Automatic clustering of a network protocol with weakly-supervised clustering

Tobias Schrank  
Tobias.Schrank@tugraz.at  
Franz Pernkopf  
Pernkopf@tugraz.at  
Graz University of Technology

Abstract

Abstraction is a fundamental part when learning behavioral models of systems. Usually the process of abstraction is manually defined by domain experts. This paper presents a method to perform automatic abstraction for network protocols. In particular a weakly supervised clustering algorithm is used to build an abstraction with a small vocabulary size for the widely used TLS protocol. To show the effectiveness of the proposed method we compare the resultant abstract messages to a manually constructed (reference) abstraction. With a small amount of side-information in the form of a few labeled examples this method finds an abstraction that matches the reference abstraction perfectly.

Keywords: abstraction learning, automata learning, learning-based testing

1. Introduction

The implementation of complex designs is challenging even for experts. This complexity often leads to bugs in the implementation. Therefore, complex pieces of software or hardware are usually extensive tested and/or verified. This, however, is complicated by the fact that most designs are not formally specified, if at all. Due to this model-based testing with learned models has become rather popular in the recent past (e.g., de Ruiter and Poll (2015)).

However, the methods used in the field of learning-based testing – namely a family of algorithms all building upon L* (Angluin, 1987) – rely on small alphabets in order to work in practice. For instance, Smeenk et al. (2015) make use of detailed knowledge of the system under test to limit the size of the alphabet in order to make it feasible to apply L*. This reduction of the alphabet size is brought about by defining some abstraction which is typically done by hand. This process, however, relies on a considerable degree of knowledge of the system under test that is not necessarily available.

In this paper we set forth to perform abstraction of the Transport Layer Security (TLS) protocol with as little human intervention as possible. To this end, we employ a weakly supervised learning algorithm from the k-means family that takes only a few labeled examples as input. It uses this kind of side-information to build a set of constraints of which data points need to be assigned to the same cluster and which must not. These constraints are then in turn used to both guide the algorithm towards both an optimal cluster assignment and learning a distance metric with which the clusters can be optimally separated. We evaluate this semi-automatic method by comparing the cluster assignments to a reference abstraction. This reference abstraction is of the form as a human would have to provide one
when using common methods. With a small amount of side-information in the form of a few labeled examples this method finds an abstraction identical to the reference abstraction.

The choice to perform automatic abstraction of TLS is the direct consequence of critical position TLS takes up in modern internet-based communication. On top of this semi-automatic abstraction one can learn automata that can be used in model-based testing – a practice known as learning-based testing.

This paper is structured as follows: In Section 2 we present the semi-supervised clustering algorithm. In Section 3 we discuss the experimental setup, the data used and the evaluation procedures employed. Section 3.3 reports results obtained from the experiments and discusses their implications for the task of (semi-)automatic abstraction. We conclude with a general discussion in Section 5.

2. Method: MPCK-means

Metric learning and pairwise-constrained $k$-means (MPCK-means) clustering (Bilenko et al., 2004) is an approach to semi-supervised learning which employs pairwise constraints. Pairwise constraints come in two forms: must-link constraints and cannot-link constraints. MPCK-means employs these pairwise constraints for both learning a metric space which separates data points of cannot-link pairs and brings data points of must-link pairs closer together as well as avoids constraint violations when assigning data points to clusters.

MPCK-means employs the following objective function in (1). It minimizes cluster dispersion under the learned metric and at the same time reduces constraint violations:

$$J_{mpckm} = \sum_{x_i \in X} (d(x_i, \mu_{l_i})^2_{A_{l_i}}) - \log(\det(A_{l_i})) + \sum_{(x_i, x_j) \in M} w_f_M(x_i, x_j) \mathbb{1}[l_i \neq l_j] + \sum_{(x_i, x_j) \in \bar{C}} \bar{w}_f_C(x_i, x_j) \mathbb{1}[l_i = l_j],$$

where $X$ is the set of data points, $l$ is the cluster assignment of the current data point, $d(\cdot, \cdot)_{A_{l_i}}$ is the current metric for this particular cluster, that is a weight matrix, $w$ and $\bar{w}$ are the penalties imposed on violations of must-link constraints and cannot-link constraints, respectively, $M$ and $\bar{C}$ are the sets of must-link constraints and cannot-link constraints, respectively, $f_M$ and $f_C$ are functions defining the penalty imposed violations depending on the closeness of the involved data points under the current metric and $\mathbb{1}$ is the indicator function.

