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Online Malware Detection in Cloud Auto-Scaling Systems Using Shallow Convolutional Neural Networks

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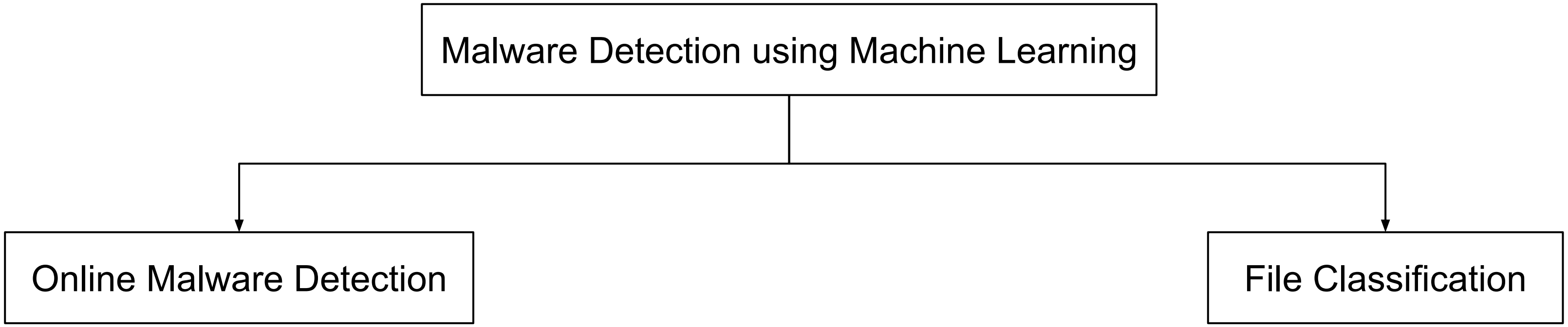
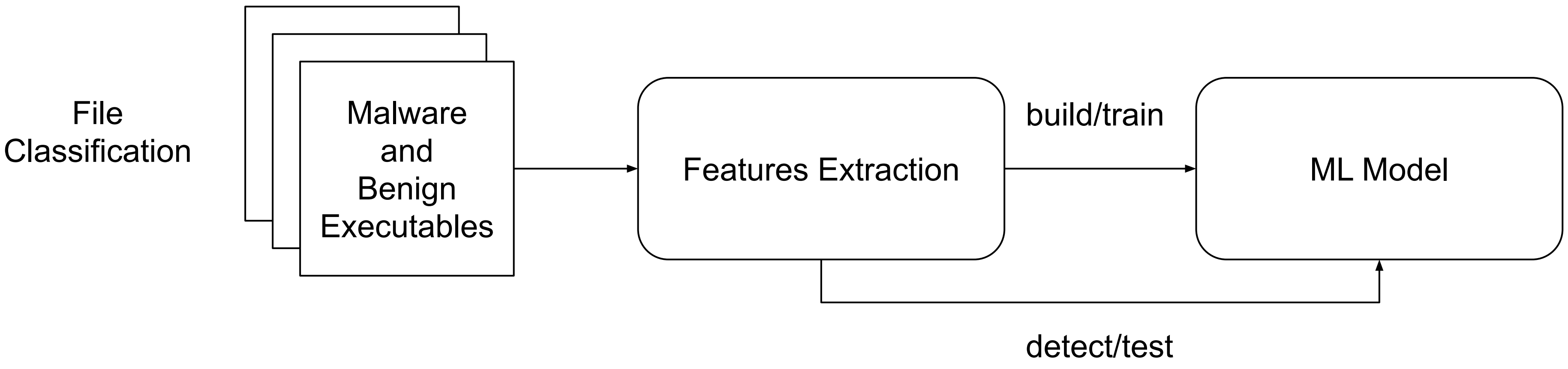
Introduction and Motivation

Malware Detection Classification

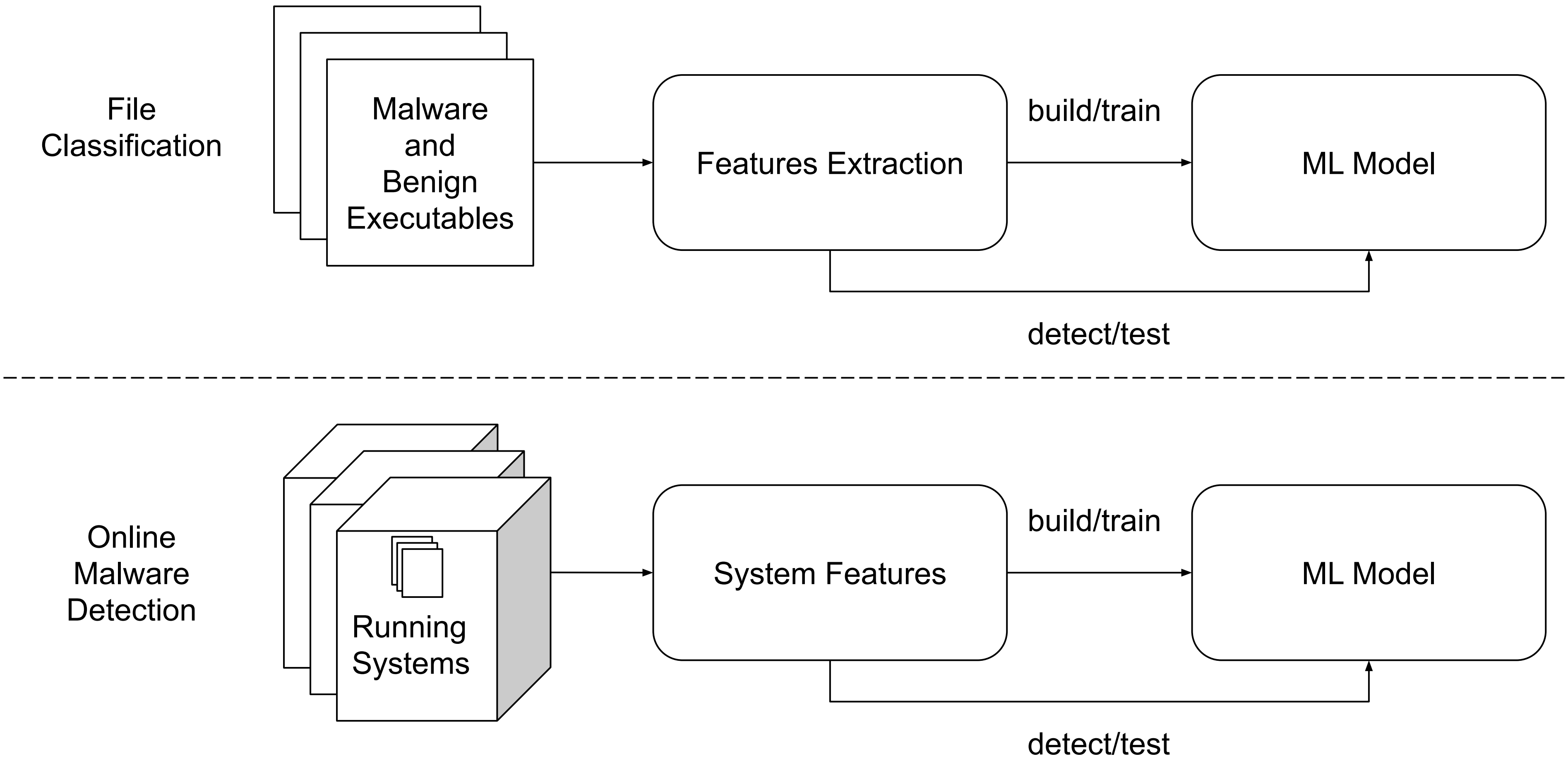


1. File classification:
    - Given a file/executable, classify if it’s a malware or not by running it and observing its behavior.
    - You have a file as a suspect.
    - You don’t keep monitoring them once they are clean.
2. Online malware detection:
    - Assume that the malware got into the system and is executing.
    - You keep monitoring the system’s behavior for malware detection.
    - You don’t just focus on a given file, but the entire system (processes).

