Processing SPARQL Aggregate Queries with Web Preemption

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Abstract. Executing aggregate queries on the web of data allows to compute useful statistics ranging from the number of properties per class in a dataset to the average life of famous scientists per country. However, processing aggregate queries on public SPARQL endpoints is challenging, mainly due to quotas enforcement that prevents queries to deliver complete results. Existing distributed query engines allow to go beyond quota limitations, but their data transfer and execution times are clearly prohibitive when processing aggregate queries. Following the web preemption model, we define a new preemptable aggregation operator that allows to suspend and resume aggregate queries. Web preemption allows to continue query execution beyond quota limits and server-side aggregation drastically reduces data transfer and execution time of aggregate queries. Experimental results demonstrate that our approach outperforms existing approaches by orders of magnitude in terms of execution time and the amount of transferred data.

1 Introduction

Context and Motivation: Following the Linked Open Data principles (LOD), data providers published billions of RDF triples [4,15]. Executing SPARQL aggregate queries on the web of data allows to compute useful statistics ranging from the number of properties per class in a dataset [8] to the average life of famous scientists per country. However, processing aggregate queries on public SPARQL endpoints is challenging, mainly due to quotas enforcement that prevents queries to deliver complete results as pointed out in [8,17].

Related Works: To overcome quotas limitations, Knowledge Graph providers publish dumps of their data. However, re-ingesting billions of triples on local resources to compute SPARQL aggregate queries is extremely costly and raises issues with freshness. Another approach is to build servers that only process queries that **complete** in a predefined time, *i.e.*, deliver complete results under quotas. Then a smart client interacts with the server to process full SPARQL queries. The Triple Pattern Fragments (TPF) [19] relies on a server that only processes paginated triple pattern queries. The TPF smart client decomposes SPARQL queries into paginated triple pattern subqueries and recombines results

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to deliver final query answers. However, processing aggregate queries with TPF generates tremendous data transfer and delivers poor performance. Recently, the Web preemption approach [12] relies on a preemptable server that suspends queries after a quantum of time and resumes them later. The server supports joins, projections, unions, and some filters operators. However, aggregations are not supported natively by the preemptable server. Consequently, the server transfers all required mappings to the smart client to finally compute groups and aggregation functions locally. As the size of mappings is much larger than the size of the final results, the processing of aggregate queries is inefficient. This approach allows to avoid quotas, but delivers very poor performance for aggregate queries, and could not be a sustainable alternative.

Approach and Contributions: In this paper, we propose a novel approach for efficient processing of aggregate queries in the context of web preemption. Thanks to the decomposability of aggregate functions, web preemption allows to compute partial aggregates on the server-side while the smart client combines incrementally partial aggregates to compute final results. The contributions of the paper are the following: (i) We introduce the notion of partial aggregations for web preemption. (ii) We extend the SaGe preemptive server and the SaGe smart client [12] with new algorithms for the evaluation of SPARQL aggregations. The new algorithms use partial aggregations and the decomposability property of aggregation functions. (iii) We compare the performance of our approach with existing approaches used for processing aggregate queries. Experimental results demonstrate that the proposed approach outperforms existing approaches used for processing aggregate queries by orders of magnitude in terms of execution time and the amount of transferred data.

This paper is organized as follows. Section 2 reviews related works. Section 3 introduces SPARQL aggregation queries and the web preemption model. Section 4 presents our approach for processing aggregate queries in a preemptive SPARQL server. Section 5 presents experimental results. Finally, conclusions and future work are outlined in Sect. 6.

2 Related Works

SPARQL Endpoints. SPARQL endpoints follow the SPARQL protocol[1], which "describes a means for conveying SPARQL queries and updates to a SPARQL processing service and returning the results via HTTP to the entity that requested them". Without quotas, SPARQL endpoints execute queries using a First-Come First-Served (FCFS) execution policy [7]. Thus, by design, they can suffer from *convoy effect* [5]: one long-running query occupies the server resources and prevents other queries from executing, leading to long waiting time and degraded average completion time for queries.

To prevent the convoy effect and ensure a fair sharing of resources among end-users, most SPARQL endpoints configure quotas on their servers. They mainly

[1] https://www.w3.org/TR/2013/REC-sparql11-protocol-20130321/.

restrict the arrival rate per IP address and limit the execution time of queries. Restricting the arrival rate allows end-users to retry later, however, limiting the execution time leads some queries to deliver only partial results. Delivering partial results is a serious limitation for public SPARQL services [2,12,17].

Centralized Query Answering. Big data processing approaches are able to process aggregate queries efficiently on a large volume of data. Data has to be first ingested in a distributed datastore such as HBase [20], then SPARQL queries can be translated to Map/reduce jobs or massively parallelized with parallel scans and joins. Many proposals exist in the semantic web including [3,14]. All these approaches require to download datasets and ingest data on a local cluster to process aggregate queries. Consequently, they require a high-cost infrastructure which can be amortized only if a high number of aggregate queries have to be executed. Our approach processes aggregate queries on available public servers without copying the data and delivers exact answers.

Query Answering by Samples. Approximate query processing is a well-known approach to speedup aggregate query processing [11]. The approach relies on sampling, synopses or sketches techniques to approximate results with bounded errors. The sampling approach proposed in [17] scales with large knowledge graphs, and overcomes quotas but computes approximate query answers. In this paper, we aim to compute the exact results of aggregate queries and not approximate answers.

