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Detection State Machine
Redirection
Anomaly Detection
Embedding and Similarity Measures
Anomaly Score
Implementation
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An Architecture for Inline Anomaly Detection

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Outline

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5 Implementation

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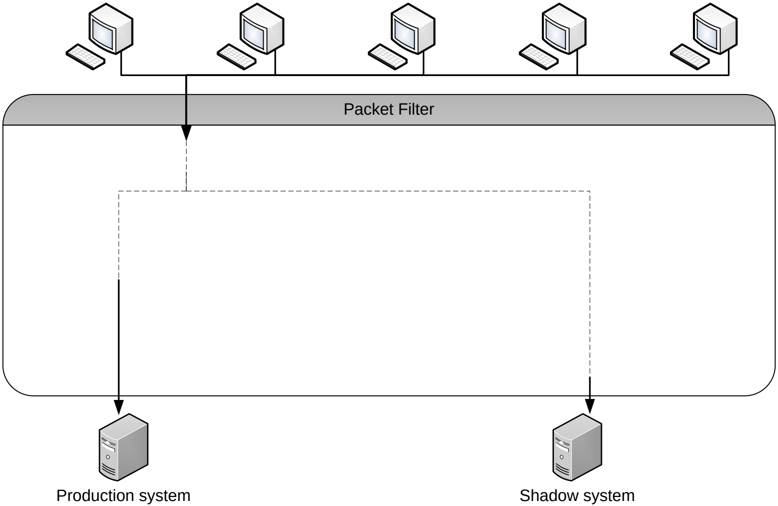
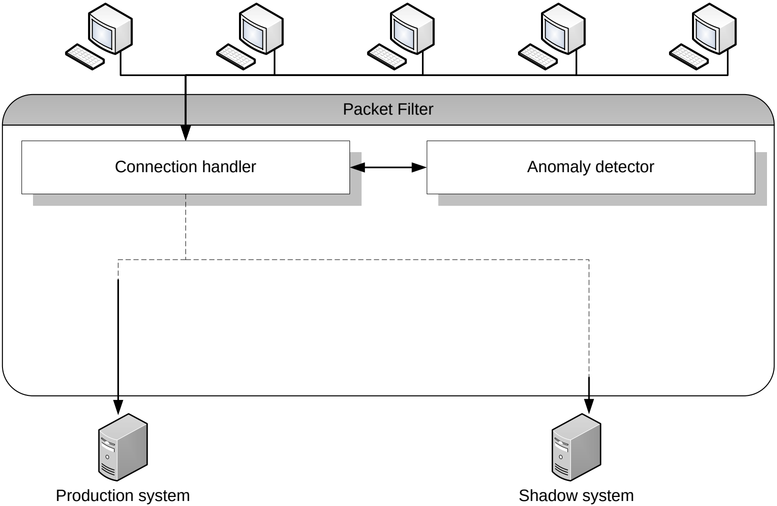
Overview

- **Goal**: exploit anomaly detection in an *inline* intrusion prevention system:
  - ... with an *application-independent* architecture
  - ... where decision-making is performed at the *network layer*
  - ... where anomaly detection runs at the *application layer*
- Inline defense policies
  1. forwarding to a production system
  2. redirection to a hardened system (*shadow system*)
  3. redirection to a monitored network sink (*forensic sink*)