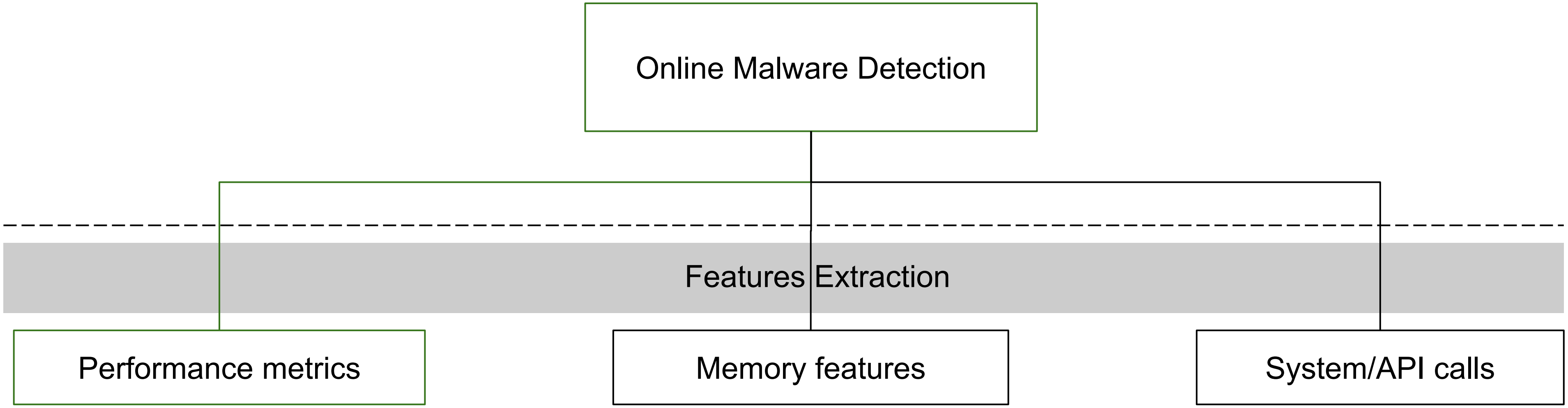
Malware Detection using ML



Malware Detection using ML



Motivation



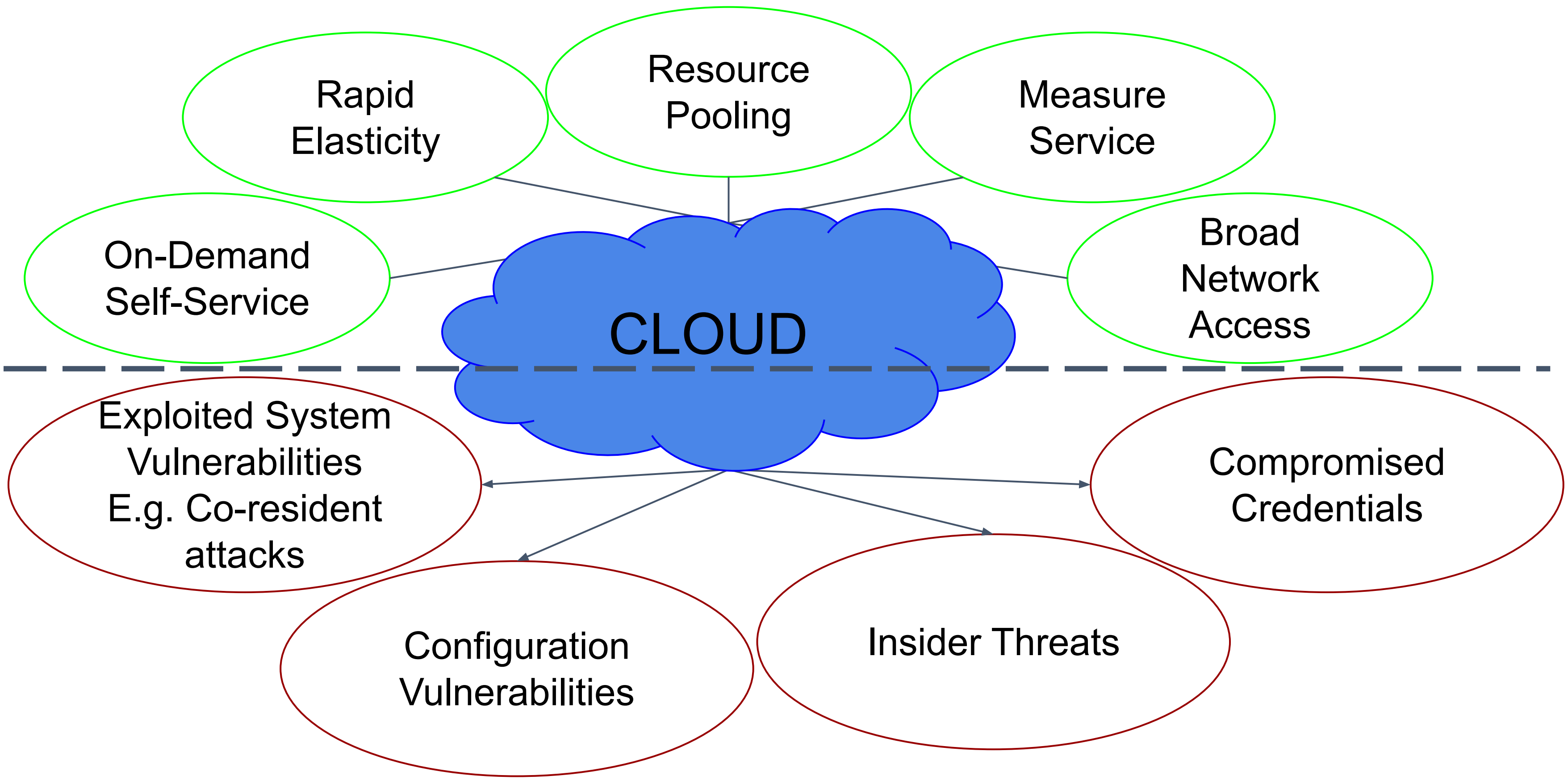
What makes an approach cloud-specific?

Most, if not all, **cloud-specific** research:

✓ Restrict the selection of features to those that can only be fetched through the hypervisor.

✘ Leverage cloud characteristics for online malware detection.

Motivation (cont.)



