On measuring performances of C-SPARQL and CQELS

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Abstract. To cope with the massive growth of semantic data streams, several RDF Stream Processing (RSP) engines have been implemented. The efficiency of their throughput, latency and memory consumption can be evaluated using available benchmarks such as LSBench and City-Bench. Nevertheless, these benchmarks lack an in-depth performance evaluation as some measurement metrics have not been considered. The main goal of this paper is to analyze the performance of two popular RSP engines, namely C-SPARQL and CQELS, while varying a set of performance metrics. More precisely, we evaluate the impact of stream rate, number of streams and window size on execution time as well as on memory consumption.

1 Introduction

With the emergence of Big data's velocity aspect, new platforms are needed to efficiently handle data streams. In the context of the Semantic Web, a dedicated W3C community[1] extended standard SPARQL [2] queries with the ability to continuously query unbounded RDF streams. This is a key component of RDF (Resource Description Framework)[3] Stream Processing, henceforth denoted RSP. The development of RSP engines integrates some streaming features such as windowing operations and periodical execution. Examples of popular RSP engines are C-SPARQL [2] and CQELS [5]. Each engine has its specific architecture, query language, execution mechanism and operational semantics. In order to determine which RSP engine to adopt for a particular application, it is primordial to conduct an in-depth and complete performance analysis.

Since 2012, benchmarks and comparative research surveys of RSP engines have been conducted. Examples of RSP benchmarks are SRBench [8], CSR-Bench [4], LSBench [7] and CityBench [6]. While SRBench and CSRBench have

[1] https://www.w3.org/community/rsp/
[2] https://www.w3.org/TR/rdf-sparql-query/
[3] https://www.w3.org/TR/rdf11-primer/

studied query functionalities and output correctness, LSBench and CityBench go a step further by tackling performance criteria. However, current benchmarks do not distinguish between the different mechanisms, namely time-driven and data-driven, employed by RSP engines. Moreover, some performance criteria have not been considered in their evaluation plans. Thus, we conduct a redesigned experiment to have a comprehensive view on current RSP systems. We separately target several performance criteria, i.e., impacts of stream rate, window size, number of streams, number of triples, and static data size on query execution time and memory consumption for C-SPARQL and CQELS, which are all further detailed in the remaining of this paper.

This paper is organized as follows. Section 2 provides an overview of existing RSP engines and benchmarks. In Section 3, we describe our evaluation plan and novel performance criteria. Section 4 presents the results of our experiments, and we discuss them in Section 5. We conclude and outline future work in Section 6.

2 Related Work

In this section, we first present two popular RSP engines and then we describe existing RSP benchmarks.

2.1 RSP engines

C-SPARQL [2] and CQELS [5] represent two mature and mostly used RSP engines. Each engine proposes its own continuous query language extensions to query time-annotated triples, and employs a specific RSP mechanism. We precisely distinguish two kinds of RSP mechanisms: time-driven and data-driven. The time-driven mechanism periodically executes SPARQL queries within a logical window (time-based) or physical window (triple-based). Whereas, the data-driven mechanism executes SPARQL queries immediately after the arrival of new data streams. In the following, we present the main features supported by each aforementioned engine.

C-SPARQL supports time-driven query execution and extends the standard SPARQL query language with keywords such as `RANGE` and `STEP`. The `RANGE` keyword defines the time-based window (e.g., `RANGE 5m` means a window of 5 minutes), and the `STEP` keyword indicates the frequency at which the query should be executed. Standard SPARQL 1.1 operators can be used over the data within the window such as aggregation, ordering and comparison. C-SPARQL streams out the whole output at each query execution, which refers to Rstream operator among the different streaming operators [1] (e.g., Rstream, Istream, Dstream) that can be supported by an RSP engine.

CQELS is developed in a native and adaptive way proposing a pre-processor and an optimizer to improve performance [5]. It supports data-driven query execution following the *content-change policy*, in which queries are triggered immediately at the arrival of new statements in the window. Even if the `SLIDE` keyword is supported in CQELS syntax (like `STEP` keyword in C-SPARQL),

it does not have any effect on the engine behavior. The frequency execution depends on the arrival of new data in the stream. CQELS compares the current output with the previous one, and streams out only the new results, which refers to Istream [1] operator in terms of streaming operators.

