QFlock – Design Documentation

1. Abstract

The amount of geographically distributed massive data is constantly increasing. Novel frameworks are expected to process geographically distributed data at their locations without moving entire raw datasets to a single location. In this document, we discuss challenges, requirements, and solutions in designing geographically distributed data processing frameworks and protocols.

Specifically, we will talk about a solution we have been developing called QFlock, which will allow for distributing and even federating queries across data centers. The idea here being to make it possible for the user at a single pane of glass to issue a query across data that is distributed across some set of data centers. And to not only allow this for homogenous data schemas, but also allow the federation of queries across data sets that are not homogeneous.

2. Document Layout

We will be performing research on a variety of approaches. As each approach is completed, we will update this section with details.

Versions 1 and 2 are detailed in sections 3-9

Version 3 is described in section 10

We discuss the changes of Version 4 and version 5 together in sections 11+

3. Overall JDBC Architecture

Here we will describe the overall architecture and the relationships between the major components. We will keep the descriptions at a high level. In the below diagrams the green color indicates components that we have written.

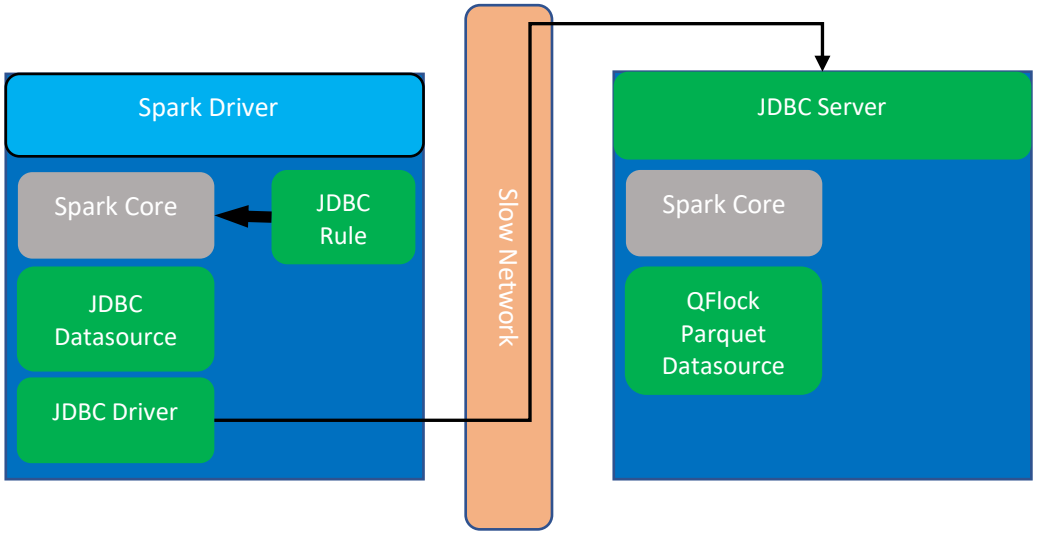


Figure 1. Overall Architecture JDBC Rule, JDBC Datasource, JDBC Driver, JDBC Server

4. QFlock JDBC Rule

The QFlock Rule is a custom Spark Rule, whose purpose is to intelligently detect when it is necessary to direct a query to our remote QFlock JDBC Server. Once the determination is made, the rule transforms the plan to inject the QFlock JDBC Datasource, which will execute the query using the remote JDBC Server.

4.1. Rule Engagement Criteria

The first task the rule needs to complete is to parse the logical plan and decide if it should engage at all. The criteria for engagement of the rule are:

1. Is the data remote?
   We currently only engage for remote data since our JDBC Server is only available for remote data.
2. Can and should we engage to reduce data?
   This criterion simply checks if the queries for this plan can be handled. There is a small set of non-trivial query filter operators we still need to add support for, and for those we will not engage. In cases where the rule does not engage, the query in question executes using standard Spark behavior.

3. It is worth pointing out that additional criteria are a potential focus of future efforts, so expect future enhancements here.

4.2. Transforming Plan

When the rule is engaged, it needs to transform the Plan to include our QFlock JDBC Datasource for any relation that is located remotely and requires optimization.

