



Assessing & Selecting Al Pilots for Tactical and Training Skill

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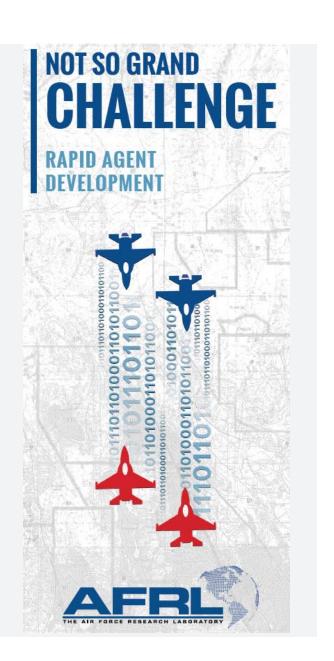
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Overview

- The challenge
 - Tactical expertise is a function of practice, but...
 - Expert human adversaries are scarce
 - Many CGFs are relatively inexpert adversaries
 - Lowest value for the most accomplished pilots
 - Potential for negative transfer for all pilots
- AFRL solution strategy
 - Robust Al pilots
 - Testbed for accelerated AI development
 - Assessment of Al
 - Train with tactical Al





Al Pilots

Challenge

 Develop adversary (Red) AI that is tactically proficient & robust to trainee behavior in 1v1 & 2v2 engagements

Solutions

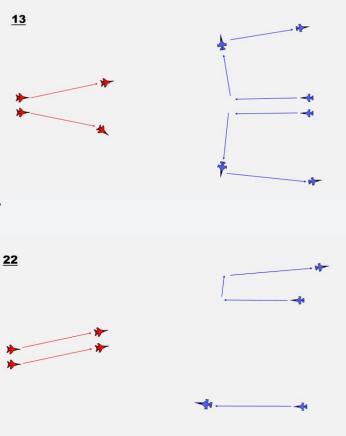
- TiER1 Performance Solutions
 - Task network model represents operator goals & functions. Accumulator model controls transitions through the task network.



 SimBionic architecture integrates multiple behavior transition networks. Dynamic scripting ML algorithm adapts agents.

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 Reinforcement learning models tactical state and response. Behavior Definition Language (BDL) represents these plus goals, behavioral constraints, measures.





Al Pilots

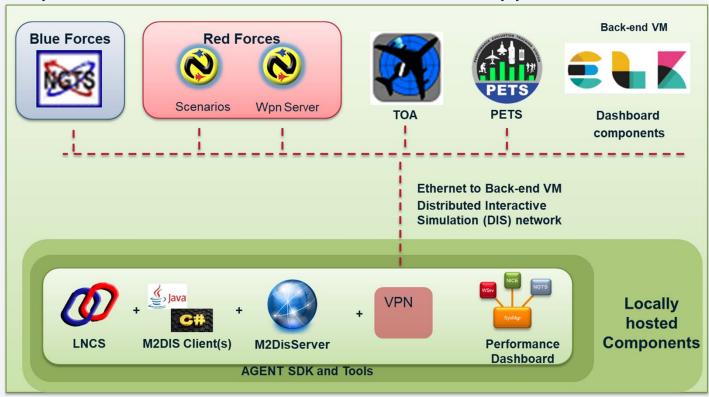
Solutions

- Soar Technology
 - A production system -- the Soar-based cognitive architecture -- dynamically processes environmental states to accomplish deconflicted goals.
- Eduworks
 - Brahms-Lite models work systems in which humans and technologies interact.
- Discovery Machine
 - DMInd represents hierarchies of prespecified problem spaces and response strategies, which are retrieved as a function of fit to context.
- CHI Systems
 - Personality-enabled Architecture for Cognition (PAC) uses narrative threads and personality characteristics (e.g., risk tolerance) to control perception and behavior.
- Charles River Analytics
 - Hap manages competing goals and generates behaviors for dynamic situations, using rapid loops of information gathering, assessment, and decision-making.



Testbed

- Challenge: Rapid agent development
- Solution:
 - Testbed* enables independent, distributed exercise and assessment of Al pilots on 72 scenarios, with reduced support from SMEs



^{*}Key components of the testbed are freely available to partner nations.



Testbed

- Generate constructive players
 - Red -- AFRL's Network Integrated Combat Environment (NICE), driven by AI
 - Blue -- Next Generation Threat System (NGTS)
- Capture data
 - Measure performance -- Performance Evaluation and Tracking System (PETS™)
- Record & play back
 - Simulation protocol -- Distributed Interactive Simulation (DIS) comms Al intent to distributed CGFs
- Tactical data
 - Syntactic -- Wrappers around native M&S data
 - Semantic
 - Tactical Observation Agent (TOA) simulates airborne control operator
 - Fighter Combat-Tactical Awareness Capability (FC-TAC) API relays overall state of and beliefs about the environment
- Data storage -- Data lake architecture



Assessment

- Method: Periodic assessment
 - Automated: Kills & Losses; deconfliction between Red Aircraft; aircraft location relative to adversary weapon lethality range; time in adversary weapon lethality range; Airspeed;
 - Expert judgment: Intercept geometry, adherence to contract, split decisions, spike awareness, post merge maneuvers, fuel & weapons management.
- Findings:
 - Process measures predict outcomes (right)
 - High variance on process and outcome measures within agents between scenarios, & between agents within scenarios

