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Privacy-friendly machine learning algorithms for intrusion detection systems supervisor: Pr. dr. ir. Bart Preneel

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0 – Outline 2/26

- Introduction
- Intrusion detection systems
- Multiparty computation
- Methodology
- Conclusion

1 – Outline 3/26

- Introduction
- 2 Intrusion detection systems
- Multiparty computation
- 4 Methodology
- Conclusion

- As computers are used more and more (including for sensible data), and the connection between them increases as well, there is a constant need for better intrusion detection systems.
- Machine learning algorithms can increase performance of a lot of existing applications, but they need a significant dataset.
- The amount of data increases as well, but remains sensible in the case of intrusion detection systems, hence the need for encryption.



Privacy-friendly data pooling for enhancing intrusion detection systems



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Different types, based on where the intrusion takes place

- Network Intrusion Detection System (NIDS)
- Host Intrusion Detection System (HIDS)
- Hybrid Intrusion Detection System

Different detection methods

- Signature based
 - Advantages: accuracy and time
 - Disadvantages: only known intrusion types are detected
- Anomaly based
 - Advantages: new intrusion types can be detected
 - Disadvantages: malicious activity disguised as normal traffic can pass through
- Machine learning (classification)

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Different types, based on where the intrusion takes place

- Network Intrusion Detection System (NIDS)
 - Advantages: detects attack before it occurs
 - Disadvantages: needs to be implemented on the network
 - Host Intrusion Detection System (HIDS)
 - Advantages: collects broader data type
 - Disadvantages: needs to be implemented on each machine and only detects after the intrusion
 - Hybrid Intrusion Detection System
 - Advantages: much more effective
 - Disadvantages: huge implementation necessary, not privacy-friendly

Privacy-friendly data pooling for machine learning network intrusion detection system



3 – Outline 10/26

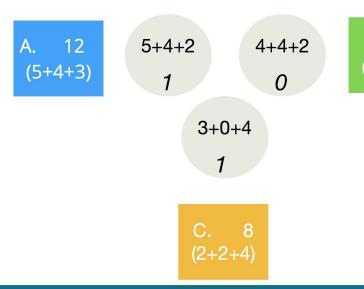
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Addition over \mathbb{Z}_2

- i players have each a secret number n_i
- they want to know if the sum of their numbers is even or uneven. $\Sigma n_i \mod 2 = 0$ or 1 ?
- they don't want anybody except them to know their number

Solution

- ullet each players divides its number n_i into j $m_{i,j}$ parts. $\Sigma m_{i,j} = n_i$
- j players each receive the $m_{i,j}$ -part of each i players, sums it up and say if it is even or not. $\Sigma_i m_{i,j} \mod 2 = 0$ or 1.
- the results of all j players is then summed up and is even if $\Sigma n_i \mod 2 = 0$ and uneven otherwise. The problem is resolved.



B. 7 (4+3+0)

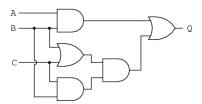
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Garbled

- Boolean circuit
- Based on OT
- Constant number of rounds

Arithmetic

- Based on somewhat homomorphic encryption (SHE)
- Allows for addition and multiplication



- The receiver doesn't get any information on the strings he didn't recieve
- The sender doesn't know which string was asked

Alice		Bob			
$(E.n) \& x_0, x_1$	$\xrightarrow{N,e,x_0,x_1}$	$b \in \{0,1\}$ $v = (x_b - k^e) \bmod N$			
	<i>v</i>				
$k_0 = (v - x_0)^d \mod N$ $k_1 = (v - x_1)^d \mod N$					
$m'_0 = m_0 + k_0$ $m'_1 = m_1 + k_1$	$\xrightarrow{m_0',m_1'}$	$m_b = m_b' - k$			

g	e	output $g \wedge e$		garbled output		permuted garbled output
0	0	0		$Enc(H(W^0_G,W^0_E),0)$		$Enc(H(W^0_G,W^1_E),0)$
0	1	0	\Rightarrow	$Enc(H(W^0_G,W^1_E),0)$	\Rightarrow	$Enc(H(W^1_G,W^1_E),1)$
1	0	0		$Enc(H(W^1_G,W^0_E),0)$		$Enc(H(W^0_G,W^0_E),0)$
1	1	1		$Enc(H(W^1_G,W^1_E),1)$		$Enc(H(W^1_G,W^0_E),0)$

 $\bf Fig.\,1.$ The garbling of an AND gate

Different leads

- Fairplay (boolean, n-party)
- BMR (boolean, n-party)
- Sharemind (3-party, proprietary)
- VIFF (obsolete)
- ABY (2-party)
- SPDZ (artihmetic, n-party)

Privacy-friendly collaborative network intrusion detection system



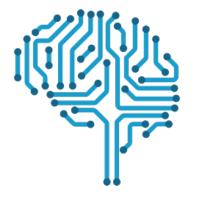
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Datasets

- KDD CUP '99
- AWID
- PCAP
- UNB ISCX
- CSIC 2010 HTTP Dataset
- West Point NSA DataSet





Current research algorithms

- Semi-supervised learning algorithms with fuzziness
- K-Nearest Neighbors
- Support Vector Machines
- Bayes Classifier
- EM-Clustering
- Genetic algorithms
- Classification Tree

- Build on existing application (e.g. Bro Network Security Monitor, OpenNMS,...), in the form of a plug-in.
- Feed with constant new data, provided from other analysis tools
- User-friendly
- Off-line



4 - Agenda 22/26



- Begin March: Benchmark and designing working machine-learning algorithm
- Begin April: Design of final algorithm including MPC
- Begin May: Prototyping as a plug-in
- Begin June: Poster and report

5 – Outline 23/26

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5 – References 24/26

- D. Catalano, R. Cramer, G. D. Crescenzo, I. Darmgård, D. Pointcheval, and T. Takagi, Contemporary Cryptology. Birkhäuser Basel, 2005.
- [2] A. R. B. S. P. F. Atmaja Sahasrabuddhe, Sonali Naikade, "Survey on intrusion detection system using data mining techniques," *International Research Journal of Engineering and Technology (IRJET)*, may 2017.

5 – Conclusion 25/26

Further optimizations

- Hybrid Intrusion Detection Systems
- Speed and complexity optimizations (research on HE)
- Deep learning



5 – Questions? 26/26



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