# Artificial Intelligence Analytics with Multi-Attribute Tradespace Exploration and Set-Based Design


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The Perduco Group



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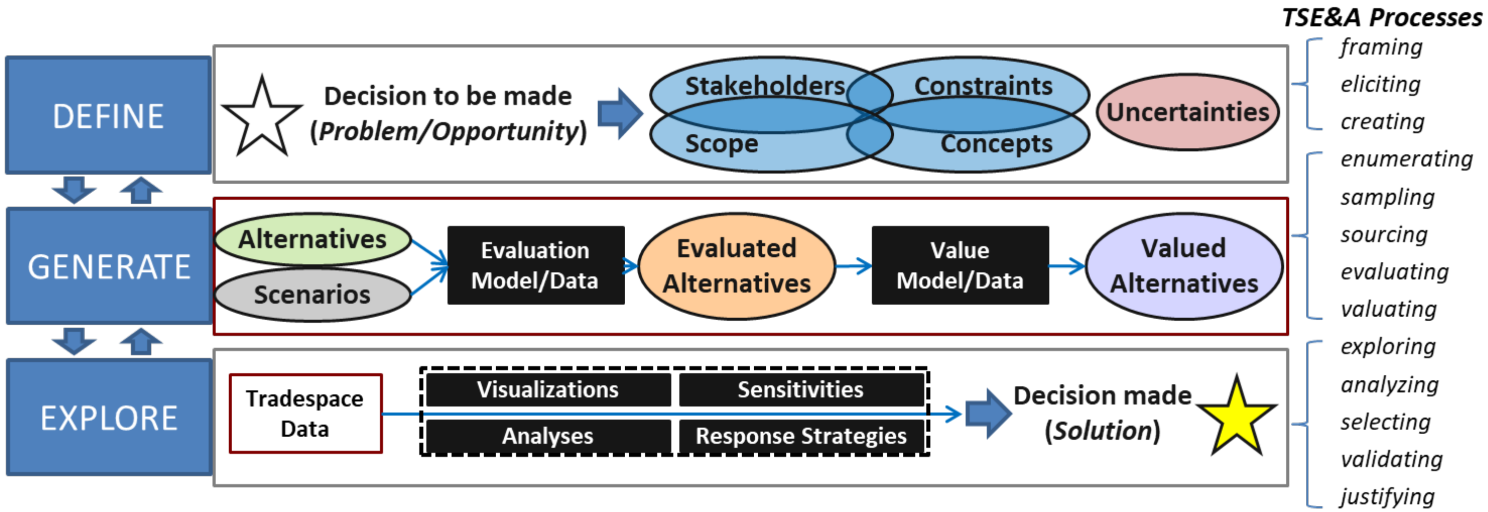
# Outline

- Multi-Attribute Tradespace Exploration (MATE)
- Set-Based Design (SBD)
- Alignment of MATE and SBD
- Leveraging MATE data with AI to support SBD
- Ground Vehicle example
- Conclusions

# What is MATE?

## Multi-Attribute Tradespace Exploration (MATE)

- Value-driven and data-supported exploration and analysis of the relationships between various cost and benefit metrics and solution characteristics across a large number of potential alternatives
- Key question answered: what are the necessary tradeoffs for achieving a “best” value solution?
- Key capabilities:
  - Identify most efficient cost-benefit solutions
  - Identify key design drivers of cost and benefit
  - Identify impact of various value propositions on “best” solutions
  - Quickly identify impacts of constraints and multi-stakeholder perspectives (i.e. win-win and tradeoffs)

