

# Deep Data Analytics in Support of Acquisitions and Tradespace Analysis

*Engineered Resilient Systems Track  
NDIA Systems and Mission Engineering Conference 2018  
October 24, 2018*

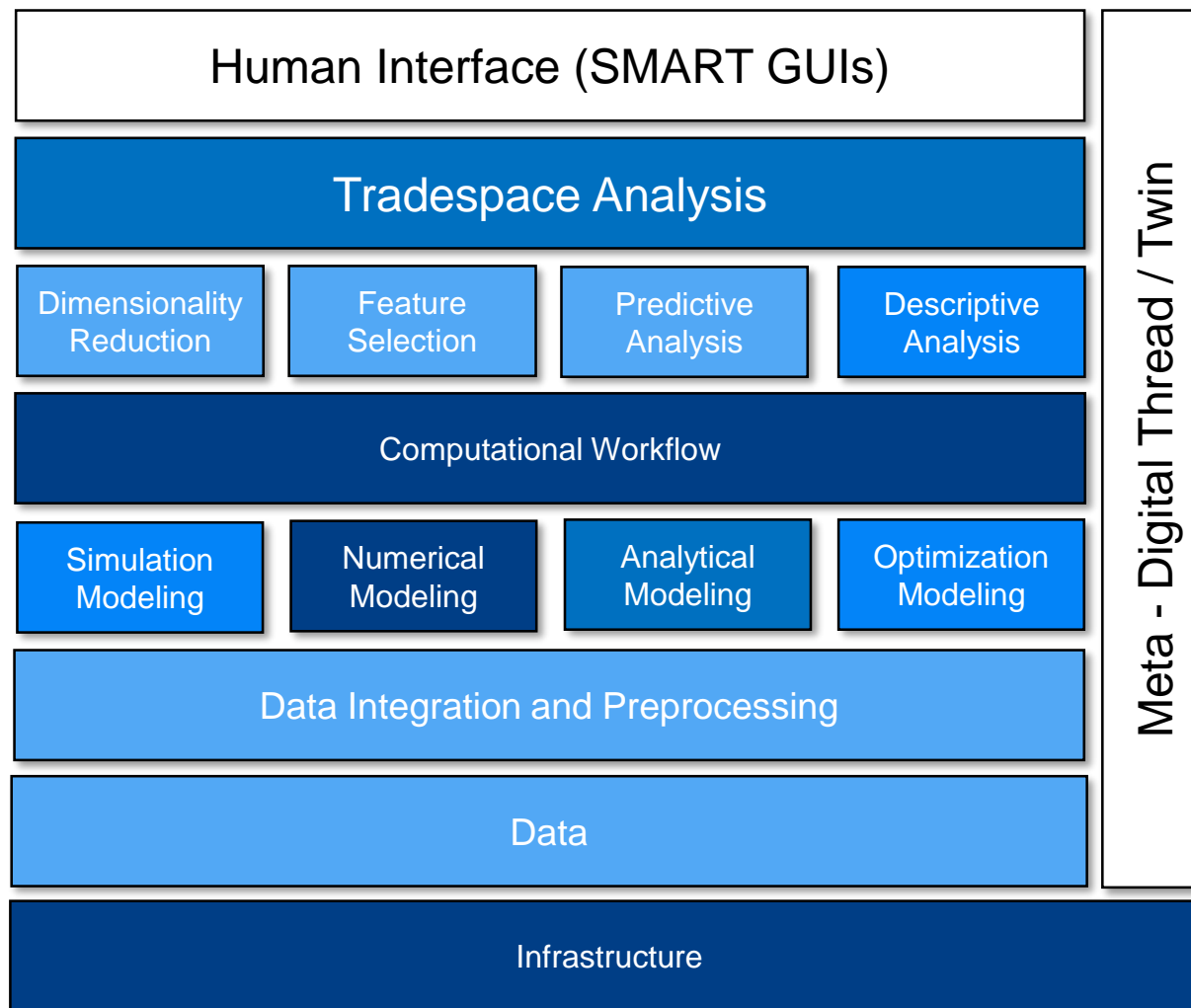
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# Topics

- **Current State of Tradespace Analysis**
- **New thinking**
- **Technology**
- **Data analytics ecosystem and processes**
- **A.I.**
- **Machine Assisted Tradespace Analysis**

# Current State



# New Thinking (10x)

*Improve decision making through the integration of advance computing into the decision-making process.  
Humans perform higher-level strategic thinking, while machines conduct lower-level decision*

## Change Drivers

### Today

- **Marginalize**
  - Analysis is severely restricted
  - Machines play a secondary role to humans
- **Limited**
  - Analytics do not scale to large large problems
  - Analysis is very swallow
- **Brittle**
  - Single point solutions

