Machine Learning Models to Enhance the Science of Cognitive Autonomy

Ganapathy Mani, Bharat Bhargava, Pelin Angin, Miguel Villarreal-Vasquez, Denis Ulybyshev, Jason Kobes*

CS & CERIAS, Purdue University
*Northrop Grumman Corporation
Intelligent Autonomous Systems

• Autonomous Systems should be
  – Able to perform complex tasks without or with limited ongoing connection to humans.
  – Cognitive enough to act without a human’s judgment lapses or execution inadequacies.

• Intelligent Autonomous Systems (IAS) are characterized as highly Cognitive, effective in Knowledge Discovery, Reflexive, and Trusted.

• The focus of this research will be on the smart cyber systems.
Motivation – A Holistic Approach

• Autonomous systems should learn at the network level as well as about their environment and context.

• Autonomous systems should be trained to work with
  – Meta-data, limited data, incomplete data, and unknown (new) data
  – Dynamic, unpredictable, and adversarial environment

• In this presentation, we will present theoretical framework and our implementation details.
Comprehensive IAS Architecture

Adaptive action

reward + context

Data Stream Processor
- Data Sampling
- Dimensionality Reduction
- Data Analytics

Cognitive Computing Engine
Anomaly Detection
Deep neural network

Provenance Data

Blockchain-based Provenance Data Ledger
Implementation of Components of IAS

• **Cognitive Autonomy & Knowledge Discovery:**
  – Monitors and records system’s activities (Data provenance and sequence of system calls)
  – Conducts privacy-preserving aggregated analytics on provenance data.
  – Utilizes Deep learning based anomaly detection by analyzing sequence of system calls.

• **Reflexivity:**
  – Adaptive actions are performed through graceful degradations without disrupting the ongoing critical processes by incremental learning.

• **Trust:**
  – Uses blockchain to store provenance data for trust.
Cognitive Autonomy
A Deep Learning Based Anomaly Detection Solution
Comprehensive Architecture of IAS

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Programs store Return Addresses (control flow) along with data in the stack.

Control-hijacking attacks execute arbitrary code on the target IAS program by hijacking its control flow.

A Deep Learning based anomaly detection technique has been developed to protect IAS programs against these attacks.
• Programs store Return Addresses (control flow) along with data in the stack.
• Control-hijacking attacks execute arbitrary code on the target IAS program by hijacking its control flow.
• A Deep Learning based anomaly detection technique has been developed to protect IAS programs against these attacks.
Research Approach

• An event $e_i$ is defined as a function call (system or library call) in the execution trace of a program.

• Use Deep Learning to answer the binary classification problem of given a sequence of function calls (or system events) $e_1e_2e_3...e_k$ whether or not the sequence should occur?
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Given this sequence at time $t-1$
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![System Events Diagram]
Types of attacks and mitigation

Attacks:

• **Code injection**: Malicious instruction sequences are executed using injected codes in the data portion of the stack. Examples: Buffer overflow and buffer specified injection.

• **Code reuse**: Malicious instruction sequences are executed without injecting external code. Examples: Return-oriented programming and memory disclosure.

Mitigation:

• Control Flow Integrity (CFI) is required.

• Deep Learning is used to guarantee Control Flow Integrity (CFI) as the model detects non-conforming sequences of execution traces in run time.
Deep Learning Based Anomaly Detection

• For a given program, a code coverage is conducted to obtain all the possible execution traces.
• An event $e_i$ is defined as a function call (system or library call) in the execution trace of a program.
• Each possible system event (function calls) is uniquely identified as they will form the vocabulary of system events.
• The Deep Learning model (neural network) is trained with the obtained sequences of events.
• The model is based on Recurrent Neural Networks: Long-Short Term Memory (LSTM) and Gated Recurrent Units (GRU.)
Deep Learning Based Anomaly Detection

- After training, given a sequence of events as input, the neural network produces as output an array of probabilities, one for each of the possible events in the system.
- At any time $t$ each possible event (system call or library call) in the system is assigned a probability estimated with respect to the sequences of events observed until time $t-1$.
- At classification time $t$, the decision is made with respect to a pre-defined threshold of the top-$k$ most likely events.
Deep Learning Based Anomaly Detection

Set of all system events

Neural Network
Deep Learning Based Anomaly Detection

Sequence of system events at time $t-1$

Set of all system events

Neural Network
Deep Learning Based Anomaly Detection

Sequence of system events at time $t-1$

Set of all system events

New event at time $t$

Neural Network
Deep Learning Based Anomaly Detection

Sequence of system events at time $t-1$

New event at time $t$

Set of all system events

Neural Network

Input
Deep Learning Based Anomaly Detection

Sequence of system events at time $t-1$

New event at time $t$

Set of all system events

$[p_1, p_2, p_3, p_4, p_5, p_6, p_7]$ Probabilities of possible events

Neural Network

Input → Output

Deep Learning Based Anomaly Detection

Sequence of system events at time \( t-1 \)

New event at time \( t \)

Set of all system events

Probabilities of possible events

At time \( t \), the new event is classified as **normal** if its probability is in the top-\( k \) probabilities; **anomalous** otherwise.
Deep Learning Based Anomaly Detection

**Input:** Sequence of events in the system  
**Output:** normal or anomalous

- **Step 1:** Define a finite set $E$ of events $e_1, e_2, ..., e_N$ in the system. Events occur in a time-series fashion.

