

Automating Variation in Training Content for Domain-general Pedagogical Tailoring

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Distribution Statement A

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SOARTECH

Modeling human reasoning.
Enhancing human performance.

Variation in Army Training

- The Army has a need to objectively define variation in training
 - Example of varying factors in OE →
- GIFT pedagogical module can select variants during training but needs choices that meet needs
 - Authoring challenge to create enough variants and make use of learner model
 - Definitional challenge to describe what is different that should make GIFT choose one variant over another

Plan and Prepare				Execute					Assess	
Operational Environment			Training Environment (L/V/C)	% Leaders present at training/authorized	% Present at training/authorized	External evaluation	Performance measures	Critical performance measures	Leader performance measures	Task proficiency rating
SQD and PLT	CO and BN	BDE and above								
Dynamic (single threat)	Dynamic and complex (4 + OE variables and hybrid threat)	Dynamic and complex (all OE variables and hybrid threat)	Proponent establishes training environment standards	≥85%	≥80%	Yes	≥90% GO	All	≥90%	T
				75-84%			80-90% GO		80-89%	T-
65-74%	75-79%	65-79% GO			P					
Static (single threat)	Dynamic (single threat)	Dynamic and complex (all OE variables and single threat)		60-64%	60-74%	No	51-64% GO			P-
	Static (single threat)	Dynamic & complex (< all OE variables and single threat)		Day	<60%		<60%	<51% GO	<All	<80%

BDE	brigade	OE	operational environment	T	fully trained
BN	battalion	P	practiced	T-	trained
C	constructive	P-	marginally practiced	U	untrained
CO	company	PLT	platoon	V	virtual
L	live	SQD	squad		

Note:
 1. The percentages used in this figure are for illustration only. See the collective task's published training and evaluation outline for the applicable percentages.
 2. Dialogue between commanders at multiple echelons is essential when assessing METs. See para 2-23 of this guide.

