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DATAWorks 2024: A Practitioner's Framework for Federated Model Validation Resource Allocation

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Executive Summary

Recent advances in computation and statistics, as well as constraints on live testing, have led to an increasing use of federated models for end-to-end system test and evaluation. A federated model is a collection of interconnected models where the outputs of a model act as inputs to subsequent models. However, the process of verifying and validating federated models is poorly understood, especially when testers have limited resources, knowledge-based uncertainties, and concerns over operational realism. Additionally, testers often struggle with allocating limited test resources among the interconnected models for validation.

To address these issues, we propose a network-based representation of federated models. Nodes of the network are given by models. A directed edge from node a to node b is drawn if a inputs into b. Each node of the network has two types of input parameters, exogenous and propagated. Exogenous input parameters are those that are independent of all other nodes. Propagated input parameters are inputs via connected nodes. Slide 5 gives an example of these relations.

We propose a five-step process to better understand the uncertainty of the federated model for better informed decision making. In step 1, we assign appropriate distributions for all exogenous input parameters. For knowledge-based parameters, we recommend using subject matter and statistical expertise to pick appropriate distributions. In step 2, for each node we build a meta-model when necessary to model uncertainties and reduce complexity.

In step 3, we quantify the uncertainties in each node. We use a variance-based approach to break down how much of each node's variance is explained by its connecting nodes, which is then assigned to an edge weight. Then in step 4, we leverage the network structure to propagate the uncertainties through the network, thus allowing us to quantify how much each model contributed to overall uncertainty of the federation.

Lastly, in step 5, we use the propagated uncertainties to make informed decisions for allocation of test resources. Note that this framework does not reduce uncertainty in the federation of models. It does however inform decision

makers on where uncertainty is highest and which aspects of the federated model need to be validated further.

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17 April 2024

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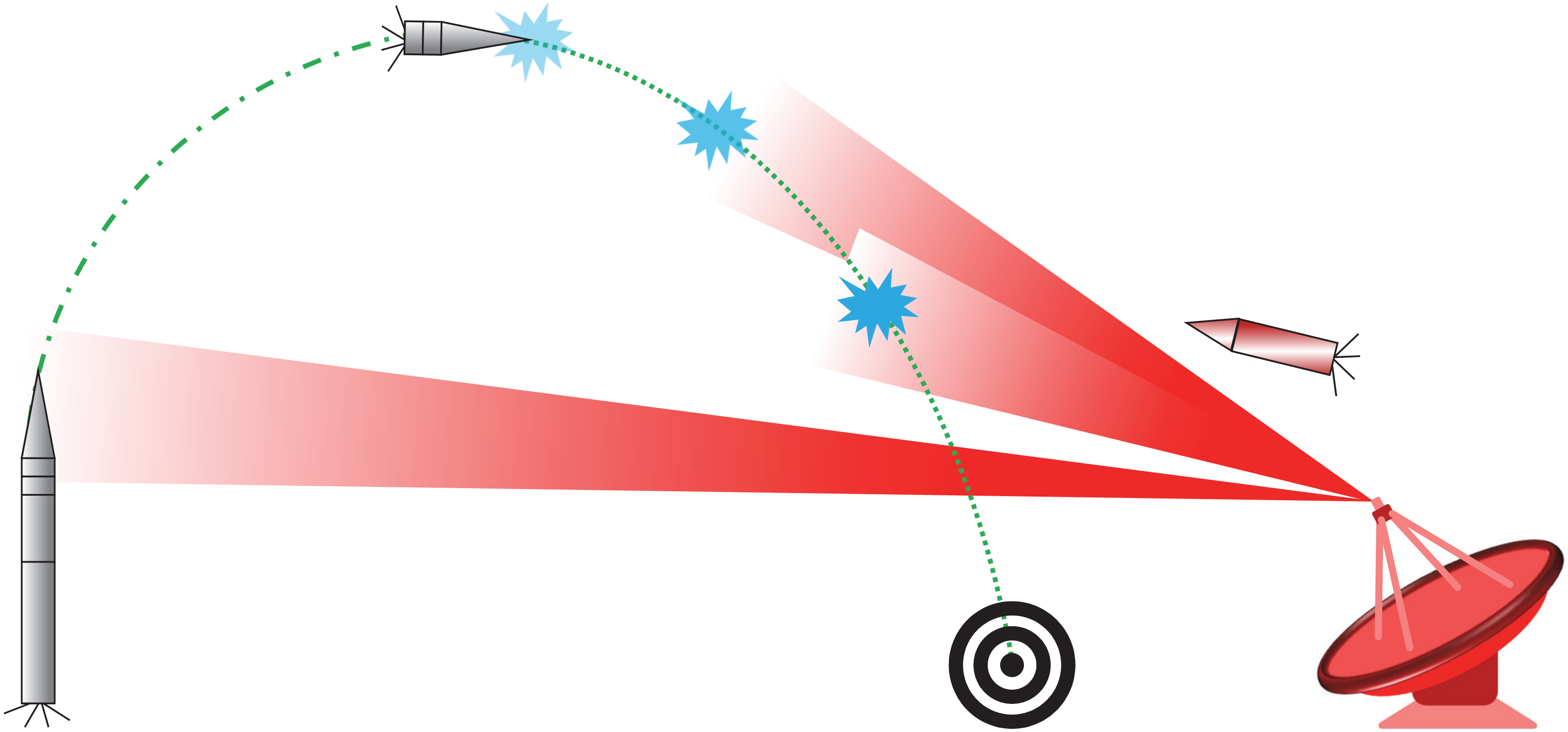
Federated model – interconnected system of models



- A federated model is used to test and evaluate end-to-end system performance
- Goal: To better understand the uncertainty of the federation to make informed decisions about validation resource allocation

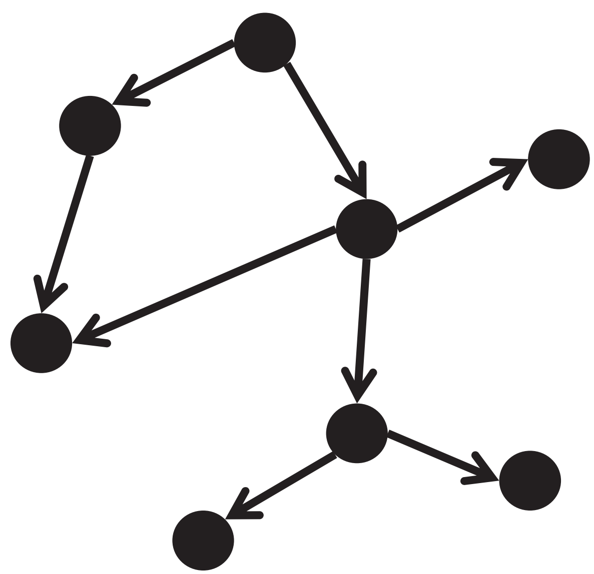
IDA is extending the framework proposed by others to consider an operational test perspective for end-to-end federated models

