AI-Centric Cyber Laboratory Services:
Operationalizing Specific White Box Architectures for Fuzzers

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I. INTRODUCTION

Lab services must contend with cyber issues, and in some cases, the use of black-box architectural tools, such as certain fuzzers, may lead to cyber blindspots.
II. BACKGROUND

- Simplistically, a fuzzer is a software program that injects pseudo-random data into a target application for the purpose of detecting bugs.

- Fuzzing or Fuzz testing is the technique by which a fuzzer is utilized.
Prototypical fuzzers have coverage issues (i.e., they only fuzz certain lines of code or certain sections of the software program).

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Benefits of Fuzzing

- The benefits of fuzzing have been well documented, such as when researchers found dozens of vulnerabilities in wireless networks.
We will not be discussing grey-box fuzzers today.

In general, black-box fuzzers tend to have better computational performance, but we tend to be unsure of the coverage, and white-box fuzzers tend to have worse computational performance, but we tend to be more sure of the coverage.

Fuzzers can be divided into Black-box and White-box.

There are also grey-box fuzzers, but for the purposes of our discussion today, we shall focus on black-box and white-box.
For many cases, the more white-box the fuzzer, the better we are able to discern which parts of a software program it visits and how consistent it is in doing so.

Specifically, the more white-box the fuzzer, the more insight we have into the utilized seed schedules (i.e., varying distributions of the fuzzing time spent among the seeds) for coverage.

The significance of this resides in the fact that the fuzzer’s Enhanced Context Module or ECM selects a seed, mutates it, and serves it as input to the test target. If the input causes a crash, it will be added to the ECM’s crash set. Alternatively, if the input segues to new coverage, it will be added to the search seed pool.
This coverage feedback serves as input to the Numerical Stability-Centric Module or NSCM, which processes the information and informs the Adaptive Weighting System, which dynamically weights the Class Families for Mutating Seed and Seed Schedules. This should segue to a more optimal Seed Schedules for decreasing Time-to-Exposure or TTE (i.e., speed at which bugs are found) as well as a more optimal Relative Standard Deviation or RSD (i.e., number of unique bugs found for the fuzzing iterations).
It should be noted that even when the input set is specifically designed/architected to segue to a convex paradigm, the resultant output set may still turn out to be nonconvex, thereby necessitating a transformation to a convex optimization problem via certain relaxation techniques. This transformation in itself may spawn yet other nonconvex optimization problems, thereby highlighting the need/opportunity to utilize a Robust Convex Relaxation (RCR) paradigm.

This seems prudent not only for solving the involved convex optimization problems, but also leveraging the same RCR mechanism for tuning its own hyperparameters.
• Given its advantages in terms of the reduced number of hyperparameters to tune, Particle Swarm Optimization (PSO) is often implemented. However, PSO presents its own technical challenges.
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This approach gives rise to various technical challenges. When implemented on Deep Convolutional Generative Adversarial Networks (DCGANs), PSO requires converting continuous/discontinuous hyperparameters to discrete values (e.g., integers). Yet, rounding the calculated velocities to discrete integer values creates an artificial paradigm, wherein particles may stagnate prematurely. Certain techniques, such as increasing the inertia (thereby allowing particles to advance past their current local optimum) can address this issue.
To reduce the computational cost, the notion of fire modules/layers from SqueezeNet (a deep neural network) was utilized to replace convolution layers (a.k.a. Conv) with Fire Layers (FL), and a SqueezeDet adaptation was incorporated for the replacement of certain Conv with Special Fire Layers (SFL).

The combination of FL/SFL with convex relaxation adversarial training can improve the bound tightening for each successive neural network layer to better facilitate the resolution of the various involved optimization formulations which are, in essence, Mixed Integer Non-Linear Programming (MINLP) problems that need to be optimally solved (e.g., the global optimum).
DCGAN PSO Benefit:
- Facilitates valid bounds for near-optimal convex optimization solutions.

Achieving the DCGAN PSO Benefit, via an RCR Paradigm
- Squeezed Convolutional Layers, Fire Layer (FL) or Special Fire Layer (SFL), with a specific implementation (Modified Squeezed YOLO version 3 Implementation or MSY3I, in this case).
- Convex Relaxation Adversarial Training.
- Facilitated Robust Convex Relaxations (RCR).
MIP PROBLEMS
Non-Linear, Continuous/Discontinuous

Continuous

Discontinuous

Non-Linear

Continuous/
Discontinuous

MIP
MIP PROBLEMS
Non-Linear, Discrete
MIP PROBLEMS
Non-Linear (Continuous/Discontinuous; Discrete)
Mixed Integer Non-Linear Programming (MINLP) Problems

- Continuous/Discontinuous
- Discrete
- Non-Linear

MINLP
MIP PROBLEMS
Linear, Continuous/Discontinuous

Continuous

Discontinuous

MIP

Linear

Continuous/Discontinuous
MIP PROBLEMS
Linear, Discrete
MIP PROBLEMS
Linear (Continuous/Discontinuous & Discrete)
Mixed Integer Linear Programming (MILP) Problems

MIP PROBLEMS

Continuous/Discontinuous

MIP

Linear

Discrete

MILP
Mixed Integer Non-Linear Programming (MINLP) Problems

NONCONVEX PARADIGM

- Mixed Integer Linear Programming (MILP)
- Mixed Integer Programming (MIP)
- Mixed Integer Non-Linear Programming (MINLP)

Linearization

- Non-Linear
- Linear

Continuous/Discontinuous

- Discrete
- MINLP
- MILP
ATTAINING A CONVEX PARADIGM

Pathways to Convex Problems

Convex

Nonconvex

Continuous/
Non-Linear

Discontinuous

Linearization

MINLP

Linear

MILP

Convex

Nonconvex

Convex

Exact

Relaxed

MIP
IV. POSITED APPROACH

• A Series of Robust Convex Relaxations (RCR), via PSO, Represents a Viable Posited Approach.
- Deep Generative Convolutional Adversarial Network (DCGAN) with particular attention paid at each neural network layer.

- Increased transparency at each neural network layer.
**Our Utilized Approach:**

- Convex Surrogates.
- Convex Approximations.
- Convex Relaxations.
- Series of Robust Convex Relaxations (RCR), via PSO.

**The Promise of PSO:**

- Facilitates valid bounds for near-optimal convex optimization solutions.
- Reduced number of hyperparameters to tune, via a specific implementation of PSO.
V. CONCLUDING REMARKS

- The posited RCR architecture, as an Enhanced White-box Architecture for certain fuzzers, demonstrates promise for better Insight into coverage.
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Thank you!

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