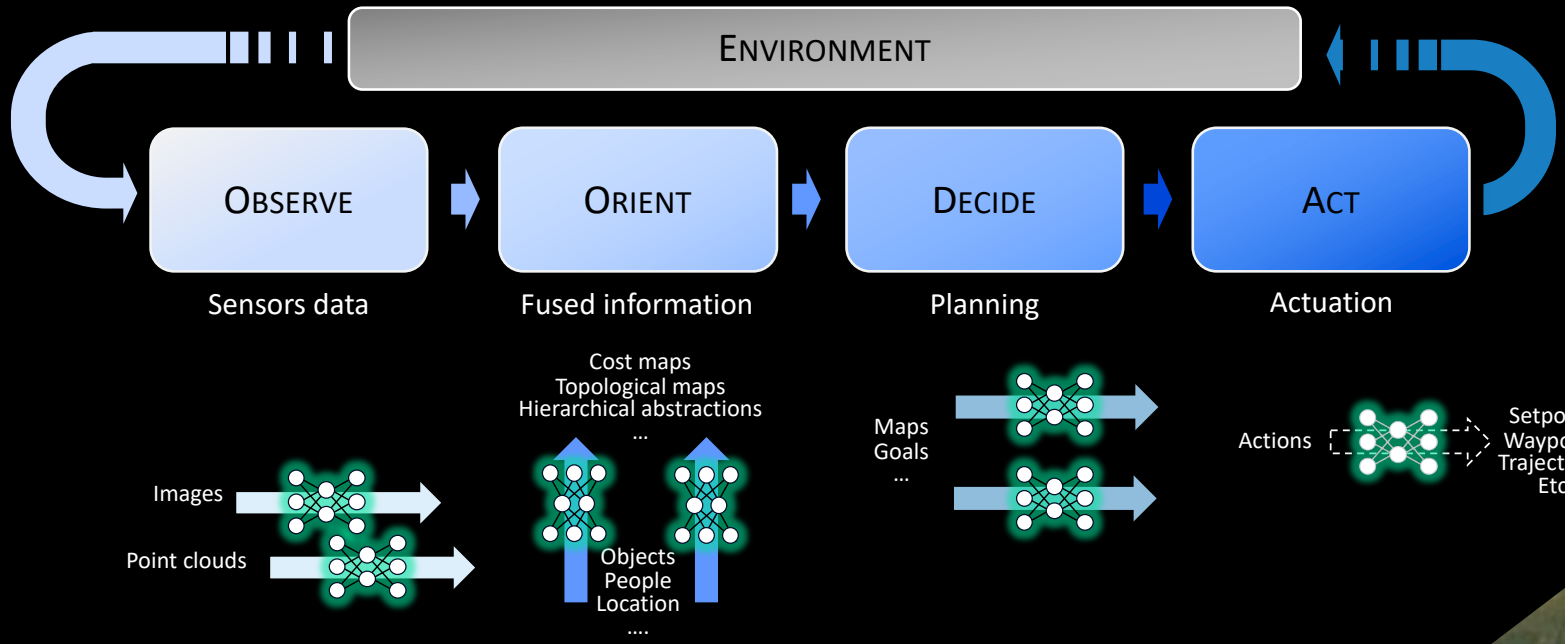
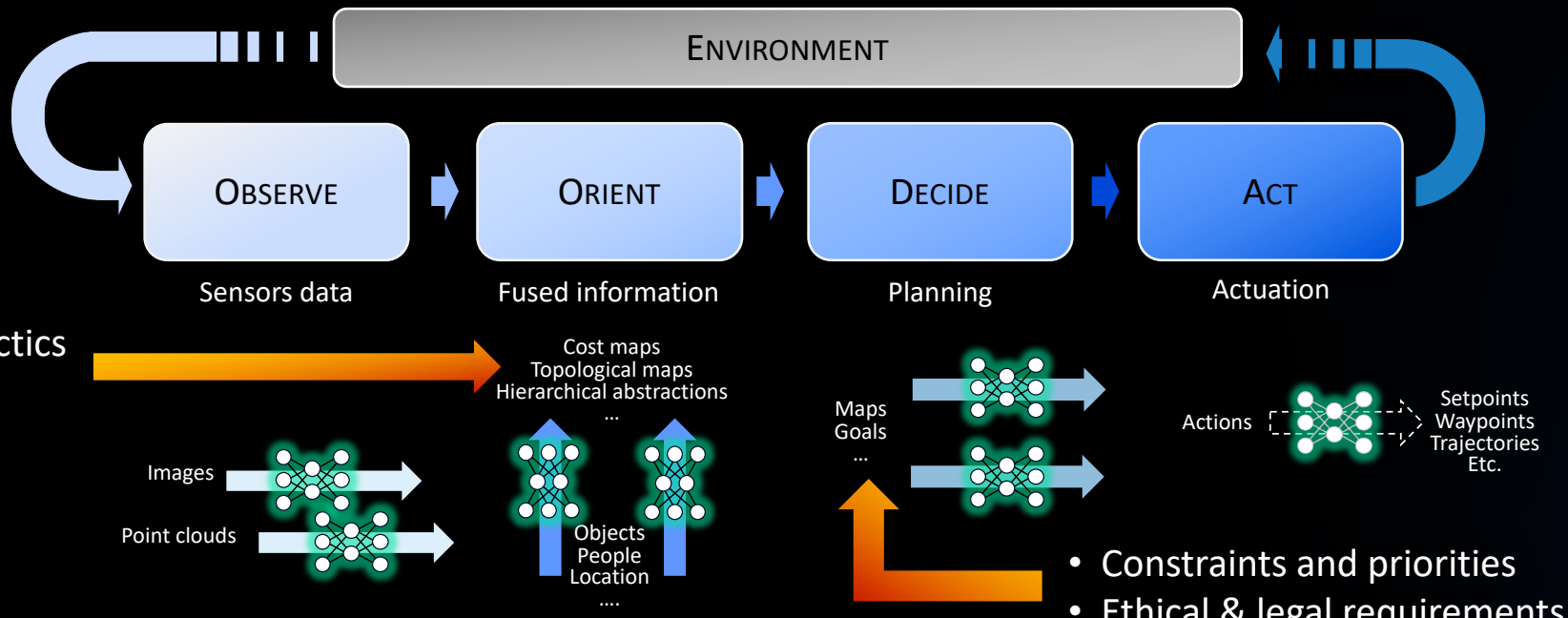


