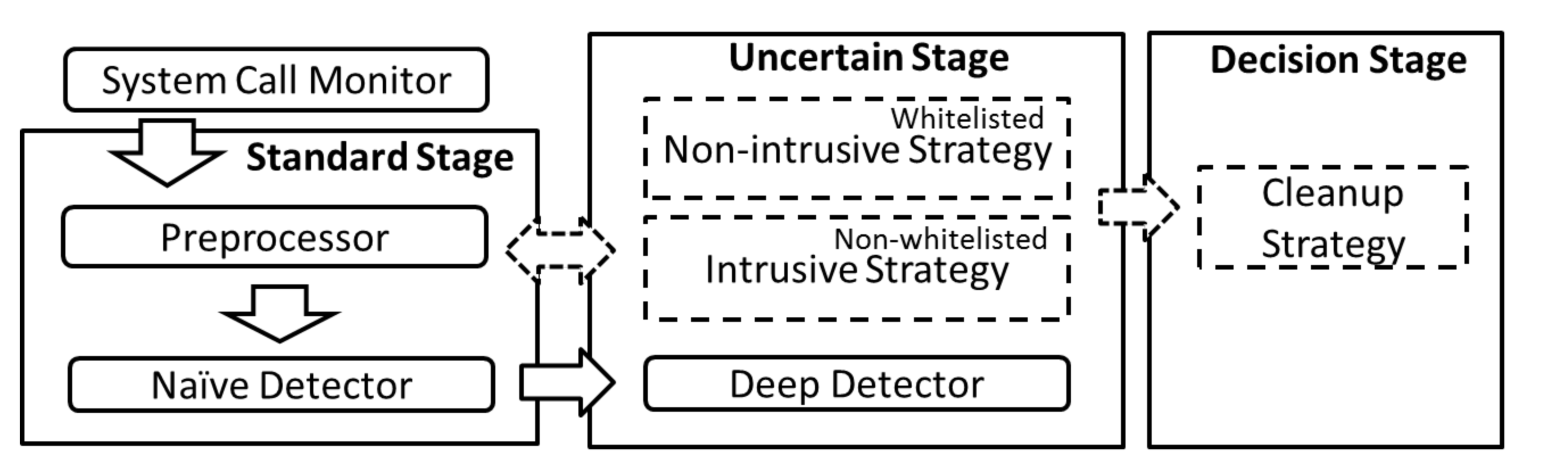
DeepMalware: Deep Models and Mechanisms for Malware Detection and Defense

PIs: Xiaolin Li, Daniela Olivera, Andre Gregio
Students: Xiaoyong Yuan*, Ruimin Sun*, Qile Zhu, Aokun Chen
University of Florida, Federal University of Parana
* equal contribution

Background

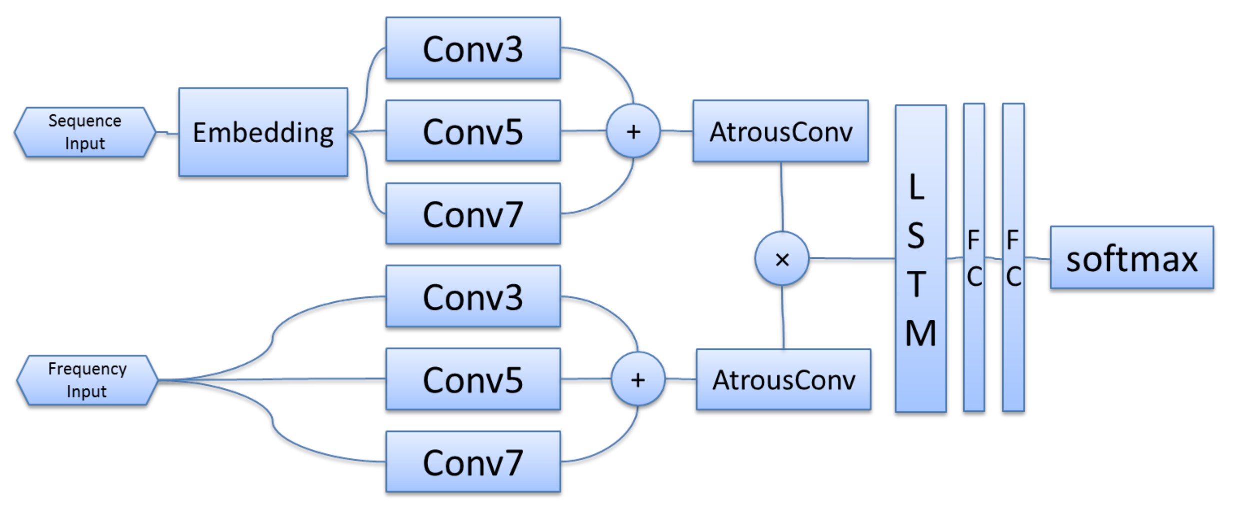
- **Conventional Malware Detection**
  - **Signature-based**
    - efficient/accurate for known attacks
    - evaded by poly/metamorphism
  - **Behavior-based**
    - address zero-day attacks
    - based on syscall sequences
- **Drawbacks** in conventional behavior detection:
  - false positives
  - cannot handle APTs
  - limited datasets for training

