

# Detecting malware even when it is encrypted

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## Machine Learning for network HTTPS analysis

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Photo



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**FACULTY OF  
ELECTRICAL ENGINEERING**

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# Introduction

- Over half of global web traffic is encrypted
  - <https://transparencyreport.google.com/https/overview>
  - <https://www.eff.org/deeplinks/2017/02/were-halfway-encrypting-entire-web>
  - <https://letsencrypt.org/stats/>

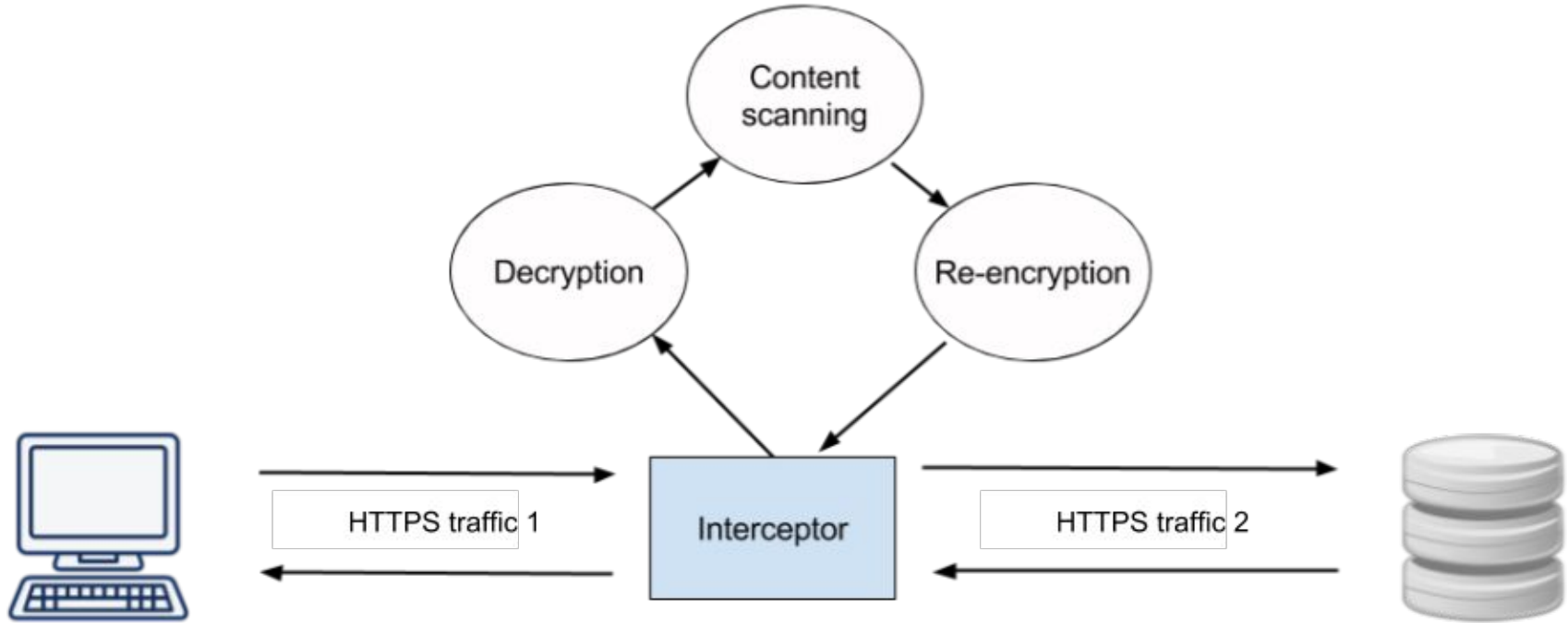
# Introduction

- 10% - 40% of all malware traffic is encrypted
  - <https://blogs.cisco.com/security/malwares-use-of-tls-and-encryption>
  - <https://blog.cyren.com/articles/over-one-third-of-malware-uses-https>

# Problem

- The encryption interferes with the efficacy of classical detection techniques

# TLS inspection



# TLS inspection

- Advantages
  - TLS inspection can use classical detection techniques
- Disadvantages
  - TLS inspection can be expensive
  - TLS inspection is computationally demanding (can be slow)
  - TLS inspection does not respect the original idea of HTTPS (privacy)



## Without decryption

- Find and discover new features and methods to detect malware without decrypting the traffic



# Without decryption



- Advantages
  - No SSL inspection
- Disadvantages
  - The need to discover new features and methods

# Goal

- To detect the malware HTTPS traffic without decryption with high accuracy, low false positive rate and false negative rate

# Goal

- True Positive (TP) - “we predicted **malware** and it is **malware**”
- True Negative (TN) - “we predicted **normal** and it is **normal**”
- False Positive (FP) - “we predicted **malware** and it is **normal**”
- False Negative (FN) - “we predicted **normal** and it is **malware**”

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

$$\text{False Positive Rate} = FP / (FP + TN)$$

$$\text{False Negative Rate} = FN / (FN + TP)$$

# HTTPS

- HTTPS = HTTP + SSL/TLS
- Verifying that you are talking directly to the correct server
- Ensuring that only the server can read what you send and only you can read what it sends back

# SSL/TLS handshake

- Client and server Hello
- Certificate Exchange
- Key Exchange

# SSL/TLS handshake



Client Hello

Server Hello with certificate and decision about the parameters.

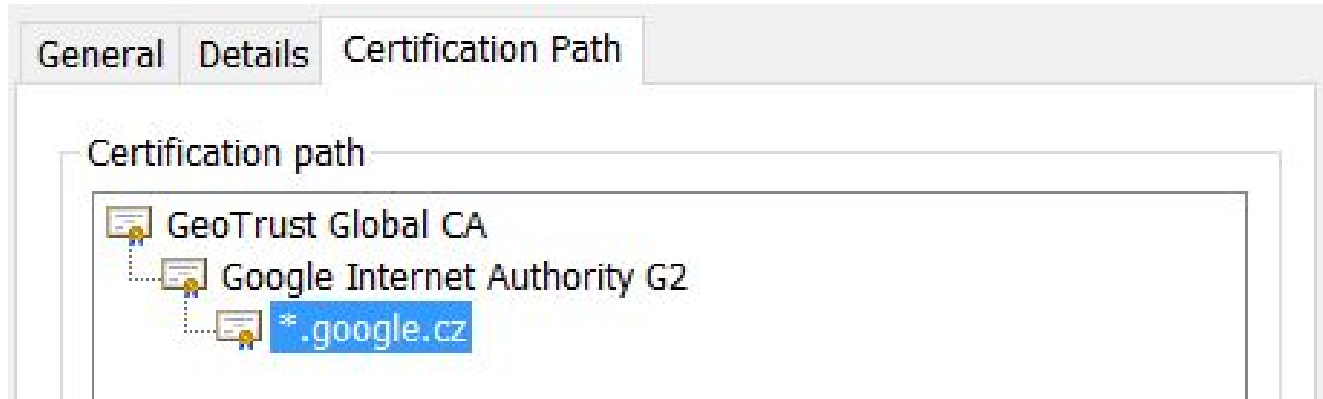
If the certificate is trusted, creates a symmetric session key and encrypts it with the server's asymmetric public key.

Server decrypts the encrypted session key using its asymmetric private key to get the symmetric session key.

Server and Browser now encrypt and decrypt all transmitted data with the symmetric session key.

# Certification path

- A root CA
- An intermediate CA



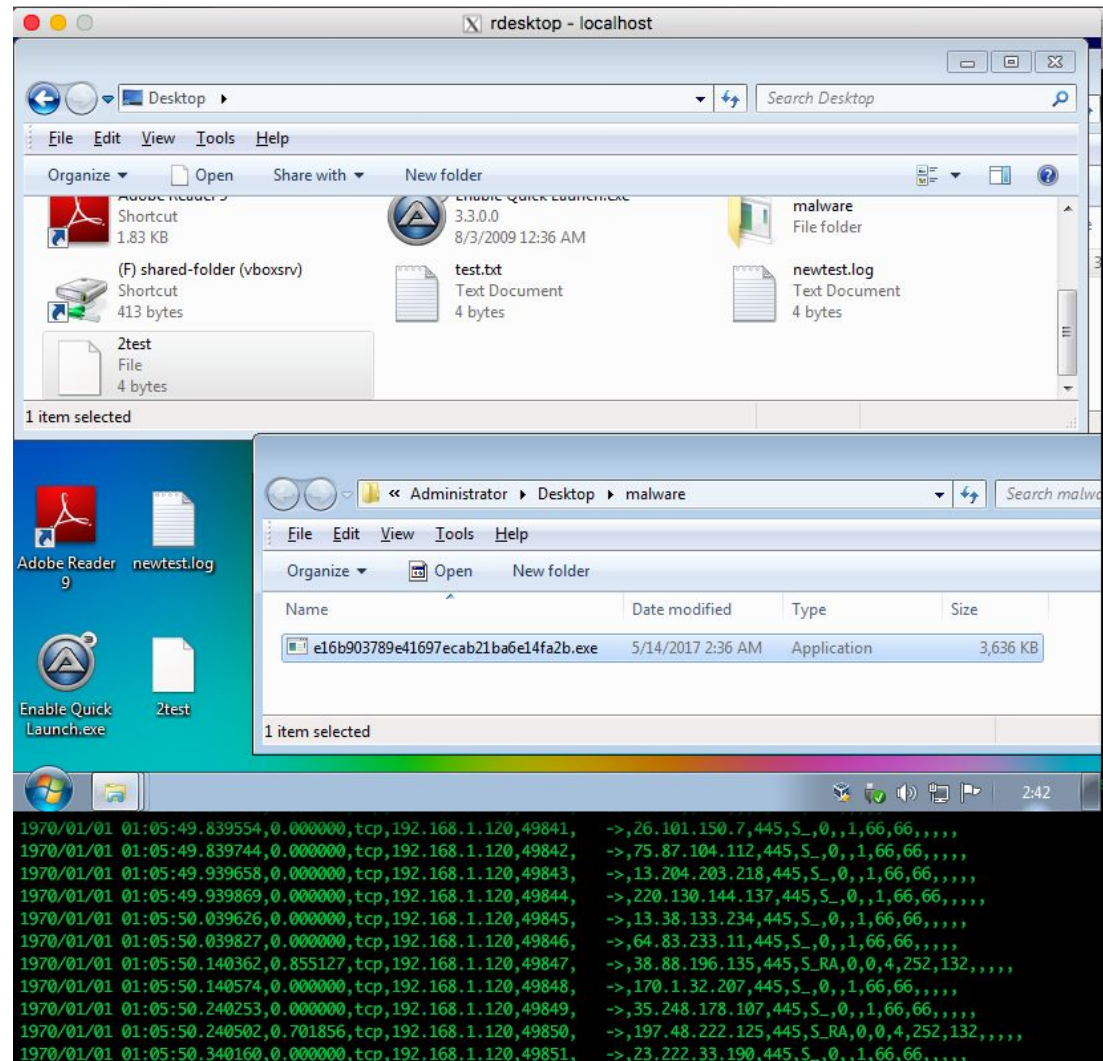


Privacy does not mean Security!

