I·C·S
The Institute for Cyber Security

C·SPECC
Center for Security and Privacy Enhanced Cloud Computing

Online Malware Detection in Cloud Auto-Scaling Systems using Performance Metrics

by
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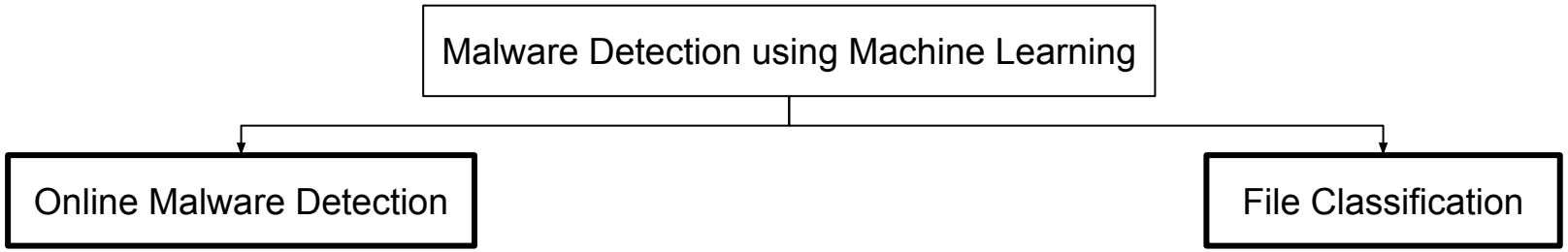
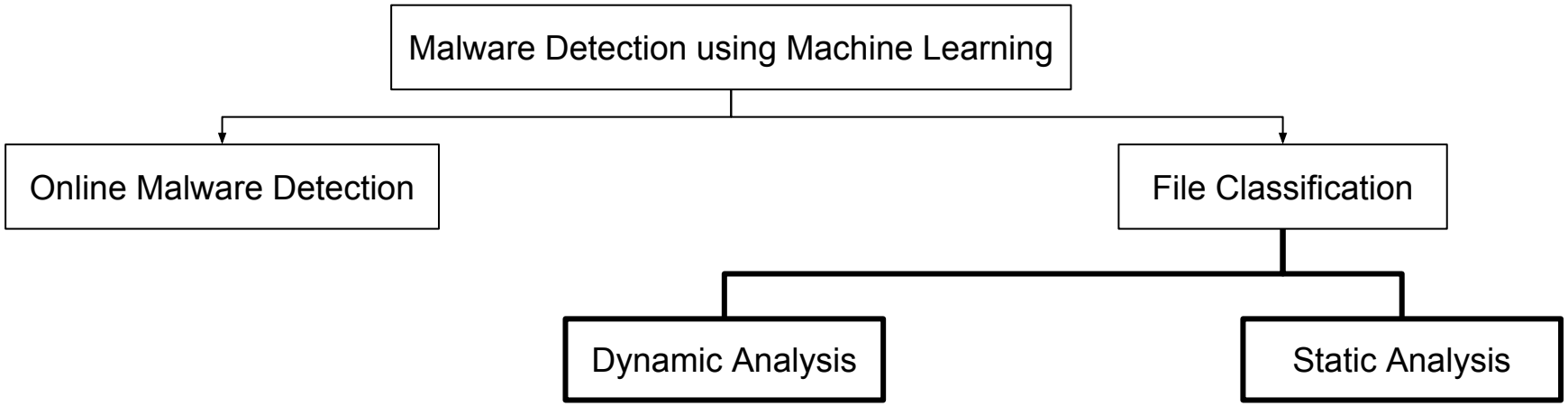
February 15, 2019

Malware Detection Classification



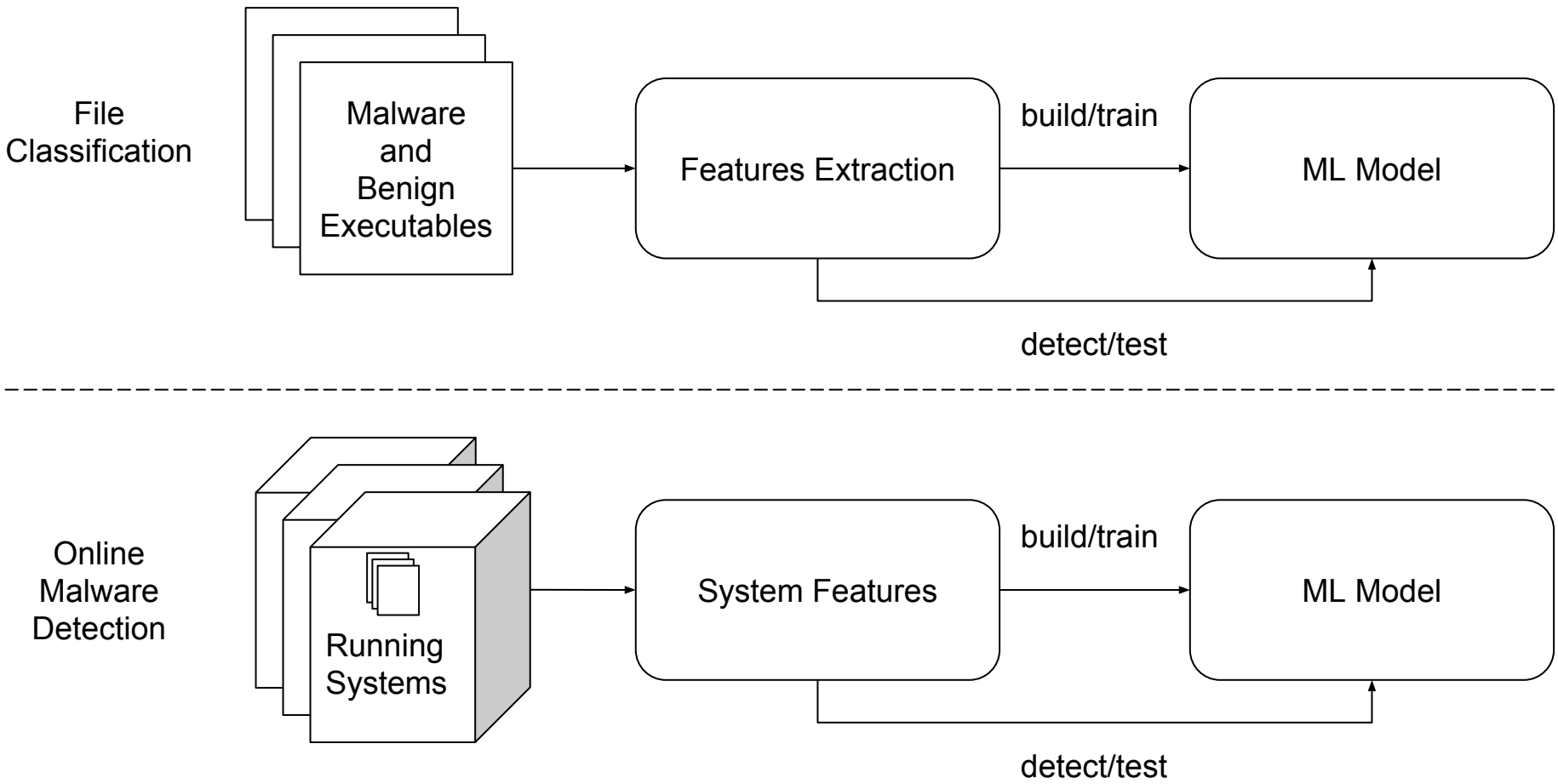
1. File classification:
   - Given a file/executable, classify if it's a malware or not by running it and observing its behavior.
   - You have a file as a suspect.
   - You don't keep monitoring them once they are clean.
2. Online malware detection:
   - Assume that the malware got into the system and 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 Classification

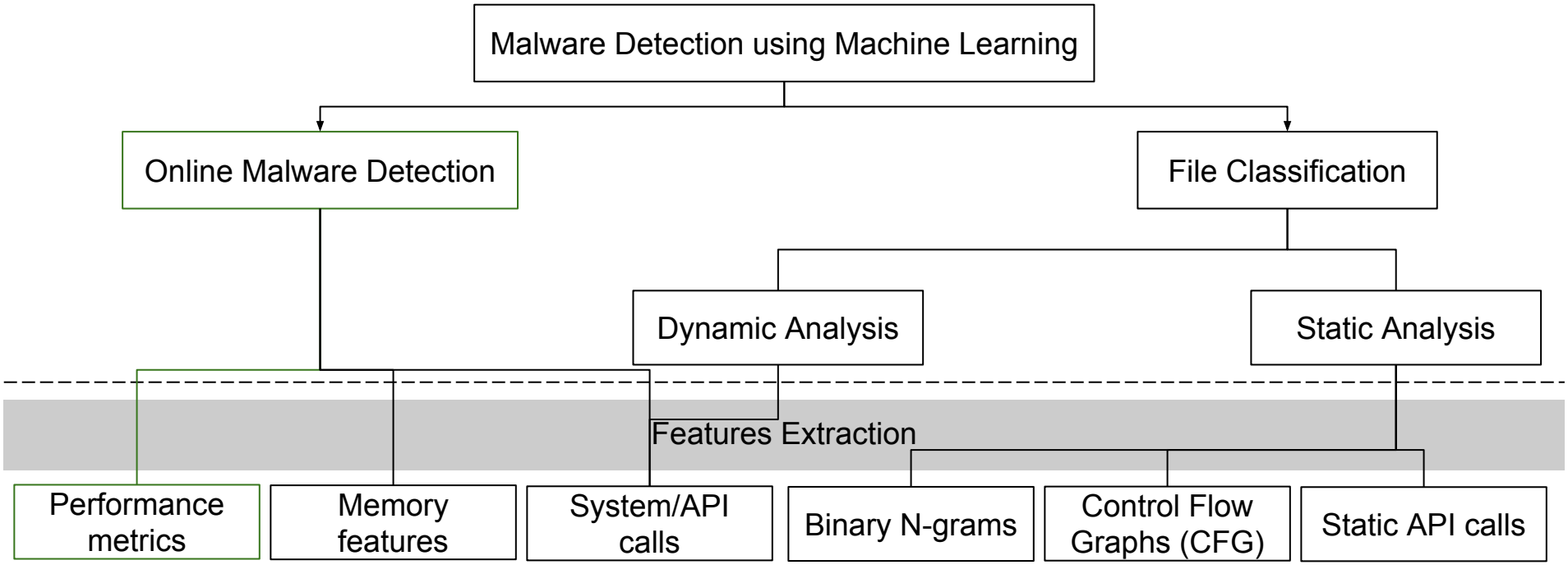


- Static Analysis
  - No malware execution takes place.
  - It is the process of analyzing executables by examining their code without actually executing them.
- Dynamic Analysis
  - Malware execute, typically, in an isolated environment and information about their behavior is logged/monitored.

Malware Detection Methods



Malware Detection Classification



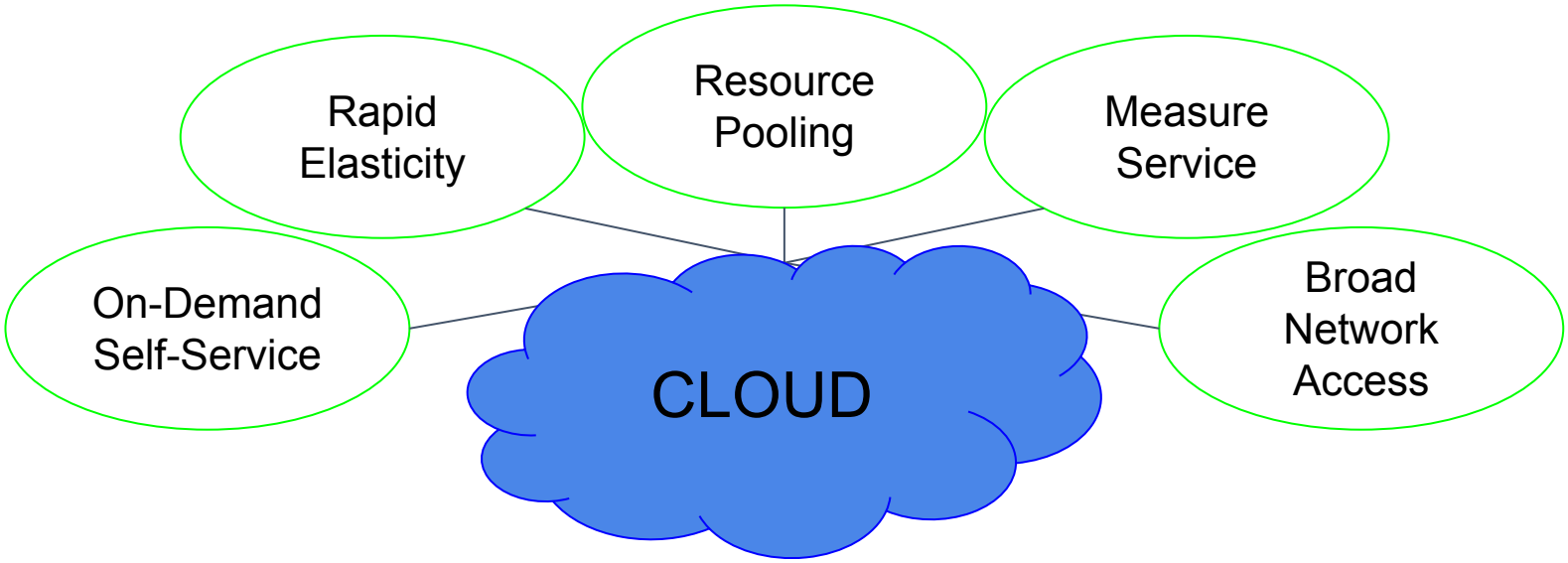
Cloud-specific falls under the “online malware detection” category.