More specifically, the rule needs to transform all project, filter relations. All these relations need to be replaced with an instance of our JDBC Relation. So, for example, a standard Spark project, filter relation such as the below:

```
- Project [i_item_sk#145L, i_item_id#146, i_item_desc#149, i_current_price#150]
   - Filter((((i_current_price#150 >= 68.0) AND (i_current_price#150 <= 98.0)) AND
i_manufact_id#158L IN (677,940,694,808))
    - Relation(
tpcds.item[i_item_sk#145L,i_item_id#146,i_rec_start_date#147,i_rec_end_date#148,i_item_desc#149,i
_current_price#150,i_wholesale_cost#151,i_brand_id#152L,i_brand#153,i_class_id#154L,i_class#155,i
_category_id#156L,i_category#157,i_manufact_id#158L,i_manufact#159,i_size#160,i_formulation#161,i
_color#162,i_units#163,i_container#164,i_manager_id#165L,i_product_name#166] parquet)
```

Might be replaced with a JDBC Relation such as this:

```
RelationV2[i_item_sk#284L, i_item_id#285, i_item_desc#288, i_current_price#289] class
com.github.qflock.extensions.jdbc.QflockJdbcBatchTable
```

4.3. Extracting query

As part of transforming the plan, the rule also needs to extract the filter and project. After extraction, there is additional logic to then re-form the SQL Query. This SQL query will be set as a parameter to the QFlock JDBC Datasource.

5. QFlock JDBC Datasource

The QFlock JDBC Datasource is a custom V2 Spark Datasource, which uses the QFlock JDBC Driver in order to communicate via the JDBC API with the remote QFlock JDBC Server.

5.1. Partitioning

Partitioning is extremely important since it allows for breaking up of a single large partition into pieces that can be processed in parallel. This is how Spark achieves its parallelism. We are using one partition per Parquet row group.

To ensure that JDBC Server honors the partitioning, we pass the row group offset and row group count to the JDBC Server along with each query. In addition, since Spark has no way to execute a query on a subset of row groups, the JDBC Server utilizes a new data source we created to only run the indicated query on a subset of row groups.

5.2. JDBC Connection

JDBC (Java Database Connectivity) defines a standard interface to be used by all drivers. The JDBC Datasource uses this standard interface to communicate with our driver. The API being used here is completely standard JDBC.

JDBC has a notion of a “connection” which needs to be established. That connection object can then be used to create a statement object. The statement object can then be used to execute a query and retrieve a result.

The query itself is passed as an argument to the execute query command, but what about other parameters that need to be sent to the JDBC Server? These can be set as properties on the connection. See below for more details on the required parameters in the JDBC Driver API.

5.3. Options

There are a few supported options for the JDBC Datasource. Keep in mind that since this datasource is inserted by our JDBC Rule, these parameters are mostly set by that Rule.

Parameter	Description	Example
format	The format of the file	parquet
url	The URL of JDBC	jdbc:qflock://hostname:1433/database
driver	The java class for the JDBC driver	com.github.qflock.jdbc.QflockDriver
query	The query text to execute	SELECT * FROM call_center
numRowGroups	The total number of row groups in the table	42
schema	The schema of the table	ss_quantity:long:true,ss_list_price:double:true

5.4. Global Options

The only global option we support is: “qflockJdbcUrl”

This is set on the spark session via something such as the below:

```
spark = pyspark.sql.SparkSession                              \
                    .builder                                  \
                    .appName(app_name)                        \
                    .config("qflockJdbcUrl",                  \
                            “jdbc:qflock://server:1433/db”)   \
                    .enableHiveSupport()                      \
                    .getOrCreate()
```

6. QFlock JDBC Driver

JDBC[1] (Java Database Connectivity) provides Java access to any type of data source. In our case we have our own JDBC Driver, which allows access from Java to our JDBC Server. The QFlock JDBC Driver is a standard Java JDBC Driver, which adheres to the standard JDBC interfaces, and uses our QFlock JDBC Thrift API to communicate with the QFlock JDBC Server.

The JDBC Driver API is very rich. We have focused on implementing and enabling the key APIs, which are required by Spark to enable executing queries. Other APIs will be considered for implementation later as needed.

6.1. Connect

6.1.1 Connect String

When the JDBC connect method is called, it can choose to accept or reject the connect based on the type of connection string. It is through this API that a driver can choose which connect requests to accept and which to allow other drivers a chance to process.

In the case of our driver, our connect string is expected to have the form:

jdbc:qflock://qflock-jdbc-server:1433/database

Where the fields are defined as:

- jdbc:qflock: is the sequence that identifies this as a connect to be processed by our Driver.
- qflock-jdbc-server - is the host name of the server that contains our JDBC server. In most of our setups it is something like qflock-jdbc-dc2.
- 1433 - is the port that our JDBC server listens on.
- database - is the name of the database we are trying to access on our JDBC server.

[1] https://docs.oracle.com/javase/8/docs/technotes/guides/jdbc/

6.1.2 Connect Parameters

The JDBC Driver's connect method takes a set of parameters that can be defined by the client.

