Verifying Security Protocols using Dynamic Strategies

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Abstract—Current formal approaches have been successfully used to find design flaws in many security protocols. However, it is still challenging to automatically analyze protocols due to their large or infinite state spaces. In this paper, we propose a novel framework that can automatically verifying security protocols without any human intervention. Experimental results show that SmartVerif automatically verifies security protocols that cannot be automatically verified by existing approaches. The case studies also validate the effectiveness of our dynamic strategy.

Index Terms—Formal verification, Machine learning, Artificial intelligence

I. INTRODUCTION

Security protocols aim at providing secure communications on insecure networks by applying cryptographic primitives. However, the design of security protocols is particularly error-prone. Design flaws have been discovered for instance in the Google Single Sign On Protocol [1], in commercial security tokens implementing the PKCS#11 standard [2], and one may also recall Lowe’s attack [3] on the Needham-Schroeder public key protocol 17 years after its publication. These findings have made the verification of security protocols a very active research area since the 1990s.

During the last 30 years, many research efforts [4]–[12] were spent on designing techniques to model and analyze protocols. The earliest protocol analysis tools, e.g., the Interrogator [13] and the NRL Protocol Analyzer [14], could be used to verify security properties specified in temporal logic. Generic model checking tools have been used to analyze protocols, e.g., FDR [3] and later Murphi [15]. More recently the focus has been on model checking tools developed specifically for security protocol analysis, such as Blanchet’s ProVerif [5], the AVISPA tool [4], Maude-NPA [6] and tamarin prover [7]. There have also been hand proofs aimed at particular protocols. Delaune et al. [16] showed by a dedicated hand proof that for analyzing PKCS#11 one may bind the message size. Similarly, Delaune et al. [17] gave a dedicated result for analyzing protocols based on the TPM and its registers. Guttman [18] also manually extended the space model by adding support for Wang’s fair exchange protocol [19].

Unfortunately, although formal analysis has been successful in finding design flaws in many security protocols, it is still challenging for existing verification tools to support fully automated analysis of security protocols, especially protocols with global states [20]–[24] or unbounded sessions [25]–[27]. They may suffer non-termination during the verification mainly caused by the problem of state explosion. To avoid the explosion of the state space, several tools, e.g., ProVerif [5] and AVISPA [4], use an abstraction on protocols, so that they support more protocols with unbounded sessions. Due to the abstraction, however, they may report false attacks when analyzing protocols with global states [23], [28]. StatVerif [23] and Set-π [28] extend the applied pi-calculus with global states, but the number of sessions they support is limited and they fail to automatically verify complicated protocols (e.g., CANauth protocol [29]). GSVerif [30] enriches ProVerif’s proof strategy and supports several protocols with unbounded sessions [20], [22], but it fails to automatically verify complicated protocols (e.g., Yubikey protocol [21]). Tamarin prover [7],
can verify more protocols without limitations of states or sessions, but it comes at the price of losing automation, for it requires the user to supply insight into the problem by proving auxiliary lemmata.

We propose and implement SmartVerif, a novel and general framework of verifying security protocols. It pushes the limit of automation capability of state-of-the-art verification tools. Our work is motivated by the observation that these tools generally use a static strategy during verification, where design of the strategy is non-trivial. Here, the verification can be simply regarded as the process of path searching in a tree: each node represents a proof state which includes a lemma as a candidate used to prove the lemma in its parent. Due to the variation of states in searching spaces, the strategy must be general so that it can correctly choose the node in each searching step; otherwise it may result in non-termination. It becomes more challenging when verifying different protocols, especially protocols with unlimited states and sessions.

Based on the observation, we design a dynamic strategy in SmartVerif. In other words, SmartVerif runs round-by-round, where in each round the strategy is either applied in searching until the complete proof path is selected, or optimized in case the current selected path is estimated incorrect. The initialization of the strategy does not need any human intervention, i.e., the initial strategy is purely random. After the strategy is sufficiently optimized, it can smartly choose the next searching nodes. Specially, it efficiently localizes the node representing a supporting lemma among the nodes, which leads to success in verification. Here, the supporting lemma is a special lemma necessarily used for proving the specified security property. Therefore, the supporting lemmata have to be proven, before the property is verified. Recall that tamarin prover can let users supply supporting lemmata to reduce the complexity of automation. In comparison, the dynamic strategy in SmartVerif can help find the lemmata automatically and smartly, such that the protocols can be verified without any user interaction.

Our dynamic strategy builds upon the insight that the node representing a supporting lemma is on the incorrect path with lower probability, when a random strategy is given (See the proof in Appendix A). Hence, we introduce Deep Q Network (DQN) [32], a reinforcement learning agent, into the verification. The DQN updates the strategy according to historical incorrect paths. It uses an experience replay mechanism [33] which randomly samples previous transitions, and smooths the training distribution over the incorrect paths. The DQN supports the training of neural networks with stochastic gradient descent in a stable manner. As a result, an optimized strategy tends to select a node representing supporting lemma among the candidates, which leads to higher probability of successful verification.

We also propose to solve other technical problems in implementing SmartVerif. For example, we present an approach of generating incomplete verification tree for reducing the memory overhead. We also design an algorithm of estimating correctness of selected paths, which is the key component for supporting the DQN. Note that since we focus on the automation capability, we design SmartVerif based on tamarin prover that we modify tamarin prover for preprocessing protocol models and acquiring information for the DQN.

Experimental results show that SmartVerif can automatically verify all the studied protocols, without any human intervention. These protocols include Yubkey protocol [21] and CANauth protocol [29], which cannot be automatically verified by state-of-the-art verification tools. The case studies also validate the efficiency of our dynamic strategy.

The main contributions of the paper are three folds:

1) We present SmartVerif, to the best of our knowledge, the first framework that automatically verifies security protocols by dynamic strategies.
2) We propose several methods to deal with technical problems in implementing the framework.
3) SmartVerif pushes the limit of automation capability of protocol verification, and it outperforms state-of-the-art tools.

The rest of the paper is organized as follows. We review some related work and introduce tamarin that we use in Section II and Section III respectively. Then, we present the overview of SmartVerif in Section IV. In Section V we show an illustrative example of security protocols. Afterwards, we solve the main problems in designing the Acquisition and Verification module in Section VI and Section VII respectively. We report our extensive experimental results in Section VIII. Finally, we present our future work and conclude the paper. We also illustrate and prove our insight in the Appendix A.

II. RELATED WORK

There are several typical model checking approaches that can deal with security protocols. AVISPA/AVANTSSAR platform [4] is a tool for the automated validation of security protocols and applications. It provides a modular and expressive formal language for specifying protocols and their security properties, and integrates different backends that implement a variety of automatic analysis techniques. It exhibits a high level of scope and robustness while achieving performance and scalability. Moreover, Fröschle et al. [34] automatically analyze APIs of key tokens using SATMC of AVISPA [35], and show that an API is not robust by finding an attack.

ProVerif [5], one of the most efficient and widely used protocol analysis tools, relies on an abstraction that encodes protocols in Horn clauses. This abstraction is well suited for the monotonic knowledge of an attacker, which makes the tool efficient for verifying an unbounded number of protocol sessions. It is capable of proving reachability properties, correspondence assertions, and observational equivalence. Protocol analysis is considered with respect to an unbounded number of sessions and an unbounded message space. StatVerif [23] is an extension of ProVerif with support for explicit states. Its extension is carefully engineered to avoid many false attacks. It is used to automatically reason about protocols that manipulate global states. GSVerif [30] extends ProVerif to global states. It provides several sound transformations that cover private channels, cells, counters, and tables. These transformations
are efficient to verify protocols with global states. However, it still fails to verify several complicated protocols (e.g., Yubikey [21] and CANauth protocol [29]) with unbounded sessions. For these protocols, it requires users to manually design a sequence of proof formulas to prove the security properties.