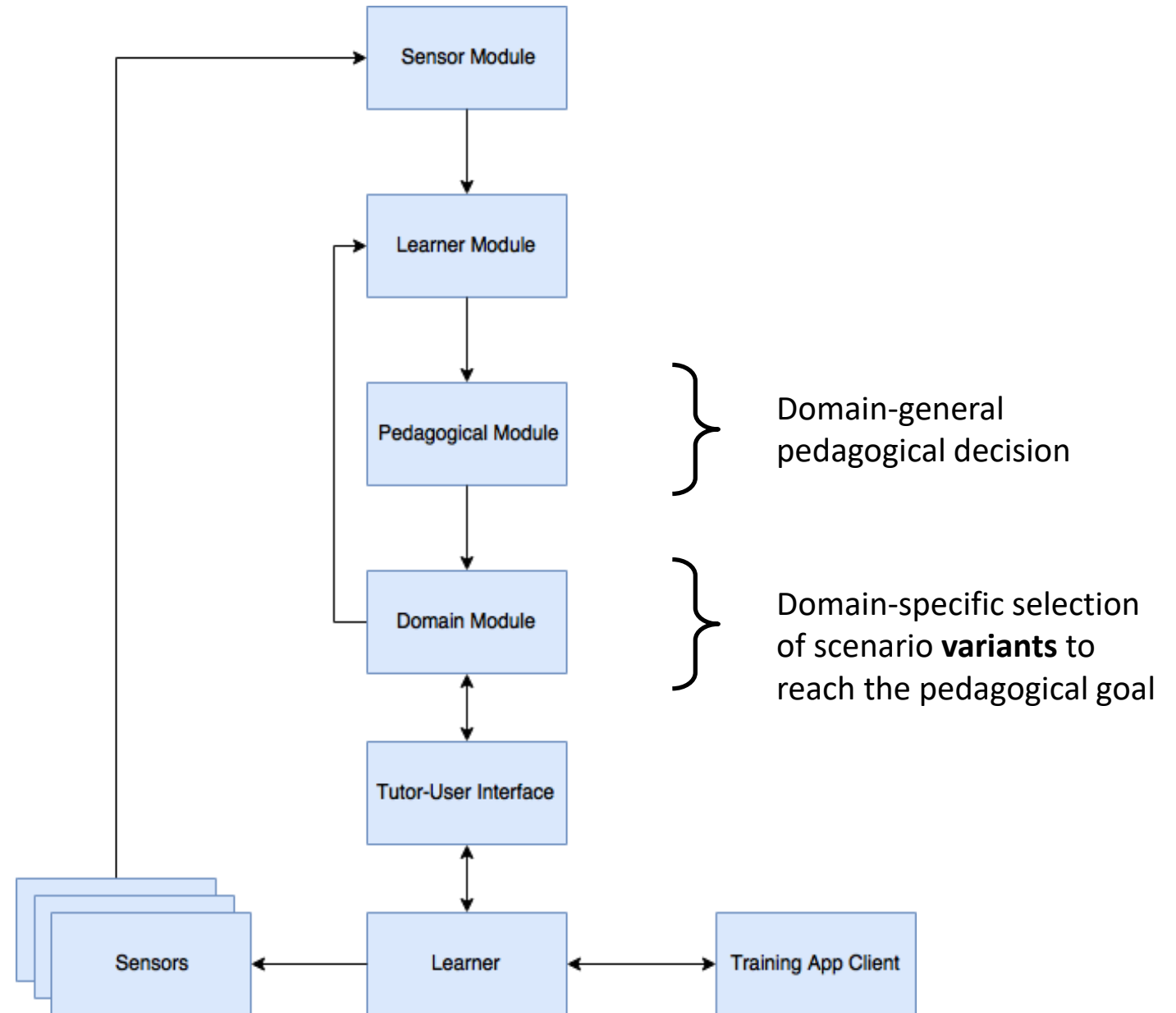
Research Challenges

- Developing unique content is difficult
 - There are many possible changes: scenario events, location of entities, scenario structure, briefing or hint text
 - Combinations and interactions between changes may have unexpected effects
- Impact on learning (support or challenge per skill or MET) must be predicted to tailor training
 - Pedagogical module needs a domain-general expression of the predicted impact
 - Impact on learning may change over time, requiring maintenance

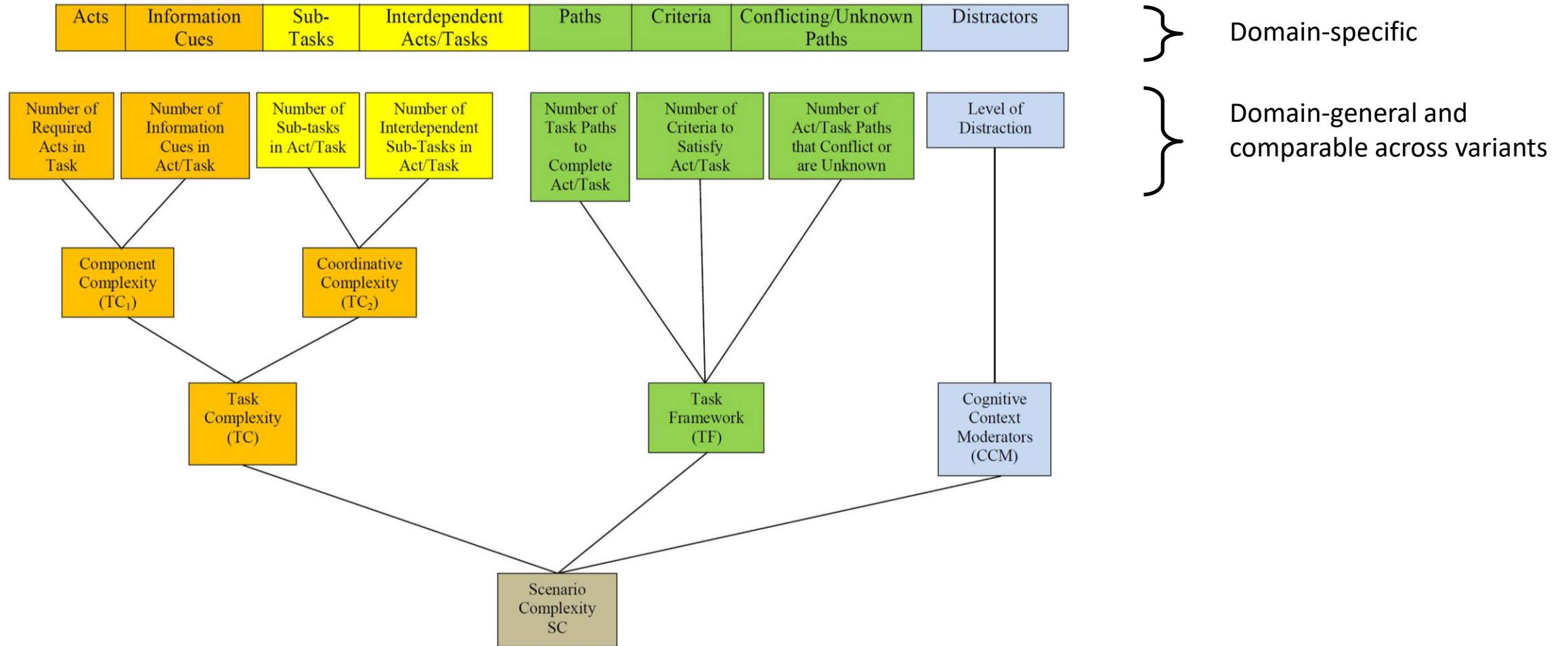


Research Goal

- Generated scenarios should be labelled in a domain-independent manner such that they can be further processed by down-stream pedagogical algorithms – the GIFT pedagogical loop