- *Growth in information requires machines to take a more activity participate in decision making*
- *Humans will conduct high-level decisioning ...machines work to make lower-level decisioning*
- *Data sizes will overwhelm decision-makers and complicate the decision making process*
- *Deep Analytics - breadth and depth of the analysis help service insights from all types of data*
- *Capable of operating on data sets at the petabyte scale*
- *Prioritize important points for analysis by humans*
- *decisions will be subdivided into levels machine-level and human-level*

### Tomorrow

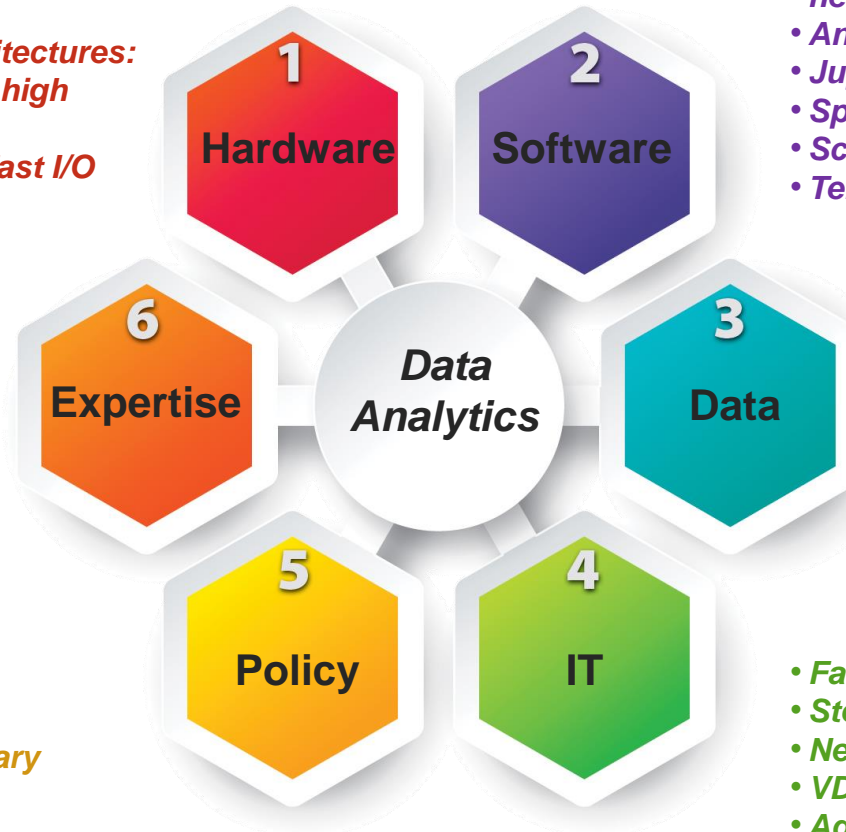
- **Go Faster**
  - Host analysis on HPC
- **Think Deeper**
  - Methods scale to address large complex problem spaces
  - Inclusion of a breadth of information
  - Data and knowledge are integrated
- **Be Resilient**
  - Identify a set of alternatives as opposed to a single solution

# Competencies

- *Machines that can address our largest problems*
- *Blended computing architectures:*
  - *Numerical - distributed, high speed interconnects*
  - *Data - shared memory, fast I/O*

- *Computational and data scientists assist in problem step up, execution, and visualization*