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

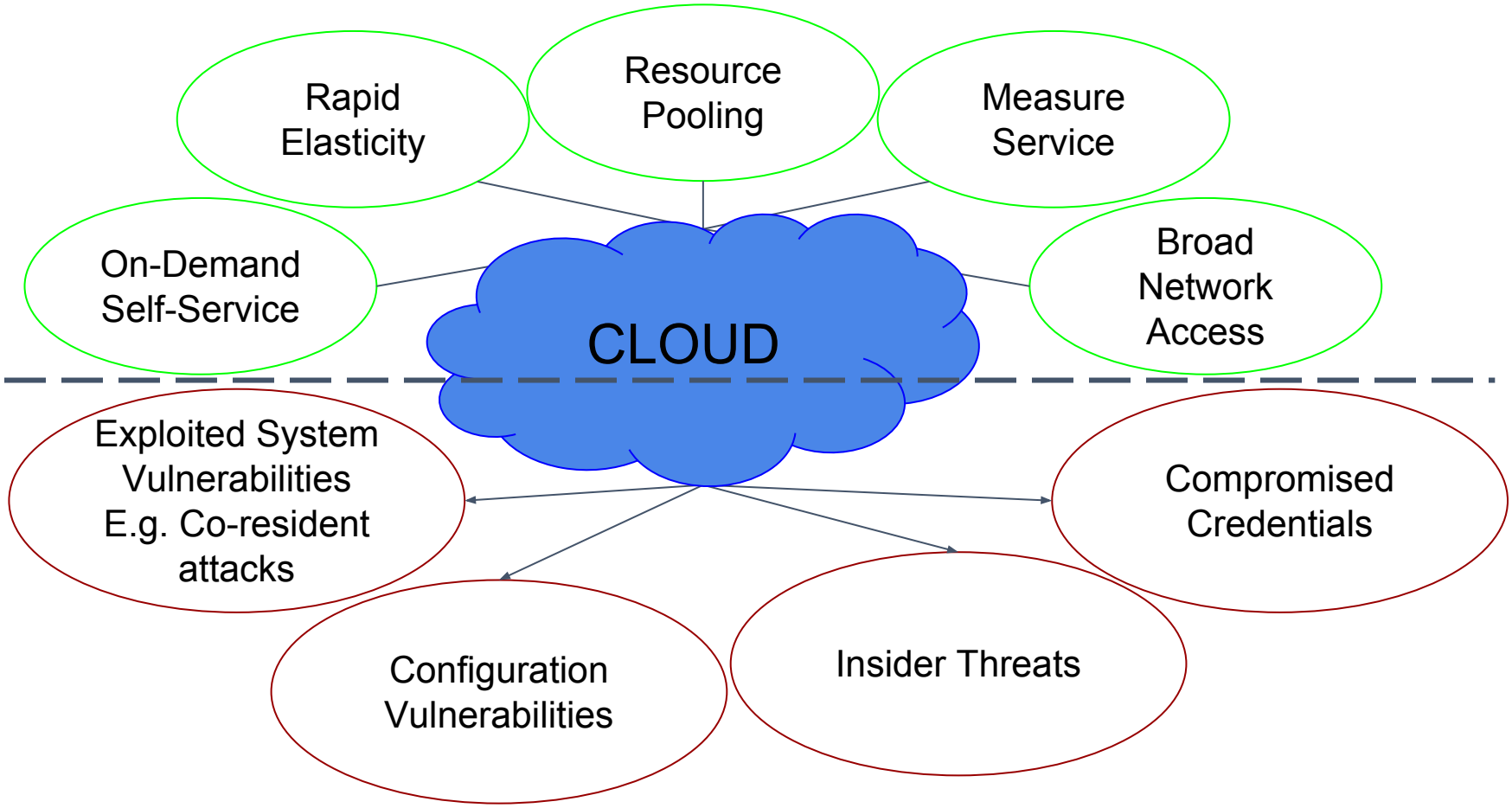
✔ Restrict the selection of features to those that can only be fetched through the hypervisor.

✘ Leverage cloud characteristics for online malware detection.

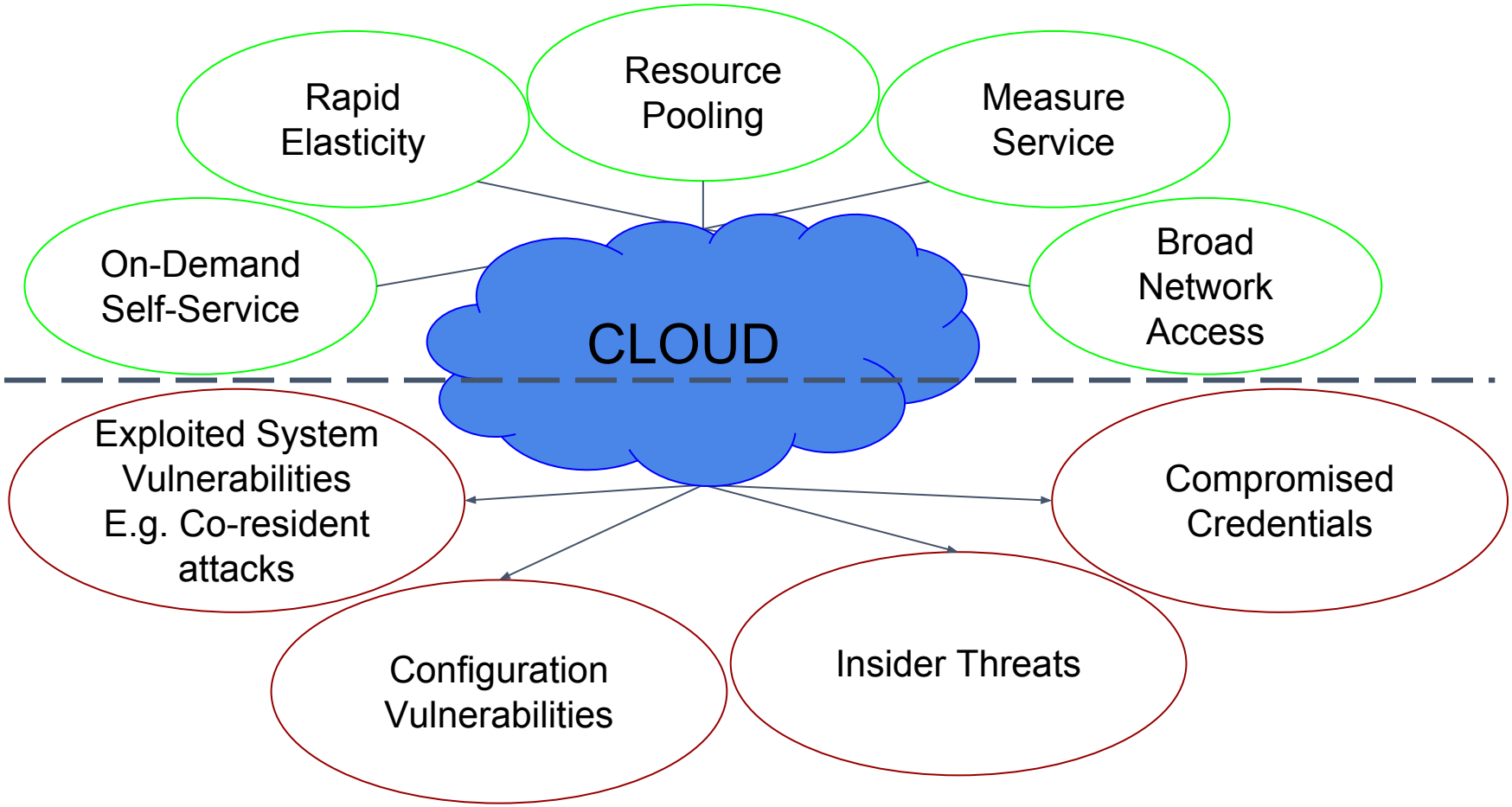
Introduction



Introduction



Introduction

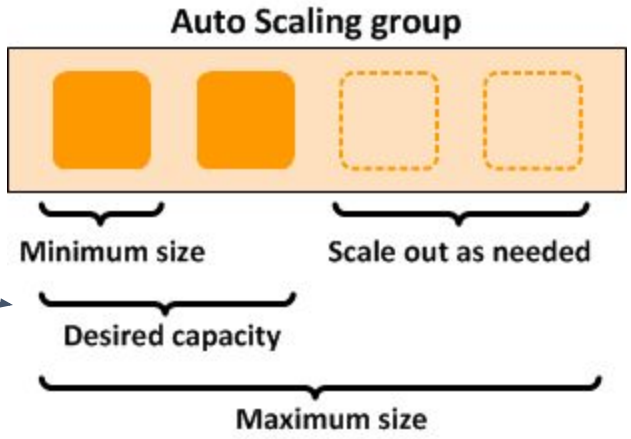


Can we leverage cloud characteristics for online malware detection?
"Auto-Scaling"

What is Auto-Scaling?

Auto-scaling is a cloud computing service feature that automatically adds or removes compute resources depending upon actual usage.

Auto-scaling Policy:
avg. CPU:
> 70% => scale-out
< 30% => scale-in



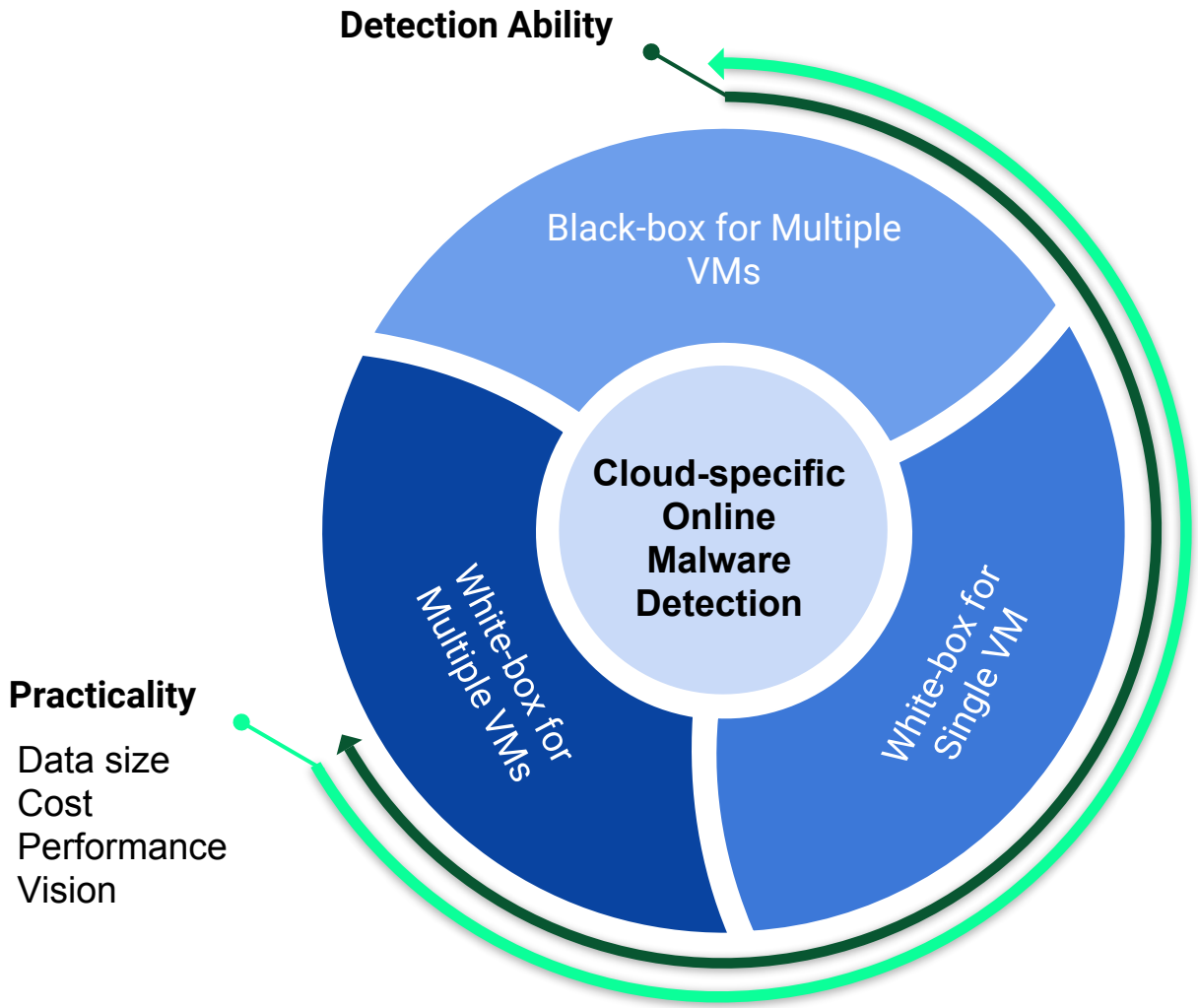
Source: AWS website

Problem Statement

- **Problem statement:**
  - Malware will always find a way-in to infect cloud infrastructures.
  - Presence of a gap between malware prevention and malware detection methods.
  - Lack of *cloud-specific* online malware detection methods.