Previous Research in Training Measures

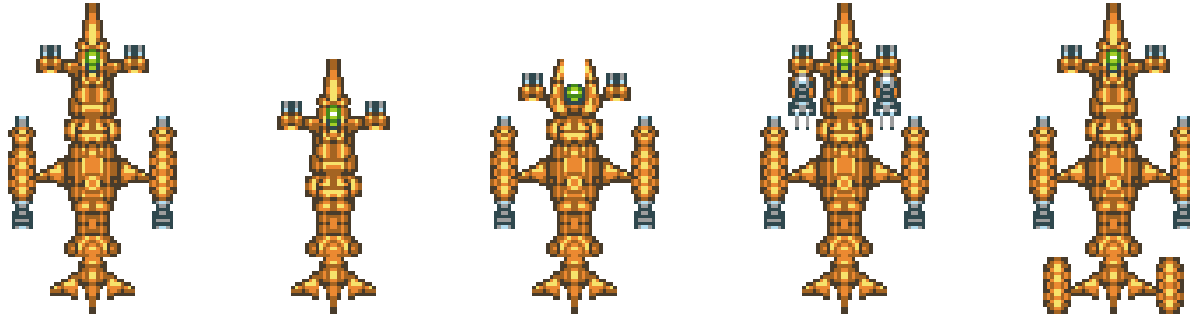


Domain-General Variant Measures

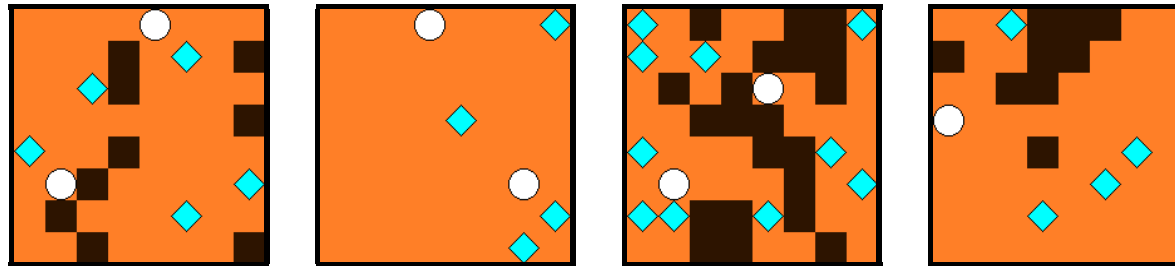
- Objectively define what measures instructors want to vary during training
- Multiple measures can describe each learning objective (LO)
- Combined measures and LOs create a high-dimensional variation space

Measuring Complexity	Measuring Helpfulness
Number of cues	Attention via perceptual arousal
Number of actions	Attention via inquiry arousal
Number of subtasks across actions	Relevance via previous link
Number of interdependent subtasks	Relevance via needs link
Number of possible paths	Confidence via evaluation link
Number of criteria to satisfy	Confidence via learner control
Number of conflicting paths	Satisfaction via feedback positivity
Number of distractors	Satisfaction via future link

Previous Research in Evolving Variants



Visual Asset Generation



2D Level Generation

Antonios Liapis, Georgios N. Yannakakis, and Julian Togelius. 2013. Enhancements to constrained novelty search

Antonios Liapis. 2016. Exploring the Visual Styles of Arcade Game Assets

Evolving Training with Novelty Search

- Novelty search is a form of evolutionary search which differs from more traditional evolutionary methods
- Rather than using a fitness-based approach, novelty search rewards individuals for exhibiting new behaviors
- The novelty score is generated by comparing an individual to its k nearest neighbors in behavior space

$$\rho(x_i) = \frac{1}{k} \sum_{j=1}^k g(x_i, x_j)$$

- Incentivizes exploration of behavior space rather than optimization

Experiment domain – SUAS COMPETE

- SUAS COMPETE is a simulation environment for training small-unit decision-making in an unmanned air system setting
 - Many training elements can be varied such as scenario map, situation text, hints, and more
 - Potential to create varied support or challenge for 9 TLOs and 48 ELOs

BOEING Defense of BP 17

Situation
You are the XO of TM B/1st CAB, 477 IN. After reading the TM B OPORD, you are instructed by Cdr, TM B to huddle with the Platoon SUAS Team Chiefs and the TM B Robotics NCO to start the integration of the TM B SUAS systems.