https://blogs.nvidia.com/blog/2021/11/09/lockheed-martin-wildfires-ai/

- Autonomous platforms with multiple sensors detecting fire fronts and predicting their propagation
- Coordination between humans and autonomous systems requires following specific guidelines
- Decisions on where to drop retardants or water, where to light controlled fires or remove burnable material

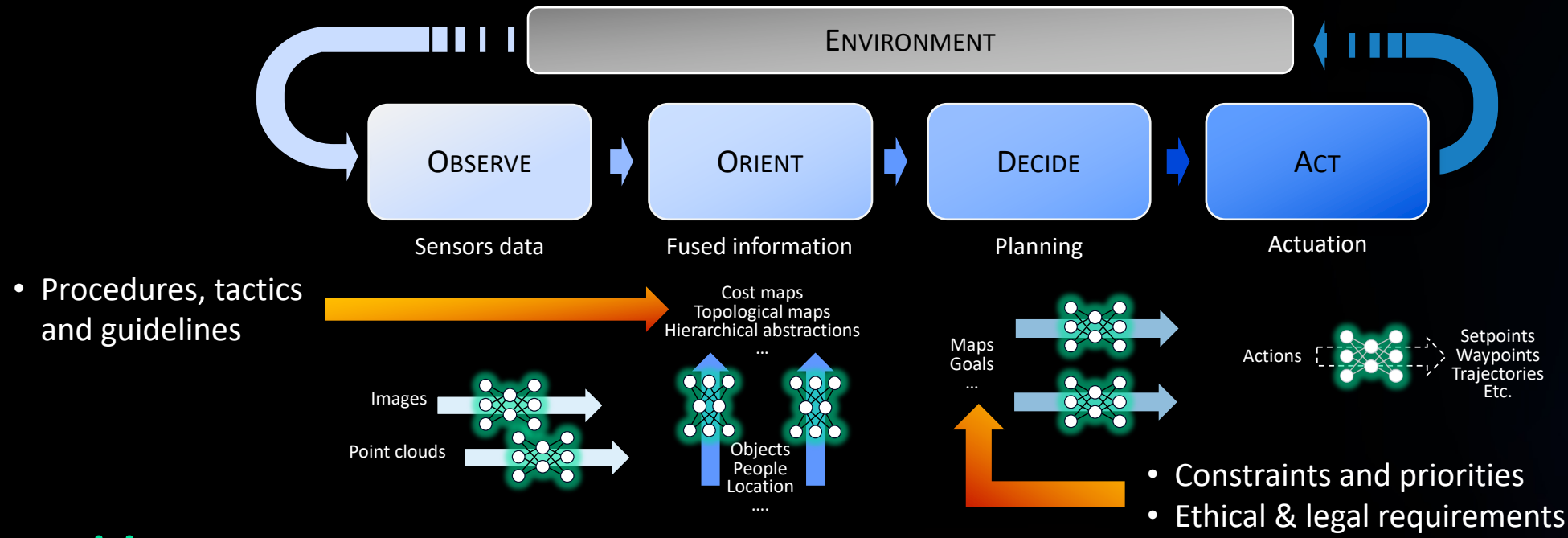
Integration of Prior Knowledge within the OODA Loop



