Design and Implementation of a Tool to Collect Execution- and Service-Data of Big Data Analytics Applications

Bachelor's Thesis

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Department Informatics and Media VI
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Matriculation number:	s786694
Date of submission:	06.09.2016

Ackknowledgements

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Abstract

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Contents

1 Introduction

1.1 Motivation

According to a survey in Germany, nine out of ten companies (89 percent) analyze large volumes of data from a variety of diffent sources for operational decision-making processes using modern Big Data Analytics Applications, where 48 percent of the respondents see the greatest potential of Big Data [Jör14a]. The analysis of continuous data streams is taking up a growing importance for companies and therefore constitutes an important factor for business success.

Collecting, storing and analyzing system and operational data of Big Data Applications is therefore an essential tool in order to ensure successful operation and to prevent failures. Even though logfiles are usefull for tracing problems in software systems, problems can be tracked and potential sources of error can be identified much earlier by collecting and storing execution and service data at runtime to describe the state of the system at a given point in time.

Due to the distributed character of Big Data Applications, where a system is composed of several interacting components, the examination of log data is not an adequate choice to gain insight into an entire system [Les14].

1.2 Objective

The main goal of the thesis is the design and implementation of a software system to ingest and store system and operational data of Big Data Analytics Applications on the example of the streaming frameworks Apache Flink and Apache Kafka. It will be examined which data is available and can be collected at all, what data is relevant and how to collect from source systems. Furhermore, the collected data must be stored in a persistence system to become available for possible consumers like visualization applications, analytical processes or as a data source for applications from the context of Machine Learning for example.

In preparation for this thesis my supervisor Prof. Dr. Stefan Edlich once said *"Sie sammeln alles, was nicht bei drei auf dem Baum ist"*. According to this statement the collection and storage of as much data as possible is the main focus of this work and excludes processing, visualization or analysis of the collected data.

1.3 Structure of thesis

After a short introduction to the topics and the main goals of the present thesis in this chapter, the Chapter 2 covers basic concepts of Big Data Analytics Applications, discusses the concept of stream processing and introduces Apache Flink and Apache Kafka as representatives of widely used stream-processing frameworks.

Chapter 3 investigates which sources for collecting data exist for Apache Flink and Apache Kafka and which data should be collected and stored in a persistence system regarding to its relevance and data quality.

The requirements and the target definition of the software system will be introduced in Chapter 4, Chapter 5 describes the software solution by giving a detailed conceptional overview of the software components whilst Chapter 6 will explain implementation details for selected items.

In chapter 7 we'll see how to setup the technical environment for the usage of the prototype to verify the correct functionality related to the requirements defined in Chapter 4.

The last Chapter 8 covers a conclusion and summary of the present work.

2 Theoretical Foundations

After a short introduction to the terminology of Big Data, this chapter will discuss the main characteristics of Big Data Analytics Applications and introduces the concept of stream processing, which is one of the main characteristics of the popular streaming frameworks Apache Flink and Apache Kafka. The underlying concepts both of these systems and how they're used in context of Big Data Analytics will be explained at the end of this chapter.

2.1 Big Data

According to [Nat15] the term "Big Data" is a misleading name since it implies that pre-existing data is somehow small, which is not true, or that the only challenge is the sheer size of data, which is just one one them among others. In reality, the term Big Data applies to information that can't be processed or analyzed using traditional processes or tools.

In the past decade the amount of data being created is a subject of immense growth. More than 30,000 gigabytes of data are generated every second, and the rate of data creation is only accelerating.[Nat15]. People create content like blog posts, tweets, social network interactions, photos, servers continuously log messages, scientists create detailed measurements, permanently.