Mödersheim et al. [24] solve the ProVerif’s limitation for supporting protocols that are based on databases of keys, contracts, or even access rights. They extend the scope of these over-approximation methods by defining a new way of abstraction that can handle such databases, and prove that the abstraction is sound. Its language, which is an extension of the low level AVISPA format, is compiled into Horn clauses which are then analyzed using ProVerif. Moreover, they show a number of examples that this approach is practically feasible for wide variety of verification problems of security protocols and web services.

There has also been work aimed at particular protocols. Delaune et al. [16] show by a dedicated hand proof that for analyzing PKCS#11 one may bound the message size. Their analysis still requires to artificially bound the number of keys. Similarly, Delaune et al. [17] give a dedicated result for analyzing protocols based on the TPM and its registers. In the goal of relating different approaches for protocol analysis, Bistarelli et al. [59] propose a translation from a process algebra to multiset rewriting, which is efficient for verifying security protocols.

Another verification approach that supports the verification of stateful protocols is the tamarin prover [37], [7]. Instead of abstraction techniques, it uses backward search and lemmata to cope with the infinite state spaces in verification. The benefit of tamarin and related tools is a great amount of flexibility in formalizing relationships between data that cannot be captured by a particular abstraction and resolution approach. However it comes at the price of loosing automation, i.e., the user has to supply insight into the problem by proving auxiliary lemmata for complex protocols. Tamarin has already been used for analyzing the Yubikey device [38], security APIs in PKCS#11 [16] and a protocol in TPM [17]. Moreover, it does not require bounding the number of keys, security devices, reboots, etc.

As a total, current approaches provide efficient ways in verifying security protocols. However, they commonly adopt a static strategy during verification, which may result in non-termination when verifying complicated security protocols. Encountering these cases, human experts are needed to analyze the reason of non-termination and supply hand proof.

At the same time, fast progress has been unfolding in machine learning applied to tasks that involve logical inference, such as natural language question answering [39], knowledge base completion [40] and premise selection in the context of theorem proving [41]. Reinforcement learning in particular has proven to be a powerful tool for embedding semantic meaning and logical relationships into geometric spaces, specifically via models such as convolutional neural networks, recurrent neural networks, and tree-recursive neural networks. These advances strongly suggest that reinforcement learning may have become mature to yield significant advances in many research areas, such as automated theorem proving. To the best of our knowledge, SmartVerif is the first work that applies AI techniques to the automated verification of security protocols.

III. PRELIMINARIES OF TAMARIN PROVER

We firstly introduce tamarin prover that we modify. The tamarin prover [7] is a powerful tool for the symbolic modeling and analysis of security protocols. It takes a security protocol model as input, specifying the actions taken by agents running the protocol in different roles (e.g., the protocol initiator, the responder, and the trusted key server), a specification of the adversary, and a specification of the protocol’s desired properties. Tamarin can then be used to automatically construct a proof that, when many instances of the protocol’s roles are interleaved in parallel, together with the actions of the adversary, the protocol fulfills its specified properties.

Protocols and adversaries are specified using an expressive language based on multiset rewriting rules. These rules define a labeled transition system whose state consists of a symbolic representation of the adversary’s knowledge, the messages on the network, information about freshly generated values, and the protocol’s state. The adversary and the protocol interact by updating network messages and generating new messages.

Security properties are modeled as trace properties, checked against the traces of the transition system.

To verify a protocol, tamarin uses a constraint solving algorithm for determining whether $P \models_E \phi$ holds for a protocol $P$, a trace property $\phi$ and an equational theory $E$ that formalizes the semantics of function symbols in protocol model. The algorithm uses constraint solving to perform a complete search for counter-examples to $P \models_E \phi$, i.e., it attempts a proof by contradiction. A proof always starts with either a simplification step, which translates the security property into an initial constraint system that needs to be resolved, or an induction step, which generates the necessary constraints to prove the security property using induction on the length of the trace. Constraint systems $\Gamma$ are used to represent the intermediate states of search. This problem is undecidable and the algorithm does not always terminate. Nevertheless, it often finds a counter-example (an attack) or succeeds in unbounded verification.

On a high level, a constraint solving algorithm consists of two components: (1) a constraint reduction strategy, which gives rise to a possibly infinite search tree, and (2) a search strategy, which is used to search this tree for a solved constraint system.

A constraint reduction strategy is a function $r$ from constraint systems $\Gamma$ to a finite set of constraint systems satisfying the following two conditions. (i) The constraint reduction relation $\{ (\Gamma, r(\Gamma)) \mid \Gamma \in \text{dom}(r) \}$ is well-formed, correct, and complete. (ii) Every well-formed constraint system not in the domain of $r$ has a non-empty set of solutions.

Intuitively, tamarin applies constraint reduction rules to a constraint system to generate a finite set of refined systems. Note that tamarin prover uses these rules to represent lemmata in verification process. The rule application process is repeated
until the constraint system is solved. Therefore, tamarin uses a search tree to store all the constraints systems in the verification process. Each node of a tree is an independent constraint system.

To search for a solved constraint system, tamarin prover uses a heuristic to sort the applicable rules for a constraint system. The design rationale underlying tamarin’s heuristic is that it prefers rules that are either trivial to solve or likely to result in a contradiction. Since the rules are sorted, tamarin always chooses the first rule to apply to the constraint system. Hence, the search tree is simplified to a finite one, which reduces the complexity of verification process.

Tamarin provides two ways of verifying protocols. It has an efficient automated mode that combines message deduction and human-designed heuristics to guide proof search. If the automated proof search terminates, it returns either a proof of correctness or a counterexample, representing an attack that violates the stated property. Since the tool may not terminate in automated mode, tamarin also provides an interactive mode for users to manually construct a proof and seamlessly combine it with automated proof search.

IV. OVERVIEW

We briefly describe SmartVerif and the main design problems in Section IV-A. Then we introduce a problem that affects the design of the framework, and present our approach in Section IV-B. Finally in Section IV-C, we illustrate the framework following the approach.

A. Brief Description of SmartVerif

Briefly, given a protocol description and a security property, i.e., the protocol model, the workflow of SmartVerif consists of the following steps:

- Step 1: The Deep Q Network (DQN) is initialized with a purely random strategy, which takes multiple candidates as input, and randomly chooses a candidate with the uniform probability as output.
- Step 2: SmartVerif conducts proof searching by using the tamarin prover as backend, where each node on the path is chosen according to the strategy.
- Step 3: If a path generated in Step 2 is correct and complete, SmartVerif terminates and outputs the path as the result.
- Step 4: Otherwise, if all the paths generated in Step 2 are estimated incorrect, the DQN is trained according to the proof paths, and the strategy is updated.
- Step 5: Go to Step 2.

As shown in Figure 1, SmartVerif contains Acquisition module and Verification module, which execute in multiple rounds:

Acquisition: The module generates a verification tree as input of Verification module. A path in the tree corresponds to a possible proof path in verification. Each node in the tree contains information for guiding the verification. We modify tamarin prover to collect the information. Since information of the nodes is transformed as input of the DQN, which is difficult for handling high dimensional data, the information must be carefully chosen to reduce complexity of designing the DQN.

Verification: The module selects a path from the verification tree as a candidate proof. The path selection is guided by the DQN. Meanwhile, the DQN is also optimized with correctness of the selection. If the selected path is correct, we achieve a successful verification. However, the selection may be incorrect due to the DQN is not sufficiently optimized in early rounds. In this case, we iteratively launch a new round to continue optimizing the DQN and selecting a new proof path. Hence, the main problems in the module are the design of the DQN and the method of determining the correctness of path selection.

