Mining SoC Message Flows with Attention Model

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Abstract—High-quality system-level message flow specifications are necessary for comprehensive validation of system-on-chip (SoC) designs. However, manual development and maintenance of such specifications are a daunting task. We propose a disruptive method that utilizes deep sequence modeling with the attention mechanism to infer accurate flow specifications from SoC communication traces. The proposed method can overcome the inherent complexity of SoC traces induced by the concurrent executions of SoC designs that existing mining tools often find extremely challenging. We conduct experiments on five highly concurrent traces and find that proposed approach outperforms several existing state-of-the-art trace mining tools.

Index Terms—specification mining, message flows, transformers, deep attention models

I. INTRODUCTION

Model inference from execution traces is a popular system analysis, verification, and testing method. An Intellectual Property (IP) block-level communication model or message flow specification is a valuable resource for understanding IP interactions or SoC execution. However inter-IP communication models are not readily available due to complex life-cycle [1], [2] an SoC design. Existing pattern or flow mining tools perform poorly on flow specification mining for SoC traces due to the highly concurrent nature of SoC executions. Trace mining for producing high-quality flow specifications becomes extremely difficult when the SoC design complexity increases with adding multiple cores, multi-level shared and private caches, and high-performance interconnects. Traces extracted from SoC communication fabrics are sequences of messages exchanged among IP blocks. A set of well-defined message flows or flow specifications govern the ordering of different messages. An incorrect ordering of the messages could fail an SoC operation. Usually, a flow consists of a set of messages and a unique sequencing rule over the messages. In addition, different flows can have a shared set of messages. Multiple instances of different flows are typically executed concurrently while an SoC is in operation. We primarily focus on mining message flows for complex SoCs.

The term message denotes the unit of exchange between two IPs in the SoC. Though complex in nature, the message flows could be represented as finite state machines (FSMs)’s. The SoC architectural simulator gem5 [3] includes such FSMs to describe its CHI ruby protocol [4]. Specification mining problem is prevalent both in hardware and software domains. Therefore many works have addressed this specification mining problem both from hardware and software perspective [5], [6]. We study several tools and techniques for trace mining and find that those tools often fail to find high-quality models. Available approaches fail to extract complex sequencing relations among the messages; therefore, inferred models are often too straightforward or not very interesting to the users. High time and space complexity are also associated with each state-of-art method. For example, a large trace (>1GB or >7M events) with a high amount of interleaving, Trace2Model (T2M) [7] can not produce any Deterministic Finite Automata (DFA) within 24hrs. Synoptic [8] reaches the heap memory limit (>24GB) before inferring any system model, and Texada [9], though very fast, produces a massive amount of linear temporal logic (LTL) rules for the same trace. Comprehending many LTL rules is another challenge; thus, the utility of Texada is questionable. Therefore, there is an urgent need for a method to find an execution/communication model from large, interleaved traces within a reasonable time.

After careful study of the SoC traces and recent advancements in sequence modeling tasks, we find that machine learning models for language or sequence understanding can overcome trace length constraints. Usually, large sequential data or traces can improve the learning of such models. However, interleaving of flow instances is still a big challenge for finding the correct event or message causation. As the traces are expressed in orderly arrangements of events or messages that follow ground truth flows, the attention mechanism in sequence modeling [10] shows a big promise for solving this problem. This paper presents a framework for addressing the message flow mining from highly concurrent and extensive SoC communication traces. The overview of our flow mining method is shown in Fig. 1. It takes as input a set of execution traces over messages observed in various communication fabrics in an SoC design and produces a set of message flow specifications or flows. At first, a lightweight masked language
Among the messages as invariants or sequential patterns using recent work [19] addresses a similar flow specification mining work in [18] presents an assertion mining method employing presented in in [13]–[17] mine assertions from hardware traces trained with software execution traces. The techniques previously produces LTL rules from Bayesian networks that often miss the true causality of the messages. The work can work with very long traces but produces too many models.