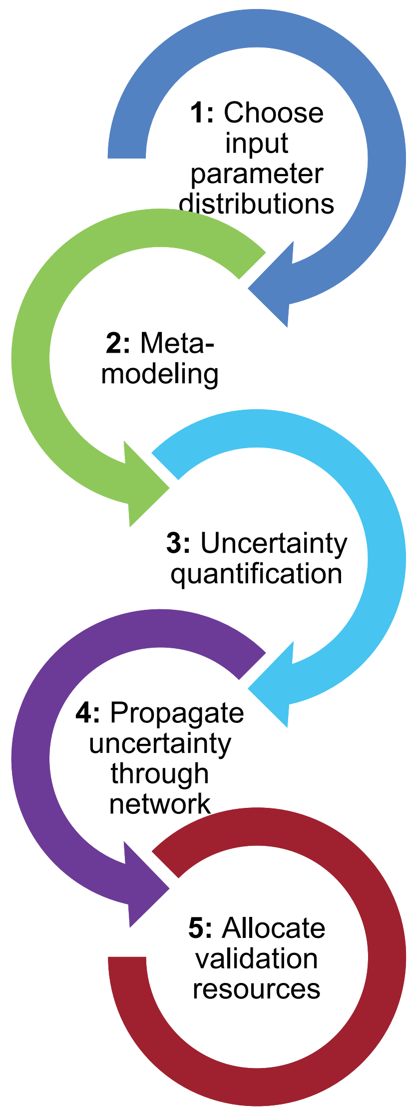
- Uncertainty quantification of systems-of-systems has been studied extensively
  - Raz AK, Wood PC, Mockus L, DeLaurentis DA. System of systems uncertainty quantification using machine learning techniques with smart grid application. *Systems Engineering*. 2020; 23: 770–782.
  - Biltgen, Patrick T. "Uncertainty quantification for capability-based systems-of-systems design." *26th International Congress of the Aeronautical Sciences, Anchorage USA, ICAS2008-1.3*. Vol. 3. 2008.
  - DeLaurentis, Daniel A., Kushal Moolchandani, and Cesare Guariniello. System of Systems Modeling and Analysis. CRC Press, 2022.
- Network-based uncertainty quantification is not new
  - Carlberg, Kevin, et al. "The network uncertainty quantification method for propagating uncertainties in component-based systems." *arXiv preprint arXiv:1908.11476* (2019).
  - Tencer, John, Edward Rojas, and Benjamin B. Schroeder. "Network Uncertainty Quantification for Analysis of Multi-Component Systems." ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering 9.2 (2023): 021203.
- We take a DoD operational testing perspective
  - Limited test resources
  - Knowledge-based uncertainties
  - Validating operational realism

Main Idea: Propagate uncertainty and allocate resources leveraging inherent network structure

A network is a collection of nodes and pairwise relationships between nodes called edges

- Nodes: models
- Edges: directed edges indicating model inputs are the outputs of another model





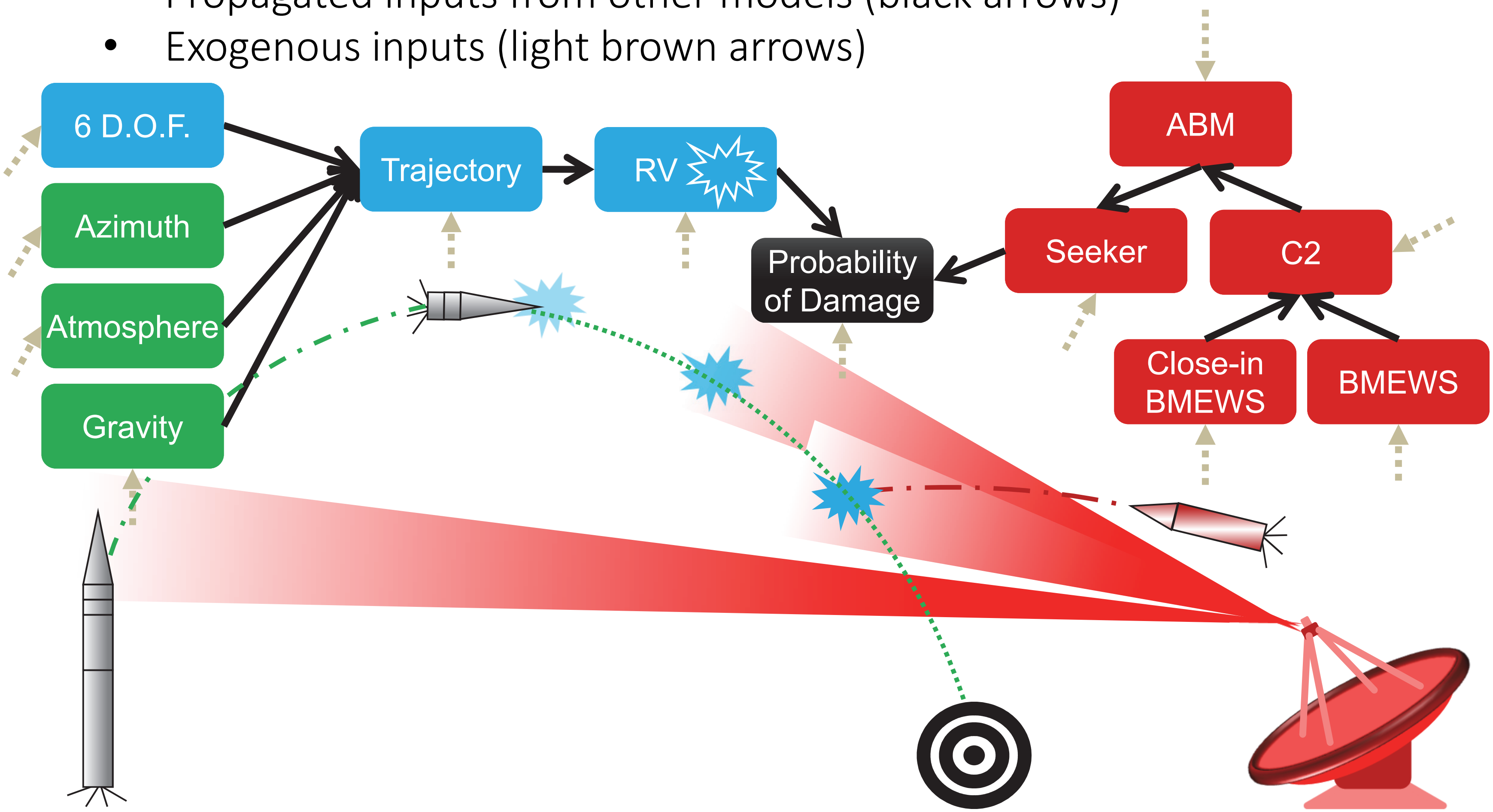
Three types of uncertainties we consider:

- Exogenous: uncertainty due to exogenous input parameter variations and errors
  - Example: parameters which are not the output of another model
- Propagated: uncertainty arising from connecting models
  - Example: inputs and associated uncertainties from connecting models in the network
- Knowledge: pseudo-quantitative uncertainty arising from SME judgement of how well a model represents the real world
  - Example: intelligence models of adversary threats

