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Machine Learning Based Intrusion Detection System for IoT Network

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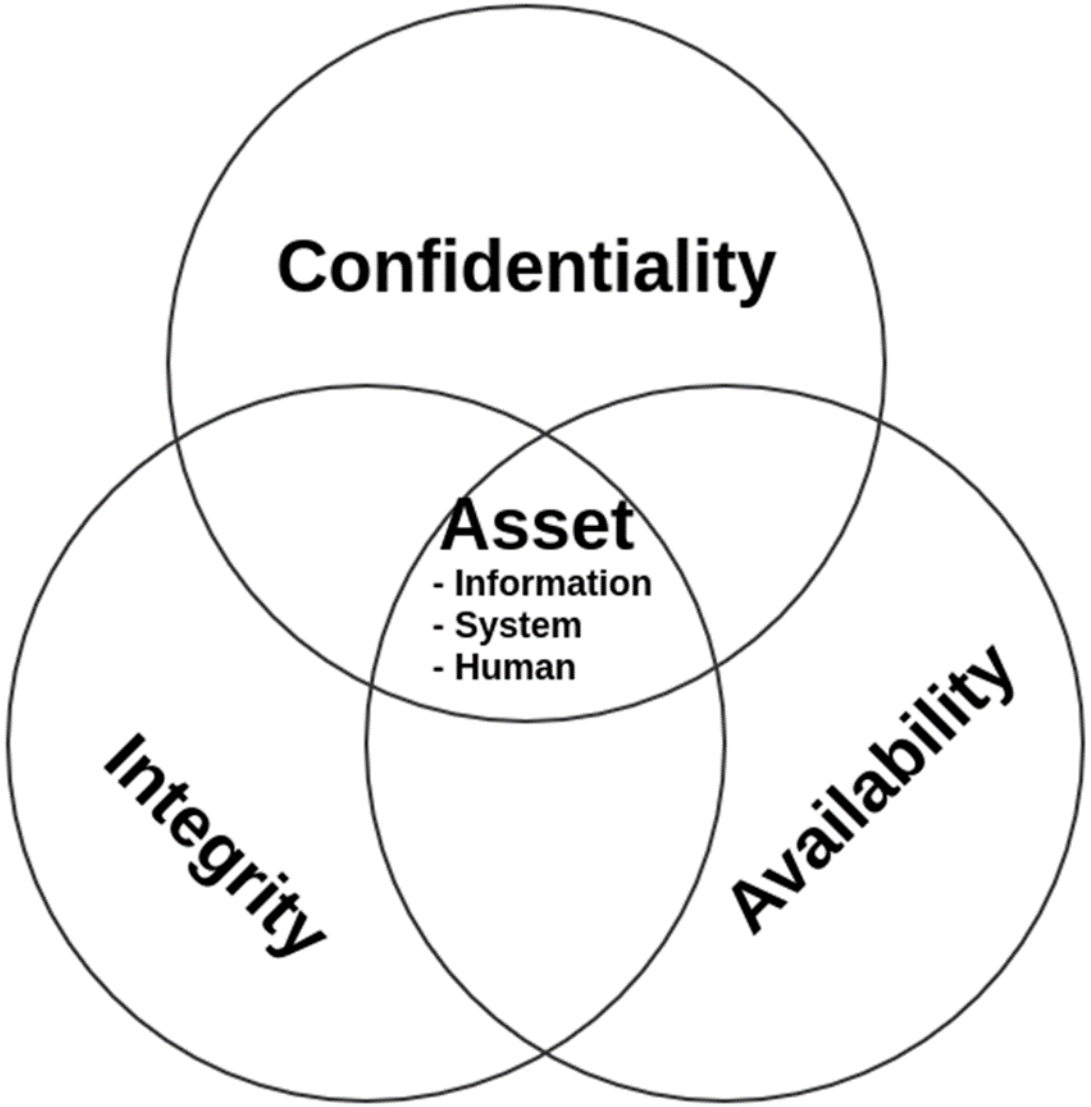


