Using distributed systems to increase data processing performance for larger than memory datasets

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Contents

List of Figures

Abstract

The explosion in data volumes in the past 15 years has resulted in increasing demands for solutions to process and analyse this data. Existing single-system solutions like SQL struggle to cope with extremely large volumes of data, suffering from performance slowdowns and long execution times.

While there is an upper limit to the performance of a single system, distributed systems do not face the same issues and can scale to as many nodes as required, therefore presenting an excellent alternative solution to this problem.

This report presents a distributed systems solution for performing various types of data processing tasks, designed around splitting the source data into manageable partitions, which can be computed by any node in the cluster. By focusing on closely integrating the persistent storage and computation nodes, the solution is able to assign partitions of the source data to the closest node, thereby reducing the effect of network latency.

As part of the solution, a domain specific language (DSL) is also presented, enabling users to succinctly describe complex data manipulations, including Select, Filter and Group By operations.

The solution is evaluated in a number of ways. Firstly, raw performance testing is conducted against SQL server, a typical single-system approach, identifying that further optimisations are required for the solution to truly compete with existing options. Testing is also performed surrounding the optimal level of parallelisation, showing that this depends on the application and data volumes. Finally, the solution has the potential to automatically adjust the number of nodes in the cluster based on demand to provide cost benefits in a public cloud environment; the results of this testing show that at small data volumes there is minimal performance impact when the number of nodes are reduced.

Chapter 1

Introduction

Data processing is required by every modern business in some form. Existing solutions like SQL fit the requirements of the majority of use cases, as the volume of data they process can be contained within a single system. However, as the volumes of data begin to increase, in particular over around 100GB of raw data, single system solutions like SQL begin to struggle as not all of the data can be loaded into memory at once.

Figure 1.0.1 shows the network model when using a single system to perform data processing on a SQL server. A number of clients are all connected to a single server, and the server can become overloaded if a large number of clients are making intensive queries, or if some of the queries operate on a large amount of data. This results in significantly reduced query performance, or even outright failure, because the system must spend a large amount of time moving data in and out of memory to complete the computation. It is possible to make extremely powerful servers, but ultimately these solutions are constrained to a single machine, meaning there is an upper limit to the compute performance based on the current technology available.

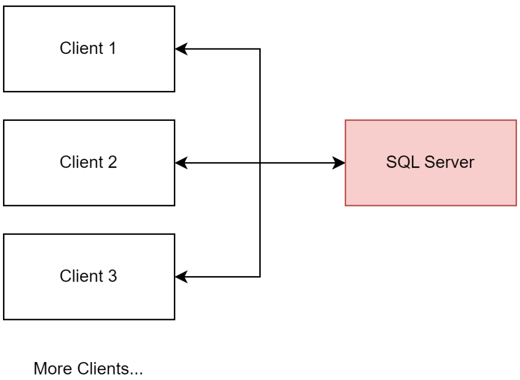


Figure 1.0.1: Single System Solution

This type of processing is generally used in *extract-transform-load* (ETL) workflows, which describe the type of workflow where data must be imported in bulk from an external source, processed in some way, then exported elsewhere for further analysis. Often, the processing to be performed acts on small groups of rows in the original dataset at once, usually a unit item like a loan, customer, or product. As a result, even if the overall dataset is extremely large, the processing can be easily parallelised, as only a small number of rows are needed at any one time to produce the required output.

Distributed systems therefore present an excellent opportunity for solving this problem. If a system can be designed to automatically split a dataset up and perform the processing over a number of nodes in a cluster, this system could potentially be able to process data of any size; larger datasets can be accommodated by simply increasing the number of nodes. Similarly, performance can be scaled by increasing the number of nodes.

1.1 Prior Work

Distributed Data Processing has existed conceptually since as early as the 1970s. A paper by Philip Enslow Jr. from this period sets out characteristics across three 'dimensions' of decentralisation: hardware (the number of machines involved in the computation), control (the management of the cluster), and database (decentralisation of storage) [14]. Enslow argued that these dimensions defined a distributed system, but acknowledged that the technology of the period was not equipped to fulfil these goals. Further research into distributed data processing can be split into two categories [50]:

- **Batch processing:** data is gathered, processed and output all at the same time. This includes solutions like MapReduce and Spark [12, 51]. Batch processing works best for data that can be considered 'complete' at some stage.
- **Stream processing:** data is processed and output as it arrives. This includes solutions like Apache Flink, Storm, and Spark Streaming [8, 48, 4]. Stream processing works best for data that is being constantly generated, and needs to be analysed in real-time.

MapReduce, a framework introduced by Google in the mid 2000s, could be considered the breakthrough framework for performing massively scalable, parallelised data processing [12]. It later became one of the core modules for the Apache Hadoop suite of tools. MapReduce provides a simple API, where developers could describe a job as a *map* and a *reduce* step, and the framework would handle the specifics of managing the distributed system. While MapReduce was Google's offering, other large technology companies released similar solutions, including Microsoft with DryadLINQ in 2009 [15].

MapReduce was not without flaws, and papers were published in the years following its release which completed performance benchmarks, analysing its strengths and weaknesses [28]. Crucially, MapReduce appears to struggle with iterative algorithms which are executed over a number of steps, as it relies on reading and writing to a persistent storage format after each step. A number of popular extensions to MapReduce were introduced to improve iterative algorithm performance, like Twister and HaLoop, in 2010 [13, 7].

MapReduce was challenging to use for developers familiar with more traditional data processing tools like SQL due to its imperative programming style, resulting in the introduction of many tools to improve its usability. Hive is one example, featuring a SQL-like language called HiveQL that allowed users to write declarative programs, compiling into MapReduce jobs [47]. Pig Latin is similar, with a mixed declarative and imperative style [32].

In 2010, the first Spark paper was released [53]. Spark aims to improve upon MapReduce's weaknesses, by storing data in memory and providing fault tolerance by tracking data 'lineage'. For any set of data, Spark knows how it was constructed from another persistent data source, and can use that to reconstruct lost data in failure scenarios. This in-memory storage, known as a resilient distributed dataset (RDD) allows Spark to improve on MapReduce's performance for iterative jobs, whilst also allowing it to quickly perform ad-hoc queries for interactive usage [52]. This approach was successful at resolving MapReduce's weakness for iterative algorithms, as keeping the data in-memory removes the read-write overhead.

Spark quickly grew in popularity, with a number of extensions being added to improve its usability, including a SQL-style engine featuring a query optimiser, and an engine supporting stream processing

[3, 4]. A second paper released in 2016 stated that Spark was used by thousands of organisations, with the largest deployment running an 8,000 node cluster containing 100PB of data [51]. Spark is designed to be agnostic of any particular storage mechanism, instead utilising existing Apache Hadoop connectors to retrieve data from various sources [36]. This provides the advantage that Spark can interface with a large number of data sources, but it is not specialised for any of them, presenting an opportunity for a new solution to improve on importing data through close integration with the persistent storage.

More recent research indicates that the field is moving away from batch processing towards stream processing. A 2015 paper by Google argues that increasing data volumes, the fact that datasets can no longer ever be considered 'complete', along with demands for improved data analytics means that streaming 'dataflow' models are the way forward [2]. Google publicly stated in their 2014 'Google I/O' Keynote that they were phasing out MapReduce in their internal systems [18]. Streaming solutions appear to be the direction of the wider industry, but they are more suited for datasets where data is produced and must be processed at a constant rate. This project is specifically aimed at implementing a generic framework for bulk processing large, complete datasets. Therefore, while a streaming solution is not in scope for the core project, there is an opportunity for further investigation into this as an extension.

1.2 Project Aims

The main objective is to design a query processing engine to perform data processing over a distributed cluster of nodes. To ensure accessibility for users of existing tools, the system should feature a SQL-like interface implemented in a widely-used language, which will allow it to be used for ETL workflows, where large data volumes often cause problems. Finally, as this will be designed as an all-in-one solution, the system should attempt to exploit the integration between the storage mechanism and cluster nodes to improve execution speed. This appears to be an area where existing distributed data processing solutions could be improved. Details of the design and implementation of the solution are described in Chapters 2 and 3.

Once complete, the implementation should be assessed in a number of ways. Testing against a single-system solution like SQL Server should be conducted, along with further tests to determine the impact of varying the level of parallelisation in the cluster. Chapter 4 provides full details of the tests.

1.3 Challenges

The project presents a number of key challenges that must be solved. The component which splits the dataset up will need to cope with small and large data volumes effectively, and the component which delegates parts of the full dataset to nodes in the cluster will have to handle clusters with any number of nodes correctly. The user's interface must be simple to use and understand, but expressive enough so the user can define any computation they need to. Finally, the persistent storage mechanism must be carefully selected to provide performance benefits when loading source data into the cluster.

Chapter 2

Design

This chapter will cover the design of the solution, in particular focusing on the following areas:

- Required Features
- Languages, Technologies and Frameworks
- Architecture

The aim of this process was to ensure that the limited development time for this project was spent developing the most effective features.

2.1 MoSCoW Requirements

Before considering specific technologies and frameworks, a list of MoSCoW requirements is produced, and is shown in the table below. The first column represents whether the requirement is Functional (F) or Non-Functional (NF), and the second column represents requirements that Must (M), Should (S) or Could (C) be completed.

F / NF	Priority	Requirement Description
		Domain Specific Language - Expressions
F	M	The language must support 5 data types: integers, floats, booleans, strings and date-time objects.
F	M	The language must be able to tolerate null values in the results of a dataset.
F	M	The language must allow users to reference a field in the current dataset.
F	M	The language must allow users to reference a constant value, which can take one of the data types defined above.
F	M	The language must support arithmetic operations like add, subtract, multiply, division and modulo.
F	M	The language must support string slicing and concatenation.
F	S	The language should utilise polymorphism in add operations to apply string concatenation, or arithmetic addition depending on the data types of the arguments.
F	C	The language could be designed in such a way to allow the user to define their own functions.
NF	S	The language should be intuitive to use, with SQL-like syntax.
		Domain Specific Language - Comparisons

F	M	The user must be able to provide expressions as inputs to comparison operators.
F	M	The language must support equals, and not equals comparisons
F	M	The language must support inequalities, using numerical ordering for number types, and lexicographic ordering for strings.
F	M	The language must support null and not null checks.
F	S	The language should support string comparisons, including case sensitive and insensitive versions of contains, starts with, and ends with.
F	S	The language should allow the user to combine multiple comparison criteria using AND and OR operators.
Data Processing		
F	M	The system must allow the user to write queries in Python.
F	M	The system must allow users to apply Select operations on datasets, applying custom expressions to the input data.
F	M	The system must allow users to apply Filter operations on datasets, applying custom comparisons to the input data.
F	M	The system must allow users to apply Group By operations on datasets, which take a number of expressions as unique keys, and a number of aggregate.
F	M	The Group By operation must allow users to apply Minimum, Maximum, Sum and Count aggregate functions to Group By operations.
F	C	The system could allow users to apply Distinct Count, String Aggregate, and Distinct String Aggregate aggregate functions to Group By operations.
F	S	The system should allow users to join two datasets together according to custom criteria.
NF	S	The complexities of the system should be hidden from the user; from their perspective the operation should be identical whether the user is running the code locally or over a cluster.
Cluster		
F	M	The system must allow the user to upload source data to a permanent data store.
F	M	The orchestrator node must split up the full query and delegate partial work to the worker nodes.
F	M	The orchestrator node must collect partial results from the cluster nodes to produce the overall result for the user.
F	M	The orchestrator node must handle worker node failures and other computation errors by reporting them to the user.
F	S	The orchestrator should perform load balancing to ensure work is evenly distributed among all nodes.
F	C	The orchestrator could handle worker node failures by redistributing work to active workers.
F	M	The worker nodes must accept partial work, compute and return results to the orchestrator.
F	M	The worker nodes must pull source data from the permanent data store.
F	M	The worker nodes must report any computation errors to the orchestrator.
F	S	The worker nodes should cache results for reuse in later queries.
F	S	The worker nodes should spill data to disk storage when available memory is low.

NF	S	The permanent data store should be chosen to provide performance benefits when importing source data.

2.2 Language

The first key design decision was to determine what languages would be used to implement the system. A decision was made to use more than one language, because the user interface requirements suit a different type of language to the rest of the system.

2.2.1 Frontend

The most important requirement for the frontend was to use SQL-like syntax. Pure SQL requires a text parser to generate queries, which would add a significant amount of development time to implement, so a language which would be able to encode queries as classes and functions was preferred. Therefore, Python was selected for the frontend, as according to the 2022 StackOverflow Developer Survey, it is the fourth most popular programming language [44]. Python also supports some of the most popular data processing frameworks, NumPy and pandas [46, 20]. Due to Python's popularity, it is likely the widest range of users will have prior experience, and there is the possibility of integrating with these frameworks to further improve the system's usability.

2.2.2 Orchestrator and Worker Nodes

It was decided that the orchestrator and worker nodes will use the same language, as feature overlap between the two is likely. A language with either automatic or manual garbage collection (GC) had to be chosen. Choosing a manually GC language would theoretically allow for higher performance due to more granular control over memory allocation. However, this could slow development, as time would have to be spent writing code to perform this process. Therefore, manually GC languages were ruled out.

The remaining options were a range of object-oriented and functional languages. Much of the project would be CPU intensive iteration over large lists of items, so a language with strong support for parallelisation was preferable. This ruled out languages like Python and JavaScript where parallelisation requires manual implementation by the developer [30, 49].

In the end, Scala was chosen [38]. It features a mix of both object-oriented and functional paradigms, which would allow the best option to be selected for each task. Furthermore, Scala has built-in support for parallelised operations through operations like *map* and *reduce*, which is particularly helpful for iterating or combining the rows of a dataset. Furthermore, it is built on, and compiles into Java, meaning that packages originally written for Java can be executed in Scala, which proved useful for later design decisions [39].