SME: Subject Matter Expert

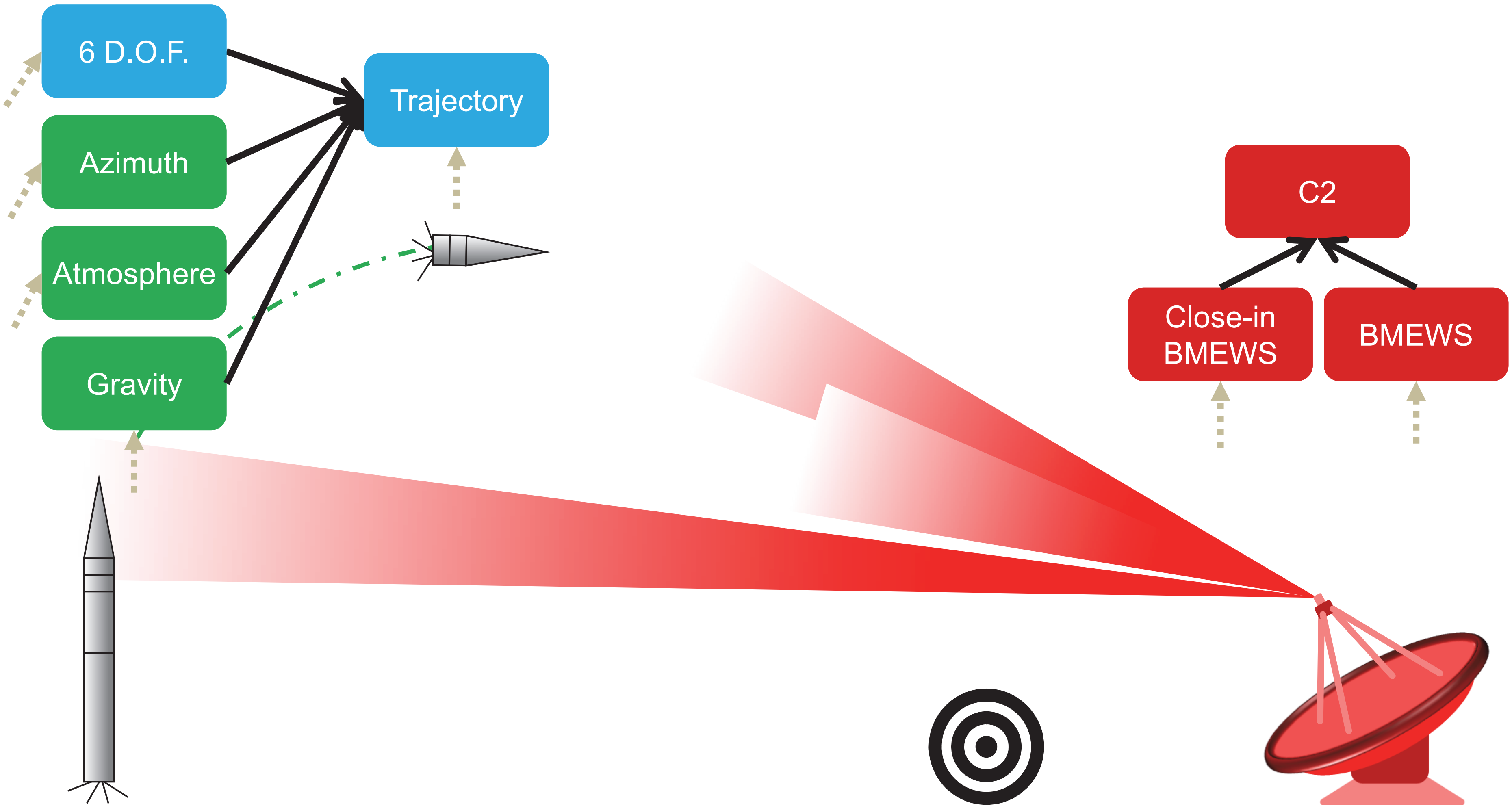
Example: ballistic missile model

- Each node has two types of inputs
  - Propagated inputs from other models (black arrows)
  - Exogenous inputs (light brown arrows)



6 D.O.F.: 6 Degrees of Freedom; ABM: Anti-Ballistic Missile; BMEWS: Ballistic Missile Early Warning System; C2: Command and Control; RV: Reentry Vehicle

Steps 1-3 need to be done iteratively through the network



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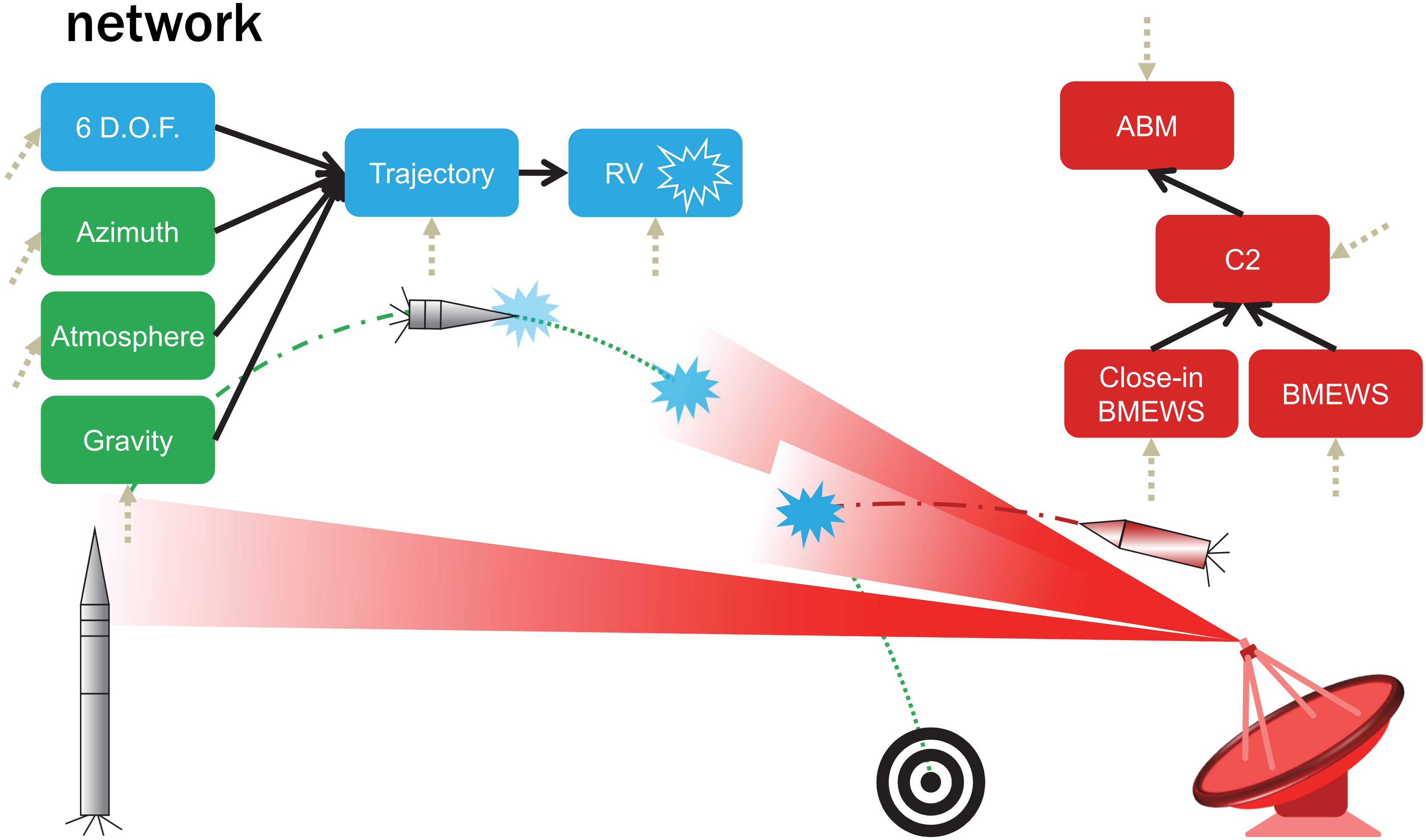