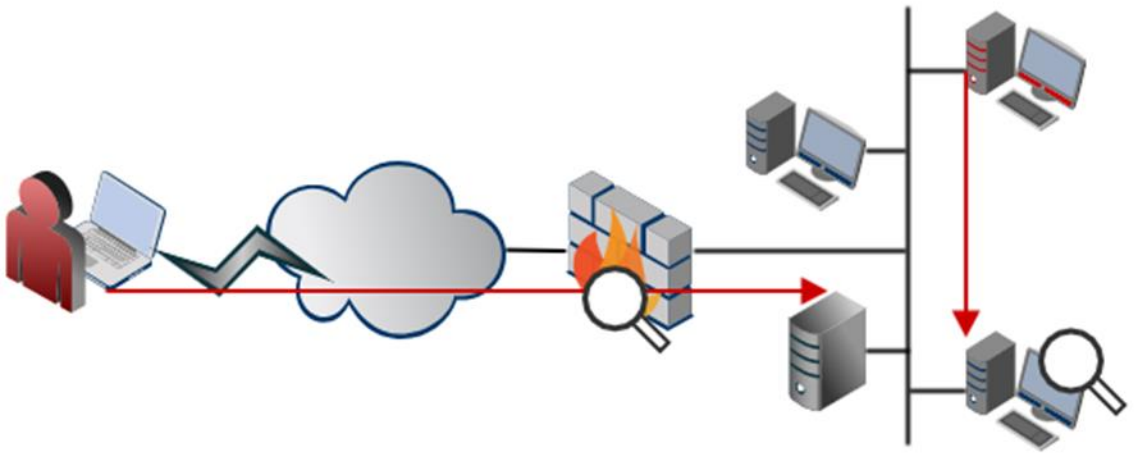
Risks = Impact x Occurrence

Threats

- unauthorized usage
- malicious usage
- alteration
- hijacking
- abuse
...

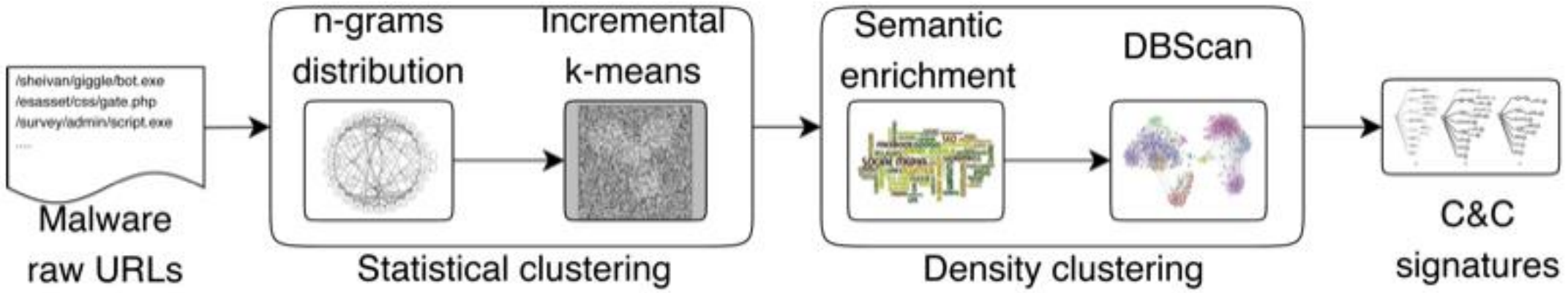
Vulnerabilities

- insufficient physical protection
- insufficient logical protection
- lack of validation of input data
- lack of traceability of input data
- reckless behavior
...



- Huge volume of traffic impacts processing time
  - Filtering
  - Correlation
- Malicious activities require a model
  - Known activities: misuse detection
  - Unknown activities: anomaly detection