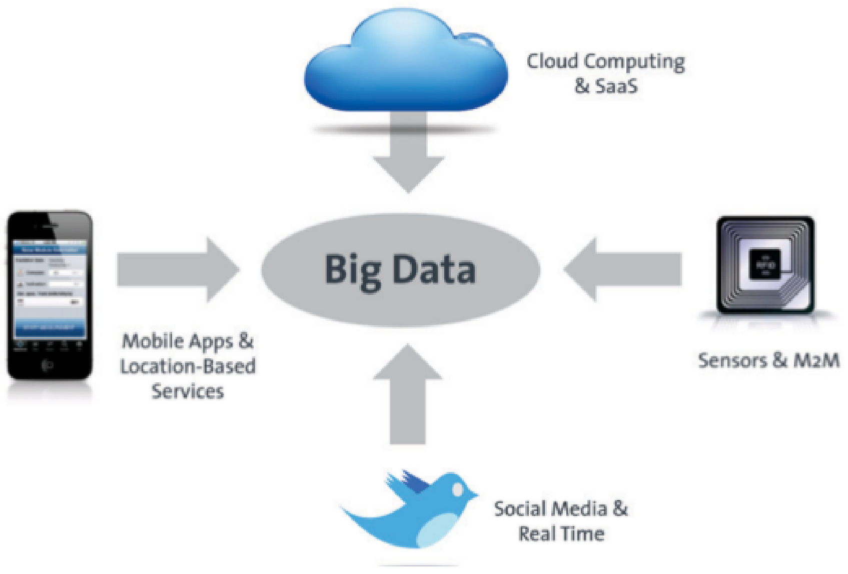

Figure 2.1: Sources of Big Data[Jör14b]

Through advances in communications technology, people and things are becoming increasingly interconnected. Generally referred to as machine-to-machine (M2M), interconnectivity is responsible for double-digit year over year data growth rates. Finally, because small integrated components are now affordable, it becomes possible to add intelligence to almost everything. As an example, a simple railway car has hundreds of sensors for tracking the state of individual parts and GPS-based data for shipment tracking and logistics.[**Ziko12**]

Besides the extremely growing amount of data, an increase in data diversity goes hand in hand. It comes in its raw and unstructured, semistructured or structured form, which makes processing it in a traditional relational system impractical or impossible.[Jör14b] describes, that around 85 percent of the data comes in an unstructured form, but containing valuable information.

According to [Nat15] [**Ziko12**], Big Data is defined by three characteristics:

Volume The amount of data present is growing because of growing amount of producers, e.g. environmental data, financial data, medical data, surveillance data.

Variety Data varies in its form, it comes in different formats from different sources.

Velocity Data needs to be evaluated and analyzed quickly, which leads to new challenges like analysis of large data sets with answers in seconds range, data processing in realtime, data generation and transmission at highspeed.

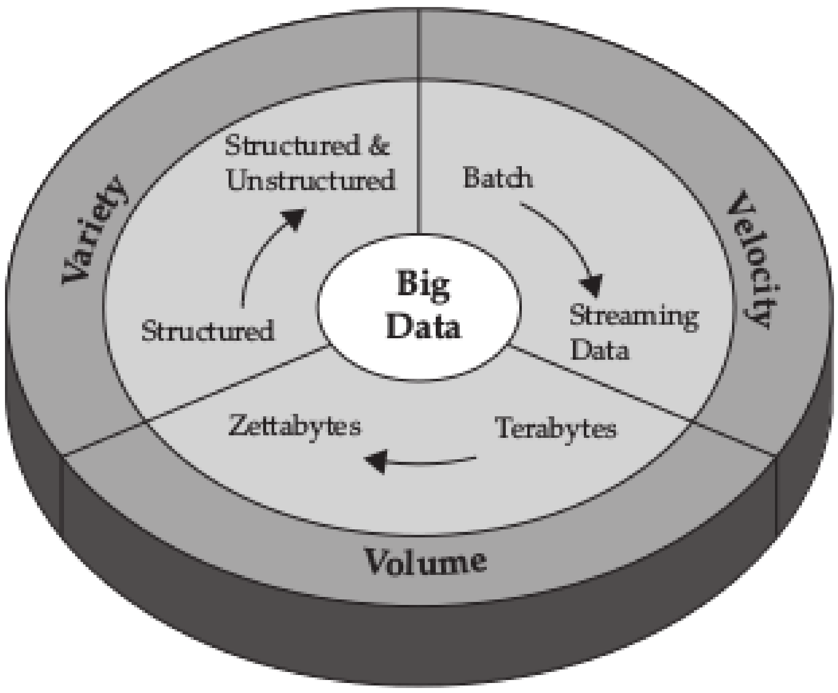

Figure 2.2: The three 'V's of Big Data[**Ziko12**]

A possible definition for Big Data could be derived as follows: *Big Data refers to the use of large amounts of data from multiple sources with a high processing speed for generating valuable information based on the underlying data.*

[Jör14b] proposes another characteristic as a fourth point called "Analytics", which will be explained in the next section.