Dataset

# Dataset

- Flows with HTTPS traffic
- Malware and Normal
- 4 sub dataset
- 163 malware and normal captures



# Dataset

- CTU-13 dataset - public
  - Malware and Normal captures
  - An Empirical Comparison of Botnet Detection Methods research
  - <http://mcfp.weebly.com/the-ctu-13-dataset-a-labeled-dataset-with-botnet-normal-and-background-traffic.html>
- MCFP dataset - public
  - Malware and Normal captures
  - Malware Capture Facility Project
  - <https://stratosphereips.org/category/dataset.html>

# Dataset

- Own normal dataset - public
  - Normal captures
  - 3 days of accessing to secure sites (Alexa 1000)
  - Google, Facebook, Twitter accounts
  - <https://stratosphereips.org/category/dataset.html>
- Normal CTU dataset - almost public
  - Normal captures
  - 22 known and trusted people from department of FEE CTU

# Dataset

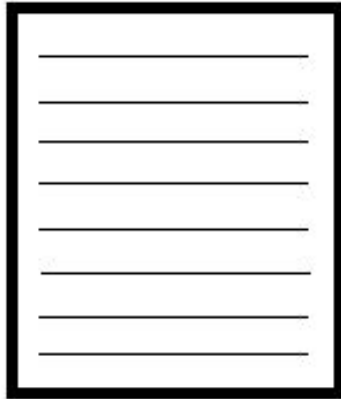
- Size of log files in dataset (include background):
  - Normal: 331 GB
  - Malware: 44 GB
  - Total: 375 GB
- All SSL/TLS flows:
  - Normal: 1,357,112
  - Malware: 552,919
  - Total: 1,910,031
- All unique certificates:
  - Normal: 7,040
  - Malware: 1,579
  - Total: 8,619

Most of datasets are public!

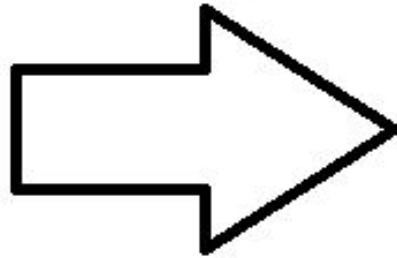
# Features and Methods

# Bro logs

pcap file



Bro IDS



Bro logs

- conn.log
- ssl.log
- x509.log
- dns.log
- ...



# conn.log

- TCP/UDP/ICMP connections
- Some of the available data:
  - Source and destination IP and Ports

# conn.log

- TCP/UDP/ICMP connections
- Some of the available data:
  - Source and destination IP and Ports
  - Number of packets
  - Number of bytes

# conn.log

- TCP/UDP/ICMP connections
- Some of the available data:
  - Source and destination IP and Ports
  - Number of packets
  - Number of bytes
  - Timestamp

# conn.log

- TCP/UDP/ICMP connections
- Some of the available data:
  - Source and destination IP and Ports
  - Number of packets
  - Number of bytes
  - Timestamp
  - State of connection

# conn.log

- TCP/UDP/ICMP connections
- Some of the available data:
  - Source and destination IP and Ports
  - Number of packets
  - Number of bytes
  - Timestamp
  - State of connection
  - Duration

# ssl.log

- SSL/TLS handshake info
- Some of the available data:
  - Version of SSL/TLS
  - Ciphersuite

# ssl.log

- SSL/TLS handshake info
- Some of the available data:
  - Version of SSL/TLS
  - Ciphersuite
  - Server name

# ssl.log

- SSL/TLS handshake info
- Some of the available data:
  - Version of SSL/TLS
  - Ciphersuite
  - Server name
  - Certificate path



# Certificate path

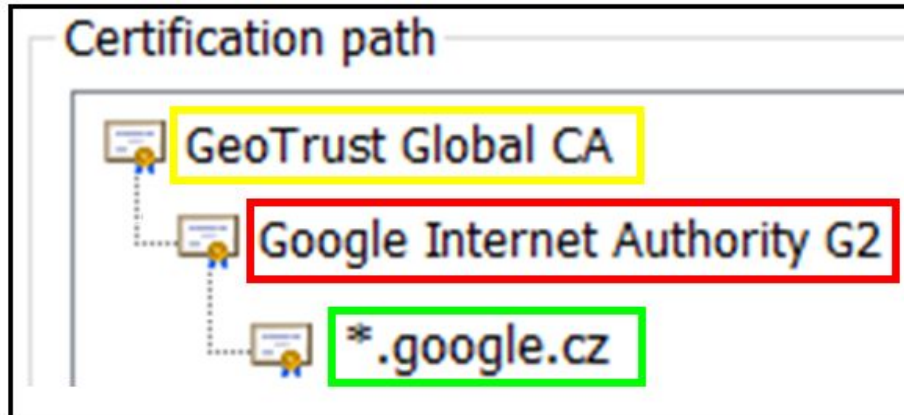
ssl.log

SSL records							Certificate path	
	3511.617809	Ctgc353XKjtCwYMPXd	10.0.2.109	443	TLSv10		FlseAT2YTTirnFNwwa	FtLQ4i1LMP06OKenK9
	3652.492566	Cfb2BM3PUzkFjD4L22	10.0.2.109	443	TLSv10		FzMJtN2WvGLBJQmAde	
	3654.509631	CeZN8N3d5uxTGKh51g	10.0.2.109	443	TLSv10		fyqU32jvPwlbeg8Sd,FmYVTL3wUsvW6p0Ko8	

x509.log

Certificate records	3504.673635	FICtgE1o1S0RuoUafe	3	02FC2E
	3511.621231	FlseAT2YTTirnFNwwa	3	0D335238E52B18BE
	3511.736478	FtLQ4i1LMP06OKenK9	3	0676549500C6A380
	3513.557920	FzMJtN2WvGLBJQmAde	3	7C653E7DFE20BF0E
	3513.573938	F5v6ic30yxSRz40Fvf	3	49853ED8F7165597

Certificate path in Google Chrome



# x509.log

- X.509 certificate info
- Some of the available data:
  - Serial number

# x509.log

- X.509 certificate info
- Some of the available data:
  - Serial number
  - Common name

# x509.log

- X.509 certificate info
- Some of the available data:
  - Serial number
  - Common name
  - Validity of the certificate



# x509.log

- X.509 certificate info
- Some of the available data:
  - Serial number
  - Common name
  - Validity of the certificate
  - Public key

# x509.log

- X.509 certificate info
- Some of the available data:
  - Serial number
  - Common name
  - Validity of the certificate
  - Public key
  - Signature algorithm name

# x509.log

- X.509 certificate info
- Some of the available data:
  - Serial number
  - Common name
  - Validity of the certificate
  - Public key
  - Signature algorithm name
  - Issuer

# x509.log

- X.509 certificate info
- Some of the available data:
  - Serial number
  - Common name
  - Validity of the certificate
  - Public key
  - Signature algorithm name
  - Issuer
  - SAN DNS (Subject alternative name extension of the certificate)



# Interconnection of logs

conn.log

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ssl.log

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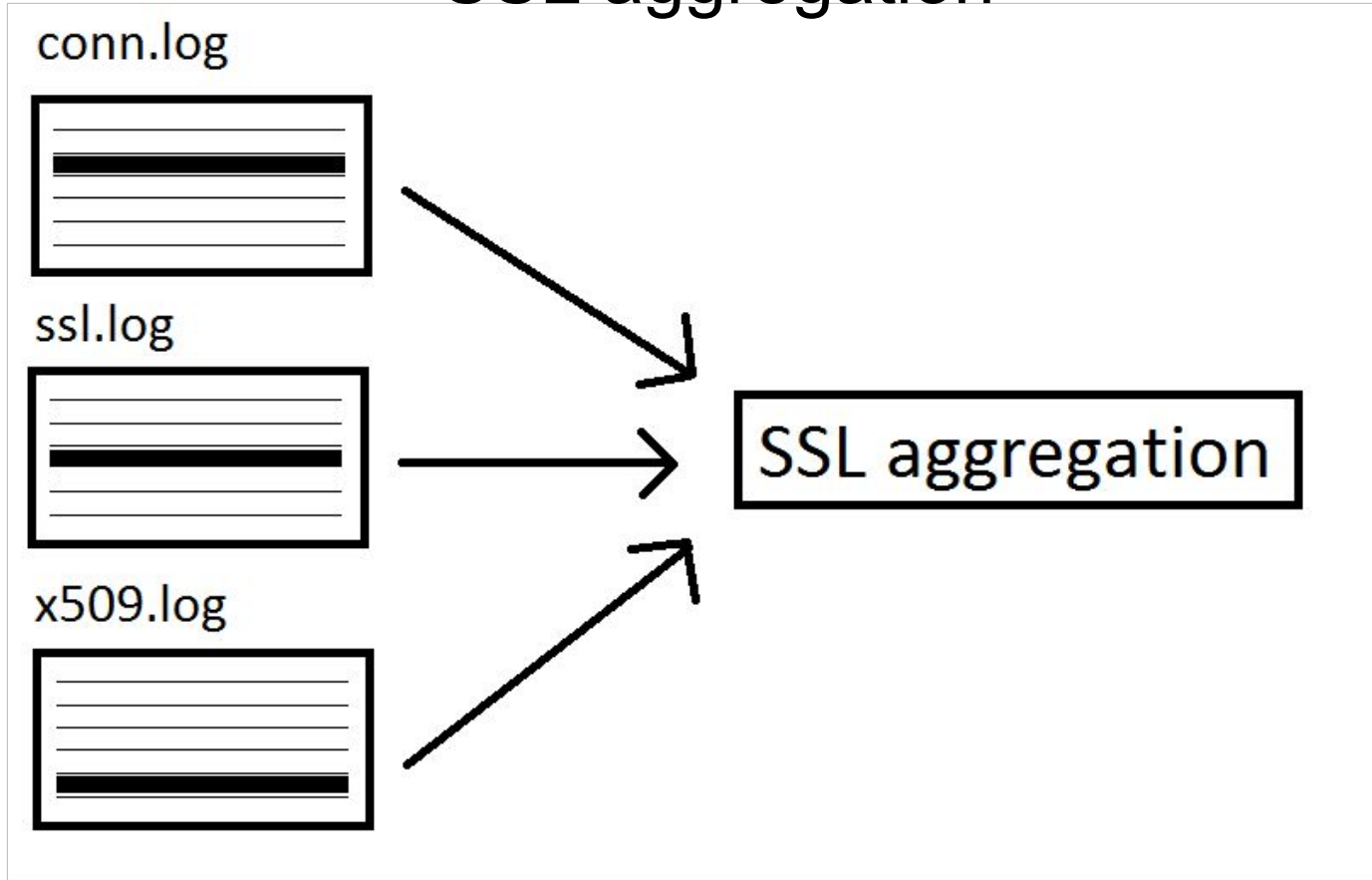
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# SSL aggregation