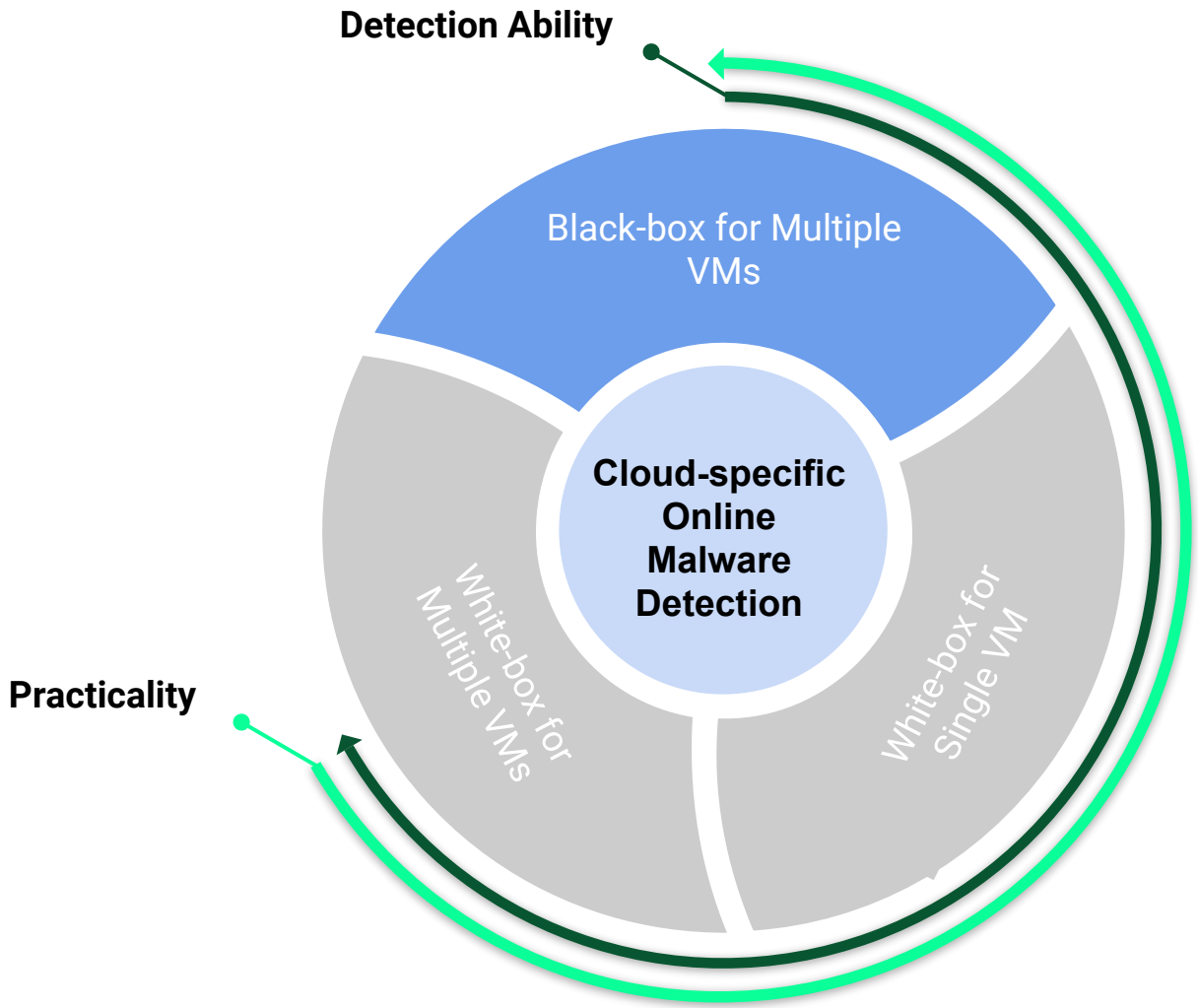
- **Thesis statement** - Cloud unique characteristic "auto-scaling" can effectively be utilized for online malware detection within a single-tenant's virtual resources, in black-box and white-box granularity using performance metrics.

Overview

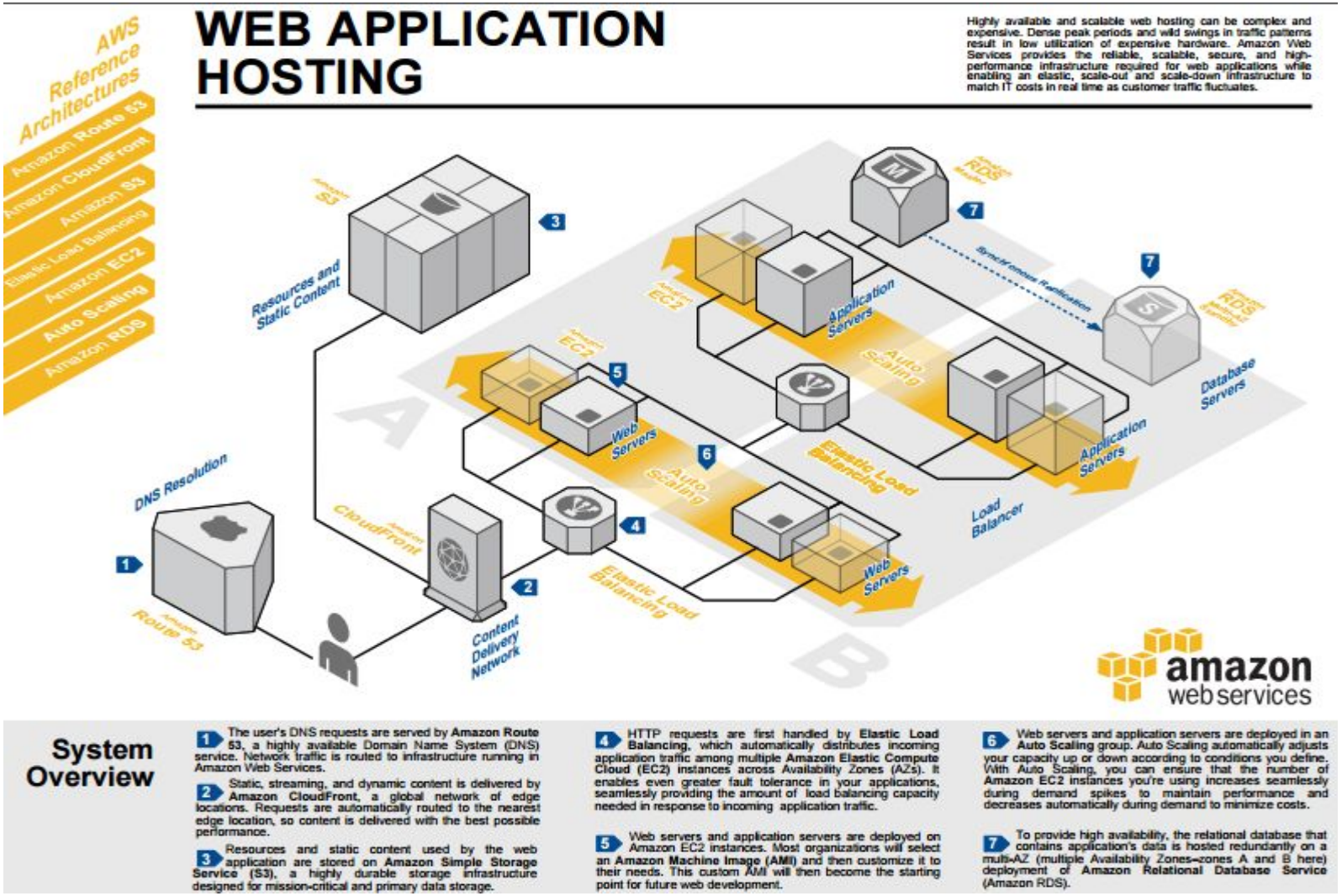


World Leading Research with Real World Impact!

Blackbox for Multiple VMs



3-tier example

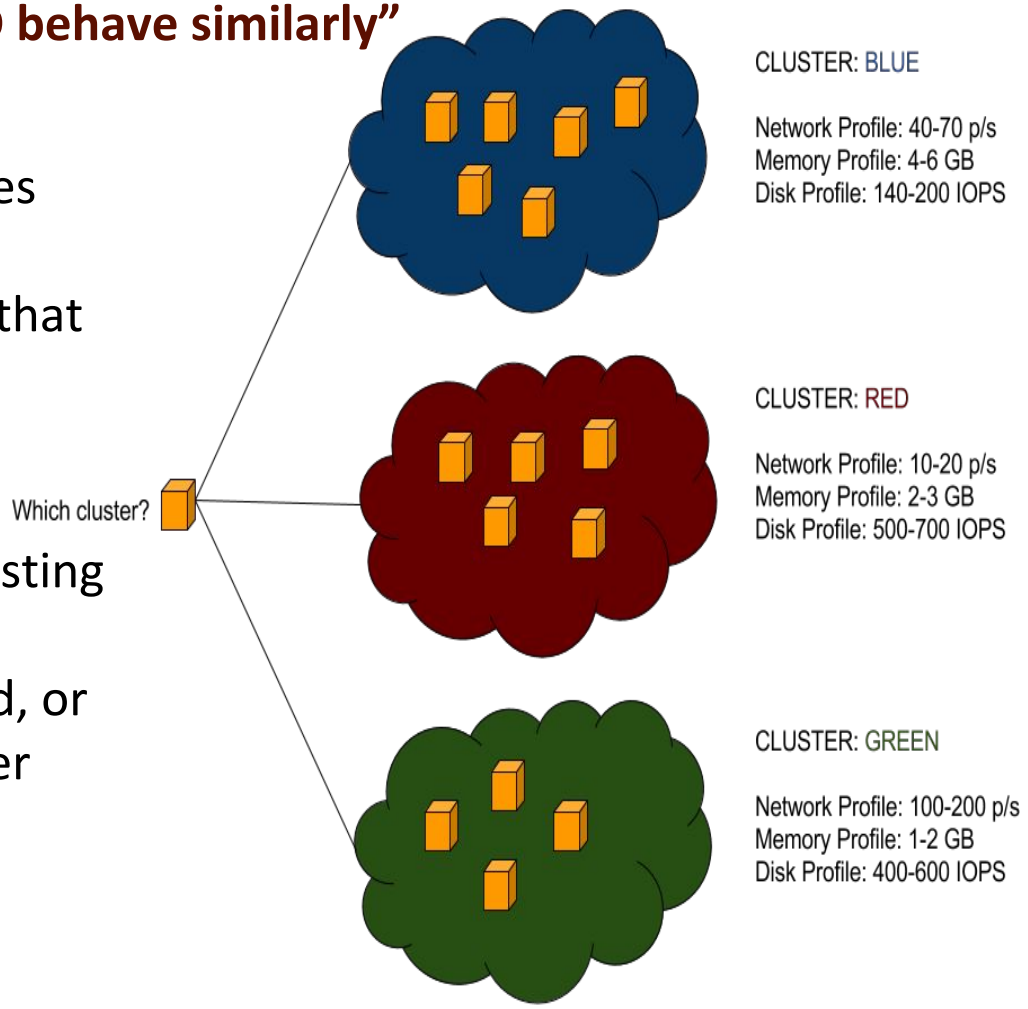


World Leading Research with Real World Impact!

Blackbox Approach

"VMs doing the same function SHOULD behave similarly"

- Cluster VMs based on their attributes
- When a new VM gets created, "fit" that VM with existing cluster
  - If successful: good
  - If not: report anomaly
    - Admin force fits into an existing category -> consequently cluster profiles are updated, or
    - Admin creates a new cluster for this VM

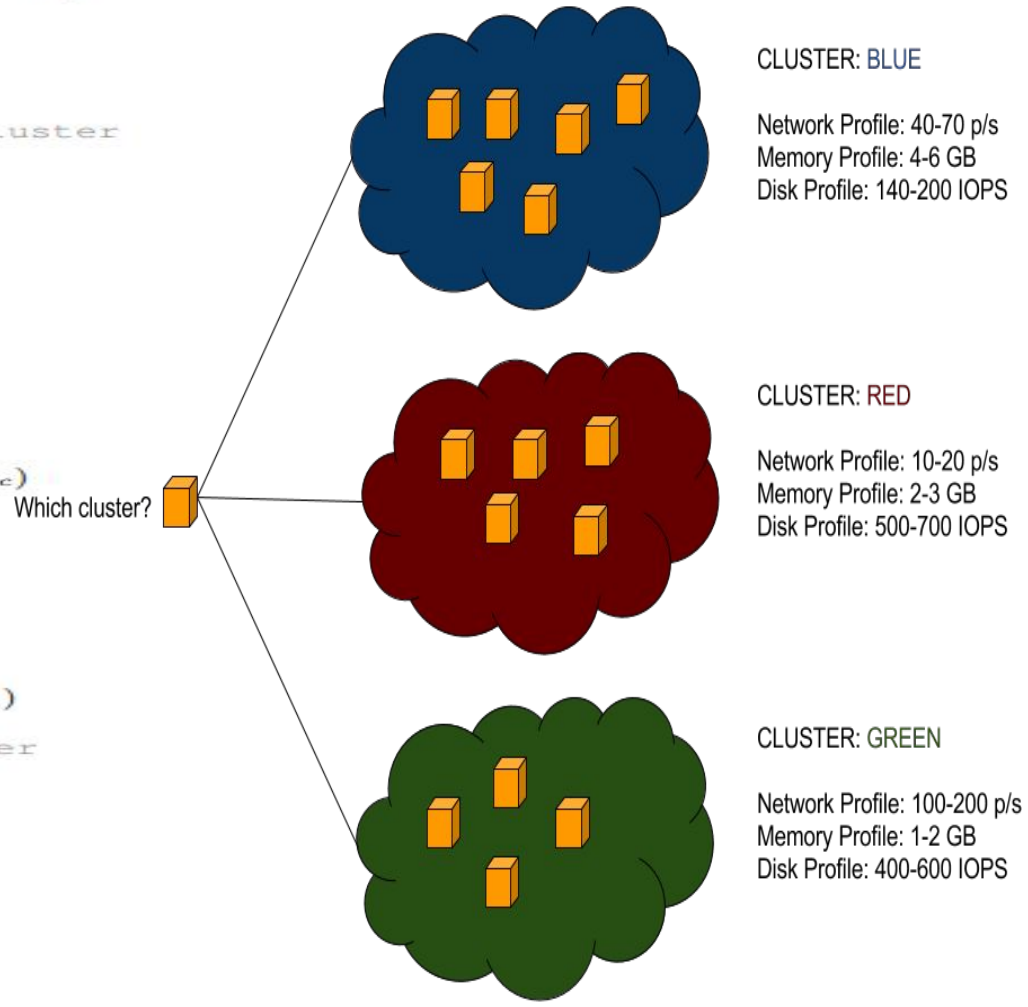


Hypervisor-level VMs Features

Metric	Description	Unit
CPU utilization	Average CPU utilization	%
Memory usage	Volume of RAM used by the VM from the amount of its allocated memory	MB
Memory resident	Volume of RAM used by the VM on the physical machine	MB
Disk read requests	Rate of disk read requests	rate/s
Disk write requests	Rate of disk write requests	rate/s
Disk read bytes	Rate of disk read bytes	rate/s
Disk write bytes	Rate of disk write bytes	rate/s
Network outgoing bytes	Rate of network outgoing bytes	rate/s
Network incoming bytes	Rate of network incoming bytes	rate/s