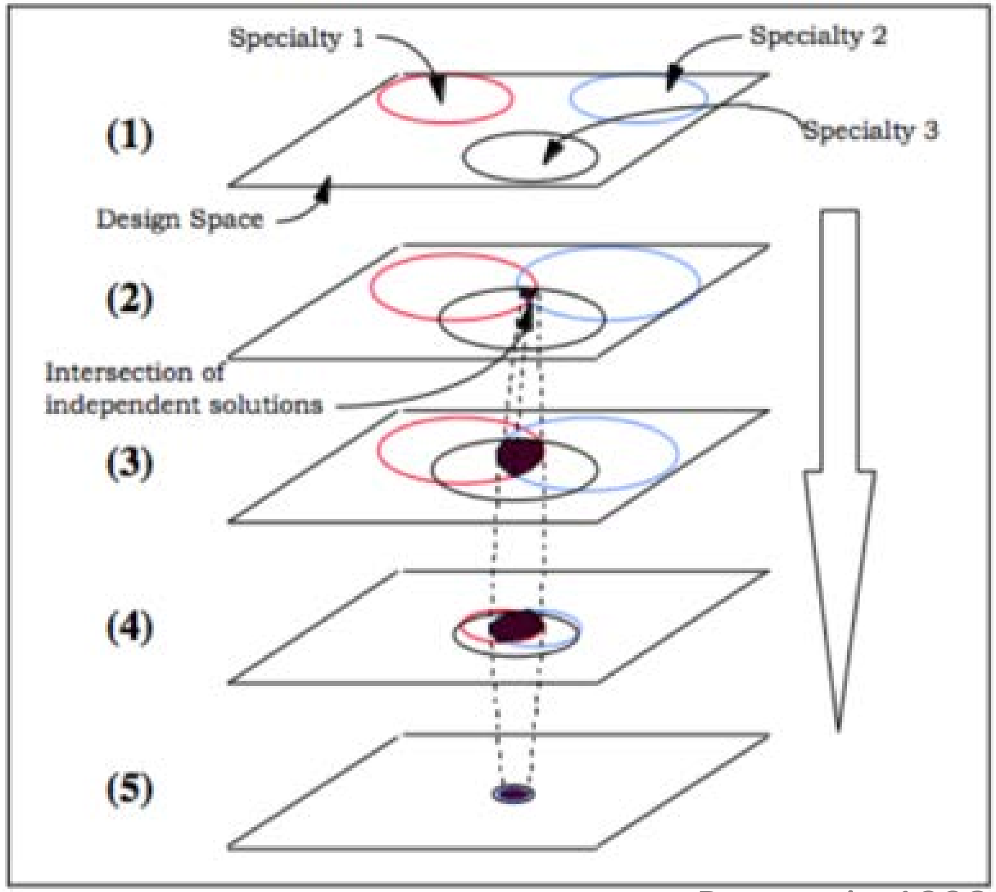



### Core enabling techniques

- Visual analytics (i.e. human-in-loop interrogation of displayed data for pattern searching and analysis direction with updating)
- Modeling and simulation (i.e. generation of various fidelities of data to support tradespace exploration and analysis for solutions without existing data)

# What is SBD?

- Design set drivers vs. design set modifiers
  - Design variables are partitioned according to how much they define/drive the platform design
  - “Sets” are defined by drivers, with the understanding that the modifiers can be locked in later in detailed design
- Individual specialties/domains design as separate teams **concurrently**
- Over time, requirements are added, restricting the sets and forcing specialties to overlap
  - Modeling fidelity is increased as scope reduces
- Eventually, solutions are reduced to one set
  - One alternative in the set may be selected as a baseline for detailed design, with the understanding that the modifiers can still change




Bernstein 1998

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# MATE and SBD

- MATE and SBD are fundamentally aligned
- Same goals, using similar techniques to "get there"
- Depending on problem structure or institutional memory for a "core" approach, either could support the other
  - **MATE in a support role**: computational framework for constructing/evaluating multiple alternatives in a set
  - **SBD in a support role**: apply MATE from perspective of domain teams, focusing on regions of the tradespace with best performance in different domains

**Goals at the end of SBD effort**

(Singer et al. 2009)

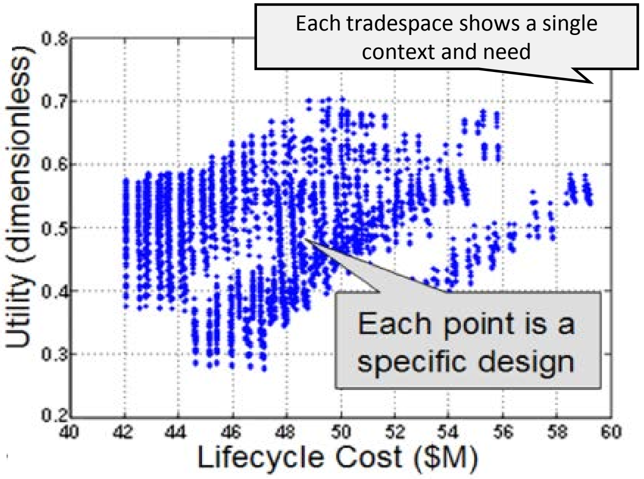
First, one would expect to have identified a manageable set of design parameters that have been determined to be principal factors in achieving maximum design value. Next, one would expect to have determined which of the set is more important than the others. One would expect to have identified which design attributes and measures are most important in differentiating among the most promising design combinations. One would also expect to be able comparatively evaluate the most promising designs in an analysis framework that capitalizes on the current best knowledge of design parameters and system attributes to assess total value. One would also expect to be able to examine the impact of changes in attribute preferences on the best design recommendation. Finally, one would expect to have a body of documented trade space analyses that substantiates all discarded or screened design solutions. And, perhaps most important from an SBD objectives viewpoint, this information would be available as a resource for design flexibility in the event of future changes in operational requirements, technology projections, program budgets and other changes in the design environment.