# SSL aggregation

## conn.log

131.728991	CgFZEv44vwsP9QlnR6	10.0.2.15	49163	104.108.46.209	80	tcp	http
128.944596	CK8hoP3M4XoQDJSxRi	10.0.2.15	49162	52.222.174.197	80	tcp	http
132.428808	Cjkwxu3NuUE4lWTAB	10.0.2.15	49167	52.222.171.204	443	tcp	ssl
132.428083	C0wDNN17b05uKwO7kf	10.0.2.15	49166	52.222.171.204	443	tcp	ssl
132.430278	CFQBuv4I7yFo9h3tP6	10.0.2.15	49169	52.222.171.204	443	tcp	ssl

## ssl.log

132.478442	Cjkwxu3NuUE4lWTAB	10.0.2.15	443	TLSv12	FA8t03GcfnculzHud, FKbqgmdc7kcsRbYHi
132.481833	CFQBuv4I7yFo9h3tP6	10.0.2.15	443	TLSv12	F1bw2G14fJaazLLjoc, FKbqgmdc7kcsRbYHi
132.483473	CHPgSDopxgJ1kZpxl	10.0.2.15	443	TLSv12	-
132.495937	C1PP1Msm5VQsGp4Si	10.0.2.15	443	TLSv12	-
132.494901	CAfZdW3MYCnWgYbuv9	10.0.2.15	443	TLSv12	FCA9ID2CxKqL6GqUgh, FRb04E4lgABeDidrCi

## x509.log

132.527217	FmF1bg1sqhde52Xjyh	3	0CA9C64361BFC92A79B1DD9CFB9E48EC	CN=
132.527217	FzYrZo28CimnSKCR01	3	01FDA3EB6ECA75C888438B724BCFBC91	CN=
133.579209	FA8t03GcfnculzHud	3	5A000529CF2A5A6396D3FD74EC0001000529CF	
133.579209	FKbqgmdc7kcsRbYHi	3	0727AA47	CN=Microsoft IT SSL SHA2,OU
134.111336	F1bw2G14fJaazLLjoc	3	5A000529CF2A5A6396D3FD74EC0001000529CF	