Distributed Query Processing Approaches. Another well-known approach to overcome quotas is to decompose a query into smaller subqueries that can be evaluated under quotas and recombine their results [2]. Such decomposition requires a *smart client* which allows for performing the decomposition and recombine intermediate results. In that sense, the query processing is *distributed* between a server and smart client that collaborate to process SPARQL queries. However, ensuring that subqueries can be completed under quotas remains hard [2]. Another approach is to build servers with a restricted interface that processes queries that **completes** within bounded times, *i.e.*, quotas. A smart client interacts with such a server to process full SPARQL queries. The Triple Pattern Fragments approach (TPF) [19] decomposes SPARQL queries into a sequence of paginated triple pattern queries. As paginated triple patterns queries can be executed in bounded times, the server does not need quotas. However, as the TPF server only processes triple pattern queries, joins and aggregates are evaluated on the smart client. This requires to transfer all required data from server to client to perform joins, and then to compute aggregate functions locally, which leads to poor query execution performance.

Web preemption [12] is another approach to process SPARQL queries on a public server without quota enforcement. Web preemption allows the web server to suspend a running SPARQL query after a quantum of time and return a link to the smart client. Sending this link back to the web server, allows executing the query for another quantum of time. Compared to First-Come First-Served (FCFS) scheduling policy, web preemption provides a fair allocation of server

resources across queries, a better average query completion time per query and a better time for first results. However, if Web preemption allows processing projections and joins on server-side, aggregate operators are still evaluated on a smart client. So, data transfer may be intensive especially for aggregate queries.

In this paper, we extend the web preemption approach to support partial aggregates. Partial aggregates are built during the execution of quanta and sent to the smart client. The smart client recombines partial aggregates to compute the final results.

3 Preliminaries

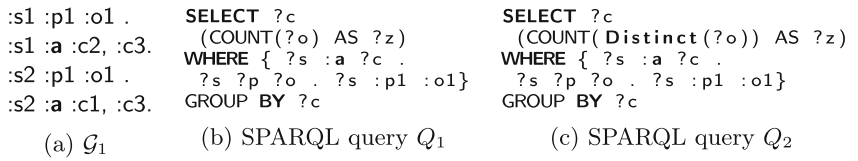
SPARQL Aggregation Queries: We follow the semantics of aggregation as defined in [10]. We recall briefly definitions related to the proposal of the paper. We follow the notation from [10,13,16] and consider three disjoint sets I (IRIs), L (literals) and B (blank nodes) and denote the set T of RDF terms $I \cup L \cup B$. An RDF triple $(s, p, o) \in (I \cup B) \times I \times T$ connects subject s through predicate p to object o. An RDF graph $\mathcal{G}$ (called also RDF dataset) is a finite set of RDF triples. We assume the existence of an infinite set V of variables, disjoint with previous sets. A mapping μ from V to T is a partial function $\mu : V \rightarrow T$, the domain of μ, denoted $dom(\mu)$ is the subset of V where μ is defined. Mappings μ_1 and μ_2 are compatible on the variable $?x$, written $\mu_1(?x) \sim \mu_2(?x)$ if $\mu_1(?x) = \mu_2(?x)$ for all $?x \in dom(\mu_1) \cap dom(\mu_2)$.

A SPARQL graph pattern expression P is defined recursively as follows.

1. A tuple from $(I \cup L \cup V) \times (I \cup V) \times (I \cup L \cup V)$ is a triple pattern.
2. If $P1$ and $P2$ are graph patterns, then expressions (P1 AND P2), (P1 OPT P2), and (P1 UNION P2) are graph patterns (a conjunction graph pattern, an optional graph pattern, and a union graph pattern, respectively).
3. If P is a graph pattern and R is a SPARQL built-in condition, then the expression (P FILTER R) is a graph pattern (a filter graph pattern).

The evaluation of a graph pattern P over an RDF graph $\mathcal{G}$ denoted by $[\![P]\!]_{\mathcal{G}}$ produces a *multisets of solutions mappings* $\Omega = (S_\Omega, card_\Omega)$, where S_Ω is the *base set* of mappings and the multiplicity function $card_\Omega$ which assigns a cardinality to each element of S_Ω. For simplicity, we often write $\mu \in \Omega$ instead of $\mu \in S_\Omega$. The SPARQL 1.1 language [18] introduces new features for supporting aggregation queries: i) A collection of *aggregate functions* for computing values, like `COUNT`, `SUM`, `MIN`, `MAX` and `AVG`; ii) `GROUP BY` and `HAVING`. `HAVING` restricts the application of aggregate functions to groups of solutions satisfying certain conditions.

Both groups and aggregate deal with lists of expressions $E = [E1, \ldots, E_n]$, which evaluate to v-lists: lists of values in $T \cup \{error\}$. More precisely, the evaluation of a list of expressions according to a mapping μ is defined as: $[\![E]\!]_\mu = [[\![E_1]\!]_\mu, \ldots, [\![E_n]\!]_\mu]$. Inspired by [10,18], we formalize Group and Aggregate.