2.3 Runtime

2.3.1 Containerisation

With this being a distributed systems project, the clear choice for executing the code was within containers. Docker is one of the most popular options for creating and executing containers, but is not suitable for running and managing large numbers of containers [33]. For this, a container orchestration tool is required, where there are two main options: Docker Swarm, and Kubernetes [45, 26]. Docker Swarm is more closely integrated within the Docker ecosystem, with direct integration into the Docker engine. However, many cloud services feature managed Kubernetes services which handle the complexity of creating and managing a cluster, so Kubernetes was chosen.

2.3.2 Network Communication

A communication method had to be selected to allow the frontend, orchestrator and worker nodes to communicate. REST API frameworks initially appeared to be a suitable option, but upon further research, remote procedure call (RPC) frameworks would be more suitable. This is because REST is designed to be stateless, providing a standard set of operations, create, read, update, delete (CRUD) [29], whereas the proposed solution is more focused on stateful operations.

In contrast, RPC frameworks are designed to implement custom function calls over a remote network, and are not usually designed around a particular data model like REST, allowing for implementation of a custom query model [43]. The chosen framework was gRPC, designed and maintained by Google [19]. This is because there are well-maintained implementations for both Python and Scala, which would make using it in all parts of the solution straightforward [40]. Also, gRPC uses protocol buffers (protobuf) as its message system, a serialisation format also maintained by Google [35]. Protocol buffers are designed to be more space efficient compared to a solution like XML or JSON, which is useful for transmitting large amounts of data.

2.4 Persistent Storage

There are a wide range of options for persistent data storage. The first key decision was whether to design a custom solution, or use an existing solution. A custom implementation would come with the benefit of being more closely integrated with the rest of the system, at the cost of increased development time. A decision was made not to create a custom solution due to time constraints, and the amount of work required to achieve this. A number of types of existing file systems and databases were instead considered, but ultimately not selected:

- Single System SQL Databases *(Microsoft SQL Server, PostgreSQL, MySQL)*: while this option would be fastest to start using due to extensive industry support, the database would quickly become a bottleneck, as all nodes would import data from the same location.
- Distributed File Systems *(Hadoop Distributed File System)*: these provide a mechanism for storing files resiliently across a number of machines, removing the data import bottleneck. However, they provide no way of querying the stored data, so this feature would have to be implemented manually.
- Distributed NoSQL Databases *(MongoDB, CouchDB)*: these spread the load of reading the data across a number of machines. However, the expected input data is tabular, meaning the features of a NoSQL architecture are not required. This is likely to result in added complexity when importing data, and increased development time.

2.4.1 Apache Cassandra

Apache Cassandra was chosen as the persistent storage mechanism for a number of reasons [27]. Firstly, the data model is tabular, as is the expected input data. Furthermore, Cassandra is a distributed database, so the source data will be stored across a number of nodes. This will increase the effective read speed when retrieving data, as the full load will be spread between the nodes.

Partitioning Cassandra's method of partitioning data is another key reason why it was selected. When data is inserted into the database, Cassandra hashes the primary key of each record, producing a 64-bit token that maps it to a node. Each node in the database is assigned part of the full token range, which determines what records it holds [27]. Figure 2.4.1 demonstrates how the full range of tokens is distributed among a number of Cassandra nodes.

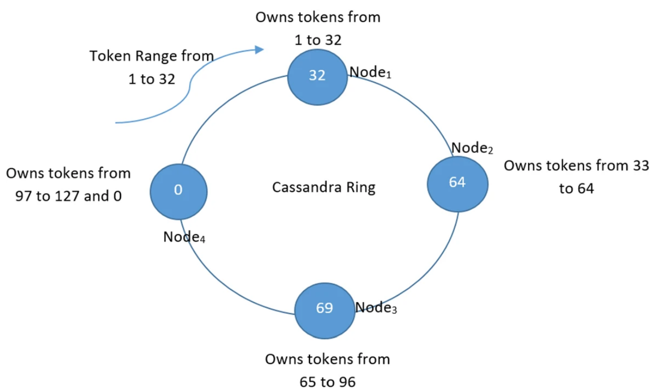


Figure 2.4.1: Cassandra Token Ring Distribution [25]

Cassandra allows token ranges to be provided as filters in queries, meaning the worker nodes can split up and control the data they read from the database, to read smaller chunks.

Data Co-Location Cassandra can be run on Kubernetes using K8ssandra [24]. This is particularly useful because the Cassandra cluster can be configured to run on the same machines as the worker nodes, enabling the source data to be co-located with the workers that will actually perform the computation. This decision meets the requirement to exploit the integration between the storage mechanism and cluster nodes, as data co-location will reduce the network latency when importing the source data, and increase transfer speed if the data never leaves the same physical machine.

Language-Specific Drivers For interfacing with the other components, there are drivers for both Python and Java which provide basic functionality for making queries and receiving results from the database [10, 11]. There are optional modules for these drivers, and Scala-specific frameworks with more complex features, but these were not included in the solution as the extra functionality was not required, and the added complexity had the potential to cause problems.

2.5 Architecture

Based on the above design choices, a high level diagram was produced, detailing each of the system's components and the interaction between them, shown in Figure 2.5.1. The user will be able to define queries using the Python frontend, which are then sent using gRPC to the orchestrator. It will break the full query up into partial queries, which will be computed on the worker nodes. When the computation is complete, the workers will return the result data to the orchestrator, which will then return the collated result to the frontend.

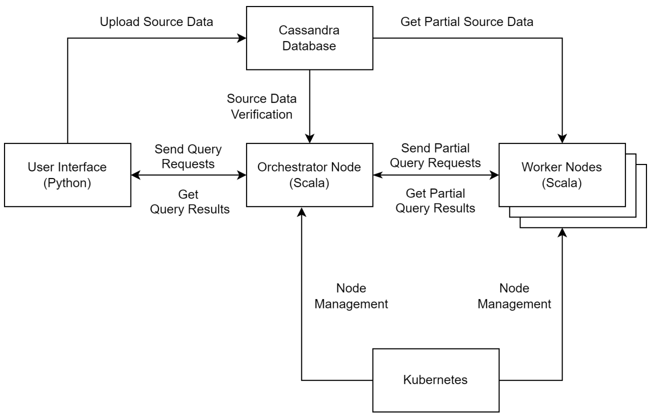


Figure 2.5.1: Proposed Solution - Overall Architecture

Chapter 3

Implementation

A number of components were created to implement the proposed architecture. This chapter will provide a high level overview of the solution, then examine each component in further detail.

3.1 Overall Solution

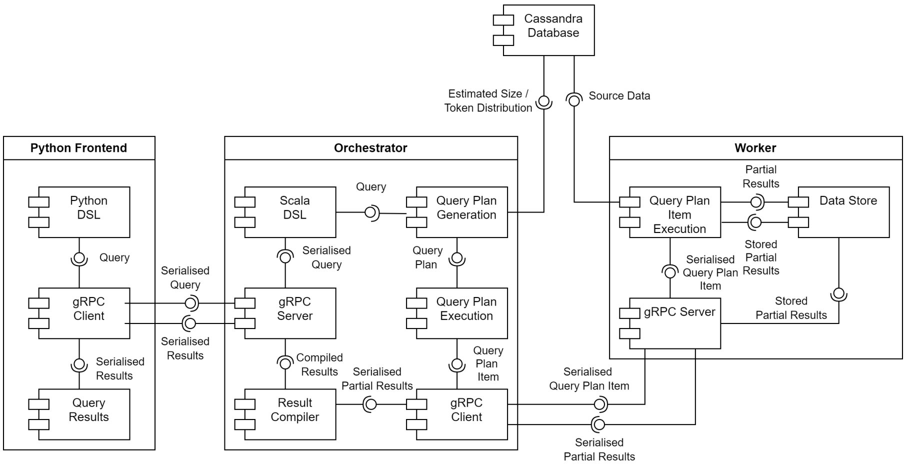


Figure 3.1.1: Solution Component Diagram

Figure 3.1.1 shows a component diagram for the core components, and their interactions. As described in Section 2.5, the frontend is the user's entrypoint to the system. It acts as a terminal, allowing the user to define queries using the Python Domain Specific Language (DSL), and receive results. Queries are sent to the orchestrator, which acts as the central state management for the system. First, it generates a query plan which describes the steps for computing a result. Then, the query plan is executed step-by-step, with the data used in each step being split up into a number of chunks of work (partitions) before being delegated to the workers. The workers are responsible for accepting these partitions, and performing the computation. Finally, when all query plan steps have been executed, the orchestrator fetches partial results from all workers, collates them into a final result, and returns this to the frontend. gRPC is used anywhere where network communication is required between the frontend, orchestrator and worker nodes.

The system supports three types of queries: Select, Filter and Group By. Both Select and Filter are row-level operations, meaning the workers do not have to pass data to one another during computation.

However, Group By does need the workers to cross-communicate, which means they also require a temporary store to cache partial results.

3.2 Type System

The type system's role is to provide a representation for every type of value the user can store within a table. However, designing the interfaces to represent these values presents a challenge. Figure 3.2.1 demonstrates the problem.

On the left, an example is shown where a table is a 2D list of raw values. As multiple types are stored in the same list, there is no shared type information between the values, they cannot be used to determine the table's contents. To discover a value's type, the system would have to perform runtime type checks against all supported types, adding a significant amount of overhead.

On the right, a conceptual model using a container class is shown. The container stored a raw value with the type information about the value, and the table is a 2D list of containers. The system only needs to perform one runtime type check in order to instantiate the correct container instance.

Header:	[	id,	name	]
Row 1:	[	1,	"Alice"	]
Row 2:	[	2,	"Bob"	]

(a) Raw Data - No Type Information Available

Header:	[	(id, int),	(name, string)	]
Row 1:	[	(1, int),	("Alice", string)	]
Row 2:	[	(2, int),	("Bob", string)	]

(b) Container Class - Value and Type Information Stored Together

Figure 3.2.1: Type System - Motivating Example

Due to Java limitations, this conceptual solution is not straightforward to implement. The container class could use a generic type parameter which stores the type information of the value, but generic type information is erased at runtime [16]. Instead, it could be defined as an interface, with subclass implementations for each supported type, but this is not much better than the raw data solution, as the runtime type check simply becomes a pattern match on the class type. A solution that exploits some kind of polymorphism is preferred.

Scala provides a feature known as *ClassTags* [9]. These save erased type information and permit equality checks between *ClassTag* instances, meaning the framework can use them to compare the type of a value to an expected type. The conceptual container class is therefore defined as an interface *ValueType*, which holds a *ClassTag* instance. This interface is implemented by *TableField*, which holds a field name and its type, and *TableValue*, which holds a value and its type. Concrete implementations for the 5 supported types described in Section 3.2.1 are provided for both subclasses. Figure 3.2.2 shows the class hierarchy.

3.2.1 Supported Types

The type system supports a subset of Scala, Python, and Cassandra's types, shown in Figure 3.2.3.

The main goal when selecting these primitive types was to ensure all types could be represented in all parts of the system. This includes protobuf format, which would allow for easy serialisation of result data. All types except DateTime can be converted to protobuf natively, and DateTimes are supported by serialising as an ISO8601 formatted string [23].

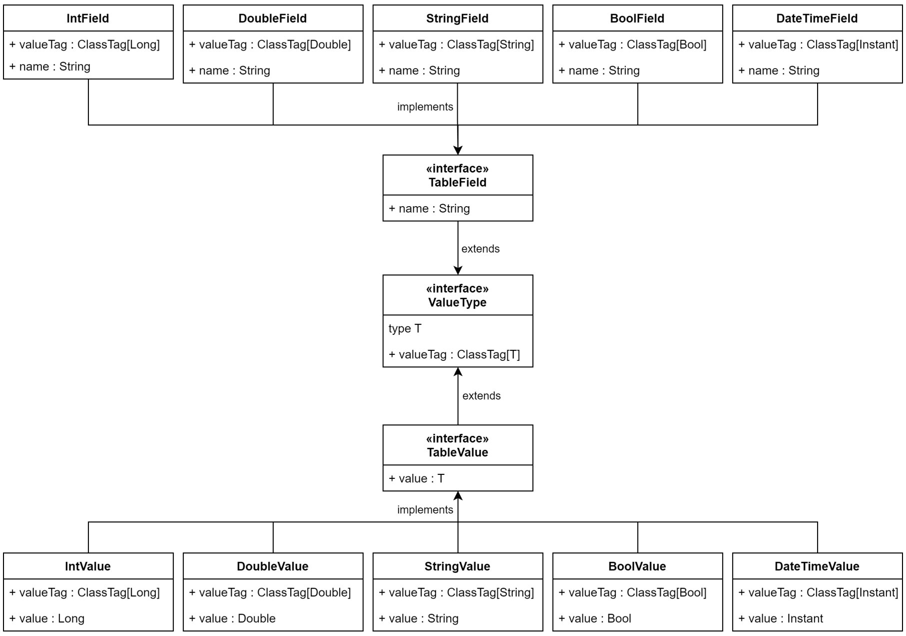


Figure 3.2.2: Custom Type System Hierarchy

Base Type	**Python**	**Scala**	**Cassandra**
Integer	int	Long	bigint
Float	float	Double	double
String	string	String	text
Boolean	boolean	Boolean	boolean
DateTime	datetime	Instant	timestamp

Figure 3.2.3: Primitive Types

3.2.2 Result Model

The hierarchy of classes and supported types provide everything needed to define a table of result data, known as a *TableResult*. Headers are a sequence of *TableFields* and result rows are a two-dimensional array of `Option[TableValue]`. As defined in the requirements, null values must be supported, but this is discouraged in Scala. Instead, Option is preferred as it is supported by all the typical functional methods. In this model, values are represented by `Some(TableValue())`, and null values are represented by `None`. Figure 3.2.4 shows an example *TableResult*.