2.2 Big Data Analytics Applications

Big Data Analytics describes the process of collecting, organizing and analyzing large volumes of data with the aim to discover patterns, relationships and other useful information extracted from incoming data streams [Nat15]. The process of analytics is typically performed using specialized software tools and applications for predictive analytics, data mining, text mining, forecasting and data optimization.

The analytical methods raise data quality for unstructured data on a level that allows more quantitative and qualitative analysis. With this structure it becomes posssible to extract the data that is relevant by iteratively refined queries.

The areas of applications may be extremely diverse and ranges from analysis of financial flows or traffic data, processing sensor data or environmental monitoring as explained in the previous chapter.

The illustration below summarises the six-dimensional taxonomy [Jör14a; Gro14] of Big Data Analytics Applications.

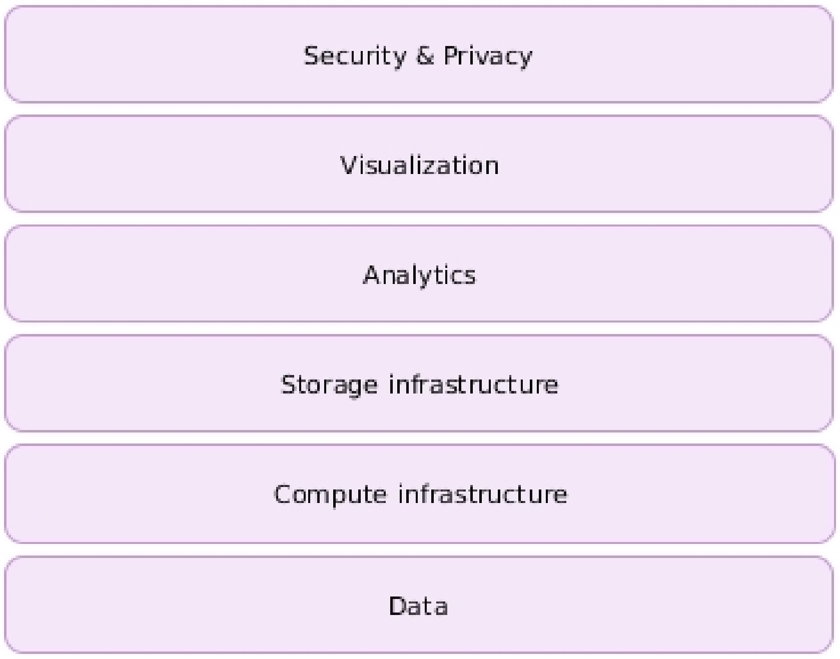

Figure 2.3: Taxonomy of Big Data Analytics Applications [Jör14a; Gro14]

The following section will discus the topic stream processing, which is part of the "Compute infrastructure" layer shown in the figure above.

2.3 Stream Processing

Computing paradigms on big data currently differ at the first level of abstraction on whether the processing will be done in batch mode, or in real-time/near real-time on streaming data. This section is focussed on processing continous data streams in real-time/near real-time and introduces Apache Flink and Apache Kafka as representants of streaming frameworks.

According to [Kle16], stream processing is the real-time processing of data continuously, concurrently, and in a record-by-record fashion in which data is treated not as static tables or files, but as a continuous infinite stream of data integrated from both live and historical sources. It is needed, if "immediate" response to each event as it occurs is demanded by the application. Various data streams could have own features. For example, a stream from the financial market describes the whole data. In the same time, a stream for sensors depends on sampling (e.g. get new data every 5 minutes).