Can we leverage cloud characteristics for online malware detection? **"Auto-Scaling"**

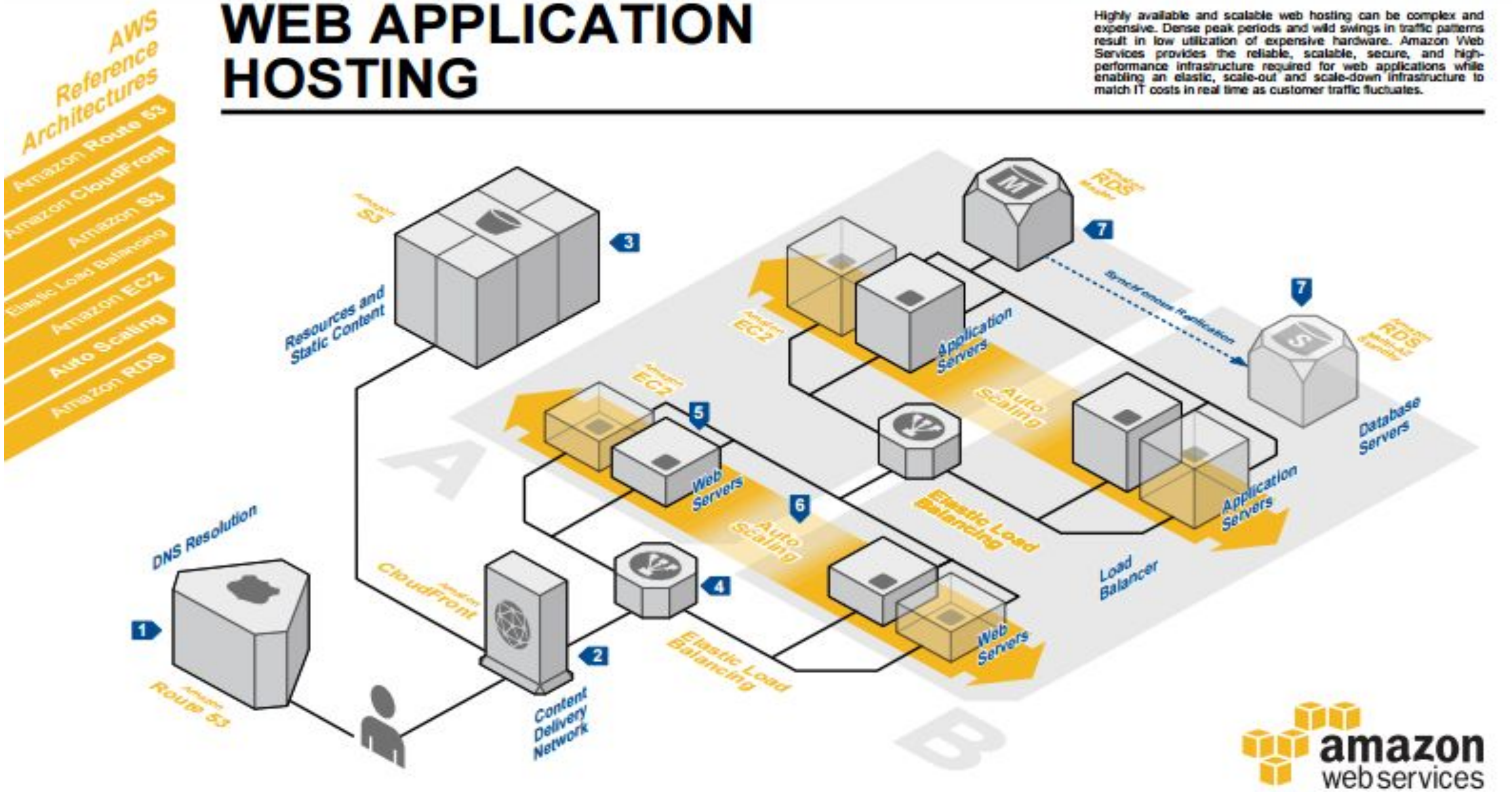
Goal: Leverage auto-scaling for online malware detection by:

- Using 2d CNN to learn processes behavior of multiple VMs.
- Introducing a novel approach of pairing samples to accommodate for correlations between VMs.

3-tier example

WEB APPLICATION HOSTING

Highly available and scalable web hosting can be complex and expensive. Dense peak periods and wild swings in traffic patterns result in low utilization of expensive hardware. Amazon Web Services provides the reliable, scalable, secure, and high-performance infrastructure required for web applications while enabling an elastic, scale-out and scale-down infrastructure to match IT costs in real time as customer traffic fluctuates.



System Overview

1 The user's DNS requests are served by **Amazon Route 53**, a highly available Domain Name System (DNS) service. Network traffic is routed to infrastructure running in Amazon Web Services.

2 Static, streaming, and dynamic content is delivered by **Amazon CloudFront**, a global network of edge locations. Requests are automatically routed to the nearest edge location, so content is delivered with the best possible performance.

3 Resources and static content used by the web application are stored on **Amazon Simple Storage Service (S3)**, a highly durable storage infrastructure designed for mission-critical and primary data storage.

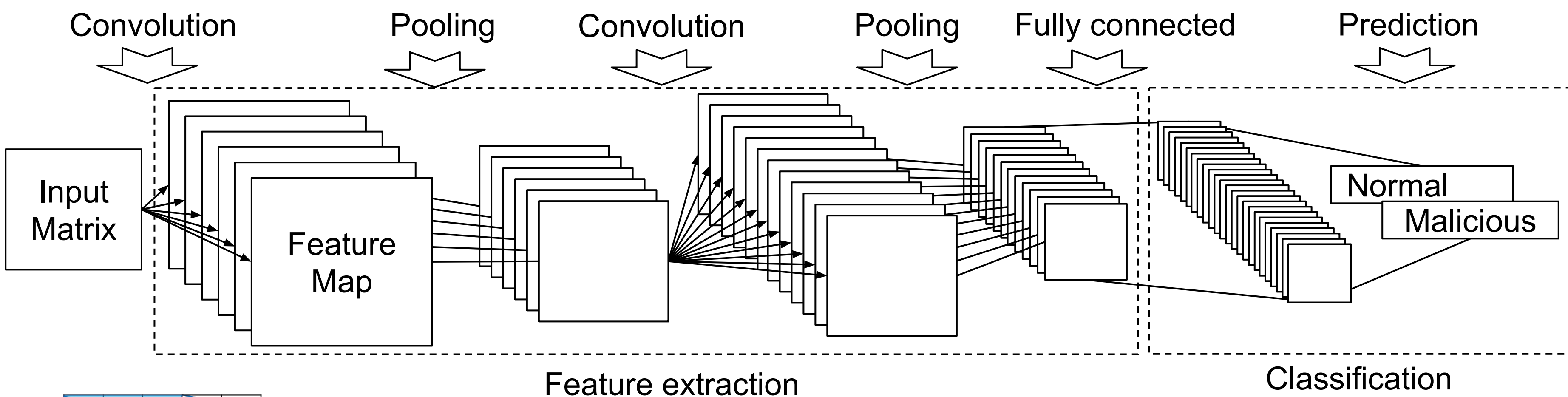
4 HTTP requests are first handled by **Elastic Load Balancing**, which automatically distributes incoming application traffic among multiple **Amazon Elastic Compute Cloud (EC2)** instances across Availability Zones (AZs). It enables even greater fault tolerance in your applications, seamlessly providing the amount of load balancing capacity needed in response to incoming application traffic.

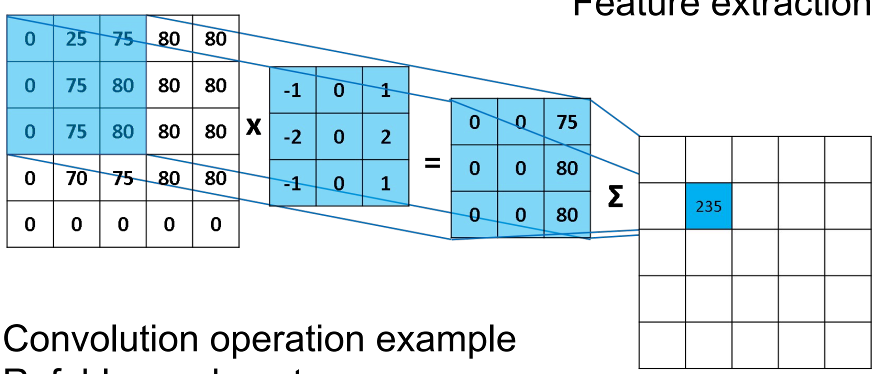
5 Web servers and application servers are deployed on Amazon EC2 instances. Most organizations will select an **Amazon Machine Image (AMI)** and then customize it to their needs. This custom AMI will then become the starting point for future web development.