(a) $\mathcal{G}_1$ (b) SPARQL query Q_1 (c) SPARQL query Q_2

Fig. 1. Aggregate queries $Q1$ and Q_2 on RDF graph $\mathcal{G}_1$

Definition 1 (Group). *A group is a construct $G(E, P)$ with E is a list of expressions*[2]*, P a graph pattern, $\mathcal{G}$ an RDF graph. Let $\Omega = [\![P]\!]_{\mathcal{G}}$, the evaluation of $[\![G(E, P)]\!]_{\mathcal{G}}$ produces a set of partial functions from keys to solution sequences.*

$$[\![G(E, P)]\!]_{\mathcal{G}} = \{[\![E]\!]_{\mu} \mapsto \{\mu' \mid \mu' \in \Omega, [\![E]\!]_{\mu} = [\![E]\!]_{\mu'}\} \mid \mu \in \Omega\}$$

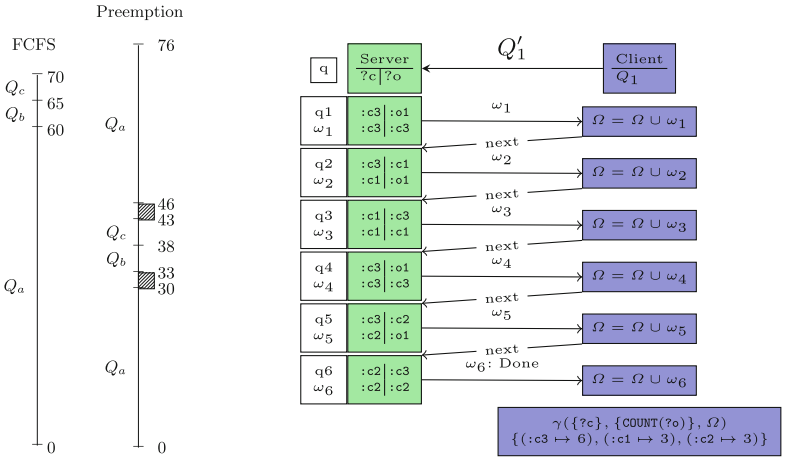
Definition 2 (Aggregate). *An aggregate is a construct $\gamma(E, F, P)$ with E is a list of expressions, F a set of aggregation functions, P a graph pattern, $\mathcal{G}$ an RDF Graph, and $\{k_1 \mapsto \omega_1, \ldots, k_n \mapsto \omega_n\}$ a multiset of partial functions produced by $[\![G(E, P)]\!]_{\mathcal{G}}$. The evaluation of $[\![\gamma(E, F, P)]\!]_{\mathcal{G}}$ produces a single value for each key.*

$$[\![\gamma(E, F, P)]\!]_{\mathcal{G}} = \{(k, F(\Omega)) | k \mapsto \Omega \in \{k_1 \mapsto \omega_1, \ldots, k_n \mapsto \omega_n\}\}$$

To illustrate, consider the query Q_1 of Fig. 1b, which returns the total number of objects per class for subjects connected to the object o_1 through the predicate p_1. Here, $P_{Q_1} = \{$`?s :a ?c.?s ?p ?o.?s :p1 :o1`$\}$ denotes the graph pattern of Q_1, and $?c$ is the group key. For simplicity, for each key group, we represent only the value of the variable $?o$, as $?o$ is the only variable used in the COUNT aggregation. $[\![G(?c, P_{Q_1})]\!]_{\mathcal{G}_1} = \{$`:c3` $\mapsto \{$`:c3, :c1, :c2, :o1, :c3, :o1,`$\}$, `:c1` $\mapsto \{$`:o1, :c3, :c1`$\}$, `:c2` $\mapsto \{$`:o1, :c3, :c2`$\}\}$ and the query Q_1 is evaluated as $[\![\gamma(\{$`?c`$\}, \{$`COUNT(?o)`$\}, P_{Q_1})]\!]_{\mathcal{G}_1} = \{(:c3, 6), (:c1, 3), (:c2, 3)\}$.

Web Preemption and SPARQL Aggregation Queries. *Web preemption* [12] is the capacity of a web server to suspend a running query after a fixed quantum of time and resume the next waiting query. When suspended, partial results and the state of the suspended query S_i are returned to the smart web client[3]. The client can resume query execution by sending S_i back to the web server. Compared to a First-Come First-Served (FCFS) scheduling policy, web preemption provides *a fair allocation of web server resources across queries, a better average query completion time per query and a better time for first results* [1]. To illustrate, consider three SPARQL queries Q_a, Q_b, and Q_c submitted concurrently by three different clients. The execution time of Q_a, Q_b and Q_c are respectively 60 s, 5 s and 5 s. Figure 2a presents a possible execution of these queries with a FCFS policy. In this case, the throughput of FCFS is $\frac{3}{70} = 0.042$ queries per second, the average completion time per query is $\frac{60+65+70}{3} = 65$ s

[2] We restrict E to variables, without reducing the expressive power of aggregates [10].
[3] S_i can be returned to the client or saved server-side and returned by reference.



(a) FCFS vs preemption (quantum of 30s)

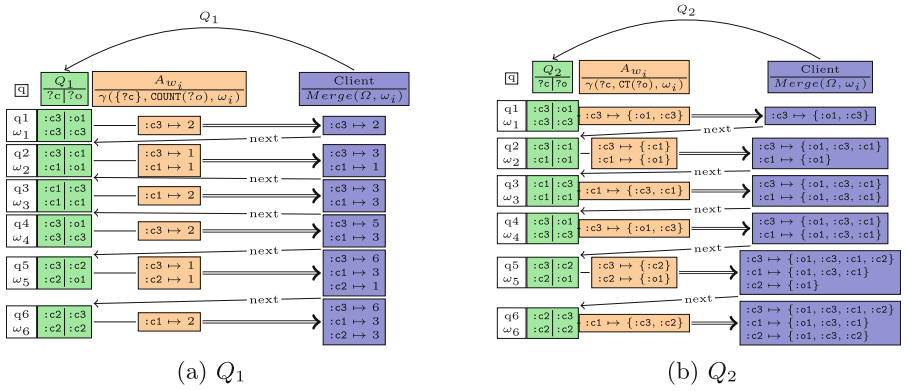
(b) Evaluation of Q_1 on $\mathcal{G}_1$ with regular Web preemption [12]

