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# A Multi-Level Framework to Identify HTTPS Services

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# Outline

- 1 Introduction
- 2 Related work
- 3 The Multi-Level Framework
- 4 Evaluation Results
- 5 Conclusion & Future work

## 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 <sup>1</sup>, 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.

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<sup>1</sup>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

Applications type  
Inspector

HTTPS

encrypted traffic

Internet

```

5c c5 e0 5b 1e ...Ar].v ...X...[
00 00 20 c0 2b E...m.R...c...+
07 c0 11 00 33 /.../.../.../.../
05 00 04 01 00 .2.9././5
64 72 69 76 65 .W...drive
ff 01 00 01 00 .google. com...
19 00 0b 00 02 .....#...3t
05 00 05 01 00 .....#...3t
05 01 02 01 04 .....#...3t

3 05 7a 47 07 c0 .....U...
5b 74 97 e0 64 -.h./...pl[t..d
7 00 00 16 c0 .....h...h...
3 33 00 30 00 f./...3.9./
3 12 00 10 00 0 .5...K...
5 2e 67 6e ff 1 .lk7in7g 7bf.gn...
7 00 18 00 19 0 .....#...
1 00 16 00 14 04 .....#...
3 06 03 02 03 04 .....#...

i 03 56 5d ff c2 20 ...X... T..V]...
i 60 ea ab d8 05 01 E.B...
i b0 00 c0 2b 00 00 .....S...
i 00 23 00 00 33 74 .....#...3t
i 2f 33 2e 31 08 68 ...h2.sp dy/3.1.h
i 02 01 00 16 03 03 ttp/1.1.

33 03 56 5f 27 73 8f ...?... .V *s.
3b 31 03 b7 81 4b ca K.f...;1...K.
37 ab 00 c0 2f 00 00 .Tf...n] l7.../.
30 08 23 00 00 00 0b .....#...
3b 00 27 7d 00 27 7a .....}.'z
1e e0 a0 03 02 01 02 .....0...0

```

???

xyz  
index pageWebsite  
Fingerprinting  
Inspector

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 → Classification → 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.

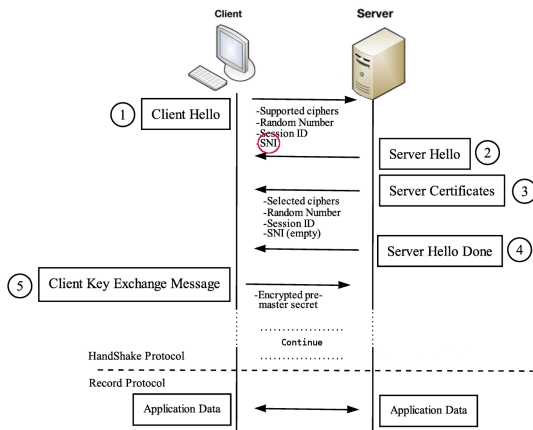


Figure : TLS handshake



# 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.

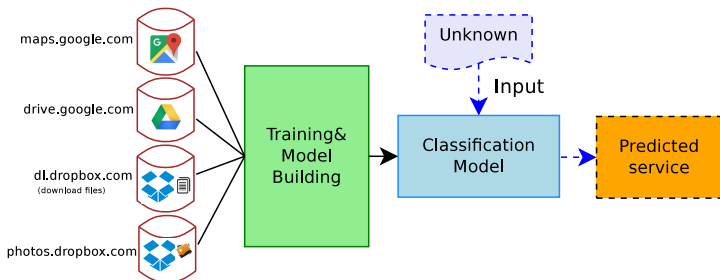


Figure : Flat classification view

## Legacy machine learning flat classification

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

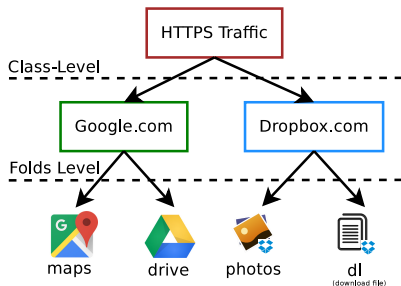


Figure : Multi-level presentation (inspired from Biology field)

## A Novel Multi-Level Classification Approach

- Reform the training dataset into a tree-like fashion.
- The top level is referred 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  
→ **Perfect identification.**
- If service provider is predicted but not the service name  
→ **Partial identification.**
- If neither service provider nor the service name are predicted  
→ **Invalid identification**

