## February 9, 2021 Intrusion Protection



- Changes
  - Syllabus
- Today
  - Authentication
  - Security Orchestration
  - Intrusion Detection
- Assignments
  - Lab 1: Due Monday, Feb 22
  - Project
    - Topic Due: Monday, Feb 22

#### Authentication

- Passwords
  - Internal (imbedded in code)
  - External (user)
- Other approaches?

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A fit out to ENV file

-environment variables

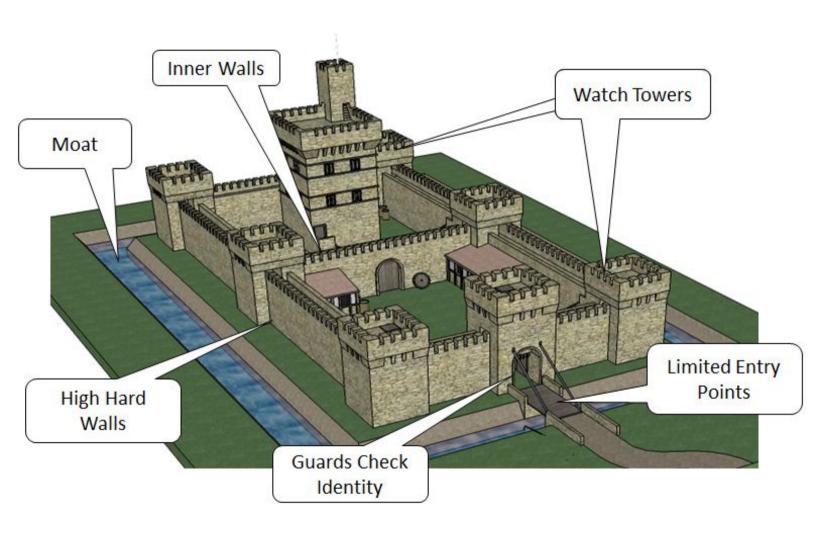
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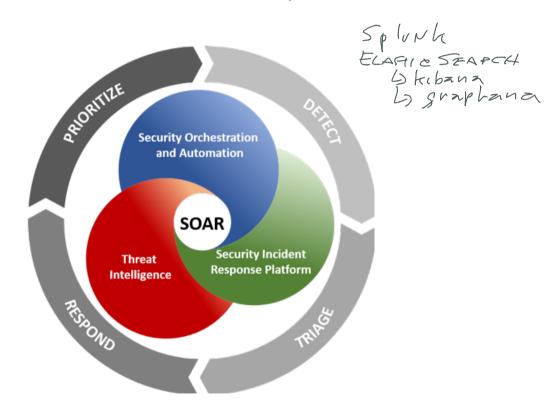
CERTIFICATER
```

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FINDUL SECURITY EXPOSITES
- SOURCE CODE SCANNITC
- PEN TEMINO TOOLS

PEN OPS
- DEVOLUTIONS
- AUTOMATION
```



## Security Orchestration, Automation and Response (SOAR)



# Network Intrusion Detection Systems (NIDSs)

- Authorized eavesdropper that listens in on network traffic
- Makes determination whether traffic contains malware
  - usually compares payload to virus/worm signatures
  - usually looks at only incoming traffic
- If malware is detected, IDS somehow raises an alert
- Intrusion detection is a classification problem

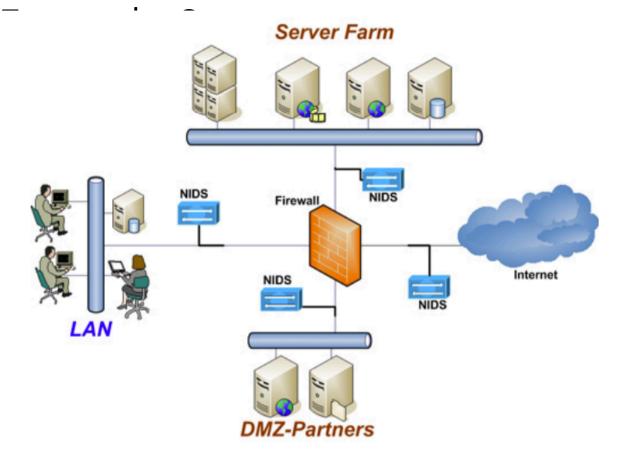
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ALTERNATIVE 15
PECRESSIAN Problem
```

## Host Intrusion Detection Systems (HIDSs)

- Intrusion detection that takes place on a single host system.
- Agent monitors and reports on
  - system configuration
  - application activity
- log analysis, event correlation, integrity checking, policy enforcement, rootkit detection, and alerting<sup>1</sup>. They often also have the ability to baseline a host system to detect variations in system configuration. In specific vendor implementations these HIDS agents also allow connectivity to other security systems.

#### HIDS and Antivirus

- Are they the same? HIDS IS & SUPYUSE PAUL OF HIDS
- Do they have overlap?



### Detection via Signatures

- Signature checking: does packet match some signature?
  - Payload, e.g., shellcode
  - Header, e.g., SYN
- Problem: not so great for zero-day attacks -- Q: WHY?