2.2 RSP benchmarks

SRBench, one of the first available RSP benchmarks, proposes a baseline to evaluate the functionality support for RSP engines. **CSRBench** is an extension of SRBench to automatically evaluate the results correctness.

LSBench covers functionality, correctness, and performance evaluation. It uses a customized data generator and provides insights into some performance aspects of RSP engines. Nevertheless, there is no consideration of important performance metrics such as stream rate, window size and number of streams. Besides, memory consumption of RSP engines are not given has not been considered in their experiments.

CityBench is a recent RSP benchmark based on smart city data and real application scenarios. It provides a consistent and relevant plan to evaluate performance. However, few factors have been considered in the experiments. Only the number of concurrent queries and the number of streams have been considered to evaluate the execution time and memory consumption, whereas other important factors such as window size and stream rate are missing. Moreover, the memory consumption of C-SPARQL shown in CityBench seems to be questionable, since we obtain different results.

In this paper, we aim to extend existing benchmarks by introducing important factos that have not been considered yet. The evaluation is focused on the two popular engines C-SPARQL and CQELS.

3 Evaluation Plan

3.1 Dataset and Queries design

In our experiment, we opted to use our own data generator for two main reasons: first, to be able to control the size of the generated data streams and, second, to control data content in order to evaluate the correctness of outputs computed by RSP engines. Thus, we use both streaming and static data, related to the domain of water resource management. The logical data model is presented in Figure 1. The dynamic data concerns sensors observations and their metadata, e.g., the message, observation or the assigned tags. A message basically contains an observation, and we set a fixed number of tags (hasTag predicate) for each observation. For each fifty observations, we include a *chlorine* observation. The static data provides detailed information about each sensor, namely the label, the manufacturer ID, and the sector ID to which it belongs to in the network.

We also define a set of queries $Q = \{Q_1, Q_2, Q_3, Q_4, Q_5, Q_6\}$, where $Q_1, ..., Q_5$ operate over streaming data, and Q_6 integrates static data. These queries involve

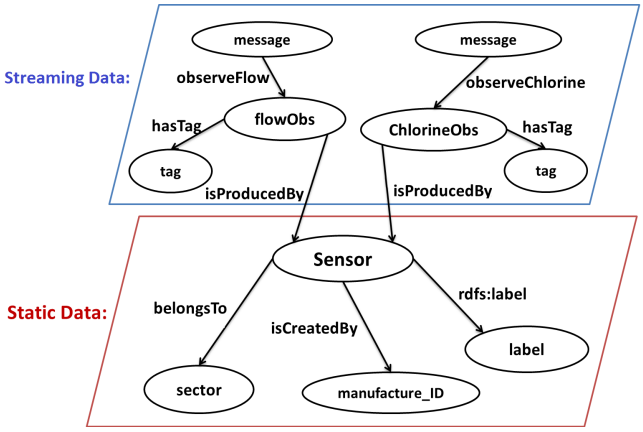


Fig. 1: Water Resource Management Context

different SPARQL operators (e.g., FILTER, UNION, etc.) and are sorted in ascending order based on the execution complexity. Only the time-based window is addressed in all these queries. As for the last query Q_6, we compare the behavior of RSP engines when varying the size of static data. Details and pseudo code of the predefined queries are available on Github[4]. They can be summarized as follows:

- Q_1: Which observation involves chlorine value?
- Q_2: How many tags are assigned to each chlorine observation?
- Q_3: Which observation ID has an identification ending with "00" or "50"?
- Q_4: Which chlorine observation possesses three tags?
- Q_5: Which observation has an identification that ends with "00" or "10" and how many tags assigned to this observation?
- Q_6: What is the belonging sector, manufacturer, and assigned label of each chlorine observation?

3.2 Definition of test criteria

Let us denote the input parameters by X={stream rate, number of triples, window size, number of streams, static data size}, and the set of output metrics by Y={execution time, memory consumption}. We next detail each of these parameters.

- X: (1) stream rate The time-driven mechanism consists in executing periodically the query with a frequency explicitly given in the query. This frequency, called `STEP`, can be time-based (e.g. every 10 seconds) or tuple-based (e.g. every 10 triples). The query is periodically performed over the most recent items.

