Adversarial AI for Solving Complex Security Problems in Engineered Systems

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AI4Sec:FND Course
Auburn University

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Appointments

Los Alamos National Laboratory (LANL)
Guest Scientist, A-4: Advanced Research in Cyber Systems

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Cyber Security Consultant, Department 05623 – Special Cyber Initiatives

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Auburn University (AU)
Interim Director and Chief Cyber AI Strategist, Auburn Cyber Research Center
Head, Biomimetic Artificial Intelligence Research Group (BioAI Group)
Director, Biomimetic National Security Artificial Intelligence (BONSAI) Lab
AU Director, LANL/AU Cyber Security Sciences Institute (CSSI)
Associate Professor, Department of Computer Science & Software Engineering
Affiliated Faculty, McCrary Institute for Cyber and Critical Infrastructure Security

Part I: Engineered Systems & Security

Why You Should Care

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- Cyber-physical engineered systems are extremely vulnerable to attack
- Cyber-physical engineered system attack surfaces tend to be astronomically large and infeasible to fully secure
- Only AI is capable of examining the combinatorially large number of unique attacks and defenses on modern engineered systems

What is an Engineered System?

NSF's Engineering Research Center website defines engineered systems as:

> "a combination of components that work in synergy to collectively perform a useful function. The engineered system could, for example, wholly or in part constitute a new technology for a new product line a new manufacturing process, a technology to improve the delivery of a service, or an infrastructure system."

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Examples:

- Modern Automobiles, Planes, and Trains
- Industry 4.0: Chemical Plant, Biotechnology, Agriculture
- Advanced Manufacturing Facility
- Smart Electric Grid
- Internet, Enterprise Computer Networks, Cloud Computing

Critical Infrastructure Sectors

DHS' Cybersecurity and Infrastructure Security Agency (CISA) lists 16 critical infrastructure sectors:

- Chemical
- Commercial Facilities
- Communications
- Critical Manufacturing
- Dams
- Defense Industrial Base
- Emergency Services
- Energy
- Financial Services
- Food and Agriculture
- Government Facilities
- Healthcare and Public Health
- Information Technology Sector
- Nuclear Reactors, Materials, and Waste
- Transportation Systems
- Water and Wastewater Systems

Engineered System Security as a Game

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- Computational game theory achieves scalability by approximating Nash equilibria

Part II: Adversarial AI

AI for security versus security of AI

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- When applying AI to solve security problems, the AI can be vulnerable itself

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- A **hyper-heuristic** is a meta-heuristic for a space of programs

Algorithmic Toolbox

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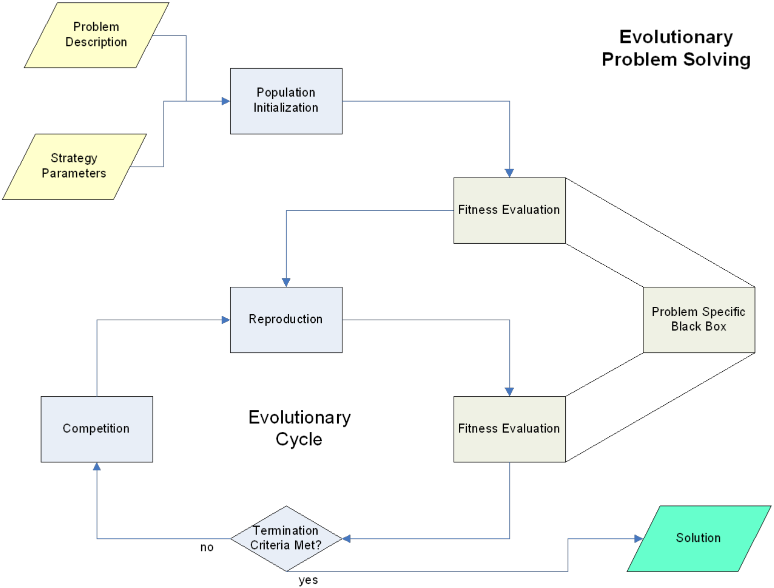
- **Genetic Programming (GP)** is a type of EA for searching a space of programs

Evolutionary Cycle



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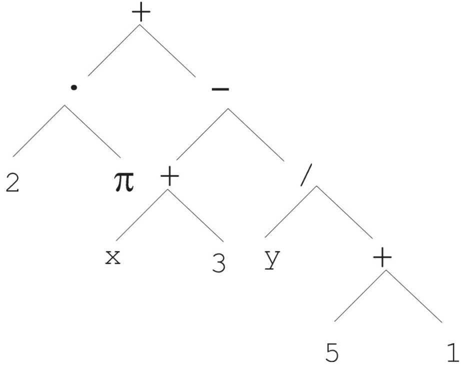