Fig. 2. Evaluation of SPARQL aggregation queries with web preemption

and the average time for first results is also 65 s. Figure 2a presents the execution of Q_a, Q_b, and Q_c using Web preemption, with a time quantum of 30 s. Web preemption adds an overhead for the web server to suspend the running query and resume the next waiting query, of about in 3 s (10% of the quantum) our example. In this case, the throughput is $\frac{3}{76} = 0.039$ query per second but the average completion time per query is $\frac{76+38+43}{3} = 52.3$ s and the average time for first results is approximately $\frac{30+38+43}{3} = 37$ s. If the quantum is set to 60 s, then Web preemption is equivalent to FCFS. If the quantum is too low, then the throughput and the average completion time are deteriorated due to overhead. Consequently, the challenges with Web preemption are *to bound the preemption overhead in time and space* and *determine the time quantum* to amortize the overhead.

To address these challenges, in [12], the SPARQL operators are divided into two categories: *mapping-at-a-time operators* and *full-mappings operators*. For mapping-at-a-time operators, the overhead in time and space for suspending and resuming a query Q is bounded by $\mathcal{O}(|Q| \times \log(|\mathcal{G}|))$, where $|Q|$ is the number of operators required to evaluate Q. Graph patterns composed of AND, UNION, PROJECTION, and most FILTERS can be implemented using mapping-at-a-time operators. So, this fragment of SPARQL can be efficiently executed by a preemptable Web server. Full-mappings operators, such as OPTIONAL, GROUP BY, Aggregations, ORDER BY, MINUS and EXISTS require full materialization of solution mappings to be executed, so they are executed by Smart clients.

Figure 2b illustrates how web preemption processes the query Q_1 of Fig. 1b over the dataset D_1. The smart client sends the BGP of Q_1 to the server, *i.e.*, the query Q'_1: **SELECT** ?c ?o **WHERE** { ?s :**a** ?c ; ?p ?o ; :p1 :o1}. In this example,



(a) Q_1 (b) Q_2

Fig. 3. Evaluation of Q_1 and Q_2 on $\mathcal{G}_1$ with a partial aggregate P_{Q_1}.

Q_1' requires six quanta to complete. At the end of each quantum q_i, the client receives mappings ω_i and asks for the next results (*next* link). When all mappings are obtained, the smart client computes $\gamma(\{?c\}, \{\texttt{COUNT}(?o)\}, \bigcup_i \omega_i)$. Finally, to compute the set of three solutions mappings $\{\{:c3 \mapsto 6\}, \{:c1 \mapsto 3\}, \{:c2 \mapsto 3\}\}$, the server transferred $6 + 3 + 3 = 12$ mappings to the client.

In a more general way, to evaluate $[\![\gamma(E, F, P)]\!]_{\mathcal{G}}$, the smart client first asks a preemptable web server to evaluate $[\![P]\!]_{\mathcal{G}} = \Omega$, the server transfers incrementally Ω, and finally the client evaluates $\gamma(E, F, \Omega)$ locally. The main problem with this evaluation is that the size of Ω, is usually much bigger than the size of $\gamma(E, F, \Omega)$.

Reducing data transfer requires reducing $|[\![P]\!]_{\mathcal{G}}|$ which is impossible without deteriorating answer completeness. Therefore, the only way to reduce data transfer when processing aggregate queries is to process the aggregation on the preemptable server. However, the operator used to evaluate SPARQL aggregation is a full-mapping operator, as it requires to materialize $|[\![P]\!]_{\mathcal{G}}|$, hence *it cannot be suspended and resumed in constant time.*

Problem Statement: Define a preemptable aggregation operator γ such that the complexity in time and space of suspending and resuming γ is bounded in constant time[4].

4 Computing Partial Aggregations with Web Preemption

Our approach for building a preemptable evaluator for SPARQL aggregations relies on two key ideas: (i) First, web preemption naturally creates a partition of mappings over time. Thanks to the decomposability of aggregation functions [21], we compute partial aggregation on the partition of mappings on the server side and recombine partial aggregates on the client side. (ii) Second, to control the size of partial aggregates, we can adjust the size of the quantum for aggregate queries.

[4] We only consider aggregate queries with Basic Graph Patterns without OPTIONAL.

Table 1. Decomposition of SPARQL aggregation functions

SPARQL aggregations functions								
	COUNT	SUM	MIN	MAX	AVG	$\texttt{COUNT}_D$	$\texttt{SUM}_D$	$\texttt{AVG}_D$
f_1	COUNT	SUM	MIN	MAX	SaC	CT		
$v \diamond v'$	$v + v'$		$min(v, v')$	$max(v, v')$	$v \oplus v'$	$v \cup v'$		
h	Id				$(x, y) \mapsto x/y$	COUNT	SUM	AVG

In the following, we present the decomposability property of aggregation functions and how we use this property in the context of web preemption.

4.1 Decomposable Aggregation Functions

Traditionally, the *decomposability property* of aggregation functions [21] ensures the correctness of the distributed computation of aggregation functions [9]. We adapt this property for SPARQL aggregate queries in Definition 3.