System Architecture



System Architecture



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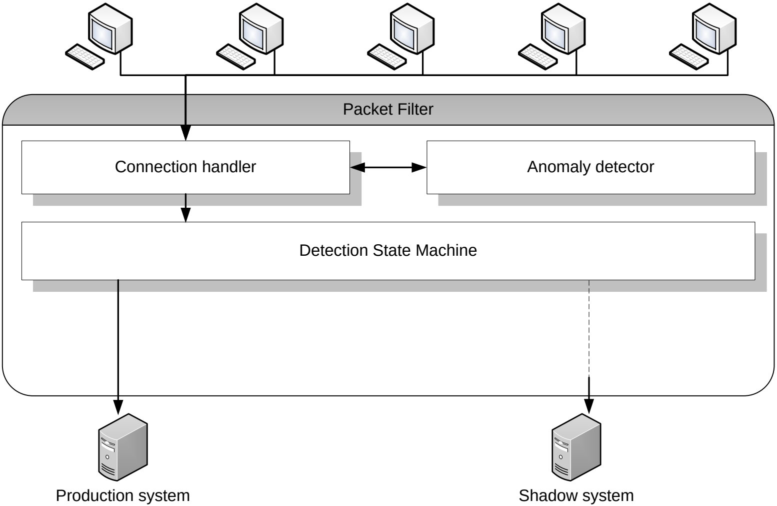
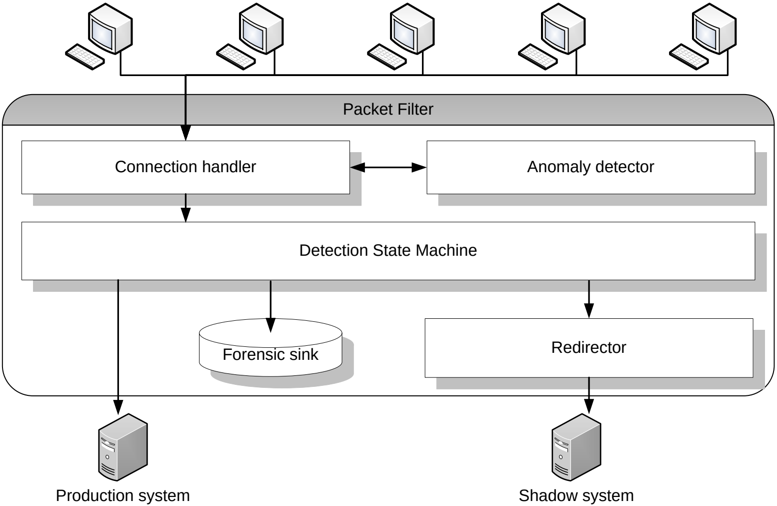
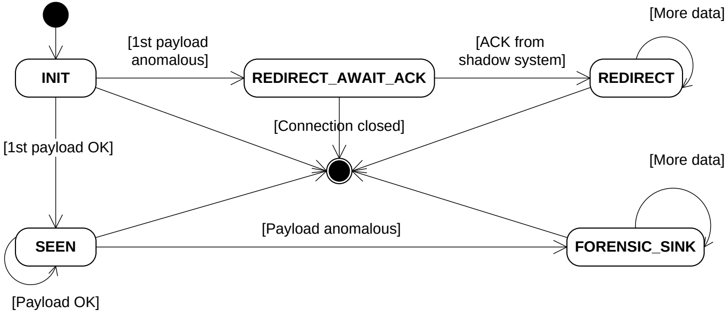


System Architecture

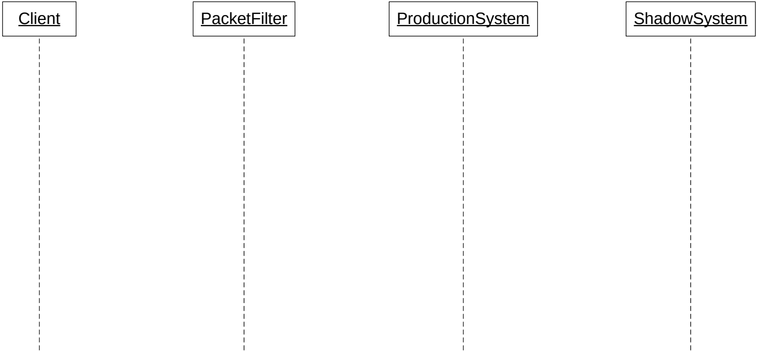


Detection State Machine



- Each connection has a detection state
- Each detection state triggers specific action for each packet of the connection

Redirection



- Memorize difference in the sequence numbers (here $d = z - y$)
- Adjust corresponding sequence / ACK numbers of packets