Goals aligning with MATE tools and techniques (key design variables, driving attributes, consistent comparisons, preference updates and "what ifs", etc.)

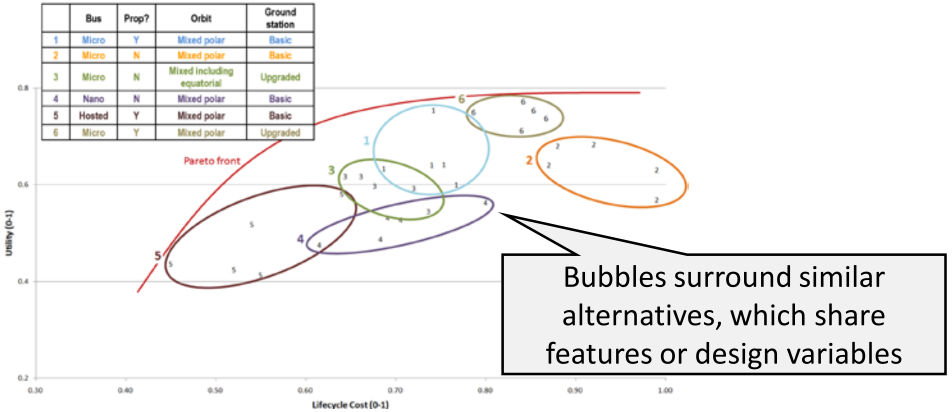
Program management and communication goals, supported by the use of a persistent MATE database

# Convergent Visualization Approaches

## "CLASSIC" TRADESPACE

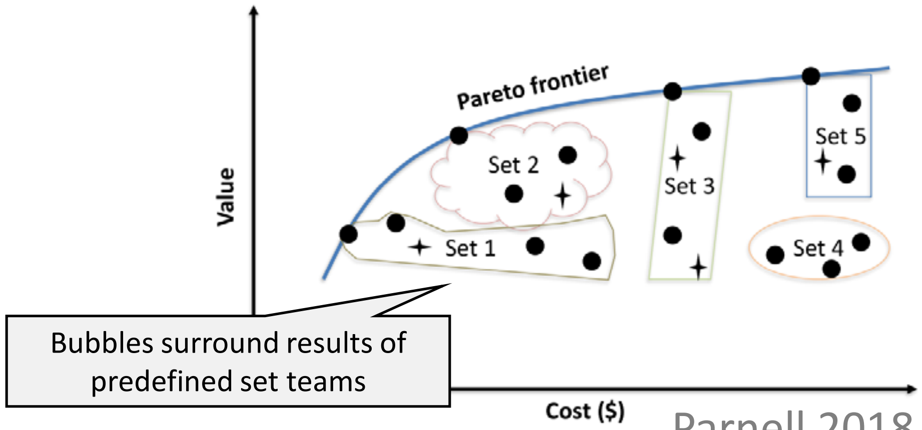



## MATE "BUBBLE" TRADESPACE




Rader et al., 2011

## SBD "BUBBLE" TRADESPACE




Parnell 2018

# Artificial Intelligence

- What constitutes “intelligence” has become a moving goalpost as people become used to machines performing more and more complicated tasks
- Regardless of the complexity of underlying mathematical technique, there are three main areas of AI tasks