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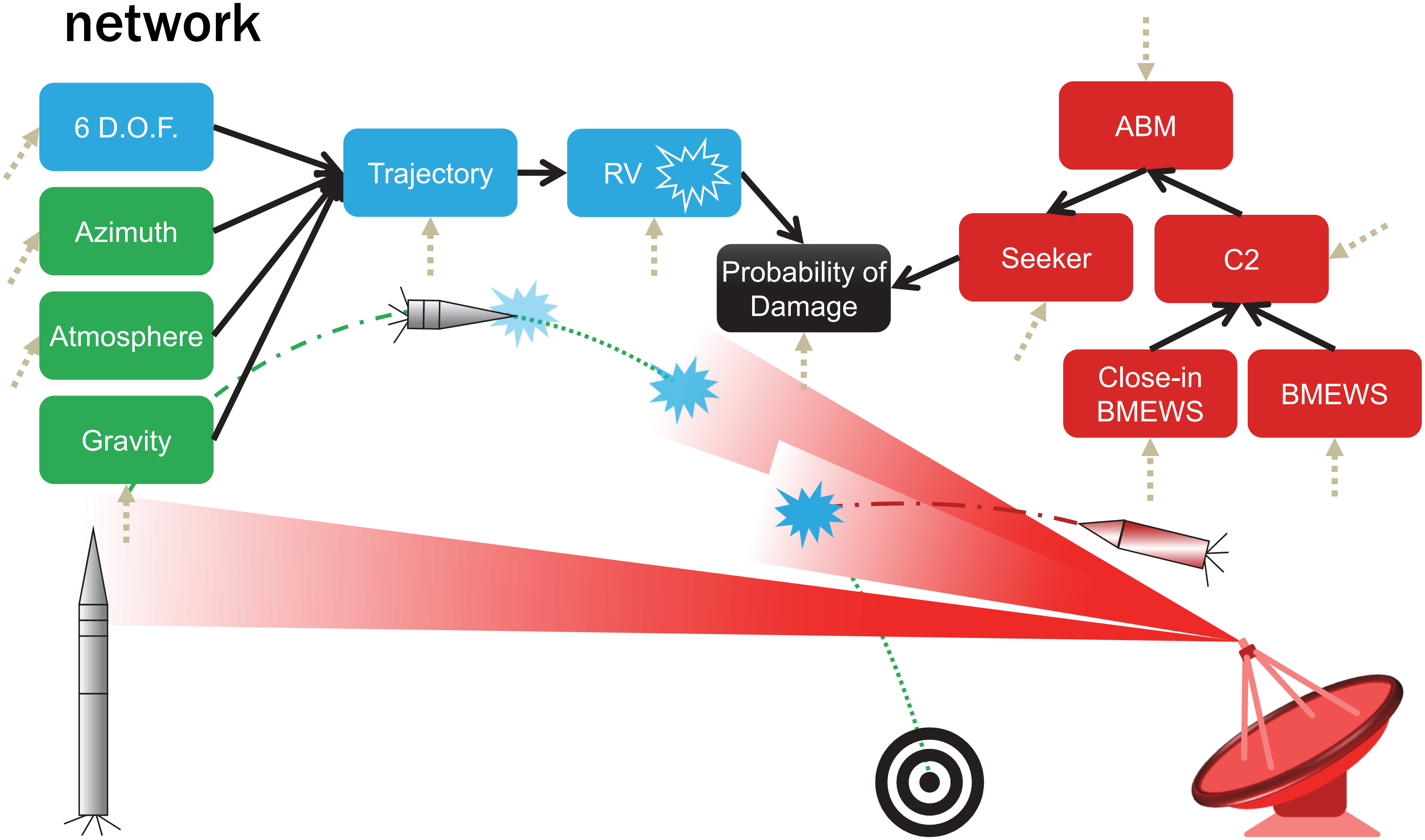

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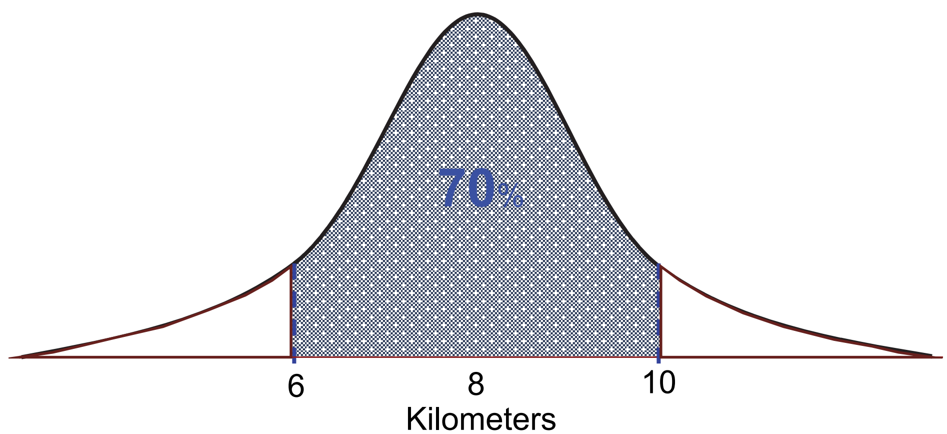
Step 1: Statistical expertise is needed to leverage SME judgement to carefully define distributions

- When sufficient a priori data is available, use data to estimate distributions

- Otherwise, combine SME judgement and statistical expertise to appropriately pick a distribution

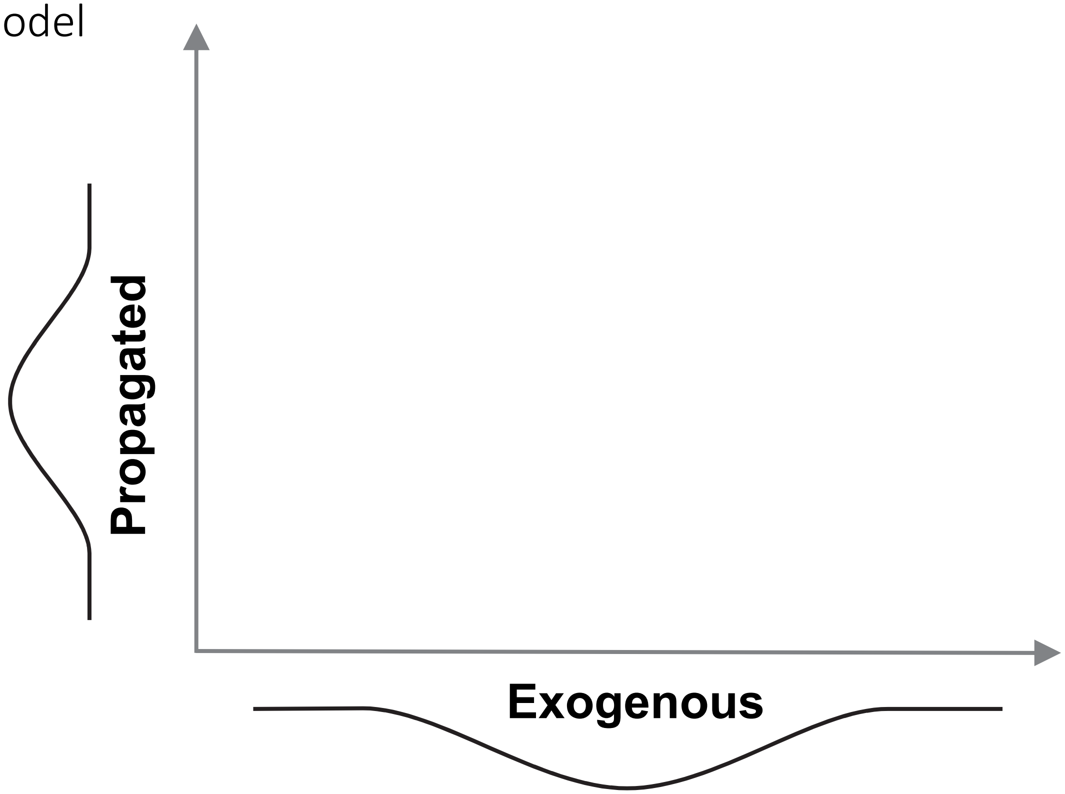
- Example: SME is 70% confident that the adversary seeker will lock onto missile between 6km and 10km.
  - We may choose a normal distribution such that 70% of the time we get a km between 6 and 10.