[4] `https://github.com/renxiangnan/Reference_Stream_Reasoning_2016/wiki`

The keyword RANGE defines the size of temporary dataset. Just like the query frequency, the window size can be time or tuple-based. In case of time-based window, the execution time and memory consumption are closely dependent on stream rate. Increasing stream rates make engines, such as C-SPARQL, process more data for each execution. The frequency (STEP value) indicates the interval between two successive executions of the same query. Therefore, input stream rate should not exceed engine's processing capacity, otherwise the system has to store an always growing amount of data. Such situation is not conceivable in the context of stream.

- X: (2) number of triples stream rate is not an appropriate factor to be considered for the data-driven mechanism because its query execution and data injection are performed in parallel. In another words, it is not feasible to precisely control the input stream rate. In this context, we need to once feed the system with a fixed number of triples, that is why we define an additional parameter called *number of triples* N. A bigger N generates a smaller error rate, but N should remain under a given threshold to respect the processing limitations of the RSP engines.

- X: (3) window size We use *window size* as a performance metric for RSP engines. Recall that window size (RANGE) is closely related to the volume of the queried dataset, for each execution of the query. According to our preliminary experiments, window size has marginal impact on the performance of CQELS. Thus, we do not consider this metric for CQELS in Section 4.

- X: (4) number of streams, (5) static data size The capacity to handle complex queries with multi-streams sources or static background information is an important criterion to evaluate RSP engines. LSBench and CityBench have already proposed these metrics. Note that C-SPARQL supports only one window per query, whereas CQELS defines a window operator on each stream.

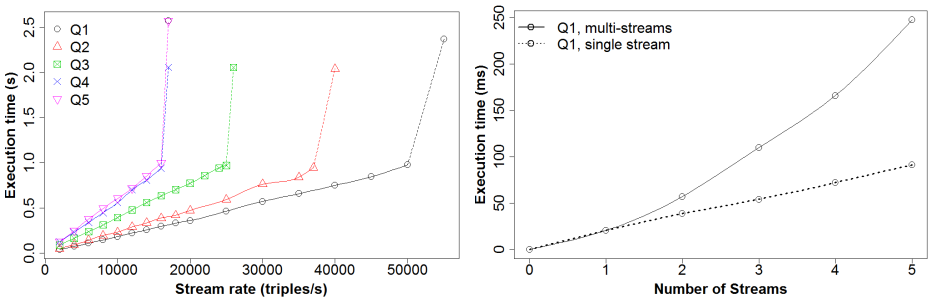
- Y: execution time, memory consumption The machine conditions are uncontrollable varying factors, we evaluate the execution time, for a given query, as the average value of n iterations of this query. Since C-SPARQL and CQELS have two different execution mechanisms (time-driven and data-driven), we adapt the definition of execution time to each context. As a consequence, for C-SPARQL, represents the average execution time over several query executions, while for CQELS, we evaluate the global query execution time for processing N triples.

4 Experiments

All experiments are performed on a laptop equipped with Intel Core i5 quad-core processor (2.70 GHz), 8GB RAM, running Windows 7, Java version JDK/JRE 1.8.

4.1 Time-driven: C-SPARQL

We conducted our experiment over C-SPARQL by testing all six previously defined queries. We start our evaluation by measuring the query execution time, then we give some results regarding memory consumption.



(a) (b)

Fig. 2: Impact of stream rate and number of streams on execution time of C-SPARQL

Execution Time We evaluate query execution time by varying stream rate, number of streams, window size (time-based), and static data size.

In Figure 2a, one can see that generally all five curves perform approximately a linear trend (up to a given threshold concerning the **stream rate**). For each query, the linear trend can be maintained only when the stream rate is under a given threshold. For all five queries, C-SPARQL normally operates when its execution time is smaller than one second, which is also the query preset `STEP` value. Let us denote by $Rate_{max}$ the maximum stream rate that can be accepted by C-SPARQL for a given query. Theoretically, execution time equals to `STEP` for an incoming stream at $Rate = Rate_{max}$. We can approximate the value of $Rate_{max}$ for each query.

Query	Q_1	Q_2	Q_3	Q_4	Q_5
$Rate_{max}$ (triples/s)	≈ 55000	≈ 40000	≈ 25000	$\approx 16000^{+}$	≈ 16000

Table 1: $Rate_{max}$ for the considered the queries.