DeepMalware Approach

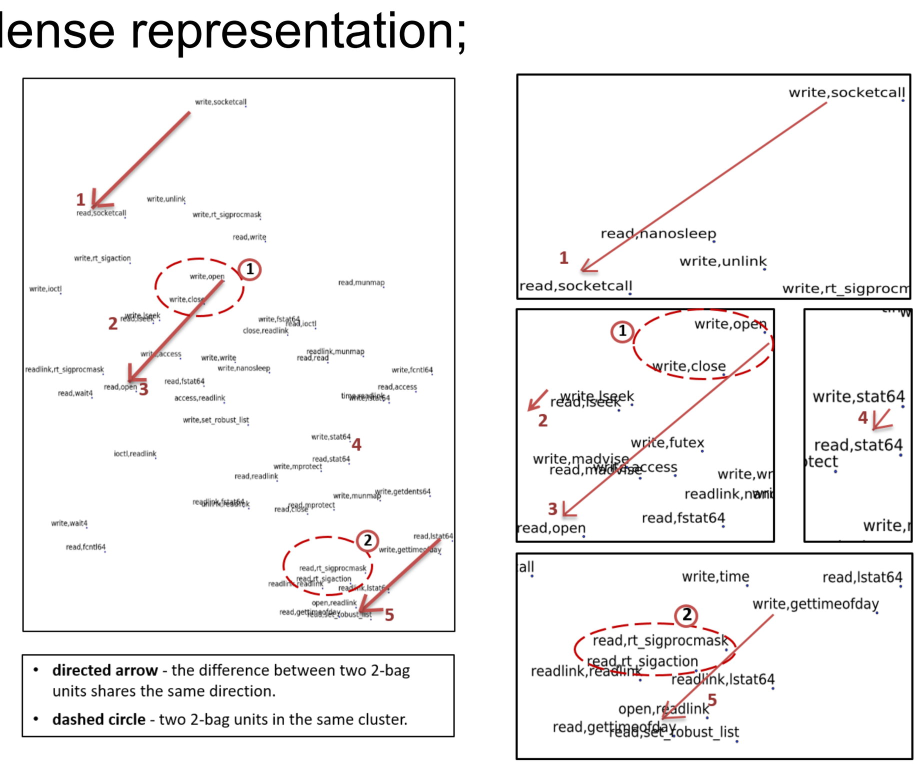


Two-stream Deep Detection Models

- ***Two*** key modules: ***filter-reconstruction module*** and ***deep learning module***.



- ***Filter-reconstruction module:***
  1) system-call filter
  2) n-gram model reconstruction
     - n-gram, n-bag, n-tuple
- ***Deep learning module***:
  1) n-gram word embedding to convert n-gram indices into dense representation;



The distribution of "read" and "write" related 2-tuple of system calls in the Embedding layer. Embedding layer extracts the high-level features in the deep learning model. Difference between "read" and "write" related bags shares the similar direction.

  2) multi-scale spatial models with inception multi-scale CNN to extract local and global information
     - Atrous-convolution layers to broaden the receptive span;
     - two streams of sequence inputs and frequency inputs;
  3) temporal models with LSTM layers to extract temporal features between system calls.