6 Web servers and application servers are deployed in an **Auto Scaling** group. Auto Scaling automatically adjusts your capacity up or down according to conditions you define. With Auto Scaling, you can ensure that the number of **Amazon EC2** instances you're using increases seamlessly during demand spikes to maintain performance and decreases automatically during demand to minimize costs.

7 To provide high availability, the relational database that contains application's data is hosted redundantly on a multi-AZ (multiple Availability Zones–zones A and B here) deployment of **Amazon Relational Database Service** (Amazon RDS).

CNN Overview





Convolution operation example
Ref: blog.csdn.net

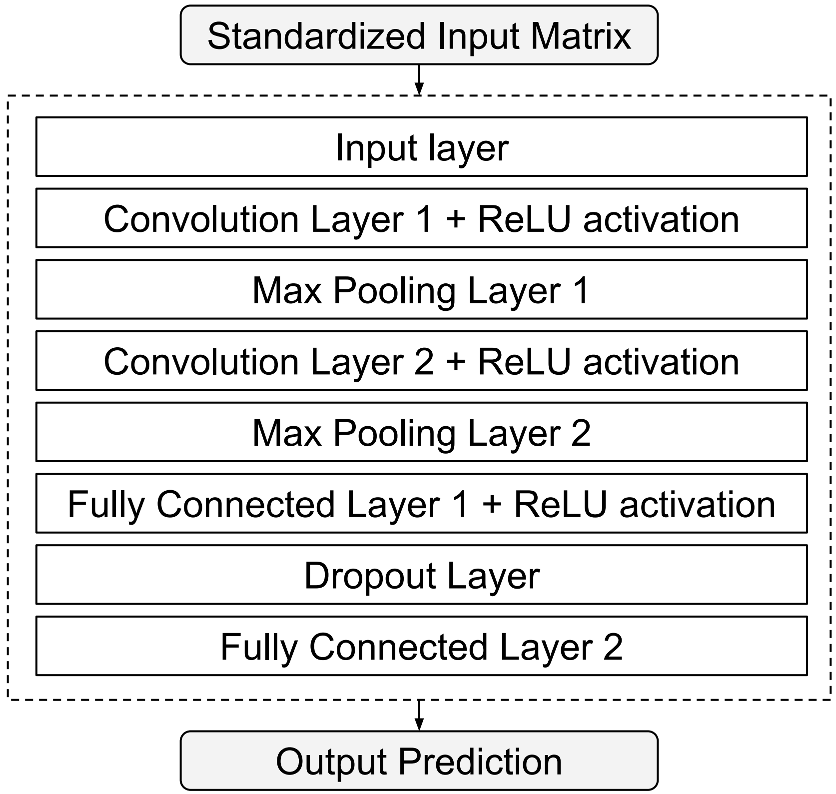
Methodology

Process-level Performance Metrics

➢ We use performance metrics as a way of defining a process behavior.
➢ 28 process-level performance metrics.
➢ These metrics can easily be fetched through the hypervisor.

Metric Category	**Description**
Status	Process status
CPU information	CPU usage percent, CPU times in user space, CPU times in system/kernel space, CPU times of children processes in user space, CPU times of children processes in system space.
Context switches	Number of context switches voluntary, Number of context switches involuntary
IO counters	Number of read requests, Number of write requests, Number of read bytes, Number of written bytes, Number of read chars, Number of written chars
Memory information	Amount of memory swapped out to disk, Proportional set size (PSS), Resident set size (RSS), Unique set size (USS), Virtual memory size (VMS), Number of dirty pages, Amount of physical memory, text resident set (TRS), Memory used by shared libraries, memory that with other processes
Threads	Number of used threads
File descriptors	Number of opened file descriptors
Network information	Number of received bytes, Number of sent bytes

Shallow CNN Model



CNN Input

We represent each sample as an image (2d matrix) which will be the input to the CNN.

Consider a sample x_t at a particular time t, that records n features (performance metrics) per process for m processes in a VM:

$$\mathbf{X}_t = \begin{array}{cc} & \begin{array}{cccc} f_1 & f_2 & \dots & f_n \end{array} \\ \begin{array}{c} p_1 \\ \vdots \\ p_m \end{array} & \begin{bmatrix} \vdots & \vdots & \dots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \dots & \vdots \end{bmatrix} \end{array}$$

CNN Input (cont.)

- CNN requires the same process to remain in the same row in each sample.
- The CNN in computer vision takes fixed-size images as inputs, so the number of features and processes must be predetermined.

Use the **max** process identification number (PID) which is set by the OS?

- The limit (max number of PIDs) is defined in /proc/sys/kernel/pid_max which is usually 32k.
- Huge input matrix!
- Change the max PID number defined?
  - Kernel confusion if wrap around happened too often.

- there is no guarantee that, for instance, a process with a PID 1000 at a particular time is going to be the same process at a later time.

Unique process

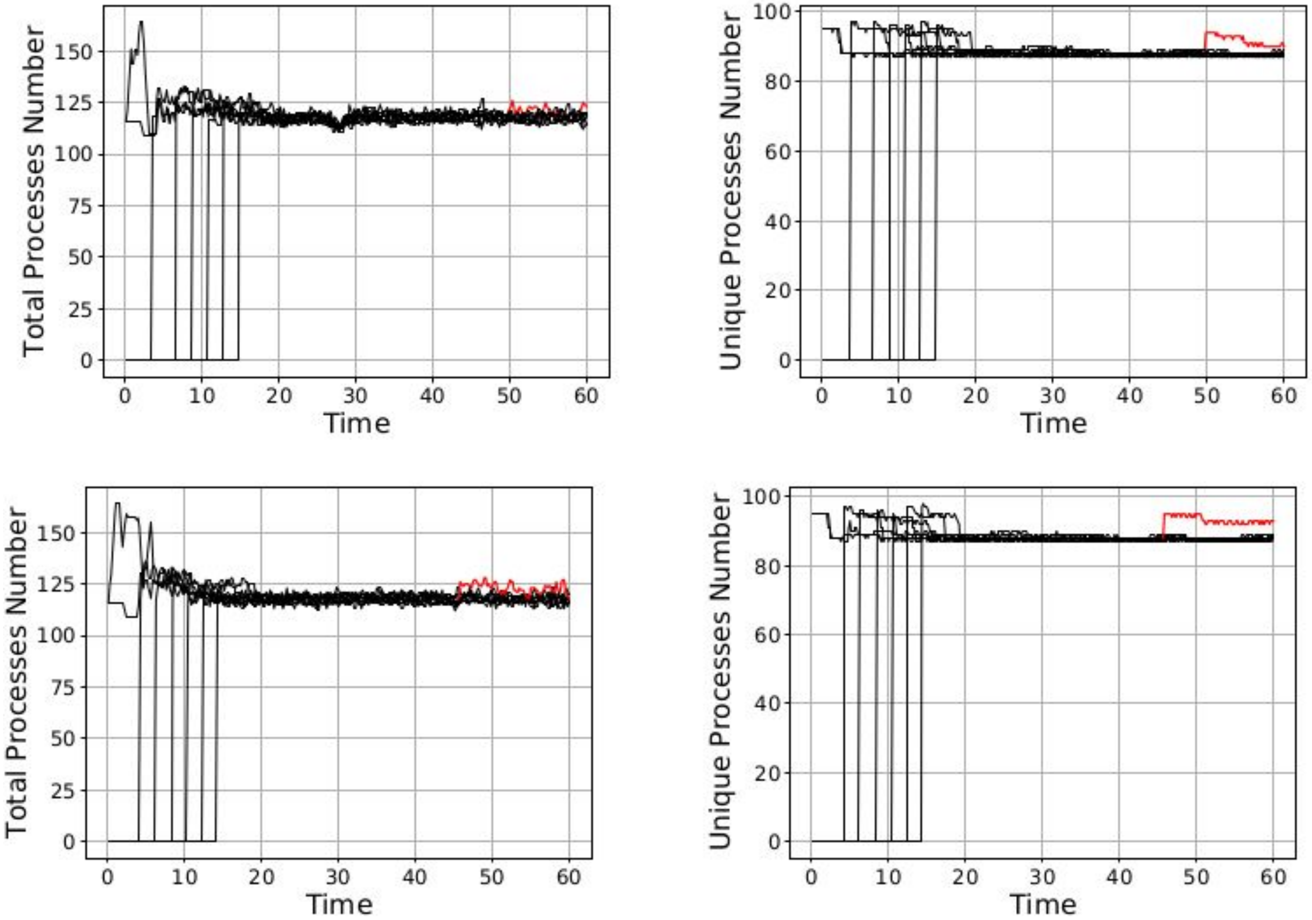
- We define a process, referred to as unique process, by a 3-tuple:
  - process name
  - command line used to run process
  - hash of the process binary file (if applicable)
- We set the maximum number of unique processes to 120 to accommodate for newly created unique processes.