- **Step 2:** At time $t - 1$, given an observed series of events \( \{e_i^1, e_i^2, ..., e_i^{t-1}\} \) (with $i = 1, 2, ...or N$) find the set $K$ of the top $k$ events to occur in time $t$.

- **Step 3:** At time $t$, the sequence \( \{e_i^1, e_i^2, ..., e_i^{t-1}, e_i^t\} \) is non-anomalous if $e_i^t \in K$, otherwise anomalous.

**Algorithm 1:** Anomaly detection algorithm
Other Deep Learning Related Projects

• User and Entity Behavior Analytics (UEBA):
  – Process of obtaining the baseline of user activity and behavior to detect potential intrusions and protect from insider threats.
  – Traffic patterns of users would represent the sequences to learn.

• Network Intrusion Detection Systems (NIDS):
  – The application of the DL approach is straightforward.
  – Network packets would represent the set of events to monitor in the system.
Knowledge Discovery

Solutions Based on Pattern Recognition
Comprehensive Architecture of IAS

Knowledge Discovery

- Data Stream Processor
  - Data Sampling
  - Dimensionality Reduction
  - Data Analytics

Adaptive action

Reward + context

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Reinforcement learning policy

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Preprocessed stream data
Knowledge Discovery in IAS

- Knowledge discovery constitutes data transformation for processing, dimensionality reduction, and feature selection, which leads to pattern recognition and visualization.
Knowledge Discovery By Light-weight ML Algorithms

• Compared to deep learning methodologies, pattern recognition through feature extraction is one of the cost effective methodologies.

• Based on the best feature selection approach, light-weight machine learning algorithms such as Support Vector Machine (SVM), k-means, Random Forests, and K-Nearest Neighbors (KNN) can be very efficient.

• Features can be selected through Filter methods (scoring each feature), Wrapper methods (set of features as a search problem), or embedded methods (learning features on-the-fly).
Knowledge Discovery – Inference Models

• Hidden Markov Models (HMM) can be used to infer the probability of observed sequences, probability of latent variables, and statistical significance.

• Models such as these cannot handle large sequences of data but for limited data, HMMs are better preforming than deep learning methodologies.

• Similarly, Bayesian inference functions as the probability update function as the new data (or context) comes to light.

• In our reflexivity module, we used Bayesian inference model to update the probabilities.
Reflexivity
A Solution Based on Graceful Degradation
Comprehensive Architecture of IAS

Reflexivity

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Sensor Data
Environment

reward + context

Reinforcement learning policy

Provenance Data
Generic Model of Dynamic Adaptation
Given a smart cyber system operating in a distributed computing environment, it should be able to:

1. Replace anomalous/underperforming modules

2. Swiftly adapt to changes in context

3. Achieve continuous availability even under attacks and failures.
Graceful Degradations: Combinatorial Replica Replacement Scheme

• Combinatorial Structure is a subset satisfying certain conditions.

• Each block contains systems and their replicas that are mathematically distributed.

• The systems and their replicas in the distributed blocks are strategically connected to receive updates from primary modules.

• Resources are mathematically balanced, enabling scalable designs for the systems.
(7, 7, 3, 3, 1)-configuration

- 7 systems \{S_1, S_2, S_3, S_4, S_5, S_6, S_7\}
- 7 Distributed Autonomous Blocks (DABs) each with 3-system subset

\[
\begin{align*}
DAB_1 &= \{S_1, S_5, S_7\}, \\
DAB_2 &= \{S_1, S_2, S_6\}, \\
DAB_3 &= \{S_2, S_3, S_7\}, \\
DAB_4 &= \{S_1, S_3, S_4\}, \\
DAB_5 &= \{S_2, S_4, S_5\}, \\
DAB_6 &= \{S_3, S_5, S_6\}, \\
DAB_7 &= \{S_4, S_6, S_7\}.
\end{align*}
\]
(7, 7, 3, 3, 1)-configuration

- 7 systems \{S_1, S_2, S_3, S_4, S_5, S_6, S_7\}
- 7 Distributed Autonomous Blocks (DABs) each with 3-system subset
- Each system appears in 3 DABs (Say, S_6)

\[
DAB_1 = \{S_1, S_5, S_7\}, \quad DAB_2 = \{S_1, S_2, S_6\}, \\
DAB_3 = \{S_2, S_3, S_7\}, \quad DAB_4 = \{S_1, S_3, S_4\}, \\
DAB_5 = \{S_2, S_4, S_5\}, \quad DAB_6 = \{S_3, S_5, S_6\}, \\
DAB_7 = \{S_4, S_6, S_7\}.
\]
(7, 7, 3, 3, 1)-configuration