B. Approach of Generating Incomplete Tree

In Acquisition module, we face a problem of choosing nodes that form the verification tree. Ideally, we may generate a complete verification tree at a time, so that the correct proof path is definitely in the tree. Nevertheless, there are protocols with large or infinite state spaces [20], [21]. Therefore, even little information stored in nodes would still lead to memory explosion in this case. An alternative method that we use is to construct an incomplete tree in the first round, and expand the tree with new nodes on-demand in next rounds. Thus the path is selected round by round according to the current tree, until it is correct and complete. The problem, however, is that it also may incur unnecessary memory overhead, if the path selection does not benefit from the new nodes.

To solve the aforementioned problem, we design the DQN to guide the tree generation. Specifically, the DQN chooses a leaf node in the incomplete tree which is estimated in the correct proof path with highest probability. We expand the tree by generating a subtree starting from the leaf and merging the subtree into the original tree. The rest children remain collapsed for reducing the complexity of the tree.

C. Framework

Following our approach, Acquisition module contains the following 3 submodules. 1) Initial Tree Construction: Given a protocol model, the submodule generates an incomplete verification tree. It is executed in the first round or in case when it gets a feedback from the Verification module. We implement the submodule by modifying the tamarin prover. 2) Subtree Construction: To expand the verification tree of the previous round, the submodule generates a subtree starting from a leaf node in the verification tree given by the Verification module. It is also implemented by modifying the tamarin prover. 3) Tree Merger: It merges the subtree into the verification tree of the previous round.

The aforementioned main problems in Verification module become more complicated, when the verification tree is incomplete in our design. Here, we additionally illustrate how
the submodules in the Verification module deal with the tree in each case. Briefly, there are 2 submodules.

1) **Correctness Determination:** It estimates whether the DQN selects the correct path. In each round, the module works according to the selected path in different cases:

**Case 1:** The path is estimated incorrect. We optimize the DQN in this round by passing a reward to the DQN. Meanwhile, we send feedback to Acquisition module, where the submodule of Initial Tree Construction is informed to regenerate a new verification tree in the next round. As a result, we can find a new path according to the optimized DQN afterward.

**Case 2:** The path is estimated correct but incomplete. The incompleteness of the path is caused by the incompleteness of the verification tree. Therefore, we follow the above approaches by informing the submodule of Subtree Construction to expand the tree in the next round, so the path is also extended in the next round for shaping a complete path. Here, the leaf node in approach 1) corresponds to the end of the path selected by the DQN afterward.

**Case 3:** The path is correct and complete. In this case, we achieve a successful verification of the protocol model, so we can terminate SmartVerif.

2) **Deep Q Network (DQN):** The DQN corresponds to the dynamic strategy for selecting paths and optimizes itself by training. As illustrated in Section [V-A], given a group of estimated incorrect paths generated by using the current strategy, the training process works as follows. First, for each node that is on a path of the group, the node is bound to a negative reward. The reward is related to the probability that the node represents a supporting lemma, according to our insight as mentioned in Section [I]. In the implementation, a tuple, which includes the node and the reward, is added into a global dataset. Then, a subset is sampled from the dataset. Finally, the parameters of the DQN are optimized by minimizing a loss function. Here, the loss function is the sum of sub-functions. Each sub-function takes an individual tuple in the subset as input, and outputs the difference between results calculated according to two pre-defined functions. One of the functions is calculated by using the parameters of current DQN, and the other is calculated by using the training parameters of the optimized DQN. Informally, the training process optimizes the network in order that the reward of each node can be estimated. In other words, the node with the highest reward among its siblings can be regarded as the one with supporting lemma, if the DQN is sufficiently optimized.

**V. Example**

To illustrate our method, we consider a simple security protocol. The goal of the protocol is that when a participant $C$ sends a symmetric key $k$ to another participant $S$, the secret symmetric key $k$ should not be obtained by the adversary.

\[
S_1. \quad C \rightarrow S : \{‘1’, k\}_{pk_S} \\
S_2. \quad S \rightarrow C : \{‘2’, hash(k)\}
\]

Fig. 2. A simple security protocol.

The brief process of the protocol is shown in Figure [2]. In step $S_1$, $C$ generates a symmetric key $k$, encrypts a tuple $\{‘1’, k\}$ with the public key of $S$, and sends the encrypted message. In step $S_2$, $S$ receives $C$'s message, decrypts it with its private key, and gets the symmetric key $k$. Finally, $S$ confirms the receipt of $k$ by sending back its hash to $C$.

The communication network is assumed to be completely controlled by an active Dolev-Yao style adversary [42]. In particular, the adversary may eavesdrop the public channels or send forged messages to participants according to the channels. Moreover, the adversary can access the long-term keys of compromised agents.

Here, we provide a brief explanation on modeling protocols in tamarin prover. A tamarin model defines a transition system whose state is a multiset of facts. The transitions are specified by rules. At a very high level, tamarin rules encode the behavior of participants and adversaries. Tamarin rules $l \rightarrow [a] \rightarrow r$ have a left-hand side $l$ (premises), actions $a$, and a right-hand side $r$ (conclusions). The left-hand and right-hand sides of rules respectively contain multisets of facts. Facts can be consumed (when occurring in premises) and produced (when occurring in conclusions). Each fact can be either linear or persistent (marked with an exclamation point (!)). While we use linear facts to model limited resources that cannot be consumed more times than they are produced, persistent facts are used to model resources which can be consumed any number of times once they have been produced. Actions are a special kind of facts. They do not influence the transitions, but represent specific states in protocol. These states form the relation between transition system and the security property.
rule Client_1:
[Fr(k),
Pk(S, pkS)]
→
[Client_1(S, k),
Out(aenc(1', k)pkS)]

rule Client_2:
[Client_1(S, k),
In(h(k))]
→
[Out(aenc(1', h(\text{snd}(\text{aenc}(request, ltkS)))))]

rule SessKeyC:
[Ltk(S, ltkS),
In(request)]
→
[Eq(fst(\text{aenc}(request, ltkS)), 1')]

Fig. 3. The model of the protocol process.

Security properties are specified in a fragment of first-order logic. Tamarin offers the usual connectives (where & and | denote and and or, respectively), quantifiers All and Ex, and timepoint ordering <. In formulas, the prefix # denotes that the following variable is of type timepoint. The expression Action(args)@#t denotes that Action(args) is logged at point t.

For instance, to model the above protocol, we first define several functions. 1) In(m) and Out(m) function which represents sending and receiving message m, respectively; 2) aenc{a}k and adec{a}k function which represent the asymmetric encryption and decryption of a variable a using key k; 3) Ltk(A, ltk) and Pk(A, pk) function which represent the participant A is bound to a public key pk and a private key ltk; 4) fst{a, b} and snd{a, b} function which get the first and second element from a tuple {a, b}; 5) Eq(a, b) function which states a is equal to b; 6) h(a) function which represents hashing.

Then, the compromise of private keys is modeled using the following rule.

\[
\text{rule Revealltk :} \\
[!Ltk(A, ltk)] - [\text{LtkReveal}(A)] \rightarrow [\text{Out}(ltk)]
\]

It has a premise !Ltk(A, ltk) which binds the private key ltk to a participant A. The corresponding conclusion Out(ltk) represents the private key ltk is sent to the adversary. Note that, this rule has an LtkReveal(A) action stating that the key of A was compromised. This action is used to model the security property.

Then, the protocol is modeled using the rules in Figure 3. Rule Client_1 captures a participant generating a fresh key and sending the encrypted message. The rule has two facts for premises. The first is a Fr(k) fact which states a fresh variable k is generated. The second is a Pk(S, pkS) fact which states the public key pkS is bound to a participant S. In this case, the second fact is a persistent fact since the public key can be used in many times (i.e., by protocol participants or adversaries). If the facts in premises are matched with the facts in the current state, two conclusions are produced. The first is an action Client_1(S, k) which states that k is sent to a participant S. The second conclusion is Out(aenc(1', k)pkS). This fact states the participant uses a public key pkS to encrypt the message {1', k} and send the message by function Out. Rule SessKeyC captures a participant receiving the message sent by S and sending the hash value of k back. Rule Client_2 captures a participant receiving the hash value and completing a run of the protocol.

