Detecting Network Intrusion through Anomalous Packet Identification

Tanjim Munir Dipon

Md. Shohrab Hossain

Husnu S Narman

Outlines

- Motivation
- Problem Definition
- Methodology
- Implementation
- Result
- Future Works

Motivation

- Increasing communication through Internet, so increased risks of network attacks.
- Using packet capture files to extract information about different network sessions.
- Detecting anomalous sessions with no prior knowledge about their behaviour.
- Mitigating the risks of network attacks.

Problem Definition

What is Network Intrusion Detection?

- Procedure of detecting malicious traffic on the network on the basis of given rules or statistics.

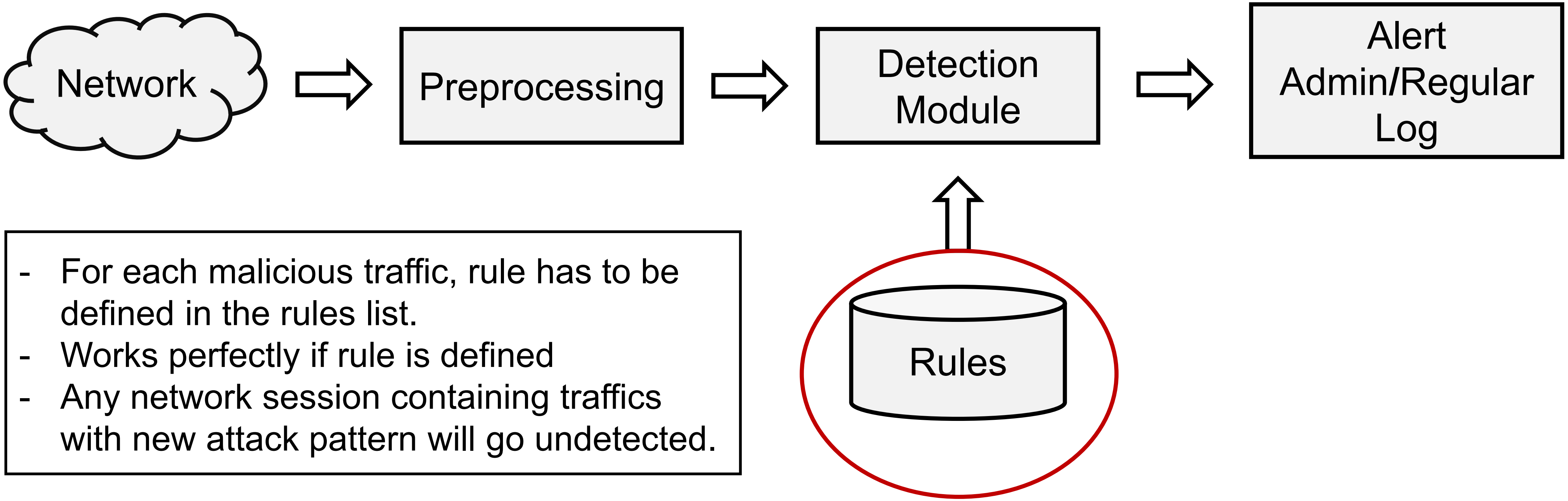
- Two types of detection scheme are possible;