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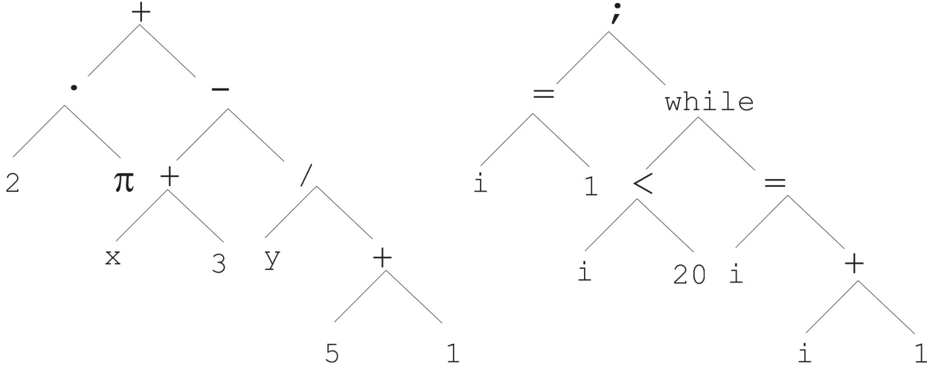
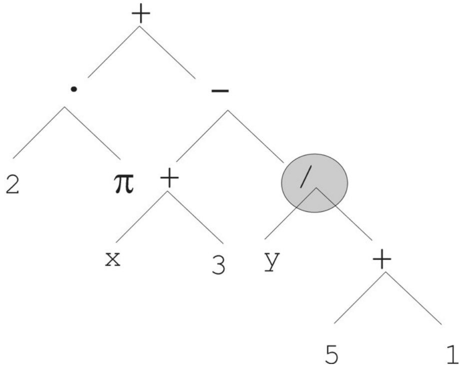


Genetic Programming - Mutation



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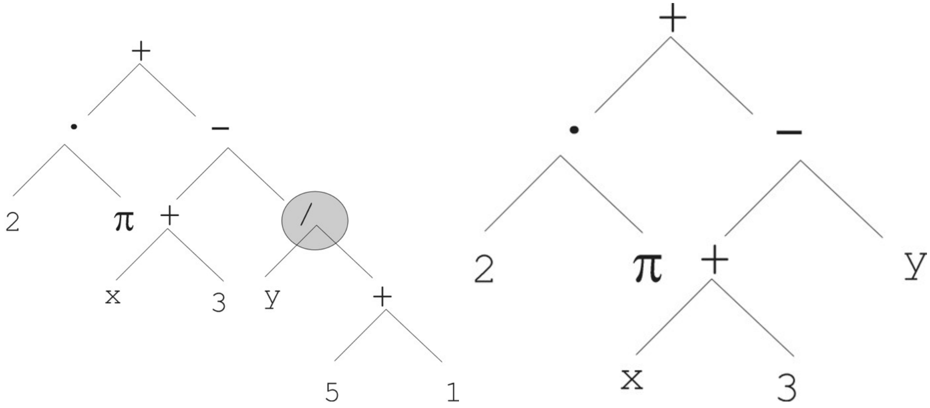
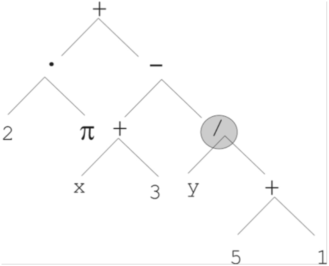
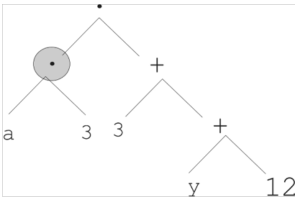


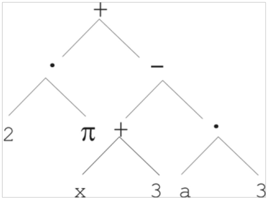
Genetic Programming - Recombination



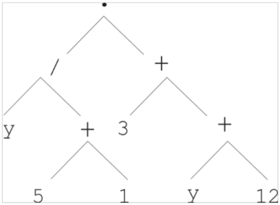
Parent 1



Parent 2



Child 1



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- Solution: Computational Game Theory

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- The simultaneous search of co-dependent spaces is naturally modeled as an armsrace

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- “Ill-behaved” search space
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- Evolution has a demonstrated ability to solve very complex problems

Coevolutionary Algorithm (CoEA)