Header:	[	IntField("ID"),	StringField("Name"),	BoolField("Passed")	]
Row 1:	[[	Some(IntValue(1)),	Some(StringValue("Alice")),	Some(BoolValue(true))	],
Row 2:	[	Some(IntValue(2)),	None,	None	],
Row 3:	[	Some(IntValue(3)),	Some(StringValue("Bob")),	None	]]

Figure 3.2.4: *TableResult* example

3.3 Domain Specific Language

The user's interaction with the framework is driven entirely by the Domain Specific Language (DSL), which is modelled with SQL-like syntax. It allows users to define expressions, then use these in computations like Select, Filter and Group By. Figure 3.3.1 shows a DSL query, with links to the sections where each part is discussed further.

3.3.1 FieldExpressions

FieldExpressions are a key part of the DSL, allowing the user to define arbitrary row-level calculations. They are defined as an interface, with three subclasses:

- Values: define literal values which never change across all rows
- Fields: get the value at the current row for the given field name.
- FunctionCalls: perform arbitrary function calls using *FieldExpressions* as arguments.

Figure 3.3.2 provides examples for each type of *FieldExpression*.

Many basic functions have been implemented, including arithmetic, string and cast operations. However, the function system is designed to be extensible. A number of helper classes are provided to allow the creation of unary, binary and ternary functions, but *FunctionCall* is itself an interface which can be given custom implementations if required, with the main constraint being that functions can only take the 5 primitive types as arguments.

Type Resolution Type Resolution is performed in two stages: resolution, and evaluation. The resolution step takes in type information from *ClassTags* in the input result header, and verifies that the *FieldExpression* is well-typed with regards to that result by comparing *ClassTags*; see Section 3.2 for details. The evaluation step performs the computation on a *TableResult* row without any type checking. Unchecked casts are used here instead, demonstrated for a binary function in Figure 3.3.3.

There are two key errors the resolution step is designed to catch. Firstly, a Field reference is invalid if the field name is not present in the table header, shown in Figure 3.3.4. Secondly, a Function call is invalid if an argument returns an invalid type, shown in Figure 3.3.5.

A two-step process has a number of benefits. The resolution step enables a form of polymorphism on some functions like arithmetic operations. These determine what types are returned by their

Initialise cluster connection and select a Cassandra source table:

```
ClusterManager("orchestrator-url")
  .cassandra_table("example", "table")
```

Select query, uses *FieldExpressions* (Section 3.3.1) and Python Operators (Section 3.3.5):

```
  .select(
    F("id"),
    (F("duration") * 2).as_name("duration2"),
    Function.Left(Function.ToString(F("date")), 8)
      .as_name("yyyy-mm")
  )
```

Filter query, uses *FieldComparisons* (Section 3.3.2) and Python Operators (Section 3.3.5):

```
  .filter(
    (F("duration2") > 40) &&
        (F("yyyy-mm").contains("2021")
  )
```

Group By query, uses *AggregateExpressions* (Section 3.3.3):

```
  .group_by(
    [F("duration2")],
    [
      Max(F("id")),
      Count(F("yyyy-mm"))
    ]
  )
```

Figure 3.3.1: Example DSL Query

Values (from left to right): string "a", integer 1, double 1.5, boolean True, date 31/12/2021.

```
V("a") , V(1), V(1.5), V(True), V(datetime.date(2021, 12, 31))
```

Fields (from left to right): fieldName, duration, id, creationDate.

```
F("fieldName"), F("duration"), F("id"), F("creationDate")
```

Top Function: convert 'field1' to a string, then take the left 10 characters of each row.
Bottom Function: multiply 'field2' by 2, then divide by "field3"

```
Function.Left(Function.ToString(F("field1")), 10)
(F("field2") * 2) / F("field3")
```

Figure 3.3.2: *FieldExpression* implementations and examples

```
val resolvedLeft = left.resolve(header)
val resolvedRight = right.resolve(header)
return ResolvedFunctionCall((row) =>
    resolvedLeft.evaluate(row).flatMap(l =>
        resolvedRight.evaluate(row).map(r =>
            // Extract inner values from left and right arguments, and perform unchecked cast
            // to convert to runtime type (type checking already performed by .resolve)
            function(l.value.asInstanceOf[LeftArgType], r.value.asInstanceOf[RightArgType])
        )
    )
)
```

Figure 3.3.3: Runtime Evaluation of Functions

For the expression F("field"):

(a)	(b)
Header: [IntField("field")]	**Header:** [StringField("differentField")]
(a) Valid - "field" is present in the header	(b) Invalid - "field" not present in the header

Figure 3.3.4: Type Resolution of Fields

Valid - both arguments to *Concat* are strings:

```
Function.Concat(V("hello"), V("Alice"))
```

Invalid - *V(1)* is not a string:

```
Function.Concat(V("hello"), V(1))
```

Figure 3.3.5: Type Resolution of Functions

sub-expressions during resolution, and change their behaviour for evaluation. For example, the add function resolves to *AddInt*, *AddDouble*, or *Concat*. It also reduces the overhead at runtime as type checking does not need to be performed for each row.

Named Expressions When performing a Select operation, the output fields are all expected to be named to allow the user to chain operations by referencing fields from the previous input. Figure 3.3.6 shows the two ways of naming a field: *FieldExpressions* can be assigned a name, and single Field references will keep their previous name.

Top Expression Name: 'twice_duration'
Bottom Expression Name: 'creation_date'

```
(F("duration") * 2).as_name("twice_duration")
F("creation_date")
```

Figure 3.3.6: *NamedFieldExpression* examples

3.3.2 FieldComparisons

FieldComparisons are another key part of the DSL, allowing the user to define arbitrary row-level comparisons. They are defined as an interface, with a number of comparison types already implemented, including null, equality, numerical and string comparisons. Examples of each are shown in Figure 3.3.7.

Null checks: verify whether an expression is null or not null.

```
F("duration").is_null()
F("duration").is_not_null()
```

Equality checks: verify whether two *FieldExpressions* are equal or not equal.

```
F("duration") == 20
F("duration") != F("other_duration")
```

Ordering checks: apply ordered comparators between two *FieldExpressions*.

```
F("duration") < 20
F("duration") <= 19
F("duration") > 20
F("duration") >= 21
```

String checks: apply contains, starts with and ends with operators (case insensitive versions also available).

```
F("name").contains("Alice")
F("name").starts_with("Bob")
F("name").ends_with("Smith")
```

Figure 3.3.7: *FieldComparison* examples

Combined Comparisons The user can combine multiple FieldComparisons using AND/OR operators, shown in Figure 3.3.8. This is a lightweight wrapper around Scala's own boolean operators, meaning optimisations like short circuiting operate as normal.

```
(F("duration") < 20) && (F("name").starts_with("Bob"))
(F("duration") < 20) || (F("name").starts_with("Bob"))
(F("duration") < 20) && (
  (F("name").contains("Bob")) || (F("name").contains("Alice"))
)
```

Figure 3.3.8: *FieldComparison* AND/OR Combinations

3.3.3 Aggregate Expressions

AggregateExpressions are the final part of the DSL. These are used only as part of Group Bys, allowing the user to aggregate all rows of a result. They take a *NamedFieldExpression* as an argument, and compute a single row output from any number of input result rows.

The supported operations are Minimum, Maximum, Sum, Average, Count, and String Concatenation, and they are polymorphic where possible. For example, minimum and maximum handle numeric types by ordering numerically and string types lexicographically. Figure 3.3.9 shows examples of *AggregateExpressions*.

```
Max(Function.ToString(F("date")).as_name("date_string"))
Max(F("duration"))
Sum(F("amount"))
Count(F("id"))
```

Figure 3.3.9: *AggregateExpression* examples

3.3.4 Protocol Buffer Serialisation

All components of the DSL are designed to be serialised to protobuf format, allowing any queries written by the user to be sent using gRPC. The results of a query are also serialisable, to allow the system to return query results to the user. gRPC has a size limit of 4MB for individual messages, so *TableResults* are streamed row-by-row.

3.3.5 Python Implementation

The Python frontend is designed to be straightforward to use, hiding the complexities of the computation being performed in the backend. A number of Python-specific features were used to help with this.

Python allows developers to override common operators with custom definitions. The Python implementation of *FieldExpression* overrides the arithmetic operators, as well as comparison operators to allow the user to automatically generate functions and *FieldComparisons*, without having to write the full definition.

Furthermore, as discussed in 2.2.1, pandas is widely used for Python data analysis [46]. The frontend is able to convert query results from protobuf to a pandas DataFrame to aid further analysis.

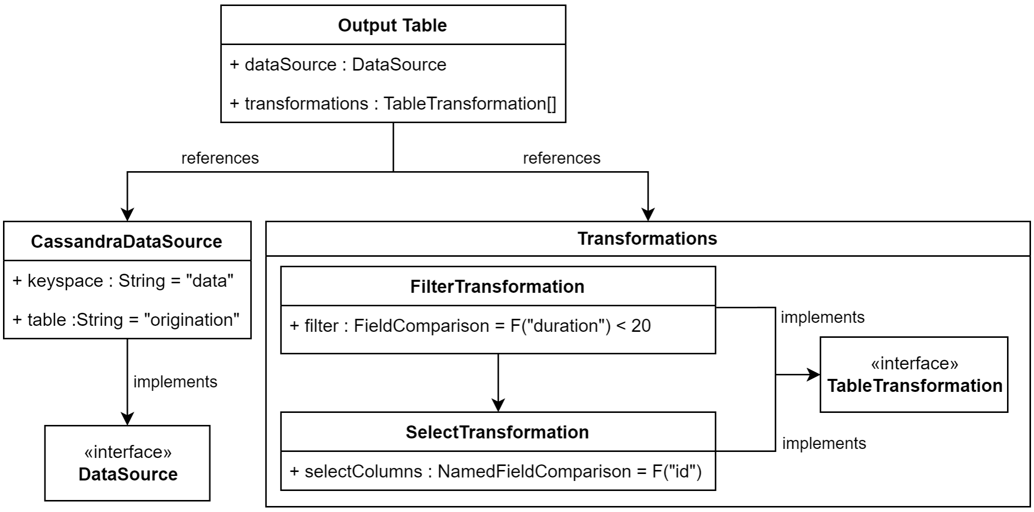
3.4 Data Model

The data model is split into two key components: *DataSource* and *Table*.

DataSource is an interface, representing any part of the query where data must be rearranged into new partitions, including Cassandra source data, and Group By operations. *Table* is a class, representing any part of the query containing purely row-level computations, like Select and Filter, which must implement the *TableTransformation* interface. It is composed of a *DataSource* and a list of row-level computations known as *TableTransformations*. To compute its output, the *DataSource* is computed first, then all transformations are applied sequentially.

Optionally, *DataSources* can have dependent *Tables* which must be calculated first. For example, a Group By *DataSource* requires a single *Table* to be computed before it can be generated. A Cassandra *DataSource* will always act as the terminal component for a query, as it has no dependencies.

Figure 3.4.1 shows a Filter and Select query in the DSL, and the data model representation. Note that any number of Select and Filter operations can be added to the Table component, as no new partitions are required to generate the result.

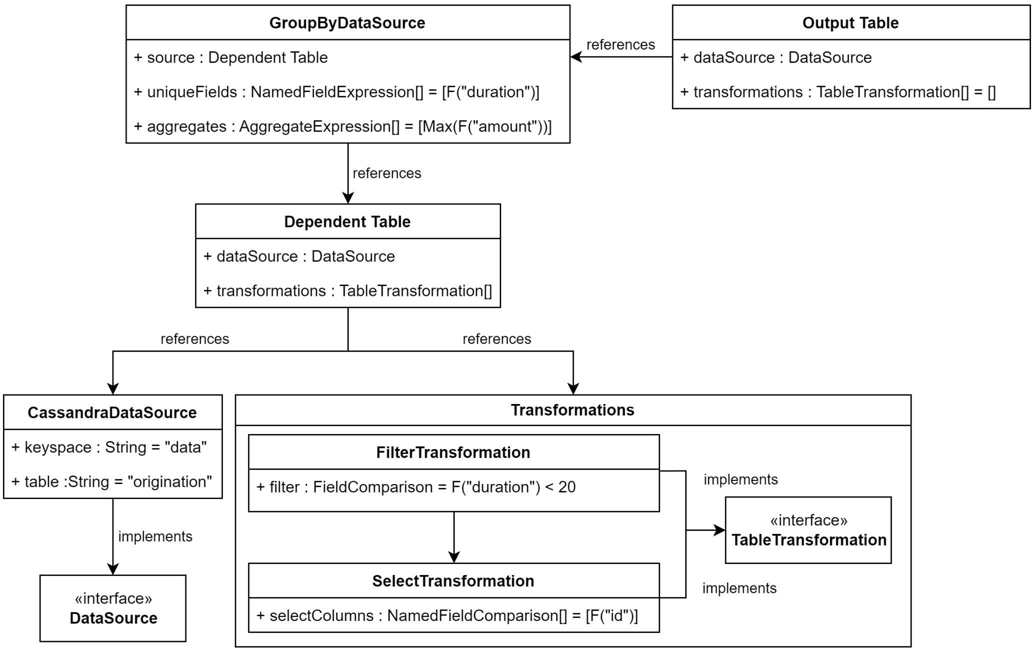



```
ClusterManager("orchestrator-service")
.cassandra_table("data", "origination")
.filter(F("duration") < 20)
.select(F("id"))
.evaluate()
```

Figure 3.4.1: Example Filter and Select Query

Figure 3.4.2 shows a query containing a Group By in the DSL, and the data model representation. The dependent table (bottom left) is calculated first, and its output is used to compute the Group By, in *GroupByDataSource*. The final output is then generated in the output table.