Definition 3 (Decomposable aggregation function). *An aggregation function f is decomposable if for some grouping expressions E and all non-empty multisets of solution mappings Ω_1 and Ω_2, there exists a (merge) operator $\diamond$, a function h and an aggregation function f_1 such that:*

$$\gamma(E, \{f\}, \Omega_1 \uplus \Omega_2) = \{k \mapsto h(v_1 \diamond v_2) \mid k \mapsto v_1 \in \gamma(E, \{f_1\}, \Omega_1), \\ k \mapsto v_2 \in \gamma(E, \{f_1\}, \Omega_2)\}$$

In the above, $\uplus$ denotes the multi-set union as defined in [10], abusing notation using $\Omega_1 \uplus \Omega_2$ instead of P. Table 1 gives the decomposition of all SPARQL aggregations functions, where Id denotes the identity function and $\oplus$ is the *point-wise sum of pairs*, *i.e.*, $(x_1, y_1) \oplus (x_2, y_2) = (x_1 + x_2, y_1 + y_2)$.

To illustrate, consider the function $f = \texttt{COUNT(?c)}$ and an aggregation query $\gamma(V, \{f\}, \Omega_1 \uplus \Omega_2)$, such as $\gamma(V, \{f\}, \Omega_1) = \{\{?c \mapsto 2\}\}$ and $\gamma(V, \{f\}, \Omega_2) = \{\{?c \mapsto 5\}\}$. The intermediate aggregation results for the COUNT aggregation can be merged using an arithmetic addition operation, *i.e.*, $\{\{?c \mapsto 2 \diamond 5 = 2 + 5 = 7\}\}$.

Decomposing SUM, COUNT, MIN and MAX is relatively simple, as we need only to merge partial aggregation results to produce the final query results. However, decomposing AVG and aggregations with the DISTINCT modifier are more complex. We introduce two auxiliary aggregations functions, called SaC (*SUM-and-COUNT*) and CT (*Collect*), respectively. The first one collects information required to compute an average and the second one collects a set of distinct values. They are defined as follows: $\texttt{SaC}(X) = \langle \texttt{SUM}(X), \texttt{COUNT}(X) \rangle$ and $\texttt{CT}(X)$ is the base set of X as defined in Sect. 3. For instance, the aggregation function of the query $Q = \gamma(V, \texttt{COUNT}_D(?o), \Omega_1 \uplus \Omega_2)$ is decomposed as $Q' = \texttt{COUNT}(\gamma(V, \texttt{CT}(?o), \Omega_1) \cup \gamma(V, \texttt{CT}(?o), \Omega_2))$.

4.2 Partial Aggregation with Web Preemption

Using a preemptive web server, the evaluation of a graph pattern P over $\mathcal{G}$ naturally creates *a partition of mappings over time* $\omega_1, ..., \omega_n$, where ω_i is produced during the quantum q_i. Intuitively, a *partial aggregations* A_i, formalized in Definition 4, is obtained by applying some aggregation functions on a partition of mappings ω_i.

Definition 4 (Partial aggregation). *Let E be a list of expressions, F a set of aggregation functions, and $\omega_i \subseteq [\![P]\!]_{\mathcal{G}}$ such that $[\![P]\!]_{\mathcal{G}} = \bigcup_{i=1}^{i=n} \omega_i$ where n is the number of quanta required to complete the evaluation of P over $\mathcal{G}$. A partial aggregation A_i is defined as $A_i = \gamma(E, F, \omega_i)$.*

As a partial aggregation operates on ω_i, partial aggregation can be implemented server-side as a *mapping-at-a-time operator*. Suspending the evaluation of aggregate queries using partial aggregates does not require to materialize intermediate results on the server. Finally, to process the SPARQL aggregation query, the smart client computes $[\![\gamma(E, F, P)]\!]_{\mathcal{G}} = h(A_1 \diamond A_2 \diamond \cdots \diamond A_n)$.

Figure 3a illustrates how a smart client computes Q_1 over D_1 using partial aggregates. We suppose that Q_1 is executed over six quanta $q_1, \ldots, q_6$. At each quantum q_i, two new mappings are produced in ω_i and the partial aggregate $A_i = \gamma(\{\texttt{?c}\}, \{\texttt{COUNT(?o)}\}, \omega_i)$ is sent to the client. The client merges all A_i thanks to the $\diamond$ operator and then produces the final results by applying g. Figure 3b describes the execution of Q_2 with partial aggregates under the same conditions. As we can see, the `DISTINCT` modifier requires to transfer more data, however, a reduction in data transfer is still observable compared with transferring all ω_i for $q_1, q_2, q_3, q_4, q_5, q_6$.

The duration of the quantum seriously impacts query processing using partial aggregations. Suppose in Fig. 3a, instead of six quanta of two mappings, the server requires twelve quanta with one mapping each, therefore, partial aggregates are useless. If the server requires two quanta with six mappings each, then only two partial aggregates $A_1 = \{(\texttt{:c3}, 3), (:c1, 3)\}$ and $A_2 = \{(\texttt{:c3}, 3), (\texttt{c2}, 3)\}$ are sent to the client and data transfer is reduced. If the quantum is infinite, then the whole aggregation is produced on the server-side, the data transfer is optimal. Globally, for an aggregate query, the larger the quantum is, the smaller the data transfer and execution time are.

However, if we consider several aggregates queries running concurrently (as presented in Fig. 2a), the quantum also determines the average completion time per query, the throughput and time for first results. The time for the first result is not significant for aggregate queries. A large quantum reduces overheads and consequently, improves throughput. However, a large quantum degrades the average completion time per query, *i.e.*, the responsiveness of the server as demonstrated in experiments of [12]. Consequently, setting the quantum mainly determines a trade-off between efficiency of the partial aggregates that can be measured in data transfer and the responsiveness of the server that can be measured in average completion time per query. The administrator of a public server is responsible for setting the value of the quantum according to the workload and dataset size.