**“Simple” application**

SUPERVISED LEARNING → REGRESSION

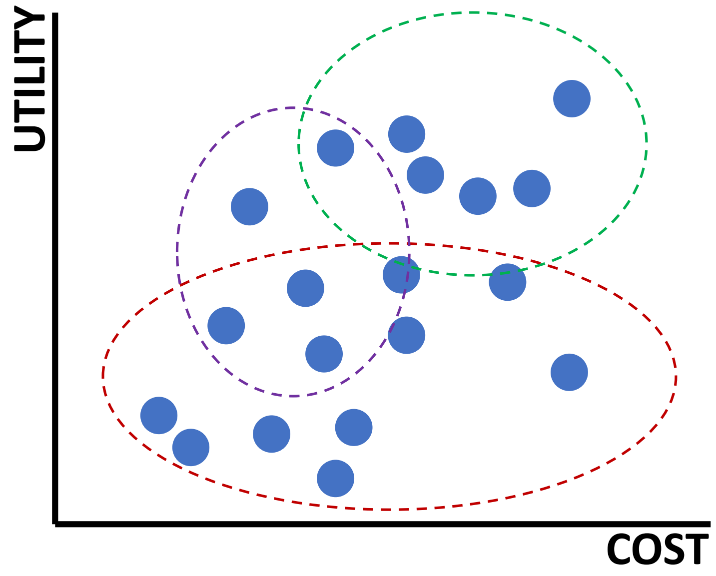
REINFORCEMENT LEARNING → OPTIMIZATION

UNSUPERVISED LEARNING → CLUSTERING

# AI with MATE and SBD

- How are sets defined?
  - SBD: **a priori** via definition of drivers/modifiers
  - MATE: **ex post facto** via the definition of “similar” found to be most appropriate/powerful
- What if an AI could define a set via unsupervised learning?
  - A set is essentially a cluster in the tradespace
  - Even if the result is not **better** than SME judgement, it may still provide compelling insight or an alternative way to frame the problem

**Clustering can occur on a combination of design variables (like classic bubble tradespaces) AND x/y value dimensions, resulting in overlapping but distinct clusters**




Demonstrating even a rudimentary AI on the clustering task serves as a proof of concept that advanced AI (e.g. neural networks, etc.) could be deployed to increase the power of MATE and SBD on prohibitively large/complex datasets

# Ground Vehicle Example

- Notional ground vehicle tradespace
- Rough size between Humvee and MRAP
- Sampling of the space is full-factorial on discrete variables, with the tradespace “filled out” by random samples of continuous variables
  - This is similar to how some SBD projects choose to populate their sets for tradespace exploration
- Evaluative model calculates performance/cost of each alternative design
  - Low fidelity, but detail is not required to demonstrate the clustering analysis

**Design variables**

The parameterization of the vehicle used as inputs to the evaluative model

| | |
|---|---|
| Wheel base | 8 – 14 ft |
| Engine power | 200 – 500 hp |
| Number of powered axles | {1, 2} |
| Fuel tank size | 4 – 10 ft$^3$ |
| Tire type | Street, weather, bulletproof |
| Suspension type | Spring, air |
| Body type | Open, closed, armored |
| Underbody | Flat, V-shape |
| Fire suppression | None, water, foam |

**Sampler**

as a simple application of MATE might

**6480 sampled designs**

30 random samples of the continuous variables for each possible combination of discrete variables