- *Integrate necessary policies*

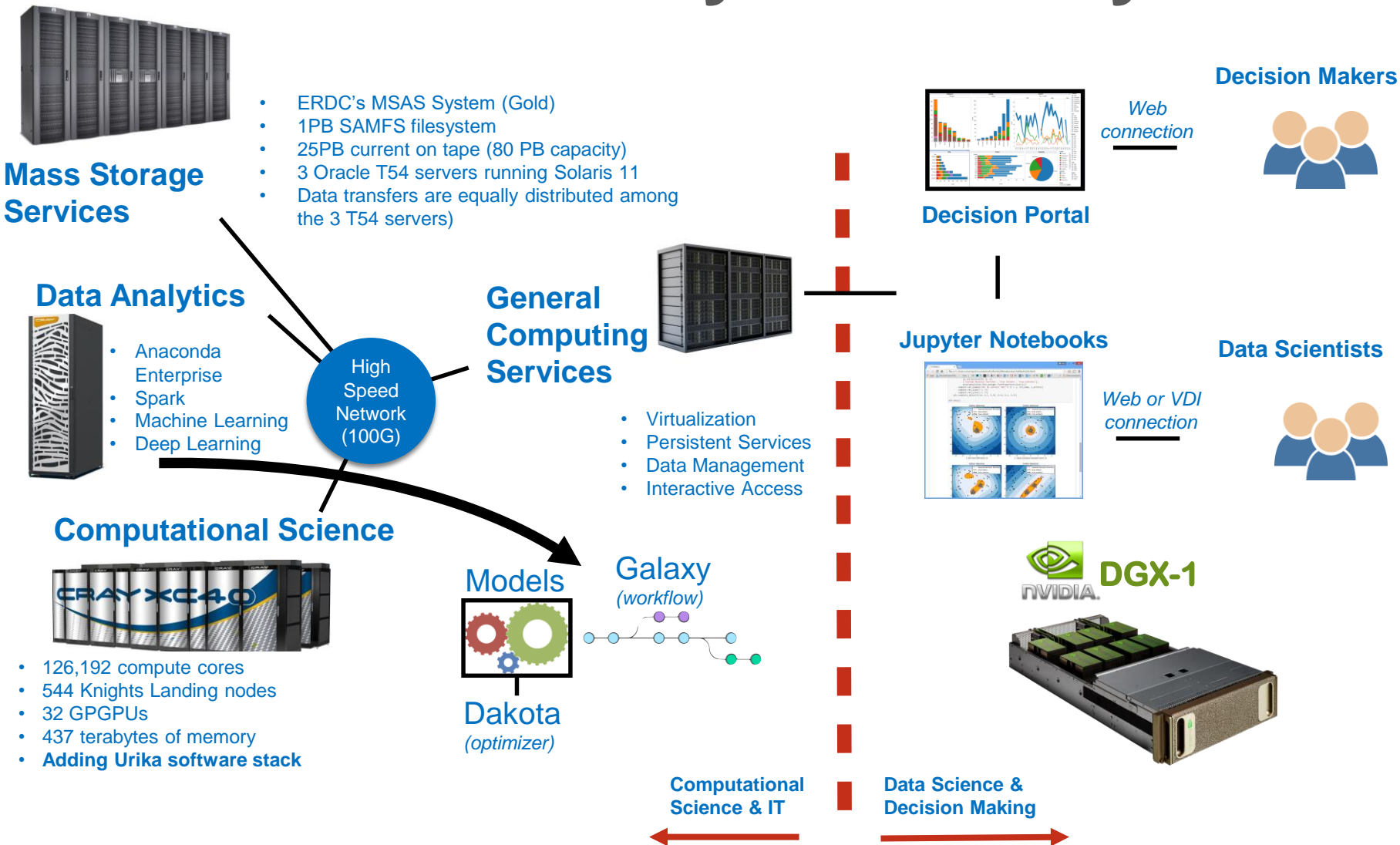


- *Leverages open source capabilities*
- *Python ,R, and C/C++ (when needed)*
- *Anaconda - package management*
- *Jupyter Notebooks*
- *Spark, Galaxy, Dakota*
- *Scikit Learn (machine learning)*
- *TensorFlow (deep learning)*