Algorithm 1: A Server-Side Preemptable SPARQL Aggregation Iterator

Require: I_p: predecessor in the pipeline of iterators, K: grouping variables, A: set of aggregations functions.
Data: G: multisets of solutions mappings

```
1  Function Open():
2      G ← ∅
3  Function Save():
4      return G
5  Function GetNext():
6      if I_p.HasNext() then
7          μ ← I_p.GetNext()
8          non interruptible
9              Ω ← γ(K, A, {μ})
10             if G = ∅ then
11                 G ← Ω
12             else
13                 G ← Merge(K, A, G, Ω)
14     return nil
15 Function Merge(K,A,X,Y):
16     Z ← ∅
17     for μ ∈ X do
18         if ∃μ' ∈ Y, ⟦K⟧_μ = ⟦K⟧_μ' then
19             for k ↦ v ∈ μ' do
20                 if type(k, A) ∈ {COUNT, SUM} then
21                     μ[k] ← μ[k] + v
22                 else if type(k, A) = SaC then
23                     μ[k] ← μ[k] ⊕ v
24                 else if type(k, A) = MIN then
25                     μ[k] ← min(μ[k], v)
26                 else if type(k, A) = MAX then
27                     μ[k] ← max(μ[k], v)
28                 else
29                     μ[k] ← μ[k] ∪ v
30         else if ∃μ' ∈ Y, μ' ∉ X, K ∈ dom(μ')
               then
31             Z ← Z ∪ {μ'}
32         Z ← Z ∪ {μ}
33     return Z
```

This is not a new constraint imposed by web preemption, DBpedia and Wikidata administrators already set their quotas to 60 s for the same reason. We offer them the opportunity to replace a quota that stops query execution by a quantum that suspends query execution.

4.3 Implementing Decomposable Aggregation Functions

For evaluating SPARQL aggregation queries on the preemptive server SaGe [12], we introduce the *preemptable SPARQL aggregation iterator*. The new iterator incrementally computes partial aggregation during a time quantum and then returns the results to the smart client, as shown in Algorithm 1. It can also be suspended and resumed in *constant time*.

When query processing starts, the server calls the `Open()` method to initialize a multiset of solution mappings G. At each call to `GetNext()`, the iterator pulls a set of solutions μ from its predecessor (Line 7). Then, it computes the aggregation functions on μ and merges the intermediate results with the content of G (Lines 8–13), using the $\diamond$ operator. These operations are **non-interruptibles**, because if they were interrupted by preemption, the iterator could end up in a non-consistent state that cannot be saved or resumed. The function *Merge(K, A, X, Y)*

Algorithm 2: Client-side merging of partial aggregates

```
   Require: Q_γ: SPARQL aggregation query, S: url of a SaGe server.
 1 Function EvalQuery(Q_γ, S):
 2     K ← Grouping variables of Q_γ
 3     A ← Aggregation functions of Q_γ
 4     Q'_γ ← DecomposeQuery(Q_γ)
 5     Ω ← ∅
 6     Ω', next ← Evaluate Q'_γ at S
 7     while next ≠ nil do
 8         Ω ← Merge(K, A, Ω, Ω')
 9         Ω', next ← Evaluate next at S
10     return ProduceResults(Ω, K, A)
11 Function ProduceResults(Ω, K, A):
12     Ω_r ← ∅
13     for μ ∈ Ω do
14         for k ↦ v ∈ μ, k ∉ K do
15             if type(k, A) = AVG then
16                 (s, c) ← v
17                 μ[k] = s/c
18             else if type(k, A) = COUNT_D then
19                 μ[k] = |v|
20             else if type(k, A) = SUM_D then
21                 μ[k] = SUM(v)
22             else if type(k, A) = AVG_D then
23                 μ[k] = AVG(v)
24         Ω_r ← Ω_r ∪ {μ}
25     return Ω_r
```

(Lines 15–33) merges the content of two solution mappings X, Y. For each $\mu \in X$, it finds a $\mu' \in Y$ that has the same group key as μ (Line 18). If so, the algorithm iterates over all aggregations results in μ (Lines 19–32) to merge them with their equivalent in μ', using the different merge operators shown in Table 1. If the aggregation is a `COUNT` or `SUM` (Lines 20–21), then the aggregation results are merged using an addition. If the aggregation is a `SaC` aggregation (Lines 22–23), then the two results are merged using the *pointwise sum of pairs*, as defined in Sect. 4.2. If it is a `MIN` (Lines 24–25) or `MAX` aggregation (Lines 26–27), then the results are merged by keeping the minimum or maximum of the two values, respectively. Finally, in the case of a `CT` aggregation (Lines 28–29), the two sets of values are merged using *the set union operator*. When preemption occurs, the server waits for its non-interruptible section to complete and then suspends query execution. The section can block the program for at most the computation of γ on a single set of mappings, which can be done in constant time. Then, the iterator calls the `Save()` method and sends all partial SPARQL aggregation results to the client. When the iterator is resumed, it starts back query processing where it was left, but with an empty set G, *i.e.*, the preemptable SPARQL aggregation iterator is fully stateless and resuming it is done in constant time.