Network Intrusion Detection → Signature/Rule Based

Network Intrusion Detection → Anomaly Based

Problem Definition

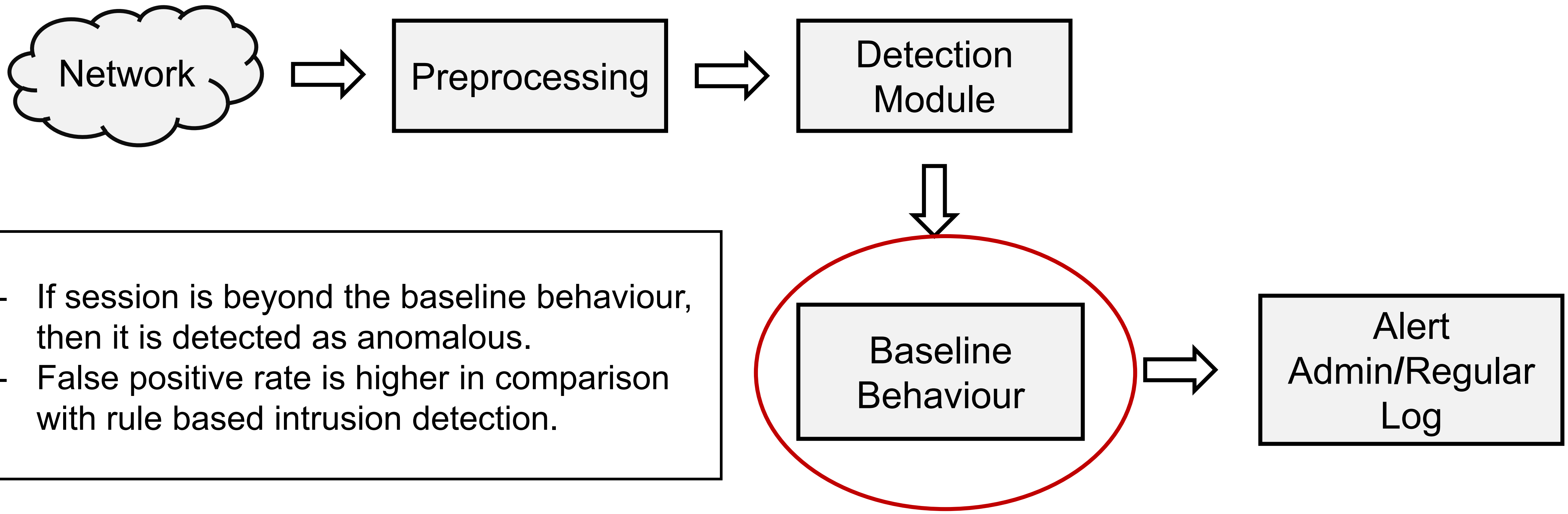
Signature based Intrusion Detection



- For each malicious traffic, rule has to be defined in the rules list.
- Works perfectly if rule is defined
- Any network session containing traffics with new attack pattern will go undetected.

Problem Definition

Anomaly based Intrusion Detection



- If session is beyond the baseline behaviour, then it is detected as anomalous.
- False positive rate is higher in comparison with rule based intrusion detection.

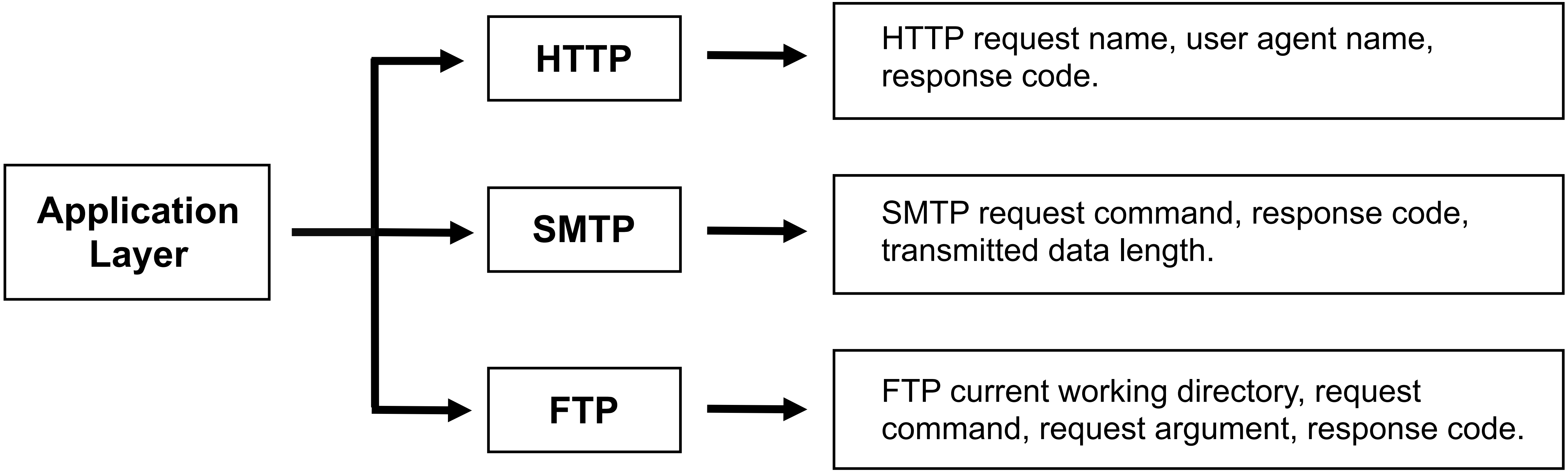
Methodology

- Data extraction from different services of network traffics.
- Reducing the dimensionality of the extracted data from network sessions.
- Clustering the sessions in all possible **3-**dimensions.
- Identifying the anomalous sessions on the basis of their outlier count in all possible combinations.

Implementation

Data Extraction from Network Traffic

- In this module, data is extracted from different protocols of network packets and then recorded as statistics inside corresponding sessions.



Implementation

Data Extraction from Network Traffic

Transport Layer (TCP) →

- Source and destination port numbers
- Average TCP segment length from client to server
- Average TTL value of SYN flagged packets
- SYN, SYN-ACK, PUSH, URG, RST and FIN flag percentage
- RST and FIN flag count from client to server and server to client.

Network Layer →

- Source and destination IP addresses
- Don’t and More Fragment rate
- ICMP packet type
- ICMP checksum status
- Avg. data length of ICMP packets

Implementation

Dimensionality Reduction

- Dimensionality reduction is applied to consider only the essential features in detecting anomalous sessions. Also any dependency in between the attributes is omitted.

Dimensionality Reduction → **Principal Component Analysis** → **Includes**

- Standardize the attributes to avoid any biasing.
- Calculate the co-variance matrix from the standardized data.
- Determine the eigenvalues and eigenvectors and take the eigenvectors with maximum variance.
- Project the sessions into the eigenvectors.