As shown in Figure 2a and considering our preset test conditions, if the stream rate exceeds the corresponding $Rate_{max}$, the result provided by C-SPARQL is erroneous. The reason behind is that C-SPARQL does not have enough time to process both current and incoming data. Indeed, newly incoming data stream are jammed in memory, and the system will enforce C-SPARQL to start the next execution causing errors. Thus, $Rate_{max}$ represents the maximum size of data (number of triples) which can be correctly processed by C-SPARQL within a duration equals to the `STEP` value.

In some cases, queries require data from multiple streams. In Figure 2b, we focus on C-SPARQL's behavior by varying the **number of streams** with a stream rate set at 1000 triples/s (i.e. the dotted line in Figure 2b). This figure reports the execution time of Q_1 for different number of streams. The dotted line represents the execution time of Q_1 on a single equivalent (e.g. same workload for each

query execution) stream with a rate $Stream\ Rate_{single} = Number\ of\ Streams \times Stream\ Rate_{multi}$, where $Stream\ Rate_{single}$ and $Stream\ Rate_{multi}$ denote the stream rate for respectively single and multi streams. The curve of query execution time increases as a convex function over the number of streams. C-SPARQL has a substantial delay by the increasing number of streams. Indeed, C-SPARQL has to repeat the query execution for each stream [3], then executes the join operation among the intermediate results from different stream sources. This action causes an important waste of computing resources. As a consequence, C-SPARQL is more efficient to process single stream than multi-streams.

In addition, according to our evaluation, we find that query execution time linearly increases with the growth of **time-based window size** and **static data size**. E.g., C-SPARQL has a constant overhead for delay with increasing these two metrics.

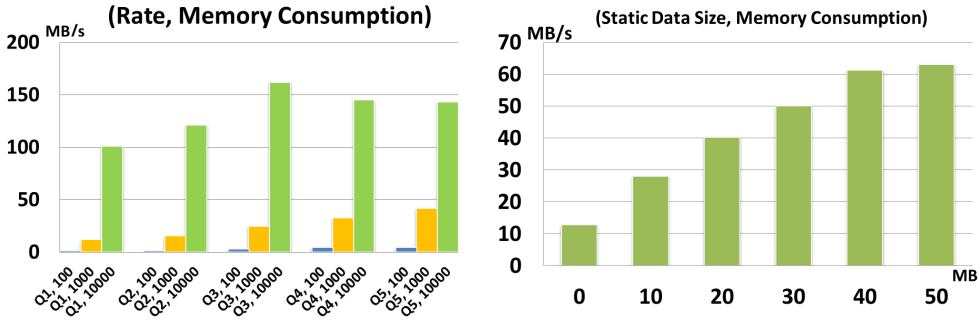
Memory Consumption We used VisualVM to monitor the Memory Consumption of C-SPARQL. An example of visualization about Java Virtual Machine Garbage Collector (GC) activity is given **here**[5].

Since the Java Virtual Machine executes the Garbage Collector lazily (in order to leave the maximum available CPU resource to the application), using the maximum memory allocated during execution is not an appropriate way to measure the memory consumption. Practically, the processing of a simple query, while allocating far less memory on each execution, can also reach the maximum allocated heap as the processing of a complex query, it just takes longer. Thus, instead, we chose the Memory Consumption Rate (MB/s) as the evaluation metric. Measuring the amount (megabytes) of allocated and freed memory by GC per unit time comprehensively describe the memory consumption on RSP. MCR(MB/s) $= \frac{\overline{Max} - \overline{Min}}{\overline{Period}}$, $\overline{Max}$ and $\overline{Min}$ refer to the average maximum and minimum memory consumption, respectively. $\overline{Period}$ is the average duration of two consecutive maximum memory observed instances.

$\overline{Max}$, $\overline{Min}$, $\overline{Period}$ are computed over 10 observed periods. MCR signifies the memory changes in heap per second. A higher MCR shows a more frequent activity of garbage collector. MCR intuitively shows how many bytes have been released and reallocated by GC per unit time. Figure 3a shows the impact of stream rate on MCR. For each query, the period decreases and MCR increases with the growth of Stream Rate. Query Q_3 has the highest MCR. This can be explained by the aggregate operator which produces more intermediate results during query execution. Note that MCR is not a general criterion for measuring memory consumption. In some use case, we could not observe periodical activity on GC. The main goal of using MCR is to give a comprehensive description of memory management on C-SPARQL.