The general approach is to have a small component that processes each of the events separately. In order to speed up the processing, the stream may be subdivided, and the computation distributed across clusters. Stream processing frameworks primarily addresses parallelization of the computational load; an additional storage layer is needed to store the results in order to be able to query them.

Benefits of stream processing:

- Accessibility: live data can be used while still in motion, before being stored.
- Completeness: historical data can be streamed and integrated with live data for more context.
- High throughput: high-velocity and high-volume data can be processed with minimal latency.

In a formal way, a data stream is described as an ordered pair (S, T) where:

- S is a sequence of tuples.
- T is a sequence of positive real time intervals.

It defines a data stream as a sequence of data objects, where the sequence in a data stream is potentially unbounded, which means that data streams may be continuously generated at any rate [Nam15] and leads to the following characteristics:

- the data arives continous
- the arrival of data is disorderen
- the size of the stream is potentially unbounded

After this short introduction to the basics of stream processing, the following sections covers a short introduction of the streaming frameworks Apache Flink and Apache Kafka.

2.3.1 Apache Flink

As described in the documentation [Fli16], *"Apache Flink is an open source platform for distributed stream and batch data processing. Flink's core is a streaming dataflow engine that provides data distribution, communication, and fault tolerance for distributed computations over data streams. Flink also builds batch processing on top of the streaming engine, overlaying native iteration support, managed memory, and program optimization."*

The main components of Flink applications are formed by streams and transformations, in which streams define intermediate results whereas transformations represent operations computed on one or more input streams with one or more resulting streams.

The following code from [Fli16] shows a basic Flink application, a working example of streaming window word count application, that counts the words coming from a web socket in 5 second windows:

```
public static void main(String[] args) throws Exception {
        StreamExecutionEnvironment env = ↩
            StreamExecutionEnvironment.getExecutionEnvironment();
        DataStream<Tuple2<String, Integer>> dataStream = env
                .socketTextStream("localhost", 9999) (1)
                .flatMap(new Splitter()) (2)
                .keyBy(0) (2)
                .timeWindow(Time.seconds(5)) (2)
                .sum(1); (2)

        dataStream.print(); (3)
        env.execute("Window WordCount");
    }

    public static class Splitter implements FlatMapFunction<String, ↩
        Tuple2<String, Integer>> {
        @Override
        public void flatMap(String sentence, Collector<Tuple2<String, ↩
            Integer>> out) throws Exception {
            for (String word: sentence.split(" ")) {
                out.collect(new Tuple2<String, Integer>(word, 1));
            }
        }
    }
```

Codeauszug 2.1: Basic Apache Flink streaming application

On execution, Flink applications are mapped to streaming dataflows, consisting of streams and transformation operators (3) where each dataflow starts with one or more sources (1) the data is received from and ends in one or more sinks(3) the resulting stream is written to.

The following overview summarises the most important streaming features of Apache Flink:

Event time and out of order streams Due to the distributed character of Big Data Analytics Applications, data doesn't arrive necessarily in the order that they are produced. Since version 0.10, Flink provides the concept of "event time", the processing of events by the time they happened in the real world to support "out of order" streams what enables consistently processing of events according to their timestamps.

Windows Flink uses a concept called windows to divide a data stream that can be potentially infinite into finite slices based on the timestamps of elements or other criteria. This division is required when working with infinite streams of data and performing transformations that aggregate elements

Consistency, fault tolerance, and high availability Flink guarantees consistent state updates and data movement in the presence of failures between selected sources and sinks. Such failures include machine hardware failures, network failures, transient program failures, etc. It supports worker and master failover, eliminating any single point of failure by providing a checkpointing mechanism that recovers streaming jobs after failures.

Connectors and integration points Flink integrates with a wide variety of open source systems for data input and output (Kafka, Elasticsearch and others) which makes technical decisions regarding the infrastructure quite flexible.

2.3.2 Apache Kafka

Apache Kafka is publish-subscribe messaging rethought as a distributed commit log. [Kaf16]. It is written in Scala and was initially developed at LinkedIn.