SME: Subject Matter Expert

Step 2: Build meta-models to capture uncertainty and reduce complexity

- For nodes requiring meta-models, use a space-filling design to characterize model output space
- Use statistical modeling, e.g. Gaussian Processes, to develop a meta-model describing model output space and uncertainty
  - The meta-model is necessary to decrease the complexity and dimensionality of the model



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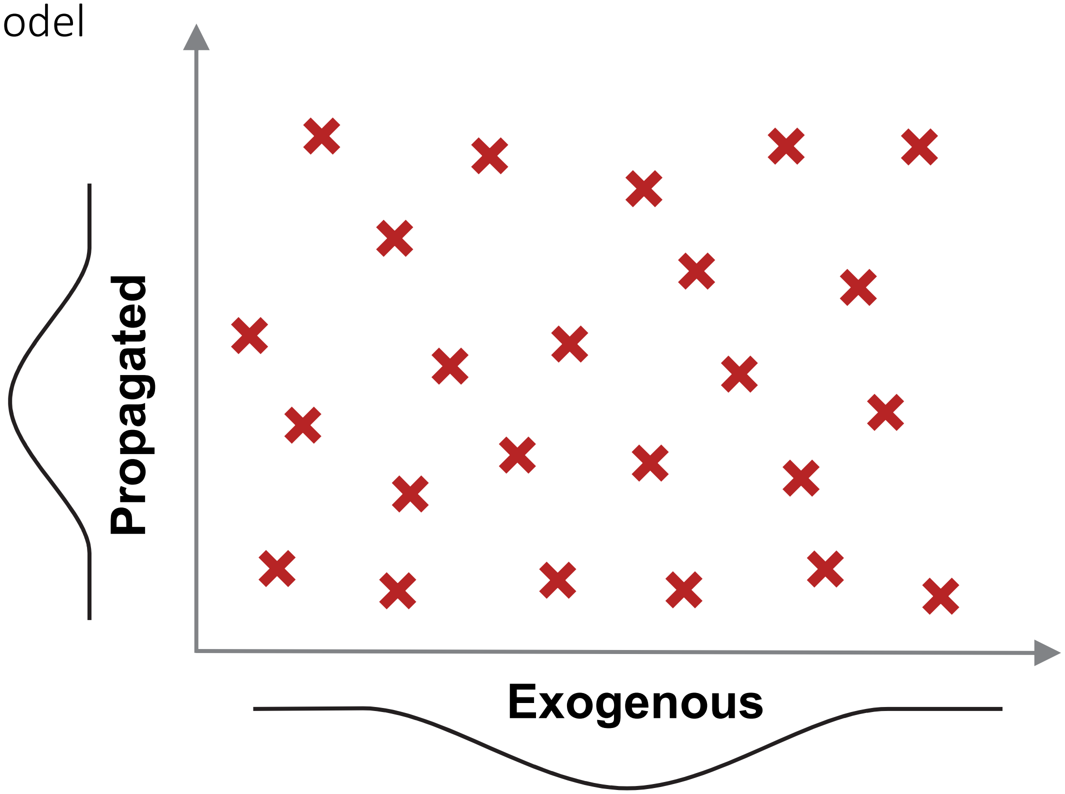

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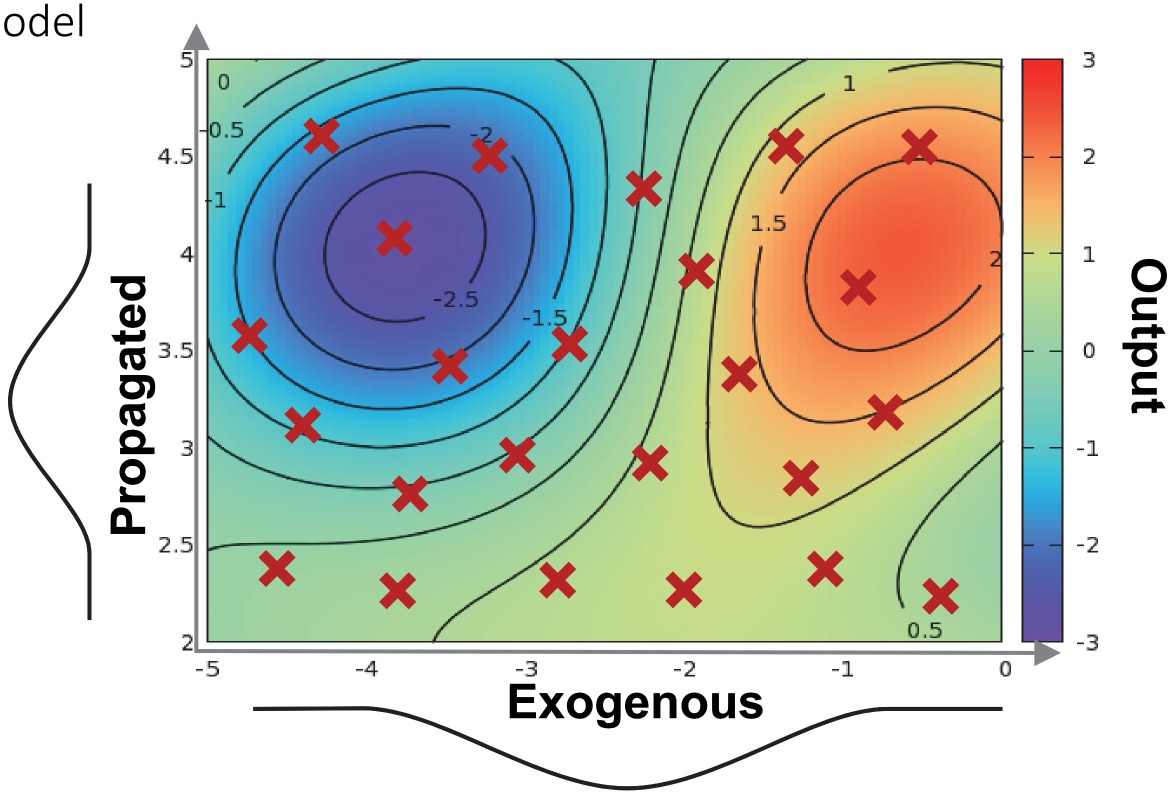
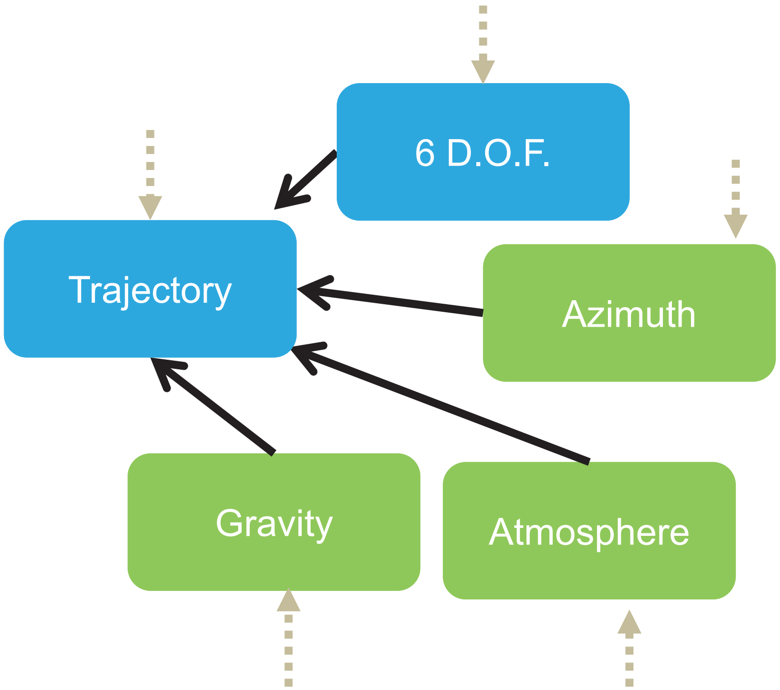
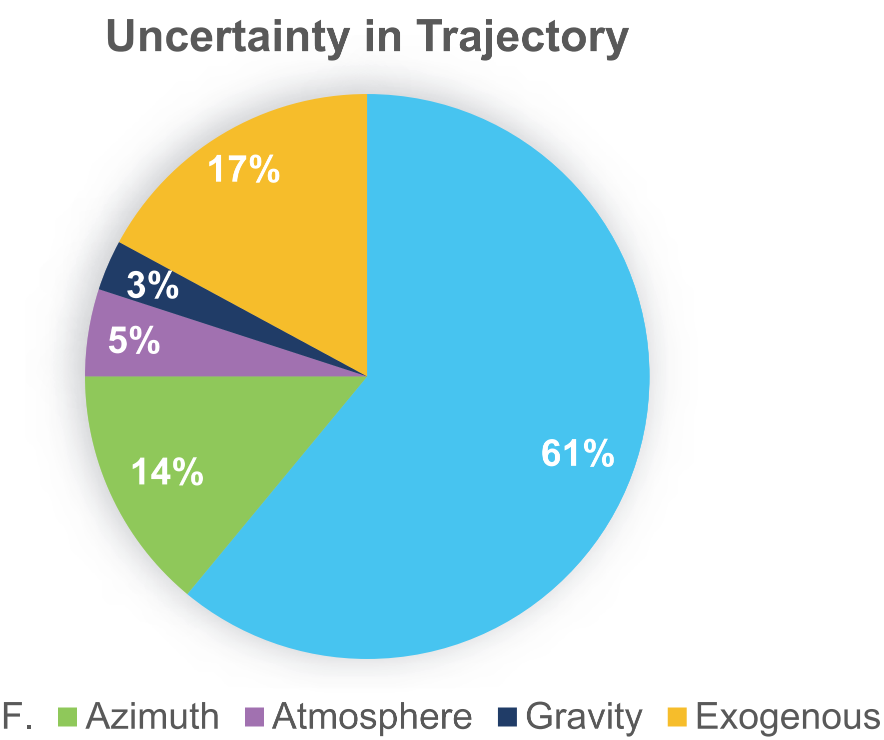