Figure 3b displays the increase of memory consumption rate over the growth of **static data size**. For query Q_6, memory peak varies marginally while increasing static data size, but minimum consumed memory is directly impacted by the size of injected static data. One possible explanation is that C-SPARQL produces

[5] `https://github.com/renxiangnan/Reference_Stream_Reasoning_2016/wiki`



(a) (b)

Fig. 3: The impact of stream rate (a) and static data size (b) on memory consumption

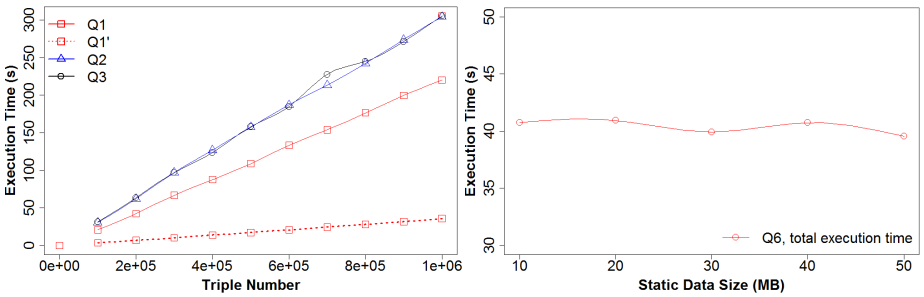
additional objects to process static data, and keeps these objects as as long-term in memory.

4.2 Data-driven: CQELS

This section focuses on the performance evaluation of CQELS. The variant parameters are number of triples, number of streams, and static data size. Q_4 and Q_5 are not included in this evaluation since CQELS does not support the timestamp function.

Execution Time Since CQELS uses a so-called probing sequence to support its execution plan, getting the running time for each query execution is not experimentally feasible.

Thus, we evaluate the global execution time of N triples for CQELS. More precisely, we keep the same strategy as LSBench, i.e. inject a finite sequence of stream into the system which contains N triples. N should be big enough to get more accurate result ($N \geq 10^5$).



(a) (b)

Fig. 4: The impact of number of triples and static data size on queries execution time.

Figure 4a shows the impact of **number of triples** on execution time. N should also be controlled within a certain range to prevent the engine from crashing (c.f. "Memory Consumption" part of CQELS). Queries Q_1, Q_2, Q_3 contain chain patterns (join occurs on subject-object position) that select chlorine observation: {T_1*: ?observation ex:observeChlorine ?chlorineObs .* T_2: *?chlorineObs ex:hasTag ?tag .* }. Pattern T_1 returns all results by matching the predicate "observeChlorine", then T_2 filters among all selected observation in T_1 those assigned tags. Be aware that T_2 does not practically affect the functionality of queries. In Figure 4a, there is not much difference between Q_2 and Q_3. Based on Q_2, Q_3 adds a "FILTER" operator to restrict that preselected observation has an ID that ends by "00" or "50". The additional filter in Q_3 slightly influences the engine performance, which lets us say that CQELS is very efficient at processing "FILTER" operator. The dotted line Q_1' represents Q_1 without the pattern T_2. Its corresponding execution time is reduced to one-sixth of Q_1 since T_2 plays a key role in term of execution time. Indeed, without T_2, CQELS will return the results immediately if T_1 is verified, but pattern T_2 makes the engine wait till T_2 is verified.

CQELS supports queries with **multi-streams**, CQLES allows to assign the triple patterns which are only relative to the corresponding stream source. This property gives the engine some advantages to process complex queries. I.e., each triple just needs to be verified in its attached stream source. However, C-SPARQL has to repeat verification on all presenting streams for the whole query syntax, and this behavior leads a waste of computing resources on C-SPARQL.

Due to data-driven mechanism, serious mismatches occur in output for a multi-streams query, especially when the query requests synchronization among the triples. Asynchronous streams are illustrated in [6].

Suppose that we have two streams, S_1 and S_2, sequentially sent (due to the data-driven approach adopted by CQELS) into the engine. If the window size defined on S_1 is not large enough, ?*observation* in pattern T_2 will not be matched with ?*observation* in T_1. This problem can be solved by defining a larger window size in T_1 with a small number of streams.