Challenges:

- Data versus symbolic knowledge -- “more/less” data versus “less/more” axioms dichotomy
- Should symbolic knowledge capture be adapted/re-defined for NS architectures?
  - Knowledge capture is typically done to share common understanding, for reusability, make domain assumptions explicit, separate domain from operational knowledge, analyze/query domain knowledge;
  - In various NS approaches knowledge is typically very focused and used to shape constraint/loss functions
- Should symbolic priors be represented/integrated differently in eachpart of the OODA loop?

Integration of Prior Knowledge within the OODA Loop

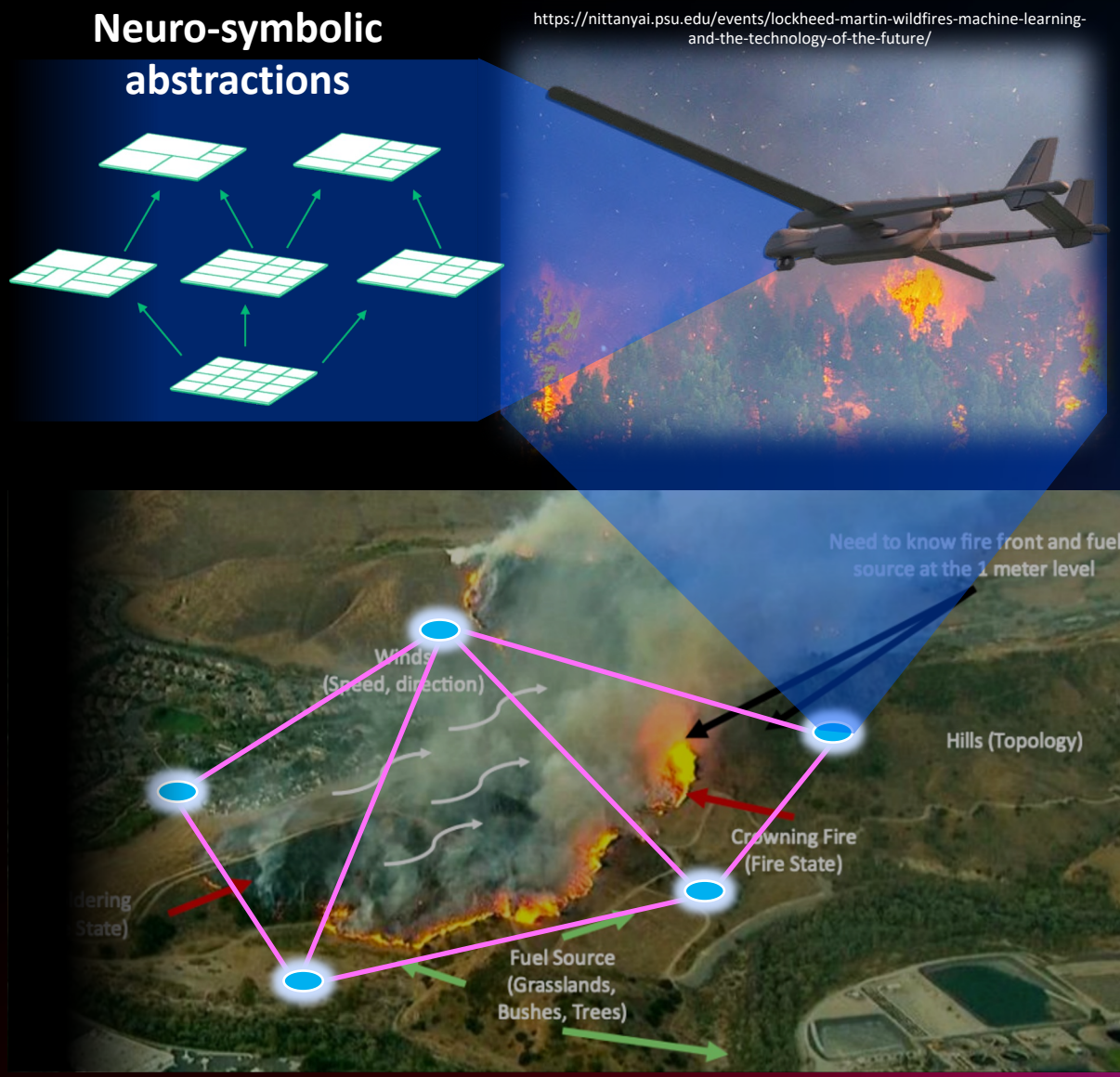


Opportunities:

- Multi-Modal Large Language Models (mmLLMs) may provide an approach to extract knowledge in a semi-automatic fashion, reducing the cost of the task