A *Table* or *DataSource* cannot be computed directly, but must first be split into partitions, which are provided by the *DataSource*. These partitions are represented by the interface *PartialDataSource*, with the partitioning method being specific to each implementation. The *Table* class has a similar partial form, *PartialTable*, which references a *PartialDataSource* and can be computed directly. To demonstrate how to produce a final result from a set of partial results, Figure 3.4.3 shows a high level example of one possible way of partitioning and computing the previous Filter and Select query.




```
ClusterManager("orchestrator-service")
.cassandra_table("data", "origination")
.filter(F("duration") < 20)
.select(F("id"))
.group_by([F("duration")], [Max(F("amount"))])
.evaluate()
```

Figure 3.4.2: Example Group By Query

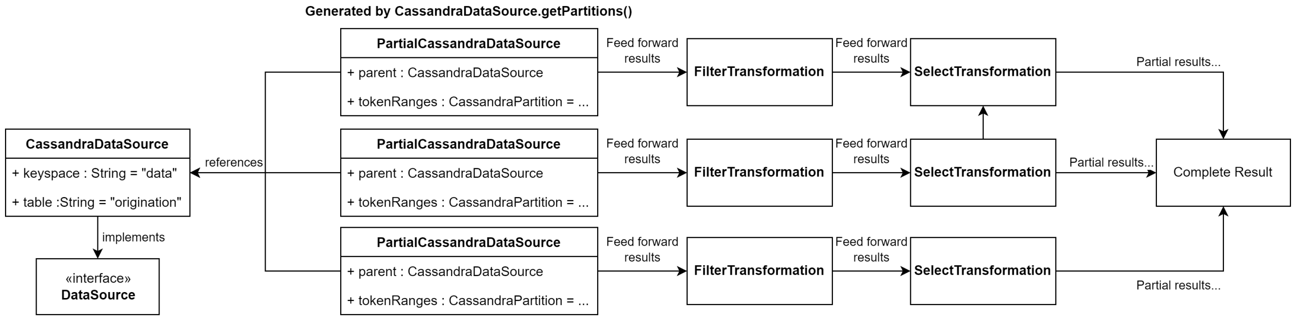


Figure 3.4.3: Example Filter and Select Query

3.5 Data Store

The data store is the most important component of the worker. It allows the workers to store partially computed data, which can be reused in later parts of the query execution. In particular when workers are communicating with one another, it is likely that the worker will be processing more than one request at the same time, which presents issues with handling concurrency and synchronisation.

The approach taken to solve this uses the actor model, first introduced in 1973 by Carl Hewitt [21]. Specifically, the Akka Actors framework was chosen as an implementation of the actor model in Scala [1]. The actor model abstracts away the complexity of synchronisation and thread management. Instead, components of the system become actors. Each actor defines a set of messages that it accepts, and the response to each message, and the framework provides a guarantee that an actor will only ever process one message at a time.

The data store is modelled as an actor which stores results as key-value pairs. Three kinds of data can be used as keys for storage: *Table* computation results, *DataSource* computation results and hashed data results, which are used in the process of computing a Group By partition.

For each supported type of data, the data store uses a two-stage lookup, internally implemented using nested HashMaps. First, the full version of the data (*Table* or *DataSource*) is looked up, then the partial version (*PartialTable* or *PartialDataSource*). Partial forms always contain a reference to the full version, but not the other way around. Therefore, this decision does not increase the time taken to insert new data significantly, but it is particularly useful when fetching the results for a *Table*, or removing a *Table* or *DataSource*. Without this approach, completing these operations would require searching the entire HashMap to find any matches, turning the O(1) lookup time into O(n).

3.5.1 Spill to Memory

When operating over very large datasets, the workers will have less memory available than is required by to load the dataset. In this case, it is likely that the JVM will run out of heap space, causing a crash when it attempts to allocate more memory. Therefore, workers have a module which allows them to move cached data onto disk to free up heap space. This module is part of the data store, and functions transparently for the other worker components - data store queries operate identically whether the result is in-memory or on-disk.

Storage Interface To implement the spill process, an interface, *StoredTableResult*, is defined. This interface holds a key which corresponds to a result, and a *get* operation to retrieve the result data. There are two main subclasses with implementations: *InMemoryTableResult* and *ProtobufTableResult*.

InMemoryTableResult simply contains the result and holds it in memory. It also features a *spillToDisk* method which moves the data onto disk by creating a file under a randomised folder name for each execution, with the name set to the key's hashcode.

ProtobufTableResult only holds a pointer to the data on disk, and reads the data from there when the *get* operation is called. A cleanup method removes the stored data from disk when called.

Spill Process The data store is responsible for managing in-memory and on-disk data. Before almost every operation on the data store, it checks current memory utilisation, which is calculated using a set of methods on Java's *Runtime* class [37]. If the memory utilisation is over a given threshold, the data store attempts to spill data to get below the threshold.

Figure 3.5.1 shows how the amount of bytes over a percentage threshold is calculated. The division calculates the current memory utilisation percentage, then the threshold is subtracted to get the percentage amount over the threshold. This is multiplied by the total number of bytes to get the result.

$$\left(\frac{\text{Bytes in Use}}{\text{Total Bytes Available}} - \text{Threshold}\right) * \text{Total Bytes Available}$$

Figure 3.5.1: Number of Bytes Over Memory Threshold

To perform the spill, the data store will follow the decision tree shown in Figure 3.5.2. Afterwards, the data store forces the JVM to perform Garbage Collection to immediately free the spilled memory.

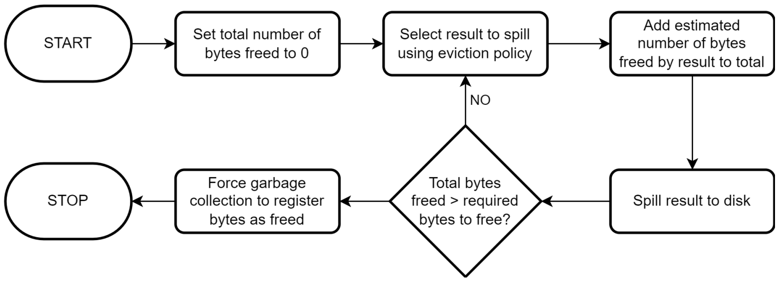


Figure 3.5.2: Spill to Disk Decision Tree

This process is not without flaws. It relies on no other classes in the current JVM instance holding references to any spilled results. In the controlled worker environment, it is possible to guarantee this, meaning the spill works reliably, but this approach would not work more generally. Furthermore, this approach is reliant on size estimates, meaning the actual amount of memory freed is not equal to the estimated memory freed. With a suitably low spill threshold (60-70% of maximum memory) and regular checks of memory utilisation, this approach works successfully.

Eviction Policy Finally, the policy for determining results to spill is important. A policy that does not fit the data store's access patterns could result in large performance impacts, as it could cause antipatterns like the data store spilling a result, then immediately reading it back to memory.

The data store uses a least-recently-used (LRU) policy to select a result to spill, implemented using an ordered list containing all in-memory results. When results are inserted into the data store, they are appended to the list. When results are read from the data store, they are moved to the end of the list. When a result must be selected for spill, the head of the list is chosen and removed.

3.6 Partitioning

One of the most important roles of the orchestrator during a computation is to calculate partitions. There are two situations where this is required: when pulling source data from Cassandra, and when computing a Group By. The *DataSource* interface is the representation for computations that require new partitions. The goal of partitioning is to split the dataset into roughly equal chunks of a manageable size, two things are required to do this: an estimate of the full size of the dataset, and a way of splitting the dataset up to keep unique keys together. These are referred to as the partitioning requirements.

3.6.1 Cassandra

Cassandra was selected for persistent storage because its features already meet the partitioning requirements. As discussed in Section 2.4.1, Cassandra natively provides a way of splitting the source dataset through its token range system. Furthermore, Cassandra provides size estimates for the full size of any table automatically in the `system.size_estimates` table.

A table size estimate can be used to derive the size estimate of a token range using the equation in Figure 3.6.1. The division calculates the percentage of the full token range that the given token range represents.

$$\frac{\text{Number of Tokens in Token Range}}{\text{Total Number of Tokens: } ((2^{63}-1)-(-2^{63}))} \times \text{Estimated Table Size}$$

Figure 3.6.1: Token Range Size Estimation Equation

Using this equation, the token ranges which each node is responsible for storing are collected. Then, the orchestrator performs a joining and splitting process over each node, depending on the size of the token ranges. The set of token ranges produced by this process are the partitions used during the computation. Figure 3.6.2 shows the full process for generating the output partitions.

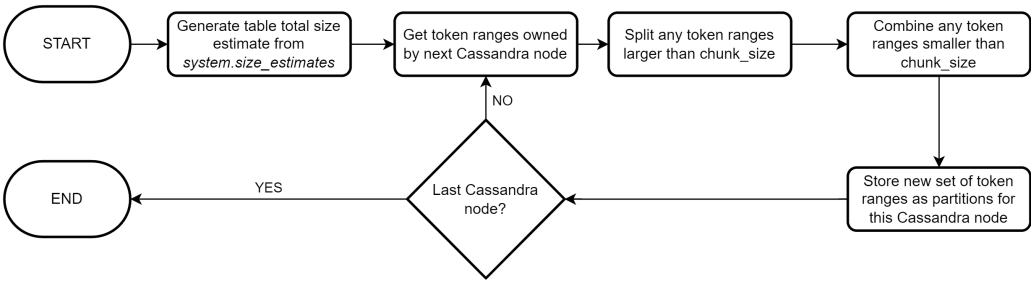


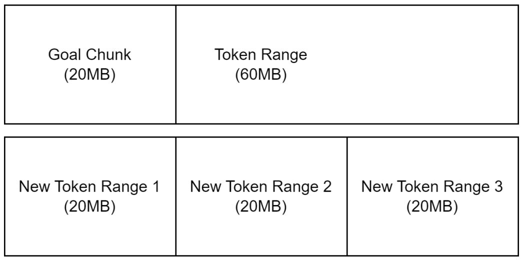
Figure 3.6.2: Cassandra Partitioning Process

Figure 3.6.3 demonstrates the token splitting process. The system calculates how many times larger the token range is than the goal partition size, then splits the token range evenly by that amount.

Figure 3.6.4 provides an example of the joining process. Given a list of token ranges, the orchestrator combines sequential elements until they are larger than the goal partition size, then it marks this as a new partition. The list is sorted by size ascending to ensure the smallest number of partitions are created - if there are a large number of very small token ranges, these will be combined into a single large partition.

$$\text{Number of Splits} = \frac{\text{Token Range Size}}{\text{Chunk Size}}$$

(a) Equation



(b) Example

Figure 3.6.3: Token Range Splitting

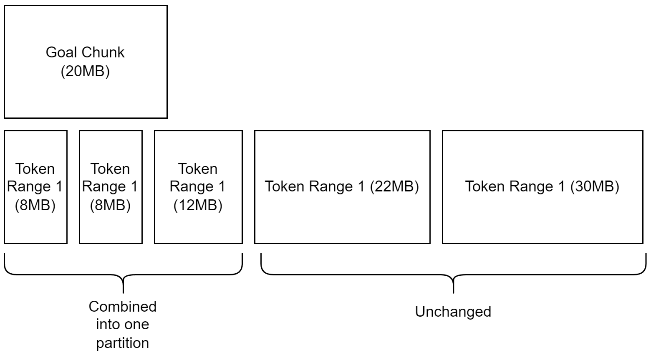


Figure 3.6.4: Token Range Joining Example

The Cassandra Java Driver provides helper functions to perform the joining and splitting of token ranges; the system simply calculates how much joining or splitting is required.

3.6.2 Cassandra Data Co-Location

From a list of partitions for each Cassandra node, the system attempts to co-locate workers to Cassandra nodes. The goal of this process is to produce an *optimal assignment*, where each partition is matched to one or more workers to minimise network latency when fetching the data from Cassandra.

To do this, each worker first calculates its closest Cassandra node by opening a TCP connection with each Cassandra node, and averaging the latency over multiple attempts. The node with the lowest latency is selected. The orchestrator uses this information to match each worker to a Cassandra node and its corresponding list of partitions, producing an optimal assignment between workers and partitions. More than one worker can match with the same set of partitions, and a set of partitions can have no co-located worker nodes. In this case, the partitions are unassigned, and the work assignment algorithm handles their allocation. Figure 3.6.5 shows an example cluster with three physical nodes, and the resulting optimal assignment.

3.6.3 Group By

The Group By operation takes any number of *NamedFieldExpressions* for unique keys, and any number of *AggregateExpressions* to calculate for each combination of unique keys. This operation is not reliant on external components, so custom implementations must be used to meet the partitioning requirements.

The process of calculating a Group By is described below. These steps are controlled by the orchestrator during the execution of *GetPartition*; see Section 3.8.1 for details.

