Evolutionary Computing Approaches for Wickedly Hard National Security Problems

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Auburn University

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Part I: Preliminaries

Terminology

- Many computational problems can be formulated as **generate-and-test** search problems

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

Algorithmic Toolbox

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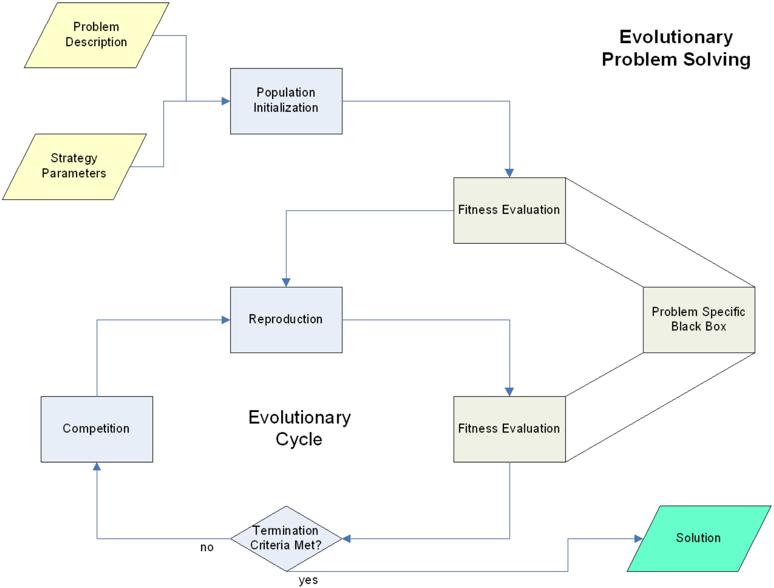
- **Genetic Programming (GP)** is a type of EA for searching a space of programs
- Hyper-heuristics are predominantly implemented with GP; they work by trading off adequate performance on general problem classes with high performance on targeted problem classes

Evolutionary Cycle



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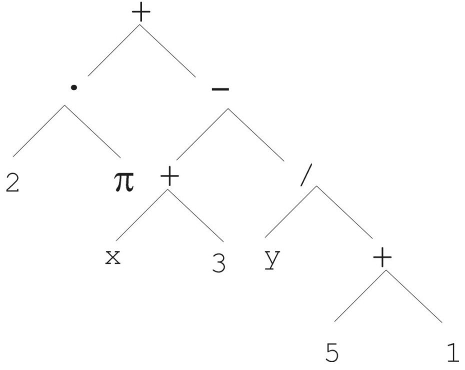

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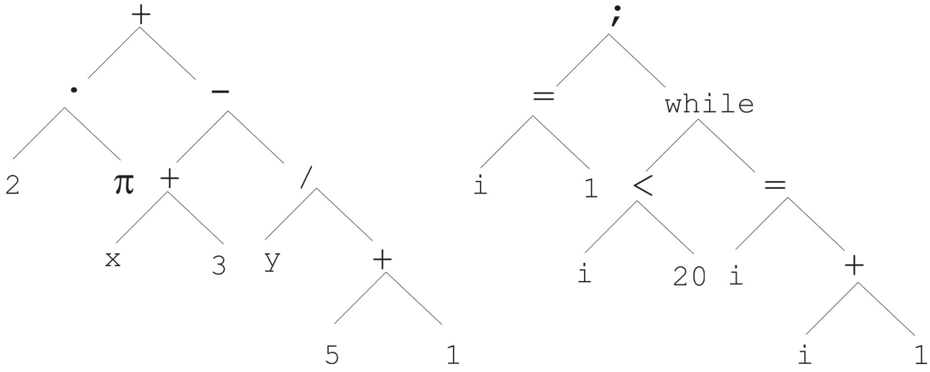
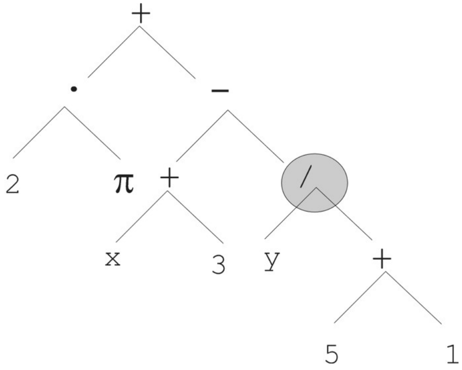