Finally, we define a security property, which states that when a participant C sends a symmetric key k to another participant S, the secret symmetric key k should not be obtained by the adversary. The security property is modeled as a lemma Client_session_key_secrecy in Figure 4. The lemma indicates that, there must not exist a state, where action SessKeyC(S, k) happens and the adversary K obtains k, without the happening of the compromise action LtkReveal(S).

\[
\text{lemma Client_session_key_secrecy :} \\
'\neg(Ex S k \#i \#j, SessKeyC(S, k) @ i \& K(k) @ \#j \& \neg(Ex \#r, LtkReveal(S) @ r))''
\]

Fig. 4. The security property.

Note that, the above security property of protocol can be successfully verified by tamarin prover. To better understand the following sections, we use this protocol as an example. We describe how we generate the verification tree of the protocol in Section VI. Then we explain how SmartVerif verifies the protocol in Section VI-B.

VI. ACQUISITION MODULE

There are two technical problems in generating a verification tree. 1) We convert information in the nodes into the input of the DQN. There is a large amount of intermediate data in the verification process. It is hard to design a network which handles high dimensional data. Hence, the information stored in the nodes should be carefully chosen. 2) We expand the tree according to feedback of Verification module. The number of the nodes increases during the expansion, which takes up more memory space. To avoid high memory overhead, the constructed tree should only contain nodes relevant to the current verification round.

We briefly describe the information we choose to store in the tree in Section VI-A. Then we present details of tree construction process in Section VI-B.
A. Choosing Information

The information in nodes of the verification tree is used in 2 ways. 1) We transform the information to input of the DQN. In the Verification module, we use the DQN to select a proof path in verification tree. The DQN in Verification module requires an input state, which represents current proof state. We use the information to represent proof state in verification process. 2) We use the information to distinguish different proof states. Note that SmartVerif runs round-by-round, where in each round verification trees are constructed and merged. In the merging process, we compare the information in nodes in different trees to find a same proof state in each round.

The information stored in the nodes should be carefully chosen. Recall that the input of the DQN is transformed from the information. Since it is difficult for the network to handle high-dimensional data, the input of the network should not be large in dimensions. Hence, we do not choose all the intermediate data as the information. Moreover, the network selects a path from the verification tree. If there are nodes which share the same information in the tree, the network is not able to distinguish the states which information in these nodes represents, which leads to a higher possibility of selecting an incorrect proof path. Hence, the information in the node should not only be simple enough, but also represent independent state in the verification process.

There is a large amount of data in verification process of tamarin prover. Recall that the verification process in tamarin prover is based on constraint systems. Specifically, a constraint system in tamarin prover contains several parts: 1) step number represents the proof step indicating where current constraint system is; 2) unsolved goals store all the unsolved goals in the current system; 3) solved goals store all the solved goals and assumptions made in the verification process; 4) dependency graphs consist of the dependencies of the actions and facts in the unsolved goals; 5) constraint reduction rules contain all the applicable constraint reduction rules in current constrain system. Note that tamarin prover uses term constraint reduction rule to represent lemma that we explained in Section [1].

We choose constraint reduction rules and their corresponding proof step numbers as the information stored in nodes. In the constraint system of verifying complicated protocols, there may exist a large amount of goals and dependency graphs, which are large in both quantity and dimension. Moreover, tamarin prover applies a constraint reduction rule to refine a constraint system, which indicates a proof state. Hence, the constraint reduction rules are able to represent different proof states in verification process. Based on this observation, we choose the constraint reduction rules as part of the information in node. Besides, constraint reduction rules may be same in different proof steps. To distinguish different proof states in verification process, we add the proof steps to the information in nodes for indicating the position of the rules.

Hence, we modify tamarin prover to collect the information we chose. The modified tamarin prover takes a protocol model as input. During verification, it outputs the constraint reduction rules and corresponding proof step numbers at each proof step. The information is used to construct the verification tree.

Step 1: rule 1. simplify rule 2. induction
Chosen Rule: simplify
Step 2: rule 1. Client_1(S, k) ⊲ i rule 2. !KU(h(k))@# vk
Chosen Rule: Client_1(S, k) ⊲ i
Step 3: rule 1. !KU(~ k)@# vk.1 rule 2. !KU(h(~ k))@# vk
...

Fig. 5. An example on information collected from tamarin prover.

Considering the protocol in Section [V] we show the information collected from modified tamarin prover in Figure [3] Information in odd numbered lines is the constraint reduction rules in each proof step, while information in even numbered lines is the chosen rule by tamarin prover in a verification process. Specifically, in the first proof step, tamarin prover constructs the proof starting with either a simplify step, which translates the security property into an initial constraint system that needs to be resolved, or an induction step, which generates the necessary constraints to prove the security property using induction on the length of the trace. In this case, tamarin prover chooses rule simplify at proof step #1 to look for a counterexample to the lemma. In detail, it looks for a protocol execution that contains a SessKeyC(S, k) and a K(k) action, but does not use an LtkReveal(S). As shown in Figure [3] action SessKeyC(S, k) is in the protocol execution only if the protocol step that rule Client_2 captures has happened. Note that rule Client_2 has two premises Client_1(S, k) and In(h(k)). Hence these two facts are in the protocol execution. Based on this observation, tamarin prover has two constraint reduction rules to select: Client_1(S, k) ⊲ i and KU(h(k))@# vk. The first rule Client_1(S, k) ⊲ i states that the adversary knows k after action Client_1(S, k) has been executed. The second rule KU(h(k))@# vk states that the adversary K knowing k is caused by the adversary knowing its hash value. According to the protocol model and the cryptographic functions, tamarin knows that k can not be deduced from its hash value. Hence, tamarin chooses the first rule. Moreover, if action Client_1(S, k) is in the protocol execution, the premises and conclusions in rule Client_1 are also in the execution. After tamarin applies rule Client_1(S, k) ⊲ i, the constraint system is refined by adding the premises and conclusions of rule Client_1(S, k). Tamarin prover then chooses where adversary K obtains k. It gets two selections !KU(~ k)@# vk.1, !KU(h(~ k))@# vk. The first selection states that the adversary obtains k from message deduction. The second is same as the unchosen rule at last proof step.

B. Tree Construction

We construct a verification tree to store the information we collect. The tree is used in Verification module to generate a candidate proof by guidance of the DQN. Ideally, we generate...
induction

Figure 6 (c). The merged tree is shown in Figure 6 (c).

a complete verification tree at a time. Given the complete tree, the DQN can select a complete proof path directly.

However, even little information stored in nodes would still lead to memory explosion. Verifying protocols with large or infinite state spaces is a complicated and difficult task. Tamarin prover has to select reduction rules for many times, which results in an exponential rise in quantity of collected rules. Moreover, there may occur infinite loops in the verification process. Since a loop does not have an end, it is impossible to construct a fully complete tree.

To avoid memory explosion, we adopt a simple and effective approach. We first construct a tree to store the collected constraint reduction rules. The root node represents the security property. Each node contains a constraint reduction rule. The depth of the node is equal to the proof step number of the node. Nodes at proof step \( i \) are the children of the chosen node at step \( i - 1 \). Afterwards, we use the DQN to select a proof path from the initial tree. The path corresponds to a leaf node in the tree. We guide tamarin prover to choose rules according to the path and collect new rules beyond the limited steps. At each round, we only collect the rules in one proof step further. After constructing a subtree using the complete rules, we merge the subtree into the original tree to expand the tree from the leaf.

We adopt a multithreading approach to increase the efficiency of our dynamic strategy. Recall that the DQN optimizes itself with its selection and the corresponding rewards. Since it makes only one decision at each round, the quantity of training data is limited, which decreases the training efficiency and lowers the performance. To solve this problem, we execute multiple threads of the Acquisition module in parallel to generate various verification trees for the DQN at a time. Using this approach, we are able to collect more training data for the network, which allows for greater data efficiency and increases the convergence rate.