pid	name	cmd	hash	kb_sent	cpu_user	sample_time
1241	php-fpm7.0	php-fpm: pool www	7eb8522425...	33.61710	0.03000	2018-06-15 11:19:04
1240	php-fpm7.0	php-fpm: pool www	7eb8522425...	38.79308	0.00000	2018-06-15 11:19:04
1221	php-fpm7.0	php-fpm: master process (/etc/php/7.0/...	7eb8522425...	0.00000	0.02000	2018-06-15 11:19:04
1287	python	python	23eeeb4347…	0.00000	0.15000	2018-06-15 11:19:04

Unique Process

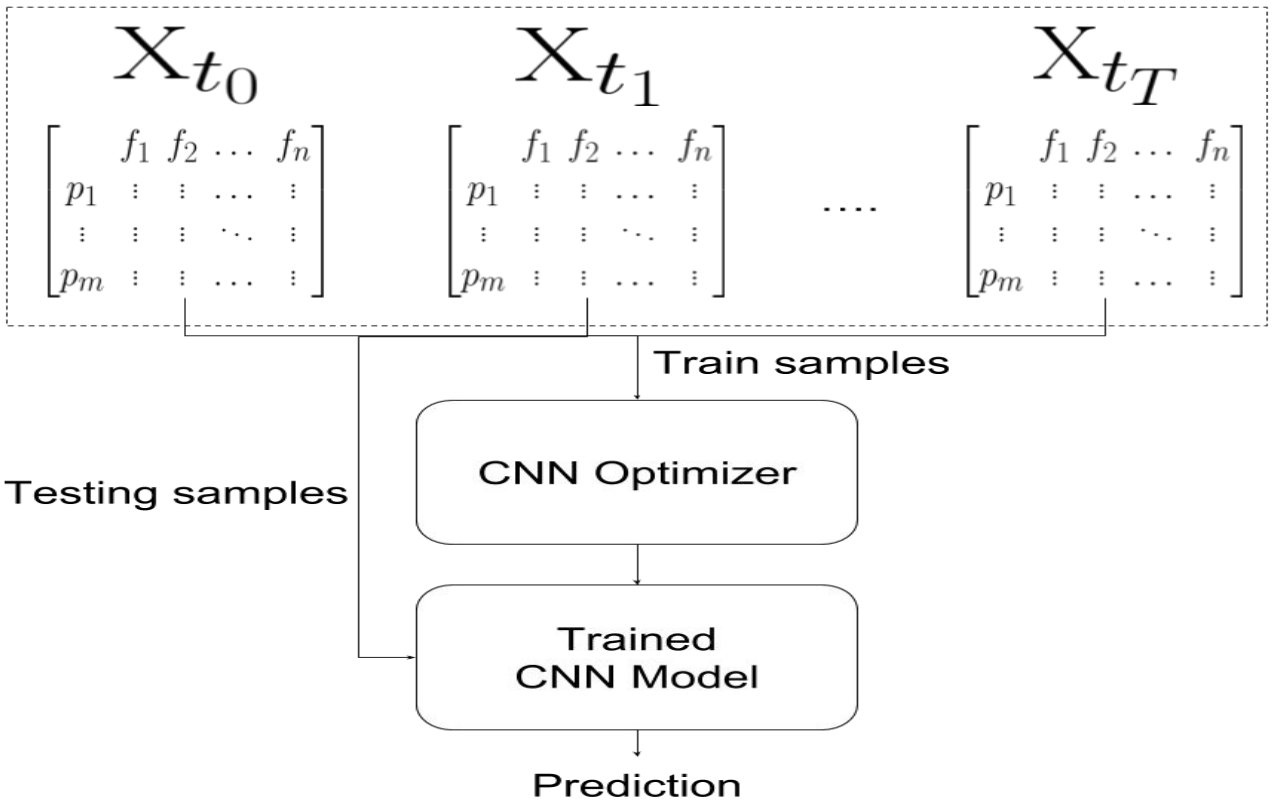
name	**cmd**	**hash**	AVG(kb_sent)	AVG(cpu_user)	sample_time
php-fpm7.0	php-fpm: pool www	7eb8522425...	36.2051	0.0150	2018-06-15 11:19:04
php-fpm7.0	php-fpm: master process (/etc/php/7.0/...	7eb8522425...	0.00000	0.0200	2018-06-15 11:19:04
python	python	23eeeb4347…	0.00000	0.1500	2018-06-15 11:19:04

Unique process (cont.)