The first term of objective (Eq. 1) accounts for the dispersion given the current metrics $A_l$ (one for each cluster). The second term is needed as normalization of the magnitude of the weights in $A_l$. The third and forth term measures the number of violated constraints weighted by a hyper-parameter ($w_{ij}$ and $\bar{w}_{ij}$, respectively) and the distance between the two involved data points. Therefore, violated must-link constraints which are considered to be far away under the current metrics $A_{l_i}$ and $A_{l_j}$ result in larger penalties:
\begin{equation}
    f_M(x_i, x_j) = \frac{1}{2} d(x_i, x_j)^2_{A_{li}} + \frac{1}{2} d(x_i, x_j)^2_{A_{lj}}
\end{equation}

Similarly, violated cannot-link constraints which are considered to be close together under the current metric \( A_{li} \) result in larger penalties:

\begin{equation}
    f_C(x_i, x_j) = d(x_i', x_j')^2 - d(x_i, x_j)^2_{A_{li}}
\end{equation}

where \((x'_i, x'_j)\) are the two maximally separated data points according to the current metric \( A_{li} \). This ensures that \( f_C(x_i, x_j) \) is non-negative.

For the experiments we use – in contrast to the MPCK-mean’s original formulation – a weighted hamming distance for \( d(\cdot, \cdot)_{A_{li}} \). Therefore, the weighting matrix \( A_{li} \) is diagonal. In this sense employing a diagonal weighting matrix corresponds to feature weighting.

### 3. Experiments

All experiments presented in this text are implemented with the R programming language (R Core Team, 2018) and use TLS traces gathered with the logging component of nqsb-tls (Kaloper-Meršinjak et al., 2015), a modern TLS implementation. In total, the data consists of approximately 53k decoded TLS traces comprising nearly 370k messages. There are just over 81k unique messages. In this work, we used a random sub-set of 5k messages where each message is truncated to a maximum of 32 fields (uninformative fields RANDOM and SESSIONID are filtered). A sample TLS message is given in Table 1.

| HANDSHAKE-IN | CLIENTHELLO |
|--------------|-------------|
| VERSION      | TLS_1.2     |
| CIPHERSUITES | TLS_RSA_WITH_AES_128_CBC_SHA256 |

Table 1: A sample TLS message (decoded and truncated).

### 3.1. The TLS protocol

One of today’s most widely used cryptographic security protocol is Transport Layer Security (TLS), predecessors of which are also known as Secure Sockets Layer (SSL). It is used to secure communications over insecure channels in applications as diverse web browsing (as HTTPS), email (as SMTPS), voice-over-IP (in SIP) and virtual private networks (in OpenVPN). For a long time, TLS implementations had been considered very secure OpenVPN. A number of high-profile vulnerabilities starting in 2014 have changed this picture, most famously a security bug called Heartbleed. Most TLS implementations provide a wide array of TLS versions, protocol extensions, authentication modes and key exchange modes in order to be maximally compatible with clients.

For this text’s endeavor the interesting part of TLS is the process of establishing a secure connection between two nodes. In this process three sub-protocols are in use: To establish
session parameters and cryptographic keys the Handshake protocol is used. Authentication, if asked for, is also done by means of this sub-protocol. To start the session with the keys established via the handshake sub-protocol the ChangeCipherSpec sub-protocol is used. To signal errors or warnings to the other node the Alert sub-protocol is used.

### 3.2. Evaluation Measure

In order to evaluate the quality of the automatic abstraction we manually construct a reference abstraction which is generated by a set of hand-written rules. This reference abstraction consists of $J = 21$ classes and is similar to the abstraction found in the literature (cf. for instance Beurdouche et al. (2015) or de Ruiter and Poll (2015)).

To measure the mismatch between the automatic abstraction and the reference abstraction we employ two common measures for clustering performance, namely, purity and the adjusted Rand index (ARI).