Taking the protocol in Section VII as an example, we construct a tree using the rules in Figure 5. The root node represents the lemma Client_session_key_secrecy. As shown in Figure 6 (a), the initial tree contains two rules. The DQN selects Client_1(S, k)▷0 #i from the initial tree. So we guide modified tamarin prover to choose it to collect the new rules. Combining the rules, we construct a new subtree, i.e., the tree in Figure 6 (b). Using these rules, we merge the original tree with the subtree. construct a expanded verification tree in Figure 6 (c). The merged tree is shown in Figure 6 (c).

VII. VERIFICATION MODULE

Briefly, the Verification module selects a proof path from the verification tree. The selection is guided by the DQN. Then, we determine the correctness of the selection by the DQN. We present details of our DQN in Section VII-A. In Section VII-B, we describe our method of correctness determination.

A. Deep Q Network

In Algorithm 1, the DQN in SmartVerif maintains an action-selection policy which takes a state \( s_t \) as input, and outputs an action number \( a_t \). Here, \( s_t \) represents the proof state, i.e., a node in the verification tree, and \( a_t \) is the number of a chosen child of the node. The state \( s_t \) is a vector transformed from information in nodes, e.g., the constraint reduction rule. Note that since the network is optimized by the reward of its historical selection, it is important that the states of different nodes in the tree are identical. As shown in Figure 6 (c), the rule in the tree may be the same, i.e., rule \( !KU(h(k))@\#vk \) occurs both at depth 2 and 3.

The DQN runs iteratively with multiple epochs. In each epoch, recalling that we adopt a multi-threading approach for increasing the efficiency, the DQN launches \( \sigma \) threads in which the paths are selected according to the policy (line 5). If a path is estimated correct and complete, SmartVerif terminates with the proof path (line 6). If all the selected paths are estimated incorrect, the policy is optimized (line 8).

In path selection, we use two strategies in the policy (line 13): 1) an exploration strategy to choose random actions, which is to explore the values of unchosen actions; 2) a greedy strategy to choose \( a \) which may have the largest Q value currently. Here, \( Q(s_t, a; \theta_c) \) is a pre-defined function [32] that outputs comparable value, given the node \( s_t \) and its \( a \)th child. The Q function also takes \( \theta_e \) as input, where \( \theta_e \) is the set of the DQN’s parameters at epoch \( e \), and \( \theta_e \) is updated into \( \theta_{e+1} \) in policy optimization. Combining the two strategies, we use a \( \epsilon \)-greedy strategy to select actions. Here, \( \epsilon \) is a probability value for selecting random actions. We change the value of \( \epsilon \) to get different exploration ratios. Note that we choose random actions in the exploration strategy. Another possible approach is to take standard heuristic of tamarin prove as the basic strategy. However, for example, when verifying Yubikey protocol, the standard heuristic does not rank the supporting lemma at the first place in several proof steps. In this case, the DQN does not optimize itself in an efficient way and the efficiency is worse than SmartVerif.

To apply our insight, we set the reward to the same negative number for all the edges on each estimated incorrect proof path. Specifically, in line 15, a transition, i.e., tuple \( (s_t, a_t, \omega, s_{t+1}) \), is generated and added to \( D \), where \( \omega \) is the negative reward for the action \( a_t \) at the state \( s_t \). \( D \) is a replay memory [33] with capacity \( N \), i.e., in practice, our network only stores the last \( N \) experience tuples in the replay memory.

In policy optimization, \( \theta_e \) in Q function is updated as mentioned (line 22). Here, \( n \) tuples are randomly selected from \( D \). For each selected tuple \( (s_j, a_j, r_j, s_{j+1}) \), we compute \( y_t \)
Algorithm 1 Implementation of DQN

1: Initialize a replay memory $D$ to capacity $N$
2: Initialize an action-value function $Q$
3: $success = 0$
4: for $e = 1$ to EPOCH do
5:   Call $\sigma$ threads that execute path_selection
6:   if $success = 1$ then
7:     Program ends
8:   end if
9:   Execute policy_optimization
10: end for
11: function path_selection:
12:   Initialize a proof state $s_1$
13:   for $t = 1$ to ROUND do
14:     With probability $\epsilon$ select a random action $a_t$ otherwise select $a_t = \arg\max_a Q(s_t; a_t; \theta_e)$
15:     Generate next state $s_{t+1}$ according to $a_t$
16:     Store a transition $(s_t, a_t, \omega, s_{t+1})$ in $D$
17:   end for
18:   if the path is estimated incorrect then
19:     $success = 1$
20:   end if
21: end function
22: function policy_optimization:
23:   Sample $n$ random transitions $(s_j, a_j, r_j, s_{j+1})$ from $D$
24:   Set $y_j = r_j + \gamma_{max}(t_{j+1})Q(s_{j+1}, a'; \theta_e)$
25:   Perform a gradient descent step on $(y_j - Q(s_j, a; \theta_{t+1}))^2$

The advantage of applying DQN is that DQN can update our dynamic strategy efficiently if the reward in DQN is designed effectively. In other words, sufficient transitions are required to be updated in $D$, and the reward in each transition should be correct. A naive algorithm is to execute line 15 only when the path estimated incorrect, i.e., only the reward corresponding to the last node on the incorrect path is set negative. However, the number of updated transitions is limited. Instead, we improve the efficiency by storing multiple transitions according to our insight, and the correctness of the insight is proved in Algorithm 2. The algorithm takes a string sequence $[s_1, s_2, ..., s_k]$ as input. The sequence is transformed from the selected path (line 16, Algorithm 1). Each element, e.g., $s_1$, is the constraint reduction rule of the corresponding node, i.e., the $i$th node, on the path. The algorithm runs iteratively by generating a sequence $S$ (line 4), and counting the number of pairs of similar elements that are both in $S$. If the number is not less than $\delta$, a loop is detected. For example, given the aforementioned sequence $[\ldots, a, b, c, a, b, c]$, $S = (c, c, \ldots)$, when $j = 3$. Note that the length of $S$ is restricted to the limit of $\rho$ for efficiency. For the same reason, the algorithm is activated only when the length of the selected path reaches $\alpha$ (line 1).

We use levenshtein distance to measure the similarity between two rules (line 8 to 17). The distance between two strings $x$ and $y$ is the minimum number of single-character edits (insertions, deletions or substitutions) required to change $x$ into $y$. If the distance between $x$ and $y$ is less than $\beta$ of the length of $x$, we assume these two strings are similar. For example in Figure 7 the difference points among the similar strings are often the numbers at corresponding positions, e.g., ni.1, ni.2, ni.3. Informally, the number of difference points are counted as the distance.

Note that there is not necessarily a loop on every incorrect path. In other words, if a loop is found given a selected path, there may be multiple incorrect nodes, i.e., the nodes that do not represent supporting lemmata, on the path. Therefore, it is not sufficient to use naive search algorithms, e.g., DFS, to locate proof paths. We make further studies on analyzing the effectiveness of the algorithms in Section VIII. Finally, in our implementation, we set $\alpha$ to 20, $\beta$ to 0.1, $\rho$ to 20 and $\delta$ to 3.