The additional properties that are required to be set for our Driver include:

- rowGroupOffset
- rowGroupCount
- tableName

These parameters define the options for the operations to be executed on this connection. These parameters are communicated to the server as part of the connect method execution, and then can be used later by the server. For instance, these can be used by the server when a query is executed.

7. QFlock JDBC Thrift API

This QFlock JDBC Thrift API allows the JDBC Driver to communicate with the JDBC server.

Since we are using a Thrift[2] API, it means that we will utilize Thrift libraries for all aspects of the connection between client and server. It's worth also mentioning that since our client Driver is written in Java and our server is written in Python, this solution fits our scenario well.

We have defined a Thrift API between client and server, based on the API found at https://github.com/damiencarol/thrift-jdbc-server

This API provides a basic Thrift API using a JDBC object model. We have taken and adopted this approach, extending it extensively where needed to fit our solution.

[2] The Apache Thrift software framework, for scalable cross-language services development, combines a software stack with a code generation engine to build services that work efficiently and seamlessly between C++, Java, Python, PHP, Ruby, Erlang, Perl, Haskell, C#, Cocoa, JavaScript, Node.js, Smalltalk, OCaml and Delphi and other languages. https://thrift.apache.org/

8. QFlock JDBC Server

The QFlock JDBC Server is a component which uses our QFlock JDBC Thrift API to accept JDBC type requests. The server executes these requests largely using Spark itself and returns the results using the same QFlock JDBC Thrift API.

8.1. Query Handling

When the server receives a new request to perform a query, it uses pyspark to execute the query. Once the query data is retrieved, we convert the data into a pandas dataframe and NumPy array before converting it to a sequence of bytes, suitable for compression. We found this sequence of operations to be the most efficient for moving from a dataframe to a sequence of bytes. Each column is converted separately before being placed back into the thrift API which has an array of columns to be returned.

8.2. Compression

Compression is performed using the Zstandard library. Each column is compressed separately provides the best compression ratio, since the data type and data distribution have the potential to be very different between different columns.

8.3. Temporary Views and Request IDs

With Spark, the only way to execute an SQL query against a table is to use a view. View creation is expensive, and not something we can afford to do for every query. Therefore, the JDBC Server creates tables ahead of time which can be used when the queries arrive.

Every query also has a row group range (offset, count), which needs to be communicated to the QFlock Parquet Datasource. Normally we specify the datasource parameters at dataframe creation time. However, since the views (and hence the dataframe the view is based on) are computed ahead of time we cannot specify the row group parameters in the dataframe.

Instead, we have created a notion of request ID. A request ID is essentially a number that is associated with each dataframe/view. Prior to sending a request to the datasource, the JDBC server will fetch a request ID and give the datasource the row group offset/count to use for that request ID. Then when the query arrives at the datasource it will know which row group offset/count to use for that query.

9. QFlock Parquet Datasource

The QFlock Parquet Datasource allows access to specific row groups of a parquet file. For example, in our case the QFlock JDBC Server will use the QFlock Parquet Datasource to execute queries for certain row groups.

Here is an example of how to use the QFlock Parquet datasource.

```
df = self._spark.read                              \
                .format("qflockDs")                \
                .option("format", "parquet")       \
                .option("schema", schema)          \
                .option("tableName", tableName)    \
                .option("path", file_path)         \
                .option("dbName", dbName)          \
                .option("requestId", request_id)   \
                .load()
```

9.1. APIs

```
QflockTableDescriptor.addTable(tableName, view_count)
```

This API allows the data source to accept a new table for tracking row group ranges.

```
QflockTableDescriptor.getTableDescriptor(tableName): QflockTableDescriptor
```

This API allows the data source to return a table descriptor, which can be used for later operations.

```
QflockTableDescriptor.fillRequestInfo(offset, count): Int
```

This API returns an integer Request ID which is now tracking a specific row group offset/count.

```
QflockTableDescriptor.freeRequest(requestID: Int)
```

This API allows the user to free up a request.

10. Optimizations

Version 3 of our work enhances the approaches from prior versions with new optimizations designed to fit a variety of common use cases.

We have three approaches which we will list here and explain in the following sections.

- Aggregate pushdown
- Caching of query data
- Pushdown of additional Projects

10.1. Aggregate Pushdown

Aggregate pushdown is a technique where an aggregate operation like MIN, MAX, SUM or COUNT is fully pushed down to the data source and even to the remote server. In our case this means pushing the aggregate to the JDBC server to be executed by the remote Spark cluster, which has access to the data. This approach takes advantage of the remote Spark's computing power to reduce the size of the data before transferring it back to the client. In many cases the aggregate pushdown reduces the result size by 90% or more since an aggregate operation result is a tiny fraction of the data being evaluated. This will result in significant savings especially if the network between the data centers is relatively slower than local data center network.