Genetic Programming - Mutation



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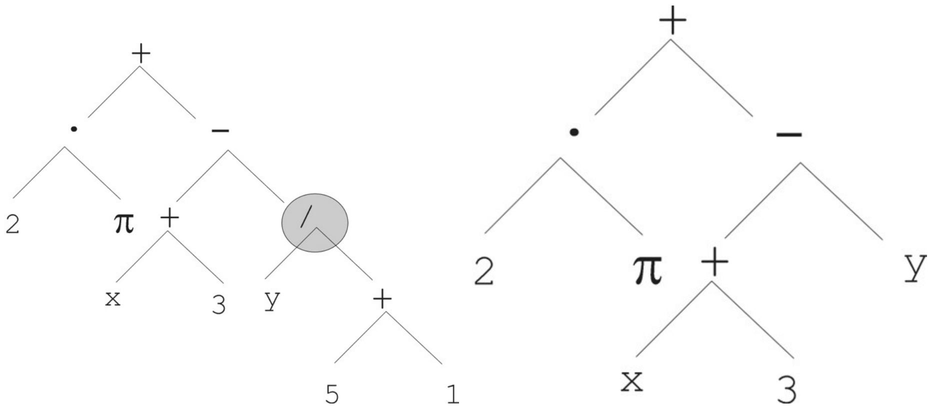
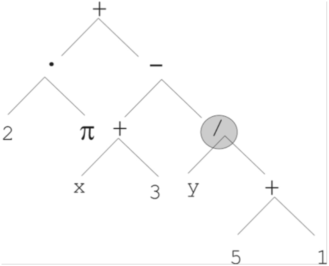
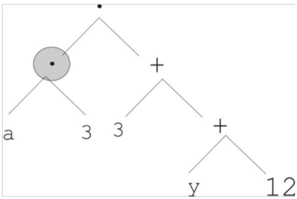


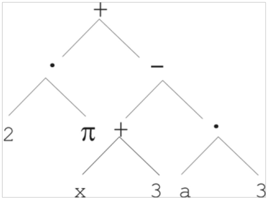
Genetic Programming - Recombination



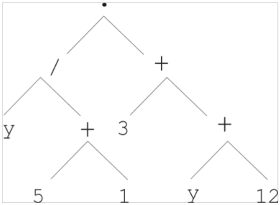
Parent 1



Parent 2



Child 1



Child 2

Part II: Hyper-heuristics for National Security Problems

Automated Design of Network Security Metrics

Aaron Pope[1,2], Robert Morning[2], Daniel Tauritz[1,2], Alexander Kent[2]

2018 Genetic and Evolutionary Computation Conference (GECCO 2018)

Kyoto, Japan, July 15-19, 2018

[1]Missouri University of Science and Technology

[2]Los Alamos National Laboratory

Motivation

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- Solutions can be complex and unintuitive
- Manual development is too slow for rapid response

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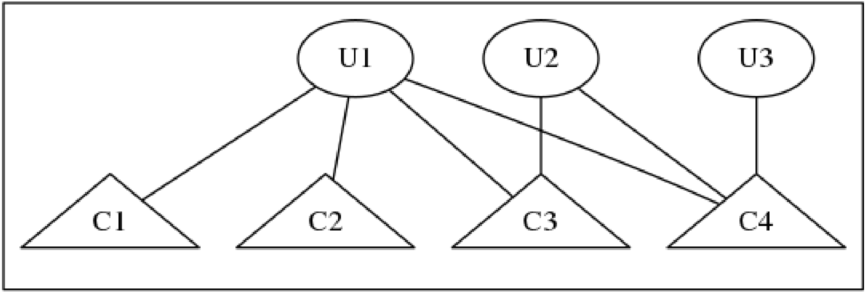
- Use hyper-heuristic techniques to generate novel graph-based security metrics
- Evaluate metrics by how well they predict attack success