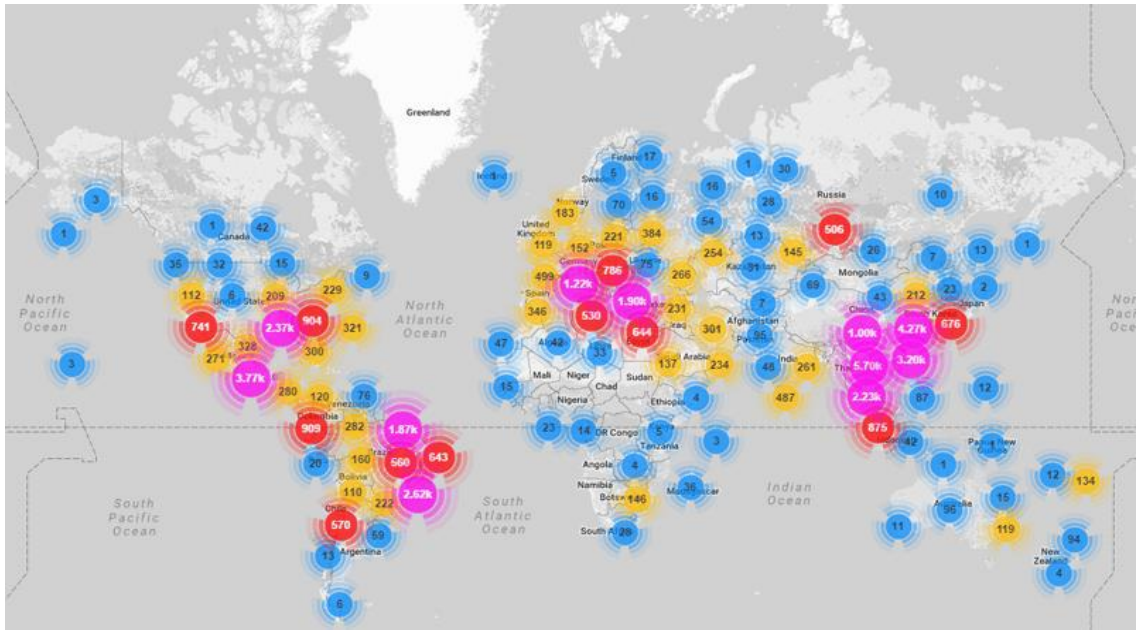
- Mostly used approach: signature-based
- Features: packet headers, flow statistics, TCP connections, etc.
- Relies on data mining and machine learning
- Challenges
  - Lack of datasets (existence, diversity, freshness, sources)
  - Requirement to update the model frequently



- Assumption: botnet machines abuse HTTP to contact their C&C
- Dataset: generated by malware (malicious HTTP requests)
- Goal: generate signatures to detect requests to C&C

Signa-tures	Malware Dataset		
	2011	2012	2013
2011	87%	64%	21%
2012	NA	86%	57%
2013	NA	NA	81%