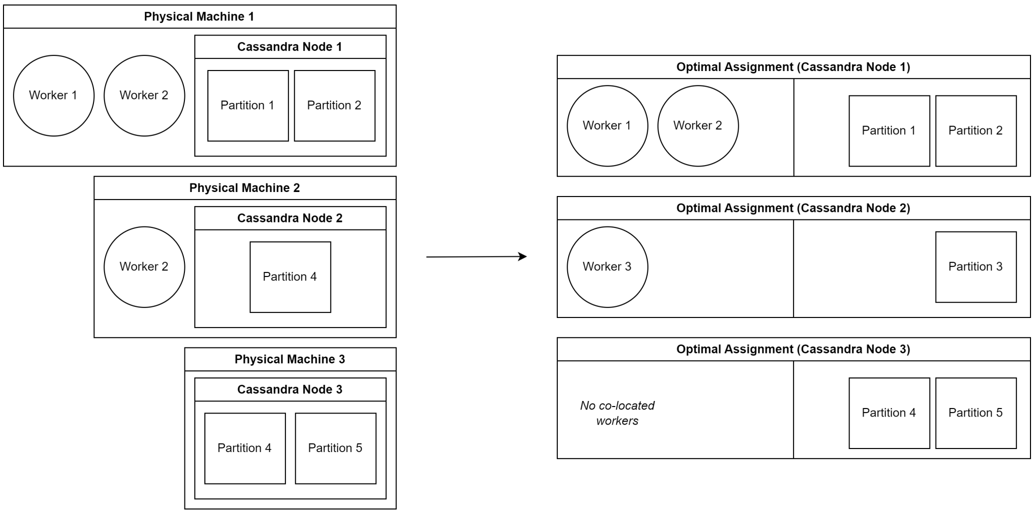


Figure 3.6.5: Optimal Assignment Example

Partitions The first step is to compute the number of output partitions for the Group By, which is based on a size estimate of the dependent *Table*. To generate this, a class from Apache Spark was reused, with some changes for compatibility with Scala 3 [51]. This class provides a static method *estimate* which produces a size estimate, in bytes, for any Scala object. The orchestrator calls this on all partial results across all workers, and the estimates are totalled to calculate the total size of all data for a *Table*. Figure 3.6.6 shows how the size estimate can be used to derive the total number of partitions to generate for a *Table*.

$$\frac{\text{Table Size Estimate}}{\text{Goal Partition Size}}$$

Figure 3.6.6: Group By - Total Partitions

Hashing A unique partition is defined as a tuple, shown in Figure 3.6.7. Hashing, combined with the modulo operation, is used to assign rows of data to partitions. In particular, Murmur3Hash is used as the hashing algorithm, used in Cassandra and provided natively by Scala [31]. Figure 3.6.8 shows the high level equation for assigning rows to partitions. This equation maps all rows with the same combination of unique keys to the same partition.

$$(\text{Total Number of Partitions}, \text{Partition Number for this Partition})$$

Figure 3.6.7: Group By - Unique Partition Definition

Computation After the hashes are computed and a worker is assigned a particular partition, it must cross-communicate with all other workers to fetch any data relating to that partition to ensure that the partition data is complete. To do this, the worker makes requests to all other workers, and they stream the header and rows of their partial data back to the worker. When a Group By is being computed, a worker will likely be simultaneously receiving data from another worker, and sending a different set of data to it. This makes the actor system driving the data store in each worker

$$Murmur3Hash(\text{Unique Key Data}) \;\%\; \text{Total Partitions}$$

Figure 3.6.8: Group By - Row Partition Assignment

particularly valuable, as it provides thread-safe concurrent access to the data store.

Once a worker has collected all data for a partition, it must compute the Group By. Scala features a built-in Group By function, which this operation uses. The values for the unique keys of the Group By are calculated for each row, and the rows are placed into groups based on those values. Then, the aggregate functions are computed for each of the groups, resulting in one output row for each combination of unique keys.

Deletion The last step of computing a Group By is to remove the hashed partition data stored on each worker, which is handled by the orchestrator automatically.

3.7 Row-Level Computations

Once partitions have been delegated to the workers, performing the computation is straightforward. Included below are descriptions of calculating the Select and Filter operations.

3.7.1 Select

This operation takes any number of *NamedFieldExpressions*. To compute a result, each *NamedFieldExpression* is applied to each row of the input result.

3.7.2 Filter

This operation takes a single *FieldComparison*, or *FieldComparisons* combined using boolean operators. To compute, each comparison is applied to each row of the input result, removing any rows where the comparison returns `false`.

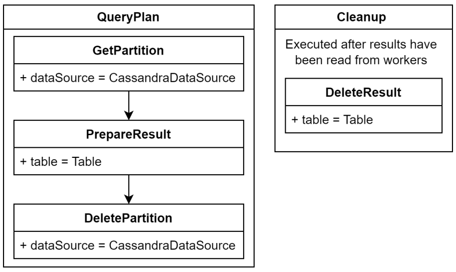
3.8 Query Plan

Query plans are the process through which the orchestrator can get from a user-defined query, to a computed result. A Query Plan is made up of a sequence of *QueryPlanItems*, which define one query plan step. Each *QueryPlanItem* has an *execute* method, which will make some change to the state of all workers in the cluster when called. There are four main QueryPlanItem implementations to calculate and delete *DataSources* and *Tables*. Both *DataSource* and *Table* have a function that generates the full Query Plan to compute their output from scratch, as well as a second Query Plan to clean any result in the data store.

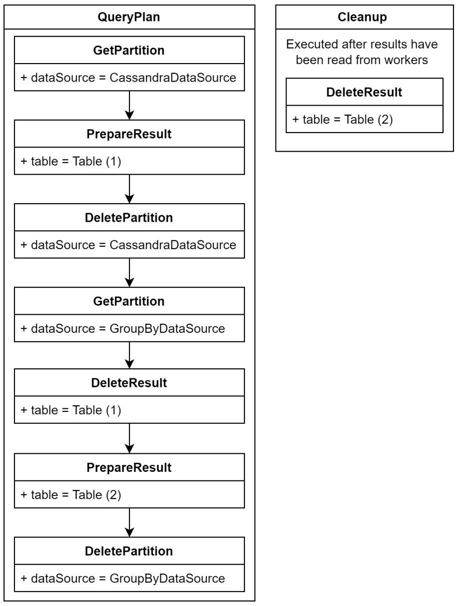
Figure 3.8.1 shows the query plans for the Filter and Select query (3.4.1) and Group By Query (3.4.2).

3.8.1 GetPartition

This is the most complex *QueryPlanItem*, encapsulating a number of steps in order to compute and store the partitions of a *DataSource*. There are two main flows depending on if the *DataSource* has dependent Tables.



(a) Filter and Select Query



(b) Group By Query

Figure 3.8.1: Query Plans - Filter-Select and Group By Query

If the *DataSource* has no dependencies, for example when pulling data from Cassandra, then Figure 3.8.2 shows the process for this item.

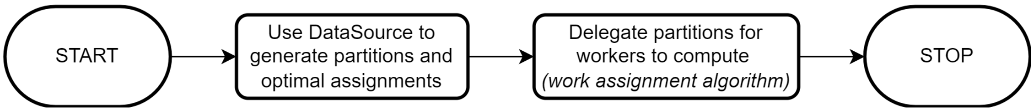


Figure 3.8.2: Get Partition Execution - Without Dependencies

If the *DataSource* has dependencies, then Figure 3.8.3 shows the process for this item. First, the partitions and optimal assignments are generated, then the dependency data is hashed based on the number of partitions to generate. Both of these steps are implementation-specific, and are therefore abstracted behind the *DataSource* interface.

The work assignment algorithm is then run to delegate partitions to the workers, followed by deleting the hashed dependency data. These steps do not change based on the *DataSource*, so are handled exclusively by *GetPartition*. These steps are the same as when calculating a Group By (Section 3.6.3).

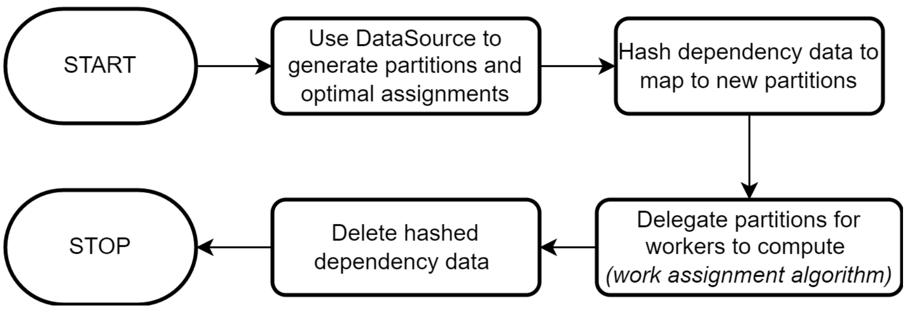


Figure 3.8.3: Get Partition Execution - With Dependencies

Work Assignment Algorithm The details of how the partitions are actually computed are abstracted behind the *DataSource* interface as they are implementation specific, but GetPartition always manages the process of sending requests to the workers to compute the partitions using the Work Assignment Algorithm.

A simple solution would be to use a round-robin process to match optimal assignments to their workers, delegating work when a request finishes and stopping when the assignments are empty. However, this can result in idle workers, for example if one worker's list of optimal assignments is shorter than the others, or if one worker is unexpectedly slow.

Ideally, workers would compute all of their own optimal partitions first, then compute the partitions that were originally assigned to other workers. This implements a form of dynamic load balancing: a faster-running worker can take on proportionally more requests, and no worker will be idle unless all partitions are computed. However, race conditions need to be avoided, like delegating same partition twice to different workers.

The actor model, used previously in the data store, is ideal for this situation. Sets of optimal partitions are modelled as *producer* actors, and the workers as *consumers*. Producers respond to requests for work with partitions to be computed. Consumers are provided with an ordered list of producers, then repeatedly request and compute work from each in order. Each consumer is given a differently ordered list, with the producer of that consumer's optimal partitions placed first in the list. A counter actor tracks the number of completed partitions, sending a signal when all partitions have been computed, or an error if any worker fails.

This solution also handles unassigned partitions with no co-located workers; this producer is placed last in the list of producers for each consumer, where they will eventually be processed.

Figure 3.8.4 provides the initial state of this model, using the example optimal assignment from Figure 3.6.5. Dark arrows represent the producer which the consumer will empty first, containing its optimal assignments. Light grey arrows represent the other producers which the consumer can access. Note that Producer 3 is not first for any worker, but will eventually be checked by the workers when all others are exhausted.

3.8.2 PrepareResult

This *QueryPlanItem* computes a *Table* from the partitions of a *DataSource* that are already stored on the workers. Therefore, it will always be called after *GetPartition*, with the new partitions as an argument. A modified version of *GetPartition*'s actor system is used to iterate through all partitions on each worker, sending a request to perform the *Table* computation for each.

3.8.3 DeleteResult and DeletePartition

DeletePartition and *DeleteResult* are *QueryPlanItems* for removing the results of a *GetPartition* and *PrepareResult* operation, respectively. They send a single request to each worker, which will remove all results that relate to a *Table* or *DataSource*, and respond with a confirmation.

3.8.4 Result Collation

After all the steps of a query are completed, the final results are stored across all the workers. The orchestrator makes a request to all workers to return the computed results, and each worker iterates over all partial results in the data store, streaming the data back to the orchestrator. An actor system pipes the concurrent responses into a single thread, which combines the results and streams them to the frontend. The request is initiated by the orchestrator because gRPC requires that one system act

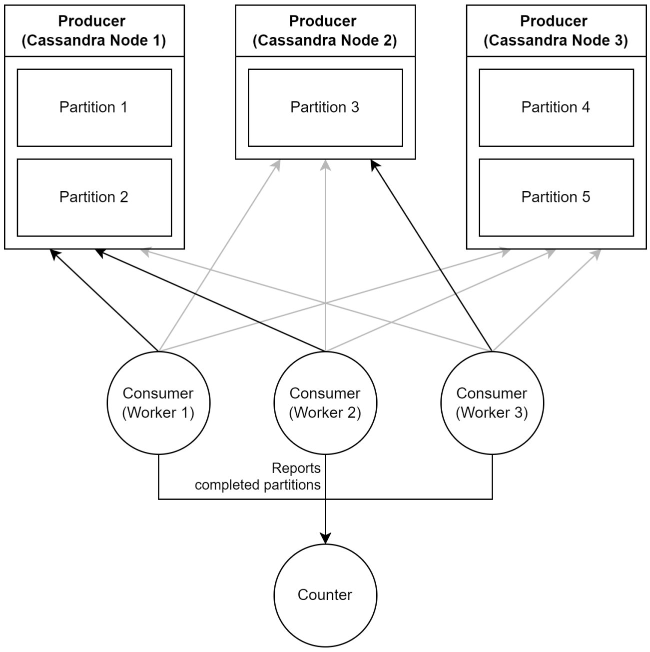


Figure 3.8.4: Producer Consumer Model Example

as a server, and another as a client. For the query plan model, it makes most sense for the workers to be servers, so this model is also used for result collation.

3.9 Deployment

As discussed in Chapter 2, Kubernetes was chosen to manage all nodes in the cluster. One feature that makes it useful for the system is scheduling rules, which provide Kubernetes with information about how containers should be assigned to physical nodes.

As previously described in 3.6.2, workers determine their closest Cassandra node automatically based on latency. To make the best use of the cluster, workers should be distributed evenly across all nodes that have a Cassandra node. This is implemented by these scheduling rules:

1. If possible, workers should be placed on the same Kubernetes node as a Cassandra node.
2. Workers should not be placed on the same node as other workers.

The scheduling rules are preferences rather than requirements, meaning Kubernetes is still able to schedule the nodes if there are more workers than Cassandra nodes.

3.9.1 CI/CD

To aid in deploying to Kubernetes, continuous integration/continuous deployment (CI/CD) pipelines are used for each major system component, specifically using GitHub Actions [17]. Each pipeline runs all unit tests for the component, and provided they succeed, builds a docker container and pushes it to a container registry, ready for use in the Kubernetes cluster.

Chapter 4

Testing

As discussed in Chapter 1, the main objective is to improve the speed of data processing for large datasets, making it essential to conduct performance testing of the overall system. This section aims to cover a number of methods in which the performance of the completed solution is evaluated.