Redirection

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Tammo Krueger

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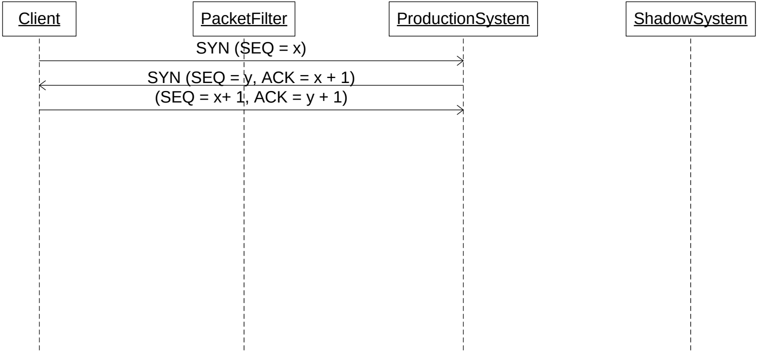

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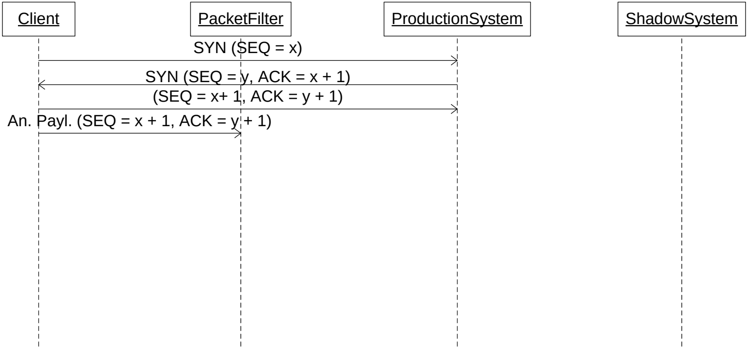

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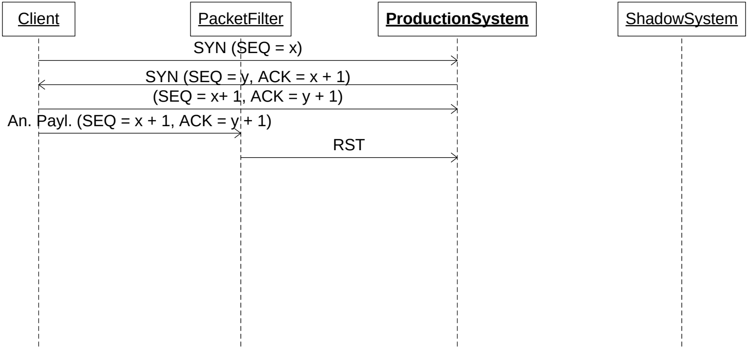

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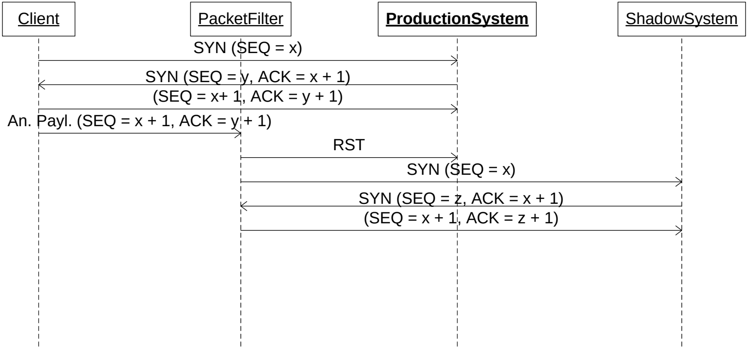

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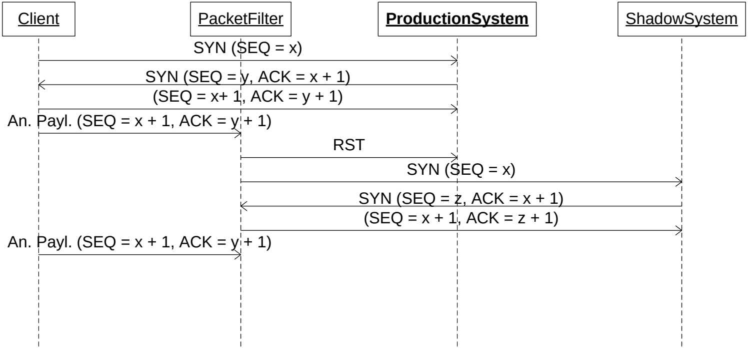