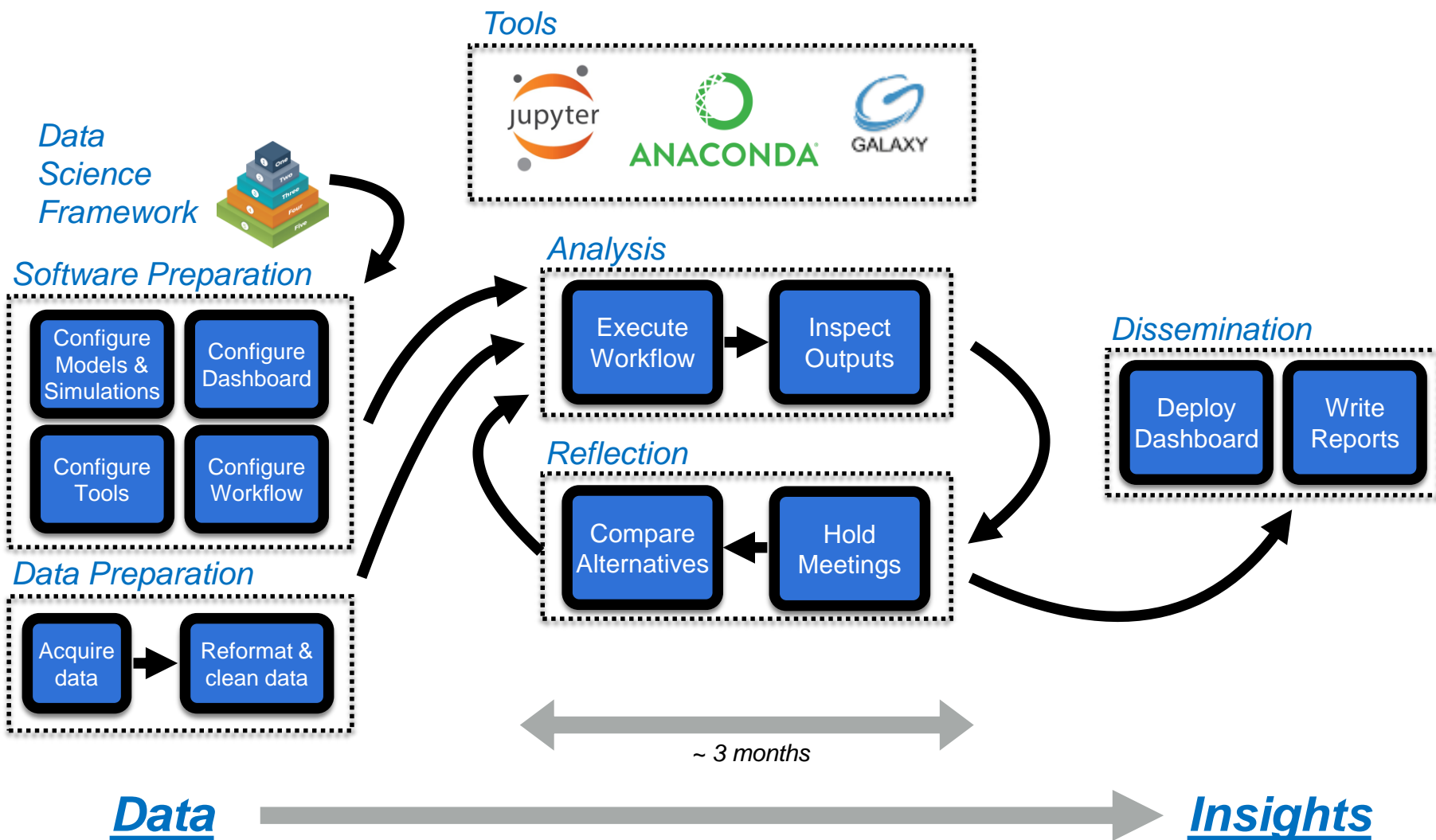
- *Terabytes collected - Unorganized and inaccessible*
- *Streamline data wrangling*
- *Minimize the movement of data*
- *Leverage database technologies*
  - *SQL and noSQL*

- *Facilities*
- *Storage (hot, warm, and cold)*
- *Networks (10G+)*
- *VDI*
- *Administration of machines*
- *Security - (monitoring, patching, etc.)*