4.1 Unit Tests

Thorough unit testing is important for any software engineering focused project. By writing tests throughout development, the expected behaviour of individual components in the system can be validated. Through the use of continuous integration/continuous deployment (CI/CD) pipelines, this behaviour can continue to be validated as other parts of the system are improved, to ensure changes do not break the behaviour of the component.

Scalatest was chosen as the unit test framework [42]. Furthermore, both gRPC and Akka Actors provide classes for writing unit tests around the frameworks, and this is combined with Mockito to mock any dependencies that cannot be run during testing like the Cassandra Driver [41, 10]. Using these tools and frameworks, unit tests have been written for the majority of core code, including the DSL, query model and partitioning code. In total, more than 350 individual tests were written for this project, split across the Python frontend, core code, orchestrator and worker code.

4.2 Test Data

To aid performance testing, fake data is created to test the different operations of the system, produced based on discussions with potential users of the system. The intended users have a financial background, as they work within Audit at PwC, so loan origination (creation) data was selected for testing. A short Python script generates this data by randomising a number of fields between specified bounds. Figure 4.2.1 shows ten example records of the data.

4.3 SQL vs Cluster Solution

This section will compare the performance of an instance of Microsoft SQL Server, against the completed solution, referred to as the Cluster Processor in this testing.

Test Plan Tests are conducted for the three types of query that the Cluster Processor supports: Select, Filter and Group By. Within each type of query, a simple, and a complex version is tested.

Loan ID	Amount	Interest Rate	Duration (Yrs)	Origination Date
0	590,418	0.041139	24	2021-04-23 18:13:00
1	697,824	0.095023	20	2021-10-06 20:07:00
2	271,853	0.029358	23	2021-03-08 05:12:00
3	329,950	0.038111	23	2021-01-18 21:05:00
4	1,381,994	0.055411	30	2021-05-13 15:54:00
5	1,365,793	0.0093872	29	2021-05-04 03:18:00
6	1,143,926	0.078929	21	2021-07-11 19:10:00
7	461,215	0.082520	23	2021-05-04 17:50:00
8	287,307	0.040382	21	2021-05-20 06:08:00
9	191,668	0.061314	25	2021-09-03 16:21:00

Figure 4.2.1: Example Loan Origination Data

See Appendix A for the full SQL and Cluster Processor queries.

Figure 4.3.1 shows the data volumes of the tables the queries will be executed on. SQL has two larger tables to provide further context of how it scales at larger data volumes; the Cluster Processor was unable to test these tables due to time and cost constraints.

SQL	Cluster Processor
1,000	1,000
10,000	10,000
100,000	100,000
1,000,000	1,000,000
10,000,000	10,000,000
50,000,000	
100,000,000	

Figure 4.3.1: SQL and Cluster Processor Testing - Number of Rows

To reduce the effect of random error, each test is run 5 times, and the results averaged across all tests. This is particularly important when running on a cloud environment, as there is less control over the hardware running the tests, so averaging a number of results should reduce any impact this has.

In all of these tests, Microsoft SQL Server was running on an instance of Azure SQL Database [6]. The Cluster Processor was running on Azure Kubernetes Service, with a pool of three nodes, each having 4 vCores, and 16GB memory available [22]. The CPU and memory available to each worker is controlled by Kubernetes.

4.3.1 Controls

A number of variables must be considered which could have an impact on the results of this test. The testing attempts to mitigate the effects of these variables in order to make the results as comparable as possible.

CPU and Memory At larger data volumes, CPU and Memory is the biggest contributing factor that will affect how quickly the computation is performed, both on SQL and the Cluster Processor. Ensuring these are comparable is essential for producing reliable test results. For Azure SQL Database, a slider can be used to set the maximum number of vCores available, and a set amount of memory is assigned based on the number of cores. In this case, a maximum of 6 vCores were used, which results in of 18GB memory accessible to the database.

As the Cluster Processor is running on Kubernetes, granular control over the number of vCores and amount of memory available to each node is possible using resource limits [26]. Workers were configured to have a maximum of 2 vCores, and 6GB memory available to each, with 3 workers in total. As a result, the cluster as a whole has 6 vCores and 18GB memory available, the same as the SQL database.

Network Latency Controlling network latency is particularly important for small data volumes which resolve quickly. For a request that takes 0.5s to complete, 100ms of latency will make the completion 20% slower. Testing was always performed on an instance of Azure Cloud Shell, which is a terminal running inside the same Azure datacenter as the test environment [34]. This ensures the network latency is minimised and comparable between environments, with 16ms average round-trip time for a TCP ping to both SQL server, and the Cluster Processor.

Warm-Up Both SQL and Cluster Processor have a warm-up periods when they are first started. Azure SQL Database is run using a serverless computation style, which means the server is scaled to 0 resources when it is unused. This has the disadvantage that when a query is first run, there is a short delay while the resources are provisioned again. Cluster Processor has a similar warm-up when it is first started, because the gRPC connections between the orchestrator and workers are not actually created until the first request is made. To overcome both of these warm-up periods, a number of queries are run just before testing begins, and the time taken to run these is not tracked.

4.3.2 Select Query

The first query is a pure select, essentially testing how fast both solutions can send results over the network. The second select query is more complex, with conversion operations to determine if this has an impact on the computation time.

Results The results for this query are shown in Figure 4.3.2. Data is only available for Cluster Processor up to 100,000 rows because of a memory issue when passing data from the workers to the orchestrator. This is analysed further in Chapter 5. Therefore, the graph is filtered to exclude the SQL results for 50 and 100 million rows.

However, the data that is available shows that the Cluster Processor is more than 10x slower at performing Select queries than SQL. This is most likely related to the format used to send the result data. See Section 4.3.5 for further analysis.

For both SQL and the Cluster Processor, there is no significant difference between the raw Select, and the Select with operations. The largest difference is at 100k rows for Cluster Processor, where there is a 0.3s increase in the complex select.

4.3.3 Filter Query

The first query is a simple filter, with no AND/OR combinations. The second filter is more complex, testing both boolean operators.

Results The results for this query are shown in Figure 4.3.3. The results show that SQL is around 15-20x faster in this test case. This is likely to be partially caused by the transmission format, as with the Select queries. However, it is also likely that SQL is able to exploit caching more extensively over

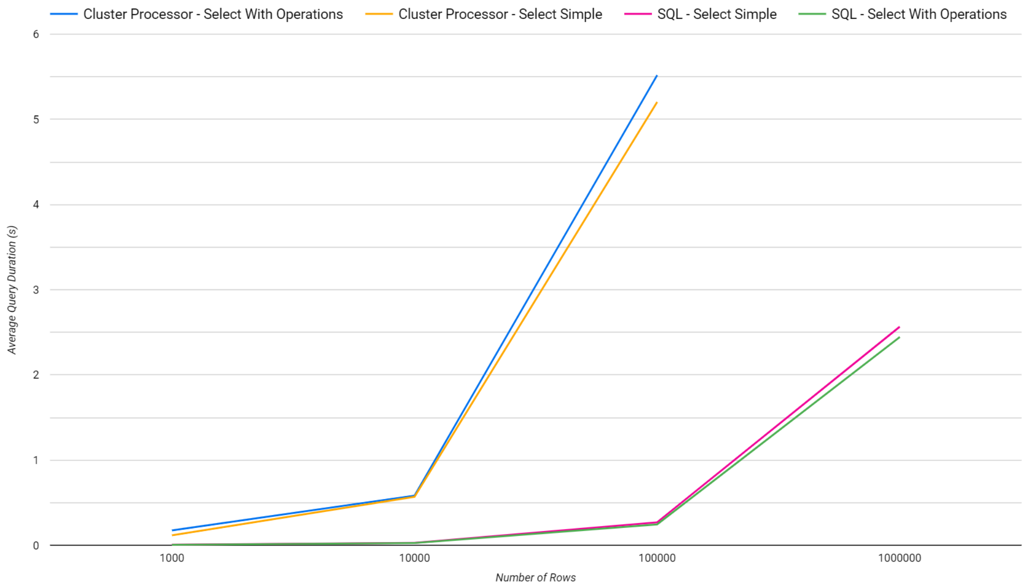


Figure 4.3.2: SQL vs Cluster Processor - Select Query Results

repeated tests when compared to the Cluster Processor, particularly with the smaller tables which can be held in memory permanently. This is because the Cluster Processor fetches fresh data from Cassandra every time the query is called.

Another relevant insight from this data is that the complex filter reliably executes faster than the simple filter across all results in both environments. This is expected, since the complex filter is more restrictive in the results that it returns, resulting in less data to transfer over the network.

4.3.4 Group By Query

The first query is a simple group by, essentially performing a `DISTINCT` operation. The second group by is more complex, featuring a number of aggregations.

Results The results for this query are shown in Figure 4.3.4, where again testing was performed for the full range of datasets in both solutions. SQL is significantly faster, and scales much better as the data sizes increase. For the Cluster Processor, the aggregate group by is over twice as fast on average than the simple version at 10 million records. The testing was performed sequentially, with no break between tests, so it is unclear why this result is faster. Furthermore, the same difference in computation time is not present at smaller data volumes. This could be caused by the less controlled cloud environment, meaning perhaps some unexpected load was present during the simple test, resulting in slower computation. Another round of testing would need to be performed to determine if this was the case.

Despite this unexpected difference, there is still a significant performance drop-off compared to the results at 1 million records. Analysing the outputs from the workers, the results could not be stored entirely in-memory, resulting in a large amount of computation time being spent swapping partial results to and from disk. Group By operations suffer from memory shortages worse than other types of queries, as around twice the normal data volume is stored at one time: the source data for the Group By, data for the new hashes, and the newly computed group by partitions are all kept in the data store at the same time.

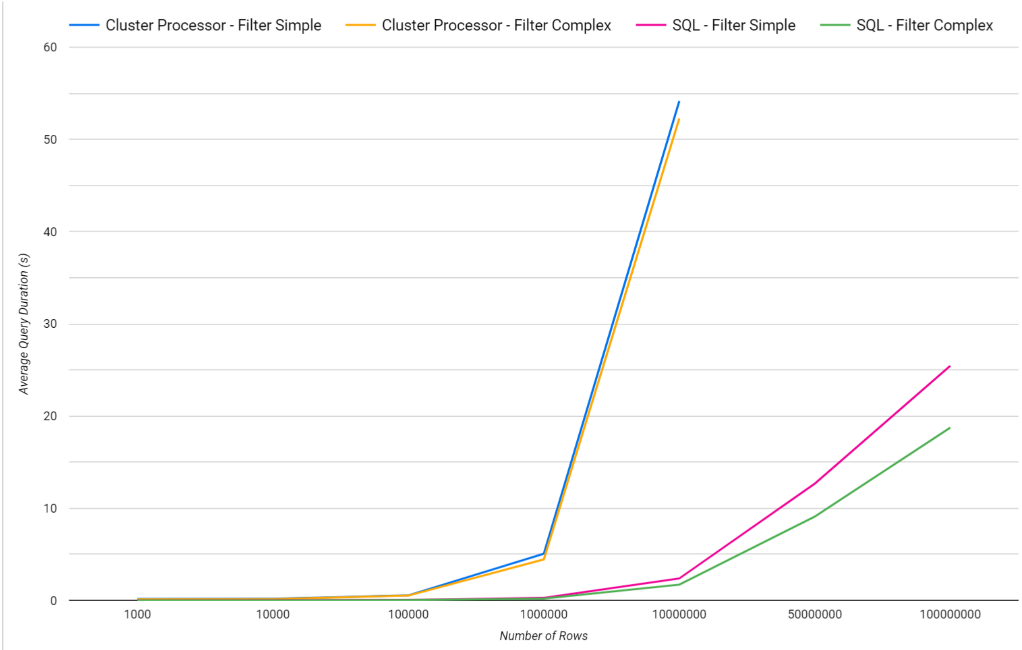


Figure 4.3.3: SQL vs Cluster Processor - Filter Query Results

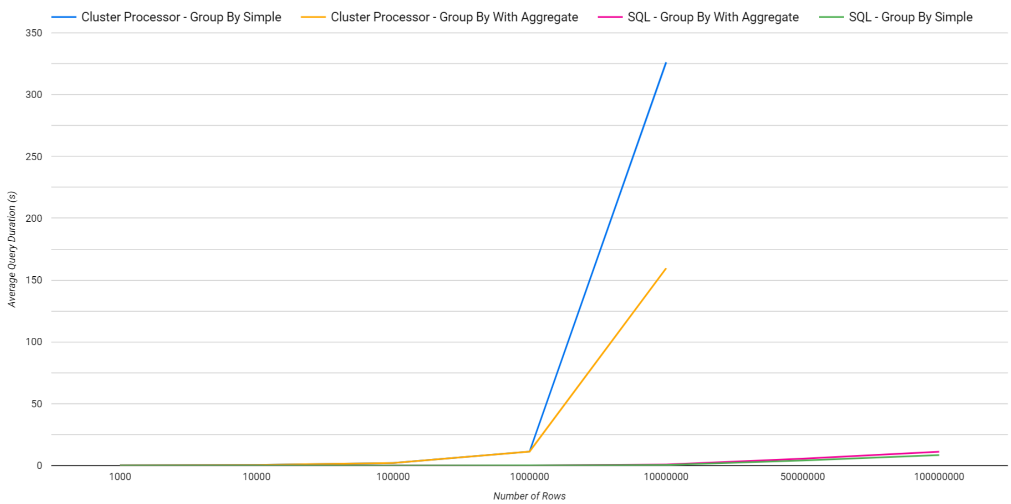


Figure 4.3.4: SQL vs Cluster Processor - Group By Query Results

4.3.5 Analysis

As the raw performance testing results show, a significant amount of optimisation would be required for the Cluster Processor solution to truly compete with SQL with regards to computation speed. The system appears to be weakest at transmitting raw data quickly across the network, and computing Group Bys.

