Network Intrusion Detection Using Neural Networks on FPGA SoCs

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Introduction

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- Mainstream approaches in intrusion detection do not scale well to the embedded domain, mainly due to computational complexity
- Limited computing power at the nodes, not intended for significant security mechanisms
- More lightweight security mechanisms required, adaptable to updates
- Explore the use Neural Networks as a more lightweight Network Intrusion Detection approach

Intrusion Detection Neural Network

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- NSL-KDD dataset:
  - Used 29 of the 41 features of each record (3 in categorical form)
  - 110 inputs after one-hot encoding
- Trained a NN with 110-21-2, similar to that in [1], with Tensorflow [2]
- Obtaining at best:
  - **96.02%** accuracy on the train set
  - **80.52%** accuracy on the test set

Test set classification results

Predicted Class	Actual Class	
	Normal	Malicious
Normal	9257	3937
Malicious	454	8896

HLS Implementation

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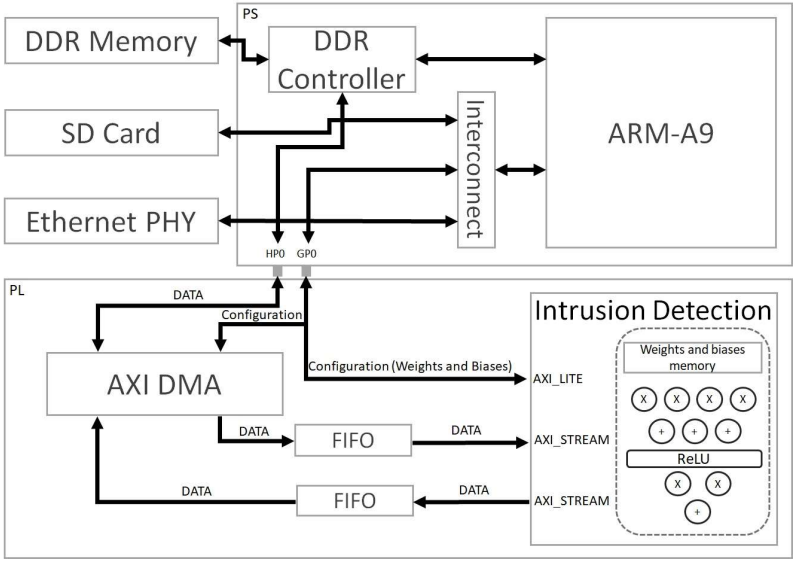
- Vivado High Level Synthesis 2016.4, targeting a Xilinx Zynq Z-7020
  - Use of memories as Look-Up-Tables, inputs restored to 29
  - Use of floating point IEEE-754 to support coefficient updates
  - Configurable weights and biases through AXI-Lite (2375) : **2.3ms**
  - Resource utilization:

	LUTs	FFs	DSPs	BRAM
Utilized	26463	56478	111	88
Available	53200	106400	220	280
% Utilization	50	53	50	31

  - Timing results:

Frequency (MHz)	Latency (Clock Cycles)	Initiation Interval (Clock Cycles)
76	237	29

FPGA System-Implemented System



- Execution time-Test set:

Arm-A9 [a] @667MHz	Arm-A9 [b] @667MHz	Accelerator [b] @76MHz	Idhammad et al. [3] (normalized)
4751.440ms	1458.1ms	9.018ms	240.136ms

[a] Unoptimised, 110 inputs.
[b] Optimised, Look-Up-Table.

- Detection rate (IPv4 min-576B):

Transfer Rate (Packets/Second)	Platform	Latency (µs)	Detection Rate (Packets/Classification)
1Gbps (217,014)	Arm-A9	64.678	14.036
	Accel	0.4	0.0868
10Gbps (2,170,139)	Arm-A9	64.678	140.360
	Accel	0.4	0.8680

Conclusion

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- Network Intrusion Detection NN with moderate complexity
- Flexible accelerator that adapts to newly trained weights dynamically
- Offers fast detection rate, within a single packet

Future work

- Explore different and alternative network topologies
- Extend our approach to other datasets
- Explore approaches that reduce latency

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References

[1] B. Ingre and A. Yadav. Performance analysis of NSL-KDD dataset using ANN. In Proc. International Conference on Signal Processing and Communication Engineering Systems, pages 92–96, 2015.

[2] Martin Abadi et al. TensorFlow: Large-scale machine learning on heterogeneous systems, 2015.

[3] M. Idhammad, K. Afdel, and M. Belouch, “DoS detection method based on artificial neural networks,” International Journal of Advanced Computer Science and Applications, vol. 8, no. 4, 2017.

[4] Mahbod Tavallaee, Ebrahim Bagheri, Wei Lu, and Ali A. Ghorbani. A detailed analysis of the KDD CUP 99 data set. In Proc. IEEE International Conference on Computational Intelligence for Security and Defense Applications, pages 53–58, 2009.