- ***However***, query engineering to extract meaningful/useable ontologies may be, at this stage, as complex as developing an ontology itself and need to mitigate hallucination, model refinement, etc.

Development of NS Abstractions

- In “Orient” and “Decide” of the OODA loop an autonomous system *generates abstractions* to represent the world and plan relevant decisions
- *Symbolic representations* provide a very appealing way to model such abstractions



Development of NS Abstractions

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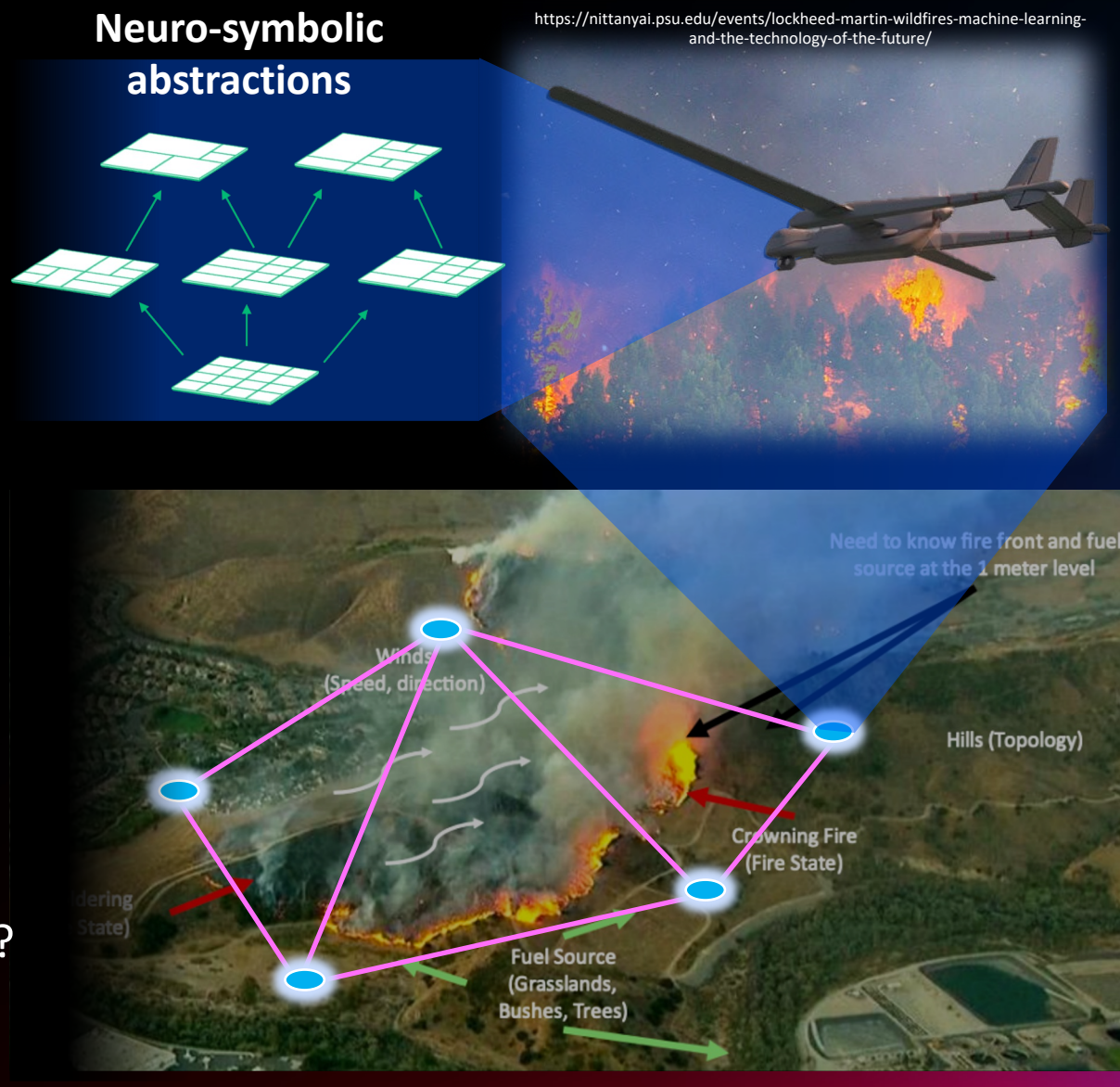
- *Symbolic representations* provide a very appealing way to model such abstractions
  - ❖ Compositionality
  - ❖ Reusability & Transferability
  - ❖ Interpretability
  - ❖ Complexity reduction/Compression