# ssl-connect-unit

**ssl-connect-unit ID:**

- Source IP
- Destination IP
- Destination Port
- Protocol

1.SSL aggregation

2.SSL aggregation

3.SSL aggregation

4.SSL aggregation

ssl-connect-unit

## Raw data

conn.log

ssl.log

x509.log

conn.log

ssl.log

x509.log

conn.log

ssl.log

x509.log

## Connection features

- Numbers, lists, strings

### 1. SSL aggregation

{SrcIP, DstIP, DstPort, protocol}

### 2. SSL aggregation

{SrcIP, DstIP, DstPort, protocol}

### N. SSL aggregation

{SrcIP, DstIP, DstPort, protocol}

## High level features

- Mean
- Standard deviation
- Weighted mean

**ssl-connect-unit**

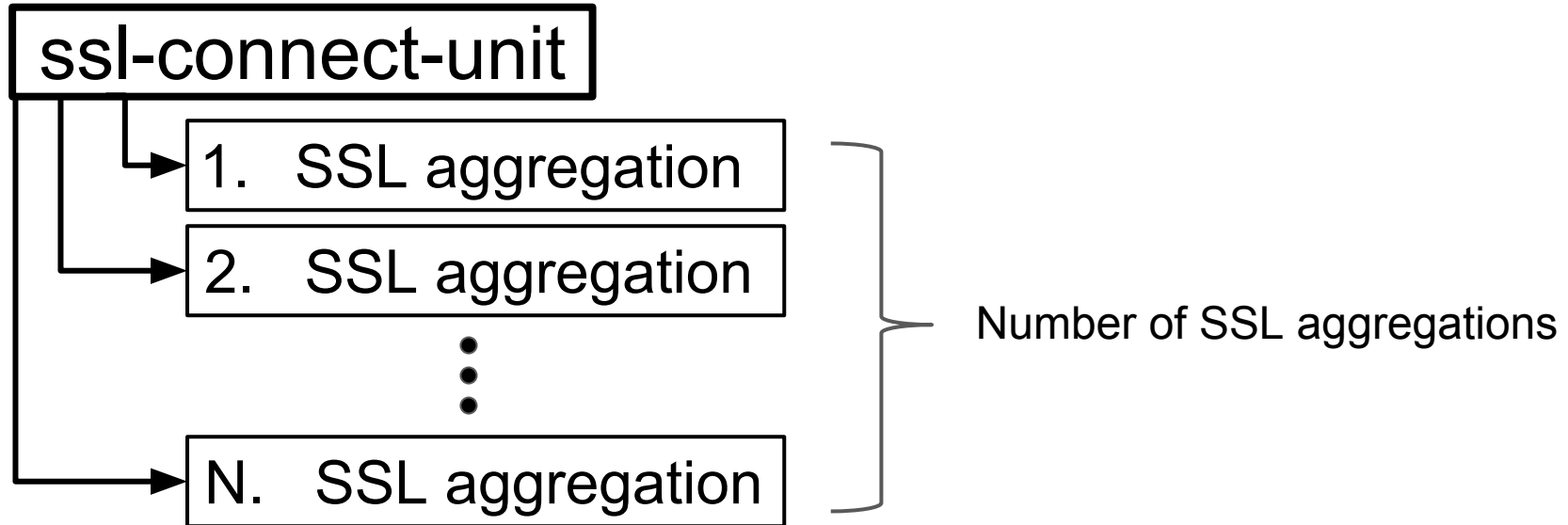
**ssl-connect-unit ID:**

{SrcIP, DstIP, DstPort, protocol}

# High level features

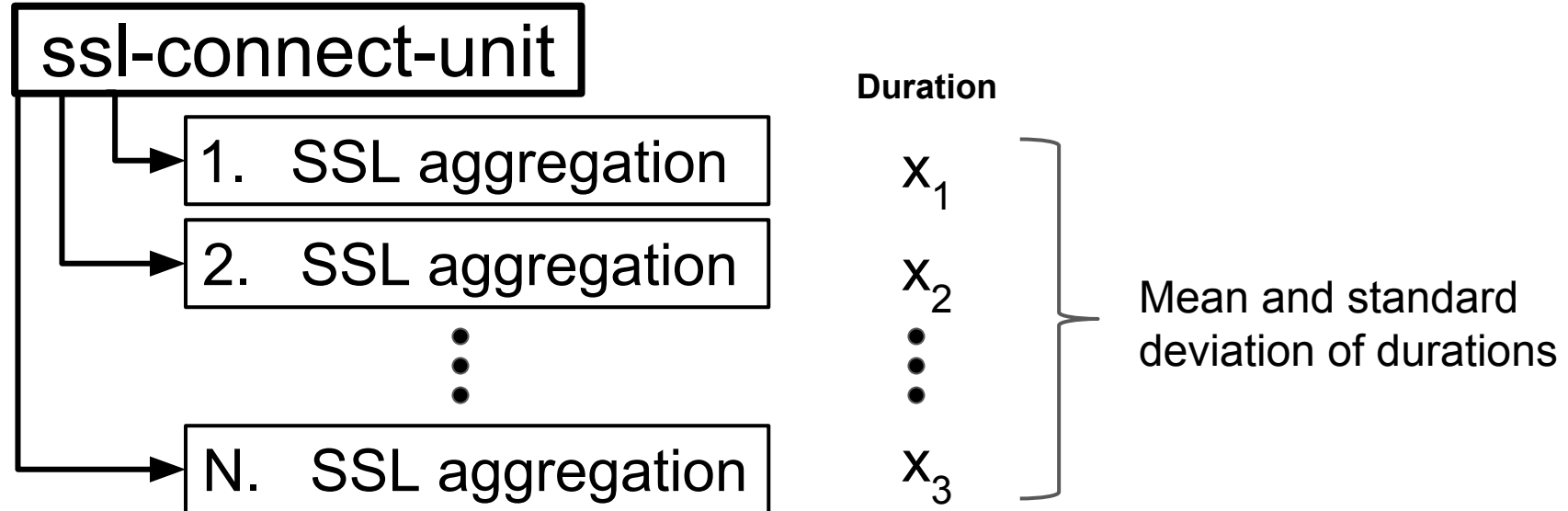
- 40 different features

## 1. Number of SSL aggregations



2. Mean of duration

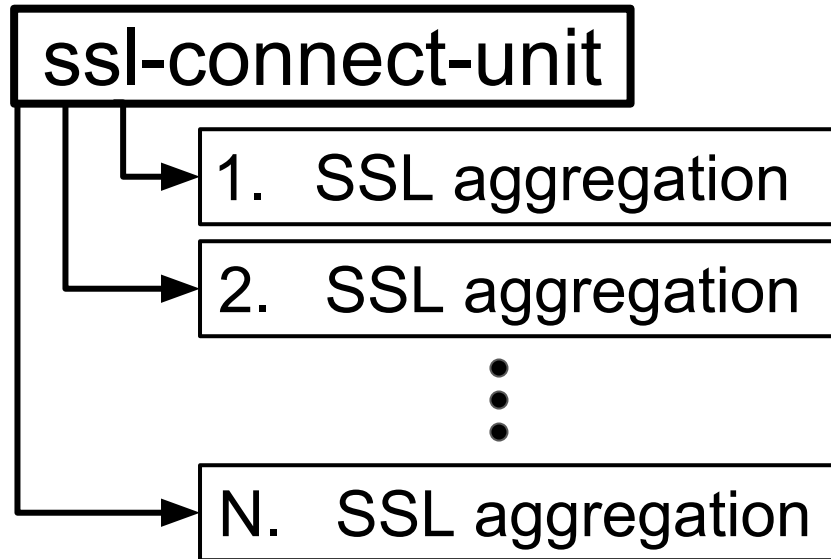
3. Standard deviation of duration





4. Mean of number of packets

5. Standard deviation of number of packets



Number of packets  
inbound      outbound

$x_1$

$x_1$

$x_2$

$x_2$

$\vdots$

$\vdots$

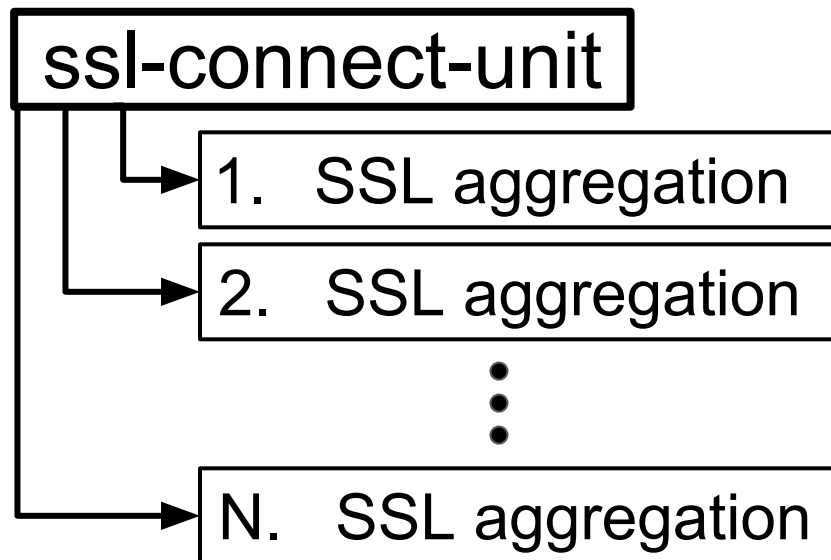
$x_3$

$x_3$

Mean and standard  
deviation of number  
of packets

6. Mean of number of bytes

7. Standard deviation of number of bytes



Number of bytes

inbound      outbound

$x_1$

$x_1$

$x_2$

$x_2$

$\vdots$

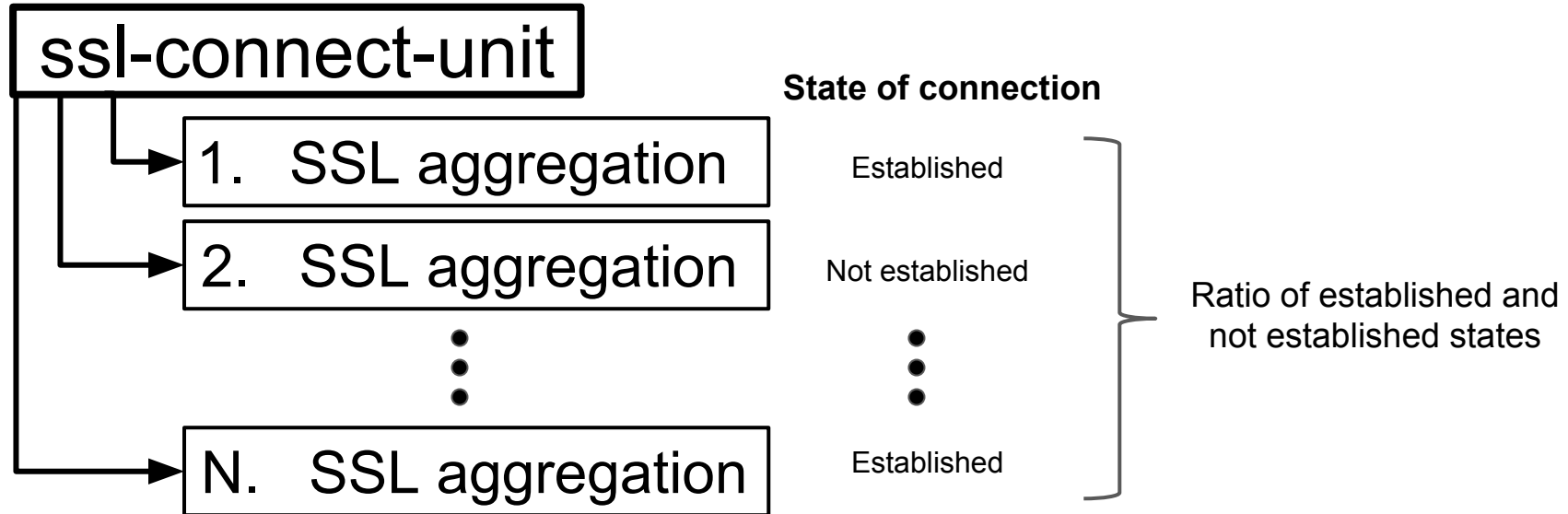
$\vdots$

$x_3$

$x_3$

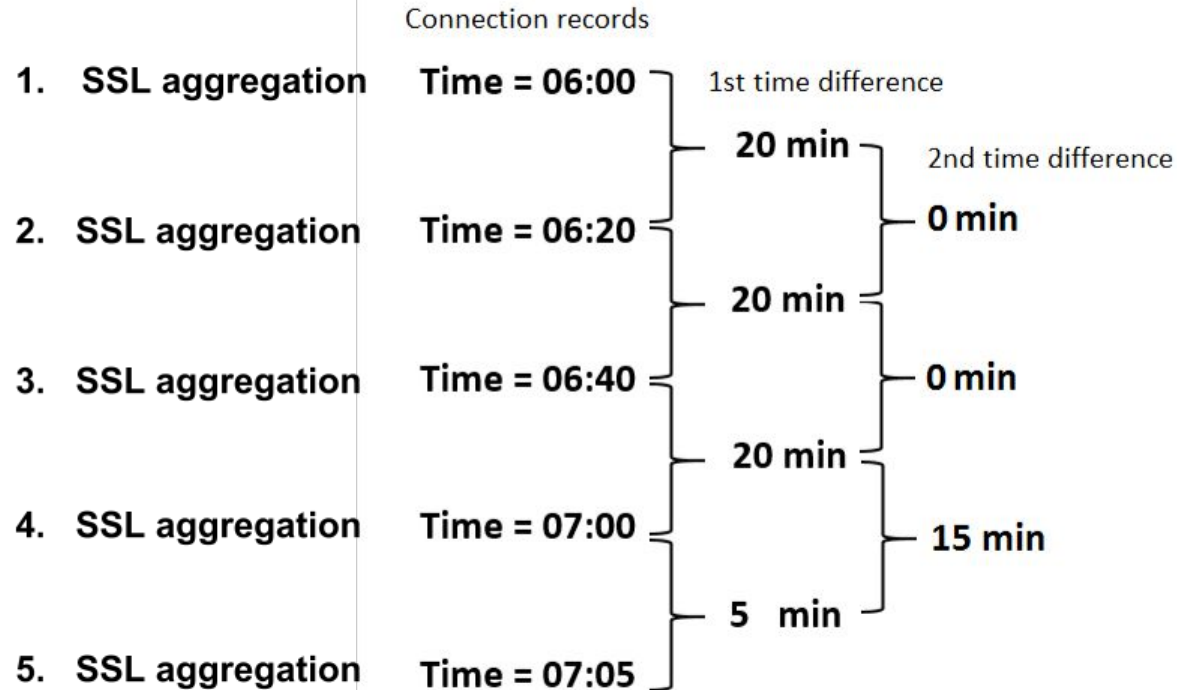
Mean and standard deviation of number of bytes