# Data Analytics Ecosystem



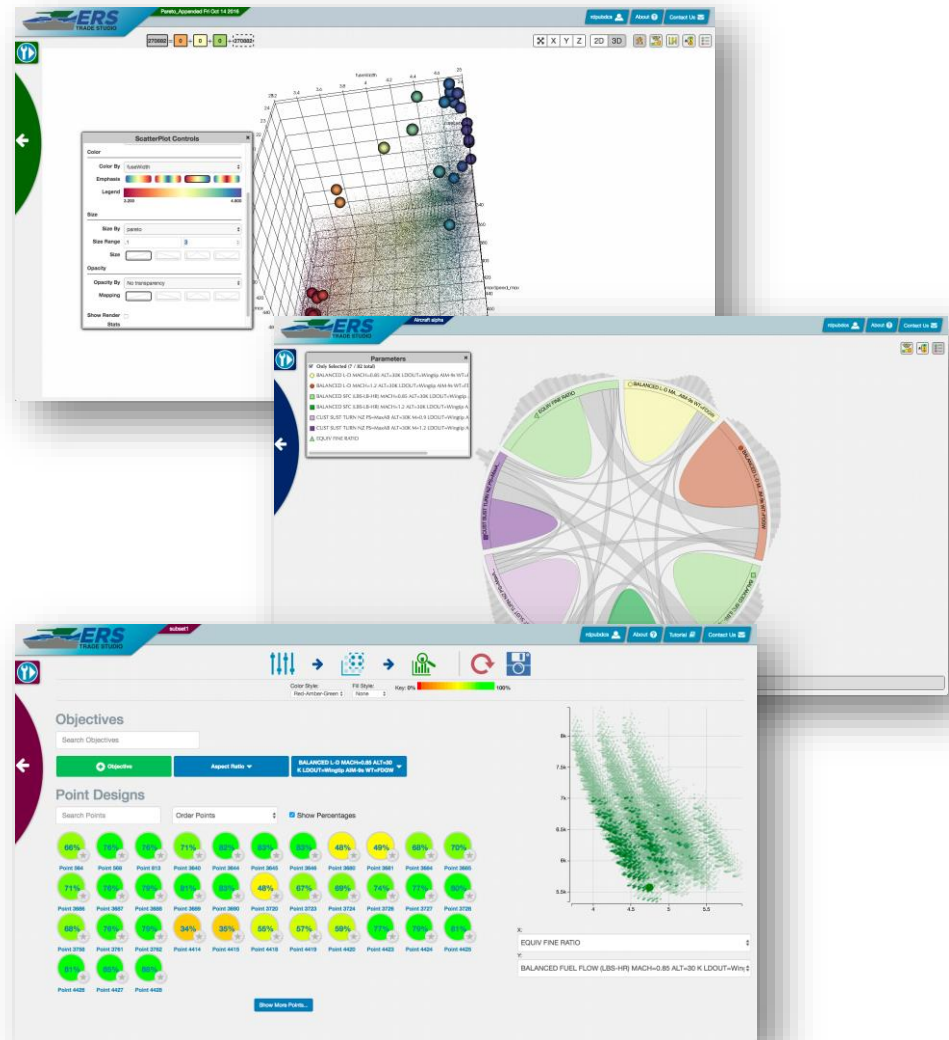
# Data Science Workflow





# Current Tradespace Workflow

- Heavy Visualization
- Manual process
- Millions of designs considered, but only a few in detail



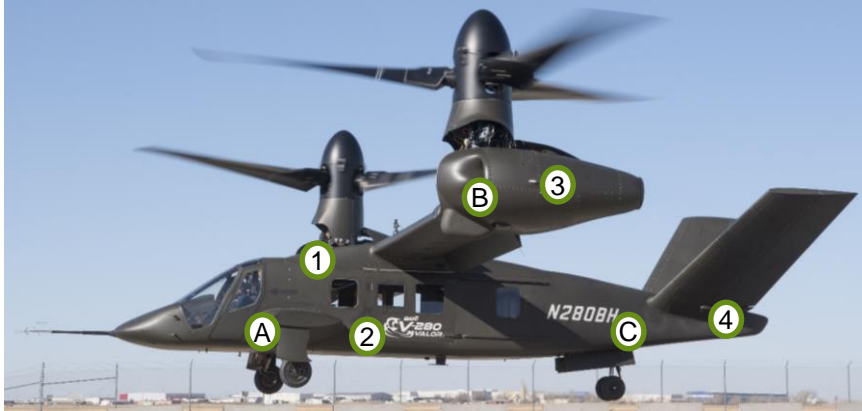




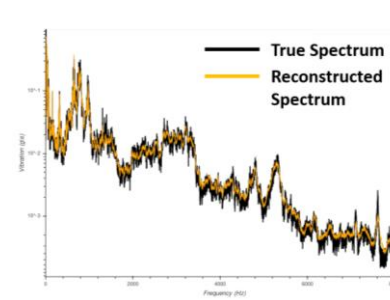
With data...

Without data...

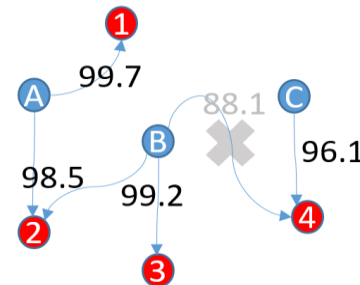
# With Data - Virtual Sensors



Historical operational sensor data can be used to study how many sensors are needed and where they need to be placed.



If a sensor can be inferred from other sensors with a high degree of accuracy then instead of fielding a physical sensor, a “virtual sensor” model, developed on DSRC-HPC, can be used.



The minimum virtual sensor cover is the minimum set of physical sensors necessary to infer ALL sensors with some required level of accuracy

A **minimum virtual sensor cover** for FVL would save space, weight and power, extending range and lifting capacity and **save hundreds of millions of dollars** in up front manufacture and life cycle maintenance cost.

## Without data – AlphaGo Zero

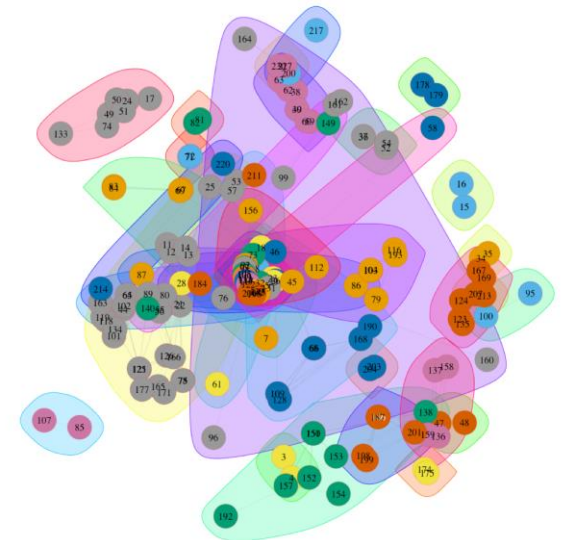
- Learn from scratch
- No historical data
- Data generated from unsupervised training
- 20 days of training to beat world champion