In our testing, we measured significant performance gains in 3 of the TPC-DS tests, 10, 35 and 69.

10.1.1 Details

Aggregate pushdown starts with our Spark Rule, which pattern matches the Aggregate operation in the Logical plan. The aggregate operation is clipped out of the plan to be replaced with a relation representing an operation to our data source. In addition, all the necessary parameters are constructed for transmission to our JDBC Data source and eventually to our JDBC Server. The most important of these is the query itself which will be executed on the remote Spark cluster. The QFlock JDBC Rule constructs a SQL query from the logical plan Catalyst nodes representing the aggregate. This SQL query is sent to the remote JDBC server to be executed.

10.2. Query Caching

In our research we found that some TPC-DS queries tended to issue the same query to the data source multiple times. In theory if we cached these queries in some way on the client side, we could help to reduce the network transfer even further and provide significant gains.

In fact, we found that providing automatic caching of repeated queries provides significant gains in many cases. One example of this is test 47, which shows repeated queries and benefits from this approach.

10.2.1 Details

Our caching implementation starts with detecting the need the need for caching during our JDBC Rule evaluation. The number of times a specific query is being pushed down is tracked here. This will allow us to decide if caching is necessary or not. Later when the data is fetched at the JDBC data source we can decide if the data needs to be cached based upon a few factors such as:

- How many times the data will be needed. Caching will be useful if the data is needed two or more times.
- How much data is being cached. We track the total amount of data being cached and if we exceed it, we will stop caching until space frees up.

Another advantage of knowing how many times the data is referenced is that we can drop the data once it is no longer needed. We track the number of references to the data and when it reaches the expected max, we drop the data, thereby freeing up more memory for caching other data.

10.3. Second Pass Pushdown of Projects

As we mentioned previously, pushdown of operations is done using a Rule Based approach. With this approach our custom Spark Rule will parse the logical plan and enable pushdown using well established Spark mechanisms. These mechanisms, which we implement in our Spark Rule, transform the logical plan by inserting our data source (with pushdown) in the place of the operations to be pushed. Our rule runs like any other Spark Rule, it receives a Logical Plan as input and returns a Logical Plan as output. Our rule will be run by Spark automatically, whenever Spark determines it needs to run all the rules.

In our research we discovered that our Spark Rule needs to be able to pushdown projects to our data source in a second pass or invocation of our Rule. Why does this occur? It is needed since there are cases where Spark runs our rule multiple times for the same query. The first time the rule runs, we insert our data source with, for example, pushdown of filter. But then the next time our rule runs, it detects additional new operations such as projects, which Spark added since the last time our rule ran. To enable optimal performance, these new projects also need to be pushed down to our JDBC data source.

This optimization enhances our rule to detect these additional operators and successfully transform a logical plan which already has pushdowns to include the new pushdowns.

10.3.1 Details

This optimization enhances our existing JDBC rule to include a second pass of project pushdown. This enhances the existing pattern matching in our rule to include matching on an already inserted JDBC data source relation which has additional inserted projects above it. After detecting the pattern, we then check that the projects themselves are suitable for pushdown and supported by our JDBC data source. Assuming all checks pass, we then insert a new relation, with a new enhanced query to include the additional projects.

11. Join Pushdown

Joins[3] are another flavor of operation that we considered for pushdown. Join pushdown is a technique where a join operation across two tables is fully pushed down to the data source and even to the remote server. In our case this means pushing the join to the remote server to be executed by the remote Spark cluster, which has access to the data. This approach takes advantage of the remote Spark's computing power to join the table remotely and has the potential to reduce the size of the data before transferring it back to the client.

11.1. Join Pushdown Criteria

We mention that there is only potential for join pushdown since only some join operations can be considered a data reduction. Data reduction is meaning that the output size of the join is less than the input size of the join, which is the size of data that needs to be read in to execute the join. Some joins will generate much more data than exists in both individual tables involved in the join. Assume table A has 1 million rows and table B has 100 rows. If we join these two tables and if each row of B is added to each row of A, you can see that you will end up with significantly more data than you started with.

However, some joins can also significantly reduce the data. For instance, a join of two filtered tables can result in less data. Another case which can result in a reduction is a join with an expression, where that expression matches a subset of rows in the two tables being joined.

Another criterion in determining join pushdown is the data placement of the tables being joined. In our case we are looking to push down the join to the remote server. Thus, we require both tables in the join being pushed down to be located on that remote server.