Step 3: For each node, capture uncertainty using meta-model and network structure

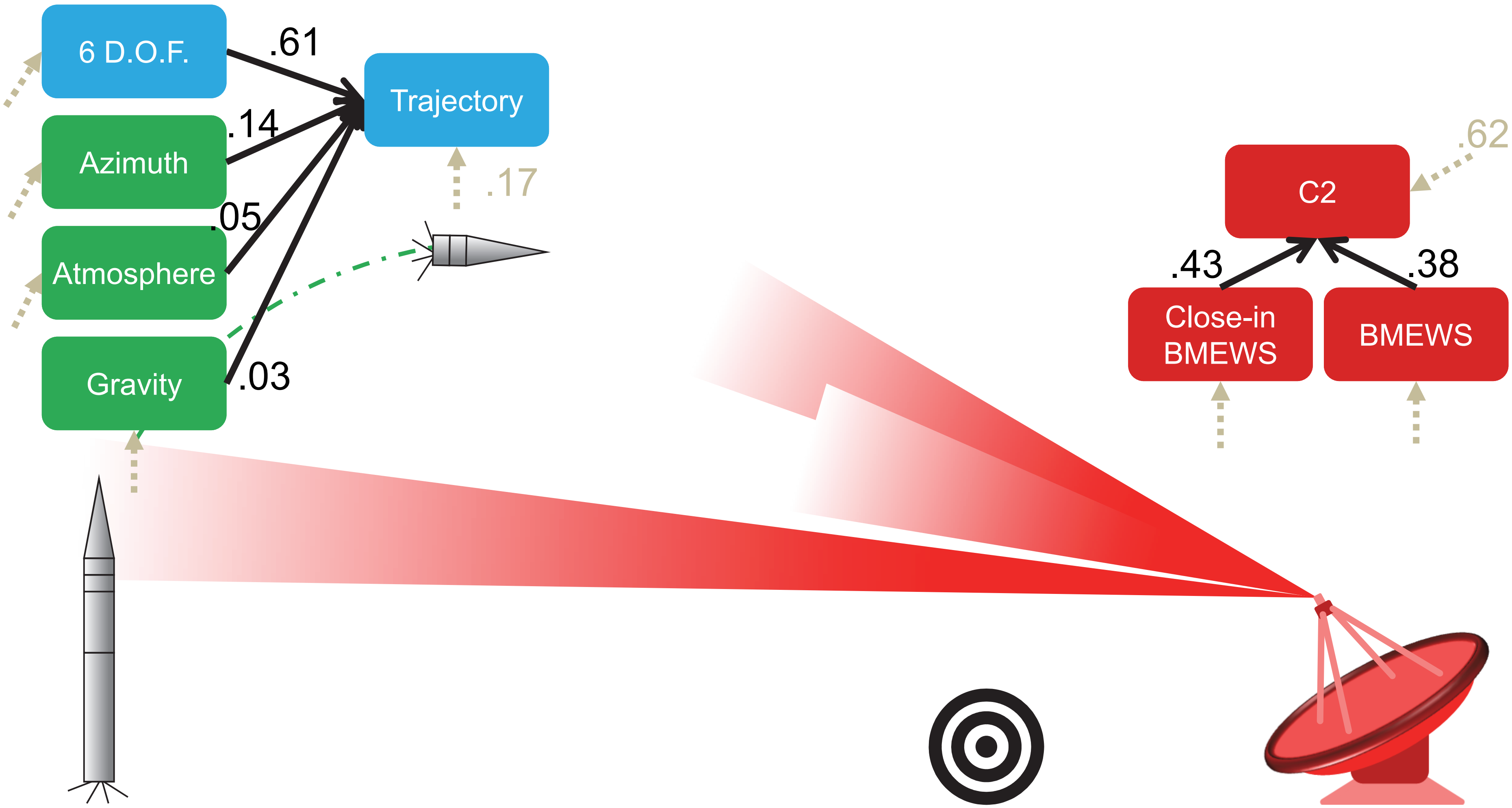
- We choose to quantify uncertainty using variances
  - The variances of each meta-model can be decomposed based on input parameters





6 D.O.F.: 6 Degrees of Freedom

Iterate meta-model and conduct uncertainty quantification through network



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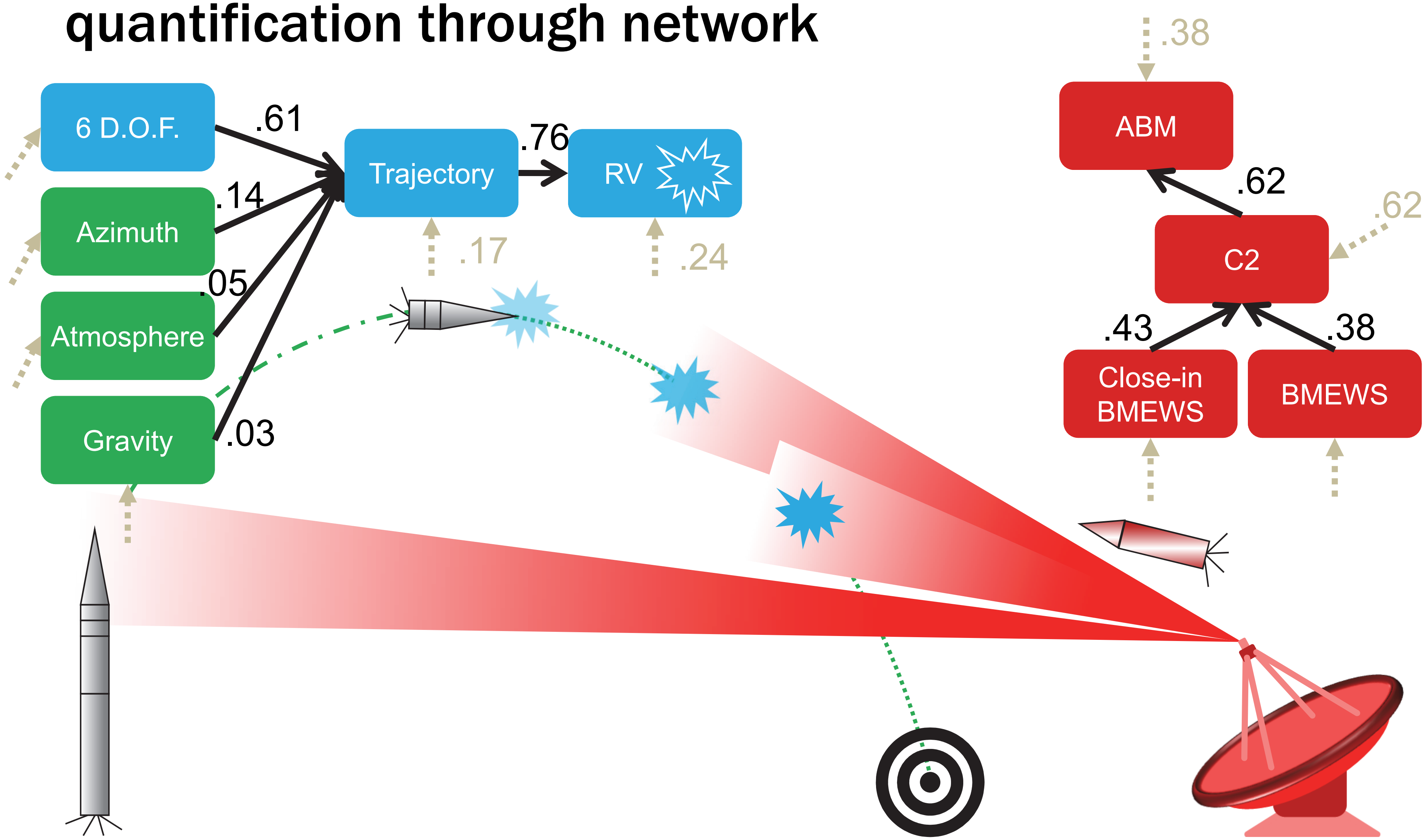

