Benchmarking of triple stores scalability for MPSoC trace analysis

Leon Constantin Fopa  
University of Grenoble, LIG  
681 rue de la passerelle  
St Martin d’Heres, France  
fopal@imag.fr

Fabrice Jouanot  
University of Grenoble, LIG  
681 rue de la passerelle  
St Martin d’Heres, France  
fabrice.jouanot@imag.fr

Alexandre Termier  
University of Grenoble, LIG  
681 rue de la passerelle  
St Martin d’Heres, France  
alexandre.termier@imag.fr

Maurice Tchuente  
University of Yaounde 1  
LIRIMA and IRD-UMI 209  
UMMISCO  
BP 337 Yaounde, Cameroon  
maurice.tchuente@lirima.org

Oleg Iegorov  
STMicroelectronics  
850 Rue Jean Monnet  
Crolles, France  
oleg.iegorov@st.com

ABSTRACT
A Multi Processor System-on-Chip (MPSoC) is a complex embedded system used in consumer electronic devices, such as smartphones, tablets and set-top boxes. In order to cope with the complexity of MPSoC architectures, software developers rely on post-mortem trace analysis for application debugging or optimization. The traces are explored to localize expected and unexpected programs behaviors. However, the low semantic value of low-level trace events make the trace exploration difficult. We propose to perform trace exploration through an ontology which adds semantics to events and provides a declarative language for querying data. Because traces can be huge, such an ontology contains a large number of instances stored as RDF triples. Because analysts need fast results on classical computer, an efficient system for query answering is preferred. However, saturating, loading and querying those triples pose a scalability challenge to state-of-the-art knowledge base repositories (KBR). In this paper, we have conducted a benchmark of 7 KBRs: Jena, Sesame-native, Sesame-memory, tdb, sdb, rdf-3x and vertical-mdb, to test their scalability in a non-distributed environment close to analyst environment. We used these KBRs to analyze real traces through VIDECOM, an ontology we designed for trace analysis of applications on MPSoC. Results show that vertical-mdb has a loading rate 3 times faster than the others. It is the only KBR able to saturate the biggest trace of our dataset without exceeding system memory and to run complex queries on it in an acceptable time. Other approaches failed, due to memory limitation or inefficient join implementation.

1. INTRODUCTION
Multi Processors Systems-on-Chip (MPSoC) are small chips containing multiple components like processors, memory units, buses, Graphical Processor Unit (GPU), input/output ports. They are widely used in our everyday life through mobile phones, washing machines, automotive control, flight control and set-top boxes. Developing embedded software on MPSoC is difficult because of the inherent parallelism of these chips. Indeed, industrial studies on quality control of embedded softwares indicate high defect densities of 13 major bugs per 1000 lines of code [13]. In multimedia applications, such inefficient code can cause, for example, frozen images or desynchronized images and sound.

The main task in embedded software debugging or optimization is to track bugs or inefficient code manifestations in order to correct them. Inefficient codes and bugs related to parallelism manifest themselves mostly at runtime. Developers, therefore, rely on post-mortem trace analysis methods to debug embedded software [3]. The basic idea is to run the program against specific tests and to explore its execution trace, in order to compare the observed program behavior with expected behavior. The semantics of the trace events, such as relations and constraints between them, are known by the developers, but are not explicit in the trace. Therefore, characterizing program behaviors in a trace is a challenge.

Interpreting events as program behavior is quite similar to data interpretation in the semantic web. The key idea of the semantic web is to propose logical assertions that relate a resource to some concepts in predefined ontologies [2]. Thus, by using a domain ontology for trace analysis, trace exploration can be done through declarative queries whose results will be closer to developer expectations. Because a trace can consist of several million of events for only few minutes of execution, such an ontology will contain a large number of instances stored as RDF triples, which will definitely pose scalability challenges to knowledge base repositories (KBR).

In this paper, we present VIDECOM, an ontology that we have designed for trace analysis of applications on MPSoC. We present a benchmark of 7 KBRs to test their scalability when they are used to saturate, load and query RDF
triplies obtained from real trace events mapped to classes and properties of VIDECOM. Because the analyst environment is mainly non-distributed, and because we focus on query answering efficiency on a saturated knowledge base, such KBRs have been chosen mainly for their support of query engine and storing system on a non-distributed environment, but not for their inference capabilities.