One way to optimise the transmission format for results is to reduce the size of the serialised row data. Currently, every serialised table cell stores value and type information, but the type has already been sent within the header. Therefore, the system could reduce the serialised size by only sending values, using the header to perform a conversion when the row is received.

The main inefficiency that causes the poor Group By performance is the workers holding onto more data than necessary. Currently for simplicity, the workers hash a copy of all rows in the data before cross-communication occurs. It should be possible to partially perform the Group By operation for each partition on each worker, then finalise those partial results when the partition is computed, significantly reducing the amount of stored and transferred data. As testing has already established that the transmission format is suboptimal, by sending more data than is required, the network inefficiencies have an increased impact on performance.

Furthermore, when computing Group Bys at 10 million rows, the workers ran low on free memory, and began spilling data to disk, which is significantly slower than in-memory storage. By reducing the amount of stored data, spilling would occur at larger data volumes, improving the overall performance.

4.4 Level of Parallelisation

This section will compare the performance of the Cluster Processor when the number of workers is varied, but the overall performance in terms of available resources is the same. The aim is to determine how changing the level of parallelisation in the cluster impacts the computation speed.

In these tests the simple versions of each query type were executed, with different data volumes depending on the test. See Appendix A for query details.

Figure 4.4.1 shows the cluster layouts for each test case; the number of workers, and the resources available to each worker. As shown, the overall number of vCores and GB of memory available to the cluster is the same in each case.

Throughout all of these tests, the number of Cassandra nodes in the cluster remained consistent: 3 nodes, one placed on each Kubernetes node.

Workers	vCores	Worker Memory	Total vCores	Total Memory
2	3	9GB	6	18GB
3	2	6GB	6	18GB
6	1	3GB	6	18GB
9	0.666	2GB	6	18GB
12	0.5	1.5GB	6	18GB

Figure 4.4.1: Parallelisation - Number of Workers and Resources

4.4.1 Select Query

The results of this test are shown in Figure 4.4.2. Due to the same memory issue as in the SQL test, only 1000 to 100000 row tables were tested. The cluster layout with 3 nodes appears to execute around twice as fast across all data volumes compared to the other layouts, which all have similar execution times on average. Ultimately, this test is checking how fast each layout can pull data from Cassandra, and send it to the Orchestrator. It is likely that the extra overhead introduced by the higher levels of parallelisation slowed down data transfer, and there was no computation to perform which would benefit the increased number of nodes.

However, at 100,000 rows the 9 node cluster ran marginally faster than the other slower layouts. These are still tightly clustered with all results within 0.4s of one another, suggesting this is likely caused by random variation, rather than the 9 node cluster being specifically faster. Further testing, particularly at higher data volumes, would be required to confirm any trends here.

Interestingly, the 2 node cluster performed slower than the 3 node cluster. This is likely because this layout has one less worker node than Cassandra node, which adds latency to retrieve data from the Cassandra node without a co-located worker.

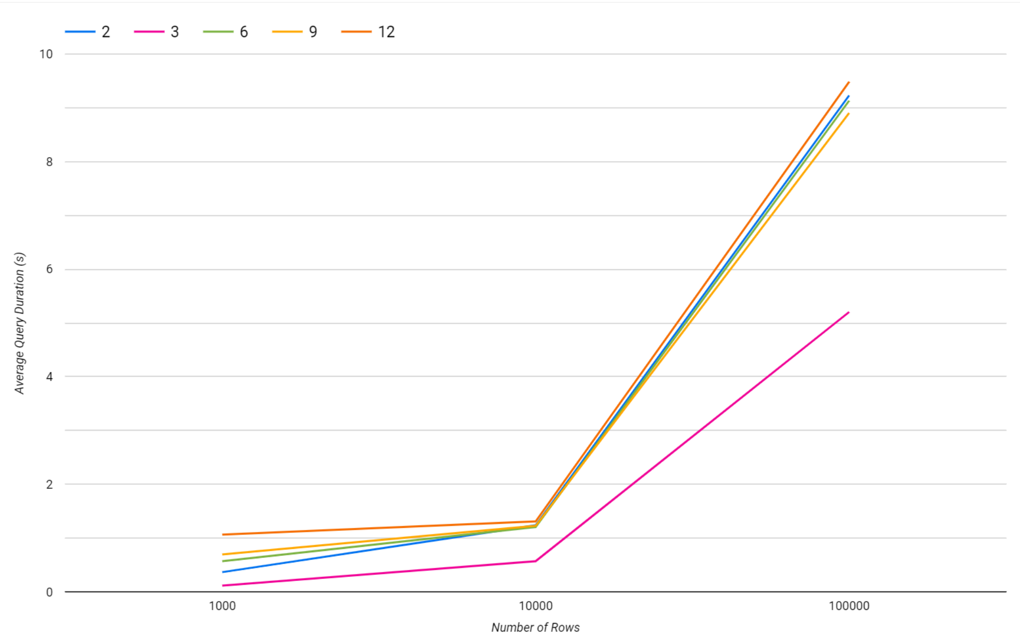


Figure 4.4.2: Parallelisation - Select Query Results

4.4.2 Filter Query

The results of this test are shown in Figure 4.4.3. The 3 node cluster is fastest until 100,000 rows, but is then overtaken by the 9 node cluster, showing an interesting trend.

To investigate this trend further, the test was also run for all cluster layouts at 10 million rows, shown in Figure 4.4.4. The larger clusters (6, 9 and 12 nodes) are all faster than the 3 node cluster, with 9 nodes executing quickest. This shows that as the amount of work increases, the increased level of parallelisation becomes a benefit. The fact that 12 nodes is slower than 9 suggests there is an optimal point that maximises parallelisation without introducing too much overhead from the number of nodes.

4.4.3 Group By Query

The results of this test are shown in Figure 4.4.5. They again suggest that there is a balancing point for the level of parallelisation. The 3 node cluster is consistently faster than all other layouts. The larger

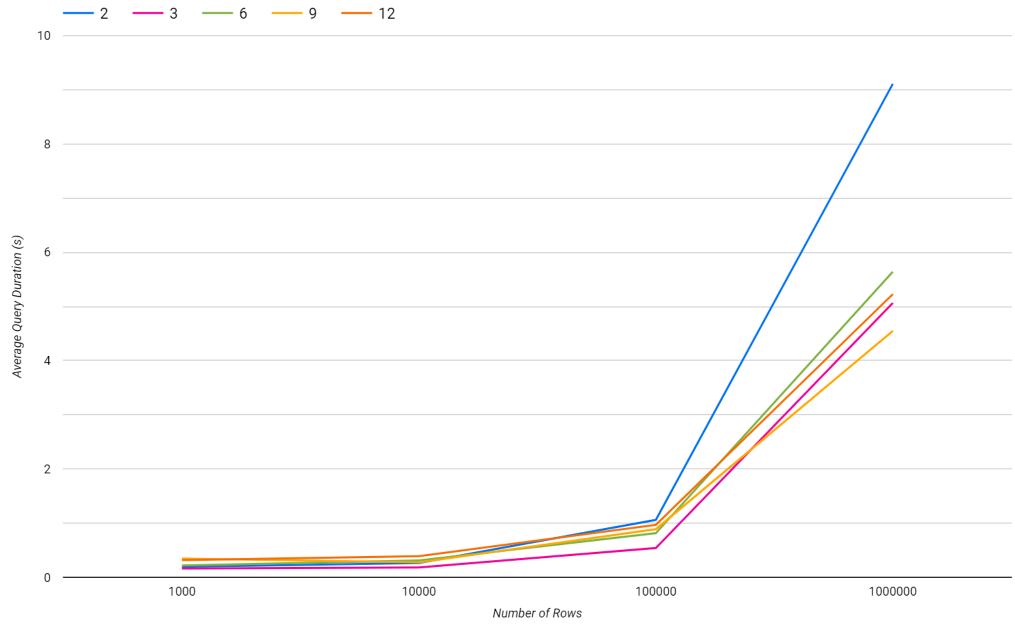


Figure 4.4.3: Parallelisation - Filter Query Results

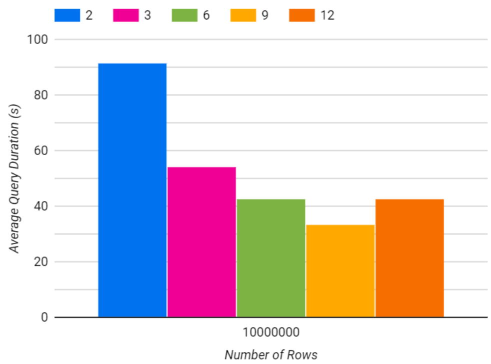


Figure 4.4.4: Parallelisation - Filter Query Results, 10 Million Rows

clusters are likely to be slower because increasing the level of parallelisation increases the amount of cross-communication, and network transfer is a weak area, as identified in the SQL test.

Interestingly, the 2 node cluster is second fastest until 1 million rows, when its performance significantly reduces. This is likely to be because the increased memory demands on each node resulted in some data being spilled to disk, which reduced the overall performance.

4.4.4 Analysis

The outcomes of this test show that there is no clear solution to the level of parallelisation. As a general rule, having the same number of workers as Cassandra nodes will result in good performance, but the Filter test also shows that increasing parallelisation can result in better performance for the same resources at larger query sizes.

The best solution depends on the queries and data volumes being calculated. This presents an opportunity for further research designing a system that analyses the queries being executed, automatically adjusting the cluster layout to match the requirements of those queries.

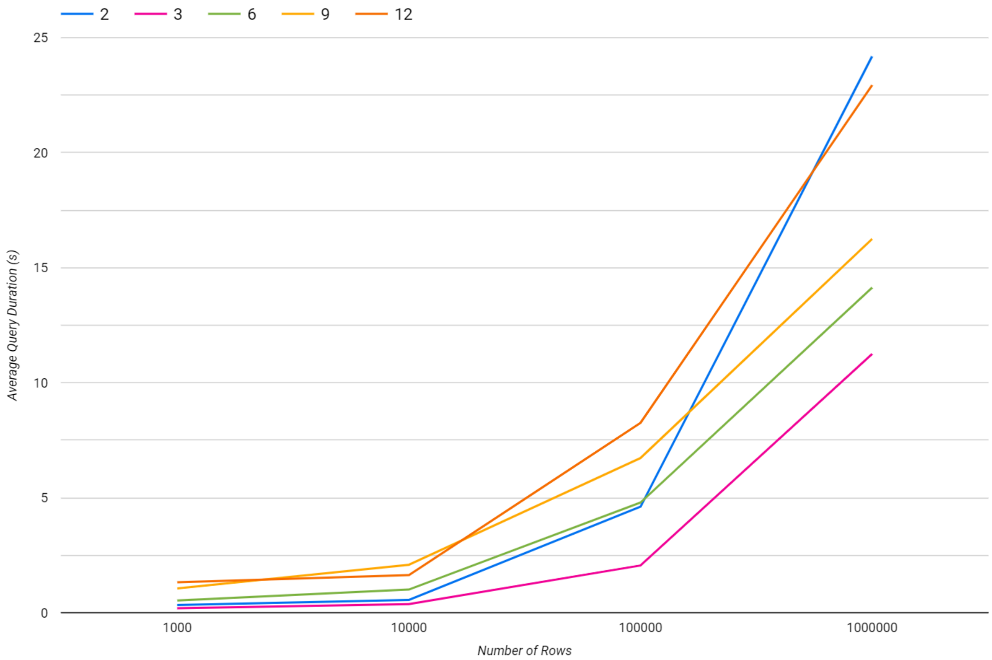


Figure 4.4.5: Parallelisation - Group By Query Results

4.5 Autoscaling

This section will compare computation speed of the Cluster Processor when reducing the overall performance, motivated by the autoscaling feature present in many cloud services, including Azure Kubernetes Service. It continually analyses the load of the Kubernetes cluster, changing the number of physical nodes based on current demand [5]. By doing this, applications with fluctating demand can save costs by reducing the number of machines they pay for when demand is low.

While the Cluster Processor would not currently support autoscaling, this test aims to identify the effectiveness of autoscaling on this solution. In these tests the simple versions of each query type were executed, with different data volumes depending on the test. See Appendix A for query details.

Figure 4.5.1 shows the cluster layouts for each test case. Each layout has one less worker, and 33% less resources.

Throughout all of these tests, the number of Cassandra nodes in the cluster remained consistent: 3 nodes, one placed on each Kubernetes node.

Workers	vCores	Worker Memory	Total vCores	Total Memory
3	2	6GB	6	18GB
2	2	6GB	4	12GB
1	2	6GB	2	6GB

Figure 4.5.1: Autoscaling - Number of Workers and Resources

4.5.1 Select Query

The results of this test are shown in Figure 4.5.2. As expected, the query performance decreases as the number of workers decreases. However, at 1000 rows the difference between 3 workers and 1 worker is around 0.3s, and at 10000 rows it is 0.9s.