**Evaluative model**

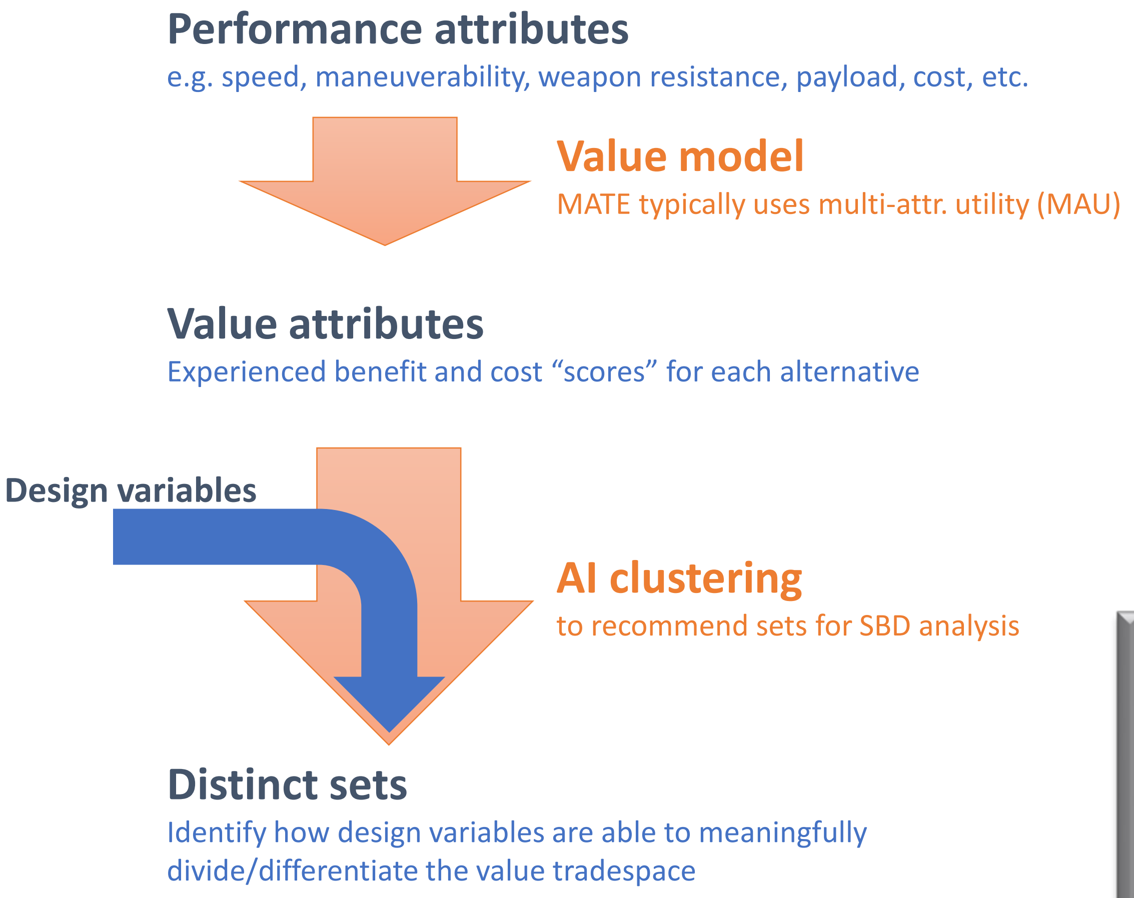
**Performance attributes**

e.g. speed, maneuverability, weapon resistance, payload, cost, etc.

# Defining Sets

- Sets are partitions of the tradespace along one design variable
  - Future work could increase complexity via consideration of sets defined by N-d groups of variables
- Value modeling step is a part of MATE but not strictly necessary for the following analysis (which could be performed on any variables of interest)
- We will perform a clustering task using basic AI to define partitions as clear/meaningful as possible

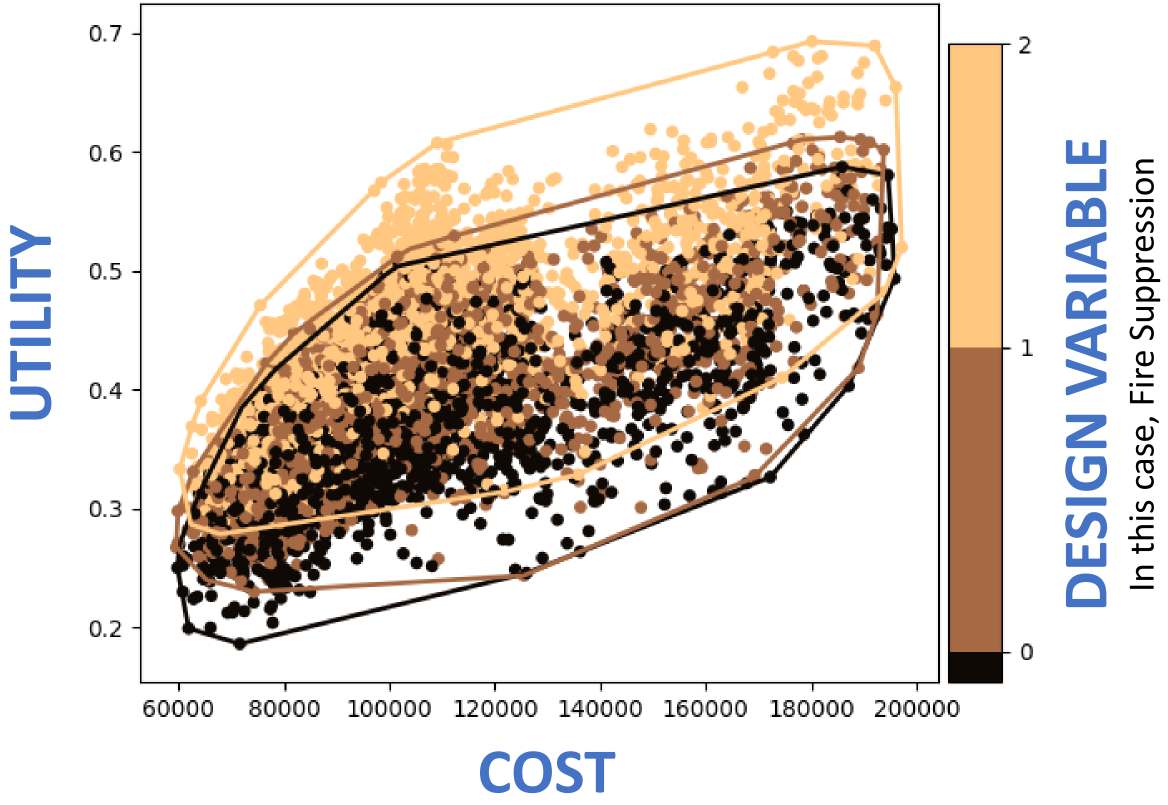
Goal: automatically find/capture insights about sets of alternatives that are useful but would normally require manual searching of the space