## 8. Ratio of established and not established states

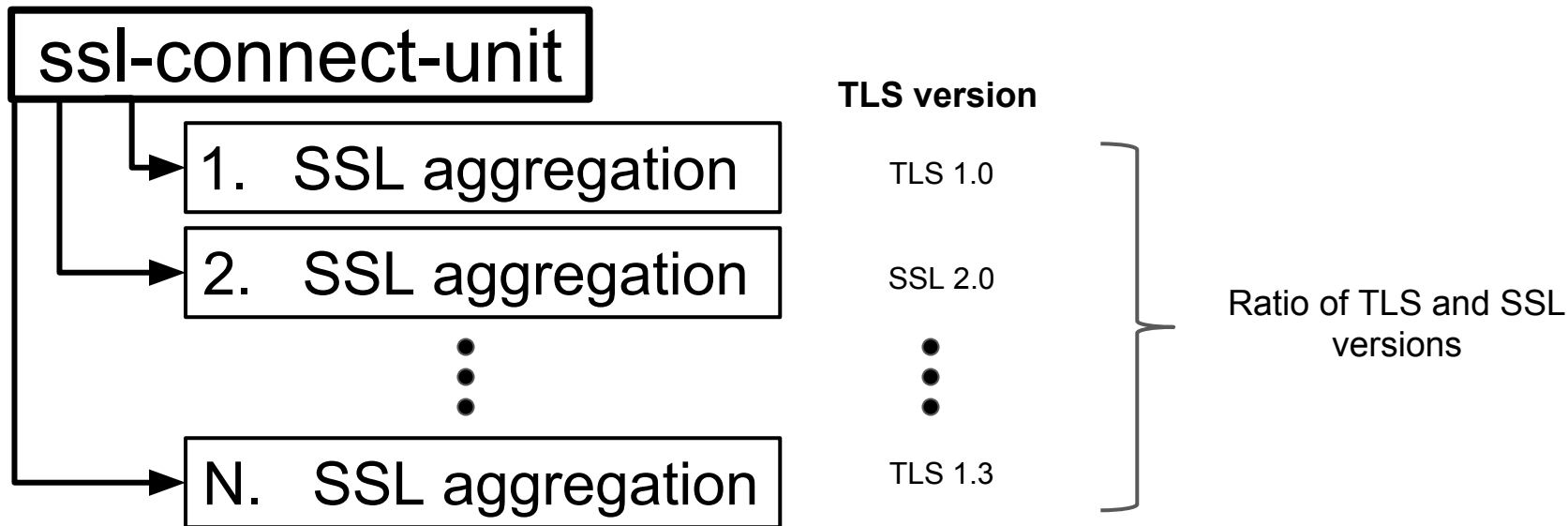


9. Mean of 2nd level time difference

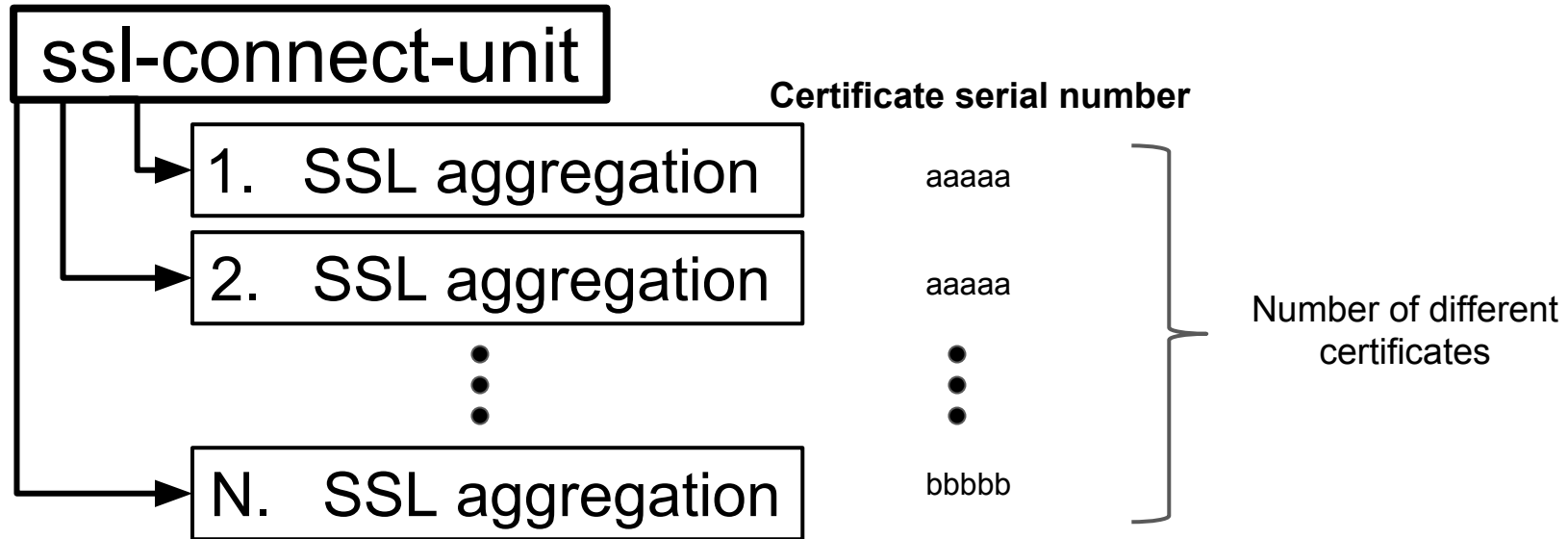
10. Standard deviation of 2nd level time difference