11.2. Details

Join pushdown starts with our Spark Rule, which pattern matches the Join operation in the Logical plan. Next, the rule will select a rule only if it matches our join pushdown criteria. Namely:

- Both tables in the join are local to the server we will be pushing the join to.
- The join contains some sort of reduction. This is most simply determined by checking if the join has an expression that selects rows, or if the tables being joined are reduced by for example a filter.
- It is worth mentioning that there are many other possible criteria that could be used to determine if the join will reduce the data, but we choose a relatively straightforward criteria to help check the proof of concept of join pushdown. These other techniques could be the focus of future research.

Assuming the join is selected, the join operation is clipped out of the plan to be replaced with a relation representing an operation to our data source. In addition, all the necessary parameters are constructed for transmission to our data source and eventually to our remote server. The most important of these parameters is the query itself which will be executed on the remote Spark cluster. The QFlock Rule constructs a SQL query from the logical plan Catalyst nodes representing the join. This SQL query is sent to the remote Qflock server to be executed.

[3] Spark supports many kinds of joins. For simplicity, we will only consider the most common joins, which are inner joins and left outer joins.

12. Query Caching (version 5+)

Query caching was introduced originally in version 3 with the JDBC API. In this section we describe the enhancements to query caching from version 5.

As we stated previously, we found that some TPC-DS queries tended to issue the same query to the data source multiple times. In theory if we cached these queries in some way on the client side, we could help to reduce the network transfer even further and provide significant gains.

In fact, we found that providing automatic caching of repeated queries provides significant gains in many cases. One example of this is TPC-DS test 47, which shows repeated queries and benefits from this approach.

It is also worth noting that with Spark it is possible to know within the context of a single query if data needs to be cached or not. That is, during the planning phase our rules can detect the queries that repeat and therefore should be cached. This makes caching extremely efficient since caching is only used for the queries that need it and then drop the data when we know it is no longer needed.

12.1. Overview

Our enhancements to query caching are introduced to solve issues with the prior implementation. Specifically, we wanted to reduce the amount of memory consumed since Spark performs less optimally with higher memory utilization. To help reduce memory use we now cache query data to disk rather than in memory. This frees up the memory usage and removes any significant limits on how much data we can cache. The cache data is read in on demand as it is needed.

12.2. Details

This new method of caching has been designed to work with the new Qflock Remote Server Binary API. The system only caches data that our Qflock Remote Rule identifies as needing to be cached. If the data needs to be cached, then on first reference, the cache is first checked for the data. Since no data is available, the data is fetched from the remote server, and then streamed to disk. For simplicity we keep the same data format as the Qflock Remote Server Binary API. This is advantageous since the code we use to access the data can be the same regardless of the source of the data (local file cache or remote server). Also, since the Qflock Remote Server Binary API compresses the data, we can save the data on disk efficiently in a compressed format.

13. Overall Qflock Remote Server Architecture (Version 5.0+)

Here we will describe the second major version of our architecture introduced in version 5.0. This introduces the notion of a Remote Qflock Server, which is a different implementation than that of the original JDBC server. The below shows the overall architecture and the relationships between the major components. We will intentionally keep the descriptions at a high level. In the below diagrams the green color indicates components that we have written.