Sequential K-means

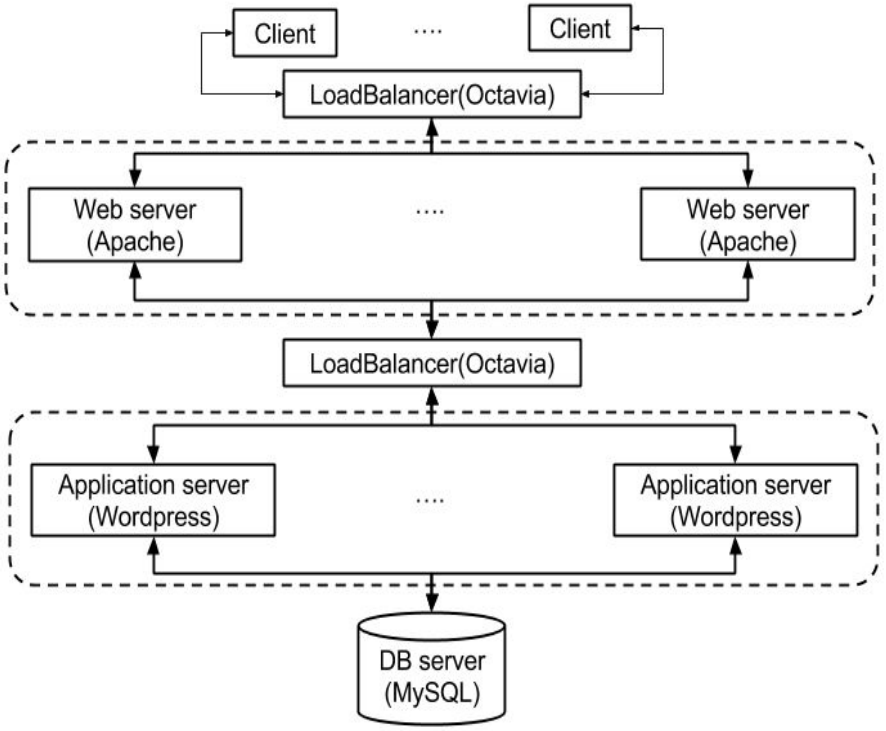

```
make initial guesses for means (centroids)
    m_1, m_2, ..., m_k
set the counters n_1, n_2, ..., n_k to zero
counter j //Number of current VMs
set stabilizingTime[1..j] to y minutes
set assigningTime[1..j] to z minutes
def VMClusters[1..k] //VM i belongs to cluster
    [1..k]
set VMClusterCounts[1..j][1..k] to zero
until interrupted
  get the next sample x
  get VM v //x sample belongs to VM v
  if stabilizingTime[v] > 0
    decrease stabilizingTime[v]
    continue //get next sample
  end_if
  if v is assigned to a cluster
    c = VMClusters[v]
    if x is not anomaly
      increment n_c
      replace m_c with m_c + (1/n_c) * (x - m_c)
    else
      //Anomaly code here
      Report anomaly
    end_if
  end_if
  if v is not assigned to any cluster
    if m_i is closest to x
      increment n_i
      replace m_i with m_i + (1/n_i) * (x - m_i)
    end_if
    //If time end assign it to a cluster
    if assigningTime[v] <= 0
      set VMClusters[v] to index of
          max(VMClusterCounts[v])
    else
      if m_i is closest to x
        increment VMClusterCounts[v][i]
      end_if
      decrease assigningTime[v]
    end_if
  end_if
end_until
```



Experimental Setup

Simple & realistic traffic generation

- Poisson
  - Used in many cases due to its simplicity.
- On/Off Pareto
  - Internet traffic is proved to be of self-similar nature.

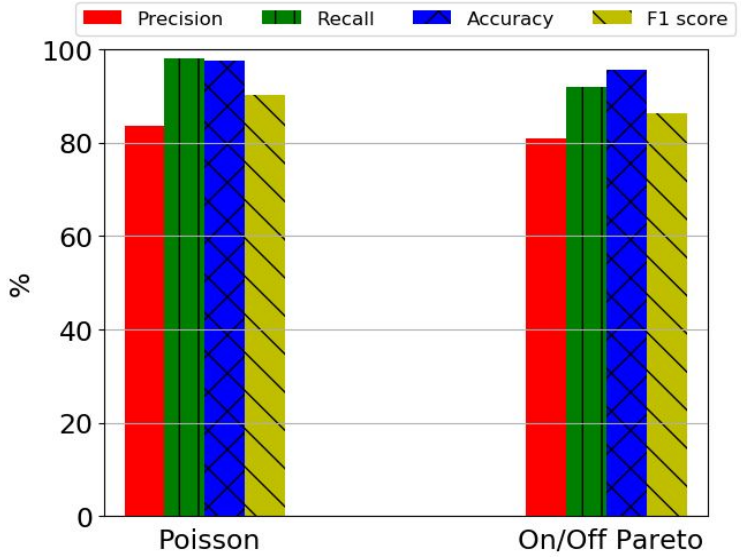


The simulation parameters are as follows:

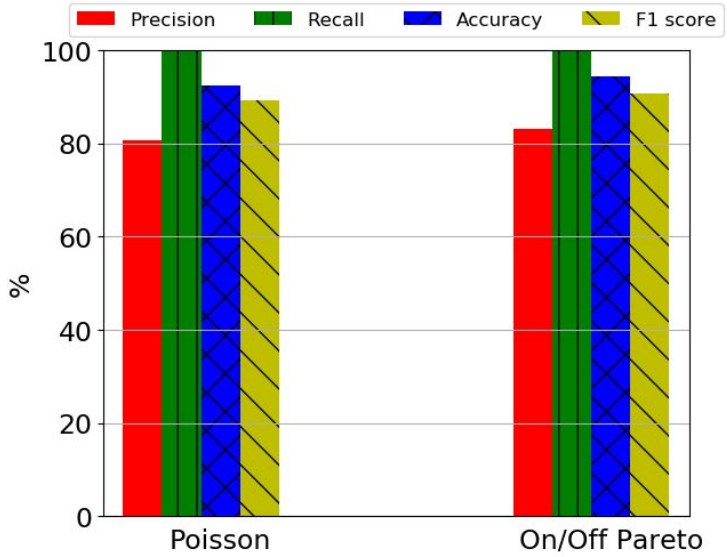
- Generator: On/Off Pareto, Poisson
- Number of concurrent clients: 50
- Requests arrival rate/hour: 3600
- Type of requests: GET and POST (randomly generated)

Results

- Injected Anomalies:
  - cpu, memory and disk intensive



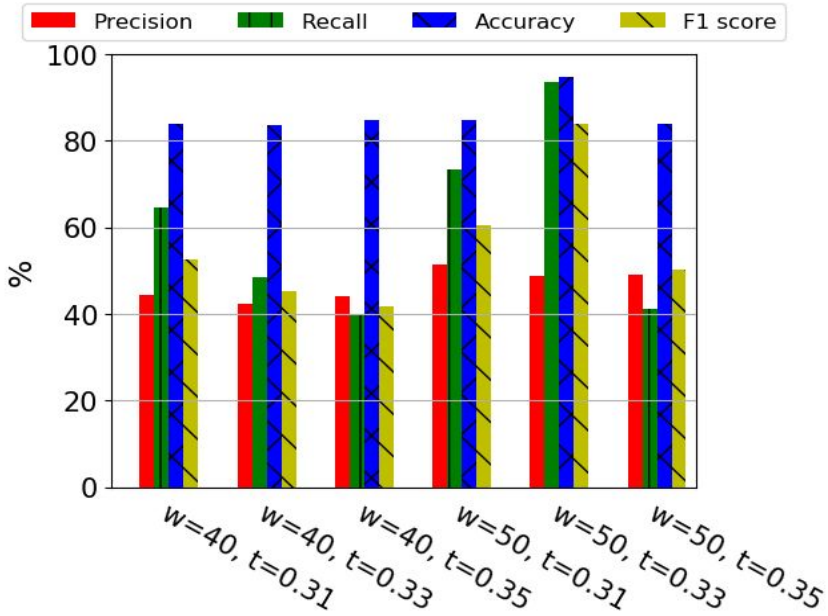
- EDoS: One form of EDoS is to create some VMs while remaining dormant and idle



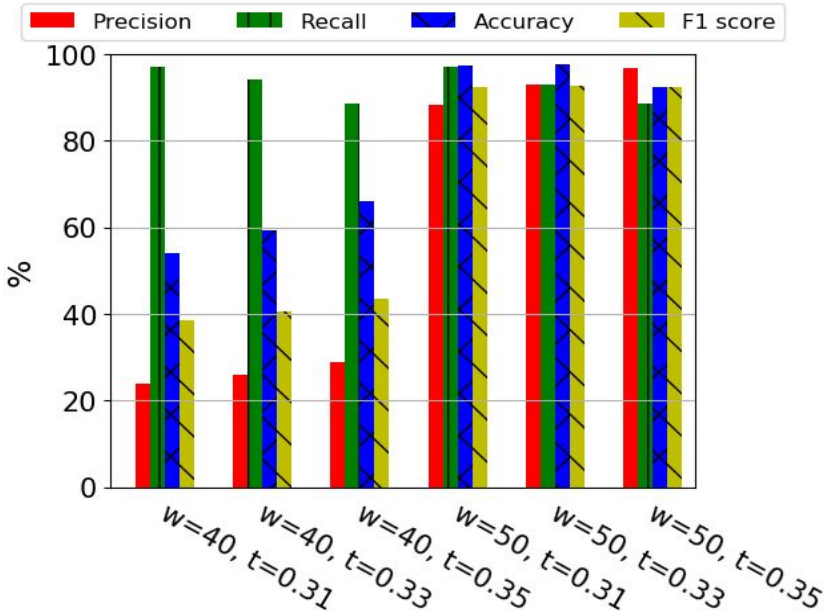
Results

- Ransomware is a very critical threat to cloud.
- Netskope's quarterly cloud report states that 43.7% of the cloud malware types detected in cloud apps are common ransomware delivery vehicles.

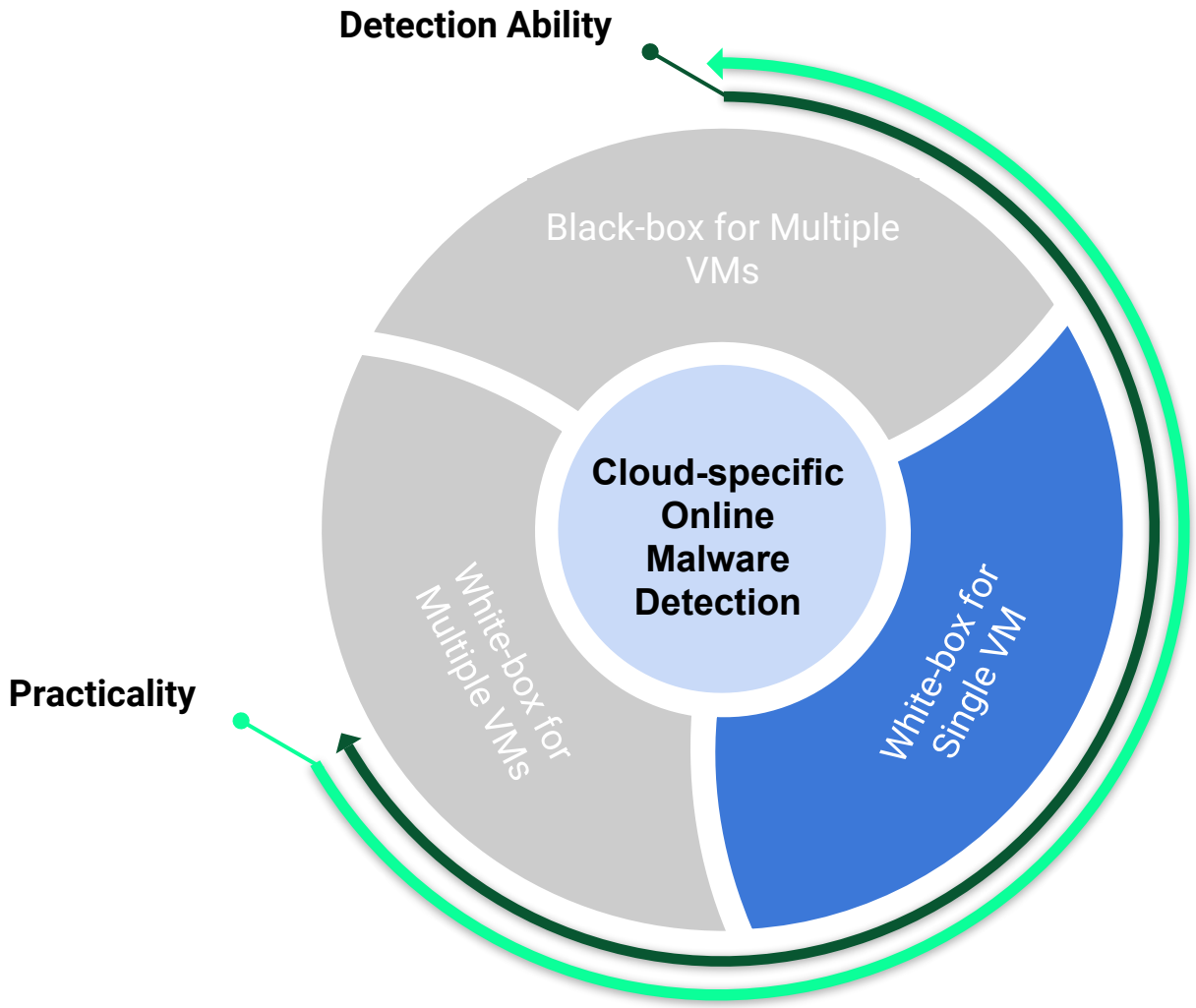
Ransomware (KillDisk) - Poisson



Ransomware (KillDisk) - On/Off Pareto



Whitebox for Single VM



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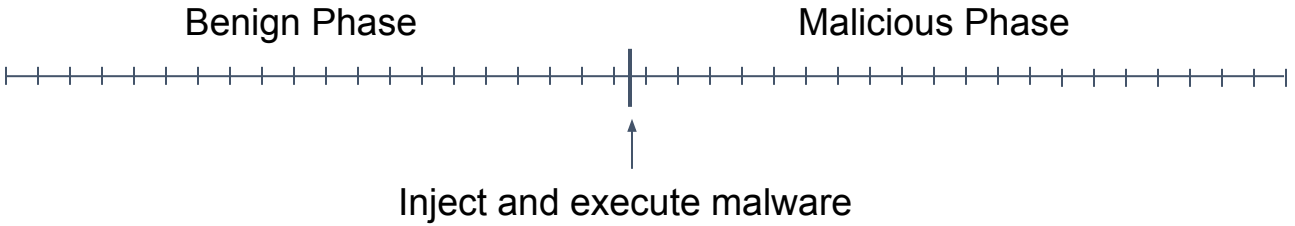
Whitebox Single VMs