The rest of the paper is organized as follows. The VIDE-COM ontology is presented in Section 2. In Section 3 we present data storage mechanisms in KBR and the performance criteria for our comparative study. In Section 4 we present results of our experiments. We present some related work in Section 5. In Section 6 we conclude the paper and propose some future work.

2. THE VIDE-COM ONTOLOGY

One important contribution of this paper is the VIDE-COM ontology. VIDE-COM is based on a deductive triple store composed of two parts. The first part is a domain ontology built on RDFS triple patterns extended with rules expressing domain knowledge. The second part is a popu-lated ontology consisting of triples coming from trace events and the saturation mechanism.

Domain ontology. In this section, we briefly present some classes and properties of VIDE-COM. We also present how developers can enrich VIDE-COM using their knowledge about expected and unexpected behaviors.

Trace captures events that occurred during execution, such as interrupts, task running and context switches. Each event carries basic information like the start time, the duration, the task or the interrupt executed, the processor, the function called and arguments used. Table 1 shows an example of 8 trace events. The first event starts at timestamp 3771 and ends at timestamp 3781. It corresponds to a sys_read operation executed by the task ts_record on cpu 0 with argument 0x46d.

Table 1: Illustration of 8 events from a real trace.

<table>
<thead>
<tr>
<th>id</th>
<th>Start</th>
<th>End</th>
<th>Operation</th>
<th>Task</th>
<th>CPU</th>
<th>Arg</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>3771</td>
<td>3781</td>
<td>sys_read</td>
<td>ts_record</td>
<td>0</td>
<td>0x46d</td>
</tr>
<tr>
<td>1</td>
<td>3792</td>
<td>3873</td>
<td>sys_write</td>
<td>ts_record</td>
<td>0</td>
<td>0x11b</td>
</tr>
<tr>
<td>2</td>
<td>3879</td>
<td>3884</td>
<td>switch_to</td>
<td>sshd</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>3884</td>
<td>3885</td>
<td>Interrupt</td>
<td>mdtpl</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>4260</td>
<td>4260</td>
<td>switch_to</td>
<td>kworker</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>4502</td>
<td>4602</td>
<td>sys_poll</td>
<td>ts_record</td>
<td>0</td>
<td>0x11c</td>
</tr>
<tr>
<td>6</td>
<td>4605</td>
<td>4647</td>
<td>sys_read</td>
<td>ts_record</td>
<td>0</td>
<td>0x11d</td>
</tr>
<tr>
<td>7</td>
<td>4792</td>
<td>4873</td>
<td>sys_write</td>
<td>ts_record</td>
<td>0</td>
<td>0x11e</td>
</tr>
</tbody>
</table>

In VIDECOM, RDF triple patterns can be enriched with Datalog rules of the form φ ⇒ ψ, where φ = φ1 ∧ ... ∧ φn is a conjunction of atoms (triple patterns) called premise, and ψ = {ψ1, ..., ψm} is a conjunction of atoms called conclusion. An atom is a triple with variables at subject, property or object positions. The variable identifiers start with ?. An atom holds if there are triples that matched the triple form of the atom. Therefore, the inference rule works as follows. If the conjunction of atoms of the premise holds, then the set of triples from the conclusion is added to the triple store. For example, let’s consider the following inference rule

\[ \langle ?e, \text{runningTask}, ?t \rangle \Rightarrow \langle ?e, \text{rdf:type}, \text{TASK\_RUNNING} \rangle \]

if there is a triple in the triple store with runningTask in the property position and whatever in the subject (?e) and the object (?t) positions, then a triple is built and added to the triple store based on the atom of the conclusion with the corresponding value of variable ?e.

We consider safe rules, that means that all variables in the conclusion are also in the premise, even the so-called blank node that is interpreted here as a constant for the safety property. RDFS semantics are captured by inference rules listed in the W3C recommendation1. Rules expressing domain knowledge corresponding to program behaviors are also captured using the same type of rules.