Network Representation

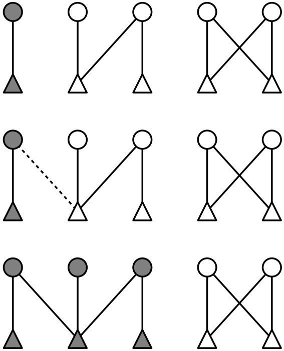
Bipartite Authentication Graphs (BAG)

- Vertices represent networked hosts and user accounts
- Edges indicate an account being used to access a host
- Especially useful for centralized single-sign-on systems



Credential Theft Attack Model

1. Adversary starts on a random host
2. Harvests credentials to follow legitimate user traffic
3. Repeats, traversing a growing portion of the network



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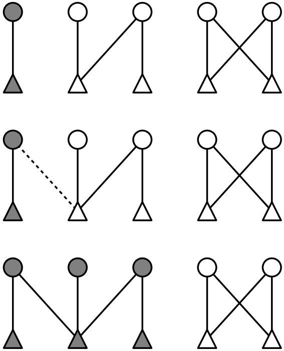

Given a specific credential policy and time limit, what is the expected portion of the network an adversary can reach?

Credential Policies

Possible credential policies:

- Time limit on credential expiration

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- Some combination of these or others

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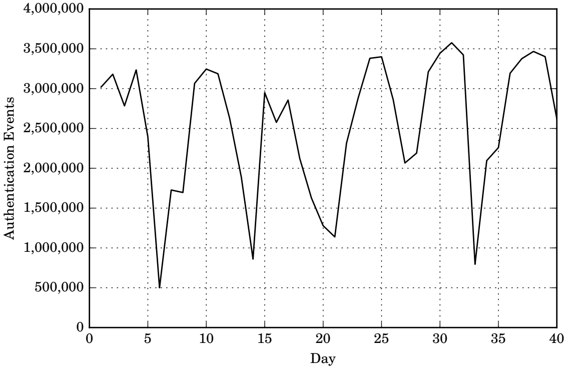
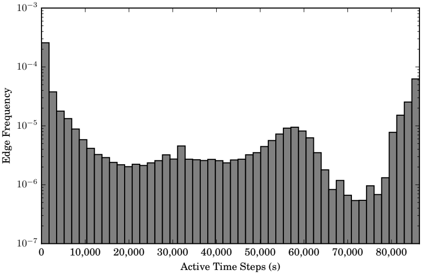
- Simpler, static input graphs are produced for each day
- Edge weights equal the number of time-steps an authentication edge is active that day

LANL Authentication Dataset Details

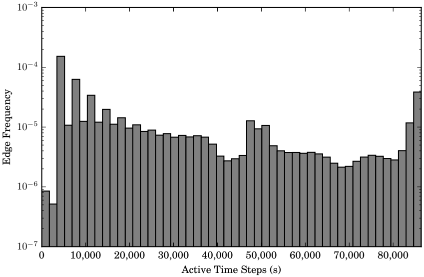
Unique Users	10,044
Unique Computers	15,779
Unique (User, Computer) Pairs	124,020
Total Authentication Events	101,918,344
Average Daily Authentication Events	2,547,959