For determining Purity each cluster of the automatic abstraction is assigned to the reference abstraction where the intersection of samples is maximal. The number of intersecting samples is accumulated over all clusters and normalized (Manning et al., 2008). It is formally defined as

$$purity(\Omega, C) = \frac{1}{N} \sum_k \max_j |\omega_k \cap c_j|,$$

where $N$ is number of samples, $\Omega = \{\omega_1, \omega_2, ..., \omega_K\}$ is the set of clusters provided by the algorithm, $C = \{c_1, c_2, ..., C_J\}$ is the set of classes of the reference abstraction, $\omega_k$ denotes the set of samples in cluster $k$ and $c_j$ is the set of samples of the reference abstraction in class $j$. Purity is thus closely related to accuracy and a good indicator of goodness for practical applications.

We also measure quality of abstraction through the ARI (Hubert and Arabie, 1985), a measure for similarity between two partitioning that is adjusted for chance. The ARI equals 0 if the clustering equals the expected value, and 1 for a perfect clustering. Moreover, the ARI is geared more towards a fair evaluation of methods than purity.

### 3.3. Results and Discussion

In the present experiments we envision a scenario where constructing a manual abstraction is considerably more costly than having a domain expert deciding on whether two TLS messages should be considered equal or unequal for the task at hand.

The confusion matrix of the classical $k$-means algorithm (unsupervised) is shown in Figure 1(a). It achieves a purity of 0.69 and an ARI of 0.48. In this experiment $K$ is set equal to $J = 21$. Figure 1(b) shows the results for the MPCK-means using $K = J$. Additionally MPCK-means uses 5 labeled samples per class, i.e. in total 105 labels samples are used. Note that from these samples the must-link and cannot-link constraints can be formed. In this setting, we obtain an abstraction that matches the reference abstraction perfectly.

In Figure 2(a) we show results for MPCK-means by varying $K \in \{20, \ldots, 40\}$. The best ARI is obtained for $K = 22$. In this experiment only one labeled sample per class is used. Hence, only cannot-link constraints can be formed. In Figure 2(b) we show results for MPCK-means by varying the number of labels per class from 1 to 5. The best ARI is
Automatic clustering of a network protocol with weakly-supervised clustering

Figure 1: Confusion matrix: (a) Confusion matrix for baseline (unsupervised k-means). 69% purity, 48% ARI. (b) Confusion matrix for MPCK-means; 5 labeled samples per class are used for the must-link and the cannot-link constraints; 100% purity, 100% ARI. Dark spots in the main diagonal correspond to small cluster sizes, not errors.

obtained for 5 labels. In this experiment \( K \) equals \( J \). We achieve an ARI of 1 when using 5 labeled samples per class. In this case the cluster assignment of MPCK means matches the reference abstraction.

4. Related work

Whalen et al. (2010) learn hidden Markov models of the message format of text-based network protocols (HTTP, FTP). Cui et al. (2007) apply recursive clustering and merging to learn the format of both text-based and binary network protocols (HTTP, RPC, SMB).

Some research in this field assume additionally access to the software binary in order to perform dynamic binary analysis, i.e. analyze the interaction between the executing system and the executed software (Caballero et al., 2007; Wondracek et al., 2008; Wang et al., 2009; Milani Comparetti et al., 2009). This condition is not met in the scenario envisioned in this paper where we only assume access to the system under test over the network.

In a different line of research, (Aarts et al., 2012) integrate the task of finding valid abstractions into the loop of learning a finite state machine of the system under test.

5. Conclusion

In this paper, we investigated the semi-automatic abstraction of the network protocol TLS. In particular, we use a small amount of side-information in the form of a few labeled examples. This enables to find an abstraction that matches the reference abstraction perfectly.
Figure 2: MPCK-means: (a) Variation of number of clusters $K$; 1 labeled sample per class is used for the cannot-link constraints; no must-link constraints can be formed. (b) Variation of number of labels per class (top: balanced, bottom: unbalanced).

In future work, we aim to use our automatic abstraction to feed an automaton learning algorithm to show its usefulness in frameworks currently in use in model-based testing. Furthermore, we plan to use MPCK-means for other protocols beyond TLS.

Acknowledgments

This work was supported by the LEAD Project Dependable Internet of Things funded by Graz University of Technology.