```
- NORMAC PATTERUS OF ACTURTY
```

## Detection via Machine Learning

- Underlying assumption:
  - Malware will look different from non-malware
  - Anomaly in traffic will look different than regular traffic
- Supervised Learning:
  - IDS requires learning phase in which operator provides preclassified training data to learn patterns
  - Sometimes called anomaly detection (systems)
  - {good, 80, "GET", "/", "Firefox"}
  - {bad, 80, "POST", "/php-shell.php?cmd='rm -rf /", "Evil Browser"}
  - ML technique builds model for classifying never-before-seen packets
  - Problem: is new malware going to look like training malware?

#### Metrics

- True positives (TP): number of correct classifications of malware/anomaly
- True negatives (TN): number of correct classifications of non-malware/regular
- False positives (FP): number of incorrect classifications of non-malware as malware/anomaly
- False negatives (FN): number of incorrect classifications of malware as non-malware/regular

#### Metrics

False positive rate:

$$FPR = \frac{FP}{FP+TN} = \frac{\#benign\_marked\_as\_malicious}{\#total\_benign}$$

ative rate:

- True negative rate:
- False negative rate:
- True positive rate:

### Base Rate Fallacy

- Occurs when we assess P(X|Y) without considering prior probability of X and the total probability of Y
- Example:
  - Base rate of malware is 1 packet in a 10,000
  - Intrusion detection system is 99% accurate (given known samples)
    - 1% false positive rate (benign marked as malicious 1% of the time)
    - 1% false negative rate (malicious marked as benign 1% of the time)
  - Packet X is marked by the NIDS as malware. What is the probability that packet X actually is malware?
    - Let's call this the "true alarm rate," because it is the rate at which the raised alarm is actually true.

### Probability and Bayes' Rule

- Pr(x) function, probability of event x
  - Pr(sunny) = .8 (80% of sunny day)
- Pr(x|y), probability of x given y
  - Conditional probability
  - Pr(cavity|toothache) = .6
  - 60% chance of cavity given you have a toothache

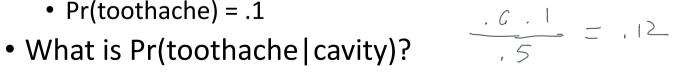
## Probability and Bayes' Rule

Bayes' Rule (of conditional probability):

$$Pr(D|\theta)Pr(D) = Pr(\theta|D) Pr(\theta)$$

$$Pr(D|\theta) = \frac{Pr(\theta|D) Pr(\theta)}{Pr(D)}$$

- Assume:
  - Pr(cavity|toothache) = .6
  - Pr(cavity) = .5
  - Pr(toothache) = .1



#### Base Rate Fallacy

- How do we find a true alarm rate?
   Pr(Is Malware | Marked As Malware)
- We know:
  - 1% false positive rate (benign marked as malicious 1% of the time); True negative rate= 99%
  - 1% false negative rate (malicious marked as benign 1% of the time); True Positive Rate= 99%
  - Base rate of malware is 1 packet in 10,000
- What is?
  - Pr(MarkedAsMalware|IsMalware) = 0.99
  - Pr(IsMalware) = 0.0001
  - Pr(MarkedAsMalware) = 0.01

### Base Rate Fallacy

How do we find the true alarm rate?
 Pr(IsMalware | MarkedAsMalware)

$$\begin{split} Pr(IsMalware|MarkedAsMalware) &= \frac{Pr(MarkedAsMalware|IsMalware) \cdot Pr(IsMalware)}{Pr(MarkedAsMalware)} \\ &= \frac{0.99 \cdot 0.0001}{0.01} = 0.0099 \end{split}$$

- Therefore, only about 1% of alarms are actually malware!
  - What does this mean for network administrators?

### Base Rate Fallacy Summary

- Let Pr(M) be the probability that a packet is actually malware (thebaserate)
- Let Pr(A) be the probability that the IDS raises an alarm (unknown)
- Assume we also know for the IDS
  - Pr(A|M)=TPR=1-FNR
  - Pr(A|!M)=FPR

• 
$$Pr(M|A) = \frac{Pr(A|M) \cdot Pr(M)}{Pr(A|M) \cdot Pr(M) + Pr(A|M) \cdot Pr(M)}$$

## Where is Anomaly Detection useful?

System	Intrusion Density P(M)	Detector Alarm Pr(A)	Detector Accuracy Pr(A M)	True Alarm P(M A)	
Α	0.1	0.38	0.65	0.171	
В	0.001	0.01098	0.99	0.090164	<
С	0.1	0.108	0.99	0.911667	
D	0.00001	0.00002	0.99999	0.5	

#### Problems with IDSs

- VERY difficult to get both good recall and precision
- Malware comes in small packages
- Looking for one packet in a million (billion? trillion?)
- If insufficiently sensitive, IDS will miss this packet (low recall)
- If overly sensitive, too many alerts will be raised (low precision)

#### Snort

- Open source IDS
- Signature detection
- Lots of available rulesets