VIII. Experiments & Evaluation

We perform experiments on several security protocols. The experiment results are described in Section VIII-A. In Section VIII-B we briefly overview Yubikey protocol and Mödersheim’s example to validate the efficiency of SmartVerif. All files of our prototype implementation and protocol models used in benchmark are available at here [43].
Algorith 2 Loop Detection Algorithm

Require: \((s_1, s_2, \ldots, s_k)\)

1: if \(k \geq \alpha\) then
2:     for \(j = 1\) to \(k - 1\) do
3:         count = 0
4:         \(S = (s_k, s_{k-1}, s_{k-2}, \ldots)\) \(l[S] \leq \rho\)
5:         for each element \(x\) in \(S\) do
6:             for each element \(y\) in \(S\) do
7:                 if \(x \neq y\) then
8:                     \(n = \text{length of } x, m = \text{length of } y\)
9:                     for \(a = 1\) to \(n\) do
10:                        for \(b = 1\) to \(m\) do
11:                            if \(y[a] = x[b]\) then
12:                               cost = 0
13:                               else
14:                                   cost = 1
15:                                   \(v[b] = \min \{ v[b-1]+1, b \}\)
16:                                   if \(v[m]/m < \beta\) then
17:                                       count = count + 1
18:                               if count \(\geq \delta\) then return TRUE
19:                               return FALSE
20:                           else
21:                               return FALSE

A. Main Experiments

We compare SmartVerif with other verification tools in verifying security protocols. We evaluate the efficiency of SmartVerif.

Experiment Setup: Experiments are carried out on a server with Intel Broadwell E5-2660V4 2.0GHz CPU, 128GB memory and four GTX 1080 Ti graphic cards running Ubuntu 16.04 LTS. We use and modify tamarin prover v1.4.0 in SmartVerif.

We use the same network architecture, learning algorithm and parameter settings across all chosen protocols. Since the security property varies greatly in protocols, we set all the positive rewards to 10 and all the negative rewards to -10. In these experiments, we use the DQN with 0.01 learning rate and memory batch of size 80. Moreover, we execute eight threads of Acquisition module in parallel. The behavior policy during training was \(\epsilon\)-greedy with \(\epsilon\) annealed linearly from 0.99 to 0.1 over the first hundred epochs, and fixed at 0.1 thereafter. We use the term epoch to denote the time step in which the DQN is optimized with a new reward.

Chosen Tools: For each protocol with unbounded sessions, we inspect whether it can be automatically verified by SmartVerif and other verification tools. These verification tools include StatVerif [23], Set-\(\pi\) [28], tamarin prover [7], [51] and GSVerif [30]. The tools are typical verification tools which support verification of security protocols with global states. Moreover, these tools both provide automated verification modes to verify security protocols, which is the same as SmartVerif. Besides, we attempt to verify protocols in three altered versions of tamarin prover. We first attempt to use the “brute-force” mode (i.e., with ‘c’ heuristic) of tamarin prover. This mode adopts a simplest method to verify protocols: it solves goals in the order they occur in the constraint system. Unlike other default static strategies, this method does not contain any human-designed heuristics or expertise. We compare SmartVerif with this mode of tamarin prover to demonstrate the generality of our framework. Moreover, we implement two naive algorithms (DFS and BFS) with our loop detection method and compared these two with our algorithm to show the efficiency of SmartVerif. Note that we do not choose classical verification tools, i.e., ProVerif and AVISPA, since their support for protocols with global states and unbounded sessions is limited.

Chosen Protocols: We carefully choose security protocols to be testified in our evaluation. The chosen protocols include a simple security API similar to PKCS#11 [20], the Yubikey security token [21], the optimistic contract signing protocol by Garay, Jakobsson and MacKenzie (GJM) [22], mobile EMV protocol [44], TPM-envelope protocol [17], CANauth protocol [29], etc. We choose these protocols because they are typical protocols with global states and unbounded sessions, and many research efforts [7], [23], [28], [31] were spent on verification of these protocols. Hence, the experimental results in the protocols are more persuasive. We also perform detailed analysis on performance of analyzing the protocols to validate the efficiency of SmartVerif. Note that we do not choose protocols which are specifically verified in one tool, which can not be used to compare with other tools, e.g., protocols with properties of observational equivalence [46] - [48].

Comparative Results: The experimental results are summarized in Table I. Compared with these verification tools,
SmartVerif is sufficient for generality and automation capability: it is able to verify all the given protocols with unbounded sessions, without any human intervention.

1) Generality. SmartVerif achieves a 100 percent success rate in verifying the studied protocols, which outperforms all the other verification tools. For example, StatVerif does not terminate and the verification fails encountering complicated protocols like security API in PKCS #11 and mobile EMV protocol [44]. Set-π fails in verifying TPM-envelope protocol [17] and some others with unbounded sessions. GSVerif outperforms the previous tools in generality but it still can not automatically verify complicated protocols such as Yubikey protocol. Tamarin prover is effective in automatically verifying simple protocols with unbounded sessions, e.g., GJM Contract-Signing protocol and Security API in PKCS#11. Nevertheless, it does not achieve automated verification of Yubikey protocol and Mödersheim’s example, with or without the ‘c’ heuristic. Moreover, the quantities of protocols which tamarin prover is able to automatically verify are increasing with version updating. This validates the effects of different static strategies in these versions on generality.

2) Automation capability. Currently, only SmartVerif can fully automatically verify Yubikey and CANAuth protocol [29]. For protocols which existing tools cannot automatically verify, GSVerif and tamarin prover provide an interactive mode for users to manually guide the verification. In our experiments, we find Yubikey and CANAuth protocol are able to be verified by manually designing proof formulas using these tools. Comparing with these tools, SmartVerif fully automatically verifies these protocols, without any human intervention. In Section VIII-B, we briefly overview several protocols to demonstrate SmartVerif’s sufficiency in automation capability.

Efficiency and Overhead: To evaluate the efficiency and overhead of SmartVerif, we collect statistics of the running time and training epochs in verification. The running time contains two parts: 1) Training time: the time spent in information acquisition and network training; 2) Verification time: the time spent in verification after network convergence. As presented in this paper, SmartVerif is a novel and general framework to verify protocols. For each protocol to be verified, it takes time to acquire information and train the network. Once the DQN is sufficiently optimized according to the current protocol model, it can be directly used to verify the corresponding protocol, like the static strategies in existing tools. Hence, we use the verification time to demonstrate the performance of SmartVerif. Besides, since SmartVerif uses the DQN to select proof paths, the efficiency of the DQN directly affects the performance and overhead of SmartVerif. Recall that the number of epochs denotes the times that the DQN is optimized with a new reward, which equals to the number of generated incorrect paths, if the protocol has not been successfully verified. Therefore, we use the quantities of training epochs and time of DQN to evaluate the efficiency of our framework.

As demonstrated in Table I, the experimental results show that SmartVerif verifies the studied protocols in a very efficient way. For most protocols, it succeeds in verification only after about 35 times of one-way forward traversing (i.e., 35 epochs). As the challenge is time explosion when traversing infinite state spaces, our dynamic strategy solves the problem in a general and adequate way. For instance, existing verification tools can not automatically verify Yubikey protocol with unbounded sessions due to memory explosion or infinite verification loops. In contrast, SmartVerif only takes 87 epochs to find the correct proof path using the dynamic strategy.

Moreover, the statistics of the running time also validate the efficiency of SmartVerif. Comparing to existing verification tools, SmartVerif does not require any extra time and effort in training human for interactive proving or designing heuristics. Instead, it spends the training time on optimizing the dynamic strategy for protocols, which is sufficient. More specifically, it only takes less than one hour to find the correct proof path for most protocols. Even in the worst case, it costs 148 minutes to verify the security API in PKCS #11. After the DQN is sufficiently optimized, the verification time is only 16 minutes.

Performance Analysis: Besides proving our insight theoretically, we also perform empirical analysis by comparing SmartVerif with two naive algorithms: 1) DFS. The algorithm searches along a path as long as possible before backtracking. The backtracking occurs only when a loop is detected according to Algorithm 2. 2) BFS. The algorithm searches all the paths at the present depth prior to searching at the next depth level. It also uses the loop detection algorithm to shrink the size of searching space. The BFS is optimized by multi-threading that each threads searches in parallel. Note that DFS is running in a single thread since the ordering and parallel tends to conflict in searching. Both DFS and BFS are implemented based on tamarin prover.