Simulation Policies Considered



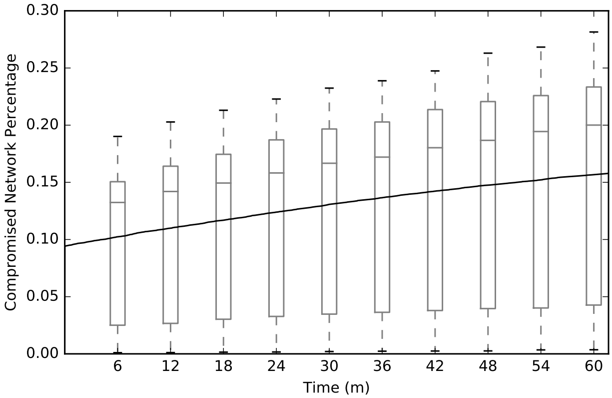
10 credential limit policy



1 hour expiration policy

Distribution of authentication edge activity levels

Simulation Results



1-hour ticket lifetime policy simulation results

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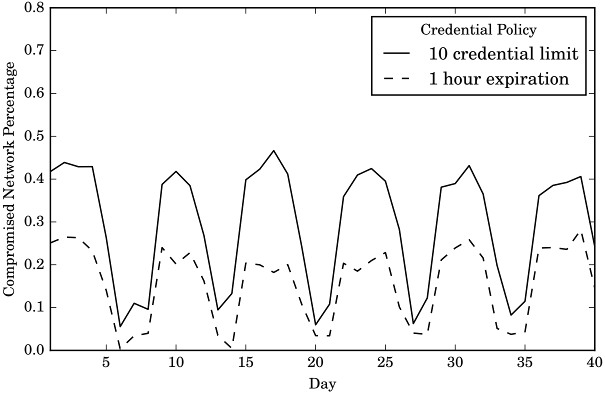

Daily simulation results for both credential policies

Hyper-Heuristic Approach

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- Solutions take a graph representation of the network as input and return a predicted percentage
- Measure evolved solution's output against simulation results

$$fitness = -\frac{\sum_{d \in days} \left| \frac{simulated\_result - predicted\_result}{simulated\_result} \right|}{|days|}$$

GP Primitive Set

Inspired by previous work evolving graph-based heuristics

- Math operations: add, subtract, etc.
- Numerical constants: integer or probability
- Boolean nodes: true, false, random
- Control flow: if [else], for, while
- Graph elements: vertices, edges
- Local and global graph metrics: average degree, centrality measures
- Collection manipulation: concatenation, filtering, mapping
- Subgraph induction

GP Parameter Values

Parameter	Value[3]
Population size	400
Offspring per generation	600
Parent selection tournament size	8
Minimum initial parse tree height	4
Maximum initial parse tree height	7
Recombination probability	70%
Mutation probability	30%
Convergence threshold	10

[3] Values tuned by a random-restart hill-climbing search.

Evolved Solutions

- Complex (200+ lines of code)
- Common functional elements:
  1. Induce a subgraph with the most active edges
  2. Find the connected components in the induced graph
  3. Filter out the account vertices in each component vertex set
  4. Return a value based on the number of computers in each component relative to the number of computers in the original graph

Comparison of Evolved Metric Heuristics

	10 Credential Limit		**1 Hour Expiration**	
Method	**Result**	**Error**	**Result**	**Error**
Simulation	29.797%	N/A	17.484%	N/A
GP-A	29.151%	6.15%	21.411%	60.93%
GP-B	27.093%	14.85%	17.571%	11.23%
GP-C	26.427%	28.00%	20.387%	71.79%

GP-A: heuristic trained on 10 credential limit policy

GP-B: heuristic trained on 1 hour expiration policy

GP-C: heuristic trained on combined data from both policies

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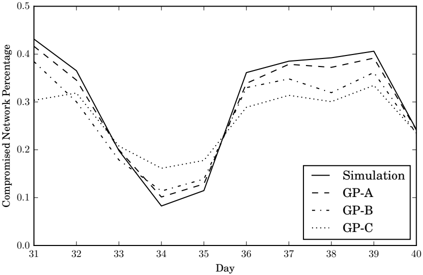

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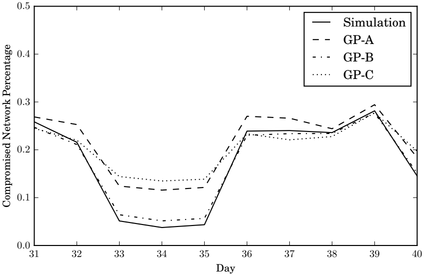