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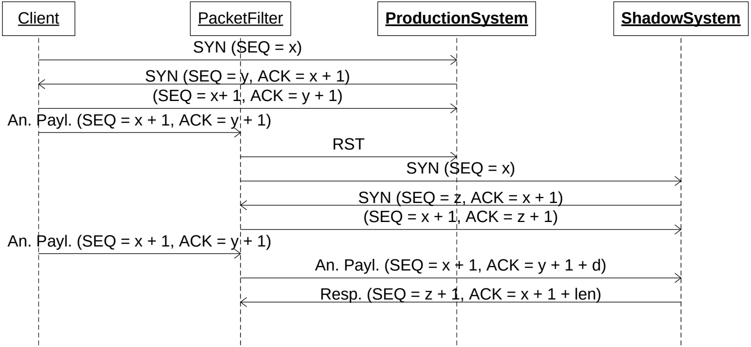

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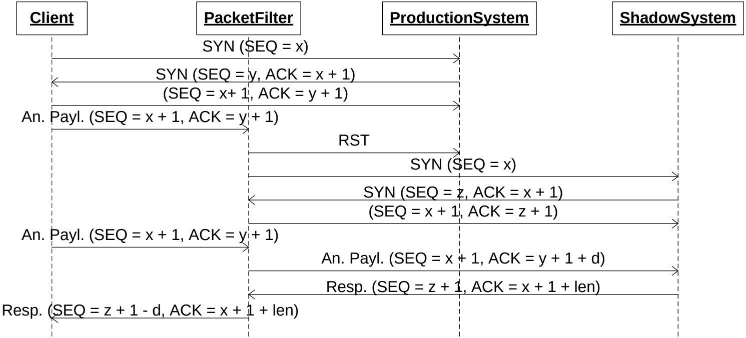

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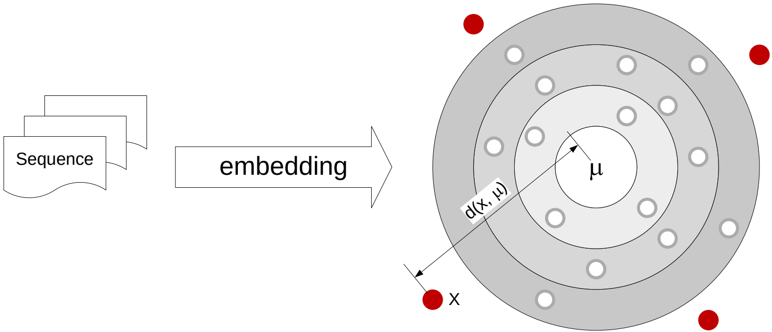
Anomaly Detection – Overview



- Idea: An anomaly is a *deviation* from a model of *normality*
- Implementation:
  1. Embed data in *vector space* via embedding function
  2. Learn the center μ of the data as a model of normality
  3. Anomaly score for new data point is distance to μ

Embedding and Similarity Measures

- Given the set of all possible n-grams over byte sequences $S = \{0, \ldots, 255\}^n$, we define the embedding function ϕ as

$$\phi(x) = (\phi_s(x))_{s \in S} \in \mathbb{R}^{|S|} \quad \text{with} \quad \phi_s(x) = \#_s(x)$$

- Example ($n = 3$):

$$\phi('Hello') = (0, \ldots, \overset{Hel}{\frac{1}{3}}, \overset{ell}{\frac{1}{3}}, \overset{llo}{\frac{1}{3}}, \ldots, 0)^T \in \mathbb{R}^{16777216}$$

- With embedding function we can define distances between byte sequences, for instance Euclidean distance:

$$d(x, z) = \|\phi(x) - \phi(z)\|_2 = \sqrt{\sum_{s \in S} |\phi_s(x) - \phi_s(z)|^2}$$