AutoModel in SoC executions. Model synthesis technique produces LTL rules from Bayesian networks that often miss the true causality of the messages. The work can work with very long traces but produces too many models.

The key feature of this work is that it targets highly concurrent and large-scale communication traces. Furthermore, it utilizes the latest language understanding model to capture the long-term dependency among the messages. This work makes the following contributions:

- To the best of our knowledge, the proposed method utilizes an attention mechanism for automatically mining SoC message flow specifications. It only depends on the static design information found in the traces.
- The proposed method is scalable to very long traces, as shown in the experiments with realistic SoC traces.
- An evaluation method is also proposed to measure the quality of mined flows.

The organization of this paper is as follows. Section II reviews some closely related work in trace mining. Section III provides necessary background for related concepts, and formulates the problem. Section IV describes the proposed trace mining method. Section V presents the experimental results, and the last section concludes the paper.

II. RELATED WORK

Message flow mining aims to construct execution models from various design artifacts. Synoptic [8] presents an FSA model-based approach that mines invariants from logs of sequential execution traces. Generated FSA satisfies the mined invariants. However, this tool performs poorly when there is a high degree of interleaving in the trace, a common scenario in SoC executions. Model synthesis technique AutoModel [11] extracts concise models from the highly interleaved traces. It can work with very long traces but produces too many models that often miss the true causality of the messages. The work Bayspec [12] produces LTL rules from Bayesian networks trained with software execution traces. The techniques presented in in [13]–[17] mine assertions from hardware traces in either gate-level models [13], or RTL designs [14]–[17]. The work in [18] presents an assertion mining method employing episode mining from the transaction level simulation traces. A recent work [19] addresses a similar flow specification mining problem as in this paper. It captures the temporal relations among the messages as invariants or sequential patterns using the association rule mining technique. However, a lot of complex message relations are not captured in the invariants, which limits the capability of this tool.

Work [20] proposes a security property validation method focusing on the communication fabrics of an SoC. It builds a CFG for each IP in the SoC and efficiently explores connections between various CFGs for any given security property. This work considers system-level interaction and demonstrates that communication fabrics could be a vital point for vulnerability. Therefore, understanding the fabric-level communication model is essential for validation. Recently, Trace2Model is introduced in [7] that learns non-deterministic finite automata (NFA) models from platform-agnostic execution traces using C bounded model checking technique. Similar work is also done in [21]. Another tool called Texada [9] works with user-specified templates in the form of LTL and produces instances of that formula using some interestingness measures. The above approaches do not consider the concurrent nature of SoC design communication traces and rely on traces’ temporal dependencies to identify execution models.

III. MESSAGE FLOWS, CAUSALITY GRAPH, LANGUAGE MODELS

Message Flows: Message flows specify protocols of how system components communicate to implement the system-level functions. For example, high-level operations such as copying a chunk of bytes from a USB device to the hard drive and performing some update on the data can be viewed as a set of small primitive functions that must be executed in a specific order to complete that operation. This ordering of primitive tasks can lead to unique directed graphs: causality graphs (CG) for each system-level function. In a causality graph, each node represents a unique message, and each edge represents causal relations among the nodes or messages. For example, in a multi-core system with multilevel caches and IO peripherals, there could be multiple ways of completing an operation based on the cache-coherence protocols and available peripheral devices, thus yielding multiple branches on each graph. A flow is a collection of messages as nodes and edges as their causal relation expressed as a directed graph. Several previous works [22] have formalized the message flow mining problem in the literature.