References

Fides Aarts, Faranak Heidarian, Harco Kuppens, Petur Olsen, and Frits Vaandrager. Automata learning through counterexample guided abstraction refinement. In Dimitra Giannakopoulou and Dominique Méry, editors, *FM 2012: Formal Methods*, pages 10–27, Berlin, Heidelberg, 2012. Springer Berlin Heidelberg. ISBN 978-3-642-32759-9.

Dana Angluin. Learning regular sets from queries and counterexamples. *Information and Computation*, 75:87–106, 1987.

B. Beurdouche, K. Bhargavan, A. Delignat-Lavaud, C. Fournet, M. Kohlweiss, A. Pironiti, P. Y. Strub, and J. K. Zinzindohoue. A messy state of the union: Taming the composite state machines of tls. In *2015 IEEE Symposium on Security and Privacy*, pages 535–552, May 2015. doi: 10.1109/SP.2015.39.
Mikhail Bilenko, Sugato Basu, and Raymond J. Mooney. Integrating constraints and metric learning in semi-supervised clustering. In *ICML 2004*, 2004.

Juan Caballero, Heng Yin, Zhenkai Liang, and Dawn Song. Polyglot: Automatic extraction of protocol message format using dynamic binary analysis. In *Proceedings of the 14th ACM Conference on Computer and Communications Security, CCS ’07*, pages 317–329, New York, NY, USA, 2007. ACM. ISBN 978-1-59593-703-2. doi: 10.1145/1315245.1315286. URL http://doi.acm.org/10.1145/1315245.1315286.

Weidong Cui, Jayanthkumar Kannan, and Helen J. Wang. Discoverer: Automatic protocol reverse engineering from network traces. In *Proceedings of the 16th USENIX Security Symposium, Boston, MA, USA, August 6-10, 2007*, 2007. URL https://www.usenix.org/conference/16th-usenix-security-symposium/discoverer-automatic-protocol-reverse-engineering-network.

Joeri de Ruiter and Erik Poll. Protocol state fuzzing of TLS implementations. In *24th USENIX Security Symposium*, pages 193–206, August 2015. ISBN 978-1-931971-23-2.

Lawrence Hubert and Phipps Arabie. Comparing partitions. *Journal of Classification*, 2 (1):193–218, 1985.

David Kaloper-Meršinjak, Hannes Mehnert, Anil Madhavapeddy, and Peter Sewell. Not-quite-so-broken TLS: Lessons in re-engineering a security protocol specification and implementation. In *24th USENIX Security Symposium*, pages 223–238, 2015. ISBN 978-1-931971-23-2.

Christopher D. Manning, Prabhakar Raghavan, and Hinrich Schütze. *Introduction to Information Retrieval*. Cambridge Univ. Press, 2008.

Paolo Milani Comparetti, Gilbert Wondracek, Christopher Kruegel, and Engin Kirda. Prospex: Protocol Specification Extraction. In *IEEE Symposium on Security and Privacy*, 2009.

OpenVPN. URL https://openvpn.net/index.php/open-source/337-why-openvpn-uses-tls.html.

R Core Team. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria, 2018. URL https://www.R-project.org/.

Wouter Smeenk, Joushua Moerman, David N. Jansen, and Frits W. Vaandrager. Applying automata learning to embedded control software. In *17th International Conference on Formal Engineering Methods (ICFEM 2015)*, pages 1–17, 2015.

Zhi Wang, Xuxian Jiang, Weidong Cui, Xinyuan Wang, and Mike Grace. Reformat: Automatic reverse engineering of encrypted messages. September 2009. URL https://www.microsoft.com/en-us/research/publication/reformat-automatic-reverse-engineering-of-encrypted-messages/.
Sean Whalen, Matt Bishop, and James P. Crutchfield. Hidden markov models for automated protocol learning. In Sushil Jajodia and Jianying Zhou, editors, *Security and Privacy in Communication Networks*, pages 415–428, Berlin, Heidelberg, 2010. Springer Berlin Heidelberg. ISBN 978-3-642-16161-2.

Gilbert Wondracek, Paolo Milani Comparetti, Christopher Krügel, and Engin Kirda. Automatic network protocol analysis. In *NDSS*, 2008.