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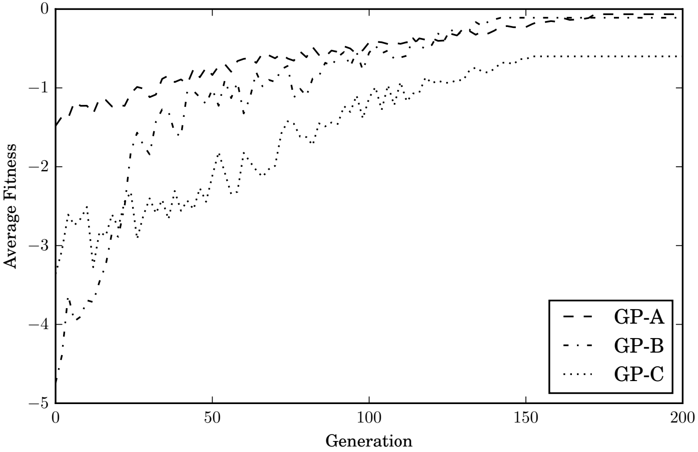
Evolution Progress



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- In this work, the hyper-heuristic was trained against a simulation, but this could be replaced with penetration testing or real-world incident data.
- This work demonstrates the potential of hyper-heuristics in finding novel network security metrics with less reliance on subject matter expertise.

Scalable Automated Tailoring of SAT Solvers with Cyber Security Applications

Funded by Sandia National Laboratories

Sandia collaborators are Samuel Mulder, Denis Bueno, Shelly Leger, Richard Barrett, and Alex Bertels

Boolean Satisfiability Problem (SAT)

- A SAT instance is a boolean formula, typically in Conjunctive Normal Form (CNF) like:

Example SAT Instance in 3-CNF

$$(x_1 \lor x_3 \lor \neg x_2) \land (x_2 \lor \neg x_1 \lor \neg x_3) \land (\neg x_2 \lor x_3 \lor x_1)$$

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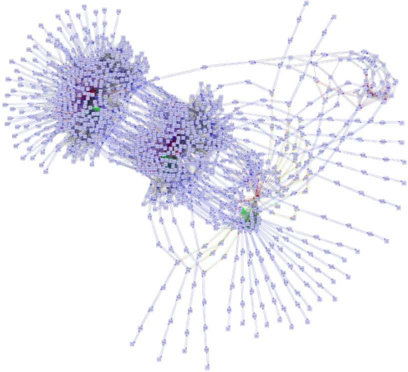
- Solving a SAT instance means deciding whether there exists an assignment of truth values for its boolean variables to make the formula true (i.e., satisfy the instance)
- NP Complete

SAT Applications

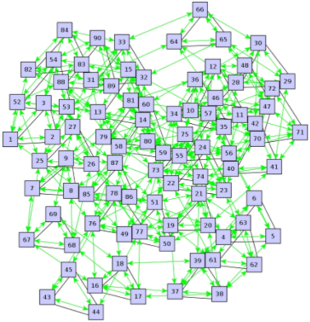
- Encryption at Galois Inc.
- Embedded circuits of Centaur Technology
- Repairing cosmic ray damage of FPGAs at NASA
- Designing the Intel Core i7 processors
- Mapping out mutations in DNA
- Static code analysis
- Program understanding for cyber security

SAT Instance Structure

Long Multiplier



Graph Coloring



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- Among the most efficient known SAT solvers are conflict-driven clause learning (CDCL) solvers
- The *Automated Design of Boolean Satisfiability Problem Solvers Employing Evolutionary Computing (ADSSEC) system* evolves CDCL SAT solvers to target arbitrary, but particular, SAT classes