Complexity  
Chess:  $10^{120}$   
Go:  $10^{174}$

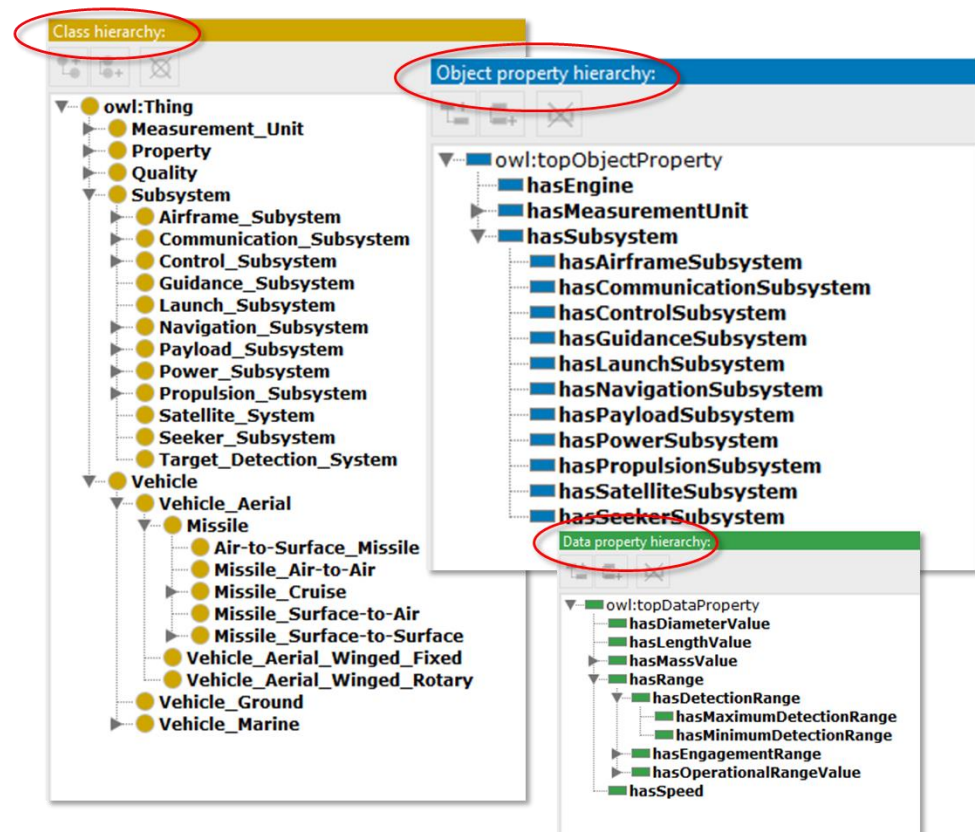
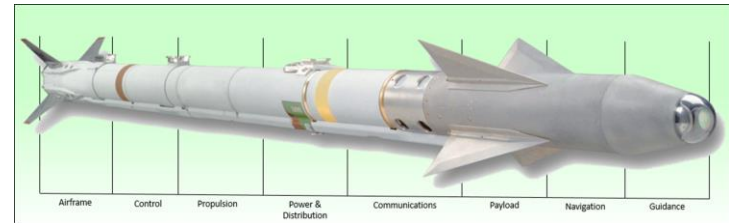
# Machine Assisted Tradespace Analysis - Needs

- Full definition of the problem
- Need win condition and rules
  - Capabilities
  - Constraints
- Functional Framework (Driver)
- No beginning tradespace