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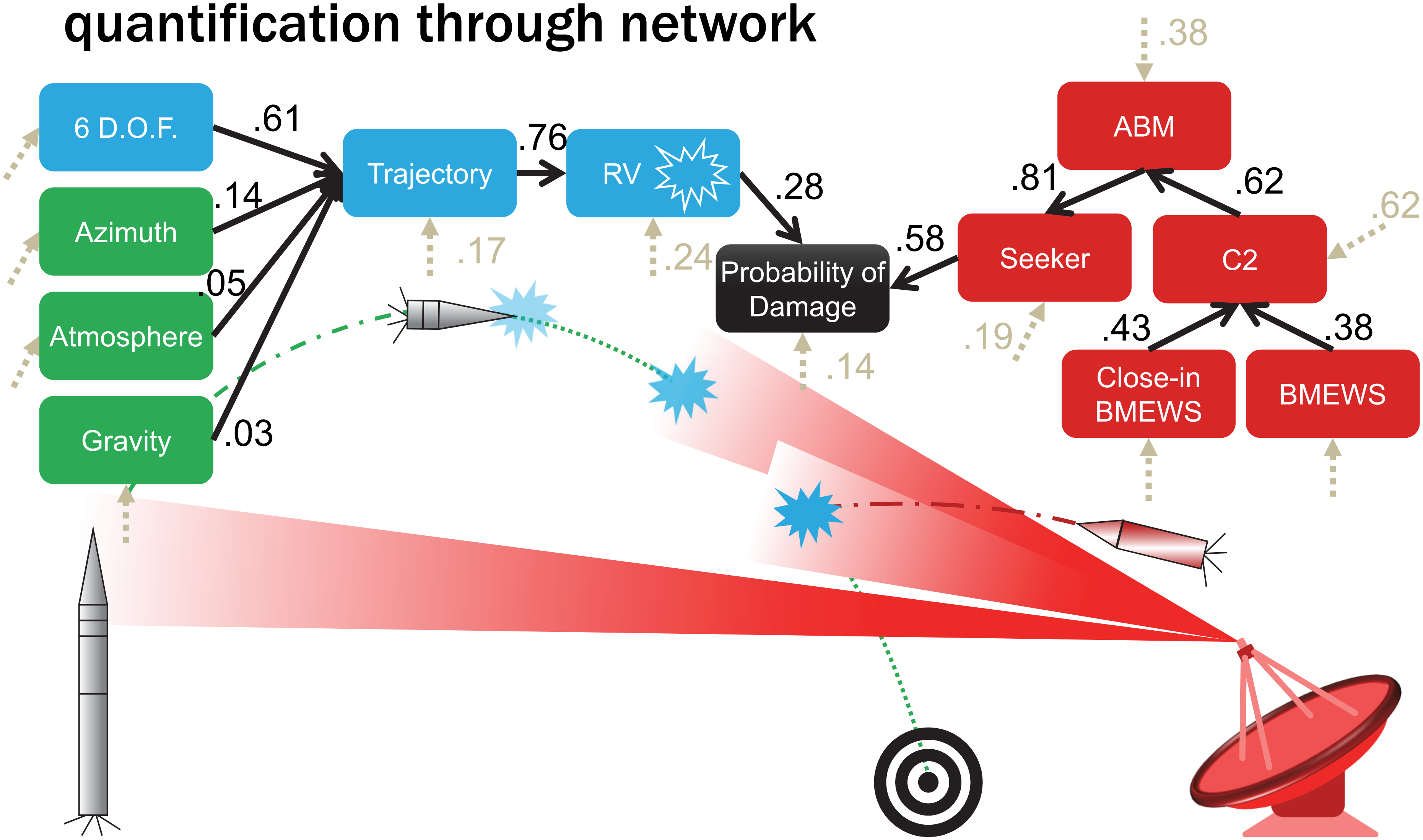

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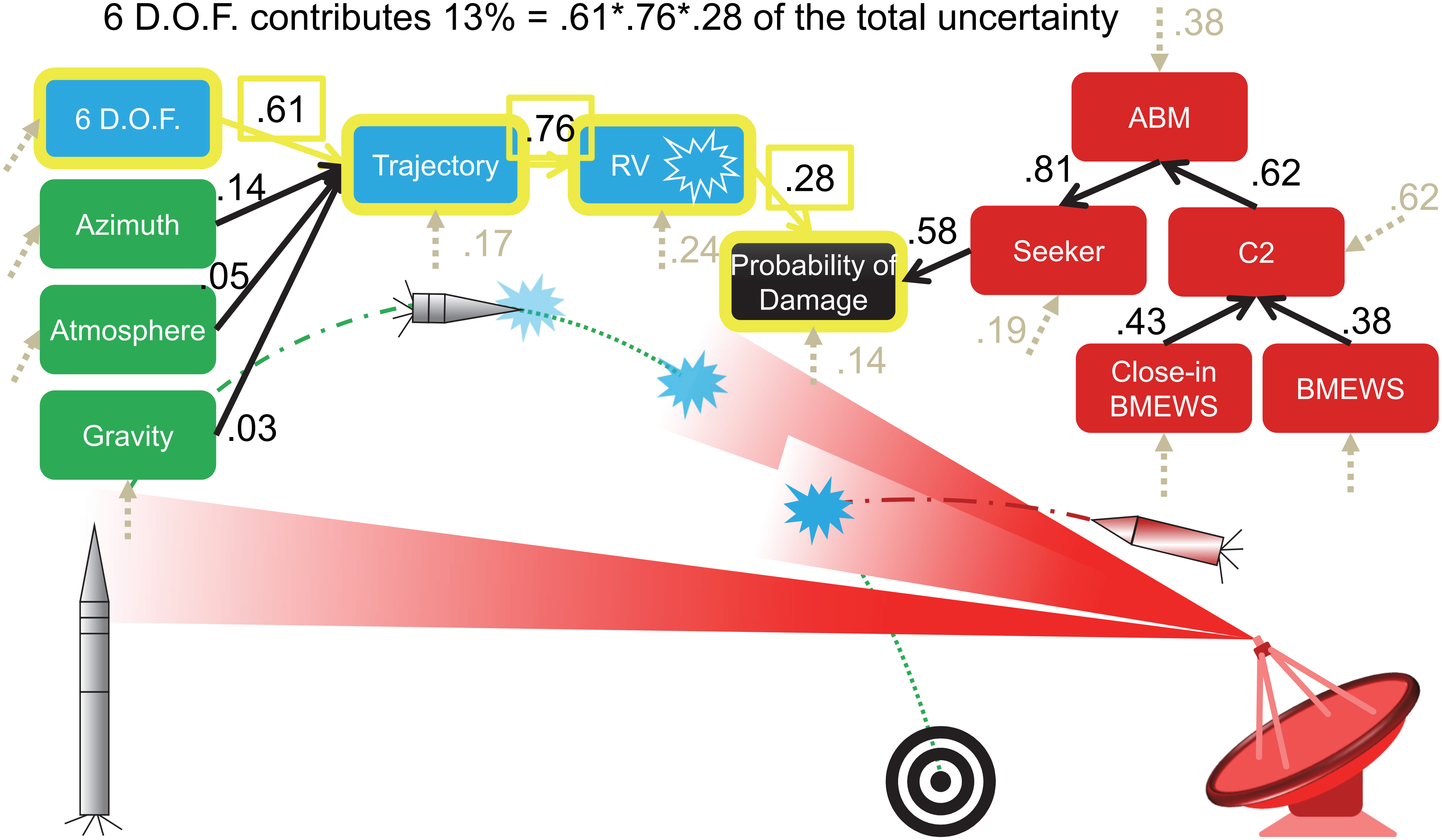
Step 4: Propagate uncertainty