# Clustering Approach (1) – Convex Hulls

- A given partitioning creates “buckets” that each alternative falls into
- We automatically recreate the “bubble” tradespace by drawing the **convex hull** around each bucket
- We can computationally generate many partitionings at high speed
  - For this proof-of-concept scale problem, we will brute force all possible partitionings at fixed levels of discrete variables and 10% quantiles of continuous variables
  - Future applications will seek to apply more advanced AI search methods to find “good” partitions faster, as well as considering fully-continuous partitioning and disjoint sets

Benefit/Cost scatterplot, colored by Design Variable being used to partition the space into sets



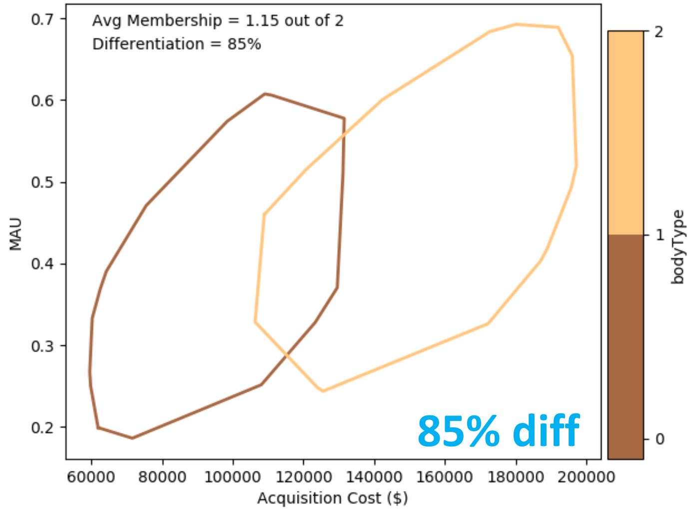
# Clustering Approach (2) – Differentiation

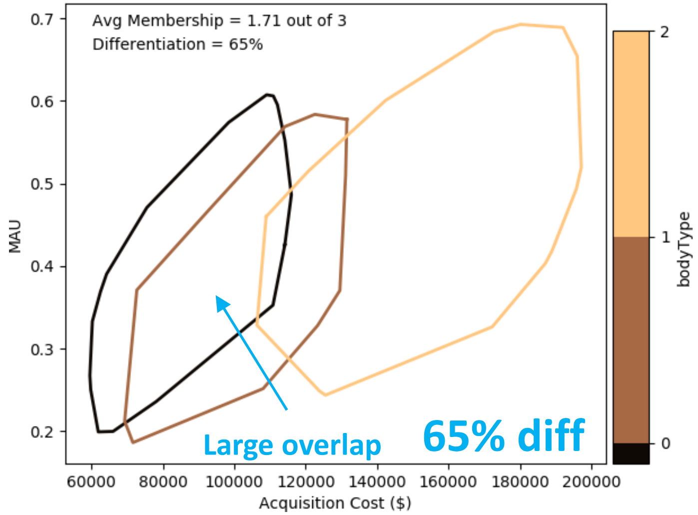
- How do we know if a partitioning is "good"?
- Use a **differentiation** metric that scores the convex hulls by how much they overlap

$$\text{diff} = 1 - \frac{avgMembership - 1}{\#\ hulls - 1}$$

  - avgMembership = the number of convex hulls an alternative is "inside" on average
  - Function ranges from 0 (all points are inside all hulls = complete overlap) to 1 (all points are in 1 hull = complete disjoint)
  - Important: valid even on non-ratio scales such as MAU
- Clustering algorithm returns the partition (for each variable) that <u>maximizes</u> differentiation

If a design variable highly differentiates the value space (using a certain partition), it is a **value driver** and that partition is an important insight for designers to know




Example: differentiation is higher for Body Type when Open (0) and Closed (1) are partitioned into the same set since they have significant overlap in the value space – if we want our set architectures to offer distinctly different performance, it would be better to group these designs than to create 3 sets conference on systems engineering research