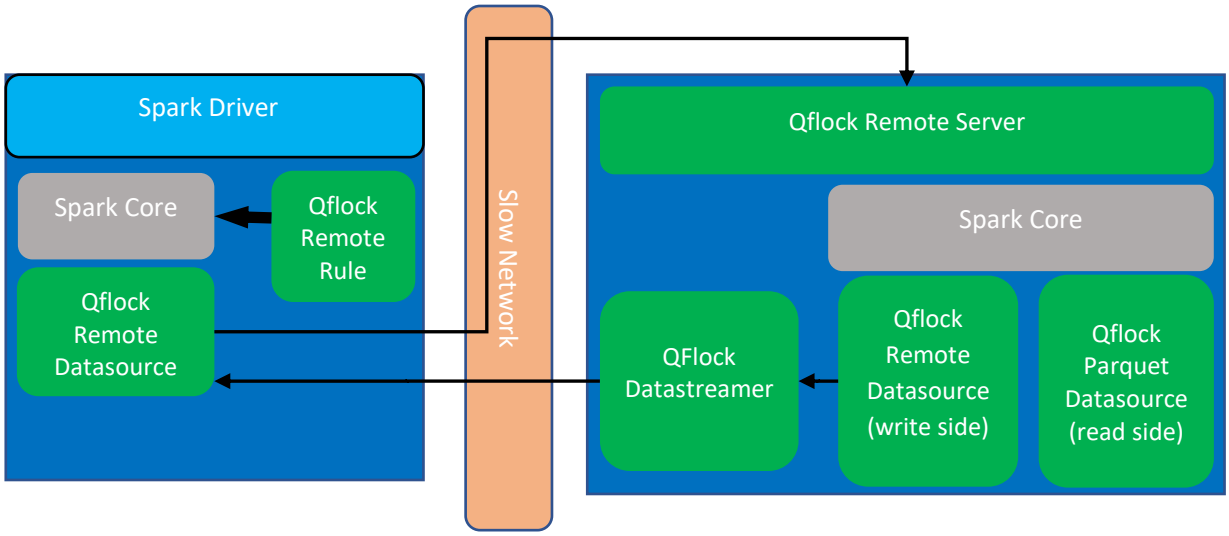


Figure 2. Overall Architecture including Qflock Remote Rule, Qflock Remote Datasource, Qflock Remote Server

In the above diagram our Qflock Remote Rule intervenes in the Spark planning in order to insert our Qflock Remote Datasource. Our Qflock Remote Datasource will fetch the data using the Qflock Remote Server. The Qflock Remote Server uses Spark on the remote side to 1) perform the query and 2) stream the data back to the Qflock Datasource. When the query is performed the Qflock Parquet data source is used, which allows for reading a range of row groups from a parquet file. The write side of the Qflock Datasource queues the data buffers to the Qflock Streamer, which invokes the process method on the intelligent data buffers, which understand how to transfer the data back to the original client using the Qflock Remote Server Binary Format.

It is worth mentioning that we sometimes (especially in the code) refer to this version as Qflock Remote, to differentiate this version from Qflock Jdbc.

14. QFlock Remote Rule

The QFlock Remote Rule is a custom Spark Rule, whose purpose is to intelligently detect when it is necessary to push down a query to our Remote QFlock Server. Once the determination is made to push down, the rule transforms the plan to inject the QFlock Remote Datasource, which will execute the query using the remote Qflock Server.

14.1. Rule Engagement Criteria

The first task the rule needs to complete is to parse the logical plan and decide if it should engage at all. The criteria for engagement of the rule are:

1. Is the data remote?

   We currently only engage for remote data since our Qflock Remote Server is only available for remote data.

2. Can and should we engage to reduce data?

   This criterion simply checks if the queries for this plan can be handled. There is a small set of non-trivial query filter operators we still need to add support for, and for those we will not engage. In cases where the rule does not engage, the query in question executes using standard Spark behavior.

3. It is worth pointing out that additional criteria are a potential focus of future efforts, so expect future enhancements here.

14.2. Transforming Plan

When the rule is engaged, it needs to transform the Plan to include our QFlock Remote Datasource for any relation that is located remotely and requires optimization.

More specifically, the rule needs to transform all project, filter relations. All these relations need to be replaced with an instance of our Qflock Remote Relation. So, for example, a standard Spark project, filter relation such as the below:

```
- Project [i_item_sk#145L, i_item_id#146, i_item_desc#149, i_current_price#150]

   - Filter((((i_current_price#150 >= 68.0) AND (i_current_price#150 <= 98.0)) AND
i_manufact_id#158L IN (677,940,694,808))

    - Relation(
tpcds.item[i_item_sk#145L,i_item_id#146,i_rec_start_date#147,i_rec_end_date#148,i_item_desc#149,i
_current_price#150,i_wholesale_cost#151,i_brand_id#152L,i_brand#153,i_class_id#154L,i_class#155,i
_category_id#156L,i_category#157,i_manufact_id#158L,i_manufact#159,i_size#160,i_formulation#161,i
_color#162,i_units#163,i_container#164,i_manager_id#165L,i_product_name#166] parquet)
```

Might be replaced with a Qflock Relation such as this:

```
RelationV2[i_item_sk#284L, i_item_id#285, i_item_desc#288, i_current_price#289] class
com.github.qflock.extensions.remote.QflockRemoteBatchTable
```

14.3. Extracting query

As part of transforming the plan, the rule also needs to extract the filter and project. After extraction, there is additional logic to then re-form the SQL Query. This SQL query will be set as a parameter to the QFlock Datasource.

15. QFlock Remote Datasource

The QFlock Remote Datasource is a custom V2 Spark Datasource, which uses an http connection to communicate with the QFlock Remote Server, using that server's API and semantics. The Datasource retrieves the data and provides it to Spark using the columnar APIs provided by spark for efficiently retrieving columnar data.