Populated ontology. Instances of VIDECOM classes and properties are built from events and stored as RDF triples (subject, property, object) in a triple store. Table 2 shows 10 RDF triples that represent the basic information contained in event1 from table 1.

\[1\text{http://www.w3.org/TR/2014/REC-rdf11-mt-20140225/#rdfs-entailment} \]
The saturation ensures the completeness as well as the soundness of the query answering. It is done through an inference engine called reasoner. The reasoner implements a forward-chaining algorithm that applies all users and rdfs inference rules to populate the triple store with new facts. The saturated triple store is loaded in a KBR for querying purpose. In the next section we will briefly describe state-of-the-art KBRs.

3. KBR DESCRIPTION

In this section, we will briefly present several state-of-the-art KBRs. We classify the KBRs by the data storage mechanism they use to store the RDF triples.

3.1 Data storage mechanism

Various data storage layouts are presented in [6]. They distinguished native and non-native storage.

3.1.1 Native storage

This solution provides a way to store RDF triples in a model similar to the graph model. These solutions can be classified as persistent disk-based and main memory-based.

The persistent disk-based storage of RDF triples uses proprietary file format in many cases. Among the existing solutions we can mention tdb, Sesame-native and rdf-3x. tdb\(^2\) uses a file system and stores triples in B+ Tree data structures. Sesame-native uses dedicated on-disk data structures for storage [14]. rdf-3x stores all the triples in a compressed clustered B+ Tree and uses an exhaustive index for all permutations of subject-property-object triples [12].

The main memory-based storage of RDF triples allocates a certain amount of the available main memory to store the whole RDF graph structure. Jena [10] and Sesame-memory [5] fall into this category.

3.1.2 Non native storage

The non-native storage solution makes use of Relational Database Management Systems (RDBMS) to store RDF triples. Storage of RDF triples in RDBMS exists in three models: triple table, property table and vertical partitioning.

In the triple table approach RDF triples are stored under the form (subject, property, object) in one large table with a three-columns schema corresponding to subject, property and object. Usual RDBMS indexes are built on each column to optimize access. sdb\(^3\) is an example of this solution.

<table>
<thead>
<tr>
<th>id</th>
<th>(subject, property, object )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>( event1, eventStartAt, &quot;3792&quot; )</td>
</tr>
<tr>
<td>2</td>
<td>( event1, eventEndAt, &quot;3873&quot; )</td>
</tr>
<tr>
<td>3</td>
<td>( event1, isExecutedOn, cpu0 )</td>
</tr>
<tr>
<td>4</td>
<td>( event1, runningTask, ts_record )</td>
</tr>
<tr>
<td>5</td>
<td>( event1, requestComponent, sys_write )</td>
</tr>
<tr>
<td>6</td>
<td>( event1, eventPrecedeInTrace, event2 )</td>
</tr>
<tr>
<td>7</td>
<td>( event1, eventPrecedeInCPU, event4 )</td>
</tr>
<tr>
<td>8</td>
<td>( event1, eventPrecedeOccurrence, event7 )</td>
</tr>
<tr>
<td>9</td>
<td>( event1, hasDuration, &quot;81&quot; )</td>
</tr>
<tr>
<td>10</td>
<td>( event1, hasDurationToNextOccurrence, &quot;1000&quot; )</td>
</tr>
</tbody>
</table>

Table 2: Set of RDF triples representing the basic information contained in event1 from table 1.

The property table technique improves triples organization by allowing multiple triple patterns referencing the same subject to be retrieved with less join. In this model, triples are physically stored in a representation close to traditional relational schema in order to speed up the queries over the triple stores. In this approach each named table includes a subject and several fixed properties. The main idea is to discover clusters of subjects that appear frequently with the same set of properties. 4store uses this approach [9].

Abadi et al suggested the vertical partitioning as an alternative to the property table. They illustrated the approach in swStore [1]. In this approach the triple table is divided into n two-columns tables, one table for each property in the data. In each of these tables, the first column contains the subject and the second column contains the object value related to this subject. Tables are stored by using a column-oriented RDBMS as a collection of columns rather than a collection of rows.

3.2 Inference support

Not all KBRs provide an RDFS reasoner. In those that we cited above only Jena and Sesame provide reasoners. The Jena reasoner implements a configurable subset of RDFS inference rules using the RETE algorithm [7] for forward chaining. We retained Jena reasoner because it is the only one that allows the implementation of user defined inference rules.