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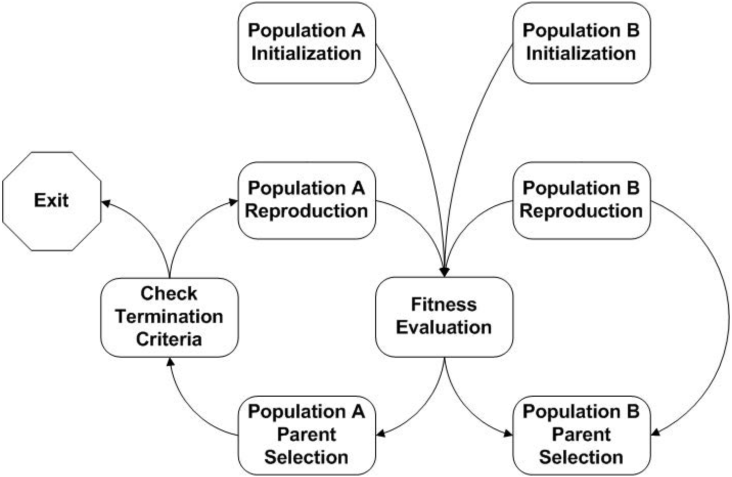
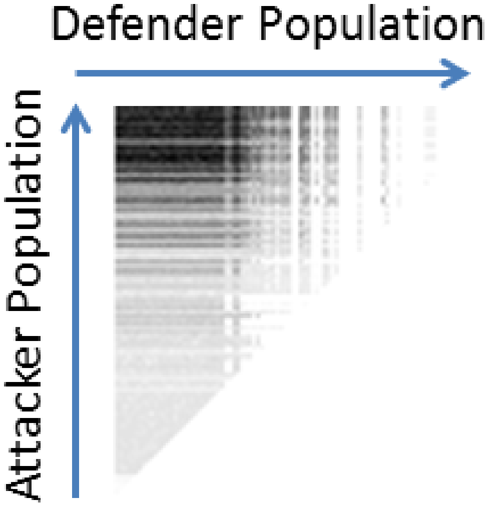
- Single species vs. multiple species
- Cooperative vs. competitive coevolution

Two-Population Competitive Coevolutionary Cycle

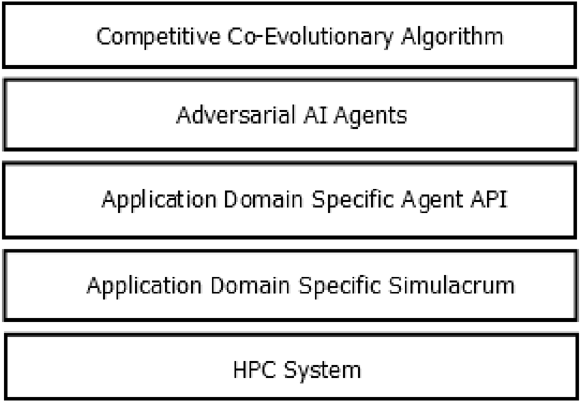


CIAO Plot Example

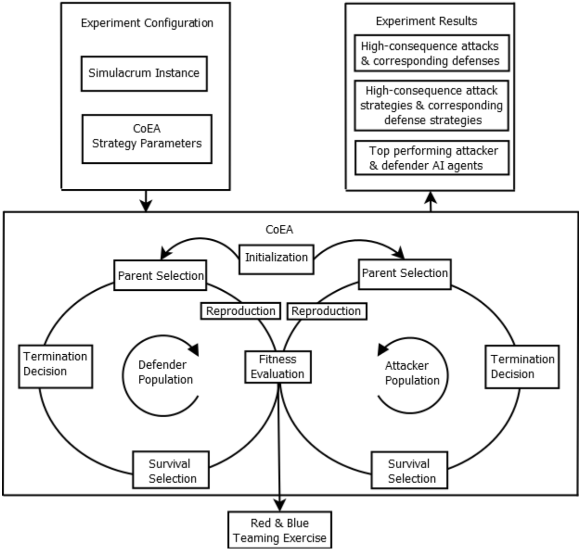


Part III: Engineered System Security through AI Armsraces

CEADS system diagram



CEADS CompCoEA operation



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Attacker & Defender AI Agents Automated generation of highly-trained AI agents that can be deployed in live systems to augment human operators, or even autonomously engage in real-time with adversaries, both human and AI.

How to Apply CEADS to an Engineered System

- Create simulacrum

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Challenges

Operationalization In order to achieve operationalization, the attack & defense actions must be comprehensive and reflective of current and future threats, and must model targeted real-world systems with very high-fidelity requiring extensive knowledge of the targeted systems and a process for testing and eventually validating on said systems.

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Scalability Running a single automated red & blue teaming exercise employing adversarial AI agents can be quite computationally expensive depending on the size of the modeled engineered system and the fidelity to which it is being modeled. CoEAs typically require on the order of thousands of red & blue teaming exercises for a single experiment.

Addressing Scalabillity

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- Partial Evaluations: By adding hooks into the simulacrum to query and control it during execution, agents performing sufficiently poorly can have their fitness estimated based on a partial evaluation, thus saving precious computational time for evaluating more promising agents. Additionally, poorly performing agents can be sampled at lower rates than promising ones for additional time savings.

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- Appropriate configuring adversarial AI and creating high-fidelity sumulacra requires human engineers
- AI is not a panacea, but can augment human experts to significantly improve results