In our experiments, we carry out the multi-streams test by constructing two streams on Q_1, Q_2 and Q_3. For Q_1, with two streams, CQELS spent approximately 26s to process ($2\times$) 10^5 triples, that is just 30% more than the single stream case. To conclude, CQELS gains some advantage in term of execution time to process queries with multi-streams. However, the output may also be influenced by asynchronous of streams. Note that C-SPARQL does not suffer from the streams synchronization since it possesses batch-oriented approach.

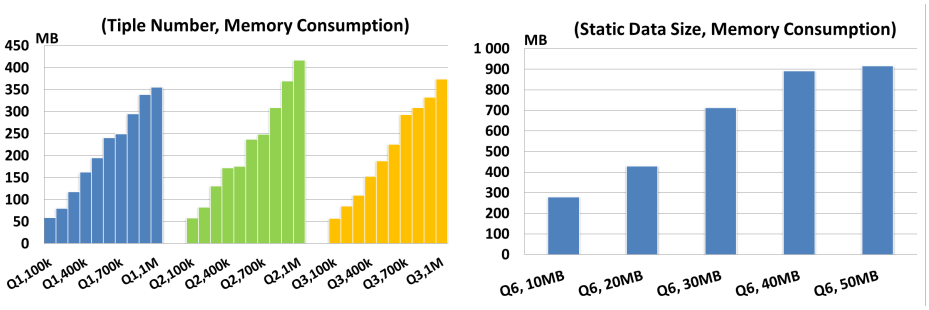
In Figure 4b, the curve gives the total execution time(s) for 1260000 triples. The execution time for N triples slightly changes while increasing the size of **Static Data** from 10MB to 50MB. The result shows that CQELS is efficient for processing static data of a large size.

[6] `https://github.com/renxiangnan/Reference_Stream_Reasoning_2016/wiki`

Memory Consumption As we directly send N triples into the system at once, CQELS's memory consumption does not behave as C-SPARQL (which follows a periodic pattern). Generally, the memory consumption on CQELS keeps growing by increasing the number N of triples. As mentioned in the previous section, N should not exceed a given threshold. If N is too big, then the memory consumption will reach its limit. In this situation, latency on query execution will increase substantially. Furthermore, since serious mismatch occurs on multi-streams query, X = Number of Stream is not considered as a metric of memory consumption.

We evaluate the peak of memory consumption during query execution. The trend of memory consumption increases over time. Generally MC reaches the peak just before the end of query execution.

Figure 5a shows that the memory consumption of Q_1, Q_2 and Q_3 is very close when varying the **number of triples**, i.e., the complexity of queries were not reflected by their memory consumption. CQELS manages efficiently the memory for complex queries. In Figure 5b, the memory consumption of Q_6 is proportional to the size of **static data**. However, according to the evaluation, we find that a lower maximum allocated heap size (e.g. 512MB) causes a substantial delay on CQELS. The consumed memory keeps growing to the limited heap size, i.e. the GC could clear the unused objects in a timely manner. This behavior is possibly caused by the built-dictionary for URI encoding [5].



(a) (b)

Fig. 5: Impact of the number of triples and the static data size on memory consumption.

5 Results Discussion

As we generate different streaming modes for time-driven (C-SPARQL) and data-driven (CQELS) engines, the memory consumption is not comparable between them. This section mainly derives a discussion of query execution time from our previous results, and we do a simple comparison between C-SPARQL and CQELS.

It is not obvious to compare the performance among different RSP engines, since each of them possesses a specific execution strategy. According to [7] and our experience, we list following conditions to support a fair cross-engines performance comparison: (i) engine outputs should be correct, at least comparable. E.g. C-SPARQL behaves untypically while the incoming stream rate exceeds the threshold. Even if the engine still produces some outputs, there will be meaningless to measure the query execution time. (ii)The execution time for different RSP engines should associate the same workload. As C-SPARQL uses a batch mechanism, it is easy to control the workload of the window operator. However, the eager mechanism practically makes the workload controlling be unfeasible. Therefore, we choose $t = \frac{T}{N}$, the average execution time per triple to support our comparison. T is the total execution time for N triples. Note that t marginally changes when varying the metrics defined in section 3.2. (iii) engine warming up is also recommended. We inject the "warming up" stream into the system before the formal evaluation.