3.3 Performance criteria

We consider the following performance criteria to test scalability of KBR: the saturation time which is the time spent to saturate the triple store, the loading time which is the time spent to load the saturated triple store into the repository, and the query response time which is the time spent to answer a query.

We consider various characteristics of queries. We first consider the selectivity, because a high selective query must efficiently return a small portion of the entire triple store as answer. Next we consider the k-complexity defined as the number of atoms with k variables in the query. A 1-complexity atom has one variable and a 2-complexity atom has variables in two positions. We do not consider the case where a variable appears at the property position because it concerns very infrequent category of queries. Moreover a conjunction between two atoms with at least a variable in common in different places will indicate a join. We next consider whether or not the query uses sorting operators on the result. Indeed, due to the temporal nature of events, results may need to be sorted to facilitate their exploitation.

4. RESULTS AND DISCUSSIONS

In this section, we present a use case on STMicroelectronics MPSoC. This use case corresponds to an analysis of a real video recorder program called ts_record. We present experimental settings and results of our comparative study.

4.1 Experimental settings

We performed our experiments on 6 traces corresponding to different execution times of ts_record. Table 3 presents details on traces, such as, the execution duration, the number of runtime events recorded and the disk size of the trace. Section A of the Appendix provides more details on the ts_record use case, and Table 6 of the Appendix provides

\(^2\)http://jena.apache.org/documentation/tdb/architecture.html
\(^3\)http://jena.apache.org/documentation/sdb/
Table 3: List of traces and their corresponding execution time, number of runtime events and number of triples before saturation.

<table>
<thead>
<tr>
<th>Traces</th>
<th>Execution duration</th>
<th># of events</th>
<th># of triples</th>
</tr>
</thead>
<tbody>
<tr>
<td>T0</td>
<td>2 m 38 sec</td>
<td>500,000</td>
<td>7,653,945</td>
</tr>
<tr>
<td>T1</td>
<td>3 m 25 sec</td>
<td>1,000,000</td>
<td>15,307,847</td>
</tr>
<tr>
<td>T2</td>
<td>7 m 43 sec</td>
<td>1,500,000</td>
<td>22,881,749</td>
</tr>
<tr>
<td>T3</td>
<td>9 m 23 sec</td>
<td>1,800,000</td>
<td>27,441,696</td>
</tr>
<tr>
<td>T4</td>
<td>10 m 25 sec</td>
<td>2,000,000</td>
<td>30,492,400</td>
</tr>
<tr>
<td>T5</td>
<td>25 m 47 sec</td>
<td>5,000,000</td>
<td>76,258,631</td>
</tr>
</tbody>
</table>

Table 4: List of characteristics of our 8 test queries.

<table>
<thead>
<tr>
<th>Selectivity</th>
<th>Q0</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
<th>Q5</th>
<th>Q6</th>
<th>Q7</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-complexity</td>
<td>H</td>
<td>L</td>
<td>L</td>
<td>H</td>
<td>H</td>
<td>H</td>
<td>H</td>
<td>L</td>
</tr>
<tr>
<td>2-complexity</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Filter</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Order by</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
</tbody>
</table>

Table 5: Saturation time, number of triples and disk size of each trace after saturation.

<table>
<thead>
<tr>
<th>Traces</th>
<th>Saturation time</th>
<th># of triples</th>
<th>Size (MB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>T0</td>
<td>08 m 01 sec</td>
<td>13,051,370</td>
<td>2,185</td>
</tr>
<tr>
<td>T1</td>
<td>18 m 28 sec</td>
<td>25,981,602</td>
<td>4,347</td>
</tr>
<tr>
<td>T2</td>
<td>22 m 43 sec</td>
<td>38,790,013</td>
<td>6,508</td>
</tr>
<tr>
<td>T3</td>
<td>1 h 12 m 18 sec</td>
<td>46,494,600</td>
<td>7,818</td>
</tr>
<tr>
<td>T4</td>
<td>1 h 41 m 01 sec</td>
<td>51,607,411</td>
<td>8,670</td>
</tr>
<tr>
<td>T5</td>
<td>x</td>
<td>95,309,610</td>
<td>16,404</td>
</tr>
</tbody>
</table>

Table 4: List of characteristics of our 8 test queries.