This excerpt from the paper [Jay11] the team at LinkedIn published about Kafka describes the basic principles:

A stream of messages of a particular type is defined by a topic. A producer can publish messages to a topic. The published messages are then stored at a set of servers called brokers. A consumer can subscribe to one or more topics from the brokers, and consume the subscribed messages by pulling data from the brokers. (. . .) To subscribe to a topic, a consumer first creates one or more message streams for the topic. The messages published to that topic will be evenly distributed into these sub-streams. (. . .) Unlike traditional iterators, the message stream iterator never terminates. If there are currently no more messages to consume, the iterator blocks until new messages are published to the topic.

TODO: Role of Kafka as broker to ingest data

2.4 Summary

3 Data Analysis

TODO

3.1 Data Quality

3.2 System data

Observation of cpu-, disk- and memory-utilization. Dstat system util introduction

3.3 Application data

3.3.1 Apache Flink

REST, JMX since version 1.1.0 What data, interesting?

3.3.2 Apache Kafka

JMX What data, interesting?

3.4 Summary

4 Requirements

TODO: Three main components. Describe general. see [Les14]

4.1 Collection

4.2 Transport

4.3 Persistence

4.4 Summary

realtime?

5 Architecture

Distributed system -> distributed collection, cloud environments, microservice architecture communication via REST, Publish(client) -> Subscribe Logstash

5.1 Data as time-series based stream

TODO see [Kle16]

5.2 "Distributed Data Collection"

clients as DS

5.3 Microservices and Service-Discovery

TODO

5.4 System components

TODO maybe split Infrastructure / Software components

5.4.1 CollectorClient

The CollectorClient tier is our entry point for bringing data into the system... A module to gather the event streams from data sources.

5.4.2 Service-Discovery

Registraction for CollectorClients

5.4.3 CollectorManager

Gives overview, uses Consul as service-discovery

5.4.4 Message-Broker

Transport, "Event-Log", see [Kre13] Collect the streams and make them available for consumption

5.4.5 Indexer

Receive messages from Kafka, roote data, create ES index, why, describe context BDAA

5.4.6 Persistence

ES as search index for time-series based data, easy vizualization with Kibana, why?

5.4.7 CollectorDataProcessor

module to analyze the streams creating derived streams

5.5 Summary

Maybe Spring alternatives, Lagom, VertX, Play? Maybe collector as agent instead of microservice, alternatives REST, maybe (Web-)Sockets

6 Implementation

Introduce software stack, why used?