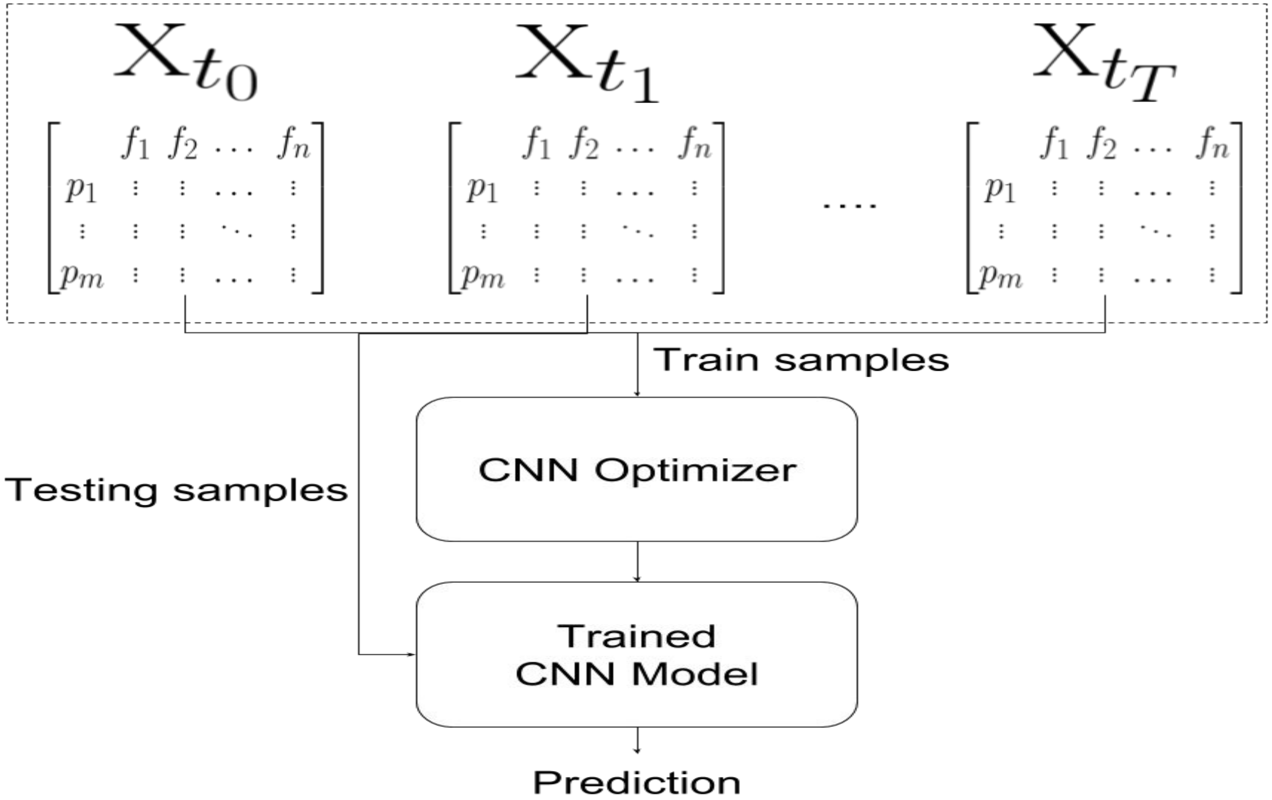


Two different experiments (each with a different malware) where the number of total standard processes are compared to the number of unique processes.

Single VMs Single Samples (SVSS)

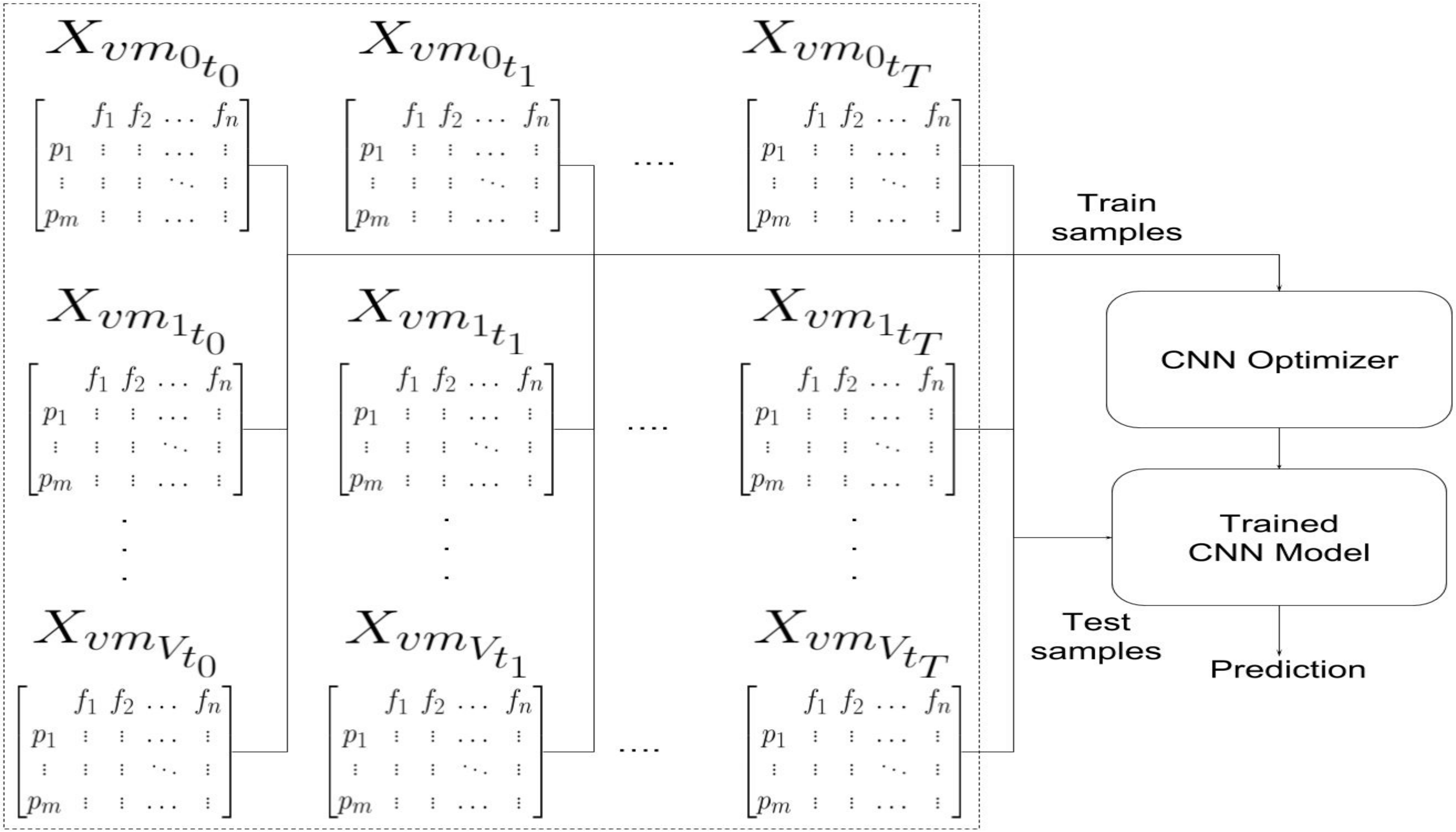


Single VMs Single Samples (SVSS)



Disadvantage: Losing information if a VM has some effects on other VMs.

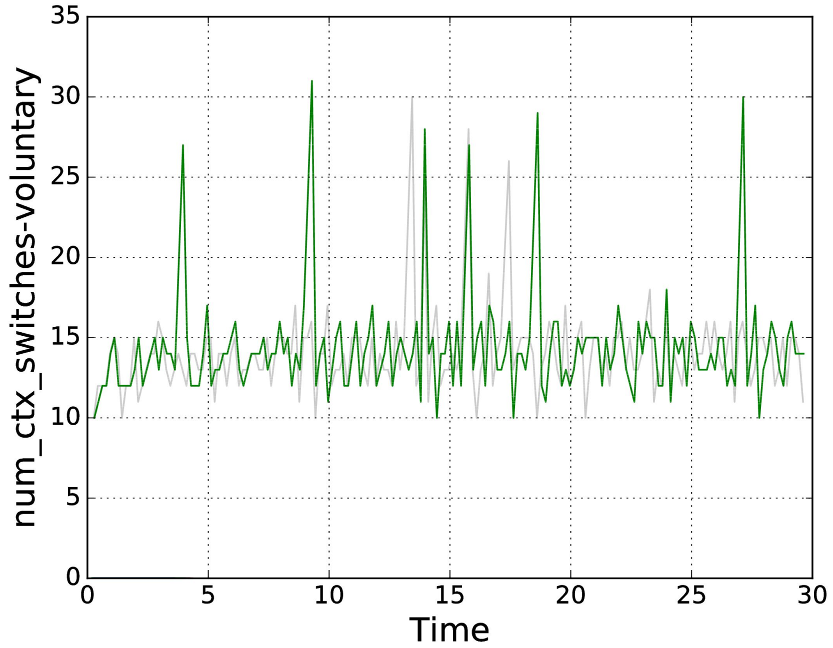
Multiple VMs Single Samples (MVSS)