We performed our experiments on a machine with a 2.27 GHz Intel Xeon CPU and 64 GB of RAM. We chose the following non-commercial KBR for our comparative study: jena and tdb, sesame-memory and sesame-native tdb, and vertical-mdb. More details on their configuration are provided in the Appendix (Section B).

The reader can find the VIDEOM ontology, non-saturated and saturated public datasets, user inference rules, 8 tests queries and experimental results, on the website hosted at http://videcom.imag.fr.

4.2 Experimental results

4.2.1 The saturation time

Table 5 shows the saturation time for each trace, the number of triples after saturation and the disk size of the ontology stored in a N-Triple format. The main memory was insufficient for Jena reasoner to saturate T5. We used a naive SQL-based implementation of forward-chaining algorithm in vertical-mdb. We saturated T5 in 2 days 11 h 35 m 8 sec, but many optimizations are possible in our implementation to have better performances.

We observed that, one trace event produces 25 RDF triples, and that saturated triple store disk size is 68 times larger than corresponding trace size. This result illustrates the difference of magnitude between the number of trace events and RDF triples, and the limitation of resource for saturation at this scale.

4.2.2 The loading time

Figure 2(a) shows the loading time for each repository and saturated triple store size. Indexes construction is included in the loading time. Because vertical-mdb uses batch import operations provided by MonetDB to copy data from file to tables and constructs index after data are loaded, it is the most efficient comparing to others considered KBRs. It is 2 orders of magnitude faster than tdb, which builds indexes before loading data and, thus, frequently updates its indexes. Figure 2(a) also shows that sesame-memory and sesame-native cannot load 95 million triples. As it took tdb more than 2 hours to load 51 million triples (see Figure 2(a)), We were not able to load 95 million triples with tdb. In conclusion, results show that vertical-mdb can load 95 million triples in 2 minutes. We also observed that loading all the 95 million triples of T5 with Jena filled all the main memory and an additional 6 GB space from the swap.

Another fact is that being non-persistent, main-memory based repositories load data for each working session.

4.2.3 Query response time

We executed our queries on each KBR and for each trace from T0 to T5. We ran each query 10 times and we collected the mean time as query response time.

Selectivity: Figure 2(b) shows response time for Q0. All KBR answered within 10 seconds. Thanks to their B+Tree based indexes rdf-3z and tdb are faster than the others. Jena scales poorly on 95 million triples because of swap-in and swap-out needed to get free space in main memory. In the case of Q1 depicted in Figure 2(c), all KBR performance dropped by one order of magnitude but rdf-3z dropped by 2 orders of magnitude. However, tdb remains the fastest, which indicates that its indexes are well adapted for both high and low selectivity queries.

Sorting: Figure 2(d) shows the performance of Q2. We observed that performance of vertical-mdb did not change, unlike the others which lost at least one order of magnitude in response time. The reason can be the efficient implementation of sorting in MonetDB. We observed that the performance of rdf-3z dropped by 2 orders of magnitude, which indicates that the implementation of its sorting operators is not efficient. Figures 2(e) and 2(f) show the performance of Q3 and Q4. Using inferred classes, Q4 returns the same result as Q3. We observed that using inferred classes leads to fast query response time. The reason can be that inferred classes have higher selectivity.
Figure 2: Comparison of saturated triple store loading time and query response time for each KBR.
**Interval of trace:** Figure 2(g) shows the result when querying the same interval of time in all traces. We observed that vertical-mdb has better performance. The reason is that vertical-mdb identifies numerical object values; therefore, indexes built on columns containing numbers are more efficient than indexes built on strings like others do.

**k-complexity:** Figure 2(h) shows results for Q5. rdf-3x did not provide results due to an internal error in the query parser. Conjunctions are implemented in RDBMS as joins. In the case of sdb it consists of self-joins on the unique table 'Triple Table', and in the case of vertical-mdb it consists of joins between multiple tables. sdb failed to produce results; we suppose the reason being the inefficiency of self-join on large triple tables. vertical-mdb has acceptable response time (2 minutes for 95 million triples) unlike tdb which needed 5 minutes for 38 million triples. Figure 2(i) shows the performance of Q7. vertical-mdb has better response time (2 minutes for 46 million triples). Other KBRs performed poorly over 13 million triples. Jena took 8 minutes, sesame-native took 48 minutes, tdb took 2 hours and sesame-native took 3 hours.