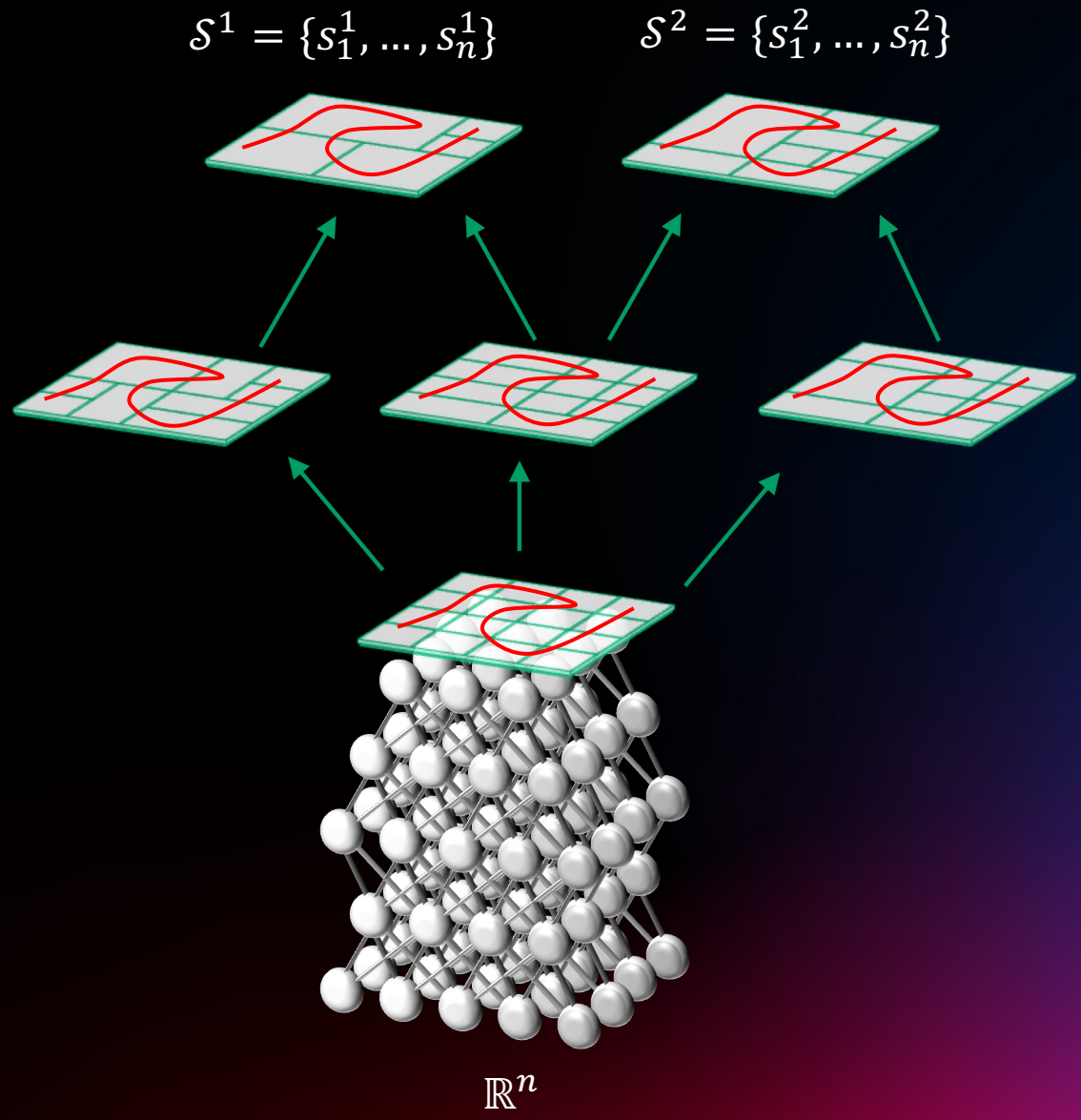
Challenges:

- Development of abstractions that are consistent
- Composability properties of symbolic abstractions:
  how do we engineer them? Is it an emergent property?
- Integrate interpretability requirements



Uncertainty and Ambiguity

- Neuro-symbolic representations are, in general, going to require a “quantization” of the concrete continuous space (e.g., state/actions) into symbols
- In general, this mapping is going to be lossy inducing both quantization error (uncertainty) as well as a non-uniqueness (ambiguity)



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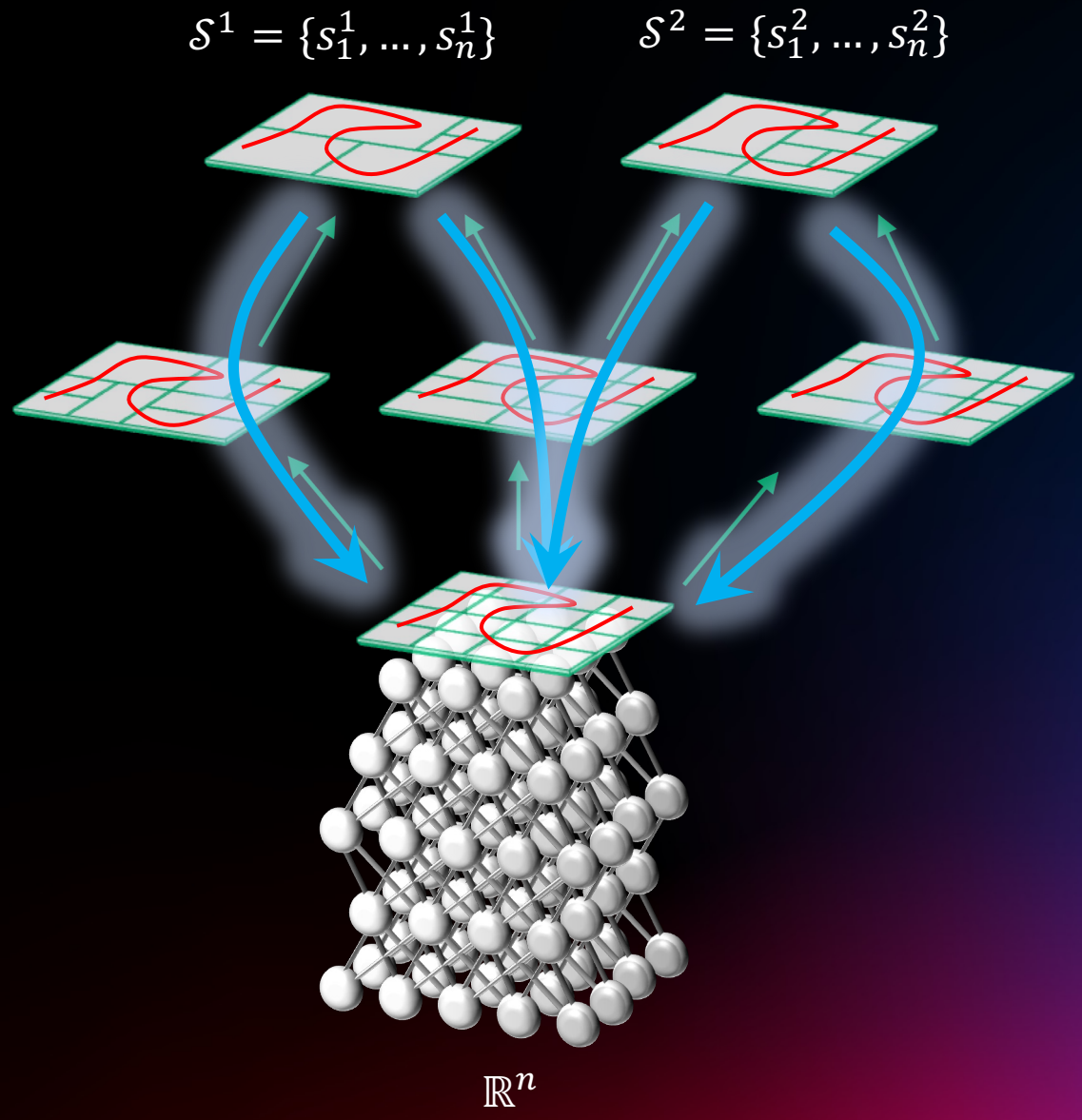
Challenges:

- Formal way of incorporating quantization error and ambiguity in the symbolic abstractions (e.g., information theoretical approaches)
- The grounding of symbols is a well known problem but in an OODA loop we need to ensure consistency of symbols across the components (e.g., “Observe” and “Orient”)



Assurance of Complex Systems

Overarching Properties[1]:

- **Intent**: The system's *defined intended behavior* must be *correct and complete* with respect to the desired behavior
- **Correctness**: The *implementation must be correct* with respect to the intent under foreseeable operating conditions
- **Innocuity**: Unintended behavior must *not have unacceptable impact*
- **Operation**: The system must possess *mechanisms for addressing correctness* or *intent deficiencies* and for mitigating unacceptable impacts manifested during operation

https://nittanyai.psu.edu/events/lockheed-martin-wildfires-machine-learning-and-the-technology-of-the-future/

[1] C. M. Holloway, "Understanding the Overarching Properties". NASA, Langley Research C

Assurance of NS Systems

Challenges & Opportunities:

- **Intent:** NS representations enable to (more) formally describe the behavior of an autonomous system, at least at the level of each subcomponent of the OODA loop
- **Correctness:** Compositional NS abstractions provide opportunities to leverage contract based design methods[2]; however, uncertainty, ambiguity and symbolic consistency across OODA loop components need to be addressed
- **Innocuity**: Safety concerns, typically described as requirements in English, can be translated into (modal) logic and thus incorporated within NS architectures
- **Operation:** NS abstractions are built by incorporating logical formulas that can be monitored and reasoned ove during execution; however ambiguity, symbol grounding and uncertainty issues need to be addressed

https://nittanyai.psu.edu/events/lockheed-martin-wildfires-machine-learning-and-the-technology-of-the-future/

[2] A. Sangiovanni-Vincentelli, W. Damm, R. Passerone, "Taming Dr. Frankenstein: Contract-Based Design for Cyber-Physical Systems", European Journal of Control, 2012

What is needed to build trust-worthy and trusted AI

Example: Mission Planning through Preference Learning

Approach: Combine strengths of automated route planners with experience and intuition of pilots using interactive learning to produce high quality personalized route

Compared to a baseline semi-manual route planning, the Preference Learning

- Produced final routes more preferred by SMEs
- Resulted in higher favorable attitude ratings by SMEs
- Lowered subjective SME workload

Needs:

- Manage AI performance/explainability trade-off
- AI-based human attention management (when and how to engage humans)
- AI agents and humans learning from each other (build trust over time)
- Immersive virtual environments for joint human-AI training

Trust-worthy does not imply trusted

Directions for future research

- The OODA loop provides unique challenges for NS architectures but they also provide huge opportunities to design **trustworthy autonomous systems**

- **Composition, interpretability and reusability** of neuro-symbolic abstractions in the OODA loop can unlock new and more scalable design paradigms

- More broadly we need methods to account for:
  - Multiple spatio-temporal scales
  - Life-long learning at the edge
  - Human-AI trust building
  - Ethical AI
  - Multiple assurance frameworks (multiple suppliers)