KGCW2024 Challenge Report: RDFProcessingToolkit

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Abstract

This is the report of the participation of the RDFProcessingToolkit (RPT) in the KGCW2024 Challenge at ESWC 2024. The RPT system processes RML specifications by translating them into a series of extended SPARQL CONSTRUCT queries. The necessary SPARQL extensions are provided as plugins for the Apache Jena framework. This year's challenge comprises a performance and conformance track. For the performance challenge, the same hardware was kindly provided by the workshop organizers in order to facilitate comparability of measurements. For the performance track, we mainly adapted the setup from our last year's participation. W.r.t. the conformance track, we updated our system with support for the *rml-core* module of the upcoming RML revision. We also report on the issues and shortcomings we encountered as a base for future improvements.

Keywords

RML, SPARQL, RDF, Knowledge Graph, Big data, Semantic Query Optimisation, Apache Spark, Challenge

1. Introduction

This is the report of the participation of the RDFProcessingToolkit (RPT) in the KGCW2024 Challenge.[1] RPT is command line toolkit that features several sub-commands for SPARQL-based processing of RDF data. RPT builds upon the Apache Jena Semantic Web framework[2] and thus leverages its SPARQL engines and SPARQL extension systems. RPT supports the translation of an RML document to a set of extended SPARQL queries which can be subsequently executed on an appropriate engine. The SPARQL extensions that are necessary to execute RML in SPARQL are all registered with Jena's plugin system. The extensions can also be added as a standalone module to any Jena-based project.[3]

Our own special purpose SPARQL engine is based on the Sansa framework.[4] This engine leverages Apache Spark[5] to read supported sources ad-hoc in parallel and to parallelise SPARQL operations, such as JOIN and DISTINCT. The Sansa engine is best used for extract-transform-load (ETL) workloads, such as RML mapping execution. RPT/Sansa [1] refers to the use of RPT

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[1]https://kg-construct.github.io/workshop/2024/challenge.html
[2]https://jena.apache.org/
[3]https://scaseco.github.io/jenax/jenax-arq-parent/jenax-arq-plugins-parent/README.html
[4]https://github.com/SANSA-Stack/SANSA-Stack
[5]https://spark.apache.org/

with the Sansa engine. The challenge was divided into an *Performance* and an *Conformance* part. The challenge description and output files were published on Zenodo [2].

The remainder of this report is structured as follows: In Section 2 we report on our setup for participation in the performance challenge. In Section 3 we provide insights into how we added support for the *core* module of the upcoming revised RML specification. We conclude this report in Section 4.

2. Performance Track

In this section we report on our setup and results for the performance track. Overall, since our last year's participation, there were no major updates to our system that targeted performance. However, we had a series of bug fixes and maintenance upgrades, the most significant one being the upgrade of the code base to Jena 5. The tasks of the performance challenge were also the same as least year's. One notable addition was that the RML mapping files were also provided in the upcoming RML revision but we did not evaluate against those. A significant improvement over last year's organization was that uniform hardware (virtual machines) was kindly provided to all participants by the challenge organizers. This allowed evaluation of all participating systems on a similar hardware, so that the results are expected to be much more comparable than the year before. The specifications reported by the VM were: 4 virtual cores (Intel(R) Xeon(R) Gold 6161 CPU), 136GB VMware virtual disk, 16 GiB RAM.

W.r.t. the benchmark tool we had to create a fork of the runner in order to deal with the following issues:

- We needed to add support to allow for configuration of the working directory of the docker container running our RPT tool
- We needed to make it possible to pass Java options to our docker container, especially for setting the maximum heap memory (-Xmx)
- the benchmark tool failed to extract system information on SUSE Linux systems.

At the time of writing, the changes are tracked in our fork[6] and there is an open pull request to the benchmark tool.

We collected our recent as well as past results for RPT/Sansa in our evaluation results repository.[7] As last year, we converted XML to JSON as part of the benchmark tool's process pipeline, such that RPT/Sansa's parallel JSON reader could be leveraged. Proper parallel ingestion of XML data in RPT/Sansa is still a matter of future work.