The experimental results are shown in Table I and Figure 8. We use two metrics: 1) the total time in searching; 2) coverage, i.e., the quantity of nodes that have been traversed when the searching succeeds, given the proof steps of verifying a security protocol using SmartVerif. Before comparison, an important observation is that it takes several seconds for a single step of new node traversing by using tamarin prover. It may take less time if using other tools, e.g., the ProVerif-based tools. We also find that it takes more time when a) traversing a new node at the deeper level of tree, and b) initializing or reconfiguring the searching environment. For example, on
verifying YubiKey protocol, the averaging time on traversing a node at level 10 and 100 is 2s and 4s, respectively, and the time on initialization is 8s. Therefore, the verification time of DFS and BFS tends to be affected by reason a) and b), respectively. Since the verification time may be affected by multiple factors, we also use the number of traversed nodes as a complement metric in comparison.

A significant result is that DFS’s coverage grows much faster than SmartVerif’s coverage, when the proof steps increase starting from 60. Afterwards, the verification time of DFS reaches 24-hour limit when the proof steps are around 130. We further find that for most protocols with steps less than 60, DFS only needs to backtrack for less than 10 steps. For instance, for the TPM-toy protocol, DFS begins backtracking when it reaches the node at the depth 57, for the corresponding path is estimated incorrect. When succeeding in searching, the top 49 nodes in the incorrect path are the correct nodes representing supporting lemmata. Hence, when the depth for which DFS has to backtrack merely grows to more than 10, the performance of DFS starts to decrease drastically.

Therefore, SmartVerif greatly outperforms DFS when verifying complicated protocols. The phenomenon can be explained by our insight informally as follows. When applying DFS, if an incorrect path is found, the algorithm starts backtracking along the incorrect path successively. However, in this case, according to our insight, the probability that a node on the path represents the supporting lemma decreases. It can be inferred that the probability that multiple nodes on the path represent the supporting lemma decreases exponentially. On the other hand, on finding an incorrect path, SmartVerif optimizes its searching strategy, and generates a new path with the highest estimated probability, by introducing the insight into DQN. Finally, SmartVerif’s coverage grows much slowly when the proof steps increase. Observe that the performance of BFS is even worse than the performance of DFS, though BFS runs in parallel. We omit the explanation due limitation of paper size.

Note that we currently train a standalone DQN for each studied protocol to keep a high level of generality. Another possible approach is to use pre-trained and optimized networks to verify protocols. However, it brings several challenges. Firstly, it is challenging to achieve a high level of accuracy on node selection in generating pre-trained network. Existing works generating pre-trained networks [49]-[52] in a similar research field, i.e., theorem proving, do not achieve a high level of accuracy on node selection. Compared with theorem proving, it is much challenging to generate pre-trained network with much higher accuracy, given much less samples of models of security protocols. Secondly, it is challenging to achieve high efficiency if using a generated pre-trained network. If using a pre-trained network, the verification time for some protocols may increase. For example, one could take the standard heuristic of tamarin prover as the basic strategy in our DQN to verify security protocols. However, in this case, the DQN does not optimize itself in an efficient way when verifying complicated protocols like Yubikey protocol. Therefore, we train a standalone DQN for each studied protocol. Similarly we currently retrain the DQN when verifying a new security property of a protocol. We will try to optimize the network design and use other learning techniques in future work.

B. Case Studies

In the following, we briefly overview some of the protocols SmartVerif verified. We provide some details in key steps of the verification. For the limitation of paper size, we do not detail all the formal models of the protocols and properties that we studied.

1) Yubikey Protocol: The Yubikey [21] is a small hardware device designed to authenticate a user against network-based services. In its typical configuration, it generates one-time passwords based on encryption of a secret value, a running counter and some random values using a unique AES-128 key contained in the device. The Yubikey authentication server accepts a one-time password only if it decrypts under the correct AES key to a valid secret value containing a counter larger than the last counter accepted. The counter is thus used as a means to prevent replay attacks.

Kremet et al. [31] modeled and verified Yubikey protocol with unbounded sessions in tamarin prover. Specifically they define three security properties. All properties follow more or less directly from a stronger invariant. By default, tamarin prover cannot automatically prove this invariant, which is caused by a non-termination problem. To successfully verify the protocol, tamarin needs additional human guidance, which is provided by experts in the interactive mode.

In the following, we analyze the choice made by tamarin prover, experts and SmartVerif. Specifically, in proof step #8, tamarin prover needs to select one rule, i.e., lemma, from the rules as follows:

\[
A : (\#vr.13 < \#t2.1) \lor (\#vr.13 = \#t2.1) \lor (\#vr.6 < \#vr.13))
\]

\[
B : State\_0111111111111\{lock11.1, n, n.1, nonce.1, npr.1, otc.1, secretid, tc, tuple\} @ (\#t2)
\]

\[
C : Insert(< Server’, n >, < n.2, n.1, otc >) @ (\#t2.1)
\]

\[
D : KU(n)@ (\#vk.2)
\]

\[
E : KU(senc(< n.2, (otc + z), npr >, n.1)) @ (\#vk.5)
\]

Here, rule A is a restriction rule to the timepoints vr.13, t2.1 and vr.6. Rule B states an action State\_0111111111111 must have been in the protocol execution in timepoint t2. Rule C states an action Insert(< Server’, n >, < n.2, n.1, otc >) must have been in the protocol execution in timepoint t2.1. Rule D states the adversary has known the nonce n in timepoint vk.2. Rule E states the adversary has known the encrypted message senc(< n.2, (otc + z), npr >, n.1) in timepoint vk.5.

Tamarin prover considers that rule A is a timepoint constraint rule, which is more likely to achieve a successful verification. It chooses the rule in the automated mode. Then, there are four rules B, C, D, E to be chosen. By default, tamarin chooses the rule A.


ever, the rule leads to a loop in verification as follows:

\[
(#vr.13 < #t.21) \land (#vr.13 = #t.21) \land (#vr.6 < #vr.13)
\]

\[\text{State}_{011111111111}[(\text{lock}11.1, n, n.1, \text{nonce}.1, \text{npr}.1, \text{otc}.1, \text{secretid}, \text{te}2, \text{tuple}) \triangleright_{\sigma} #2]
\]

...  

\[\text{Insert}(<\text{'} Server’}, n >, < n.2, n.1, \text{otc} >)@#2.11\]

\[\text{State}_{011111111111}[(\text{lock}11.2, n, n.1, \text{nonce}.2, \text{npr}.2, \text{otc}.2, n.2, \text{otc}.1, \text{tuple}) \triangleright_{\sigma} #2.21\]

...  

\[\text{Insert}(<\text{'} Server’}, n >, < n.2, n.1, \text{otc} .1 >)@#2.22\]

\[\text{State}_{011111111111}[(\text{lock}11.3, n, n.1, \text{nonce}.3, \text{npr}.3, \text{otc}.2, n.2, \text{otc}.1, \text{tuple}) \triangleright_{\sigma} #2.22\]

In this loop, tamarin prover keeps solving \[\text{Insert}(<\text{'} Server’}, n >, < n.2, n.1, \text{otc} >)@#2.1\] and \[\text{State}_{011111111111}[(\text{lock}11.2, n, n.1, \text{nonce}.2, \text{npr}.2, \text{otc}.2, n.2, \text{otc}.1, \text{tuple}) \triangleright_{\sigma} #2.12\] rules alternately. It leads to non-termination in verification.

In interactive mode, experts make 23 manual rule selections to verify the protocol, and 11 of them are different from the one made by tamarin prover. Specifically, experts choose rule B as the supporting lemma at proof step #8, which leads to a successful verification.

