Analyzing CNN Based Behavioural Malware Detection Techniques on Cloud IaaS

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Outline

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Who am I?

- Andrew McDole
- Final Semester Masters in Computer Science
- Tennessee Technological University
- Focus in CyberSecurity

Introduction & Motivation

- According to a CISCO report [1], cloud data centers will process 94% of workloads in 2021.
- In a Sophos report [2], 70% of companies suffered a cloud breach in 2019 and 59% of those breaches are from malware or ransomware.
- People may attack data centers for monetary gain, to gather information about customers, or to make use of the data centers resources for nefarious reasons.
- Common attack types: DDoS, Botnets, Rootkits, etc.

Cloud Malware is one of the most prevalent threats!

Introduction & Motivation (cont.)

- Traditional malware detection techniques falls short in detecting new malware
  - Zero-day malware, Polymorphic malware, etc..
- Deep Learning (DL) based malware detection techniques has become more adept in detecting malware.
- Many approaches has been proposed using different DL techniques (CNN, RNN, etc.)

A proper analysis for the effectiveness of state-of-the-art DL techniques tailored specifically for online malware detection in cloud is needed.

- In this paper, we focus on **CNN** using **process performance metrics**.

Related Work

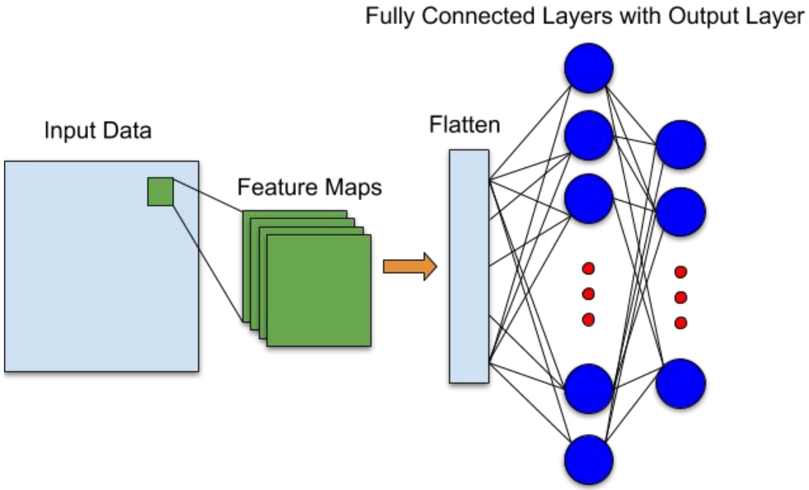
Related Work	Contribution
[3-5]	Focus on collecting API Calls
[6-8]	Focus on collecting System Calls
[9]	Focus on collecting Performance Counters
[10, 11]	Focus on collecting memory features
[3 - 11]	Limited to features that can be collected through the hypervisor
[12]	Utilizes metrics collected on the VM itself
[13]	Introduces a CNN technique to detect malware with a low profile

Our Contribution

Analyzing the effectiveness of applying **state-of-the-art CNN models** for behavioral malware detection using fine-grained light-weight **process performance metrics**.

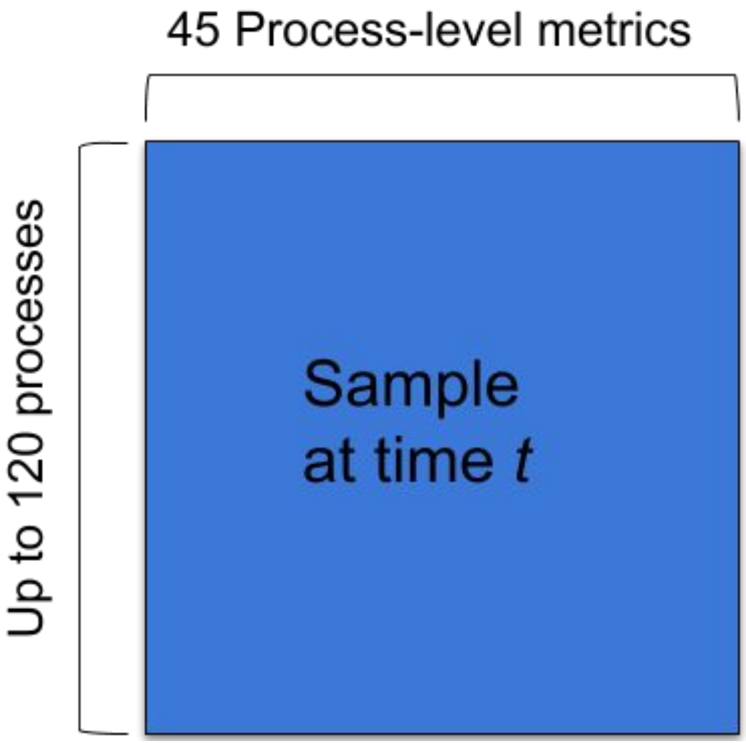
Convolutional Neural Networks

- Work on image data
- Builds spatial relationships between data



Methodology

- Up to 120 unique processes
- 45 process level metrics
- Data was organized into a matrix to represent 2 dimensional data for feeding into a CNN