The performance results for RPT/Sansa are consistent with those from last year, albeit the execution times were generally higher due to the weaker hardware. Also, we incorrectly allocated only 5 GB of heap memory to our Java process, although 16 GB of RAM would have been available. However, it also shows that our system effectively leverages Apache Spark in order to run with limited resources. A noteworthy finding is related to the GTFS Madrid benchmark[3]: The amount of RAM and disk space were insufficient to process the GTFS1000

[6]https://github.com/AKSW/kg-construct-challenge-tool/tree/code-on-new
[7]https://github.com/AKSW/RdfProcessingToolkit-Resources/tree/main/2024-05-27-KGCW-at-ESWC

task without compression. We compared the performance of Spark's built-in compression vs. a compressed hard disk volume.

```
# Commands to create and mount a compressed filesystem image
fallocate -l 60G ./filesystem.btrfs
mkfs.btrfs ./filesystem.btrfs
mount -o loop,compress=lzo ./filesystem.btrfs /compressed-fs

# Spark's built-in compression enabled via system properties
JAVA_OPTS="-Dspark.hadoop.mapred.output.compress=true \
  -Dspark.hadoop.mapred.output.compression.codec=org.apache.hadoop.io.compress.BZip2Codec" \
  rpt sansa query converted-rml.rq --out-file data.nt.bz2
```

Filesystem compression turned out to be significantly faster: 4 155s vs 10 368s. The former duration was obtained with a 5 GB heap memory limit, whereas the latter was obtained with a limit of 14 GB.

3. Conformance Track

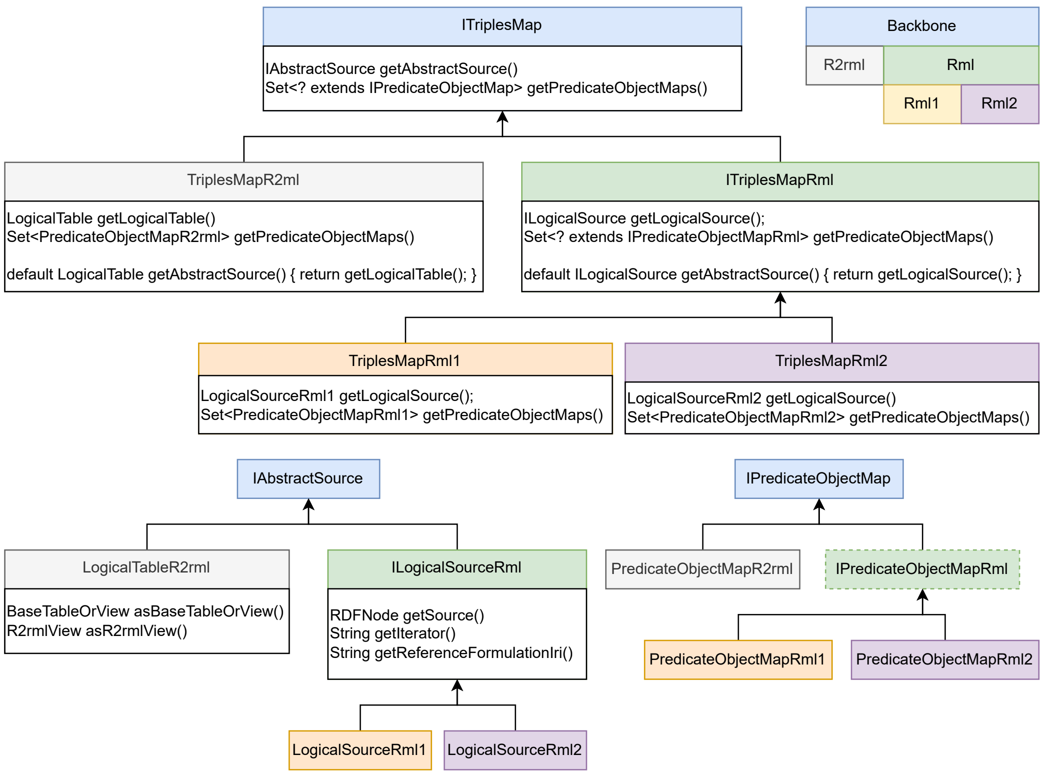
The challenge of the conformance track is to establish conformance with the upcoming revised RML specification.[8] At the point of writing, the revision did not have a final official name, so we refer to it as RML2 in the following.