In SmartVerif, we achieve a fully automated verification of Yubikey protocol without any user interaction. Figure 9 (a) shows the corresponding part of the verification tree. The Q value of each rule in proof step #8 is shown in Table III. In the initial epoch, the Q value of each rule is the same. In epoch 20, the network learns from its experience that candidate rules A, C, D, E may lead to non-termination cases with higher probability. Hence, the Q values of these rules have a slighter difference compared with Q value of rule B. Then, the difference between Q value of rule B and the Q value of other rules is getting larger in further epochs, which also validate our insight and the effectiveness of our designed strategy. In epoch 87, SmartVerif finds a correct proof path when choosing rule B. In further epochs, the difference among Q value of each rule is getting larger. Based on the Q values, SmartVerif finds the supporting lemma B automatically, such that the protocol can be verified without any user interaction.

2) Mödersheim’s Example: We also investigate the case study presented by Mödersheim, a key-server example. Kramer et al. [31] encoded a model for the protocol.

In the following, we analyze the choice made by tamarin prover, human experts and SmartVerif. In proof step #2, tamarin prover needs to select one rule from the following rules:

Rule A states that every parameters of the action \[\text{State}_{01211111}[(\text{sk}, \text{lock}11.1, \text{nsk}, \text{user}) \triangleright_{\sigma} #1)\]

\[B : \text{KU} (\text{nsk})@#vk\]

Table III

| initial epoch | rule A | rule B |
|---------------|-------|-------|
| epoch 0       | 0     | 0     |
| epoch 10      | 0.4   | 0.6   |
| epoch 100     | 2.1   | 4.7   |

In interactive mode, experts make 7 manual rule selections to verify the protocol, and one of them is different from the selection made by tamarin prover. Specifically, experts choose rule B in proof step #2, which leads to success of the verification.

In SmartVerif, the result is similar to the previous case. Figure 9 (b) shows the corresponding part of the verification tree. The Q value of each rule at proof step #2 as shown in Table III. In the initial state, the Q value of each rule is the same. In epoch 10, the DQN discovers that candidate rule A may lead to incorrect paths. Hence, the Q value of rule A has a slighter difference compared with rule B. Then, in epoch 23, SmartVerif finds a correct proof path when choosing rule B. In epoch 100, the difference continues increasing.

**IX. Future Work**

Our work opens several directions for future work. 1) Hybrid strategy. Since the initial strategy in SmartVerif is purely random, the strategy may be optimized with less epochs if it is implemented with some static strategy. However, the problem is still challenging that there is a potential risk that the epochs...
may become larger for some special protocols that the static strategy does not support. 2) Scalability. It is possible that our dynamic strategy can be used to cope with more complicated problems, such as automated formal verification of software or systems [53]. That are based on first-order logics [55]. or higher-order logics [57]. They are quite similar that they can be translated into a path searching problem. We will also explore and verify more complicated security protocols using SmartVerif. 3) Efficiency. Currently, we train a standalone DQN for each studied protocol to keep a high level of generality. Designing a universal network which can verify all the protocols may increase the efficiency and improve the performance of SmartVerif. Therefore, we will try to optimize the network design and use other AI techniques in future work.

X. CONCLUSION

In this paper we have studied automated verification of security protocols. We propose a general and dynamic strategy to verify protocols. Moreover, we implement our strategy in SmartVerif, by introducing a reinforcement learning algorithm. As demonstrated through experiment results, SmartVerif automatically verifies security protocols that is beyond the limit of existing approaches. The case studies also validate the efficiency of our dynamic strategy.

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We prove our insight of the paper that the node representing a supporting lemma is on the incorrect path with lower probability, when a random strategy is given. To illustrate our insight more comprehensively, we translate the complicated verification process into a path searching problem. Here, the verification can be simply regarded as the process of path searching in a tree: each node represents a proof state which includes a lemma as a candidate used to prove the lemma in its father. The supporting lemma is a special lemma necessarily used for proving the specified security property.

Formally, suppose there are $R$ correct and complete proof paths in a given tree, denoted as $\{n_{t_1}, n_{t_2}, \ldots, n_{t_R}\}$, where $n_{t_i}$ is the $i$th proof state at the $i$th path. Therefore, the lemmata in $\{n_{t_i}\}$ are the candidate lemmata. The random strategy here means that whenever choosing a child for searching, the probability of choosing is uniform. In other words, the probability of choosing the child $n_{t_i}$ is $\frac{1}{x_i}$. If $n_{t_i}$ has $x$ children, and $y$ of them represent supporting lemma, and the random strategy is applied in choosing child, then the probability of choosing a nodes representing supporting lemma is $\frac{y}{x}$. Suppose there are at least one child of $n_{t_i}$, that does not represent supporting lemma, i.e., $x > y$.

**Theorem 1.** Given the above assumptions, after $n_{t_1}$ has been chosen, the node representing a supporting lemma, who is the child of $n_{t_1}$, is on an incorrect path with the probability less than $\frac{y}{x}$.

**Proof.** For the $r$th path, define $\alpha_r$ as follows:

$$\alpha_r = \begin{cases} \prod_{j=i+1}^{k} \frac{1}{x_{r_j}} & \text{if } \forall j \in [1, i], n_{r_j} = n_{t_j} \\ 0 & \text{otherwise} \end{cases}$$

Denote $p_1$ as the probability that a selected path is incorrect.

$$p_1 = 1 - \sum_{r=1}^{R} \alpha_r$$

Denote $m_1, m_2, \ldots, m_y$ as the nodes representing supporting lemmata among the children of $n_{t_i}$. For the $r$th path, define $\beta_{r,s}$ as follows:

$$\beta_{r,s} = \begin{cases} \prod_{j=i+1}^{k} \frac{1}{x_{r_j}} & \text{if } n_{r_{i+1}} = m_s \land \forall j \in [1, i], n_{r_j} = n_{t_j} \\ 0 & \text{otherwise} \end{cases}$$

It can be inferred that

$$\alpha_r = \sum_{j=1}^{y} \frac{1}{x} \beta_{r,j}$$

Denote $p_2$ as the probability that a selected path is incorrect and the child representing supporting lemma is on the path.

$$p_2 = \sum_{j=1}^{y} \frac{1}{x} (1 - \sum_{r=1}^{R} \beta_{r,j})$$

Therefore, denote $p$ as the probability that a child representing supporting lemma is on an incorrect path.

$$p = \frac{p_2}{p_1} = \frac{\sum_{j=1}^{y} \frac{1}{x} (1 - \sum_{r=1}^{R} \beta_{r,j})}{1 - \sum_{r=1}^{R} \sum_{j=1}^{y} \frac{1}{x} \beta_{r,j}} = \frac{y - \sum_{r=1}^{R} \sum_{j=1}^{y} \beta_{r,j}}{x - \sum_{r=1}^{R} \sum_{j=1}^{y} \beta_{r,j}} < \frac{y}{x}$$

As a result, given a random strategy, the probability that $n_i$ is on an incorrect path is less than the probability that $n_i$ is on a given path. In other words, if an incorrect path is found, the probability that $n_i$ is on the path, which equals $\prod_{j=1}^{y} \frac{1}{x_j}$ on a given path, decreases. On the other hand, the DQN requires a reward for guiding the optimization, where a reward corresponds to a determined occurrence of an event, e.g., a dead-or-alive signal upon an action in a game [32]. However, there is no such determined event in verifications. Instead, in SmartVerif, we leverage probability of occurrence that the node representing a supporting lemma is on incorrect paths for constructing the reward according to Theorem 1. This insight enables us to leverage the detected incorrect paths to guide the path selection, which is implemented by using the DQN.

**APPENDIX**

$p$ is found, the probability that $n_i$ is on a given path, decreases. On the other hand, the DQN requires a reward for guiding the optimization, where a reward corresponds to a determined occurrence of an event, e.g., a dead-or-alive signal upon an action in a game [32]. However, there is no such determined event in verifications. Instead, in SmartVerif, we leverage probability of occurrence that the node representing a supporting lemma is on incorrect paths for constructing the reward according to Theorem 1. This insight enables us to leverage the detected incorrect paths to guide the path selection, which is implemented by using the DQN.