A Multi-Level Framework to Identify HTTPS Services

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Outline

Security vs. Privacy

- HTTPS (HTTP-over-TLS) is a protocol for secure communication over internet.
- Content providers (Google, Facebook, ...) need securing contents over the web by moving to HTTPS.
- Based on French ISP, the amount of encrypted traffic represent almost 50% in 2015, compared with 5% in 2012.
- Despite SSL/TLS good intentions, it may be used for illegitimate purposes.

The Issue

An identification of HTTPS traffic without relying on decryption.

Practical solutions

- Legacy solutions: Port Based, DNS, IP, DPI → (Don't work).
- Decryption methods: HTTPS proxy [1], Crack encryption algorithm → (**Privacy issues** & Computation complexity)
- Recent solutions: SSL certificate, SNI [1]→(Reliability issues).

Research work: flow-based statistical method

- + Applicable to encrypted traffic.
- - Low accuracy and computation overhead issues.
- - Hard to get precise information from general statistics.

[1] Used by commercial solution like FireEye & Forefront

Flow-Based Statistical improvements

- One way is to combined it with algorithms from different fields like Machine Learning (ML) [2].
- Used to identifying the Type of Applications [3]
  - such as (HTTPS, SSH, P2P, Skype, VOIP, etc.)
- Used by Website Fingerprinting technique:
  - Identify accessed HTTPS web pages base on static object size parsed from unencrypted pages [4].

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What is the proper level of identification?

Application type level OR Web pages Level

Flow-Based Statistical Method

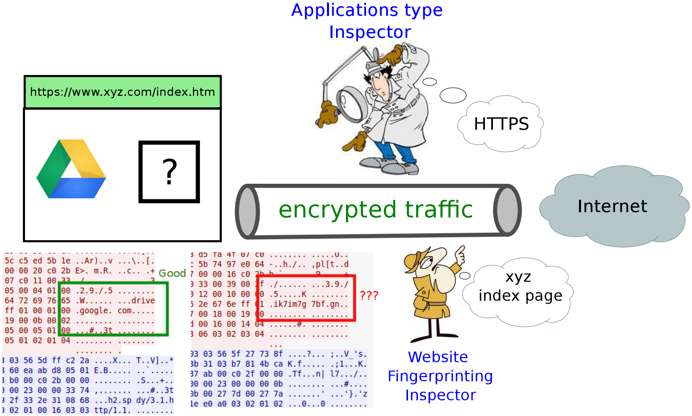


Figure : An example of suspicious HTTPS traffic

- Application Type Level (Too generic)
- Website Fingerprinting Level (Too fine-grained)

A Multi-Level Framework to Identify HTTPS Services

The motivation

- An intermediate identification level **Service-Level**.
- Identify the HTTPS services without relying on header fields.
- Do not decrypt the HTTPS traffic.

The core techniques

1. Machine Learning techniques.
2. Novel multi-level classification approach.
3. Well tuned set of features.

Machine Learning Techniques

Overview

- Machine learning (ML) is a type of artificial intelligence (AI).
- The basic requirements:
  1. Training dataset and Labelling
  2. Statistical Features and ML algorithms.
  3. Evaluation techniques.
- ML phases: Training $\rightarrow$ Classification $\rightarrow$ Validation

Dataset Collection

- We build our own dataset in a well controlled environment with volunteer users of our lab.
- We use the SNI for HTTPS dataset Labelling.

What is SNI ?

SNI indicates the actual destination hostname a client is attempting to access over HTTPS.

The Ground-Truth

Since no SNI filtering is applied in our lab, so we utilized it as Ground Truth.

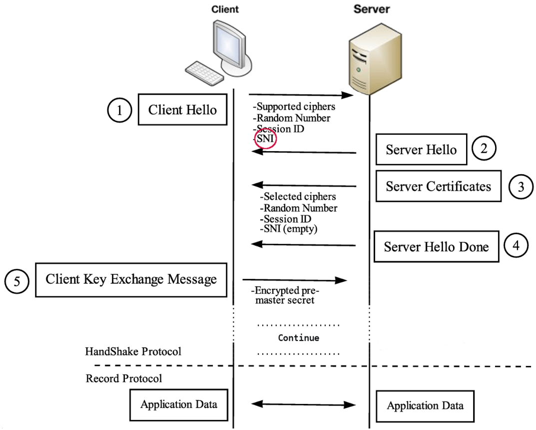


Figure : TLS handshake

Statistical features and ML algorithms

Statistical features

- A set of **42 features** over the TLS connections is used.
- Classical **30 features** from previous work [5, 6].
- New **12 features** are proposed over the encrypted payload.

ML algorithms

- The ML algorithms use them to build the classification model.
- Based on a preliminary experiments **C4.5** and **RandomForest** algorithms are selected.