6.1 The "collect"-algorithm

Java8, CPs, non-blocking streams

7 Evaluation

7.1 Local test environment

7.2 Docker environment

7.3 Observations

7.4 Discussion

7.5 Summary

8 Conclusion

TODO

8.1 Summary

8.2 Outlook

List of Figures

List of Tables

List of Source Codes

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A.1 Diagrams

A.1.1 Use Case diagram

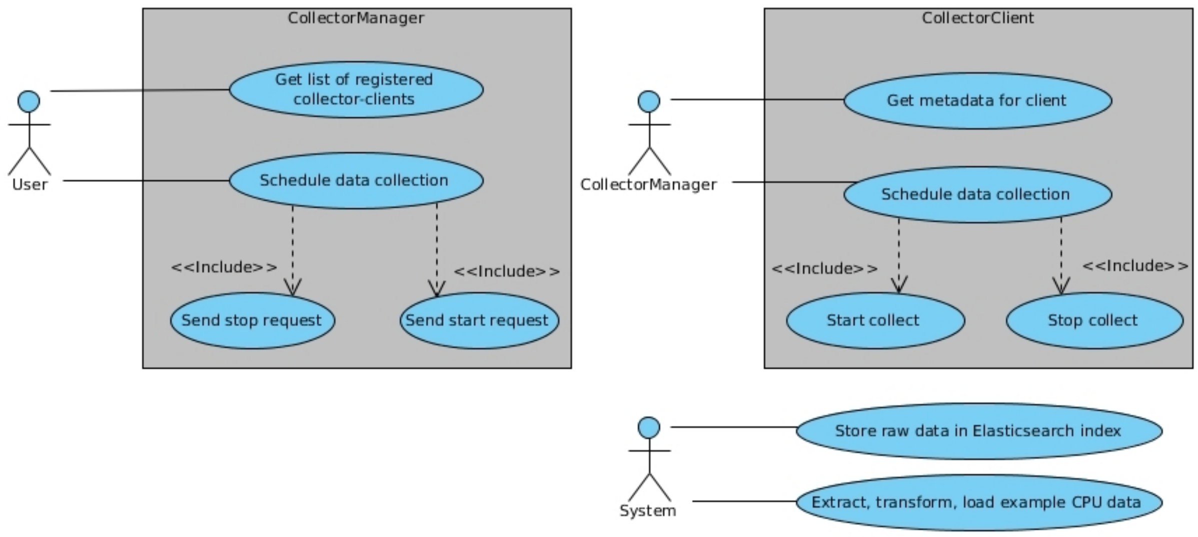
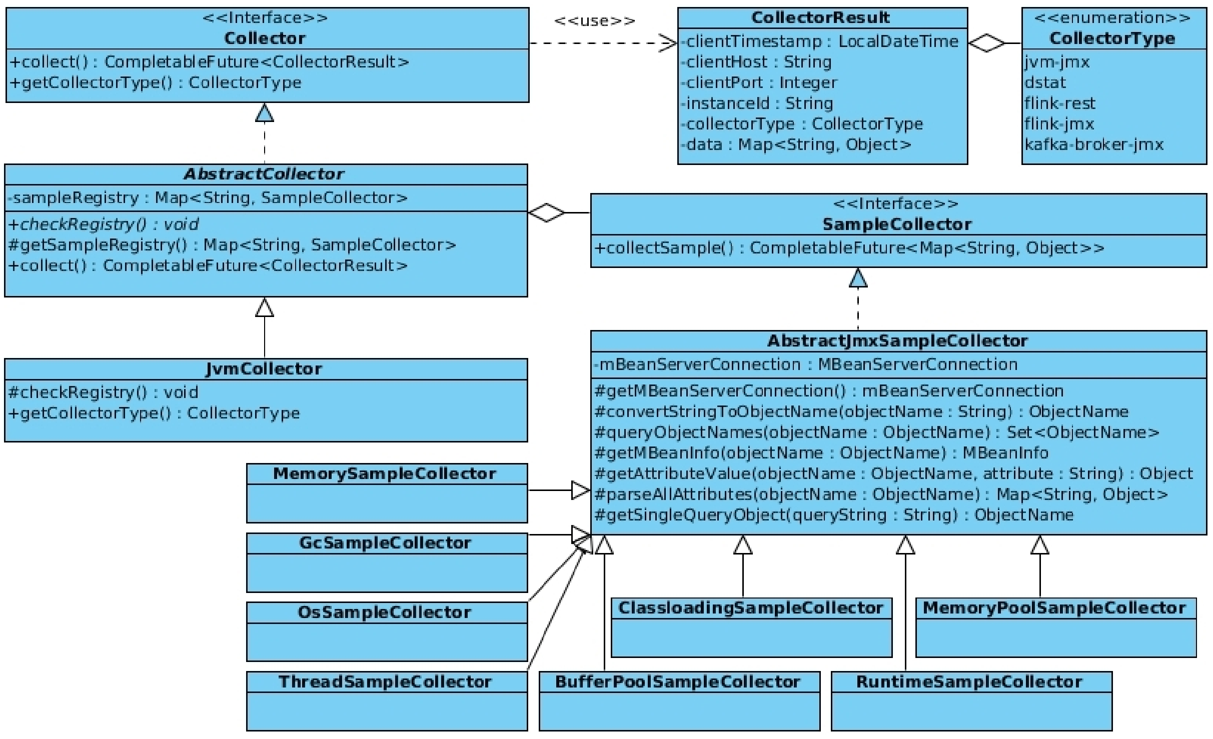


