Benchmarking of triple stores scalability for MPSoC trace analysis
Leon Fopa, Fabrice Jouanot, Alexandre Termier, Maurice Tchuente, Oleg Iegorov

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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. Therefore, 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
triple. 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 VIDECOM ONTOLOGY

One important contribution of this paper is the VIDE- COM ontology. VIDECOM 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 VIDECOM. We also present how developers can enrich VIDECOM 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 0x16d.

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

VIDECOM is based on a lightweight ontology of 608 classes and 238 properties. Figure 1 shows some of these classes and properties. The main class Event represents different types of events, such as TASK_RUNNING and CONTEXT_SWITCH. Properties eventStartAt and eventEndAt identify the start and the end timestamps of the event. The property isExecutedOn indicates the processor on which the event occurred, and the property runningTask indicates the task executed. The property requestComponent represents the software component (interrupt, system call or function call) requested by the event. The order between events is determined by the property eventPrecedeOccurrence. 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 0x16d.

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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 rdls 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-3z. tdb uses a file system and stores triples in B+ Tree data structures. Sesame-native uses dedicated on-disk data structures for storage [14]. rdf-3z 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 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. $\ast$Store uses this approach [9].

Abadi et al suggested the vertical partitioning as an alternative to the property table. They illustrated the approach in $\ast$Store [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 performances 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 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 2http://jena.apache.org/documentation/tdb/architecture.html
3http://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>L</td>
<td></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></td>
</tr>
<tr>
<td>join</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Filter</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Order by</td>
<td>x</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></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>21 185</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>

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 sdb, and vertical-mdb. More details on their configuration are provided in the Appendix (Section B).

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 compared to others coldfiltered KBRs. It is 2 orders of magnitude faster than sdb, 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 sdb more than 2 hours to load 51 million triples (see Figure 2(a)), we were not able to load 95 million triples with sdb. 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.
that even with relatively simple traces and a large server, ex-
of 7 state-of-the-art KBRs. These experiments have shown
SoC and we made a comparative study to test the scalability
COM, an ontology for trace analysis of application on MP-
6. CONCLUSION AND FUTURE WORK

Interval of trace: Figure 2(g) shows the result when querying the same interval of time in all traces. We ob-
erved that vertical-mdb has better performance. The rea-
son 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 re-
response time (2 minutes for 46 million triples). Other KBRs
performed poorly over 13 million triples. Jena took 8 min-
utes, sesame-memory 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 min-
utes 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 bet-
ter 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
cchose 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 fo-
cused 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 VIDE-
COM, an ontology for trace analysis of application on MP-
SoC 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, ex-
isting KBR have difficulties to scale up. Among the tested
KBR, vertical-mdb is the only one that exhibited low run-
ning times across all queries. Given that execution traces are
likely to grow much larger than the traces of these exper-
iments, 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 in-
terested in different strategies for query parallelization. Fol-
lowing this track we plan to consider OWLIM and Virtuoso
KBRs for comparison with the vertical database approach.

7. ACKNOWLEDGEMENT

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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 t1 collects streaming data and stores them in small IP buffers. Every 100 milliseconds, the second task t2 copies data from IP buffers to main memory. Finally, every 5 seconds, the last task t3 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 t2. For simplicity we present only two rules, but more rules can be added to VIDECOM. The number of user inference rules influence the saturation time. The rule R1 instantiates the FUNCTIONALITY subclass sysWriteNormal when two occurrences of events corresponding to t2 are separated by a period equal to 100 milliseconds. The second rule R2 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 spec, 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\footnote{https://www.monetdb.org/} (version 11.17.9) as a backend instead of C-Store because C-Store is no longer maintained. We called our implementation vertical-mdb.
Table 6: Two user inference rules to capture behavior of task t2 in ts_record.

<table>
<thead>
<tr>
<th>Queries</th>
<th>SPARQL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q0</td>
<td>finds all events which requested the program flush</td>
</tr>
<tr>
<td></td>
<td>SELECT ?event ?debut WHERE { ?event requestComponent flush _8_00 . ?event eventStartAt ?debut . }</td>
</tr>
<tr>
<td>Q1</td>
<td>finds all events which corresponded to a context switch in the program</td>
</tr>
<tr>
<td></td>
<td>SELECT ?event ?debut WHERE { ?event eventStartAt ?debut . }</td>
</tr>
<tr>
<td>Q2</td>
<td>finds all events which corresponded to a context switch in the program order by their start timestamp</td>
</tr>
<tr>
<td></td>
<td>SELECT ?event ?debut WHERE { ?event eventStartAt ?debut . } ORDER BY ?event</td>
</tr>
<tr>
<td>Q3</td>
<td>finds all sys_write called by ts_record program which occurs more than 100 ms after the previous occurrence</td>
</tr>
<tr>
<td></td>
<td>SELECT ?event ?duration WHERE { ?event requestComponent sys_write . ?event runningTask ts_record . ?event hasDurationToNextOccurrence ?duration . FILTER (?duration &gt; 100000) }</td>
</tr>
<tr>
<td>Q4</td>
<td>finds all events related to the concept sysWriteBlocked</td>
</tr>
<tr>
<td></td>
<td>SELECT ?event ?duration WHERE { ?slice sliceIsRelatedToAnomaly sysWriteBlocked . ?slice sliceHasStartEvent ?event . ?event hasDurationToNextOccurrence ?duration . }</td>
</tr>
<tr>
<td>Q5</td>
<td>finds all the tasks executed within timestamps 537756 and timestamp 19482669</td>
</tr>
</tbody>
</table>
Q6 findings 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.