What are the key tasks that the TM B Commander specifies for the Platoon SUAS?
Click on the choice that best matches your decision:

The Plt SUAS systems are to observe NAI-1 and TAI X

Observe TAI W

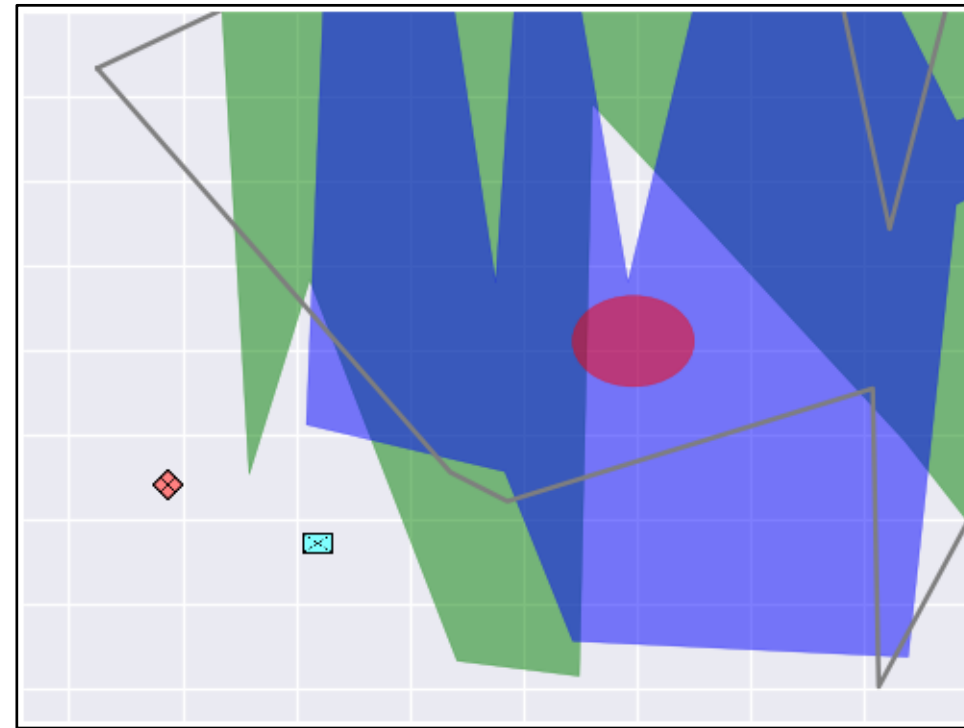
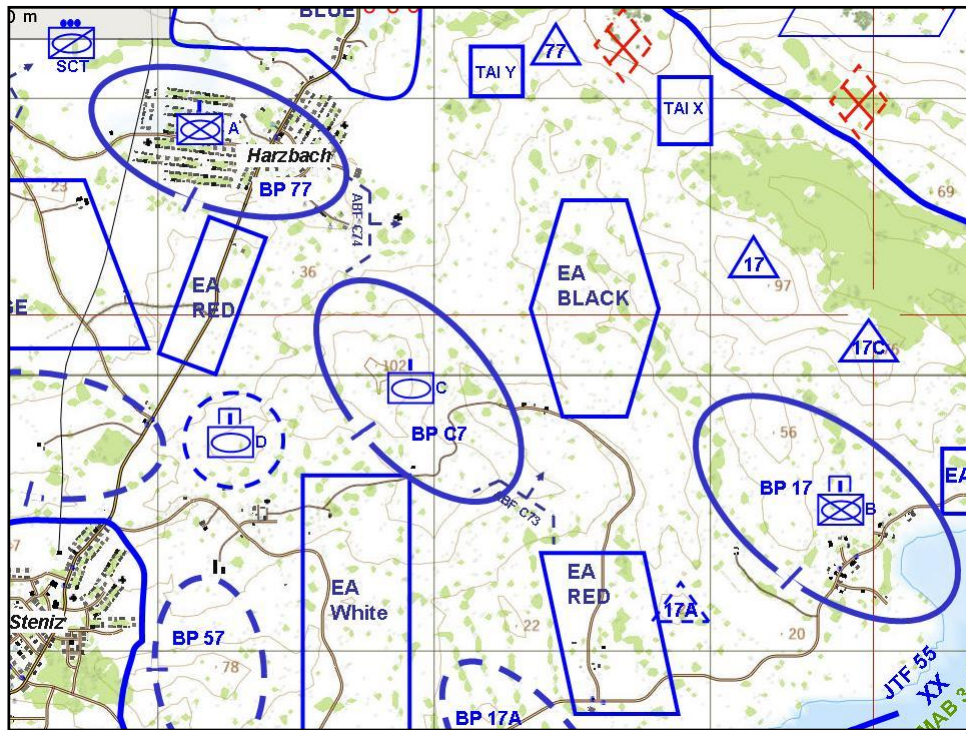
Place Ravens to observe NAI 2 & EA BLUE