Goals:

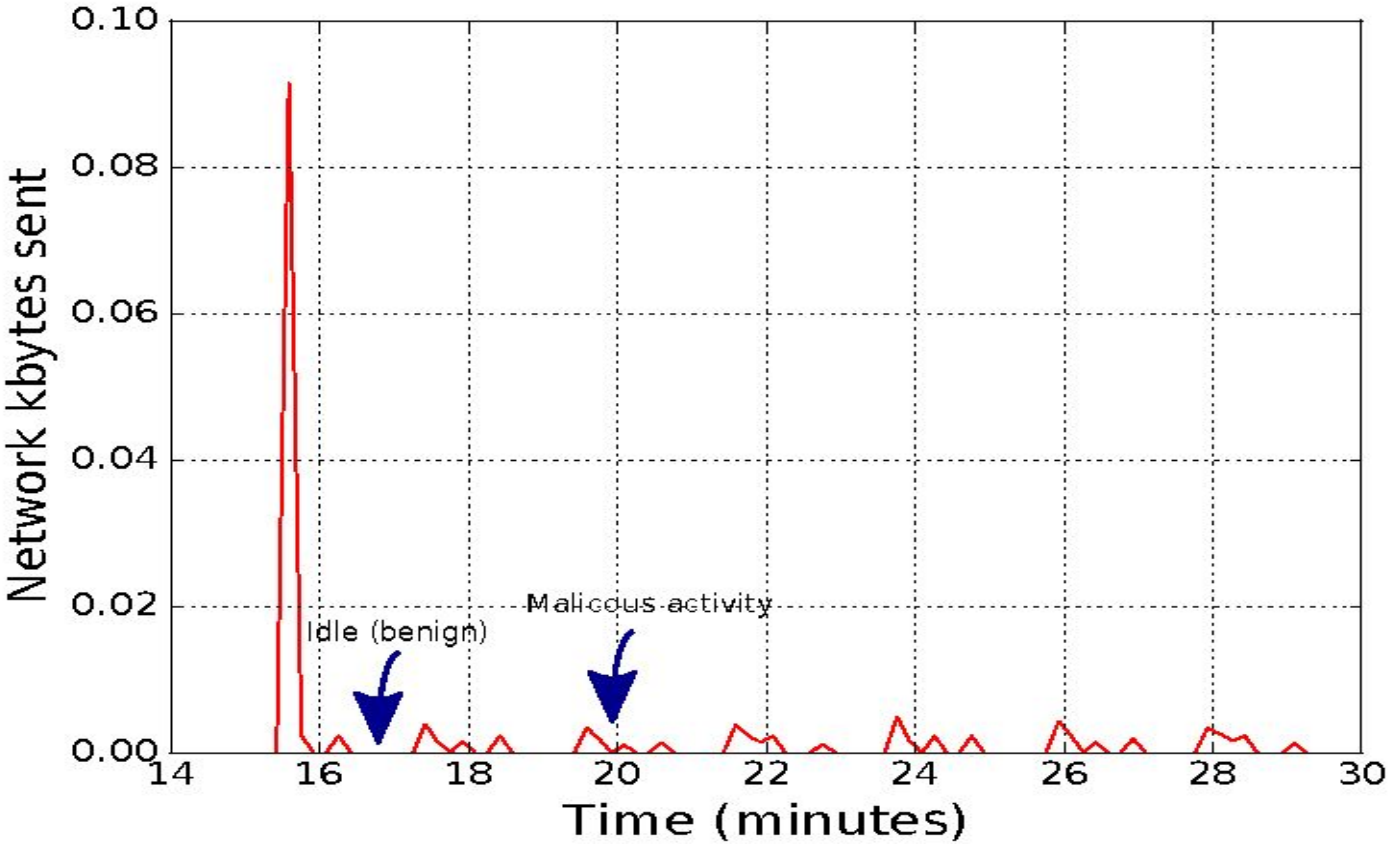
- The feasibility of applying CNN to VMs online malware detection using fine-grained process performance metrics.
- Tackling the mislabeling problem by using 3d CNNs.



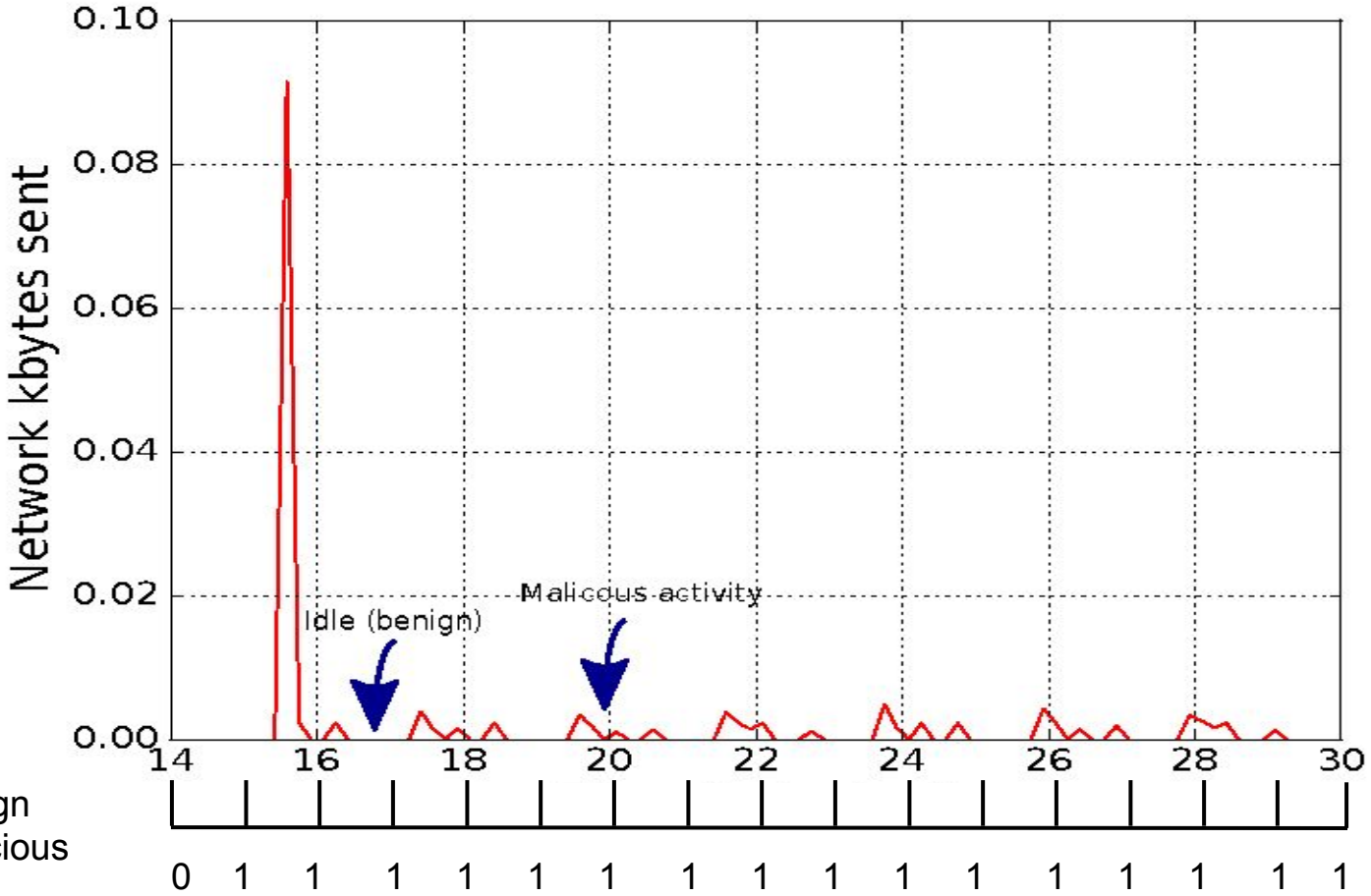
During the training phase, there is no guarantee that a malware exhibited malicious behavior.

- A malware may never show a malicious activity during the training phase at all.
+ More common scenario is when a malware periodically (e.g., every 1 minute) performs malicious activities such as stealing and sending some information to its Command and Control servers (C&Cs).