# 11. Ratio of TLS and SSL version

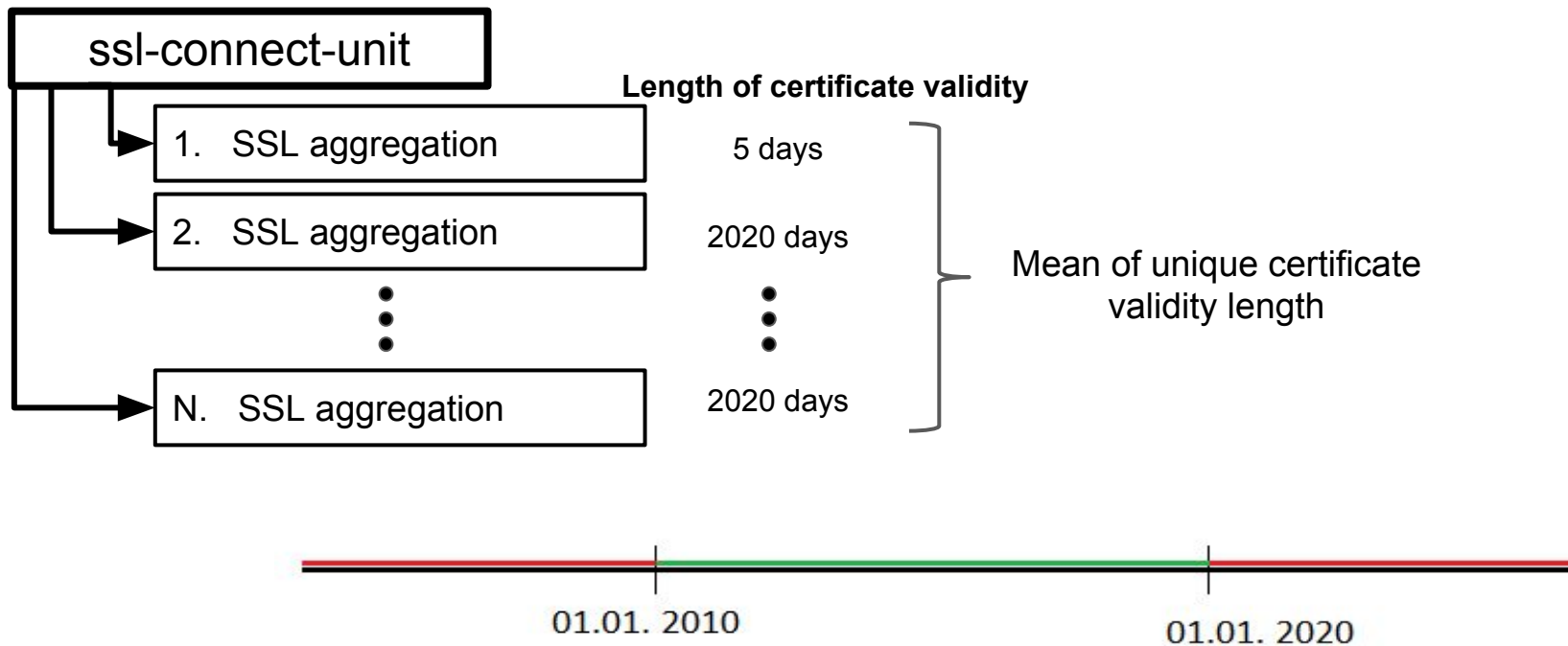


## 12. Number of different certificates

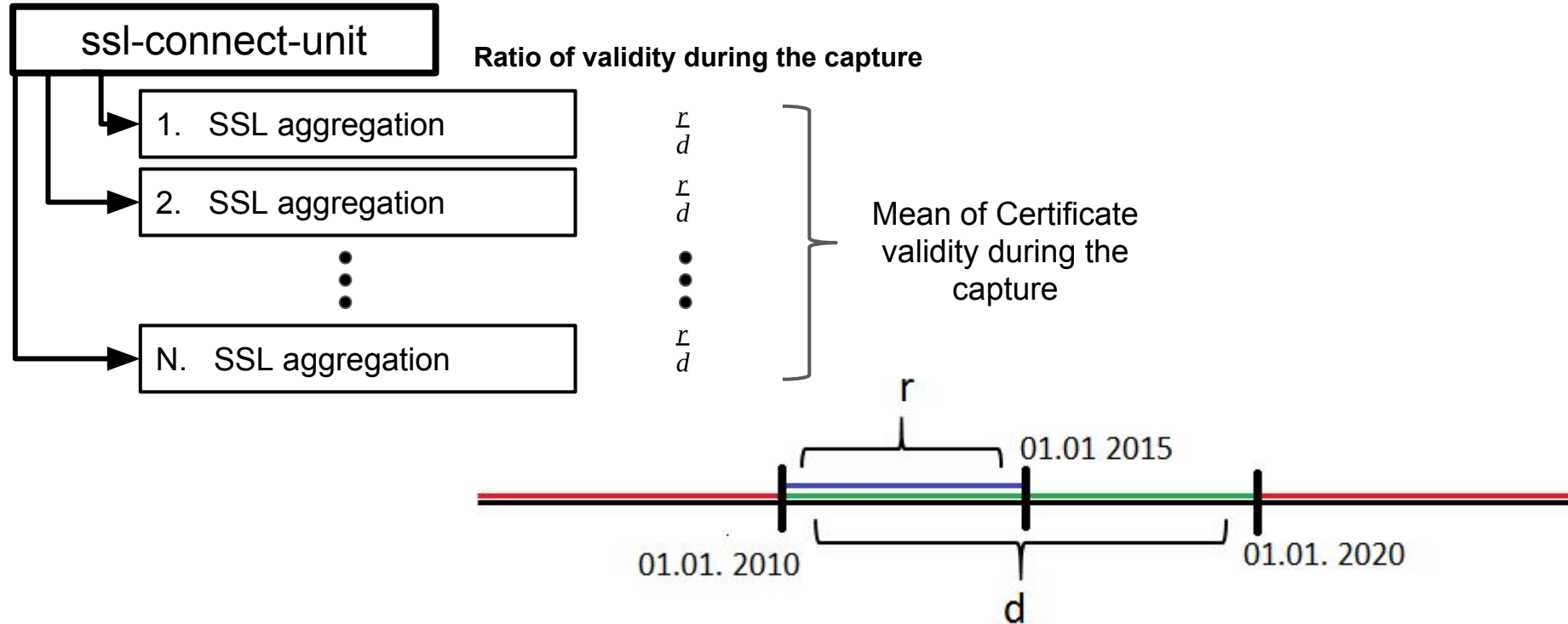


13. Mean of certificate validity length

14. Standard deviation of certificate validity length

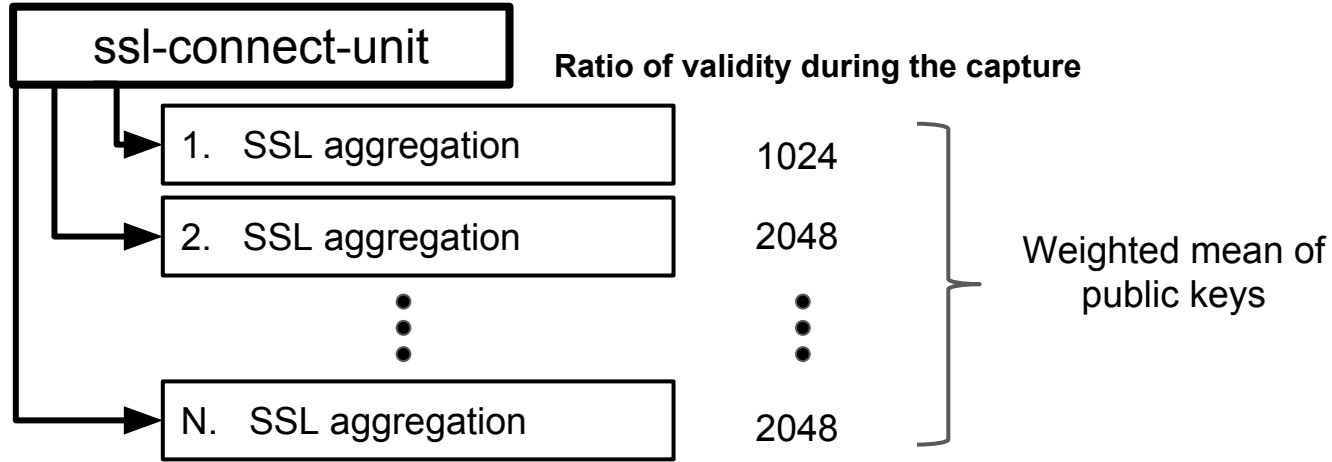


15. Mean of certificate validity during the capture
16. Standard deviation of certificate validity during the capture



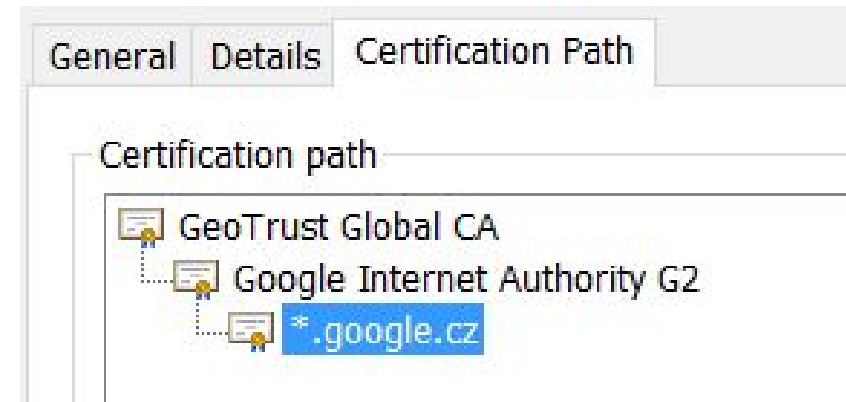


# 17. Weighted mean of public keys



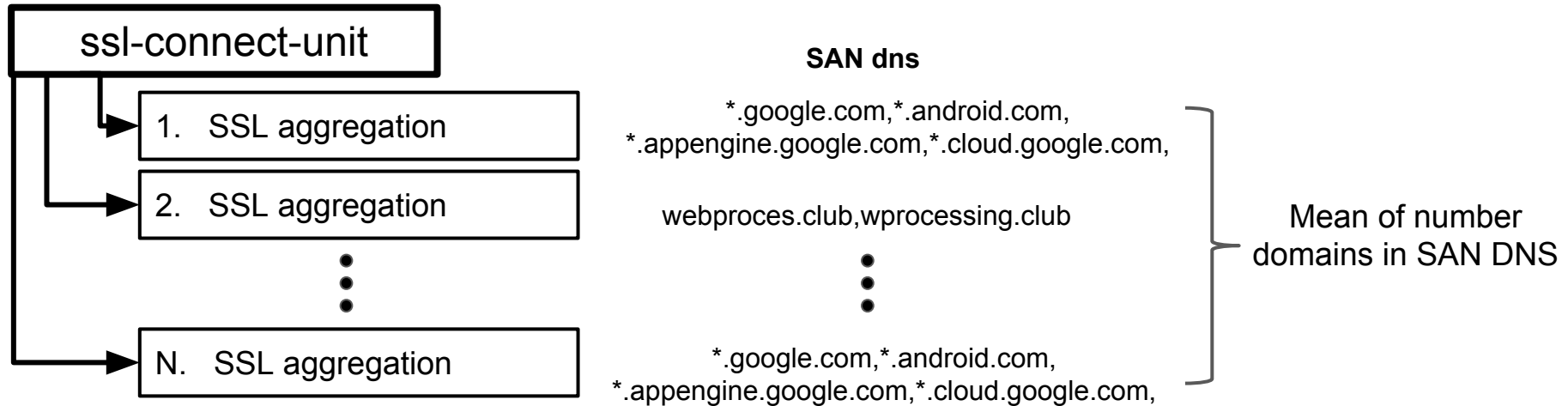
18. Mean of certificate path length

19. Standard deviation of certificate path length

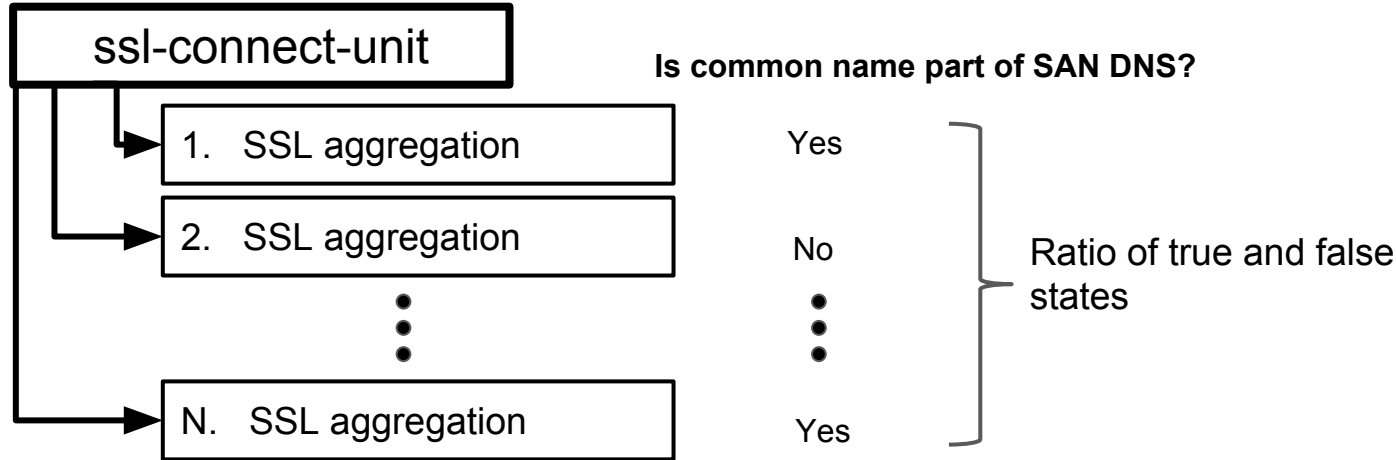


20. Mean of number of domains in SAN DNS

21. Standard deviation of number of domains in SAN DNS



## 22. Ratio of common name and SAN DNS



## Data model

ssl-connect-unit	40 features					Label
{ 10.0.2.15, 54.201.174.90, 443, tcp }	f1	f2	f3	...	f40	Normal
{ 10.0.2.109, 173.194.122.30, 443, tcp }	f1	f2	f3	...	f40	Malware
•						
•						
•						
•						

# Normal dataset

- All ssl-connect-units:
  - Normal: 46,387
  - Malware: 8,313
- All SSL-aggregation:
  - Normal: 1,357,112
  - Malware: 552,919
- All unique certificates:
  - Normal: 7,040
  - Malware: 1,579

# Machine learning algorithms

# XGBoost

- Extreme Gradient Boosting
- Tree booster with logistic regression
- Parameters:
  - max depth — describe maximum depth of a tree
  - gamma — minimum loss reduction required to make a further partition on a leaf node of the tree.
  - min child weight — minimum sum of instance weight (hessian) needed in a child.

# Random forest

- Random Forest Classifier model that is an estimator that fits a number of decision tree classifiers on various sub-samples



# Neural Network

- MLP Classifier (Multi-layer Perceptron classifier)
- stochastic gradient descent with Adam (Adaptive Moment Estimation)

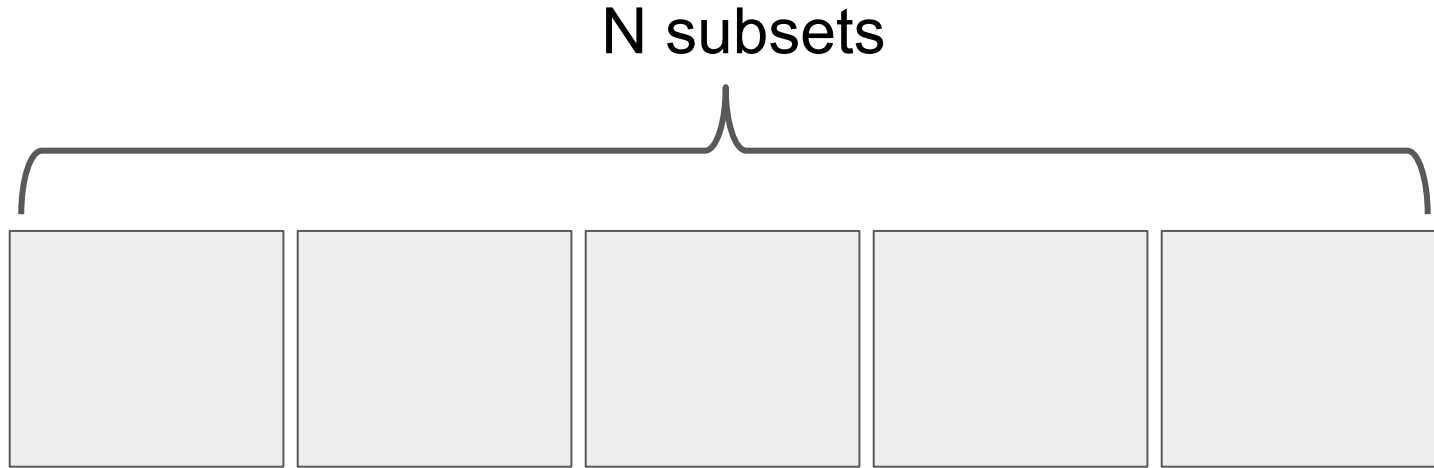
# SVM

- Radial Basis Function (RBF) kernel
- perform a non-linear classification using the kernel trick, mapping inputs into high-dimensional feature spaces

