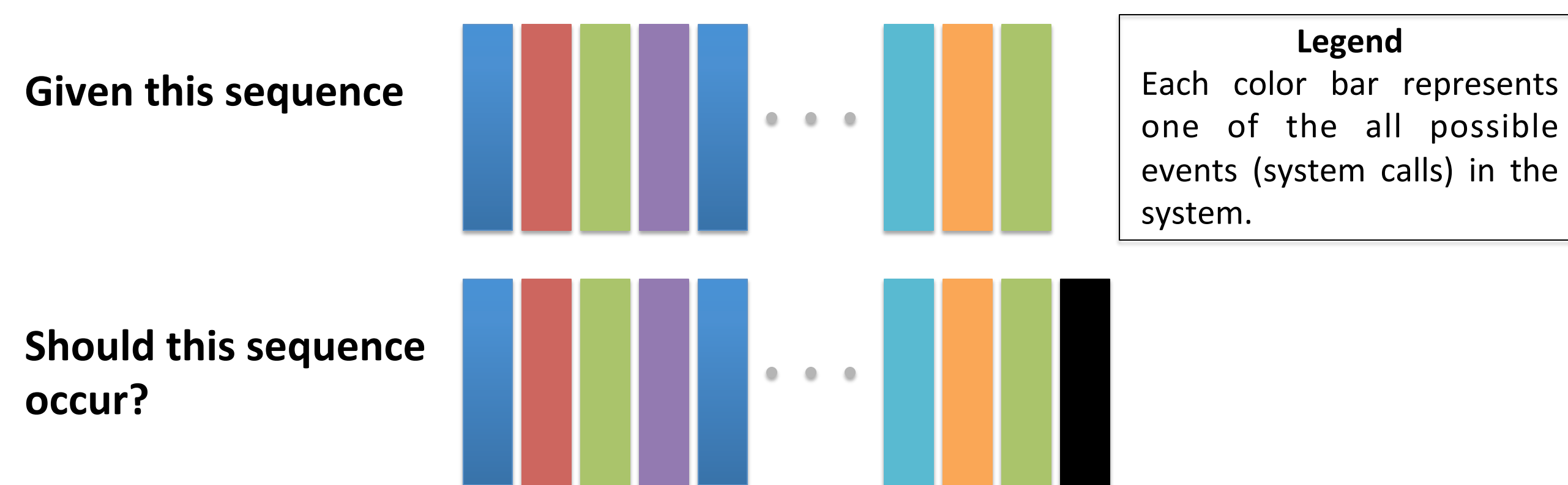


A Deep Learning Based Anomaly Detection Approach for Intelligent Autonomous Systems

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MOTIVATION



- ❑ Advanced modern exploits characterize by their sophistication in stealthy attacks.
- ❑ **Code-reuse attacks** such as return-oriented programming and memory disclosure attacks allow attackers executing malicious instruction sequences on victim systems without injecting external code.
- ❑ This research proposes a new Deep Learning based anomaly detection technique that probabilistically models program control flows for behavioral reasoning and live monitoring.
- ❑ We aim to answer **the binary classification problem** of given a sequence of events $e_1e_2e_3...e_k$ **whether or not the sequence should occur?**
- ❑ An event e_i in the sequence is a function call in a given trace.

ANOMALY DETECTION ALGORITHM

- ❑ We defined an event as a function call. Each possible function call must be identified as they will form the vocabulary of events.
- ❑ The dynamic code behaviors can be learned by training the model with non-malicious program traces.
- ❑ At any time t each possible event (system call or library call) in the system is assigned a probability estimated with respect to the sequence of events observed until time $t-1$.
- ❑ At classification, the decision is made with respect to a pre-defined threshold of the K -top most probably sequences.