	Average execution time per triple (millisecond)			
RSP engines	Q_1	Q_2	Q_3	Q_6 (50MB static data)
CSPARQL	0.018	0.025	0.040	0.952
CQELS	0.169	0.239	0.243	0.032

Table 2: Execution time of Q_1, Q_2, Q_3, Q_4, Q_5 and Q_6

Table 2 shows that C-SPARQL outperforms CQELS to deal with Q_1, Q_2 and Q_3. This can be explained by the fact that the chain pattern existing in Q_1, Q_2 and Q_3 forces CQELS to repeat the verification on matching condition for the whole window. This behavior hindered a lot engine performance. For Q_6, CQELS is almost 27 times faster than C-SPARQL, and CQELS shows its high efficiency to process the query with static data.

It is not easy to identify which RSP engine is better. We summarize our experiment over three aspects: 1) **Functionality support**. Since C-SPARQL uses the Sesame/Jena as the computing core, it supports most of the SPARQL 1.1 grammar. CQELS is implemented in a native way, it support less operations than C-SPARQL, e.g., timestamp function, property path, etc. 2) **Output correctness**. As mentioned in section 4.2, CQELS suffers from a serious output mismatching with multi-stream queries. This is due to an eager execution mechanism. C-SPARQL behaves normally with multi-stream queries since it is characterized by a time-driven mechanism. As a matter of fact, real use case often requires concurrency of join from different stream sources, from this aspect, C-SPARQL takes the advantages of correctness or completeness of outputs. 3) **Performance**. C-SPARQL shows stability with complex queries. However, in practical applications, input stream rate should be controlled at a low level to guarantee C-SPARQL's output correctness. Besides, C-SPARQL has scalability problem when dealing with static data. CQELS takes advantage from its dictionary encoding technique and dynamic routing policy, and thus, is efficient for simple queries and is scalable with static data.

6 Conclusion

This paper focuses on the performance evaluation of two state-of the-art engines: C-SPARQL and CQELS. We propose some new performance metrics and designed a specific evaluation plan. In particular, we take into account the specific implementation of each RSP engine. We performed many experiments to evaluate the impact of *Stream Rate*, *Number of Triples*, *Window Size*, *Number of Streams* and *Static Data Size* on queries *Execution Time* and *Memory Consumption*. Several queries with different complexities were considered. The main result of this complete study is that each RSP engine has its own advantage and is adapted to a particular context and use case, e.g., C-SPARQL excels on complex and multi-stream queries while CQELS stands out on queries requiring static data. In future work, we plan to evaluate the performance of RSP engines in a distributed environment.

Acknowledgments

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References

1. A. Arasu, S. Babu, and J. Widom. CQL: A language for continuous queries over streams and relations. In *Database Programming Languages, 9th International Workshop, DBPL 2003*, pages 1–19, 2003.
2. D. F. Barbieri, D. Braga, S. Ceri, E. Della Valle, and M. Grossniklaus. Continuous queries and real-time analysis of social semantic data with c-sparql. In *SDoW2009*, 2009.
3. D. F. Barbieri, D. Braga, S. Ceri, E. D. Valle, and M. Grossniklaus. Querying rdf streams with c-sparql. *SIGMOD Rec.*, 2010.
4. D. Dell'Aglio, J.-P. Calbimonte, M. Balduini, O. Corcho, and E. D. Valle. On correctness in rdf stream processor benchmarking. In *The Semantic Web - ISWC 2013 - 12th International Semantic Web Conference*, 2013.
5. D. Le-Phuoc, M. Dao-Tran, J. X. Parreira, and M. Hauswirth. A native and adaptive approach for unified processing of linked streams and linked data. In *Proceedings of the 10th International Conference on The Semantic Web - Volume Part I*, 2011.
6. F. G. Muhammad Intizar Ali and A. Mileo. Citybench: A configurable benchmark to evaluate rsp engines using smart city datasets. In *The Semantic Web - ISWC 2015*, ISWC'15, 2015.
7. D. L. Phuoc, M. Dao-Tran, M. Pham, P. A. Boncz, T. Eiter, and M. Fink. Linked stream data processing engines: Facts and figures. In *The Semantic Web - ISWC 2012 - 11th International Semantic Web Conference*, ISWC'11, 2012.
8. Y. Zhang, P. M. Duc, O. Corcho, and J.-P. Calbimonte. Srbench: A streaming rdf/sparql benchmark. In *Proceedings of the 11th International Conference on The Semantic Web - Volume Part I*, 2012.