SUAS establish observation of TAI Y and EA BLACK

Glossary Tactical Situation UAS Specs Sensor Specs Show Hint

SUAS Compete

- Content Examples:
 - SUAS scenario map
 - Simplified map to demonstrate evolution process

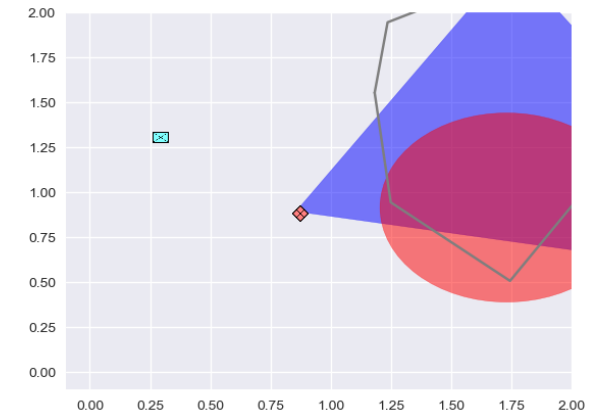
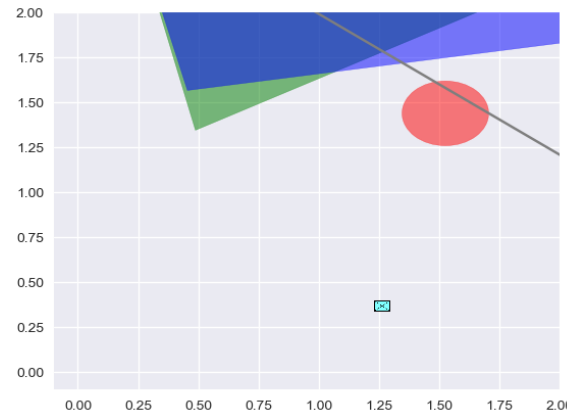
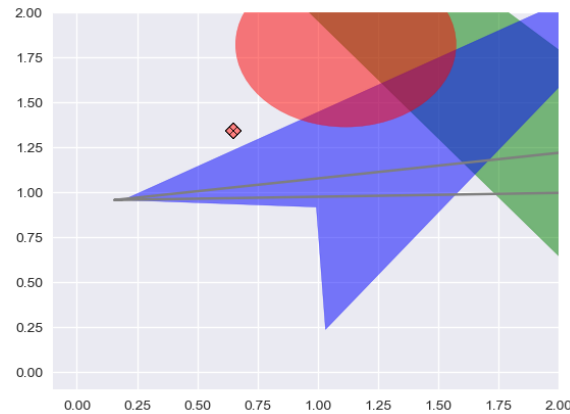


Methodology

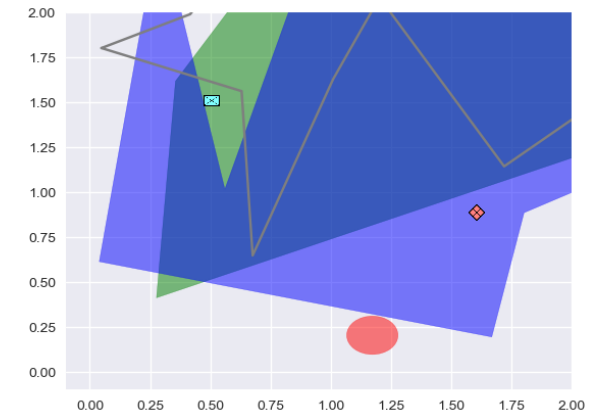
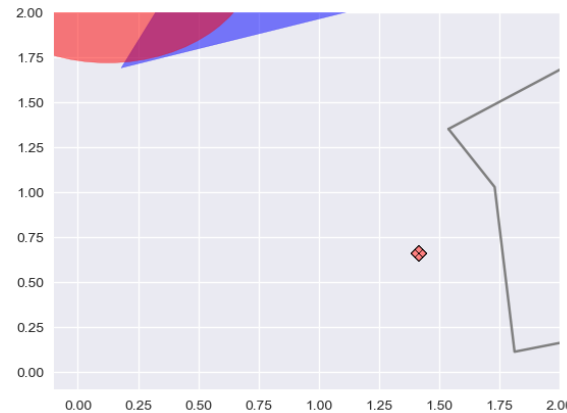
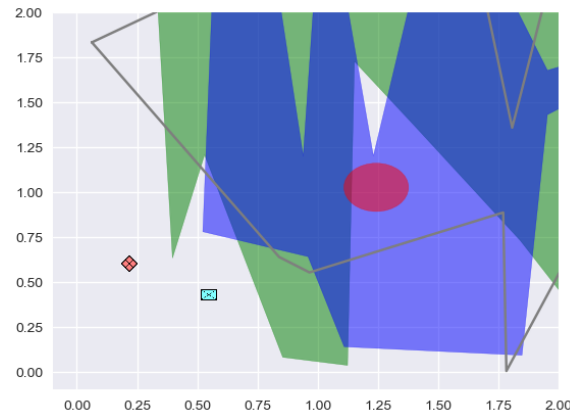
- Created an example of evolving scenario maps with:
 - Point locations of friendly, hostile units
 - Terrain regions such as forest, water, roads
 - A no-fly zone that the UAS must work around
- Created an example of training learning objectives:
 - Enemy air defense avoidance
 - Recon and surveillance
 - Airspace coordination
- So, evolving changes to the maps does NOT always change learning impact
 - Scenarios can support or challenge air defense avoidance via distance to enemy
 - Support or challenge recon and surveillance via enemy location relative to forest terrain
 - Support or challenge airspace coordination via no-fly zone – in the way or not