**Discussion:** Results show that the saturation with Jena is efficient but depends on the available memory. We also found that tdb indexes are efficient at large scale, and that vertical-mdb join implementation is efficient. Due to its fast loading speed vertical-mdb loads 95 million triples in 2 minutes and supports RDFS rule reasoning without memory limitation. The inefficiency in the saturation mechanism for vertical-mdb is mainly due to unoptimized code and far better performance should be expected. vertical-mdb is the only one that exhibited low running times across all queries. It is also the only system that could handle Q7, a complex but realistic query. Considering the type of queries the analysts are interested in, the constraints of their practice, a vertical database system is the best solution in this context. Because an efficient inference engine is not required in the solution we chose based on a saturated triple dataset, some KBRs have been discarded. Nonetheless, KBRs such as, OWLIM and Virtuoso should be considered for future works considering distribution of the dataset and parallel processing.

5. RELATED WORK

Several RDF benchmarks were previously developed. We can cite, the Lehigh University Benchmark (LUBM) [8], the Berlin SPARQL Benchmark (BSBM)[4], and DBpedia [11]. Those benchmark handle large synthetic or real datasets (300 million of triples for DBpedia). They are mainly focused on the loading time and the query response time on various KBRs, such as, Jena, TDB, SDB, Sesame, virtuoso and OWLIM. Unlike those benchmarks, our benchmark is also focused on the saturation time of triples, because our datasets are deductive triple stores and need inference rule to be provide sound and complete query answers.

6. CONCLUSION AND FUTURE WORK

In this paper we presented a benchmark of triple stores scalability for MPSoC trace analysis. We presented Videocom, an ontology for trace analysis of application on MPSoC and we made a comparative study to test the scalability of 7 state-of-the-art KBRs. These experiments have shown that even with relatively simple traces and a large server, existing KBR have difficulties to scale up. Among the tested KBR, vertical-mdb is the only one that exhibited low running times across all queries. Given that execution traces are likely to grow much larger than the traces of these experiments, we can conclude that solutions based on a vertical approach will be required to handle them, and will have to be improved.

For our future work we are interested in giving answers to query over large traces in a fixed time. We plan to develop efficient approaches to speedup saturation, and we are interested in different strategies for query parallelization. Following this track we plan to consider OWLIM and Virtuoso KBRs for comparison with the vertical database approach.

7. ACKNOWLEDGEMENT

This work was supported by French FUI project SoC-Trace.

8. REFERENCES

APPENDIX

A. THE TS_RECORD USE CASE

The program ts_record contains three tasks which can be scheduled on different CPUs of the MPSoC. The first task $t_1$ collects streaming data and stores them in small IP buffers. Every 100 milliseconds, the second task $t_2$ copies data from IP buffers to main memory. Finally, every 5 seconds, the last task $t_3$ copies them to a USB disk. The period between each task is important to avoid errors which can cause data loss. Based on this domain description, Table 6 presents 2 user inference rules that correspond to the behavior of task $t_2$. For simplicity we present only two rules, but more rules can be added to VIDEOM. The number of user inference rules influence the saturation time. The rule $R_1$ instantiates the FUNCTIONALITY subclass $sysWriteNormal$ when two occurrences of events corresponding to $t_2$ are separated by a period equal to 100 milliseconds. The second rule $R_2$ instantiates the ANOMALY subclass $sysWriteBlocked$ if the period is greater than 100 milliseconds.

B. KNOWLEDGE BASE SYSTEMS FOR EXPERIMENTS

We chose the following non-commercial KBRs for our comparative study: jena and tdb (version 2.11.2) with their default configuration. We set the java heap size to 60 GB. We also chose sesame-memory and sesame-native (version 2.7.7), we configured sesame-native to support all the combination of subject-property-object indexes known as spoc, posc, and opsc. We set the java heap size to 60 GB. We chose sdb (version 1.3.4) backed on postgresql (version 9.3), and we configured sdb with the default "layout2" indexing storage. We set the java heap size to 60 GB.