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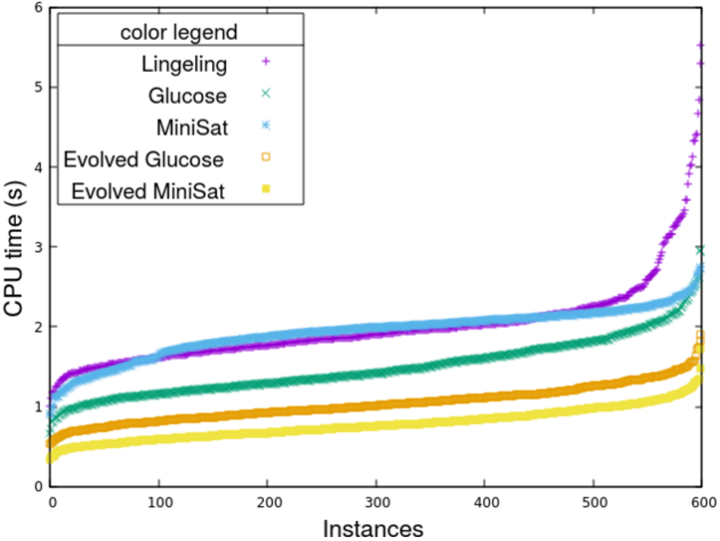
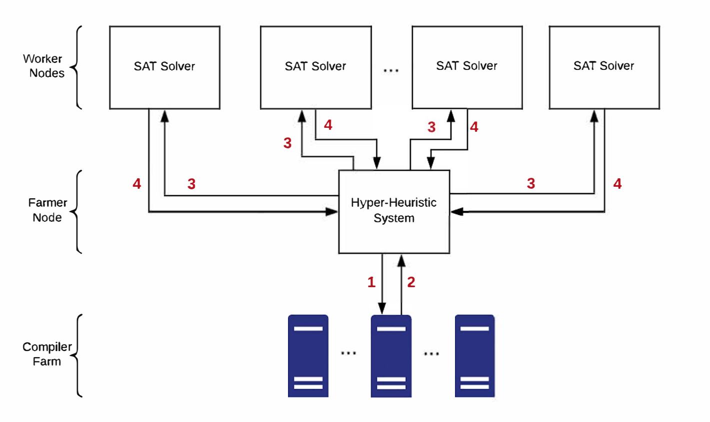
- Employs a novel asynchronous parallel evolutionary algorithm (APEA)

Comparison to a state-of-the-art solver on unif-k5 dataset



MPI Cluster Parallelization Approach



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Part III: Coevolution for Adversarial National Security Problems

Real-World Game-Theoretic Problems

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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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Complex real-world problems can be (practically) unsolvable with classic approaches

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

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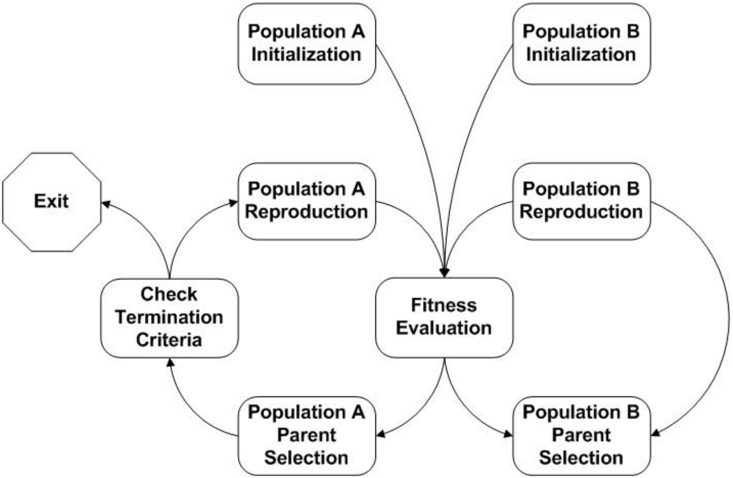
- Single species vs. multiple species
- Cooperative vs. competitive coevolution

Two-Population Competitive Coevolutionary Cycle



Coevolutionary Cyber Security

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- Builds on previous NC-LAB experience coevolving attacks and defenses for electric transmission grid protection

Coevolving Attacker and Defender Strategies for Large Infrastructure Networks (CEADS-LIN)

Funded by Los Alamos National Laboratory (LANL) via the LANL/S&T Cyber Security Sciences Institute (CSSI)

Many moving parts

- Multi-Agent System

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- Representations

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- Simulation versus Emulation

Many moving parts

- Multi-Agent System
- Representations
- Genetic Programming
- Attack Models
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Many moving parts

- Multi-Agent System
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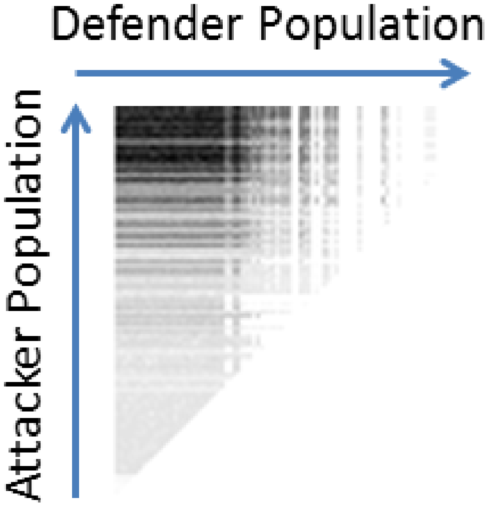
- Simulation versus Emulation
- Hardware-based Emulation: EmuLab, DeterLab
- Virtualized Network Emulation