A message flow specification is shown in Fig. 2. This simplified example specifies two memory operations via a shared cache for two CPUs. Let us say \( M \) is the set of messages that consists of the flow, \( C \) is a set of connections among the messages, such that \( C \subseteq M \times M \). Each message is a triple \((\text{src} : \text{dest} : \text{cmd})\) where the src denotes the originating component of the message while dest denotes the receiving component of the message. Field cmd denotes the operation to be performed at dest. For example, message \((\text{CPU}_0 : \text{Cache} : \text{rd} \text{-} \text{req})\) is the read request from \( \text{CPU}_0 \) to \( \text{Cache} \). Each message flow is associated with a unique start message and may terminate with one or multiple different end messages. As a message flow may contain multiple branches,
Causality Graphs: A causality graph can be constructed from the example flows in Fig. 2 if we examine the source and destination information of the message types. However, such graphs are not easy to construct for large traces. During the execution of an SoC design, instances of flows it implements are executed concurrently. When a flow instance is executed along one of its paths, messages on that path are exchanged with runtime information, e.g., specific memory addresses. Multiple instances of different flows executed concurrently are captured in the traces.

**Definition 3.1:** An SoC execution trace $\rho$ is $\rho = (\epsilon_0, \epsilon_1, \ldots, \epsilon_n)$ where $\epsilon_i = \{m_{i,0}, \ldots, m_{i,k}\}$ is a set of messages observed at time $i$, and $m_{i,j}$ is an message instance of some flow instance active at time $i$, for every $m_{i,j} \in \epsilon_i$.

An example trace from executing each path once of the example flows in Fig. 2 is $(1, 3, 5, 1, 5, 6, 2, 3, 6, 2, 4, 6, 4)$. Given two messages $m_i$ and $m_j$ and a trace $\rho$, we define $m_i < m_j$, denoting that $m_i$ occurs before $m_j$, if $m_i \in \epsilon_i$, $m_j \in \epsilon_j$, and $i < j$.

**Causality Graphs:** A causality graph can be constructed from the example flows in Fig. 2 if we examine the source and destination information of the message types. However, such graphs are not easy to construct for large traces. First, assume that the start and end messages are known, then define the causality relation.

**Definition 3.2:** Messages $m_i$ and $m_j$ satisfy the structural causality property, denoted as $\text{causal}(m_i, m_j)$, if $m_i.\text{src} = m_j.\text{dest}$

The causality as defined above is referred to as structural to differentiate from the functional causality in the flow specifications. An example trace following the flows in Fig. 1 (top left) could be as follows $(A, B, D, W, X, D, Y, E)$, where $A$ and $E$ are start messages while $W$ and $Y$ are end messages, therefore are drawn in different colors. Green nodes are start messages and purple nodes are end messages. The structural causality property among the messages $m_i$ and $m_j$ is satisfied and denoted as $\text{causal}(m_i, m_j)$, if $m_i.\text{src} = m_j.\text{dest}$. The start and end messages are required to build the causality graph.

**Algorithm 1: Flow Mining**

1: **Input:** a set of traces $\rho$, probability threshold $\theta$
2: **Output:** a set of message flows $M$
3: Extract unique messages in $\rho$ into $M$;
4: Build the causality graph $G$ from $M$;
5: Train Model $B$ on $\rho$;
6: **foreach** $(\text{Start}, \text{End}) \in G$ **do**
7: 
8: 
9: Query $B$ for next message $m.\text{score()} \geq \theta$
towards $\text{End}$;
10: Return causality subgraph as a Flow$(\text{Start}, \text{End})$

Language Models: Language modeling algorithms have significantly advanced sequence modeling tasks. For example, the self-Attention mechanism [23] is a proven technique for capturing long-term dependencies or transducing contextual information in the sequences. This method is heavily used in translation, text classification, and following sequence prediction tasks. Collectively these models are also called transformers. The basic architecture of a transformer contains a stack of encoder and decoder layers. The encoder takes the input texts or symbols and performs some natural language processing such as positional embedding. The decoder employs a masking technique so that the model learns to predict the $i^{th}$ element, relying on the sequence’s $(i-1)^{th}$ elements. Such language models are a promising candidate for SoC traces as they also have long sequential dependencies.
are known, and messages are observed on system communication fabrics and recorded as they occur. Trace processing aims to train the model with highly correlated traces. A language model is trained on the input sequences masking the input by parts. So learning on poorly correlated traces will affect the sequence prediction negatively. While training the model, we employ in-place causality slicing because messages that are not causally related will not form any message flow. Therefore causality slicing increases the message correlation.