# Experiments

# Experiments

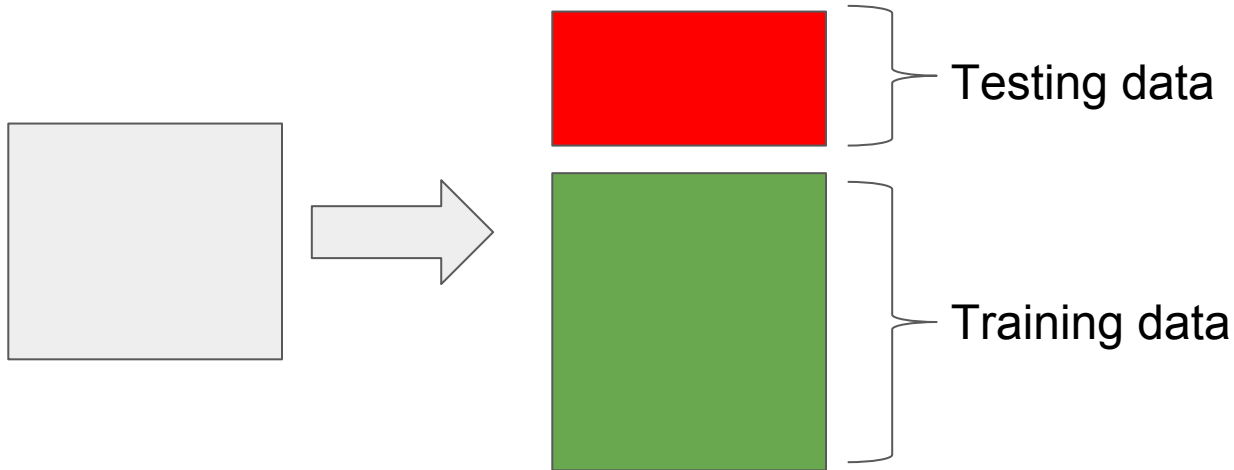
1. Split dataset to N same subsets



- Each subset contains unique malware test data

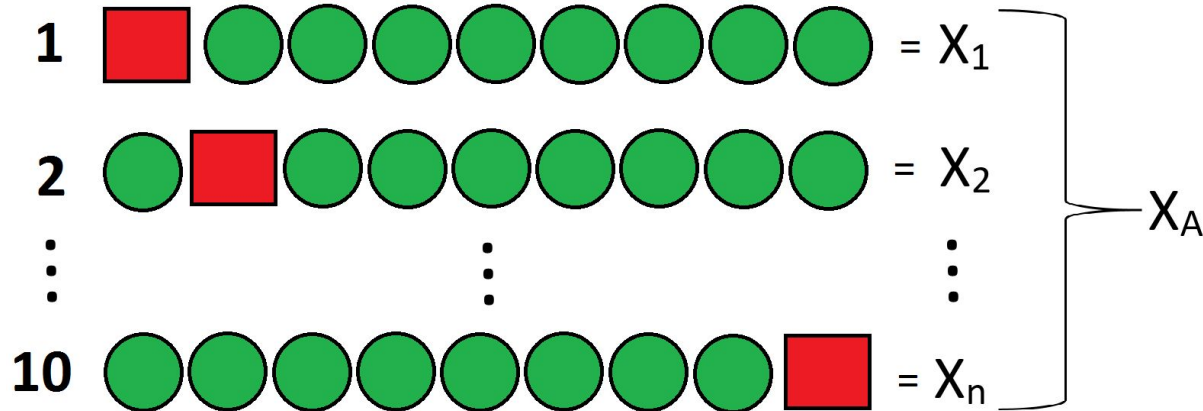
# Experiments

1. Split dataset to N same subsets
2. For each subset:
  - a. Split subset for training and testing data



# Experiments

1. Split dataset to N same subsets
2. For each subset:
  - a. Split subset for training and testing data
  - b. Cross Validation on training data



# Experiments

1. Split dataset to N same subsets
2. For each subset:
  - a. Split subset for training and testing data
  - b. Cross Validation on training data
  - c. Train on all training data and test on test data

# Experiments

1. Split dataset to  $N$  same subsets
2. For each subset:
  - a. Split subset for training and testing data
  - b. Cross validation on training data
  - c. Train on all training data and test on testing data
3. Final result is an average of all results in subsets

# Measures

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

$$\text{False Positive Rate} = FP / (FP + TN)$$

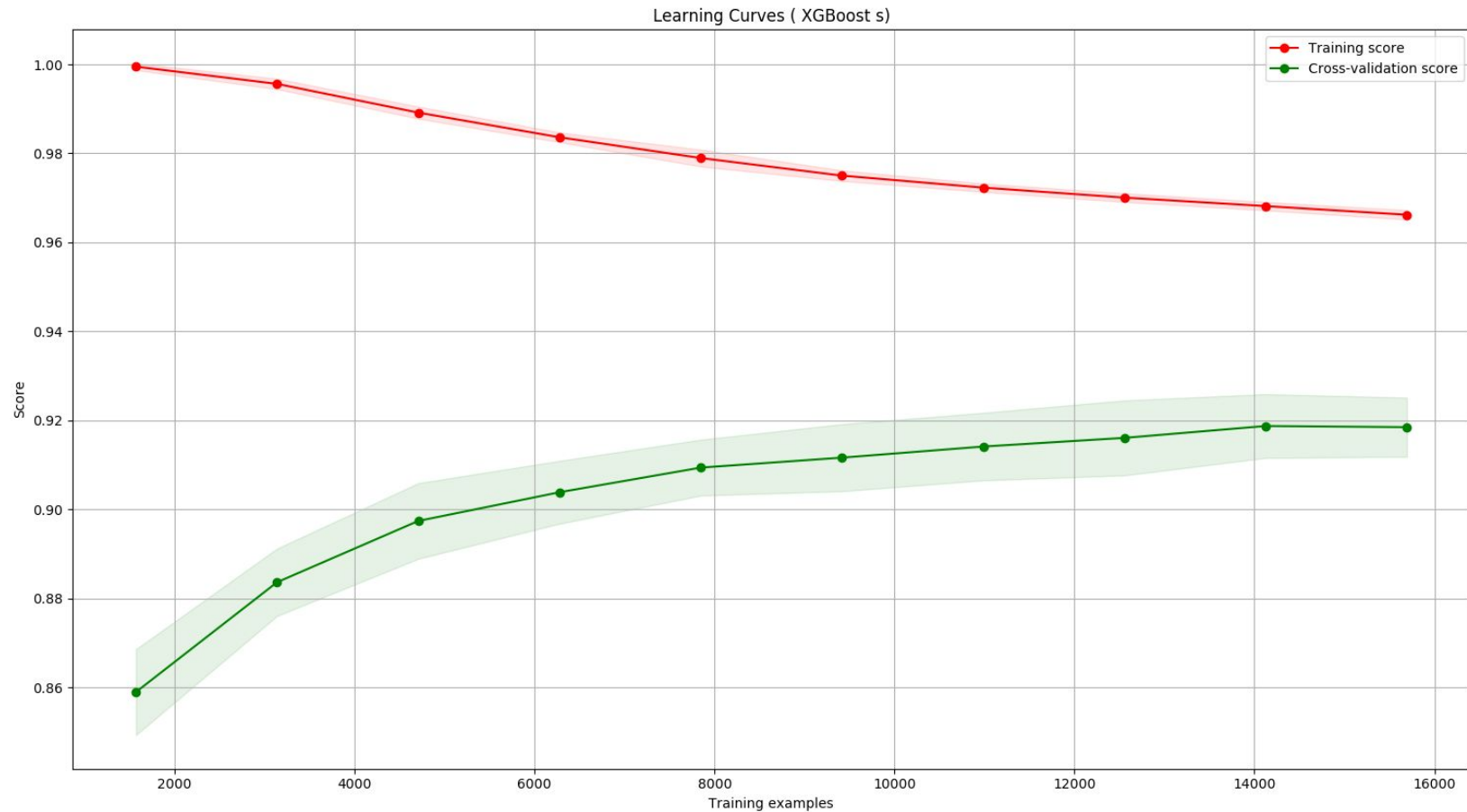
$$\text{False Negative Rate} = FN / (FN + TP)$$

$$\text{Sensitivity} = TP / (TP + FN)$$

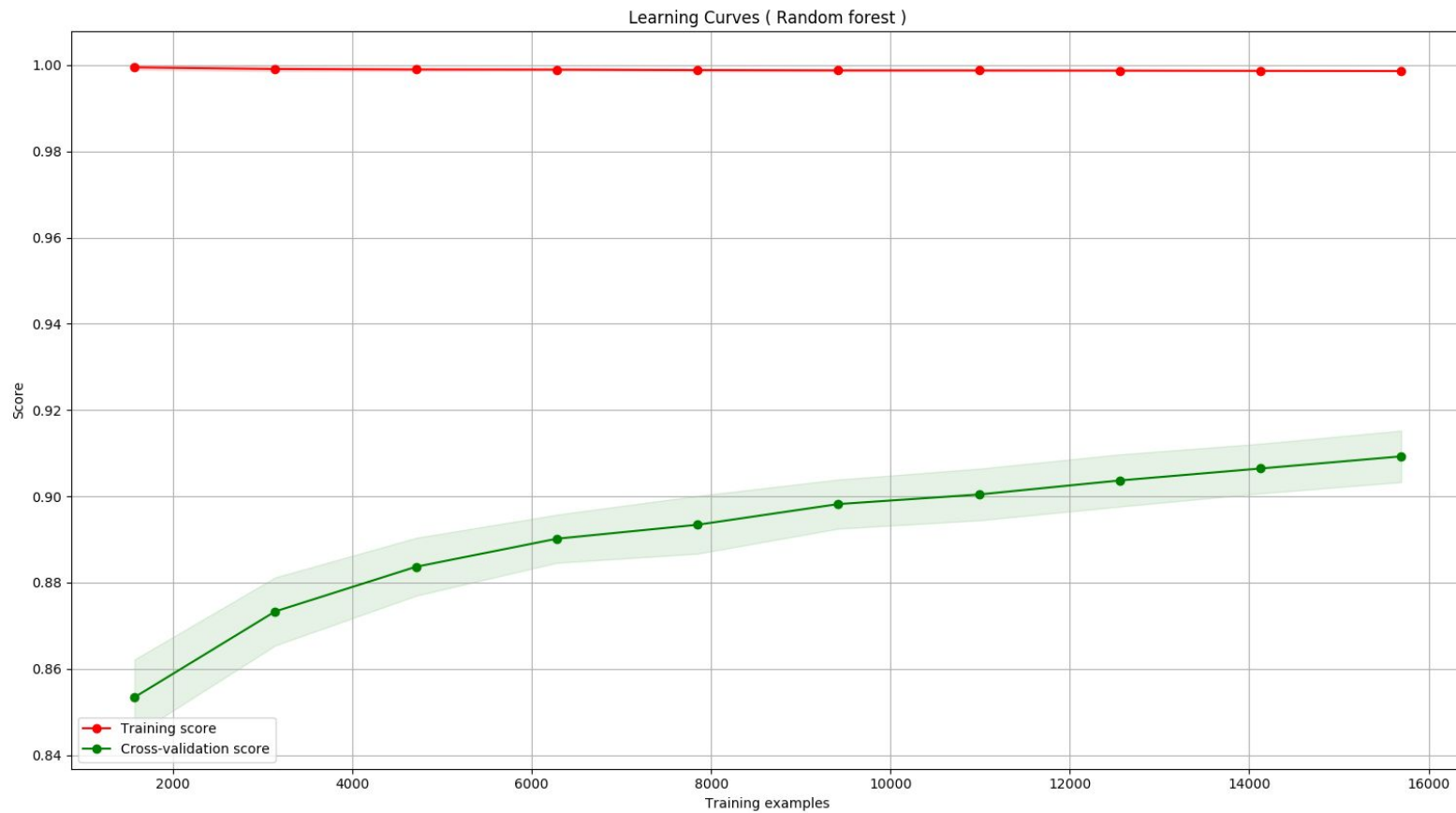
$$\text{F1 score} = 2TP / (2TP + FP + FN)$$