CIAO Plot Example



Experimental CIAO Plots

TABLE II
TYPICAL RESULTING CIAO PLOTS (ATTACKER PERSPECTIVE)

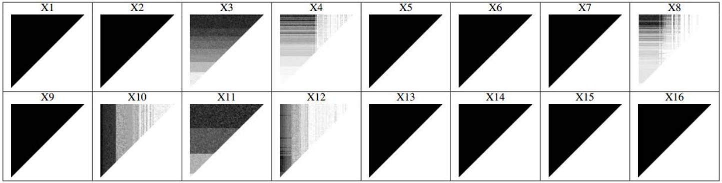
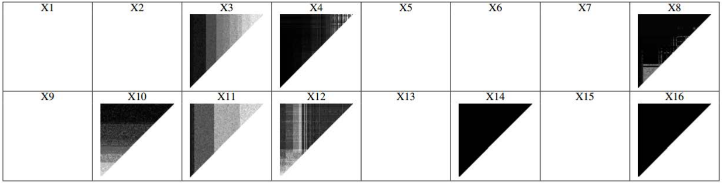
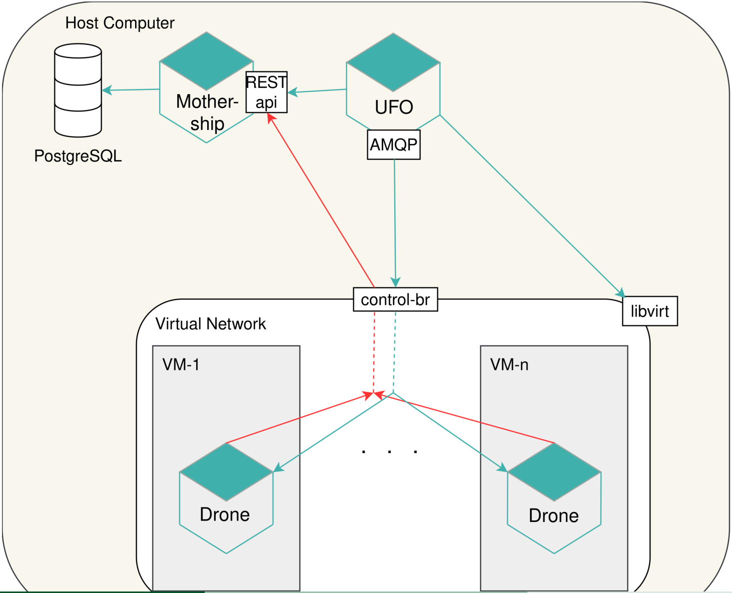


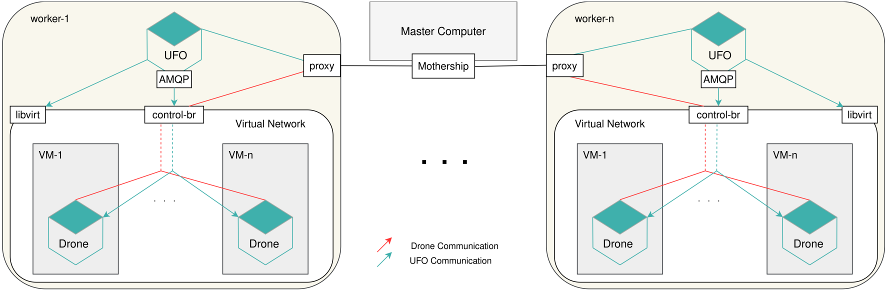
TABLE III
TYPICAL RESULTING CIAO PLOTS (DEFENDER PERSPECTIVE)