We also extend the SaGe smart web client to support the evaluation of SPARQL aggregation using partial aggregates, as shown in Algorithm 2. To execute a SPARQL aggregation query Q_γ, the client first decomposes Q_γ into Q'_γ to replace the `AVG` aggregation function and the `DISTINCT` modifier as described in Sect. 4.2. Then, the client submits Q'_γ to the SaGe server S, and follows the `next` links sent by S to fetch and merge all query results, following the Web preemption model (Lines 6–9). The client transforms the set of partial

Table 2. Statistics of RDF datasets used in the experimental study

RDF dataset	# Triples	# Subjects	# Predicates	# Objects	# Classes
BSBM-10	4 987	614	40	1 920	11
BSBM-100	40 177	4 174	40	11 012	22
BSBM-1k	371 911	36 433	40	86 202	103
DBpedia 3.5.1	153M	6 085 631	35 631	35 201 955	243

SPARQL aggregation results returned by the server to produce the final aggregation results (Lines 11–25): for each set of solutions mappings $\mu \in \Omega$, the client applies the *reducing function* on all aggregation results. For an `AVG` aggregation, it computes the average value from the two values stored in the pair computed by the `SaC` aggregation (Lines 15–17). For a $\texttt{COUNT}_D$ (Lines 18–19) aggregation, it counts the size of the set produced by the `CT` aggregation. For $\texttt{SUM}_D$ (Lines 20–21) and $\texttt{AVG}_D$ (Lines 22–23) aggregations, the client simply applies the `SUM` and `AVG` aggregation function, respectively, on the set of values. Finally, for all other aggregations, like `SUM` or `COUNT`, the client does not perform any reduction, as the values produced by the merge operator already are final results.

5 Experimental Study

We want to empirically answer the following questions: (i) What is the data transfer reduction obtained with partial aggregations? (ii) What is the speed up obtained with partial aggregations? (iii) What is the impact of time quantum on data transfer and execution time?

We implemented the partial aggregator approach as an extension of the SaGe query engine[5]. The SaGe server has been extended with the new operator described in Algorithm 1. The Java SaGe client is implemented using Apache Jena and has been extended with Algorithm 2. All extensions and experimental results are available at https://github.com/folkvir/sage-sparql-void.

Dataset and Queries: We build a workload (*SP*) of 18 SPARQL aggregation queries extracted from SPORTAL queries [8] (queries without ASK and FILTER). Most of the extracted queries have the DISTINCT modifier. SPORTAL queries are challenging as they aim to build VoID description of RDF datasets[6]. In [8], the authors report that most queries cannot complete over DBpedia due to quota limitations. To study the impact of DISTINCT on performances of aggregate queries processing, we defined a new workload, denoted *SP-ND*, by removing the DISTINCT modifier from the queries of *SP*. We run the *SP* and

[5] https://sage.univ-nantes.fr.
[6] https://www.w3.org/TR/void/.

SP-ND workloads on synthetic and real-world datasets: Berlin SPARQL Benchmark (BSBM) with different sizes, and a fragment of DBpedia *v3.5.1*, respectively. The statistics of datasets are detailed in Table 2.

Approaches: We compare the following approaches:

- SaGe: We run the SaGe query engine [12] with a time quantum of 150 ms and a maximum page size of results of 5000 mappings. The data are stored in a PostgreSQL server, with indexes on *(SPO)*, *(POS)* and *(OSP)*.
- SaGe-agg: is our extension of SaGe with partial aggregations. It runs with the same configuration as the regular SaGe.
- *TPF*: We run the TPF server [19] (with no Web cache) and the Communica client, using the standard page size of 100 triples. Data are stored in HDT format.
- *Virtuoso:* We run the Virtuoso SPARQL endpoint [6] (v7.2.4) **without quotas** in order to deliver complete results and optimal data transfer. We also configured Virtuoso with *a single thread* to fairly compare with other engines.

Servers Configurations: We run experimentations on Google Cloud Platform, on a n1-standard-2: 2 vCPU, 7,5 Go memory with a SSD local disk.

Evaluation Metrics: Presented results correspond to the average obtained of three successive executions of the queries workloads. (i) *Data transfer*: is the number of bytes transferred to the client when evaluating a query. (ii) *Execution time*: is the time between the start of the query and the production of the final results by the client.

Experimental Results

Data Transfer and Execution Time over BSBM. Figure 4 presents data transfer and execution time for BSBM-10, BSBM-100 and BSBM-1k. The plots on the left detail the results for the SP workload and on the right, the results for the SP-ND workload. Virtuoso with no quota is presented as the optimal in terms of data transfer and execution time. As expected, TPF delivers the worst performance because TPF does not support projections and joins on server-side. Consequently, the data transfer is huge even for small datasets. SaGe delivers better performance than TPF mainly because it supports projection and joins on the server side. SaGe-agg significantly improves data transfer but not execution time. Indeed, partial aggregations allow to reduce data transfer but do not allow to speed up the scanning of data on disk. When comparing the 2 workloads, we can see that processing queries without `DISTINCT` (on the right) is much more efficient in data transfer than with `DISTINCT` (on the left). For `DISTINCT` queries, partial aggregations can only remove duplicates observed during a time quantum only and not those observed during the execution of the query.