Input: Sequence of events in the system

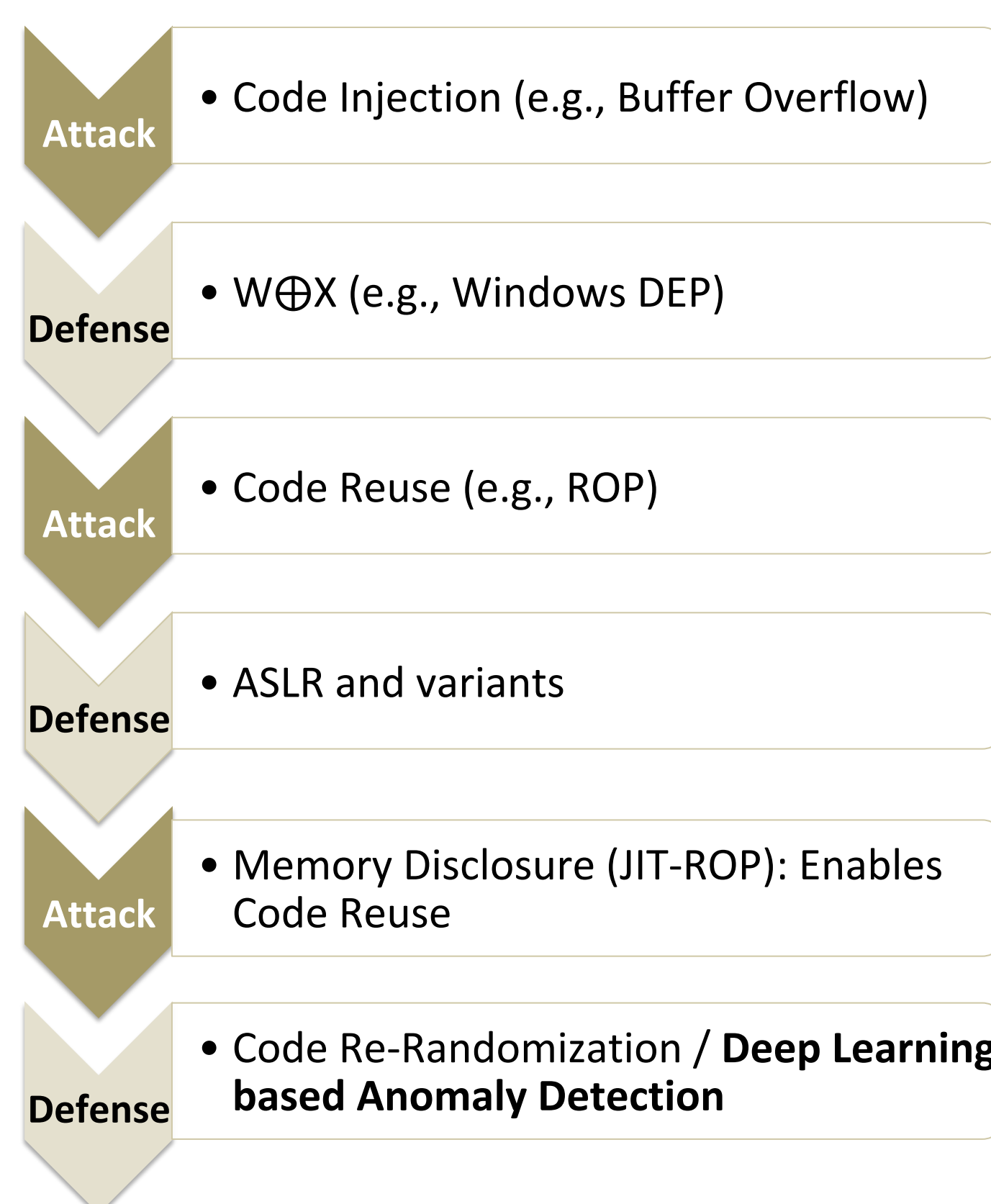
Output: normal or anomalous

- **Step 1:** Define a finite set E of events e_1, e_2, \dots, e_N in the system. Events occur in a time-series fashion.
- **Step 2:** At time $t-1$, given an observed series of events $\{e_i^1, e_i^2, \dots, e_i^{t-1}\}$ (with $i = 1, 2, \dots, N$) find the set K of the top k events to occur in time t .
- **Step 3:** At time t , the sequence $\{e_i^1, e_i^2, \dots, e_i^{t-1}, e_i^t\}$ is non-anomalous if $e_i^t \in K$, otherwise anomalous.

Algorithm 1: Anomaly detection algorithm

THREAT MODEL

The Eternal War



- ❑ **Invalid and abnormal control flow of a program:**
 - ✓ Code Injection
 - ✓ Code Reuse
 - ✓ Memory Disclosure
- ❑ **Can be caused by:**
 - ✓ Human error (e.g., unauthorized use or operation of the program)
 - ✓ Software flaws (e.g., buffer overflow vulnerabilities)
 - ✓ Attacks by remote attackers
 - ✓ Malicious insiders (e.g., through drive-by downloads)

IMPLEMENTATION

MODEL

```
1 # coding: utf-8
2 """
3 Deep Learning Based Anomaly Detection Model
4 """
5 # Imports
6 from __future__ import print_function
7 import torch
8 from torch.autograd import Variable
```



CUDA

GPU

- ❑ **Model**
 - ✓ Based on Recurrent Neural Networks (RNN): Long-Short Term Memory (LSTM) and Gated Recurrent Unit (GRU)
- ❑ **Programming Language: Python**
 - ✓ Compatible with several numerical computing libraries suitable for the use of GPUs
 - ✓ Some examples: Pytorch, TensorFlow and Theano
- ❑ **Computing Library: PyTorch**
 - ✓ Scientific computing package
 - ✓ Replacement of Numpy to take advantage of the power of GPUs
 - ✓ Python-friendly platform for neural networks (Deep Learning)
- ❑ **Parallel Computing Platform: CUDA**
 - ✓ Programming model to use GPUs for general purpose computing

CONTRIBUTIONS

- ❑ Systems can be trained with data of benign flows only in isolation (the data is full available.)
- ❑ Flow sensitive anomaly detection. Given the execution paths P_1 , P_2 and P_3 our technique captures their occurrence probabilities, vital for high-precision anomaly detection.

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Acknowledgement: This research is supported by NGC Research Consortium. We collaborated with Paul Conoval, Donald Steiner and Jason Kobes.