B. Training Model

We utilize a Masked LM DistilBertForMaskedLM model as the bidirectional transformer. We reuse the default architecture of the transformer and retrain it on our SoC traces to predict masked tokens in a sequence. We use the light version of BERT \cite{24} namely DistilBERT \cite{25} which contains only 12 encoder layers. This bidirectional model is more compelling than the shallow left-to-right or otherwise models. The objective is to train the model to predict the next word in a multi-layered context. To train the model, we randomly mask a certain percentage of the input traces in token form. We apply several optional fine-tuning to fit our traces better.

C. Flow Mining

Message flow mining happens in three steps. The first step is to build the CG from the message src and dest information. This CG is supposed to contain all the message flows and additional false branches. We can vary the confidence threshold for our desired complexity of the graph. The next step is to refine the graph. Once the model is trained, graph refining happens in a guided fashion. There is often incorrect message dependency or causality added to this graph since two messages have a common dest and src field. For example, in the causality graph Fig. 6(a), msg_19 causes msg_27, though msg_27 may not be present in the flow originating with start message msg_2 that ends at msg_26. A search starts from the start message and reaches to the end message forming a causality sub-graph $G_f \subseteq G$. The trained model predicts if $m_2$ follows $m_1$ with some probability score returned by method $m_2$.score(). If the score is greater or equal to the threshold $\theta$, the edge from $m_1$ to $m_2$ is kept in the causality graph. Otherwise, such an edge is discarded. This process is repeated until all flows in the causality graph are discovered for respective (start, end) pairs. Finally, the refined CG is transformed into an FSM model. Transformation is straightforward; therefore, the discussion is omitted. Evaluation Algorithm 2 then evaluates the FSM model against the input traces $\rho$. It reports the number of events rejected by the model. The model with the least number of rejections is reported to the user.

V. EXPERIMENTS

To evaluate the presented framework, a non-trivial SoC design is simulated in the gem5 architectural simulator, as shown in Fig. | gem5 produces a trace that has more than 7M events. The multi-core gem5 simulation contains a high degree of interleaving. Besides a set of synthetic traces taken as a benchmark from work \cite{11}. Table I summaries the traces.

\begin{table}[h]
\centering
\caption{Trace description.}
\begin{tabular}{|c|c|c|}
\hline
Traces & #Msg & Length \\
\hline
small & 22 & 920 \\
& & 1840 \\
large & 60 & 4360 \\
& & 8720 \\
gem5 & 103 & 7274984 \\
\hline
\end{tabular}
\end{table}

A. General Trace to FSA Evaluation Strategies

Many works have proposed different methods to evaluate the specification mining methods. For instance, in \cite{26} the proposed method is evaluated by reverse engineering a set of FSAs from their C implementation and the Simulink Stateflow example models have been used as the evaluation dataset. Loo and Khoo’s method \cite{27} has also been used for evaluation in \cite{28}. The method accepts a ground truth and an inferred finite-state automata as input and computes the precision of the inferred FSA based on accepted sentences by the ground truth and the overall number of sentences generated by the FSA. The evaluation method used in \cite{29} is also similar to the previous method. They will calculate the precision and recall values based on the percentage of events of traces that are generated and can be interpreted by the workflows. In this paper, we chose to evaluate the proposed specification mining method by generating an FSA based on the causality graph. For comparison, we have chosen to compare the proposed method with other state-of-the-art works using synthetic traces and also using the gem5 traces for more realistic results.