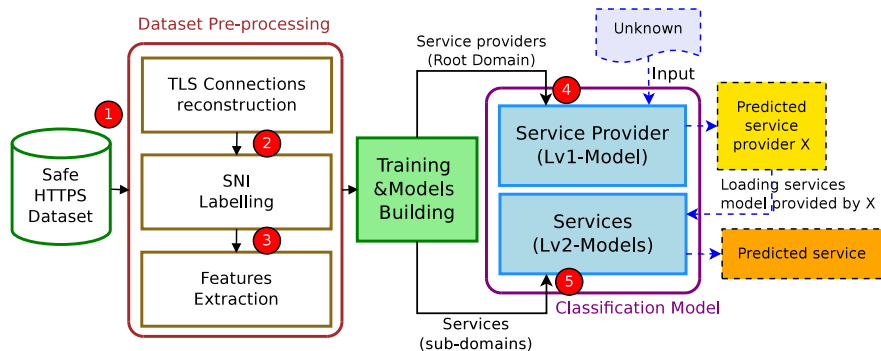


Figure : The work-flow of the HTTPS traffic identification framework





# 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

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



## The proposed features set performance

By using WEKA <sup>2</sup> tool the features set are tested by C4.5 and RandomForest algorithm:

- **Classical 30-features:**

C4.5 achieves  $83.4\% \pm 1.0$  Precision,  
RandomForest achieves  **$85.7\% \pm 0.4$**  Precision.

- **Full 42-features:**

C4.5 achieves  $86.65\% \pm 0.7$  Precision,  
RandomForest achieves  **$87.82\% \pm 0.68$**  Precision.

- **Selected 18-features:**

C4.5 achieves  $85.87\% \pm 0.64$  Precision,  
RandomForest achieves  **$87.60\% \pm 0.10$**  Precision.

---

<sup>2</sup>[www.cs.waikato.ac.nz](http://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  $k=10$ .

## The Multi-level Classification Approach Evaluation

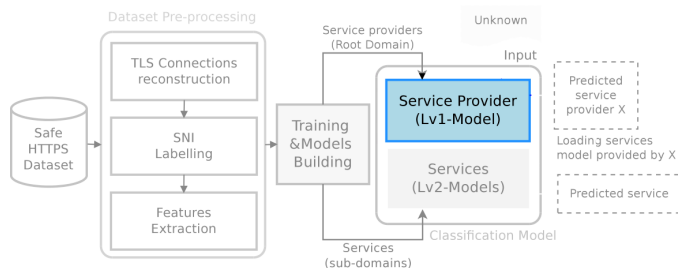


Figure : Top Level of the framework

## Top level evaluation

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

## The Multi-level Classification Approach Evaluation

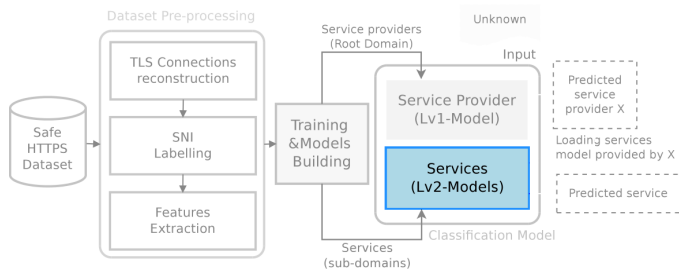


Figure : Second Level of the framework

## 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

## The Multi-level Classification Approach Evaluation

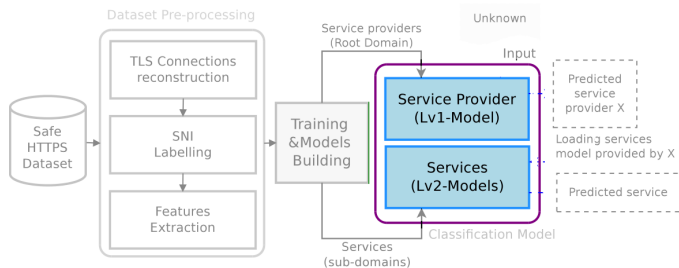


Figure : The complete classification model

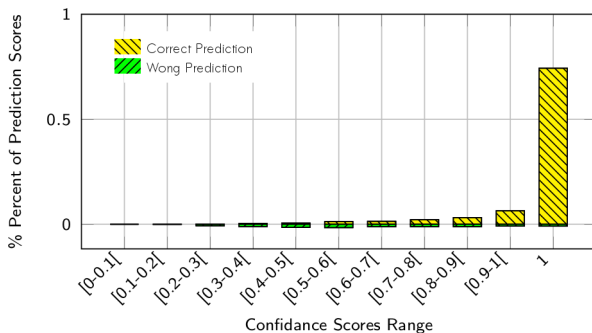
Evaluate the framework as black-box (Level1&2)

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





## The Multi-level Classification Approach Evaluation



### 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

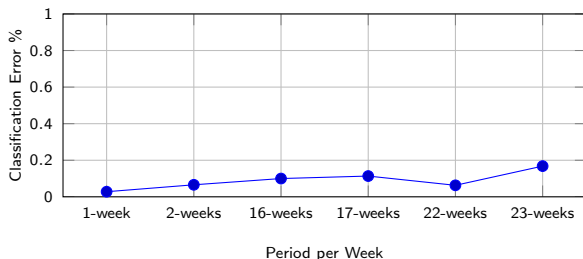


Figure : Effect upon classification error over time

## 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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