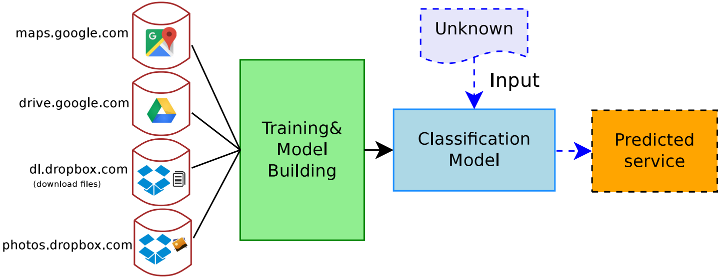


Figure : Flat classification view

Legacy machine learning flat classification

- Identifying the websites and applications directly.
- Drawbacks: low scalability, low accuracy and high error rate.

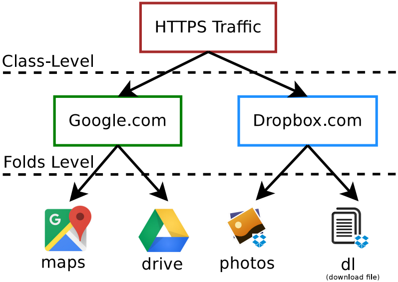


Figure : Multi-level presentation (inspired from Biology field)

A Novel Multi-Level Classification Approach

- Reform the training dataset into a tree-like fashion.
- The top level is refereed as Class-level (Root domain)
- The lower Level contains individual Folds-level (Sub-domain)

Common evaluation techniques

- A K-fold cross-validation, Precision, Recall, F-Measure.
- Receiver Operating Characteristics (ROC) analysis.
- The classification errors over time and the Confidence-Score.

A novel method more suitable for multi-level approach

- If service provider and the service name are predicted correctly $\rightarrow$ **Perfect identification**.
- If service provider is predicted but not the service name $\rightarrow$ **Partial identification**.
- If neither service provider nor the service name are predicted $\rightarrow$ **Invalid identification**

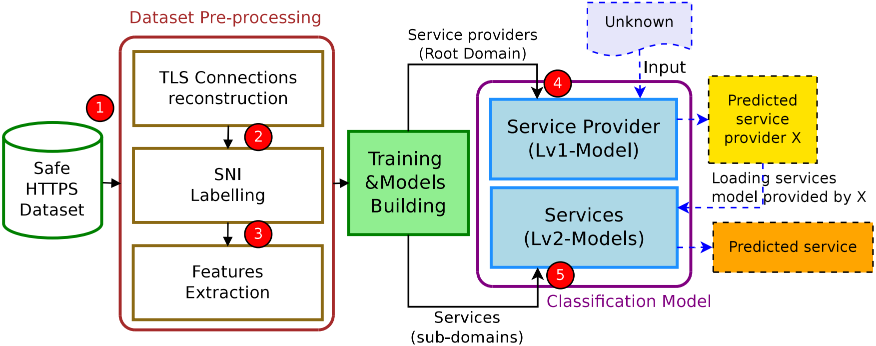


Figure : The work-flow of the HTTPS traffic identification framework

Evaluation Results

Overview

The evaluation of the proposed solution contains 3 parts:

- Evaluation of the collected dataset.
- Evaluation of the proposed features set.
- Evaluation of the multi-level classification approach.

Evaluation of the collected dataset

- Contains more than 288,901 HTTPS connections.
- Pre-processed to be suitable for multi-level approach.
- Processed to determine a reasonable threshold for the minimum number of labelled connections per service.

Optimized by Features Selection technique

- 18 features are highly relevant: 10 out of 12 from our proposed set and 8 out of 30 from the classical ones.
- This validates the rationale of the proposed features for identifying HTTPS services.

Table : The 18 selected features

Client ↔ Server
Inter Arrival Time (75th percentile)
Client → Server
Packet size (75th percentile, Maximum), Inter Arrival Time (75th percentile), **Encrypted Payload(Mean, 25th, 50th percentile, Variance, maximum)**
Server → Client
Packet size (50th percentile, Maximum), Inter Arrival Time (25th, 75th percentile), **Encrypted payload(25th, 50th, 75th percentile, variance, maximum)**

The proposed features set performance

By using WEKA [2] tool the features set are tested by C4.5 and RandomForest algorithm:

- **Classical 30-features**:
  C4.5 achieves 83.4%±1.0 Precision,
  RandomForest achieves **85.7%±0.4** Precision.
- **Full 42-features**:
  C4.5 achieves 86.65%±0.7 Precision,
  RandomForest achieves **87.82%±0.68** Precision.
- **Selected 18-features**:
  C4.5 achieves 85.87%±0.64 Precision,
  RandomForest achieves **87.60%±0.10** Precision.

[2] www.cs.waikato.ac.nz

HTTPS Identification Framework

- The framework has been evaluated in two steps:
  - Evaluate each level separately, to measure the performance of each classification model.
  - Evaluate the whole framework as one black box.
- Evaluation conditions:
  - Full features set (42 features).
  - RandomForest as ML algorithm.
  - At least 100 connections number per service.
  - K-Fold cross validation with k=10.