Unfortunately 4Store has not been maintained for 5 years and we were not able to install it in our setup configuration. The column-store-based approach swStore implementation was not available. We implemented the approach as described in [1], but used MonetDB$^6$ (version 11.17.9) as a backend instead of C-Store because C-Store is no longer maintained. We called our implementation vertical-mdb.

\footnote{https://www.monetdb.org/}
R1: \[ \langle ?e1, \text{runningTask, ts}\_\text{record} \rangle \land \langle ?e1, \text{requestComponent, sys}\_\text{write} \rangle \land \langle ?e1, \text{eventPrecedeOccurrence, ?e2} \rangle \land \langle ?e1, \text{hasDurationToNextOccurrence, ?period} \rangle \land (?\text{period} = 100) \Rightarrow \langle \_s, \text{sliceHasStartEvent} ?e1 \rangle, \langle \_s, \text{sliceHasEndEvent} ?e2 \rangle, \langle \_s, \text{sliceIsRelatedToFunctionality, sysWriteNormal} \rangle \]

R2: \[ \langle ?e1, \text{runningTask, ts}\_\text{record} \rangle \land \langle ?e1, \text{requestComponent, sys}\_\text{write} \rangle \land \langle ?e1, \text{eventPrecedeOccurrence, ?e2} \rangle \land \langle ?e1, \text{hasDurationToNextOccurrence, ?period} \rangle \land (?\text{period} > 100) \Rightarrow \langle \_s, \text{sliceHasStartEvent} ?e1 \rangle, \langle \_s, \text{sliceHasEndEvent} ?e2 \rangle, \langle \_s, \text{sliceIsRelatedToAnomaly, sysWriteBlocked} \rangle \]

Table 6: Two user inference rules to capture behavior of task t2 in ts_record.

Queries SPARQL

Q0 finds all events which requested the program flush
SELECT ?event ?debut
WHERE { ?event requestComponent flush . ?event eventStartAt ?debut . }

Q1 finds all events which corresponded to a context switch in the program
SELECT ?event ?debut
WHERE { ?event eventStartAt ?debut . }

Q2 finds all events which corresponded to a context switch in the program order by their start timestamp
SELECT ?event ?debut
WHERE { ?event eventStartAt ?debut . } ORDER BY ?event

Q3 finds all sys_write called by ts_record program which occurs more than 100 ms after the previous occurrence
SELECT ?event ?duration
WHERE { ?event requestComponent sys_write . ?event runningTask ts_record . ?event hasDurationToNextOccurrence ?duration . FILTER (?duration > 100000) }

Q4 finds all events related to the concept sysWriteBlocked
SELECT ?event ?duration
WHERE { ?slice sliceIsRelatedToAnomaly sysWriteBlocked . ?slice sliceHasStartEvent ?event . ?event hasDurationToNextOccurrence ?duration . }

Q5 finds all the tasks executed within timestamps 537756 and timestamp 19482669
SELECT ?task
WHERE { ?event eventStartAt ?debut . ?event eventEndAt ?end . ?event runningTask ?task . FILTER (?debut >= 537756 AND ?end < 19482669) }
Q6 finds all tasks executed when a sysWriteBlocked occurred

```sparql
SELECT ?task
WHERE {
  ?slice sliceIsRelatedToAnomaly sysWriteBlocked .
  ?event1 eventStartAt ?sstart . ?event2 eventEndAt ?send .
  ?event eventStartAt ?debut . ?event eventEndAt ?end .
  ?event runningTask ?task .
  FILTER (?debut >= ?sstart AND ?end <= ?send)
}
```

Q7 finds all tasks executed when a sysWriteNormal occurred

```sparql
SELECT ?task
WHERE {
  ?slice sliceIsRelatedToFunctionality sysWriteNormal .
  ?event1 eventStartAt ?sstart . ?event2 eventEndAt ?send .
  ?event eventStartAt ?debut . ?event eventEndAt ?end .
  ?event runningTask ?task .
  FILTER (?debut >= ?sstart AND ?end <= ?send)
}
```

Table 7: Test queries SPARQL description.