Mislabeling Problem

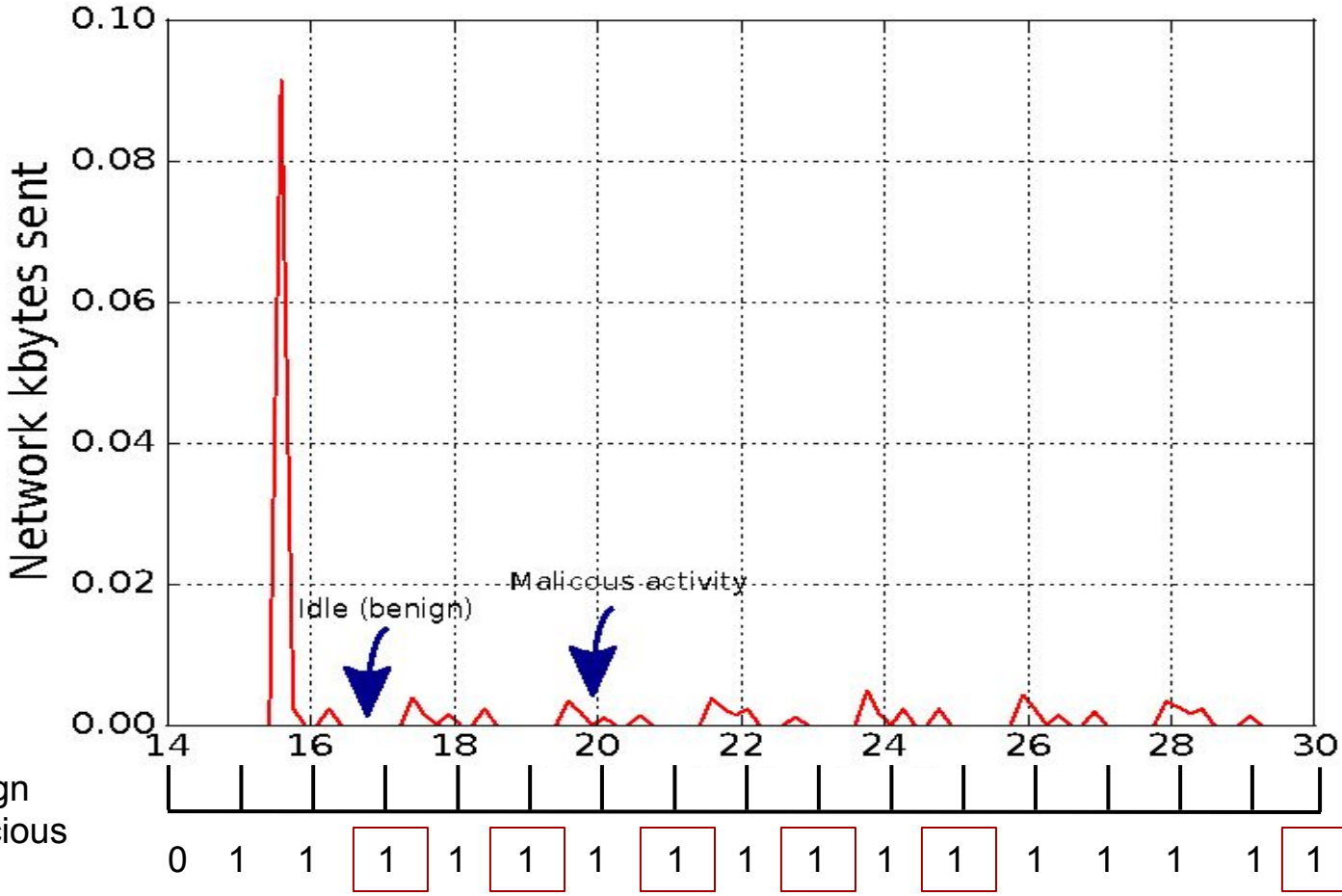


Mislabeling Problem

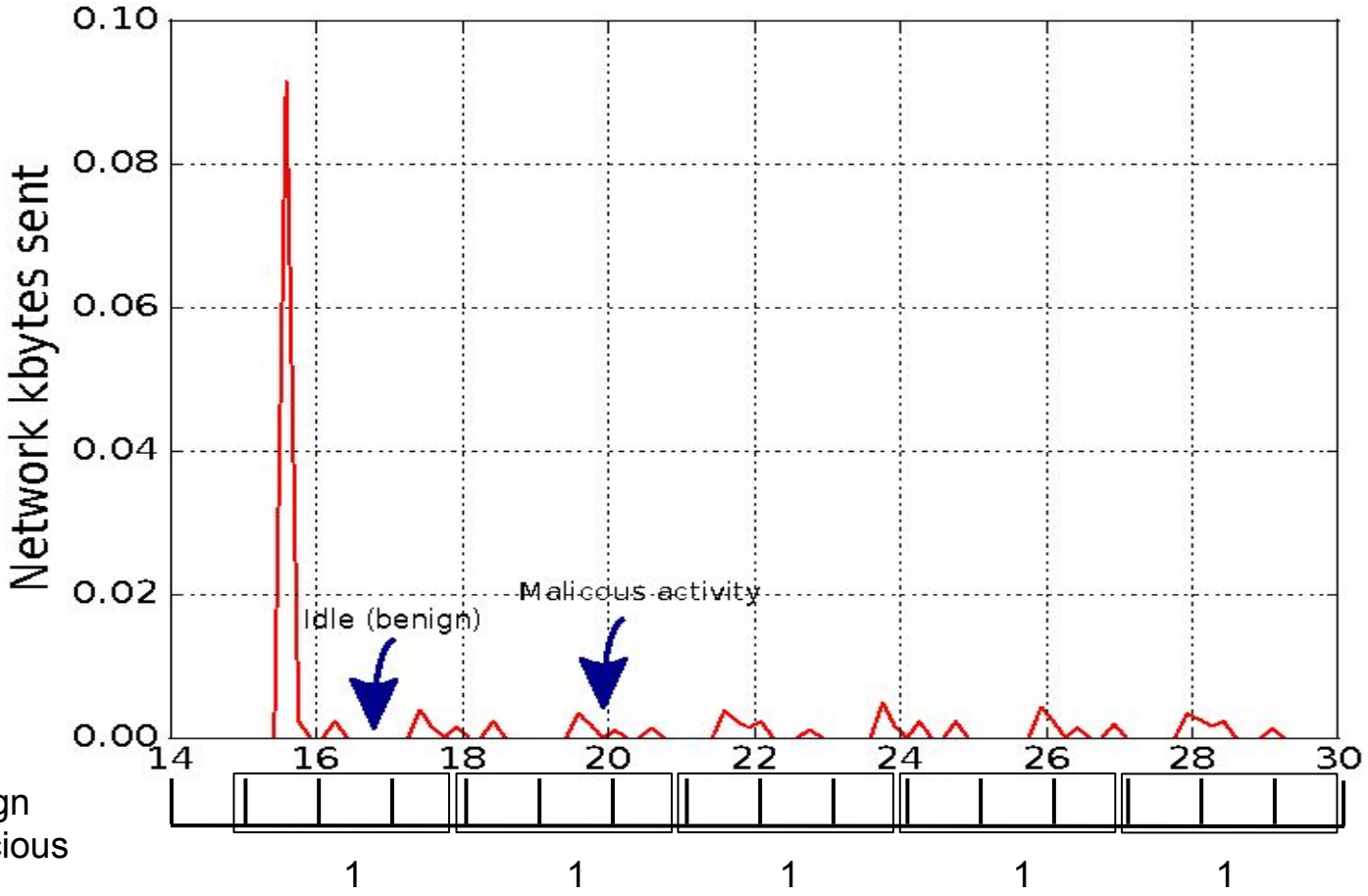


0 – Benign
1 – Malicious

Mislabeling Problem

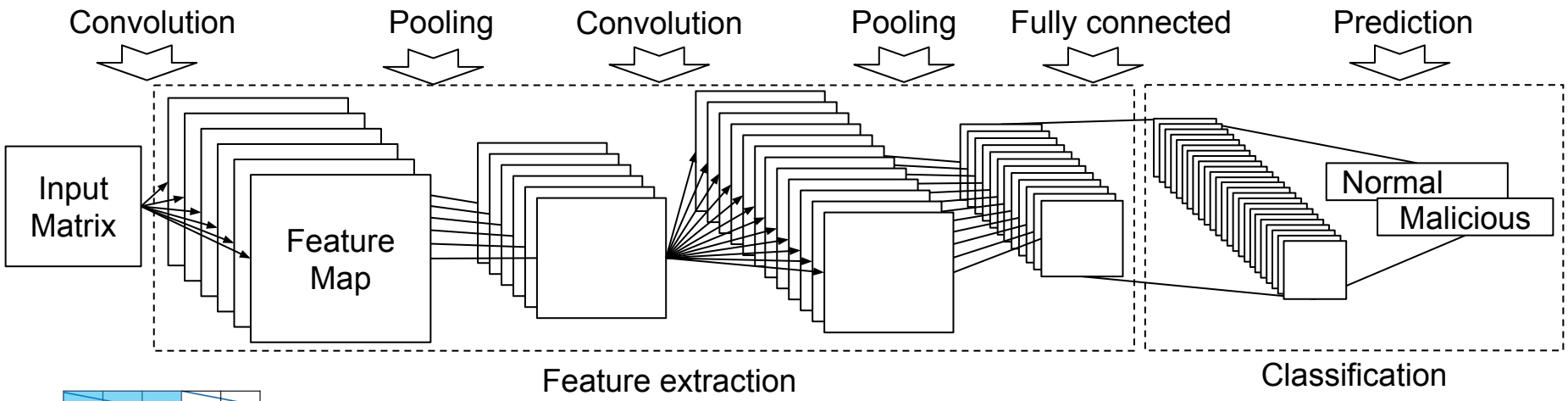


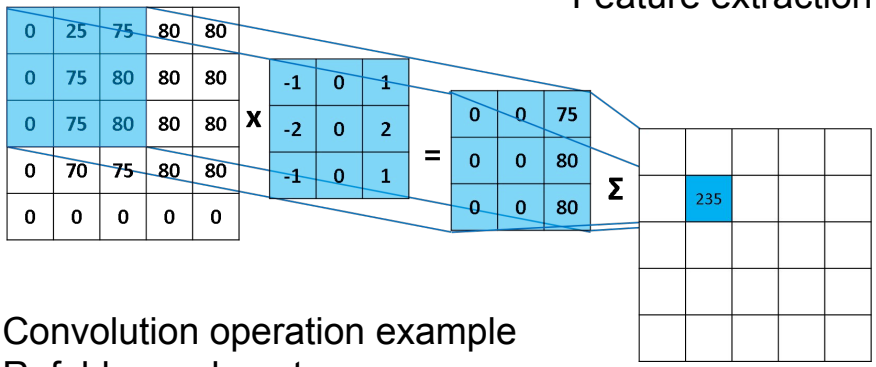
Mislabeling Problem



0 – Benign
1 – Malicious

CNN Overview





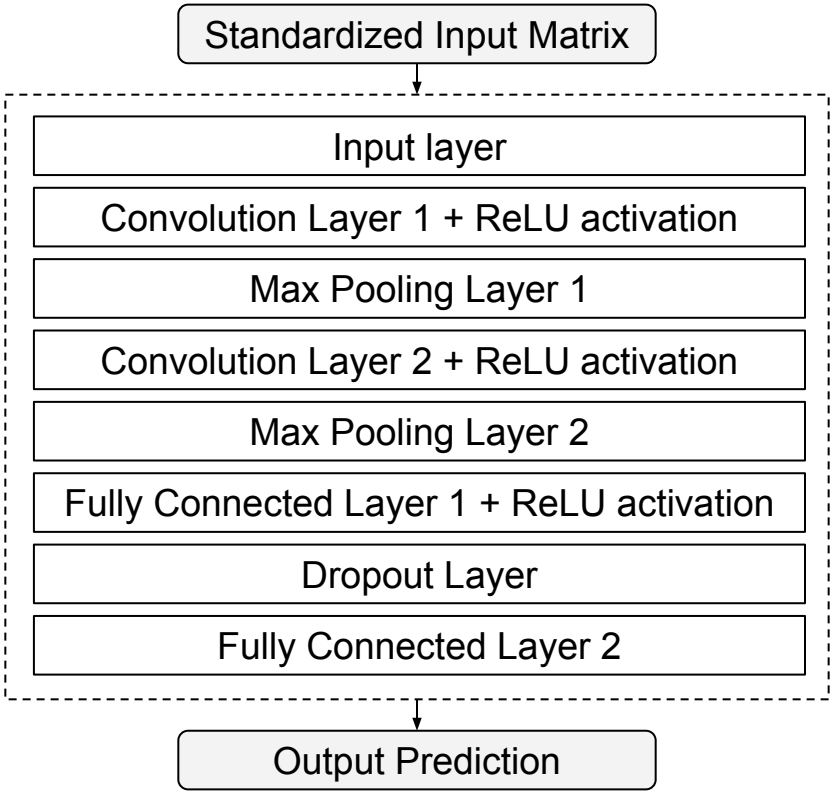
Convolution operation example
Ref: blog.csdn.net

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

CNN Model



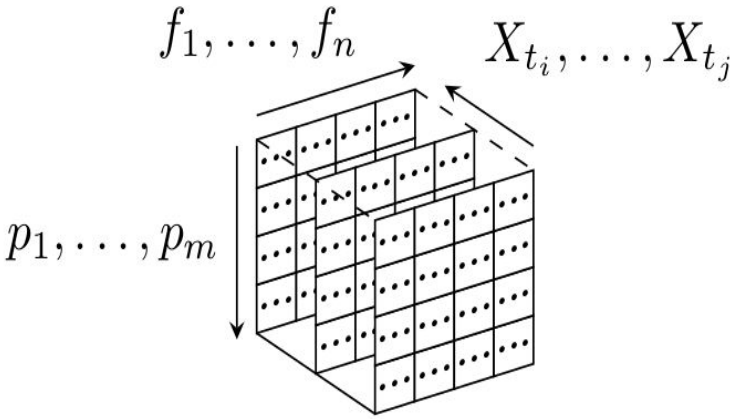
CNN Input

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:

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

The 3d CNN model input includes multiple samples over a time window. The input matrix is:



CNN Input Issues

- 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.

CNN Input Issues

- 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.

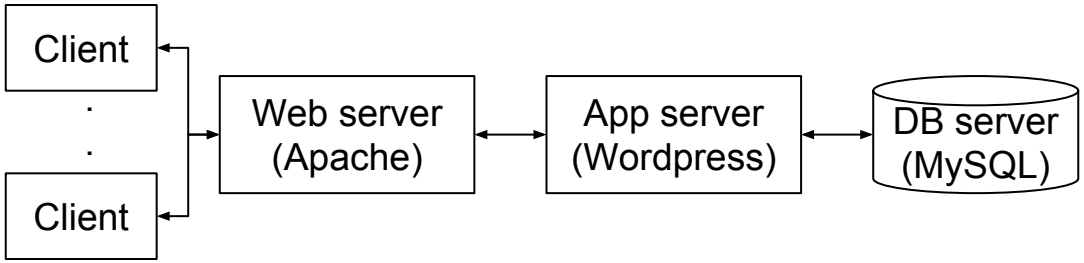
pid	name	cmd	hash	kb_sent	cpu_user	sample_time
1241	php-fpm7.0	php-fpm: pool www	7eb8522425...	33.61710	0.03000	2018-06-15 11:19:04
1240	php-fpm7.0	php-fpm: pool www	7eb8522425...	38.79308	0.00000	2018-06-15 11:19:04
1221	php-fpm7.0	php-fpm: master process (/etc/php/7.0/...	7eb8522425...	0.00000	0.02000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

Unique Process

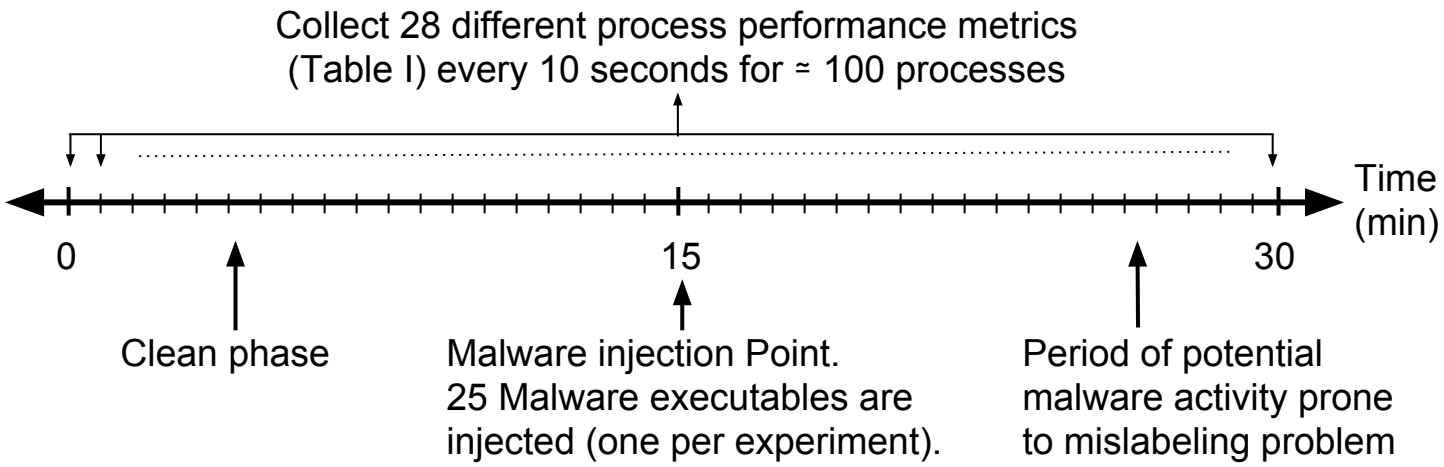
name	**cmd**	**hash**	AVG(kb_sent)	AVG(cpu_user)	sample_time
php-fpm7.0	php-fpm: pool www	7eb8522425...	36.2051	0.0150	2018-06-15 11:19:04
php-fpm7.0	php-fpm: master process (/etc/php/7.0/...	7eb8522425...	0.00000	0.0200	2018-06-15 11:19:04
python	python	23eeeb4347…	0.00000	0.1500	2018-06-15 11:19:04

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.