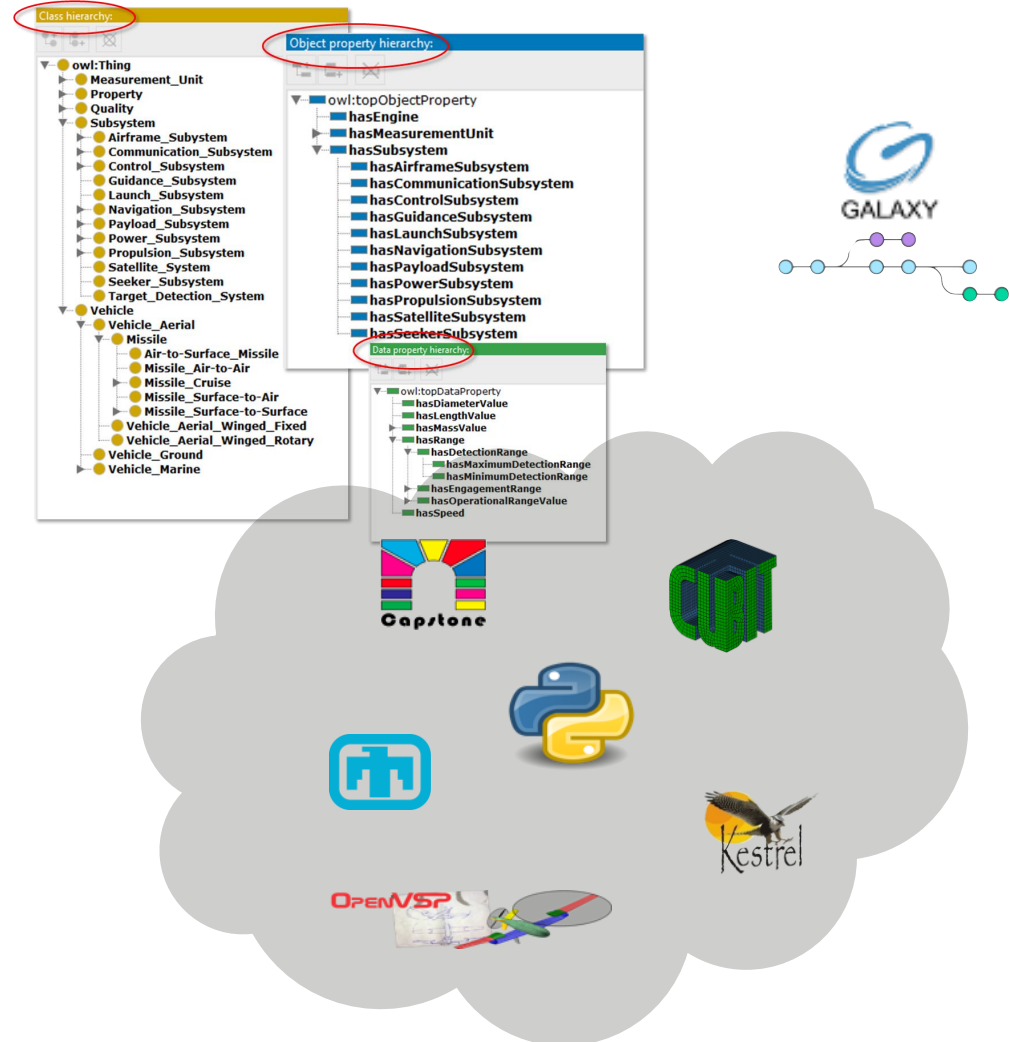
# Ontologies

- Machine Assisted Driver
- Provides Structure
- Defines Semantics
  - User understanding
  - Machine understanding
- Defines constraints
- Drive digital twin



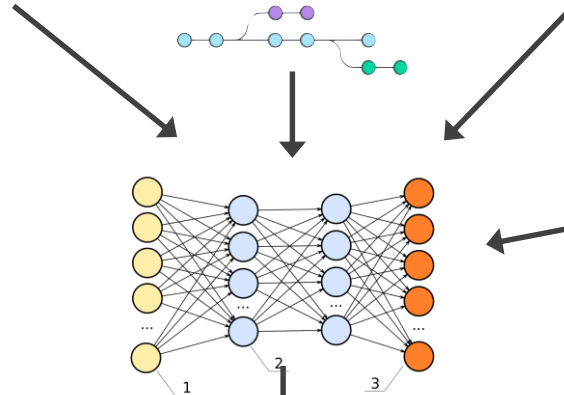
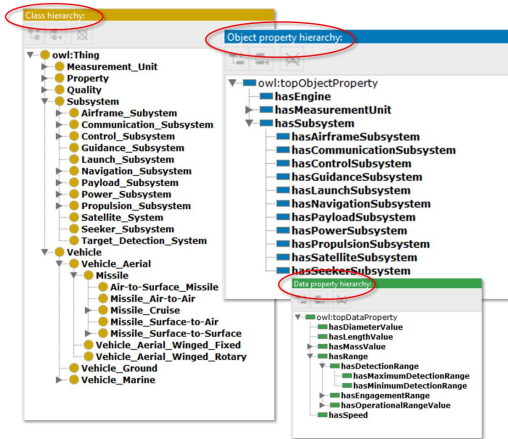
# Map Ontologies to models

- Attributes within the ontology are mapped to inputs of the available models
- Performance metrics mapped to outputs