B. Results on Different Traces

For evaluating the proposed flow specification mining method, at first, a finite state automata is created based on the generated causality graph. The corresponding trace will be evaluated using the created FSA. The algorithm for evaluation can be found in algorithm 2. Also, the achieved results are illustrated in Table II.

In Algorithm 2 after generating the FSA based on the causality graph, a search for instances of the generated FSA among trace events will begin. Every single event in a trace file will be checked and if it could be fitted in any stage of an active FSAs, that trace would be marked as accepted. However, if any event is not accepted by any active FSA nor can start a new instance of FSA, it will be marked as unaccepted. Lastly, after exploring all events in a trace file is done, the final acceptance rate will be reported as the output of the algorithm.

1) Synthetic Traces: In order to create a standardized technique for evaluating the accuracy of transformed FSMs, we generated traces synthetically for some of our tests. To synthetically generate traces, we specify a set of patterns permitted to occur concurrently on multiple simulated cores. This concurrency enables realistic interleaving of these patterns, increasing the corresponding traces’ difficulty. This difficulty is a function of the numbers and sizes of the patterns, as well as the number of concurrent cores.

Synthetic traces also enable us to test the finite state machine’s accuracy by generating traces known to be false.
Algorithm 2: Evaluation Algorithm
1: \textbf{Input:} causality graph, traces
2: \textbf{Output:} acceptance rate
3: Create an FSA based on the causality graph;
4: \textbf{foreach} event in traces \textbf{do}
5: \hspace{1em} \textbf{if} it was a start event:
6: \hspace{2em} Create an FSA instance for the start event;
7: \hspace{1em} \textbf{else if} the event can be fitted in an instance of the FSA:
8: \hspace{2em} Mark the event as accepted;
9: \hspace{1em} \textbf{else}:
10: \hspace{2em} Mark the event as not accepted;
11: \textbf{endforeach} instances of the FSA \textbf{do}
12: \hspace{1em} \textbf{if} the instance is not in the finish state:
13: \hspace{2em} Mark all of the events in that instance as not accepted;
14: \textbf{Report} the final acceptance rate;

This is essential as it allows us to distinguish an overly accepting finite-state machine from one that accurately models the behavior of valid traces. As the accurate distribution of natural traces is not known, synthetic traces whose behavior is well understood provide essential insight into the effectiveness of BERT and competing algorithms, as highlighted in Table II. The runtime contains the training time and dominates the overall time complexity.

2) \textit{Emulated Gem5 Traces:} To test on a truer-to-life setting, we also generated traces via the use of the \texttt{gem5} emulator. We tracked the flow of messages between roughly a dozen IPs, Fig. 4 and logged the flags that were used during those messages to produce a trace of the emulator running various programs, such as fast matrix multiplication and a thread scheduling algorithm. \texttt{Synoptic} fails to find any model from \texttt{gem5} traces.

\textbf{C. Discussion}

Using FSAs to validate the traces comes with a challenge. The main one is caused by the non-determinism in the choices of FSA instances. This means that when a new event is being checked with the FSA, there may be more than one possible instance for it to be added to. This situation can be seen in the causality graph in Fig 5. Two of the possible outcomes of following the trace (1, 1, 5, 1, 2, 5, 4, 3, 4) on the causality graph, are \{(1, 5, 4), (1, 2, 3, 4), (1, 5, 4)\} and \{(1, 5, 4), (1, 2, 5, 4), (1)\} which are respectively acceptable and unacceptable (incomplete). Thus, choosing an FSA instance to assign the new event can determine whether the trace will be accepted, and choosing the best FSA instance is the main challenge.

\textbf{Case Study:} We select two flows CPU0\_Read, and UART\_Upstream\_Read adopted from an industry SoC design, which are used to generate a set of traces synthetically. Each flow has three branches, 14 unique messages, and four shared messages, as shown in Fig. 6 (a). A training set is prepared to contain 600 concurrent and interleaved runs of these flows. We trained the model for ten epochs, which took around 6.00 hrs.