- Smart home
- Smart grid
- Smart transportation
- Smart industry
- eHealth

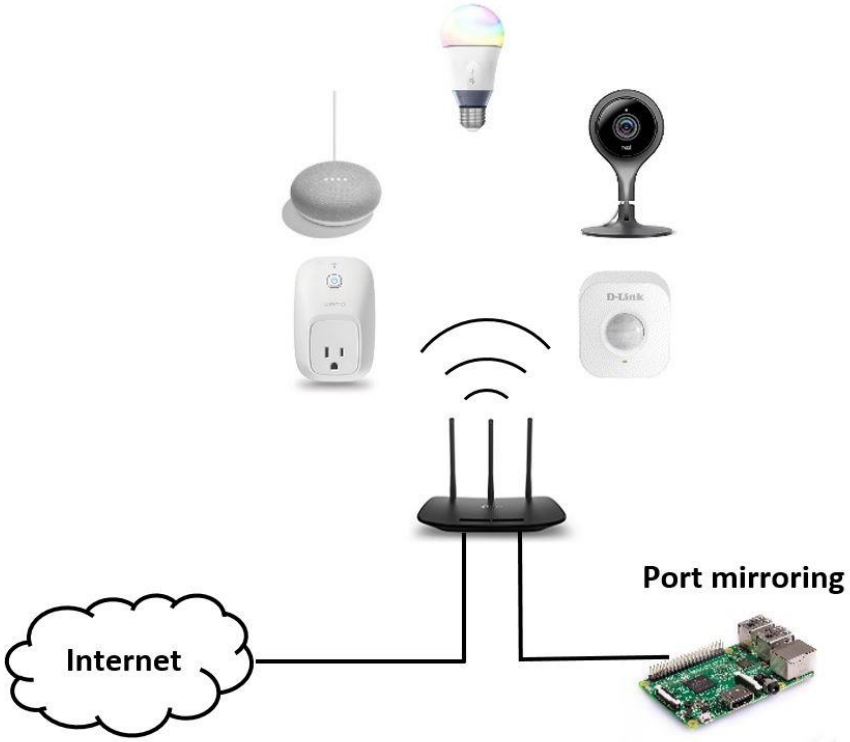


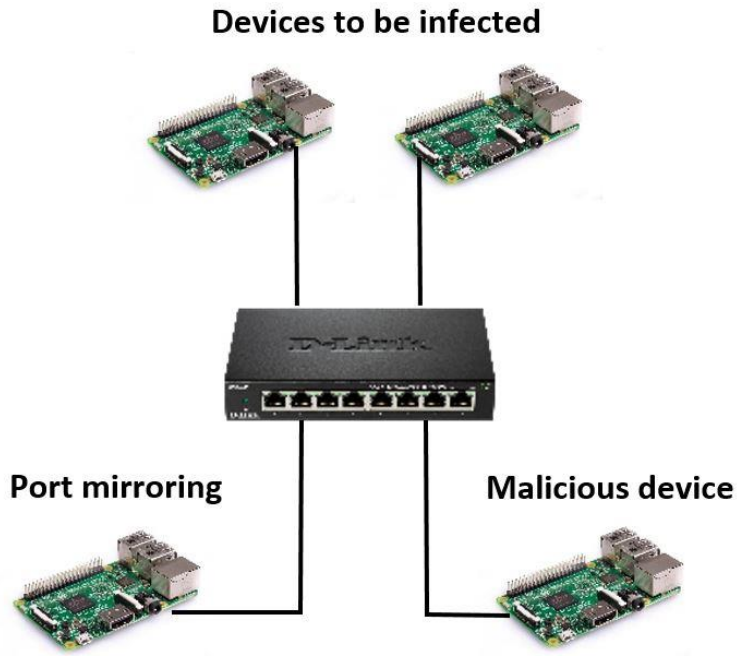
Security issues:

- Short time to market
- Vulnerable default configuration
- Example of Mirai botnet

- *Anomaly detection*: detection of any deviation from legitimate behavior. Define a profile of the legitimate traffic and perform outlier detection. Can detect new types of attacks. High false positive rate.
- IoT devices have very specific purpose, hence, the variation of the observed network traffic behavior is limited.

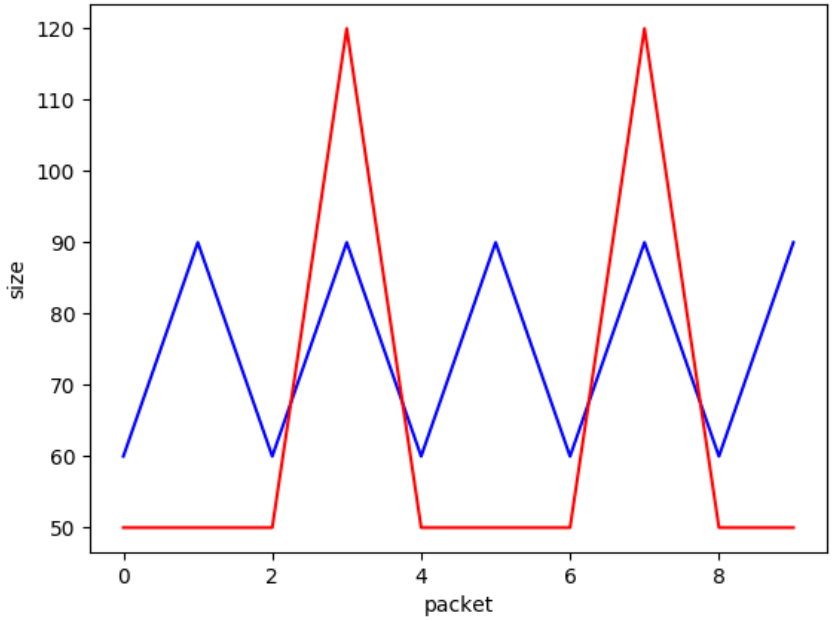
- Limitation of existing datasets (DARPA99, KDD99, NSL-KDD)
- Experimental smart home network for legitimate network traffic generation
- Malicious traffic generation





- Features selection:
  - Avoid features that can introduce bias: IP identifier, addresses, ports number, …
  - Features that can be easily extracted from a practical point of view

- Examples of feature: Individual packet size, total number of packets, TCP flags, inter packet duration, …



- Intrusion detection system for smart home network
- Mimicking legitimate behaviour to evade intrusion detection system in IoT network
- Public IoT network traffic datasets generation for benchmarking purposes

Partners:

- Nara Institute of Science and Technology (NAIST)
- Yokohama National University