Example Training Scenarios

- Generation 1 – Initial Randomization Results



- Generation 200 – Novel Combinations of Support and Challenge



Evolutionary Algorithm Process

Population Evaluation

- Measure novelty of organisms in population by comparing them to HoF

Reproduction

- Select the organism in the population with the highest novelty
- Duplicate and mutate to produce offspring

Offspring Evaluation

- Measure novelty of offspring by comparing to HoF

Update Population

- If parent is more fit than offspring, then destroy offspring and slightly increase mutation variance
- If offspring is more fit than parent, then replace parent with offspring and reset mutation variance

Update HoF

- If novelty of most-fit organism meets or exceeds the HoF novelty threshold, add the organism to the HoF and reset novelty threshold
- If the novelty of the most-fit organism is below the HoF novelty threshold, then slightly decrease the threshold

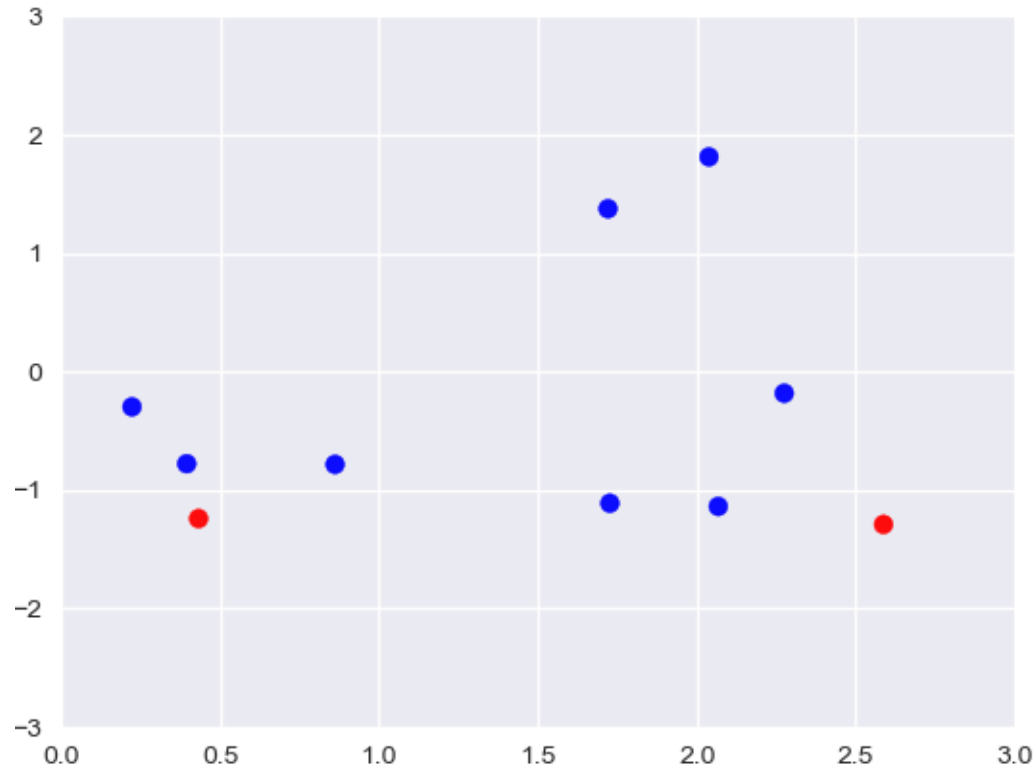
Evolutionary Algorithm Parameters

- Population size 10
 - Generation = 1 individual at a time
 - Runtime = under a second for simplified experiment
- Hall of Fame Variable Threshold
 - Default to 1.0
 - Decrease by 0.1 for each consecutive generation that does not contribute to the HoF
 - Reset to 1.0 when an organism adds into HoF
- Variable Mutation
 - Default to 0.1
 - Increases by 0.1 each time an offspring is less novel than the parent
 - Resets to 0.1 each time a more fit offspring is produced