15.1. Partitioning

Partitioning is extremely important since it allows for breaking up of a single large partition into pieces that can be processed in parallel. This is how Spark achieves its parallelism. We are using one partition per Parquet row group for most queries except join.

Join currently partitions a query into N batches. Each of these batches contains R/N row groups where R is the total number of row groups. It is also worth mentioning that we are partitioning on the first table in the join. N is chosen to guarantee a reasonable amount of concurrency. Today we are using N=4, but this is a changeable parameter.

To ensure that Qflock Remote Server honors the partitioning, the client provides as query parameters the table name to partition, the row group offset and the row group count. In addition, since Spark has no mechanism to execute a query on a subset of row groups, the Qflock Remote Server utilizes a new data source we created to only run the indicated query on a subset of row groups.

15.2. Options

There are a few supported options for the Qflock Remote Datasource. Keep in mind that since this datasource is inserted by our Qflock Remote Rule, these parameters are mostly set by that Rule.

Parameter	Description	Example
format	The format of the file	parquet
url	The URL of the Remote Server	`http://qflock-spark-dc2:9860/query`
query	The query text to execute	SELECT * FROM call_center
numRowGroups	The total number of row groups in the table	42
rowGroupBatchSize	The number of batches to group the row groups into. For instance, with 120 row groups, a batch size of 4 gives us 4 batches of 30 row groups each. Note: this parameter is optional, if it is not provided then we partition 1 row group per partition.	4
tableName	The table name according to the metastore.	“call_center”
schema	The string representation of the table schema.	ss_quantity:long:true,ss_list_price :double:true

15.3. Global Options

We support a few global options accepted by the Qflock Remote Rule.

Parameter	Description	Example
qflockServerUrl	The URL of the Qflock server	`http://qflock-spark-dc2:9860/query`
qflockQueryName	The text representation of the query	"TPC-DS query 1"

These configuration parameters are set on the Spark session as shown below:

```
spark = pyspark.sql.SparkSession                              \
                    .builder                                  \
                    .appName(app_name)                        \
                    .config("qflockServerUrl",                \
                            "http://qflock-spark-dc2:9860/query") \
                    .config("qflockQueryName",                \
                            "query 1")                        \
                    .enableHiveSupport()                      \
                    .getOrCreate()
```

16. QFlock Remote Server API

This QFlock Remote Server uses an http connection to accept incoming connections from clients. The default port for the server is 9860.

Upon connecting, a client will first send the JSON, containing the parameters for the query.

The server will process the query and send the data back to the client in a columnar batch binary format, which we will call Qflock Remote Server Binary Format.

16.1. Qflock Server Query Parameters JSON Format

Below is the JSON which describes the parameters sent from client to Qflock Remote Server on a query.

Parameter	Description	Example
query	SQL Query string	`SELECT ss_quantity from store_sales`
tableName	table name to partition on. This query will only access the specified set of row groups for this table. This is the table name as seen by the metastore.	store_sales
rgOffset	The start row group offset to access	Any row group offset valid for this table.
rgCount	The number of row groups starting at the above offset.	Any value withing the range 1..max row groups

Example JSON for a query.

```
{
  "query":"SELECT ss_quantity,ss_sales_price FROM store_sales",
  "tableName":"store_sales",
  "rgOffset":"0",
  "rgCount":"1"
}
```

16.2. Qflock Remote Server Binary Format

This is the format of the binary query data sent from the server back to the client.

This data format is self-describing, meaning that it describes the type and size of the transfer within the format itself. This is a big advantage of this format and allows streaming transfers where the size of the entire transfer is not known in advance. These streaming transfers of query data can actually begin before all of the data of the query had been produced, allowing for better pipelining of the query operation and data transfer.

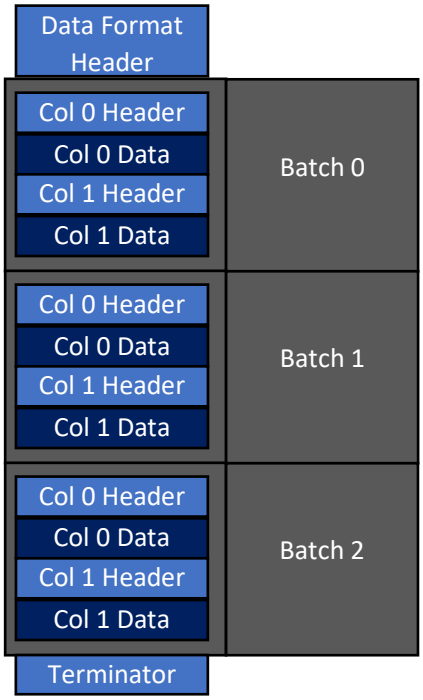
This data is columnar and batched, meaning that each batch has a set of columns, and the columnar data is sent contiguously within the batch. The data itself is compressed using the Zstandard library[4].