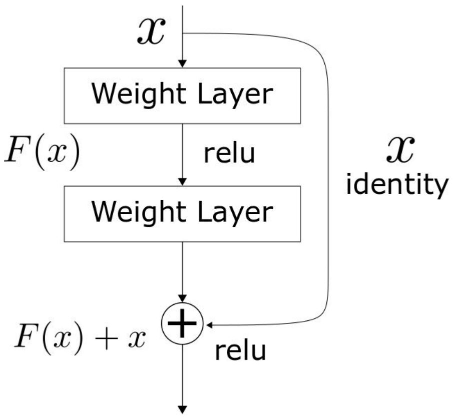
Methodology - Example Sample

Metric	Value	Metric	Value
sample_no	5672254	mem_swap	0
exp_no	23	mem_lib	0
vm_id	178	mem_text	217088
pid	1036	mem_uss	1105920
ppid	1	mem_dirty	0
sample_time	6/6/2018 19:32	mem_shared	3334144
process_creation_time	6/6/2018 19:32	mem_data	585728
status	sleeping	mem_vms	43921408
num_threads	1	mem_rss	3751936
kb_received	0	io_write_bytes	0
kb_sent	0	io_write_chars	76
num_fds	14	io_write_count	9
cpu_children_sys	0	io_read_bytes	958464
cpu_children_user	0	io_read_chars	61088
cpu_user	0.01	io_read_count	77
cpu_sys	0	ctx_switches_involuntary	43
cpu_percent	0	ctx_switches_voluntary	182
cpu_num	0	nice	0
name	dbus-daemon	ionice_ioclass	0
gid_real	111	ionice_value	0
gid_saved	111	label	0
gid_effective	111		

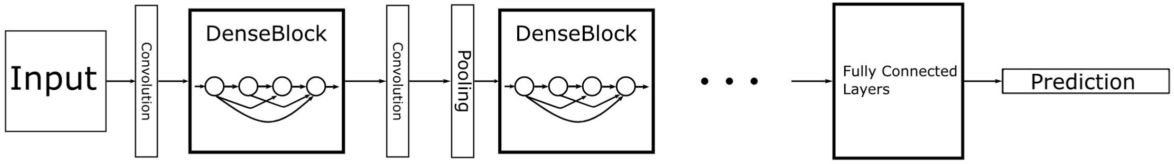
- 45 process-level features collected
- Strings were encoded using one-hot encoding

Methodology - CNN Models Used

- LeNet-5
- ResNet-50
- ResNet-101
- ResNet-152
- DenseNet-121
- DenseNet-169
- DenseNet-201



Residual Block Diagram



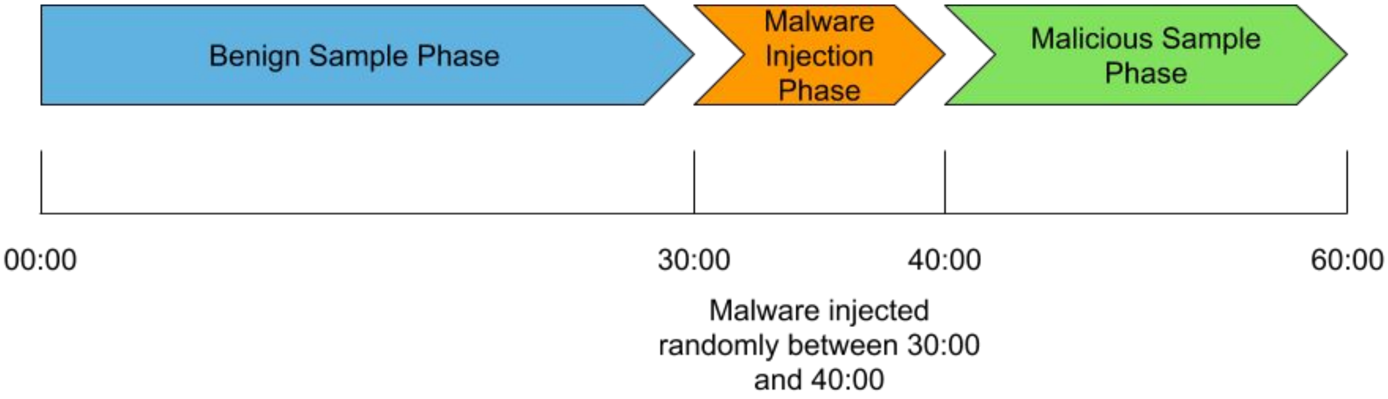
Dense Network

Experimental Setup

- Our work utilized an OpenStack testbed which allowed the malware to freely use the internet.
- This allows the malware to exhibit behavior more closely to the real world.
- Other work that involve a sandboxed environment may inhibit the malware's ability to execute, or the malware could detect the sandbox countermeasures and disable itself.