Fig. 6 (a) shows a causality graph built from the messages of the two flows. We want to identify each flow separately with the help of the trained model. A search starts with the \texttt{(start,end)} message pair (\texttt{msg\_2, msg\_26}). The branches that do not reach \texttt{msg\_26} are discarded in the first place. This gives us a causality graph with many branches to the \texttt{end} message. The trained model helps us remove additional branching edges based on the traces’ context learned for each message. For example, \texttt{msg\_27} does not come as a predicted next message for \texttt{msg\_19} for the given score threshold of 75%. Therefore, we discard message \texttt{msg\_27} from this flow. This process continues till we examine every branch leading to the end message \texttt{msg\_26}. Finally, we get the refined causality graph Figure 6 (b), which happens to be the ground truth flow for \texttt{CPU0\_Read}. Similarly, we construct \texttt{UART\_Upstream\_Read} flow.

We apply an LSTM-based pattern mining [6] and a rule-based data mining approach \textit{FlowMiner} on the same synthetic trace set. Work [6] extracts flow specification in the form of sequential patterns. We extract patterns for pattern probability as in [6], but could not produce a complete specification for any of the tests flows of our experiment. Work [5] utilizes association rule mining to find invariants from the traces. The mined rules can partially construct \texttt{CPU0\_Read} where \texttt{msg\_15} and \texttt{msg\_23} are missing. Table III summarizes results for these
### TABLE II: Mining Summary: RT = Run Time (in second), DNF = Did Not Finish, Ratio = events accepted by the FSA with respect to rejected events

| Traces   | small-10 | small-20 | large-10 | large-20 | gem5 |
|----------|----------|----------|----------|----------|------|
| **Tools** | **Ratio** | **size** | **RT** | **Ratio** | **size** | **RT** | **Ratio** | **size** | **RT** | **Ratio** | **size** | **RT** | **Ratio** | **size** | **RT** | **Ratio** | **size** | **RT** |
| Texada   | 0.41     | 231      | 0.39     | 231      | 0.08   | 231      | 0.13     | 231      | 0.35   | 1073   | 5      |
| Synoptic | 0.92     | 122      | 0.92     | 122      | 129    | 0        | 0.41     | 421      | 865    | DNF    | DNF    | DNF    | DNF    | DNF    |
| T2M      | 0.60     | 90       | 0.63     | 45       | 7235   | 0        | 0.52     | 142      | 626    | 0.55   | 1518   | 0.95   | 45     | 2240   |
| AutoModel| 0.77     | 52       | 0.69     | 65       | 68     | 0.52     | 142      | 626      | 0.55   | 1518   | 0.95   | 45     | 2240   |
| BERT     | 0.95     | 109      | 0.92     | 103      | 1600   | 0.96     | 103      | 1600     | 0.90   | 103    | 1600   | 0.95   | 262    | 4500   |

### TABLE III: Mining results for the three methods on evaluation metrics described in FlowMiner [5]. \( \theta = 0.75 \) for flow mining.

|               | #Patterns Mined | Precision | Recall |
|---------------|-----------------|-----------|--------|
| FlowMiner     | 53              | 100%      | 25%    |
| LSTM          | 22              | 100%      | 3.12%  |
| BERT          | All             | 94%       | 100%   |

three methods on the same traces. All refers to the fact that our method does not produce patterns, but DAGs, which could be used to generate all patterns found in the ground truth flows. Regarding evaluation metrics: recall and precision described in FlowMiner, BERT achieves better scores in both matrices.

### VI. CONCLUSION

We find causality graph-guided word prediction model produces the best quality message flows specifications. However, the high training time could be a limiting factor for this method to existing approaches. Message attribute slicing techniques could help reduce the training time in this regard. Besides, the off-the-shelf models use legacy embedding. An SoC trace-specific embedding could be used further to improve the quality of the mined message flows.

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