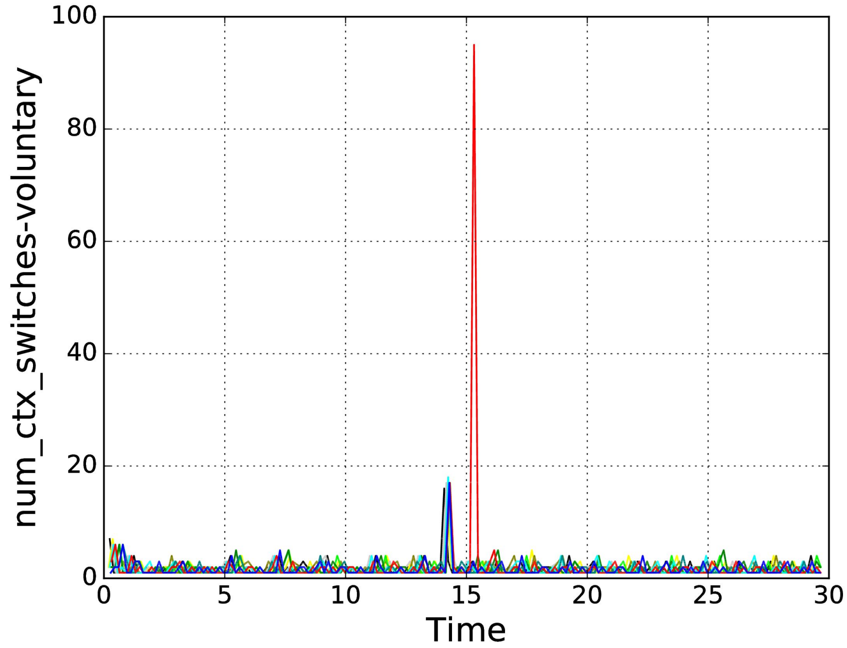
Key Intuition

What do we gain from having multiple VMs in an auto-scaling scenario?

"Correlation between VMs"

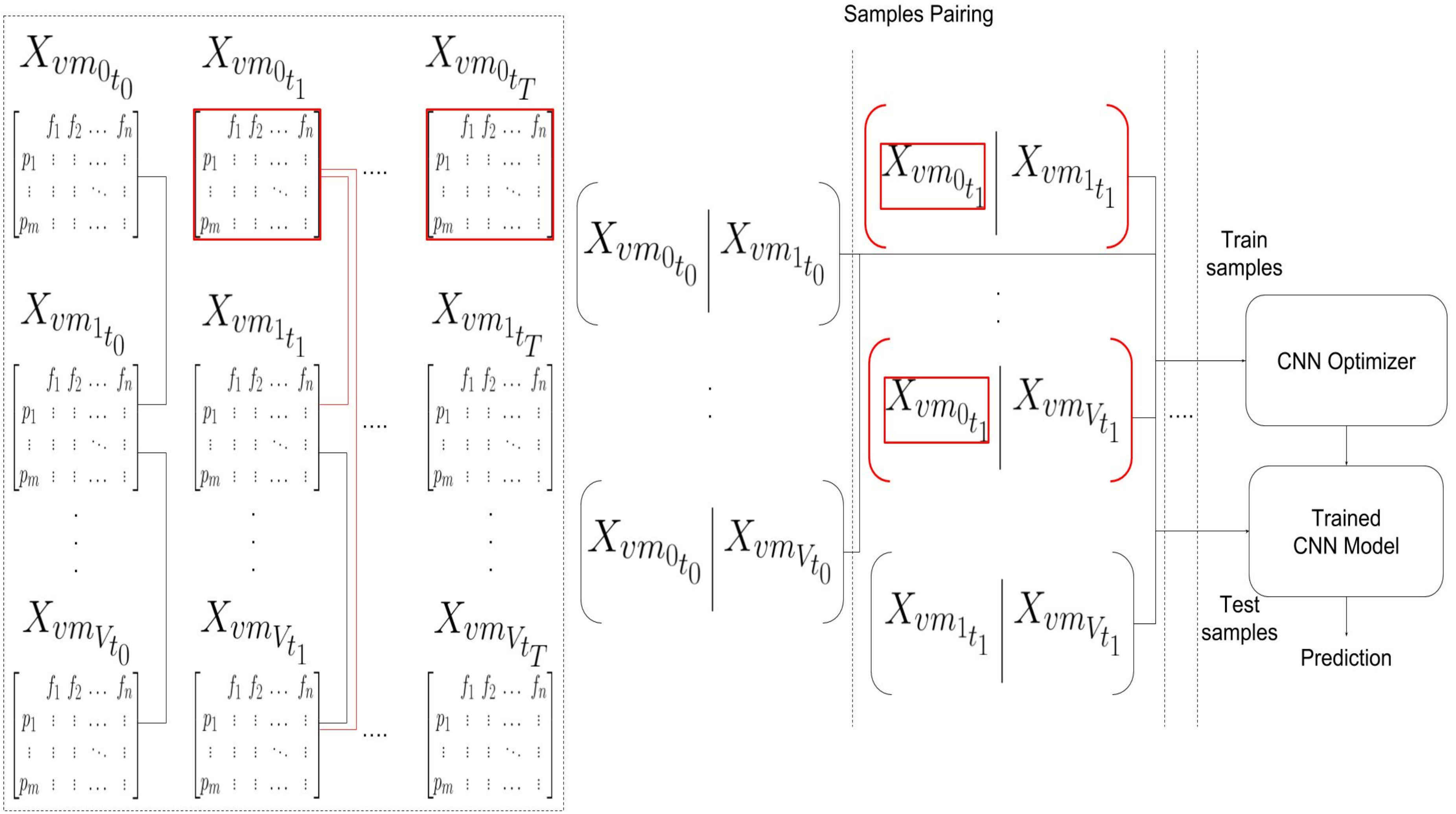


Number of used voluntary context switches over 30 minutes for two different runs of the same unique process



Number of used voluntary context switches over 30 minutes for one run of 10 VMs in an auto-scaling scenario.

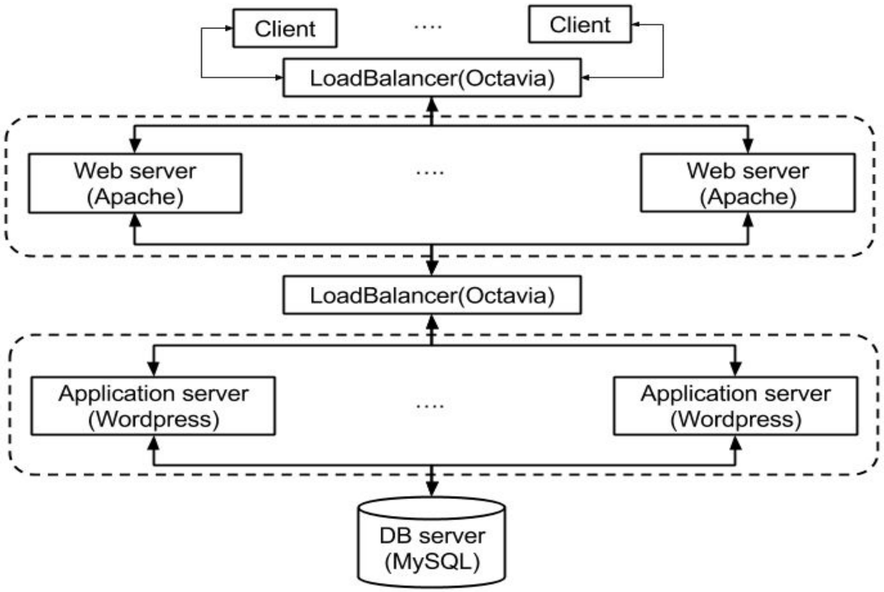
Multiple VMs Paired Samples (MVPS)