- RML2 is now a model on its own and no longer an extension of R2RML. As a consequence, most ontology elements now reside in the namespace `http://w3id.org/rml/`.
- The specification is now modular, with the modules for (a) the core (*RML-Core*), (b) sources and targets (*RML-IO*), (c) containers and collections (*RML-CC*), (d) RDF-Star generation (*RML-Star*), and (e) functions (*RML-FNML*). A further *logical views* module is being worked on.

In this work, we only attempted to establish conformance with RML-Core. We integrated the conformance test suite as unit tests using *JUnit*[9] and *Testcontainers*.[10] One issue we encountered was that the benchmark tool would download version 0.9.0 of the conformance test suite rather than v1.0.0, which caused issues in running the PostgreSQL tests. As a remedy, we downloaded the version 1.0.0 manually. This also has been fixed in the meantime. Furthermore, we were not able to generate the `results.zip` for the test cases with the benchmark tool because it would terminate abnormally. The reason has yet to be investigated. Out of the 238 test cases of rm-core we were able to successfully process 236 of them. The failing tests cases were 9a-mysql and 9b-mysql. These test cases include a join between an `int` and `varchar` column. RPT first maps the MySQL types of the columns to *xsd:int* and *xsd:string* respectively, before executing the join in SPARQL. Since these types are incompatible in SPARQL, the join fails. While the test case is arguably not ideal, the solution to mitigate the issue in the future is to push the join to the database. Interestingly, the comparable PostgreSQL test cases have the column types fixed as PostgreSQL naturally refuses such an incompatible join also on the database level.

[8] https://kg-construct.github.io/rml-resources/portal/
[9] https://junit.org
[10] https://testcontainers.com/

In order to add support for RML2, we needed to decide whether to rewrite our engine from scratch or whether to generalize the interfaces and classes used to capture the RML model. We decided to take the latter approach. An excerpt of the revised class hierarchy is show in Figure 1.



ITriplesMap
IAbstractSource getAbstractSource()
Set<? extends IPredicateObjectMap> getPredicateObjectMaps()
Backbone
R2rml
Rml
Rml1
Rml2
TriplesMapR2ml
LogicalTable getLogicalTable()
Set<PredicateObjectMapR2rml> getPredicateObjectMaps()
default LogicalTable getAbstractSource() { return getLogicalTable(); }
ITriplesMapRml
ILogicalSource getLogicalSource();
Set<? extends IPredicateObjectMapRml> getPredicateObjectMaps()
default ILogicalSource getAbstractSource() { return getLogicalSource(); }
TriplesMapRml1
LogicalSourceRml1 getLogicalSource();
Set<PredicateObjectMapRml1> getPredicateObjectMaps()
TriplesMapRml2
LogicalSourceRml2 getLogicalSource()
Set<PredicateObjectMapRml2> getPredicateObjectMaps()
IAbstractSource
LogicalTableR2rml
BaseTableOrView asBaseTableOrView()
R2rmlView asR2rmlView()
ILogicalSourceRml
RDFNode getSource()
String getIterator()
String getReferenceFormulationIri()
LogicalSourceRml1
LogicalSourceRml2
IPredicateObjectMap
PredicateObjectMapR2rml
IPredicateObjectMapRml
PredicateObjectMapRml1
PredicateObjectMapRml2

Figure 1: UML showing an excerpt of how R2RML, RML1 and RML2 are aligned in our system.

4. Conclusions and Future Work

A significant improvement in this years performance setup was that the participants could evaluate their systems on the same hardware. While the benchmark tool does a good job at collecting performance data, support for generating a uniform statistics report is a still missing a few quality-of-life improvements. The performance results showed that our tool is robust under limited resources and in the course of our evaluation it turned out that compression on the filesystem-level clearly outperforms Spark's built-in one. As future work we aim to add proper support for parallel ingestion of XML data. We will analyze to which extent the remaining RML2 modules can be translated to SPARQL elements. For example, while support for *RML-FNML* should be fairly easy to add, support for *RML-IO* will require an extra RDF vocabulary for describing how to transfer the results of SPARQL queries to specified destinations.

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