Anomaly Score

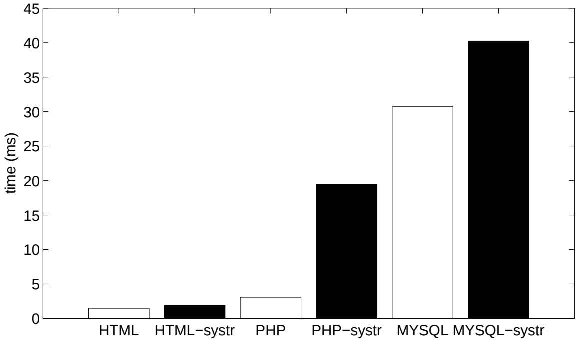
1. *Training:* collect normal data packets $X = \{x_1, \ldots, x_n\}$ and compute their mean $\mu = \frac{1}{n}\sum_{i=1}^{n} \phi(x_i)$.
2. *Validation:*
   1. collect an independent set of normal packets $\tilde{X} = \{\tilde{x}_1, \ldots, \tilde{x}_m\}$
   2. pre-define a false-positive rate ν
   3. determine anomaly threshold t_a so that the ratio of packets $\tilde{x}_i$ for which $d(\mu, \tilde{x}_i) > t_a$ is smaller than ν
3. *Deployment*: for each incoming packet y, compute the anomaly score:

$$\text{score}(y) = \begin{cases} \text{normal}, & \text{if } d(\mu, y) \leq t_a \\ \text{anomaly}, & \text{otherwise} \end{cases}$$

Implementation Details

- Mechanism for performing *inline* anomaly detection:
  - `netfilter` linux firewall
  - `libnetfilter_queue` for queueing packets to user space
- `libnet` for packet creation and delivery in the redirection mechanism
- Prototype deployed on recent `Debian` system acting as a central router between client system and the production / shadow system
- Client system: `Apache Flood`
- Production system: `OpenBSD Apache` server
- Shadow system: `OpenBSD Apache` server with `Systrace`
- Everything hosted on `VMware ESX Server 3`

Experiments – Impact of Instrumentation



Different scenarios:

HTML returns just a static HTML page

PHP returns a dynamic, PHP generated page

MYSQL returns a dynamic, PHP generated page with values read from a MYSQL database.

Experiments – Packet Filter Actions

Type	normal	anomaly	sink	red-1st	red-next
HTML	1.47	2.05	1.64	235.63	1.62
PHP	3.08	3.59	3.36	238.25	3.13
MYSQL	30.71	31.09	30.72	242.32	30.75

Packet filter action scenarios:

anomaly the distance of each packet to a centroid is calculated and compared to t_a

sink each packet is logged to the forensic sink

red-1st each connection is redirected

red-next translation of sequence numbers, addresses and ports for redirection of subsequent packets

Experiments – Evaluation Dataset

- Normal data from incoming HTTP traffic of our institute:
  - 150k unsanitized connections (totaling to roughly 240k packets) of 10 consecutive days
  - Split into three equal parts of 50k connections each for training, validation and testing
- Attack Data:
  - 100 instances (470 connections totaling to 2960 packets) of recent exploits in the `Metasploit` framework
  - `Nessus` HTTP scans
- Evaluation criterion: $AUC_{0.01}$(area under ROC-curve with false positive rate ≤ 0.01)

Experiments – Accuracy I

- Results on test dataset:
  - 3102 ($\sim 0.05\%$) packets with payload are redirected
  - 111 ($\sim 0.001\%$) packets with payload are logged to the forensic sink
  - 58,369 packets with payload are processed as normal
- Ratios for the evaluation of the system:

$$\text{broken} = \frac{\#\ \text{normal conn. in SINK}}{\#\ \text{all normal conn.}} = 0.0008$$

$$\text{jailed} = \frac{\#\ \text{attack conn. in REDIRECT}}{\#\ \text{all attack conn.}} = 0.9760$$

Experiments – Accuracy II

Type	True positive rate	False positive rate
plain AD	0.9939 ± 0.0030	0.0092 ± 0.0105
AD with redirect	0.9952 ± 0.0022	0.0017 ± 0.0009

- Comparison against "plain anomaly detector", i.e. system without the REDIRECT/SINK extension
- Improves both true positive and false positive rate

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Conclusions

- *Inline* intrusion prevention system which
  - ... is *application-independent*
  - ... decides at the *network layer*
  - ... performs anomaly detection at the *application layer*
- Minor performance impact ($\leq$ 0.5 ms per packet)
- System significantly improves both true positive and false positive rate
- Limitation: requires synchronization

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Questions? Remarks?

Thanks for your attention!

Evaluation guideline

Target	Normal Traffic	Attack Traffic
REDIRECT	True neg.	True pos.
SINK	False pos.	True pos.