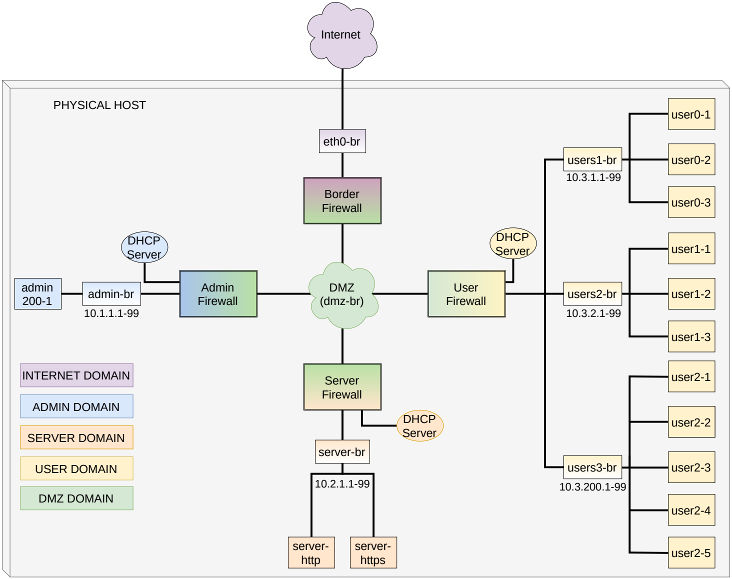
CEADS Architecture



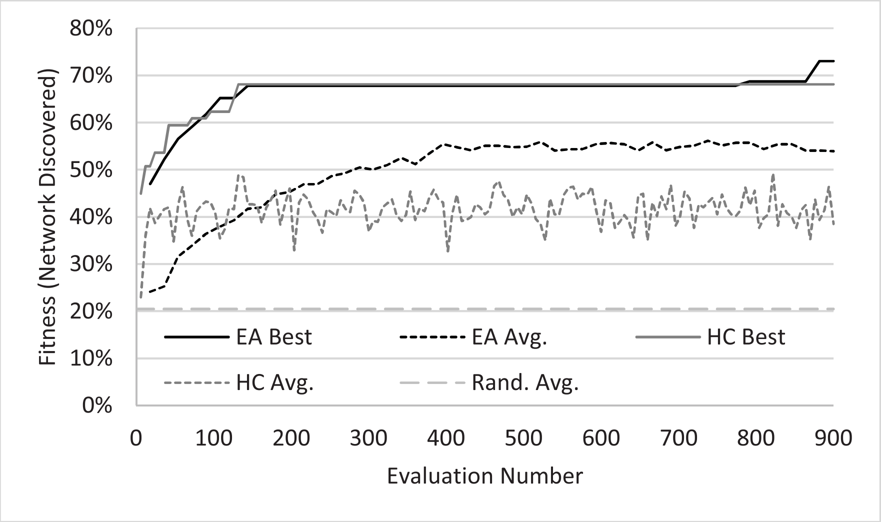
Distributed Architecture



Network Layout



Results


80%
70%
60%
50%
40%
30%
20%
10%
0%
Fitness (Network Discovered)
0
100
200
300
400
500
600
700
800
900
Evaluation Number
EA Best
EA Avg.
HC Best
HC Avg.
Rand. Avg.

Grand Challenges in Coevolving Attacker & Defender Strategies for Large Computer Networks

- Time Dilation in Computer Network Emulation

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- Time Dilation in Computer Network Emulation
- Simulating Human Users

Grand Challenges in Coevolving Attacker & Defender Strategies for Large Computer Networks

- Time Dilation in Computer Network Emulation
- Simulating Human Users
- Scaling & Operationalizing the CEADS-LIN System

Part IV: Take Home Message

Many wickedly hard national security problems map to computational problems that require...

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- repeated solving of instances of the same problem class, can be effectively addressed with genetic programming based hyper-heuristics

Many wickedly hard national security problems map to computational problems that require...

- repeated solving of instances of the same problem class, can be effectively addressed with genetic programming based hyper-heuristics
- solving game theoretic problem instances, can be effectively addressed with coevolutionary algorithms applied to high-fidelity emulations