For the below Figure 3, we will show an overview of the binary format, and will assume that there are 3 batches returned, where each batch has two columns.

The format begins with the Data Format Header, which describes the number and type of each column.

Next is the batch data. The batch data consists of a header followed by the data for each column. The data itself is compressed and the header contains the data type, uncompressed size in bytes and compressed size in bytes.

The batches repeat until there are no more batches. The transfer end is signaled with a terminator, which has the same size as a column header, but which consists entirely of zeros.



[4] ZStandard: http://facebook.github.io/zstd/

Figure 3. Qflock Remote Server Binary Format

16.3. Data Format Header

Parameter	Description
Magic	This is a 4-byte magic number designating the beginning of a transfer.
Number of Columns	4-byte Integer for the number of columns in the data
Column Type Array	Array of Column Data Types, with one 4-byte entry per column. 1 – Long 2 – Double 3 – String

16.4. Column Header

Parameter	Description
Data Type	4 byte data type 1 – Long 2 – Double 3 – String
Type Size	Size of each data type in bytes (4 byte field)
Data Length	Uncompressed size of the data in bytes (4-byte field)
Compressed Data Length	Compressed size of the data in bytes (4-byte field)

16.5. Terminator

The terminator is a sequence of 16 bytes of zeros (the same as the size of a column header), which indicates that there are no remaining batches. This is needed since the exact size of the stream of data for this query is not known in advance, as the query is still executing/not finished as the data is being streamed.

17. QFlock Remote Server

The QFlock Remote Server is a component written in Scala, which acts as a server to accept http connections and service requests, which are largely based on SQL Queries. The API for incoming requests is the Qflock Server Query Parameters JSON Format described above. The server executes these SQL Queries largely using Spark itself and returns the results using the Qflock Remote Server Binary Format.

17.1. Query Handling

When the server receives a new request to perform a query, it uses Spark to execute the query. This query is configured to be performed by Spark using our Qflock Parquet Datasource to read the data (a subset of row groups as determined by the client partitioning) and using our Qflock Remote Datasource to save/write the data. The Qflock Remote Datasource accepts the write data from Spark and streams it efficiently back to the client Qflock Remote Datasource, which is waiting to receive the data.

17.2. Temporary Views and Request IDs

With Spark, the only way to execute an SQL query against a table is to use a view. View creation is expensive, and not something we can afford to do for every query. Therefore, the Remote Server creates tables ahead of time which can be used when the queries arrive.

Every query also has a row group range (offset, count), which needs to be communicated to the QFlock Parquet Datasource. Normally we specify the datasource parameters at dataframe creation time. However, since the views (and hence the dataframe the view is based on) are computed ahead of time we cannot specify the row group parameters in the dataframe.

Instead, we have created a notion of request ID. A request ID is essentially a number that is associated with each dataframe/view. Prior to sending a request to the datasource, the Remote server will fetch a request ID and give the datasource the row group offset/count to use for that request ID. Then when the query arrives at the datasource it will know which row group offset/count to use for that query.

17.3. Write Request Id

The Remote Server also has a similar notion of request id for our Qflock Remote Datasource which is receiving write data. The write data is received via the existing Spark APIs of BatchWrite. However, our data source needs to know where to stream the data to. To send the information on where to stream the data to the Qflock Remote Datasource, we introduce the notion of a write request ID. Prior to sending the request, the Remote Server fetches a request ID (just a number) from the Qflock Remote Datasource, and gives the datasource the destination information to use for that request ID. This way, when the Qflock remote Datasource receives the write data it will also receive the request ID and be able to look up the information provided beforehand on how and where to stream the data to.

18. Qflock Datastreamer

The Qflock Datastreamer is a module that allows for streaming data from the Qflock Remote Server back to the Qflock Remote Datasource. The purpose of the module is to decouple the streaming of data from the Spark context where data is presented to our Qflock Remote Datasource (write/server side). This allows for pipelining of the data transfer back to the client.

The Qflock Datastreamer receives intelligent buffers, which are queued and later transmitted in a separate thread back to the client. The Qflock Remote Datasource (write/server side) fills these intelligent buffers with the data it receives from Spark, and enqueues them when they are full to the Qflock Datastreamer. The Datastreamer calls the process method on each buffer in order that the buffer prepare the data (compress the data) and transfer it.

19. References

Hadoop HDFS: https://hadoop.apache.org/docs/r1.2.1/hdfs_design.html#Introduction

Spark: https://spark.apache.org/