6 D.O.F. contributes 13% = .61*.76*.28 of the total uncertainty



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Identify models contributing most to overall uncertainty

Variable	Proportion of Total Uncertainty
6 D.O.F.	.13
Azimuth	.03
Atmosphere	.01
Gravity	.006
Exogenous - Trajectory	.04
Exogenous - RV	.07
BMEWS	.11
Close-in BMEWS	.13
Exogenous – C2	.06
Exogenous – ABM	.18
Exogenous – Seeker	.11
Exogenous – Probability of Damage	.14

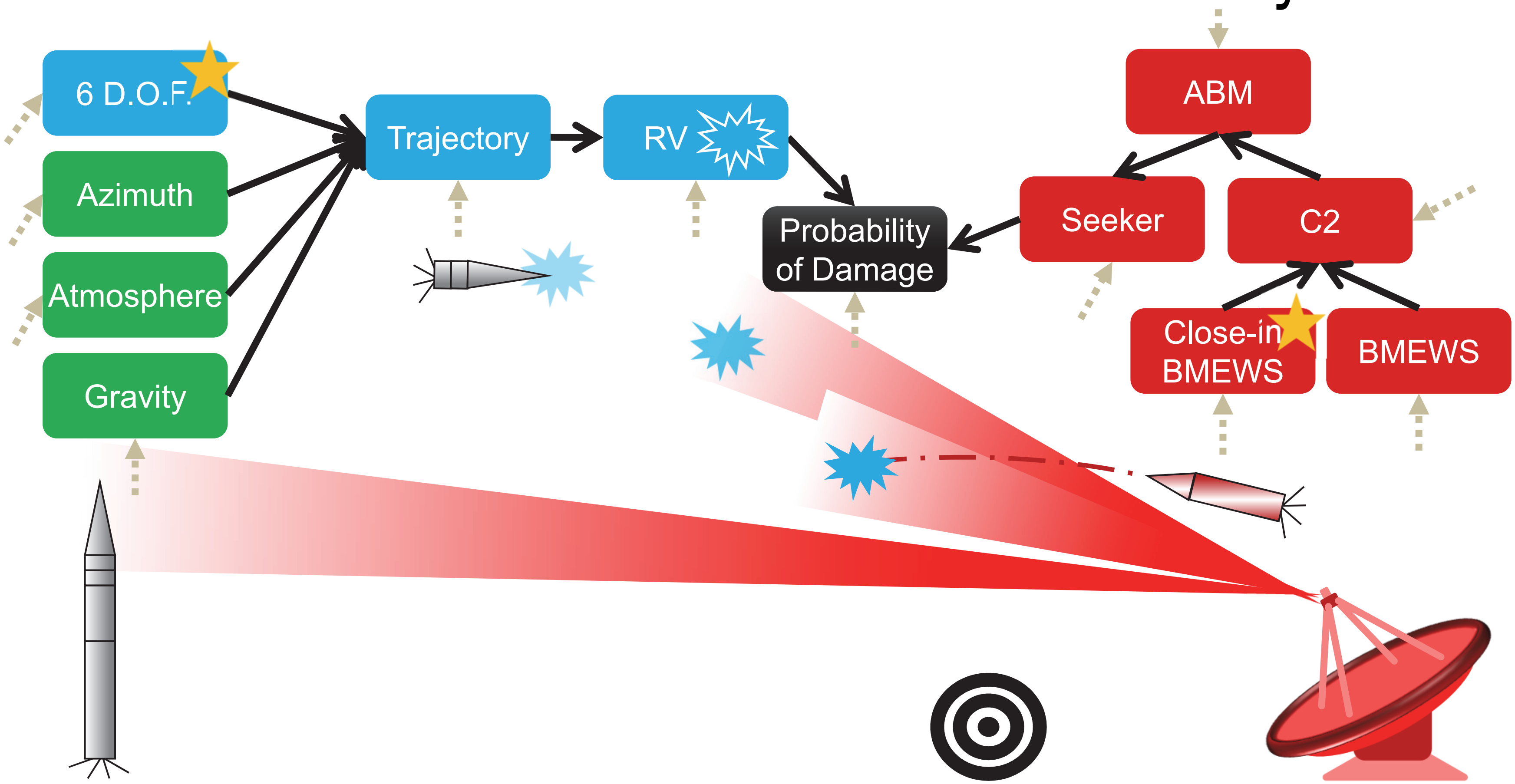
Validate model with live data

Use engineering emulator to validate model

Accept uncertainties as risk to model (uncertainties related to SME judgement on adversary TTPs.)

6 D.O.F.: 6 Degrees of Freedom; ABM: Anti-Ballistic Missile; BMEWS: Ballistic Missile Early Warning System; C2: Command and Control; SME: Subject Matter Expert; TTPs: Tactics, Techniques, and Procedures

Allocate validation resources to models which contribute most to overall network uncertainty



We assume models with high uncertainty have potential to improve. ***<u>Testers should use common sense to ensure results of framework align with SME judgement.</u>***

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Summary of recommended framework

1. Appropriately choose distributions for input parameters
   a. For parameters with a priori data, use data to estimate distribution
   b. For parameters reliant on SME judgement, choose distribution in coordination with statistical expert
2. Use Space-Filling Design to sample both exogenous and propagated input parameter space and build meta-models for each model (node)
3. Quantify proportion of uncertainty explained in each model
4. Use network structure to propagate uncertainties to determine which input parameters contribute most to total network uncertainty
5. Allocate validation resources to models with highest contributions to network uncertainty
6. *Use Common Sense!*

SME: Subject Matter Expert

Future Work

- Provide a class of distributions for exogenous input parameter distributions to account for different types of knowledge
- Provide a collection of uncertainty quantification methodologies to allow practitioners to choose from based on needs of the system
- Provide different ways to propagate uncertainty for all types of networks
- Provide recommendations on how to make choices in each of the 5 steps

Thank you! Any Questions?

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14. ABSTRACT
Recent advances in computation and statistics led to an increasing use of federated models for end-to-end system test and evaluation. A federated model is a collection of interconnected models where the outputs of a model act as inputs to subsequent models. However, the process of verifying and validating federated models is poorly understood, especially when testers have limited resources, knowledge-based uncertainties, and concerns over operational realism. Testers often struggle with determining how to best allocate limited test resources for model validation. We propose a network-based representation of federated models, where the network encodes the connections between the federation of models. Nodes of the graph are given by sub-models. A directed edge from node a to node b is drawn if a inputs into b. We quantify their uncertainties through edge weights using meta-modeling and variance-based sensitivity analysis. The network-based framework allows us to propagate the uncertainties through the federated model and optimize resource allocation for validation based on the uncertainties

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