Motivation

- **DeepMalware**
  - **two-stream deep detection** models and multi-stage on-the-fly reaction
  - **Naïve Detector**
    - fast but inaccurate
  - **Deep Detector**
    - accurate but needs to observe long syscall sequences and takes large computation time
- **Preliminary Results for Linux malware**

	Accuracy	Time
Naïve Detector	84.48%	0.010s
Deep Detector	94.36%	0.292s

Multi-stage On-the-fly Reaction

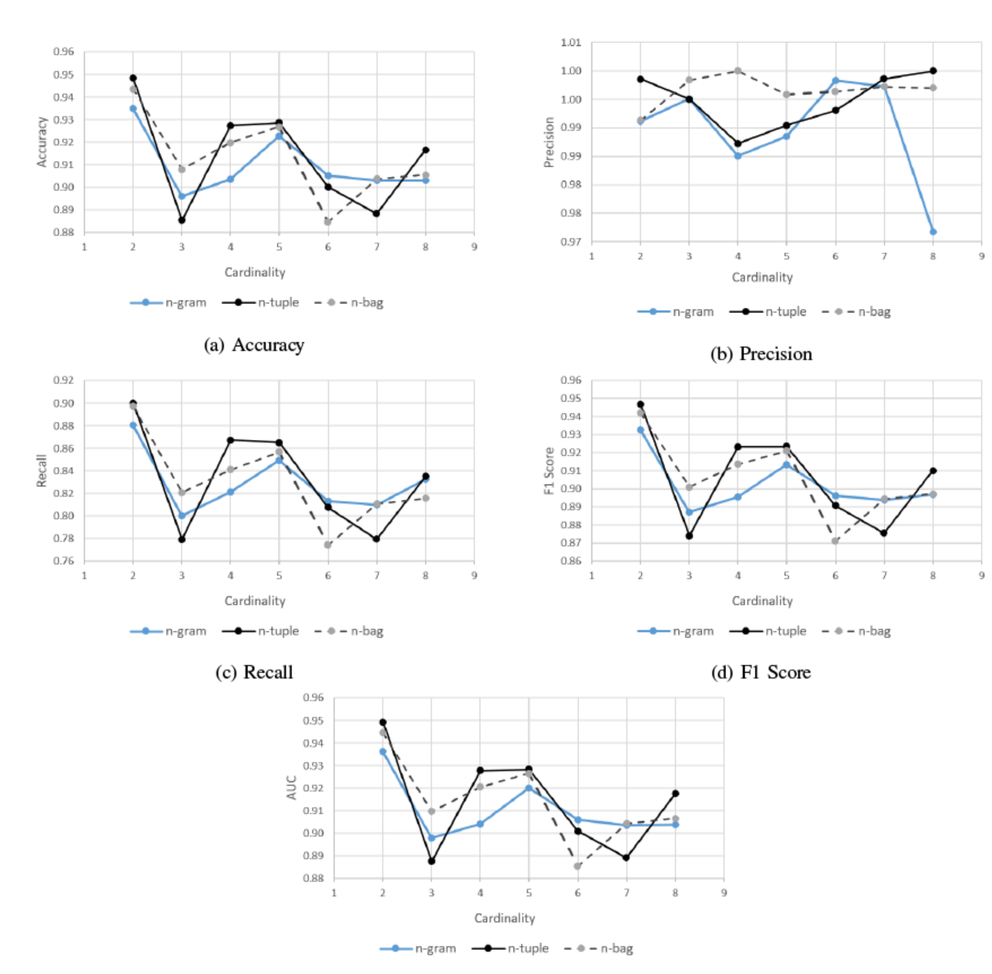
- ***Standard stage*** *(Naïve Detector)*
  - If borderline classification, software will be transferred to uncertain stage.
- ***Uncertain stage*** *(Deep Detector)*
  - Adds obstacles to process execution
  - Whitelisted software: non-intrusive strategies
  - Non-Whitelisted software: intrusive and non-intrusive strategies
- ***Uncertain stage***
  - Buys time for deep learning detection while containing actions of stealthy malware.
  - If software is found benign, transferred to *Standard Stage*.
  - If malicious, transferred to *Decision stage*.
- ***Decision stage***
  - Kill malware, clean-file system

Experiments and Datasets

- **Linux dataset** Ubuntu 14.04
  - 100 malwares from Virustotal
  - 400 benign applications
  - 120,000 samples
- **Windows dataset** Windows 7
  - 30,000 malwares collected from 2013 to 2015
  - 30,000 benign applications
  - 100,000 samples

Preliminary Results

- Deep learning model with the 2-tuple input performed best and achieved a 94.83% accuracy and a 94.66% F1 score in Linux dataset.



Deliverables and Milestones

- Q1: Linux malware detection (Done)
- Q2: Cross-platform (Linux, Windows, Android) malware detection
- Q3: Process based malware detection

References

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