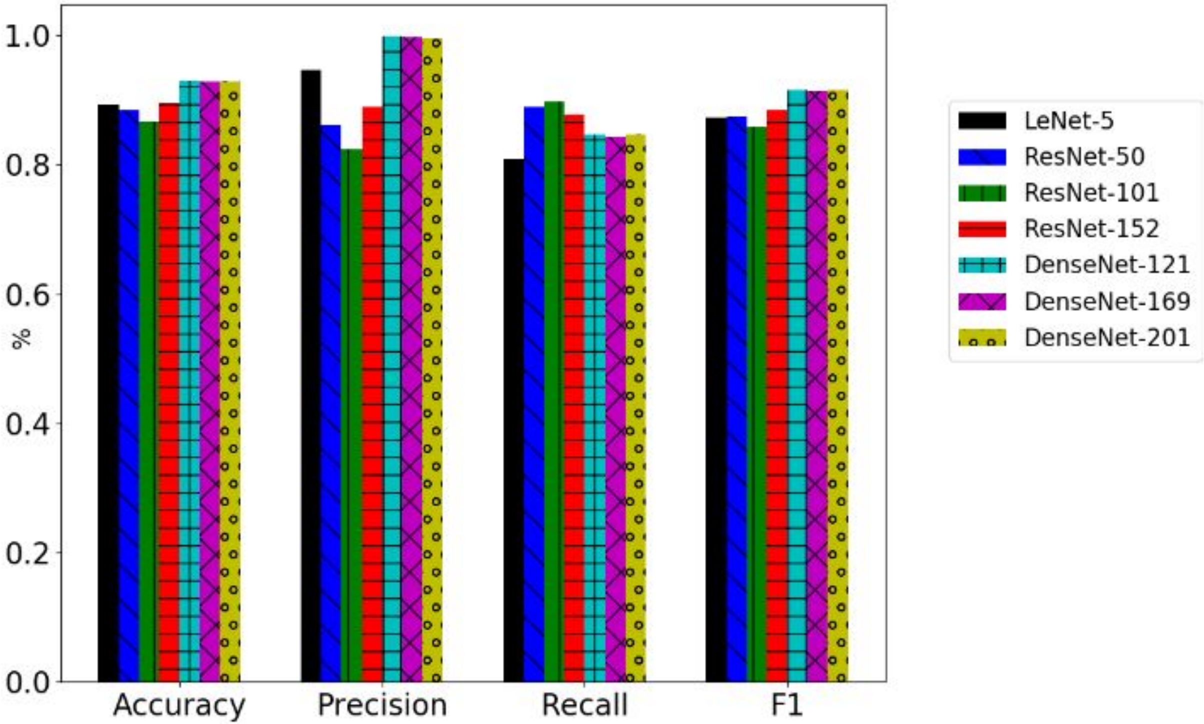
Experimental Setup

- Total runtime 60 minutes per malware
- 30 minutes of benign
- Random injection between minute 30 and 40
- Collect sample every 10 seconds on infected VM



Results

- DenseNets performed the best overall
- ResNets performed the best in Recall



Results

- DenseNet-121 performed well while having a lower time to train than all other deep models

Model	Validation Accuracy	Epoch Reached	Elapsed Time (s)	Detection Time (ms)
LeNet-5	89.9	29	170	54
ResNet-50	90.7	67	1815	96
ResNet-101	87.0	60	2940	130
ResNet-152	88.7	99	7029	165
DenseNet-121	92.1	32	1683	164
DenseNet-169	91.9	81	5848	209
DenseNet-201	91.5	36	3060	249

Future Work

- A future similar analysis of using RNNs which learns temporal dependency can be very useful.
- In the future, we plan to develop more cloud uses cases to yield different data to train on which might require new approaches to effectively detect malware.

Conclusion

- Seven CNN models were compared in performance for malware detection in the cloud.
- LeNet-5 sacrifices accuracy for speed in terms of time to train malware and time to detect malware
- ResNet models have higher recall scores than the other models tested which make them suitable for cases where allowing a false negative is unacceptable.
- DenseNet models performed the best overall with high accuracies, but took longer to train and to detect the malware.
- One limitation of using CNNs is that it does not capture the time correlation of the data samples. This is a result of using 2D CNNs which do not have a temporal dimension.

References

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