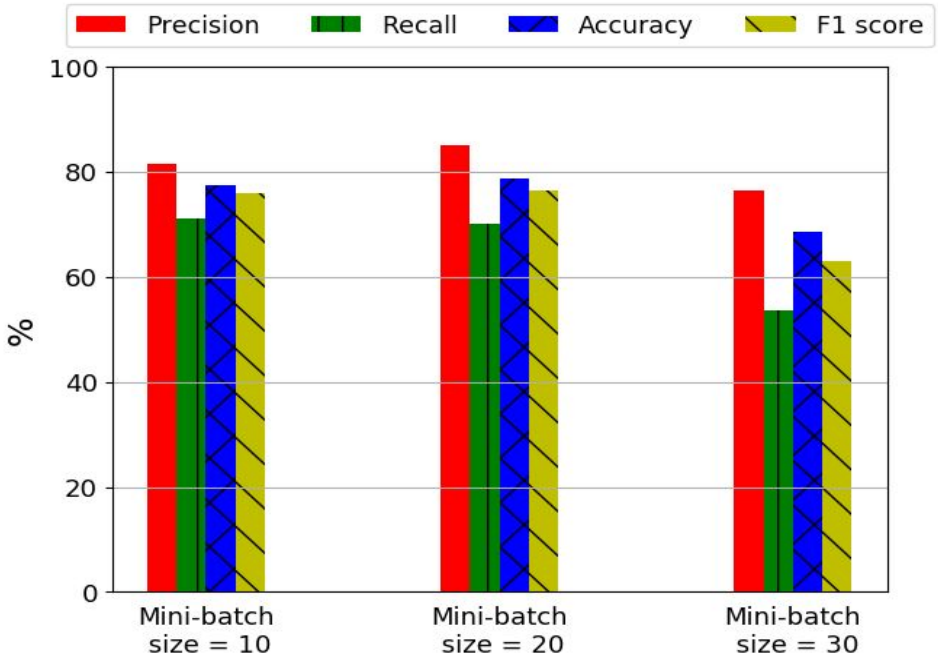


- Data collection:

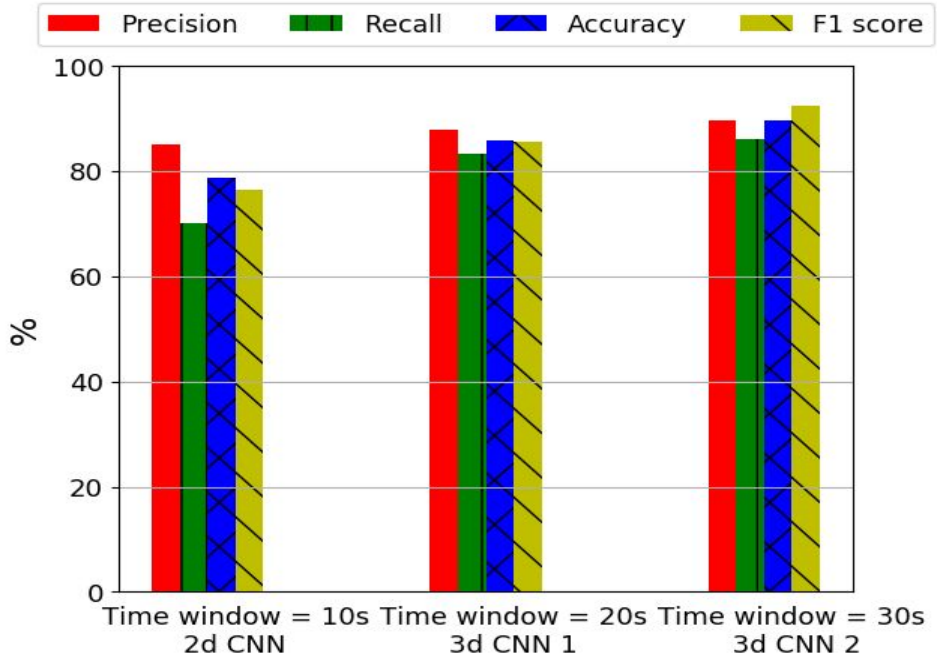


Results

2d CNN

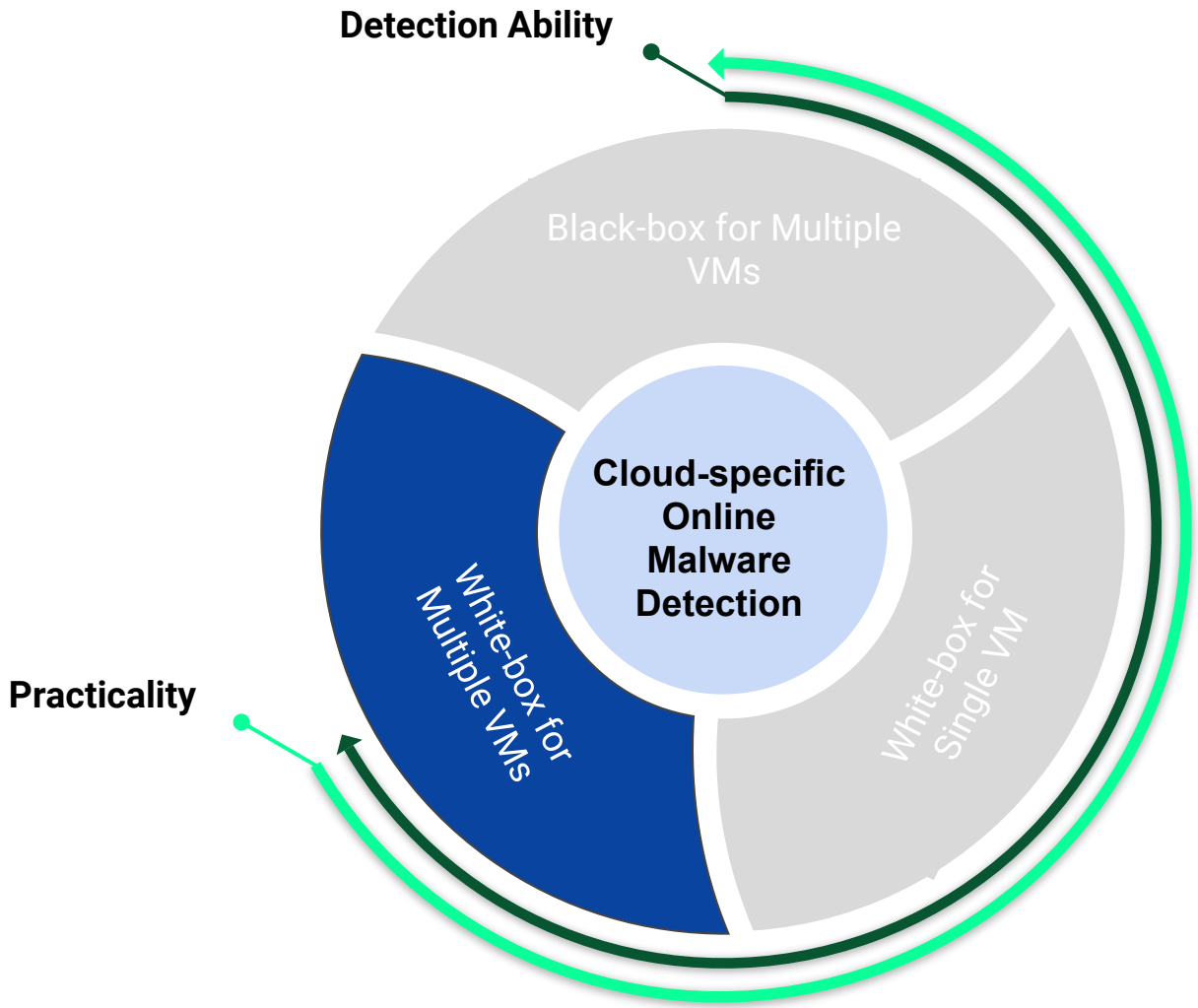


3d CNN



World Leading Research with Real World Impact!

Whitebox for Multiple VMs



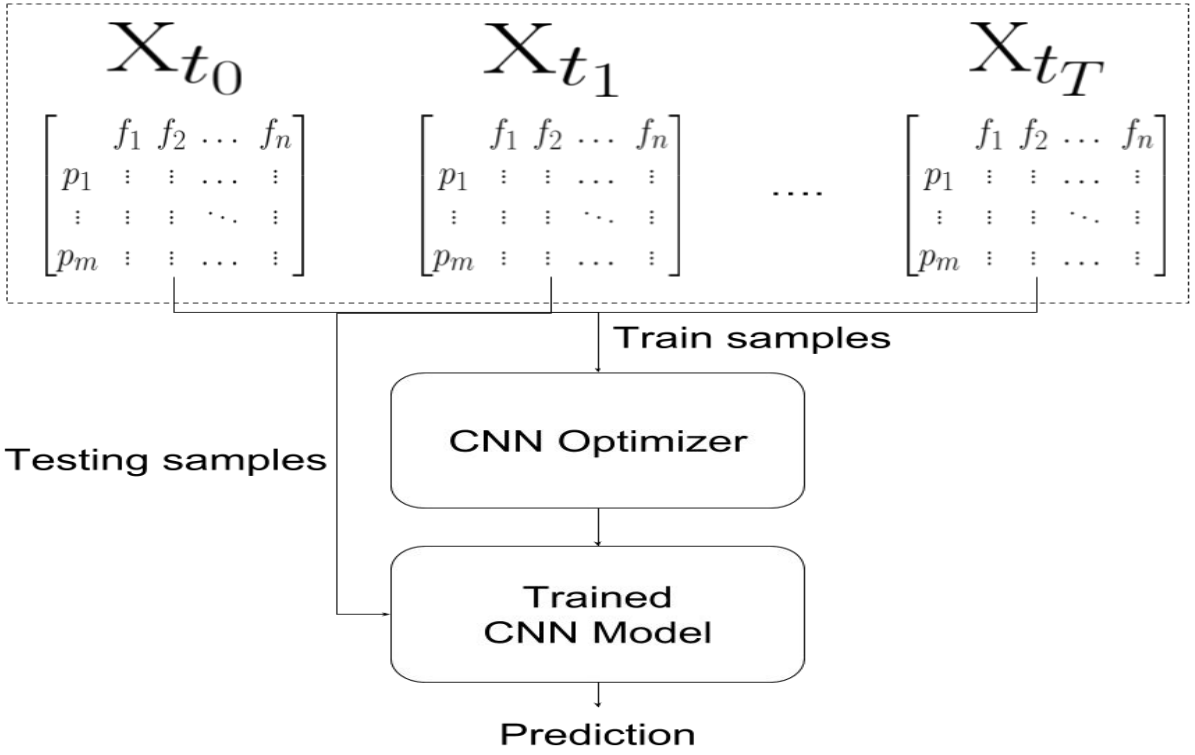
Whitebox Multiple VMs

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

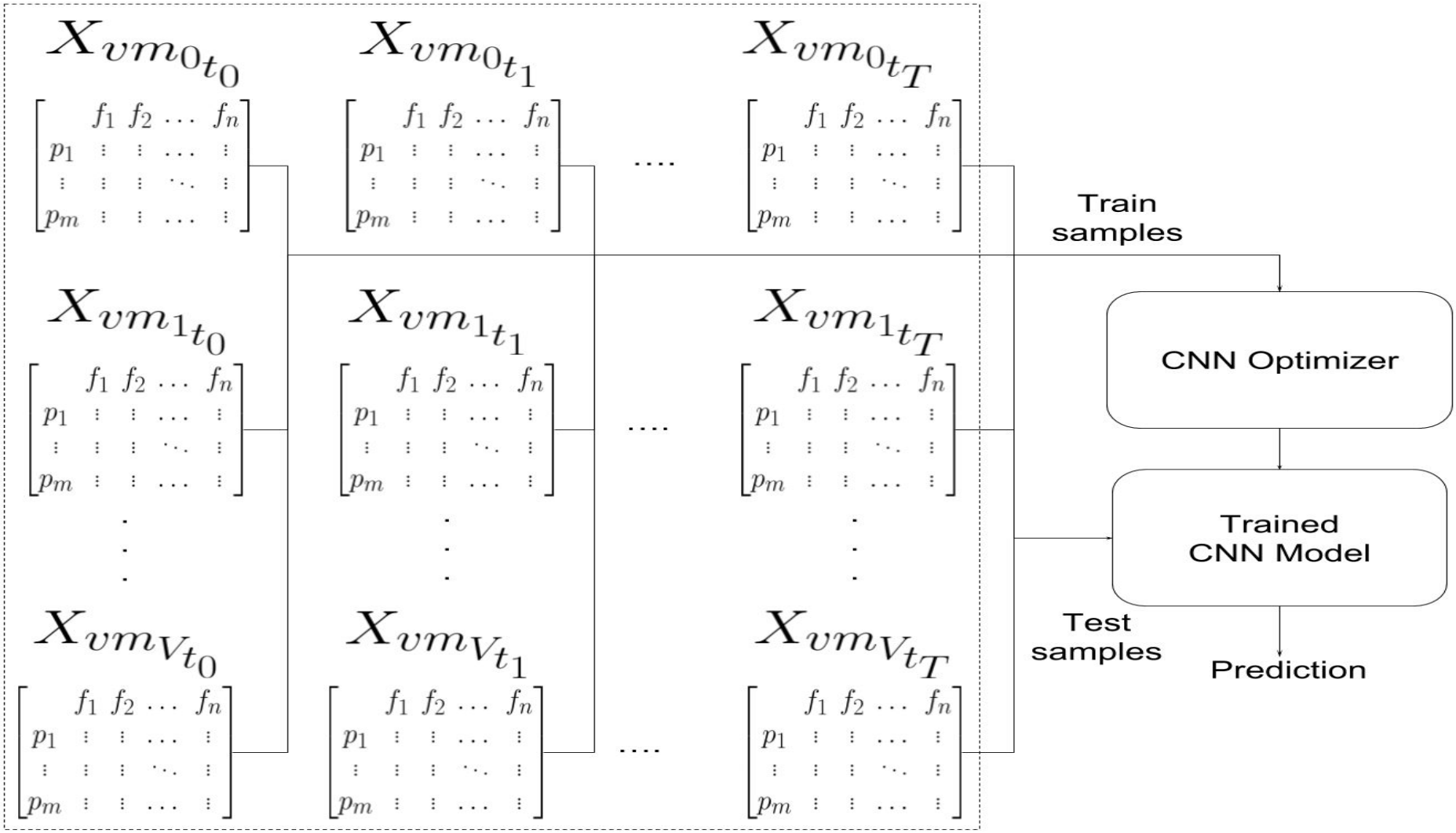
1. Using 2d CNN for multiple VMs.
2. Introducing a novel approach of pairing samples to accommodate for correlations between VMs.