# Ground Vehicle Base Results

- Running the partitioning algorithm on each design variable ultimately returns:
  - A ranking (by differentiation) of which variables are the strongest **value drivers**
  - The most distinct set definitions / clustering for each variable
- The variables with strongest differentiations are candidates for top-level definition of SBD sets

| Design Variable | Best Clustering | # Sets | Differentiation (%) | Rank |
|---|---|---|---|---|
| **Body type** | Open/Closed, Armored | 2 | 84.7 | 1 |
| **Wheel base** | 8 – 8.9 ft, 8.9 – 14 ft | 2 | 34.4 | 2 |
| **Underbody** | Flat, V-shape | 2 | 25.3 | 3 |
| **Fire suppression** | None/Water, Foam | 2 | 11.2 | 4 |
| **Engine power** | 200 – 471 hp, 471 – 500 hp | 2 | 9.8 | 5 |
| **Fuel tank size** | 4 – 4.7 $ft^3$, 4.7 – 10 $ft^3$ | 2 | 6.9 | 6 |
| **Suspension type** | Air, Spring | 2 | 2.6 | 7 |
| **# of powered axles** | 1, 2 | 2 | 1.7 | 8 |
| **Tire type** | Street, Weather, Bulletproof | 3 | 1.5 | 9 |

**Example insights**

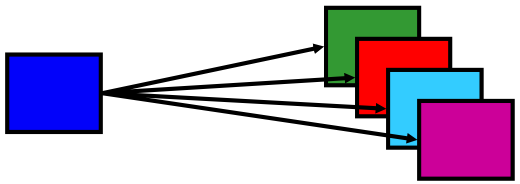
- Body type is most impactful
- Wheel base, underbody, fire suppression also somewhat impactful
- Some continuous partitions are highly uneven, suggesting extreme values of these variables are significantly different from the rest
  - Low wheel base (8-8.9 ft), high engine power (471-500 hp), low fuel tank size (4-4.7 $ft^3$)

The power of this technique lies in these insights being generated automatically, directing analyst attention immediately to high-impact decisions (rather than requiring them to create graphs and visually search)

# Exploring Uncertainty

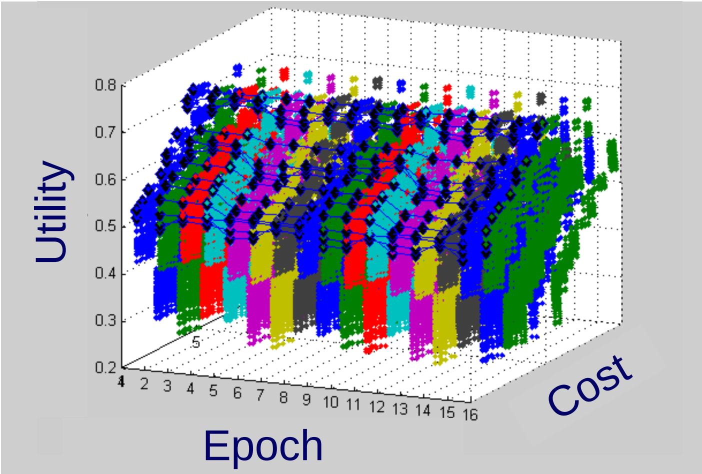
- Clustering results are a function of all assumptions and parameters in the evaluative model
- If the operational context (and associated model parameters) changes, the tradespace changes with it
- Changes in clustering results can clarify the impact of uncertainty
  - New ranking: variables rise/fall in relative impact
  - New partitions: different ranges of the variable overlap/separate

Each possible future the system may operate in has a different associated benefit/cost tradespace



Today

Possible futures (epochs)



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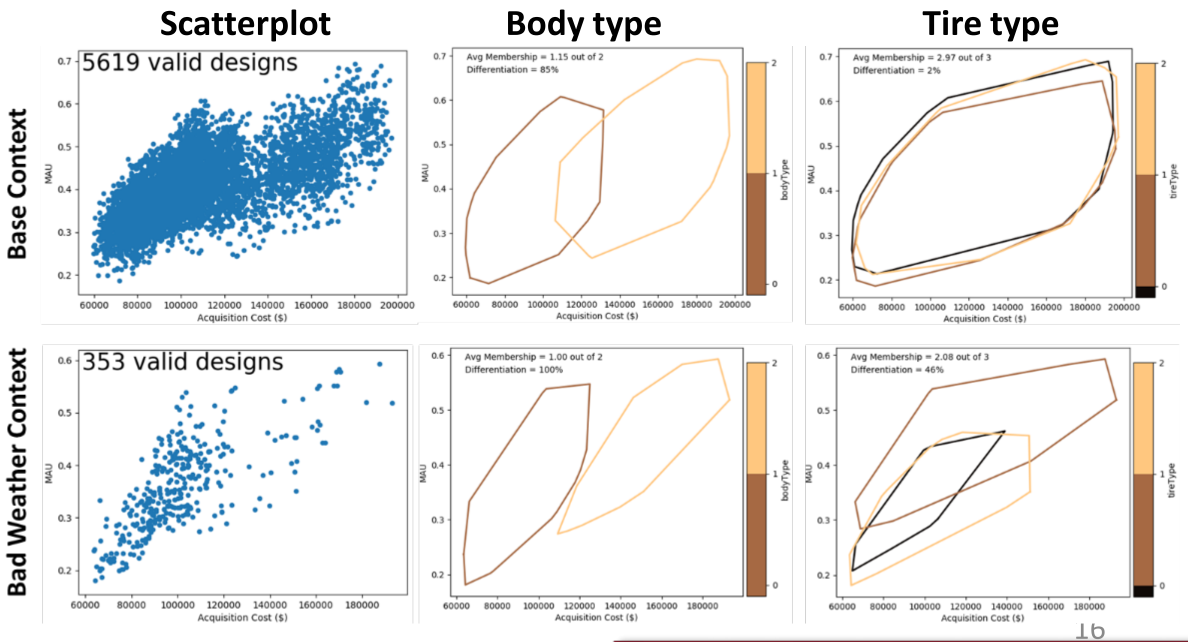
# Ground Vehicle with Bad Weather