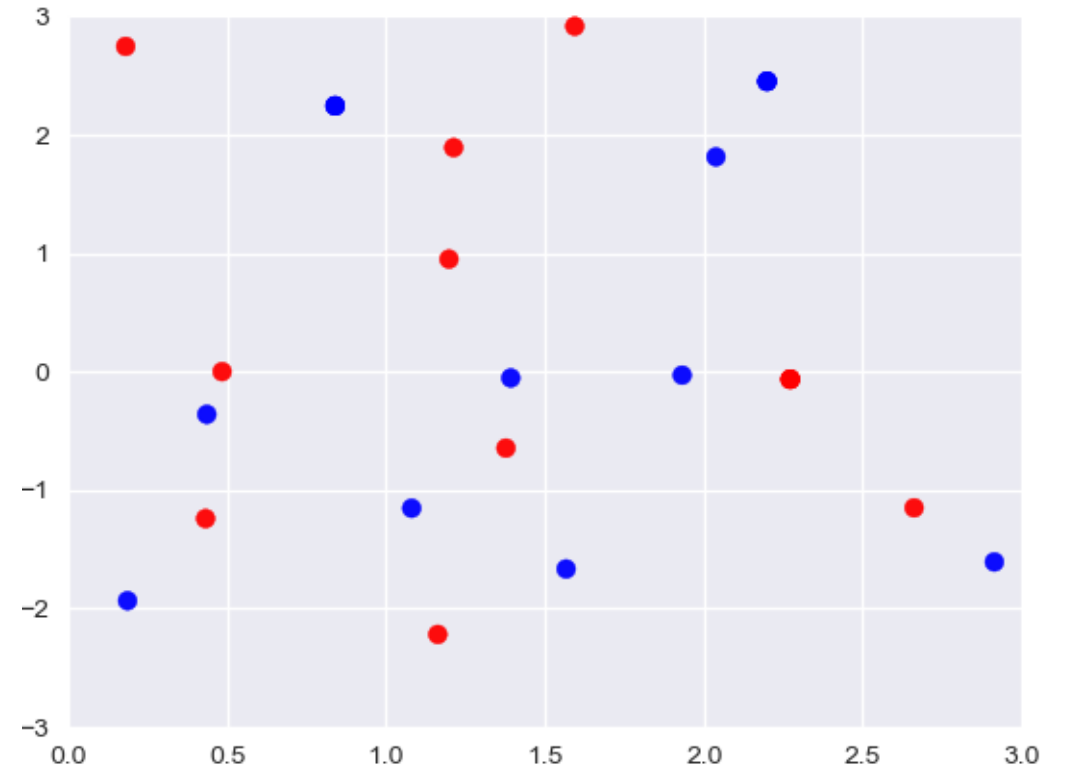
Results – More Variants for GIFT to Choose