Recall "2d CNN"

Single VMs Single Samples (SVSS)



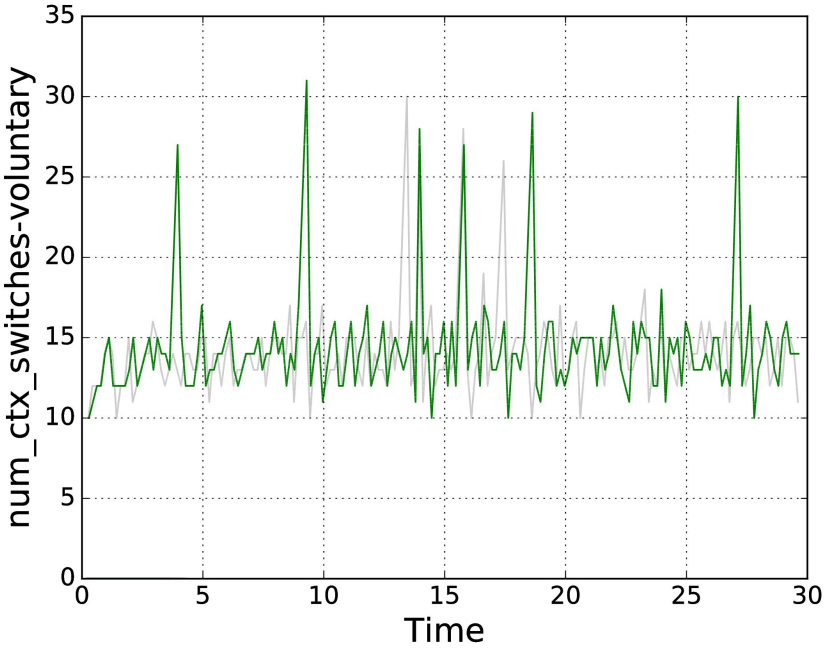
Multiple VMs Single Samples (MVSS)



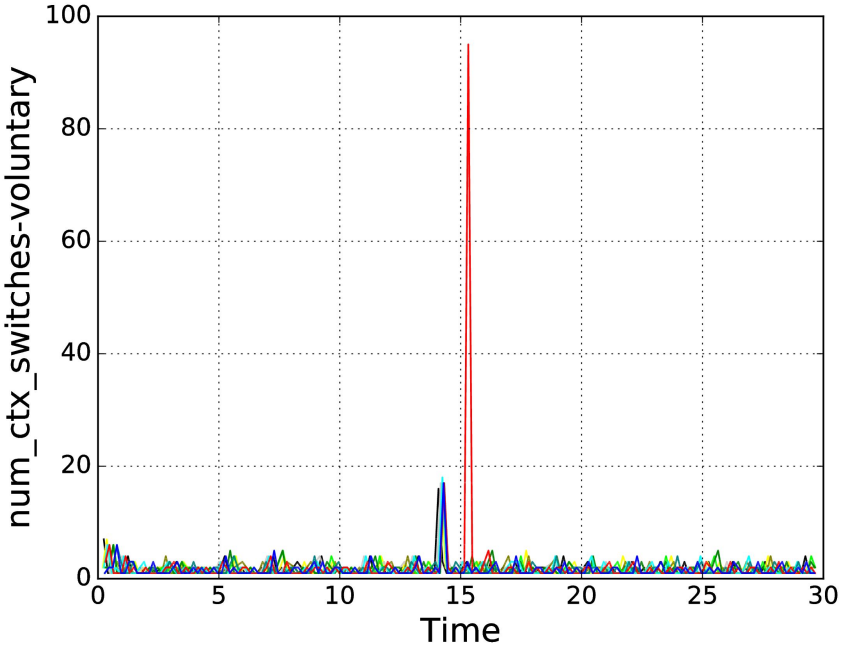
Key Intuition

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

“Correlation between VMs”

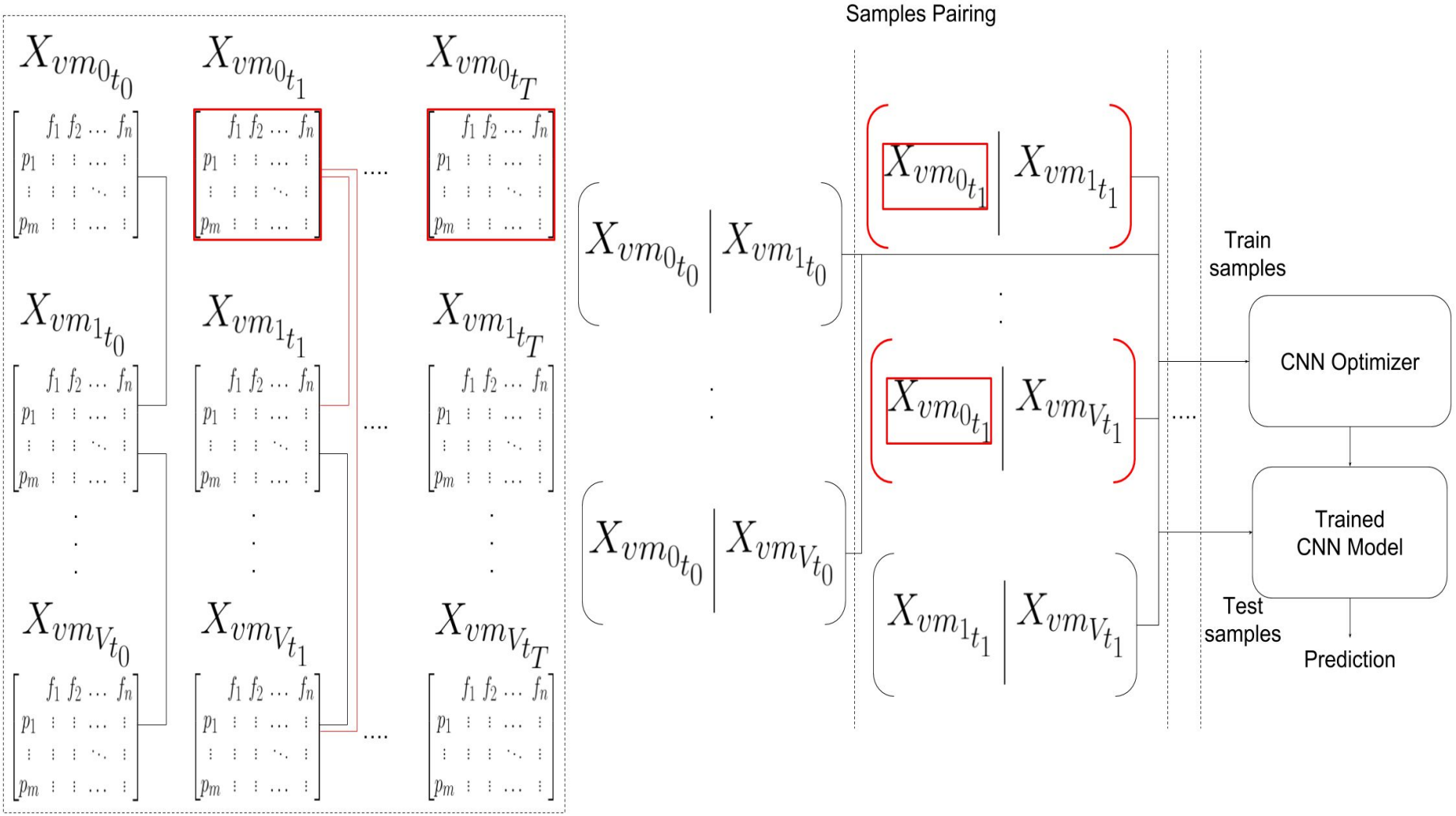


Number of used voluntary context switches over 30 minutes for two different runs of the same unique process



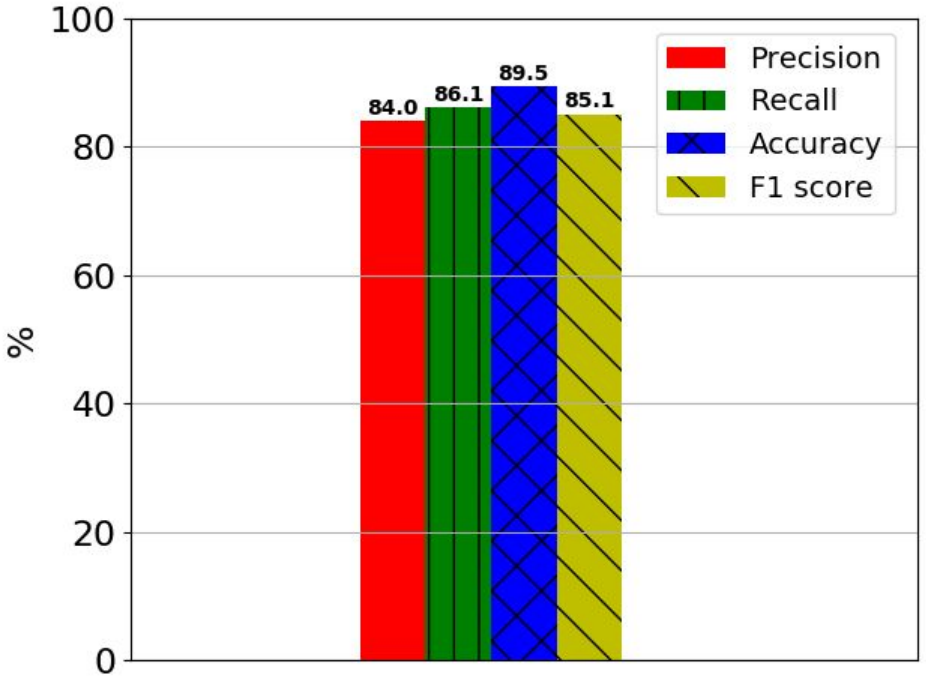
Number of used voluntary context switches over 30 minutes for one run of 10 VMs in an auto-scaling scenario.

Multiple VMs Paired Samples (MVPS)

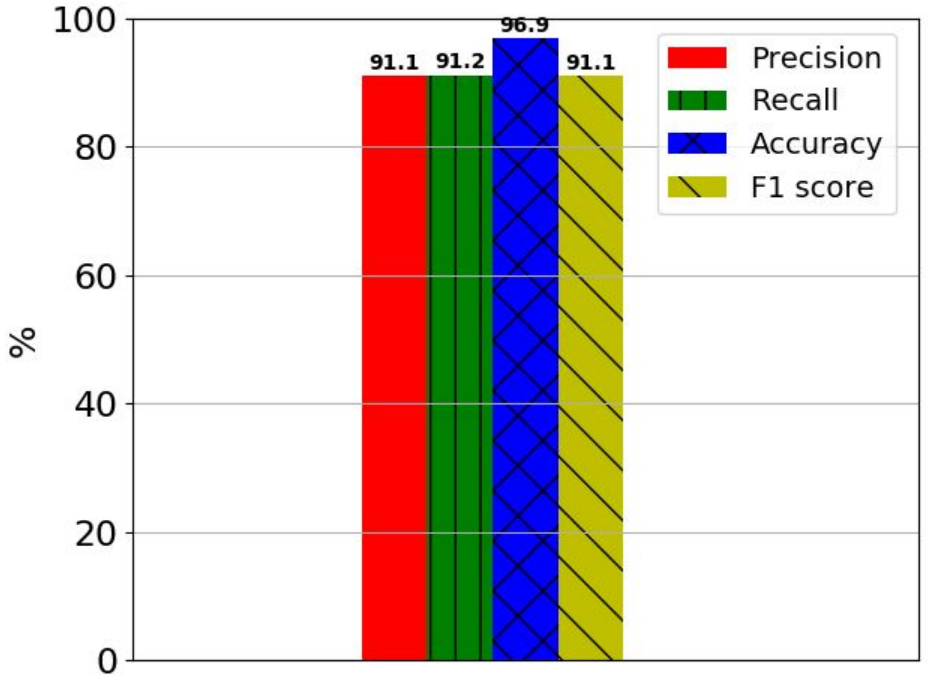


Results

MVSS



MVPS



Conclusion & Future Work

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

In satisfying dissertation objectives:

1. We developed an online anomaly detection system for cloud IaaS that targeted highly-active malware in an auto-scaling scenario.
2. We developed an effective approach for detecting malware using process-level features for low-level malware in a single VM scenario.
3. We developed a pairing samples approach for detecting malware using process-level features that targeted low-level malware in an auto-scaling scenario.

Future Work:

- Applying and testing multiple architectures (e.g., hadoop systems or containers)
- Investigating and leveraging more cloud characteristics for security.

Questions/Comments