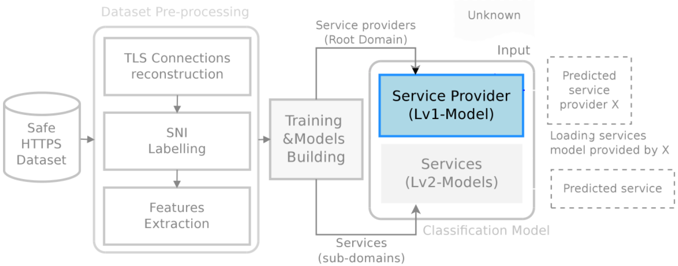


Figure : Top Level of the framework

Top level evaluation

Experiments show that we can identifying the service provider of HTTPS traffic with 93.6% overall accuracy.

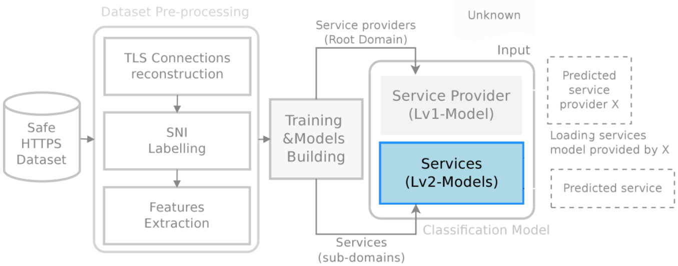


Figure : Second Level of the framework

Second level evaluation

A separate classification models are built and evaluated for each service provider with the same approach used in the Top-level.

Second level evaluation

- From 68 distinct service providers, 51 service providers have more than 95% of good classification of their own different services.
- For example, we can differentiate between 19 services run under Google.com, with 93% of Perfect identification.

Table : The second level models accuracy

Accuracy Range	Nb of service providers		
-	Classical Features	Full Features	Selected Features
100-95%	50	51	51
95-90%	5	5	5
90-80%	6	6	6
Less than 80%	7	6	6

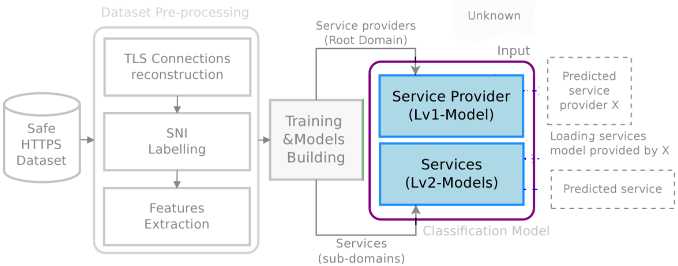
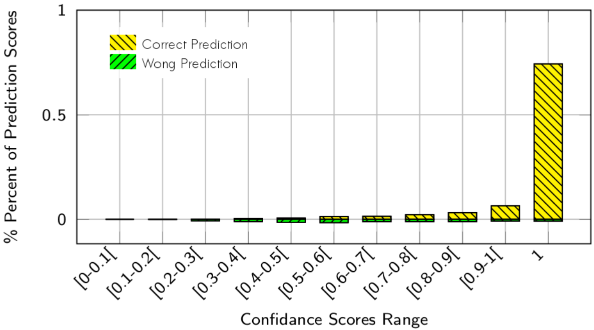


Figure : The complete classification model

Evaluate the framework as black-box (Level1&2)

Results show that we achieve 93.10% of Perfect identification and 2.9% of Partial identification.



The confidence score

- Measures the level of agreement between decision trees.
- Results shows that 86.68% of the predictions are in the sub-ranges [0.8-0.9[, [0.9,1[and 1.

The classification errors over time

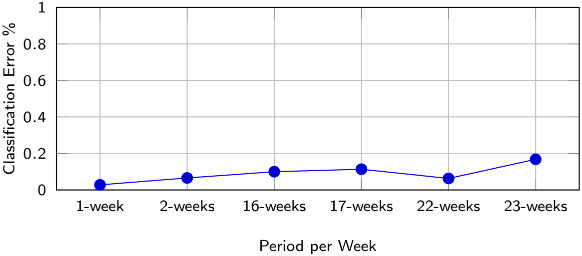


Figure : Effect upon classification error over time

Result

We can notice that even after 23 weeks without new learning phase, we still identify 80% (error <20%) of HTTPS services.

Conclusion & Future work

Conclusion

- A complete framework to identify the HTTPS services with several innovations (Multi-level classification, SNI-labelling, new set of features, without decryption).
- Based on real traffic, the results show that despite the challenging task, a high level of accuracy of 93.10% achieved.

Future Work

- To adapt and extend our current framework for real-time analysis identification of HTTPS services.
- Improve the global security of networks especially by developing a HTTPS firewall.

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