# Machine Assisted tradespace analysis

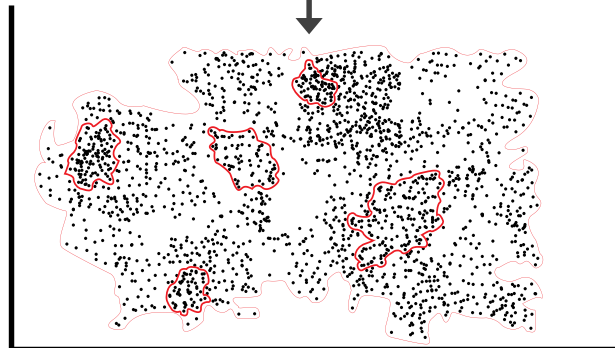
## How does it work



Win condition –  
desired capabilities

### First Iteration

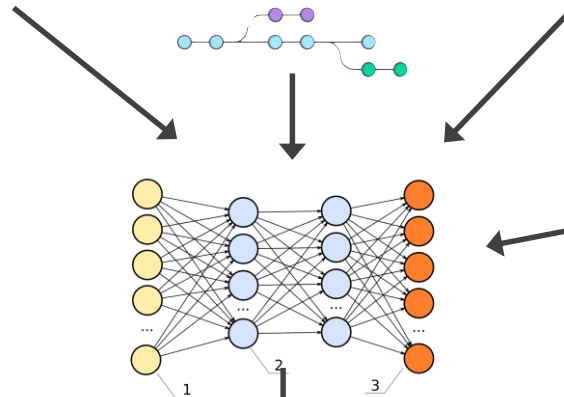
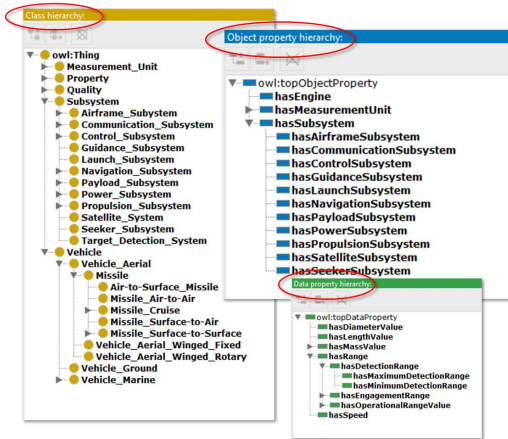
- Low fidelity
- Millions of designs
- Clusters of high performance designs
- Select 1 or more clusters





# Machine Assisted tradespace analysis

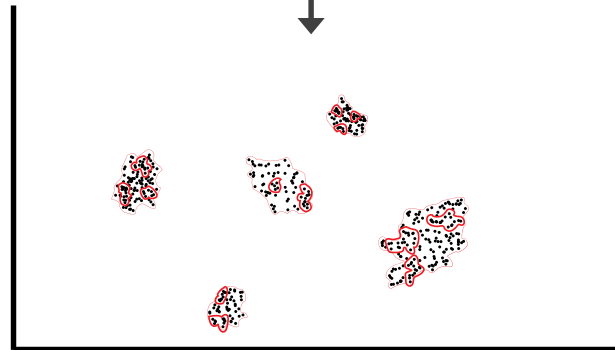
## How does it work



Win condition –  
desired capabilities

### Second Iteration

- Moderate fidelity
- 10,000's of designs
- Clusters of high performance designs
- Select clusters within clusters



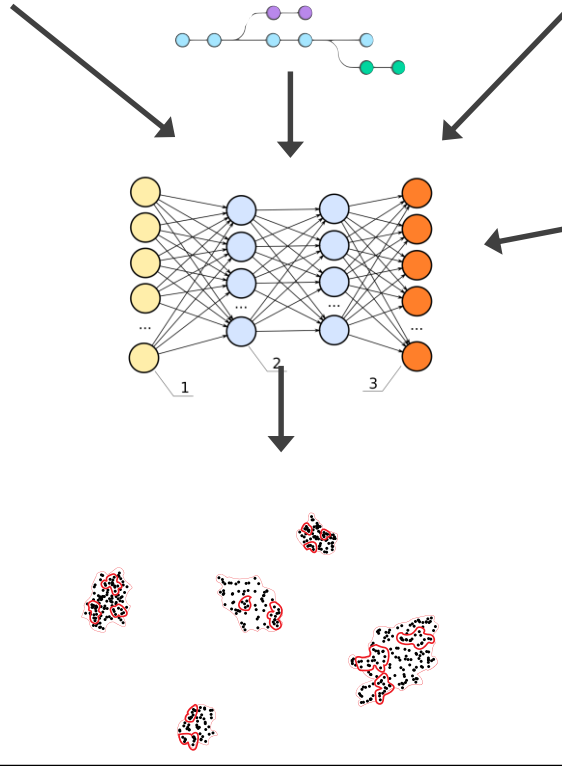
# Machine Assisted tradespace analysis

## How does it work



Nth Iteration

- Increasingly higher fidelity
- Decreasing number of designs
- Clusters of high performance designs
- Select clusters within clusters



Win condition –  
desired capabilities

Final output

- Set(s) of designs
- Complex constraint sets

# Contact

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