Measure	r(Outcom eScore,*)
OutcomeScore	
ContractAdherence	0.75
Deconfliction	0.21
ElementTargeting	0.86
FuelManagement	0.72
InterceptGeometry	0.71
PostMergeManeuver	0.64
SpikeAwareness	0.88
Split	0.39
TacticalIntelligence	0.90
WeaponsManagement	0.71

Scenario	13d	Ţ.													
Average of Score Column T															
			DecisionE		\		Intercept	/ \	PostMerg			TacticalIn	Weapons		
	Contr	actA	xplanatio	Deconflic	ElementT	FuelMan	Geometr	Outcome	eManeuv	SpikeAwa		telligenc	Manage	Grand	
Row Labels	dhere	ence	n	tion	argeting	agement	у	Score	er	reness	Split	e	ment	Total	S.D.
Agent1		1.0	1.0	2.5	1.0	1.5	1.0	1.0	1.0	1.0		1.0	1.0	1.2	0.44
Agent2		3.5	3.0			3.5	4.0	3.0	4.0			2.5	2.0	3,4	0.67
Agent3		2.0	3.0	2.5	3.0		2 5	4.0	3.0	4.0		2.5	3.0	3.0	0.60
Agent4		3.0	3.0	3.0	3.5	3.5	3.0	4.0	2.0	3.0	1.0	3.0	2.5	3.1	0.74
Agent5		1.0	1.0	3.5	1.0	2.0	1.5	1.0	1.0	1.0	1.0	1.0	1.5	1.5	0.71
Agent6		1.0	2.0	2.5	1.0	1.5	1.5	1.0	1.0	1.0	1.0	1.0	1.5	1.3	0.47
Agent7		4.0	2.0	4.0	4.0	3.0	4.0	4.0	3.0			3.0	3.5	3.6	0.65
S.D.		1.19	0.83	0.64	1.34	0.87	1.13	1.40	1.12	1.26	0.00	0.89	0.83		
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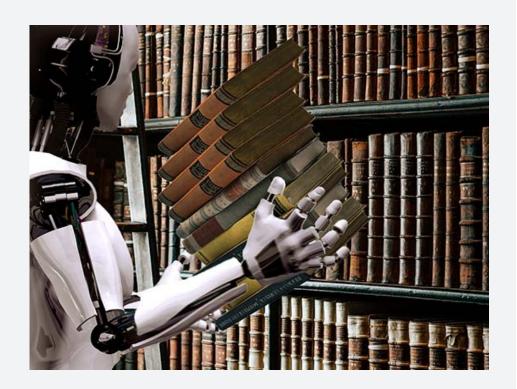
Applying tactical AI to training

Challenge

• How can we best train human pilots with AI that are tactically proficient, not instructionally expert?

Solution Strategy

 Create an automated librarian that selects the best AI for the training scenario and trainee, based on a characterization of the AI





Applying AI to Tactical Training

- Select by rule
 - Analyst computes the performance of all Al in all 72 scenarios
 - Trainer selects the next scenario in the curriculum
 - Librarian selects the AI that is (almost) the most tactically proficient
- Select by expert judgment
 - SME estimates the training effectiveness of each AI per scenario or vignette (within scenarios) for trainees at n levels of pilot expertise
 - Trainer estimates the expertise of the pilot
 - Librarian selects the most effective AI (with some systematic experiments to assess alternative AI)



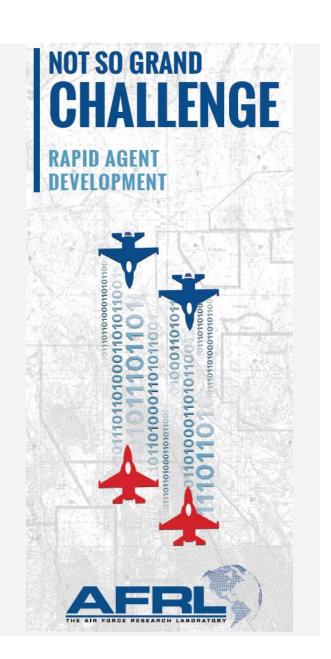
Applying AI to Tactical Training

- Select by probabilistic model
 - SME estimates the training effectiveness of each AI per scenario or vignette (within scenarios) for trainees with varied measurements of scenario performance
 - Analyst defines POMDP model of AI effects given scenario & measured trainee performance
 - Analyst computes a training policy
 - Librarian applies the policy to select the AI and scenario that most reliably advance the trainee furthest to expertise
- Select by empirical effects
 - Researcher conducts training experiments that cross scenario x
 Al x pilot expertise
 - 5 scenarios x 5 Al x 3 expertise x 8 subjects per level = 600 trials
 - Analyst identifies empirically best Al given scenario & expertise
 - Librarian selects the best AI for the training task



Summary

- Accomplishments
 - Robust Al pilots
 - Testbed for accelerated AI development
 - Assessment of Al
- Future research
 - Parallelize the testbed for efficient development, big data volume
 - Develop data and librarian to train with tactical Al





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