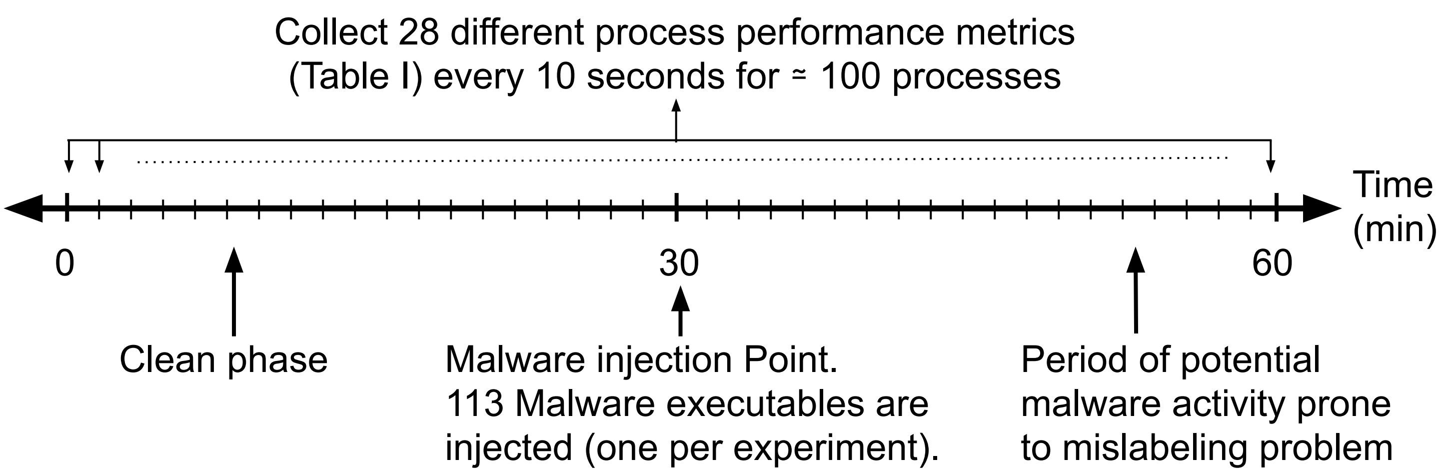


Experimental Setup and Results

Experimental Setup

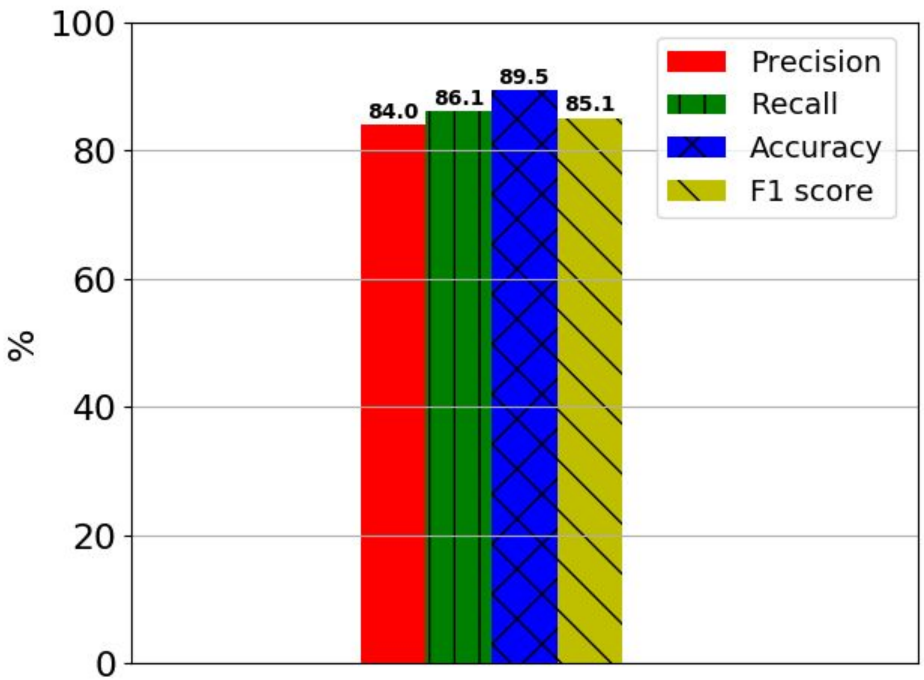
- Our experiments were conducted on Openstack.
- To simulate a real world scenario, we used a 3-tier web architecture and a self-similar traffic gen. (on/off Pareto) is used.
- Data collection:



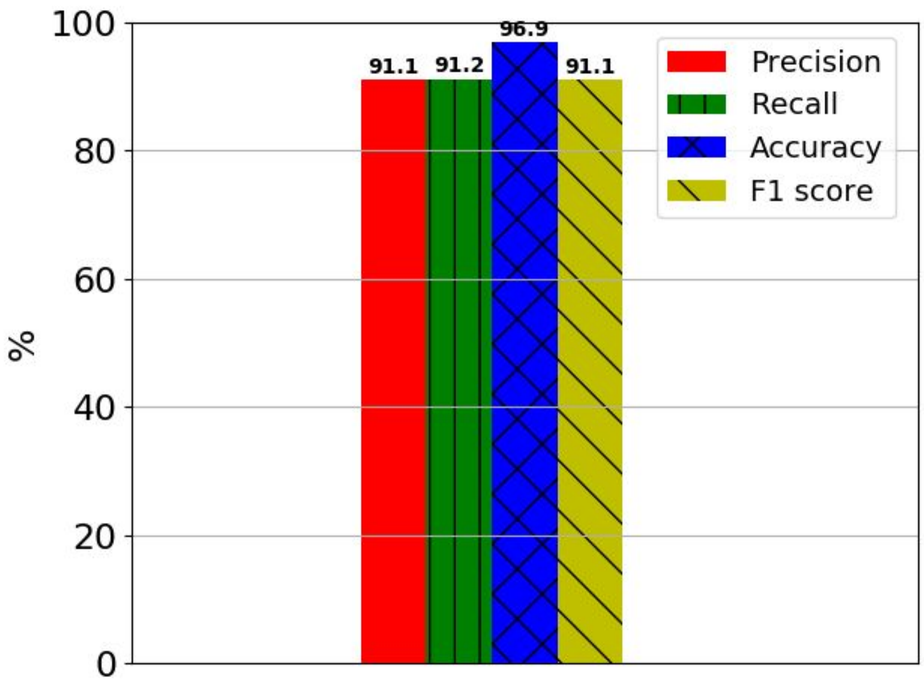


Results

MVSS



MVPS



Conclusion & Future Work

The goal of this paper was to provide a develop cloud-specific online malware detection method by leveraging cloud characteristics (i.e., auto-scaling).

1. We developed an effective approach for detecting malware using process-level features for low-level malware in an auto-scaling scenario.
2. We introduced a novel pairing samples approach for capturing correlations between VMs.

Future Work:

- Applying and testing multiple architectures (e.g., hadoop systems or containers)
- Investigating and leveraging more cloud characteristics for security.
- Develop techniques to handle the situation when multiple VMs are infected simultaneously by an attacker.

Questions/Comments