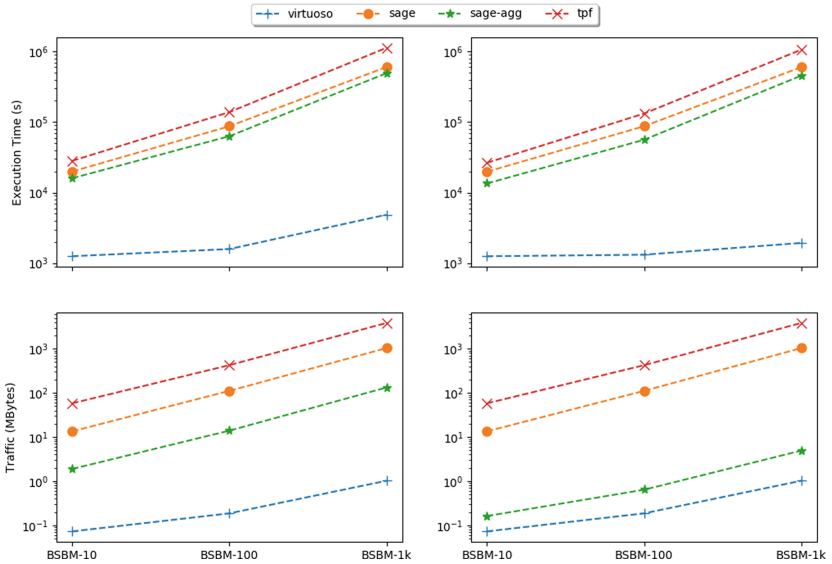


Fig. 4. Data transfer and execution time for BSBM-10, BSBM-100 and BSBM-1k, when running the *SP* (left) and *SP-ND* (right) workloads

Impact of Time Quantum. Figure 5 reports the results of running SaGe, SaGe-agg and Virtuoso with a quantum of 150 ms, 1,5 s and 15 s on BSBM-1k. The plots on the left detail the results for the SP workload and on the right the SP-ND workload. As we can see, increasing the quantum significantly improves execution times of SaGe-agg but not of SaGe. Indeed, SaGe transfers the same amount of mappings to the client even with a large quantum. Increasing the quantum reduces data transfer for the SP workload. Indeed, a large quantum allows deduplicating more elements.

Data Transfer and Execution Time over DBPedia. Figure 6 reports the results of running SaGe-agg with the SP-ND workload on a fragment of DBPedia with a quantum of 30 s compared with Virtuoso. As expected, Virtuoso delivers better performance in data transfer and execution times. Concerning execution time, the difference of performance between Virtuoso and SaGe-agg is mainly due to the lack of query optimisation in the SaGe-agg implementation: no projection push-down, no merge-joins. Concerning data transfer, Virtuoso computes full aggregation on the server, while SaGe-agg performs only partial aggregation. However, Virtuoso cannot ensure termination of queries under quotas. Five queries are interrupted after 60 s. SaGe-agg replaces a quota that stops query execution by a quantum that suspends query execution. Consequently, SaGe-agg ensures termination of all queries.

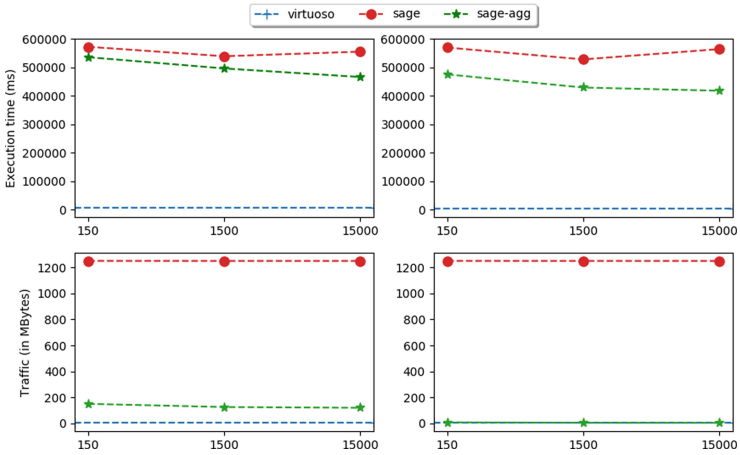


Fig. 5. Time quantum impacts executing *SP* (left) and *SP-ND* (right) over BSBM1k

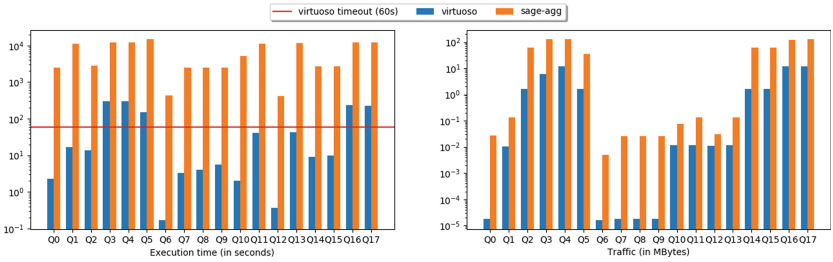


Fig. 6. Execution time and data transferred for *SP-ND* over DBpedia

6 Conclusion and Future Works

In this paper, we demonstrated how the partitioning of mappings produced by Web preemption can be used to extend a preemptable SPARQL server with a preemptable aggregation operator. As a large part of aggregations are now executed on the server-side, it drastically reduces data transfer and improves execution time of SPARQL aggregation queries compared to SaGe and TPF. However, in the current implementation, the execution time still exhibits low performance which limit the application to very large knowledge graphs such as Wikidata or DBpedia. Fortunately, there are many ways to improve execution times. First, the current implementation of SaGe has no query optimizer on the server-side. Just applying state of art optimisation techniques, including filter and projection push-down, aggregate push down or merge-joins should greatly improve execution times. Second, web preemption currently does not support intra-query parallelization techniques. Defining how to suspend and resume parallel scans is clearly in our research agenda.

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