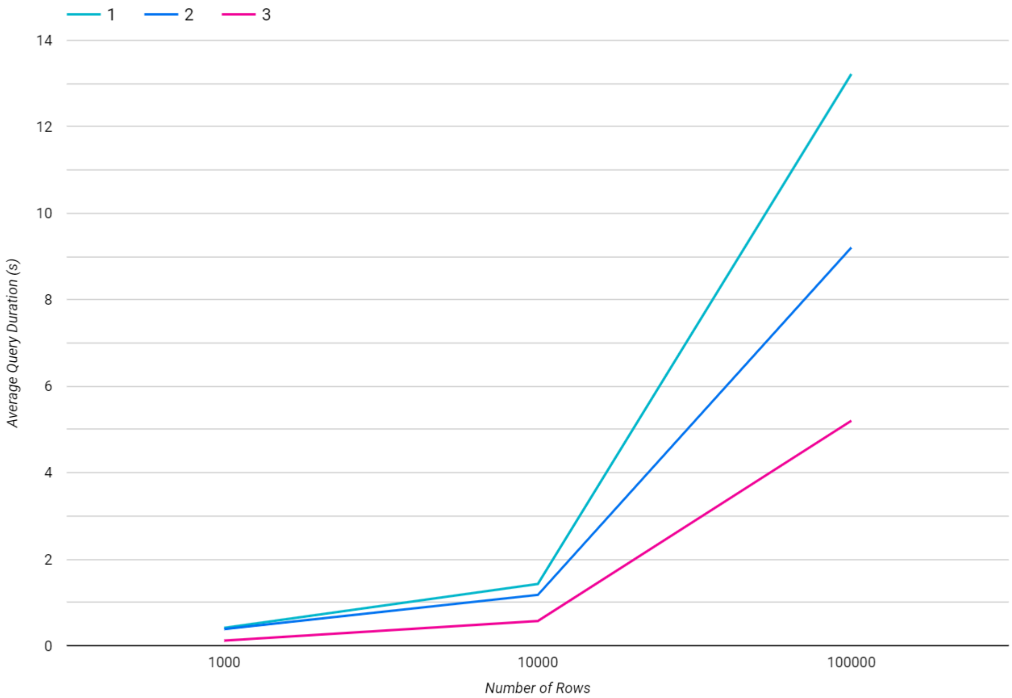


Figure 4.5.2: Autoscaling - Select Query Results

4.5.2 Filter Query

The results of this test are shown in Figure 4.5.3. As before, the query performance decreases with the number of workers. The difference between 1 and 3 workers is 0.08s at 1,000 rows, 0.2s at 10,000 rows, and 1.1s at 100,000 rows.

4.5.3 Group By Query

The results of this test are shown in Figure 4.5.4. At the two smallest volumes, there is almost no difference between the three layouts, and at 100,000 rows the 1 node cluster is fastest. This suggests that, at very small data volumes, it is faster to perform all of the computation on a single node, as it prevents the need for worker cross-communication.

4.5.4 Analysis

The outcomes of this test show that reducing the cluster size is effective at small data volumes. The time difference between the smallest and largest cluster is typically less than a second at less than 1 million rows, which is insignificant for most use cases. If a time-critical system was reliant on querying this amount of data, a single-system solution like SQL would be better suited regardless.

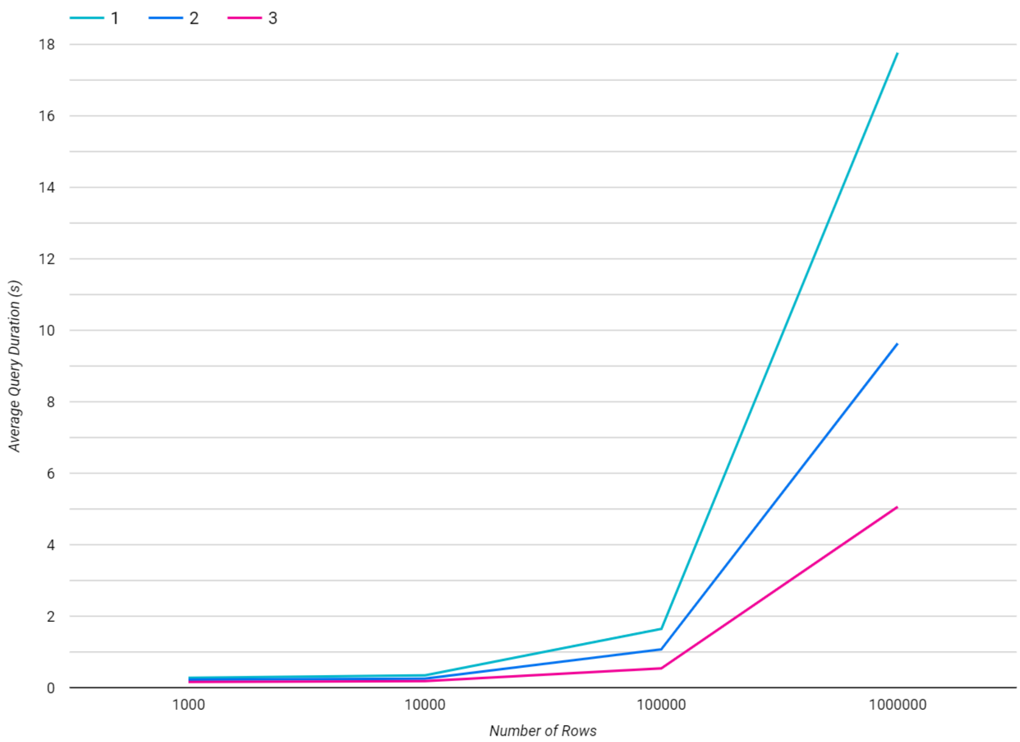


Figure 4.5.3: Autoscaling - Filter Query Results

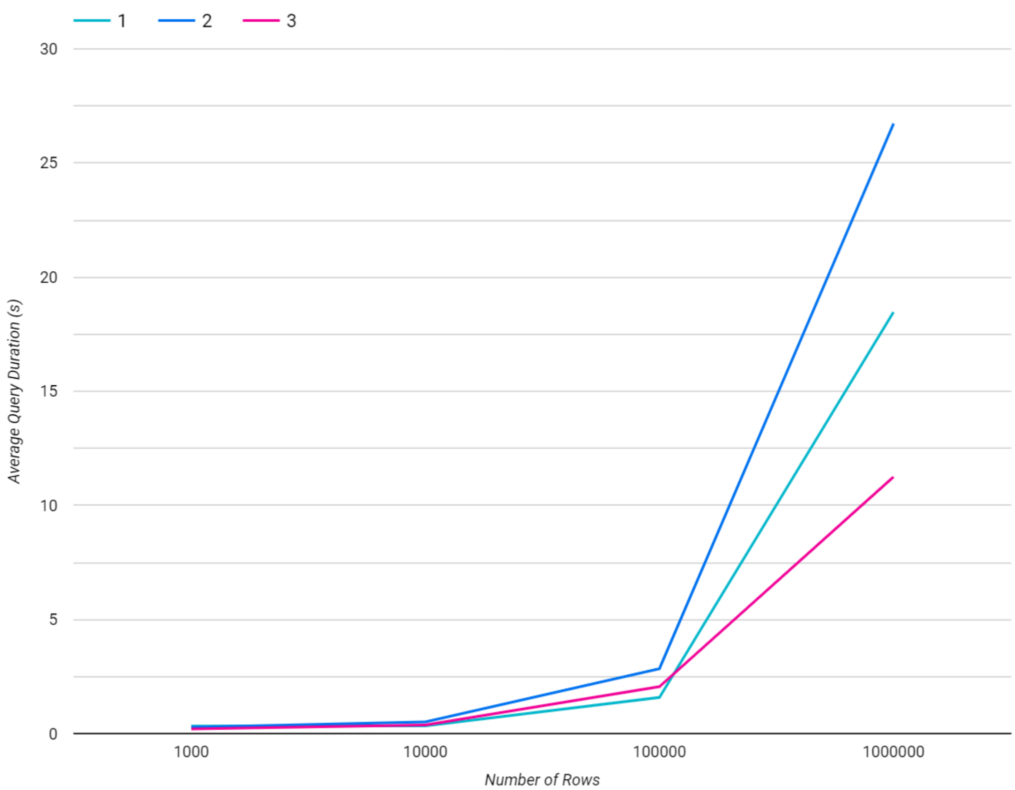


Figure 4.5.4: Autoscaling - Group By Query Results

Chapter 5

Evaluation

This section will discuss a high level evaluation of the solution, and the project as a whole.

5.1 Limitations

The solution has limitations which could not be fixed due to time constraints, but further investigation into optimisations or alternative solutions may be able to improve or fix them. These are listed below.

As discussed in Chapter 4, the Group By operation, and the method of transferring data around the network could both be further optimised.

Result data uses an extremely large amount of space when resident in memory. For example, a 100MB source data file can use up to 800MB of memory once stored. This is because of the container class described in Section 3.2. However, this class is a core component of the DSL, as it ensures the type information is accessible at runtime.

The system's security is limited, which prevents its use in a production environment. The orchestrator has no authentication, and Cassandra only has basic username and password authentication.

Finally, as discovered in Chapter 4, the result collation algorithm cannot return large amounts of results, typically more than 1 million rows. All workers send results to the orchestrator, which forwards them to the frontend. However, as there are more workers than the single orchestrator, data enters the orchestrator faster than it leaves, meaning that with a large enough dataset, the orchestrator will run out of memory and crash.

5.2 Further Work

The nature of this project means that there is a large scope for future work and improvements. As discussed in Section 4.4, different cluster layouts are more optimised for different kinds of queries. A module that runs at the Kubernetes level, monitoring the utilisation of the cluster and the types of queries being executed may be able to improve computation times by adjusting the cluster layout.

The data store is currently used to assist computations by temporarily storing partial result data. However, the design would allow it to store results between queries, improving the computation time of repeated queries to the same dataset. Join operations are also not currently implemented, but would benefit from this improvement to the data store.

The current error handling is designed to forward any errors to the frontend. In some situations, like if the Cassandra database is unresponsive, this is acceptable. For other errors, like if one worker is unresponsive, this can be handled by delegating the failed worker's partitions to others, without alerting the user at all.

Finally, Cassandra is currently only used for storage and partitioning. However, it is also a query engine, meaning some computations could be performed on Cassandra directly, improving query times by reducing the amount of data transferred. In particular, Filters on the source dataset, and Group Bys on the primary key are perfect candidates for this optimisation.

5.3 Conclusion

The objective as stated in Chapter 1 was to design a query processing engine for a distributed cluster of nodes. The types of queries possible in the system are numerous, and the data model allows easy implementation of new query types. While performance testing results showed that the solution requires further optimisation to truly compete with existing frameworks, they also showed that there is promise in the scalability of the solution. Furthermore, testing revealed interesting findings regarding the number of workers in the cluster, and raised the possibility of a stand-alone module for performing node management.

A secondary goal was to design the frontend to be easy-to-use, with SQL-like syntax. The DSL meets this goal, and is one of the defining features of the tool, with *FieldExpressions* and *FieldComparisons* allowing complex data manipulations to be defined with relative ease. The implementation of Functions permits easy extensions within the type system's bounds. The frontend operates seamlessly for the user, hiding the background operation of the framework entirely. Furthermore, the pandas integration means that users can immediately start manipulating result data using tools already familiar to them.

Todo list

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Appendix A

Testing Figures

Included in this appendix are figures with the queries used for performance testing.

```sql
SELECT * FROM data.origination_1000
```

Figure A.1: SQL - Select Simple

```python
manager = ClusterManager("orchestrator-service")
manager.cassandra_table("data", "origination_1000").evaluate()
```

Figure A.2: Cluster Processor - Select Simple

```sql
SELECT
Loan_ID + 1 as Loan_ID_Inc,
interest_rate + 1 as Interest_rate_Inc,
power(duration, 2) as Duration_Pow,
substring(cast(origination_date as nvarchar(300)), 0, 11) as
   origination_date_str
FROM data.origination_1000
```

Figure A.3: SQL - Select Complex

```
manager = ClusterManager("orchestrator-service")
manager.cassandra_table("data", "origination_1000").select(
(F("loan_id") + 1).as_name("loan_id_inc"),
(F("interest_rate") + 1).as_name("interest_rate_inc"),
Function.Pow(Function.ToDouble(F("duration")),
   2.0).as_name("duration_pow"),
Function.Substring(Function.ToString(F("origination_date")), 0,
   10).as_name("origination_date_str")
).evaluate()
```

Figure A.4: Cluster Processor - Select Complex

```
SELECT *
FROM data.origination_1000
WHERE duration = 30
```

Figure A.5: SQL - Filter Simple

```
manager = ClusterManager("orchestrator-service")
manager.cassandra_table("data", "origination_1000")
.filter(F("duration") == 30)
.evaluate()
```

Figure A.6: Cluster Processor - Filter Simple

```
SELECT *
FROM data.origination_1000
WHERE
(duration = 30 AND amount > 500000)
OR loan_id = 1
```

Figure A.7: SQL - Filter Complex

```
manager = ClusterManager("orchestrator-service")
manager.cassandra_table("data", "origination_1000")
.filter(
((F("duration") == 30) & (F("amount") > 500000.0))
| (F("loan_ID") == 1)
).evaluate()
```

Figure A.8: Cluster Processor - Filter Complex

```
    SELECT duration
    FROM data.origination_1000
    GROUP BY duration
```

Figure A.9: SQL - Group By Simple

```
manager = ClusterManager("orchestrator-service")
manager.cassandra_table("data", "origination_1000")
.group_by([F("duration")])
.evaluate()
```

Figure A.10: Cluster Processor - Group By Simple

```
SELECT
duration,
MAX(origination_date) as Max_origination_date,
AVG(interest_rate) as Avg_interest_rate,
Min(amount) as Min_amount
FROM data.origination_1000
GROUP BY duration
```

Figure A.11: SQL - Group By Complex

```
manager = ClusterManager("orchestrator-service")
manager.cassandra_table("data", "origination_1000")
.group_by(
[F("duration")],
[       Max(F("origination_date")),
Avg(F("interest_rate")),
Min(F("amount"))
]
).evaluate()
```

Figure A.12: Cluster Processor - Group By Complex

Appendix B

Test Controls