- 7 systems \{S_1, S_2, S_3, S_4, S_5, S_6, S_7\}
- 7 Distributed Autonomous Blocks (DABs) each with 3-system subset
- Each system appears in 3 DABs
- Each pair of systems appear in 1 DAB (Say, S_1 and S_5)

\[
\begin{align*}
DAB_1 &= \{S_1, S_5, S_7\}, \quad DAB_2 = \{S_1, S_2, S_6\}, \\
DAB_3 &= \{S_2, S_3, S_7\}, \quad DAB_4 = \{S_1, S_3, S_4\}, \\
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DAB_7 &= \{S_4, S_6, S_7\}.
\end{align*}
\]
(7, 7, 3, 3, 1)-configuration

- 7 systems \{S_1, S_2, S_3, S_4, S_5, S_6, S_7\} \(M\)
- 7 Distributed Autonomous Blocks (DABs) \(A\)
- each with 3-system subset \(C\)
- Each system appears in 3 DABs \(R\)
- Each pair of systems appear in 1 DAB \(O\)

The configuration \((M, A, C, R, O) = (7, 7, 3, 3, 1)\)
(7, 7, 3, 3, 1)-configuration
DAB: Distributed Autonomous Block
(7, 7, 3, 3, 1)-configuration

- Each primary module periodically updates its replicas in corresponding distributed block connected by communication links (CC).

- Update the interval dynamically through learning models with Bayesian learning by continuously updating the prior.
(7, 7, 3, 3, 1)-configuration

- Update time is defined as

\[ P(I | \text{importance (I)} \mid \text{operational context (C)}) = \frac{P(C|I)P(I)}{P(C)} \]

\[ \text{Update interval } T = | t^1_{P(I)} - t^2_{P(I)} | \]

- Operational Context can be set dynamically and importance is a binary classifier (important / not important)

- When any system in any primary module’s DAB acts in anomalous fashion, that system can be
  - Replaced with one of the replicas that can be selected in round robin fashion.
  - Anomalous module will be set for self-healing or repair by external source
(7, 7, 3, 3, 1)-configuration

- The prototype is built with FAYE framework\(^1\) with Node.js.

- It is a server-client framework where servers act as primary modules and clients as replicated system.

- Replica updates are done through a combinatorial design simulator\(^2\).

- Combinatorial simulator is loaded with finite processes to compare the updates and processing time compared to a regular or sequential processing.

\(^1\)https://faye.jcoglan.com/node.html \(^2\)https://goo.gl/pgVHdk
# Measurements for Various Process Completions

<table>
<thead>
<tr>
<th>Process Type</th>
<th>Process Name</th>
<th>Speed Up Due to Combinatorial Replica Scheme (Compared to regular sequential design)</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>FIBSEARCH</td>
<td>1.3</td>
</tr>
<tr>
<td>P2</td>
<td>DOUBLE MULT</td>
<td>1.4</td>
</tr>
<tr>
<td>P3</td>
<td>FIBB</td>
<td>1.5</td>
</tr>
<tr>
<td>P4</td>
<td>SEARCH</td>
<td>1.8</td>
</tr>
<tr>
<td>P5</td>
<td>COPY</td>
<td>1.8</td>
</tr>
<tr>
<td>P6</td>
<td>SCALAR</td>
<td>2</td>
</tr>
<tr>
<td>P7</td>
<td>SUM</td>
<td>2.1</td>
</tr>
<tr>
<td>P8</td>
<td>PRINT</td>
<td>3</td>
</tr>
<tr>
<td>P9</td>
<td>MOVEMENT</td>
<td>3.1</td>
</tr>
</tbody>
</table>
Measurements for Various Process Completions

Number of state migrations

- Combinatorial Design
- Sequential Design

Process Types

P1  P2  P3  P4  P5  P6  P7  P8  P9
Trust
A Solution Based on Blockchain
Comprehensive Architecture of IAS

Trust

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reward + context
Problem Statement

• Provide trust (integrity, confidentiality, verifiability) to provenance data in IAS
  – Interactions between services are logged
  – Log records can not be corrupted

• Provide trust for network participants in IAS
  – Ensure data confidentiality
  – Ensure data integrity

• Provide privacy-preserving data exchange in IAS
Blockchain Technology Deployment

- Fine-grained role-based and attribute-based access control with data leakage detection capabilities is provided by integration with ‘WAXEDPRUNE’

- Performance improvements:
  - Depth-robust graphs to store blockchain for faster transaction verification: no need to verify all the links in the chain
Blockhub: blockchain-platform for IAS
Future Work

- Develop cyber attribution techniques with machine learning to enhance the forensics and malware detection.

- Optimize the reflexivity property’s replacement policy with distributed voting and Hidden Markov Model to determine update interval.

- Failure recovery for blockchain framework with mobile environments.
References:


Thank you!!!