- Results shown for "bad weather" context
  - Rows are shown in same order as base context and grayed out where the sets have not changed
  - Largest rank changes highlighted with arrows

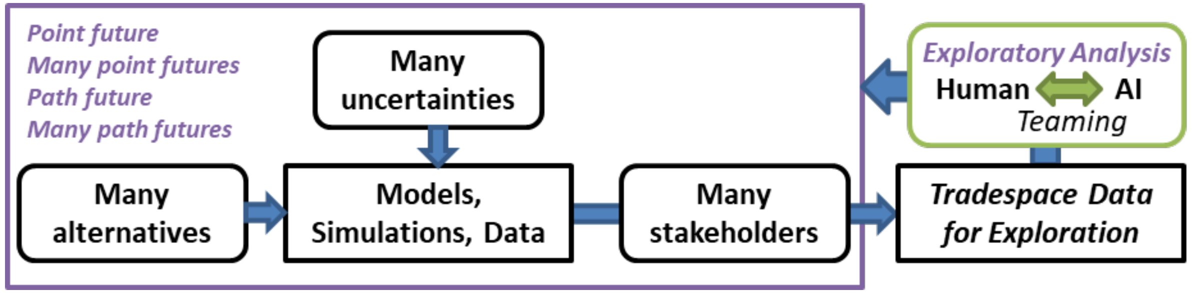
| Design Variable | Best Clustering | # Sets | Differentiation (%) | Rank |
|---|---|---|---|---|
| Body type | Open/Closed, Armored | 2 | 100 | T1 |
| Wheel base | 8 – 8.8 ft, 8.8 – 14 ft | 2 | 39.9 | 5 ↓ |
| Underbody | Flat, V-shape | 2 | 53.5 | 3 |
| Fire suppression | None/Water, Foam | 2 | 34.8 | 7 |
| Engine power | 200 – 218 hp, 218 – 500 hp | 2 | 36.3 | 6 |
| Fuel tank size | 4 – 7, 7 – 7.6, 7.6 – 8, 8 – 10 $ft^3$ | 4 | 29.5 | 8 |
| Suspension type | Air, Spring | 2 | 8.2 | 9 |
| # of powered axles | 2 | 1 | Undefined | T1 ↑ |
| Tire type | Street, Weather, Bulletproof | 3 | 46.0 | 4 ↑ |




**Example insights**

- Body type increases to 100% differentiation
- Tire type increases significantly in relative impact rank (last to $4^{th}$) due to positive impact of all-weather tires that had no benefit in the base context
- Fuel tank now split into 4 sets indicating significant stratification of tradespace
- Powered axles has undefined differentiation due to all 1-axle designs failing to meet value requirements and thus only 1 set can be measured (see: 5619 → 353 valid designs)

# Conclusions




- MATE and SBD are fundamentally aligned in goals and similar in commonly-deployed tradespace analysis techniques
- The large datasets generated by MATE and SBD can be leveraged by AI to supplement traditional analysis
- AI can recommend maximally-differentiating SBD set definitions by clustering a MATE dataset
- Comparing results across different operational contexts can reveal the impact of uncertainty on value drivers of the system and further justify the use of particular set definitions
- Future growth in this area can include:
  - Improved AI search techniques for more rapidly finding good clusters
  - More elaborate set construction (e.g. defined by multiple variables or allowing disjoint ranges to be clustered together)
  - Improved "goodness" metric for identifying meaningful sets and "true" insights, potentially including a composite of multiple measures such as differentiation, number of sets, and balance in the size of the sets

# Questions?

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