Implementation

Clustering and Outlier Marking

- Clustering is applied to all of the 3 combinations of the principal components and finally sessions having the most outlier count are recorded as anomalous.

Clustering and Outlier Detection

Includes

Create object with all possible 3 principal components

Apply Density based clustering to each object

Create Outlier count for each Session

Includes

- Cluster creation on the basis of core and border point determination.
- Label unreachable points as outliers

Results

- DARPA 1999 dataset is used to evaluate the proposed model. Anomalies detected in the dataset are given according to their respective protocols.

Network Layer

- Identical source and destination **IP** address.
- High amount of data transmitted through ICMP packets to the server.
- High amount of checksum errors.
- Request with no responses from the server.
- High amount of **TTL** values.

Attacks included
➢ Ping of Death ➢ Land

Results

Transport Layer

- High amount of data transmission through **TCP** bookkeeping packets.
- High amount of **RST** and **FIN** flag rate per session from server to client and client to server.
- High difference between **SYN** and **SYN-ACK** flag rate per session.
- **RST** and **FIN** flags with no **SYN** and **SYN-ACK** flags in a session.

Attacks included

- Back
- SYN Flood
- Portsweep

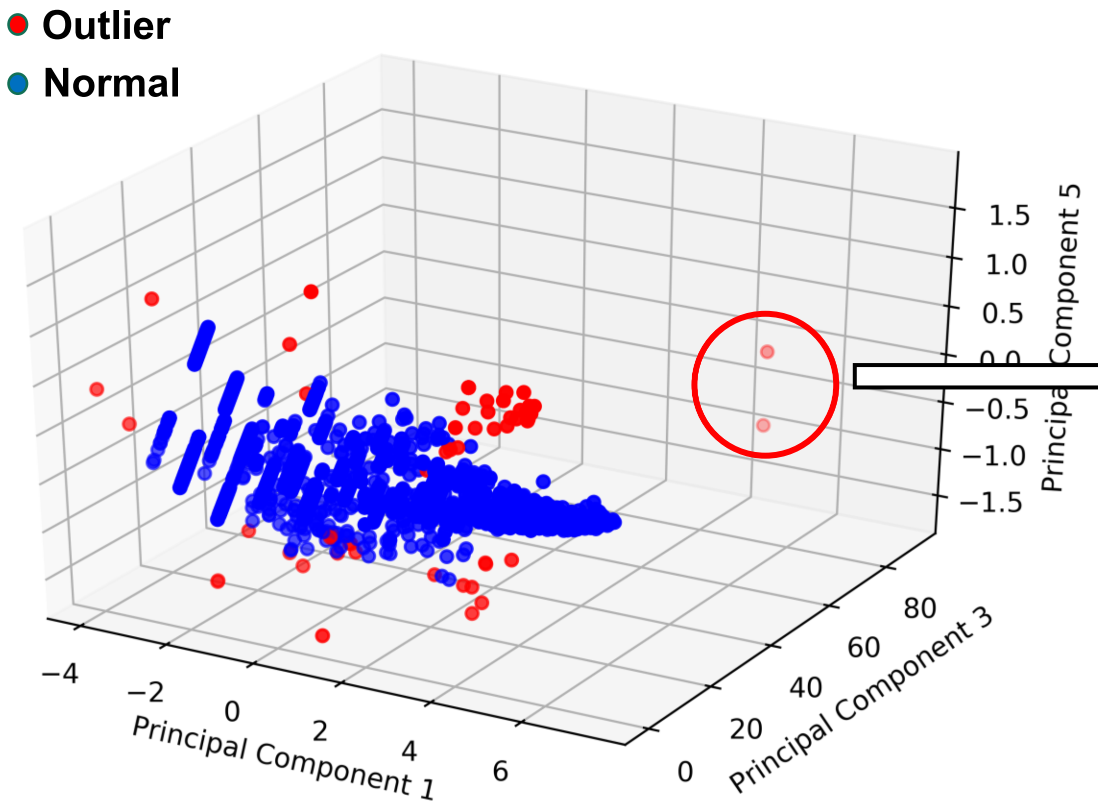
Results

Application Layer

- High amount of data transmitted as **HTTP** user agent through **TCP** bookkeeping packets.
- No **SMTP** session starting or closing command yet tried to transmit a lot of data.
- A lot amount of data transmitted in **SMTP** session with many packets full to **TCP** segment capacity.
- Trying to append a file to the **FTP** root directory with anonymous session.

Attacks included
➢ Apache2 ➢ Sendmail ➢ PP-Macro ➢ FTP-Write

Results



- All of the different clusters are shown with several bunch of blue points. These clusters show the normal **HTTP** sessions.

- Red points are recorded as outliers.
- Similar graph is achieved for all 3-combinations of principal components.
- Finally sessions those appear as outlier in most of these combinations are declared as anomalous.

HTTP Sessions as data points concerning principle components 1, 3 and 5

Future Works

- Process other services such as Telnet, UDP, SNMP, encrypted traffics for a wide range of detection.
- Use other datasets to evaluate the performance of the system in a more robust way.
- Automating the entire procedure through assigning the hyper parameter values automatically.

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Thank You!