- Novelty search creates different combinations of support and challenge

Generation 1 – Initial Randomization Results



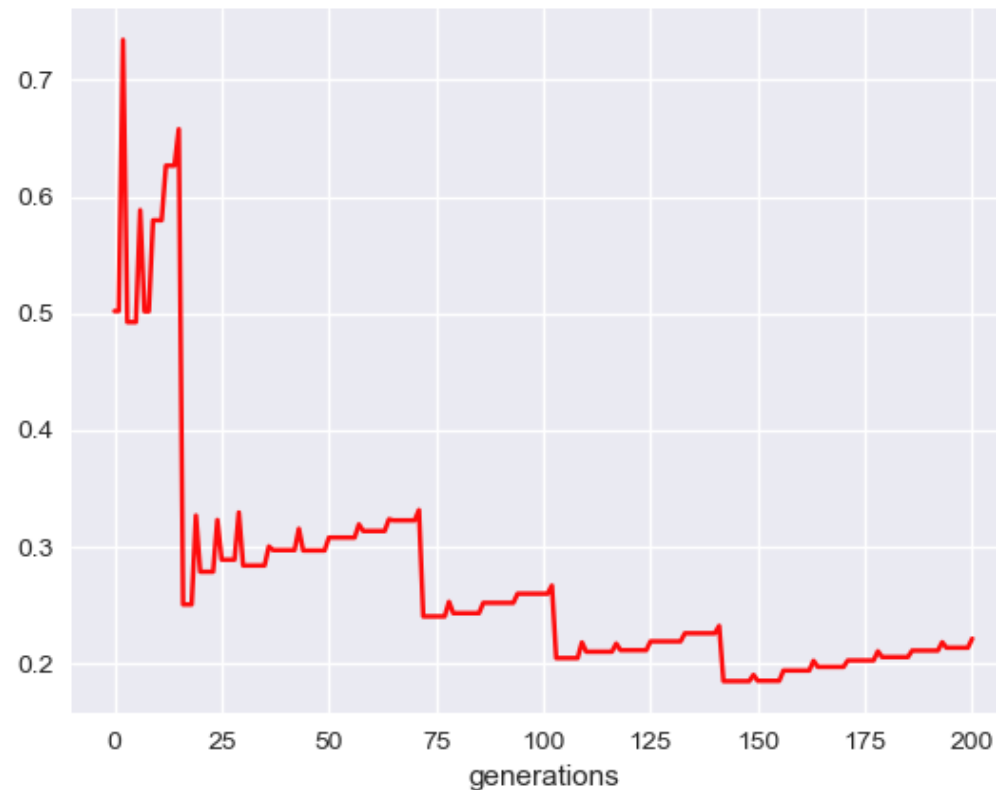
Generation 200 – Novelty Increases Coverage



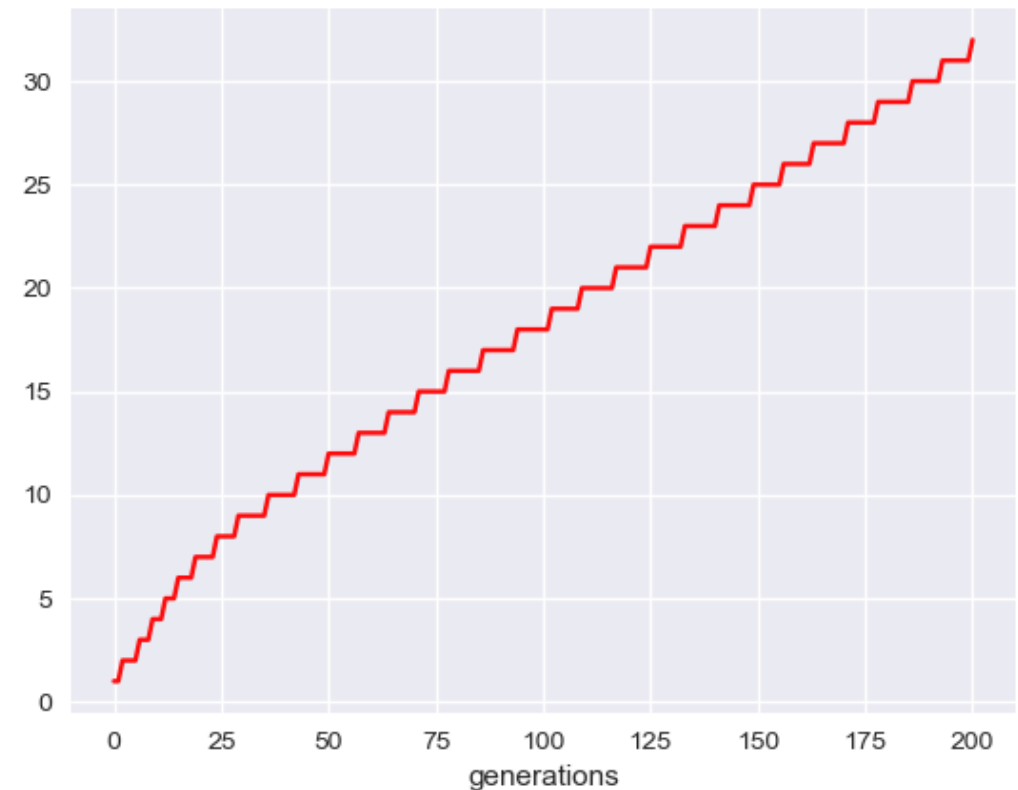
Results – Continuing Improvement over Time

- Novelty continues increasing – new variants differ in ways that change learning

Distance between variants over time



Number of variants over time



Future Work

- SME interviews to determine realistic rules that predict training impact
- Generalize to content types other than maps, e.g. text
- Use multiple training domains to show generality of the measures
- Assess performance within generated scenarios
- Machine learning on training variants to automate feature & rule discovery

Questions?

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