# Learning curve - XGBoost



# Learning curve - Random Forest



# Experiment 1

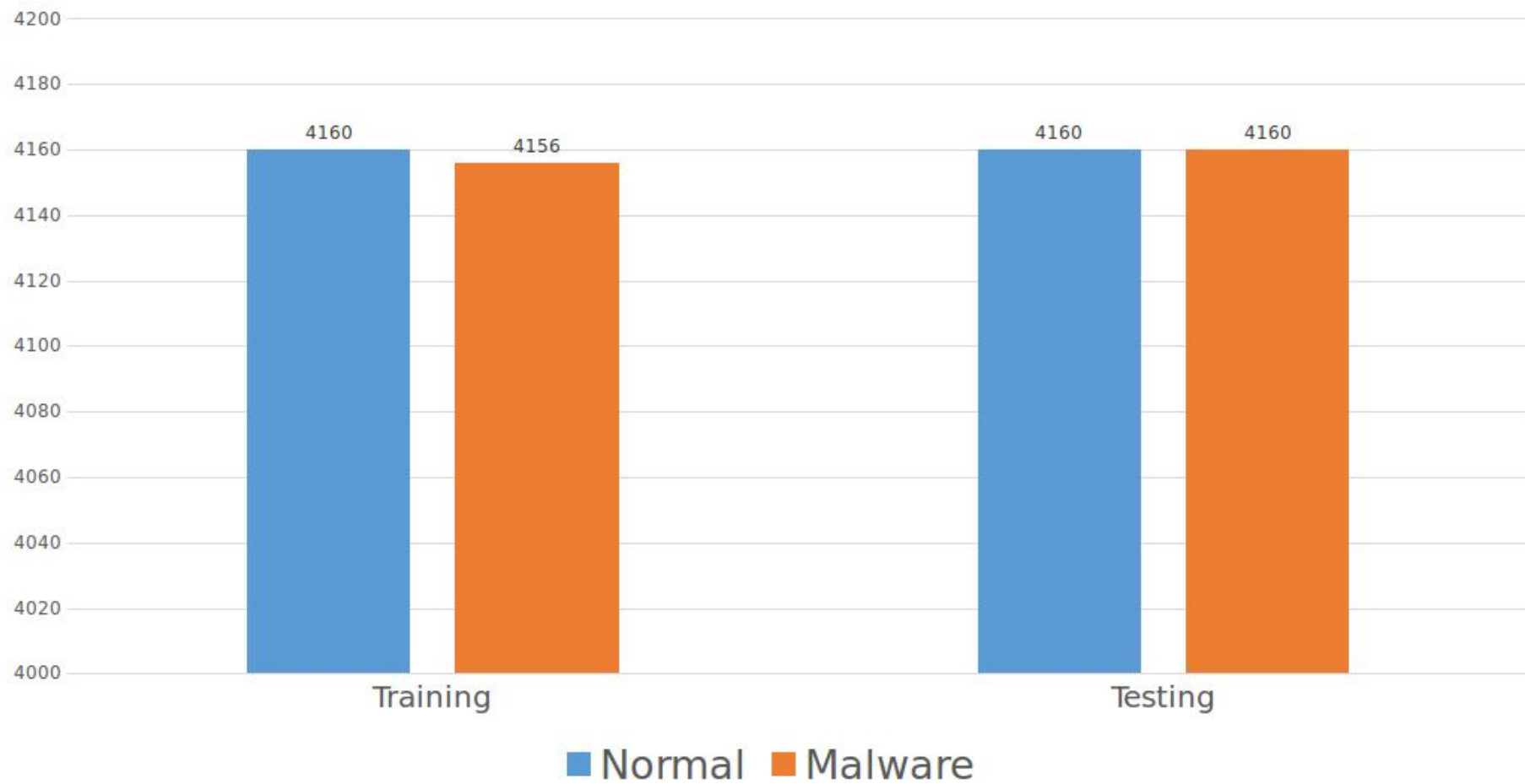
# Experiment 1

- Subset 1
  - Training
    - Normal: 4,160 ssl-connect-units
    - Malware: 4,156 ssl-connect-units
  - Testing
    - Normal: 4,160 ssl-connect-units
    - Malware: 4,160 ssl-connect-units
- Subset 2
  - Training
    - Normal: 4,160 ssl-connect-units
    - Malware: 4,156 ssl-connect-units
  - Testing
    - Normal: 4,160 ssl-connect-units
    - Malware: 4,160 ssl-connect-units

# Experiment 1

- Training: 50% - 50%
  - Normal: 4,160 ssl-connect-units
  - Malware: 4,156 ssl-connect-units
- Testing: 50% - 50%
  - Normal: 4,160 ssl-connect-units
  - Malware: 4,160 ssl-connect-units

## Experiment 1



# Experiment 1

- XGBoost
  - Cross validation accuracy: 91.58%
  - Testing accuracy: 92.11%
  - False Positive Rate: 7.5%
  - False negative rate: 8.5%
  - Sensitivity: 91.48 %
  - F1 Score: 51.96 %

# Experiment 1

- Random Forest
  - Cross validation accuracy: 90%
  - Testing accuracy: 90%
  - False Positive Rate: 8.3%
  - False negative rate: 11.7%
  - Sensitivity: 88.2%
  - F1 Score: 89.76%



# Experiment 2

# Experiment 2

- Subset 1

- Training

- Malware: 7,232 ssl-connect-units

- Normal: 10,205 ssl-connect-units

- Testing

- Malware: 1,081 ssl-connect-units

- Normal: 36,182 ssl-connect-units

- Subset 2

- Training

- Malware: 7,232 ssl-connect-units

- Normal: 10,205 ssl-connect-units

- Testing

- Malware: 1,081 ssl-connect-units

- Normal: 36,182 ssl-connect-units

- Subset 3

●  
●  
●

- Subset 8

- Training

- Malware: 7,567 ssl-connect-units

- Normal: 10,205 ssl-connect-units

- Testing

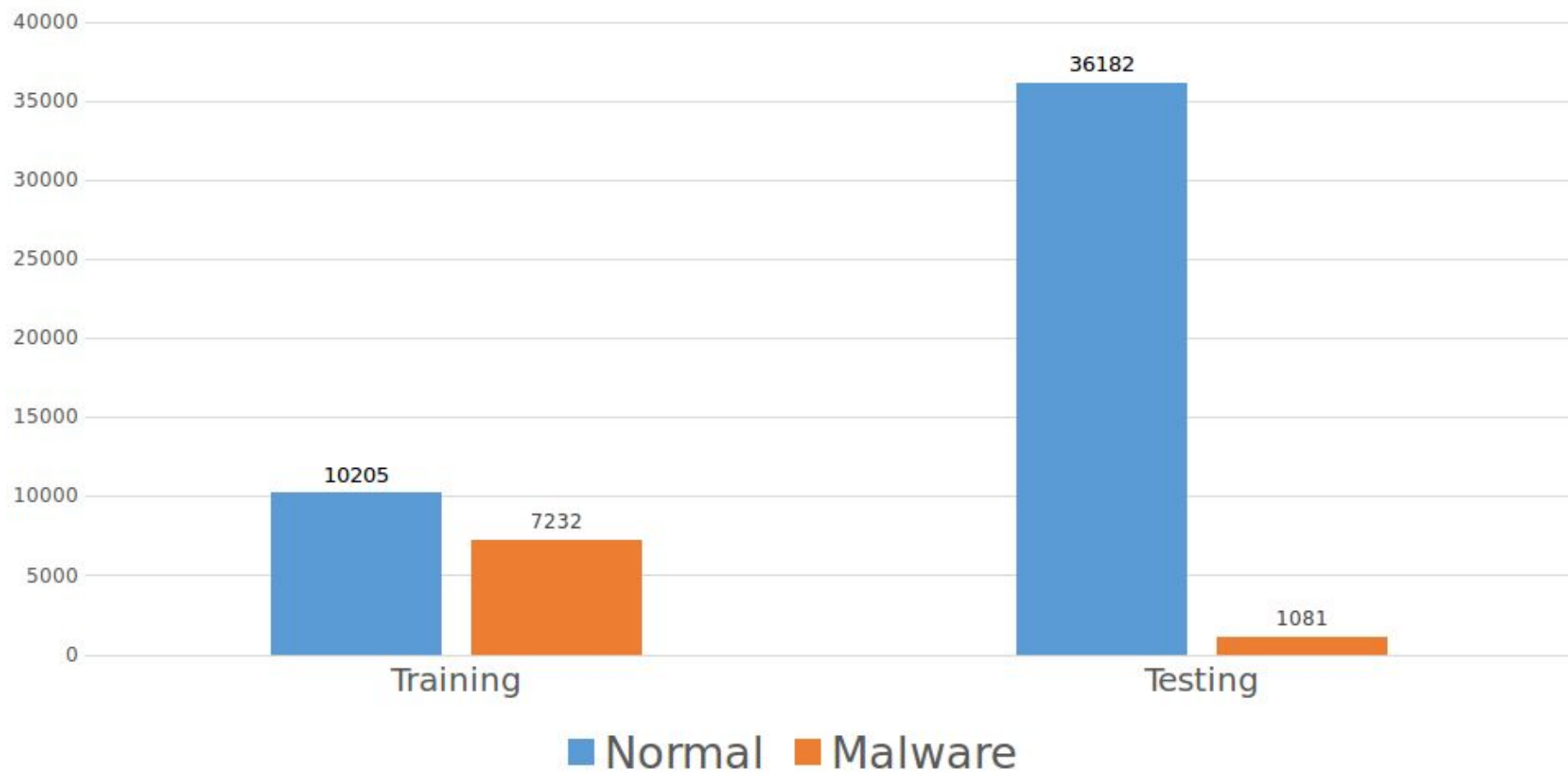
- Malware: 746 ssl-connect-units

- Normal: 36,182 ssl-connect-units

# Experiment 2

- Training: 40% - 60%
  - Malware: 7,232
  - Normal: 10,205
- Testing: 3% - 97%
  - Malware: 1,081
  - Normal: 36,182

## Experiment 2



# Experiment 2

- XGBoost
  - Cross validation accuracy: 92.45%
  - Testing accuracy: 94.33%
  - False Positive Rate: 5.54%
  - False negative rate: 10.11%
  - Sensitivity: 89.89%
  - F1 Score: 46.96 %

# Experiment 2

- Random Forest
  - Cross validation accuracy: 91.21%
  - Testing accuracy: 95.65%
  - False Positive Rate: 4.05%
  - False negative rate: 14.82%
  - Sensitivity: 85.18%
  - F1 Score: 52.24%

# Feature importance

1. Certificate length of validity
2. Inbound and outbound packets
3. Validity of certificate during the capture
4. Duration
5. Number of domains in certificate
6. SSL/TLS version
7. Periodicity

# Malware and Certificates

- Certificates used by Malware in Alexa 1000 ~ 50%
  - Certificates used by Normal in Alexa 1000 ~ 30%
- 
- Usage of certificate by Malware is almost correct



Did we achieve the goal?

# Thanks for attention!

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