Figure A.1: Use Case Diagramm

A.1.2 Class diagrams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+getCollectorType() : CollectorType
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CollectorResult
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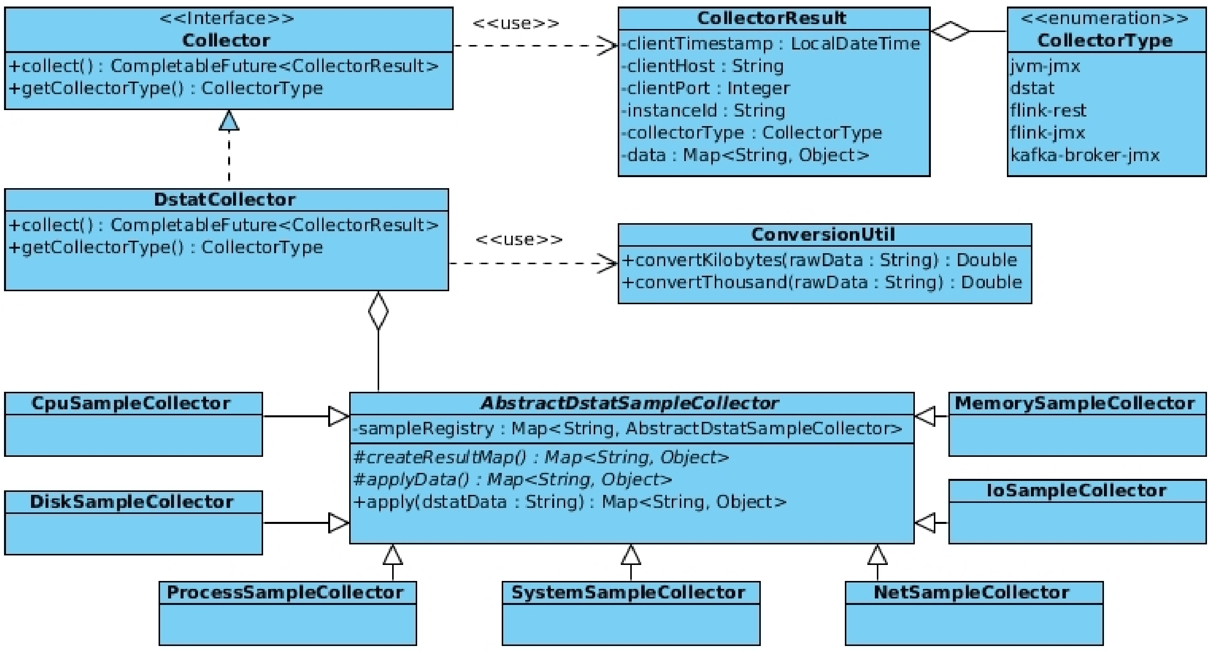
-clientHost : String
-clientPort : Integer
-instanceId : String
-collectorType : CollectorType
-data : Map<String, Object>
<<enumeration>>
CollectorType
jvm-jmx
dstat
flink-rest
flink-jmx
kafka-broker-jmx
AbstractCollector
-sampleRegistry : Map<String, SampleCollector>
+checkRegistry() : void
#getSampleRegistry() : Map<String, SampleCollector>
+collect() : CompletableFuture<CollectorResult>
<<Interface>>
SampleCollector
+collectSample() : CompletableFuture<Map<String, Object>>
JvmCollector
#checkRegistry() : void
+getCollectorType() : CollectorType
AbstractJmxSampleCollector
-mBeanServerConnection : MBeanServerConnection
#getMBeanServerConnection() : mBeanServerConnection
#convertStringToObjectName(objectName : String) : ObjectName
#queryObjectNames(objectName : ObjectName) : Set<ObjectName>
#getMBeanInfo(objectName : ObjectName) : MBeanInfo
#getAttributeValue(objectName : ObjectName, attribute : String) : Object
#parseAllAttributes(objectName : ObjectName) : Map<String, Object>
#getSingleQueryObject(queryString : String) : ObjectName
MemorySampleCollector
GcSampleCollector
OsSampleCollector
ThreadSampleCollector
BufferPoolSampleCollector
ClassloadingSampleCollector
MemoryPoolSampleCollector
RuntimeSampleCollector

Figure A.2: Class diagram 'JvmCollector'



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-data : Map<String, Object>
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CollectorType
jvm-jmx
dstat
flink-rest
flink-jmx
kafka-broker-jmx
DstatCollector
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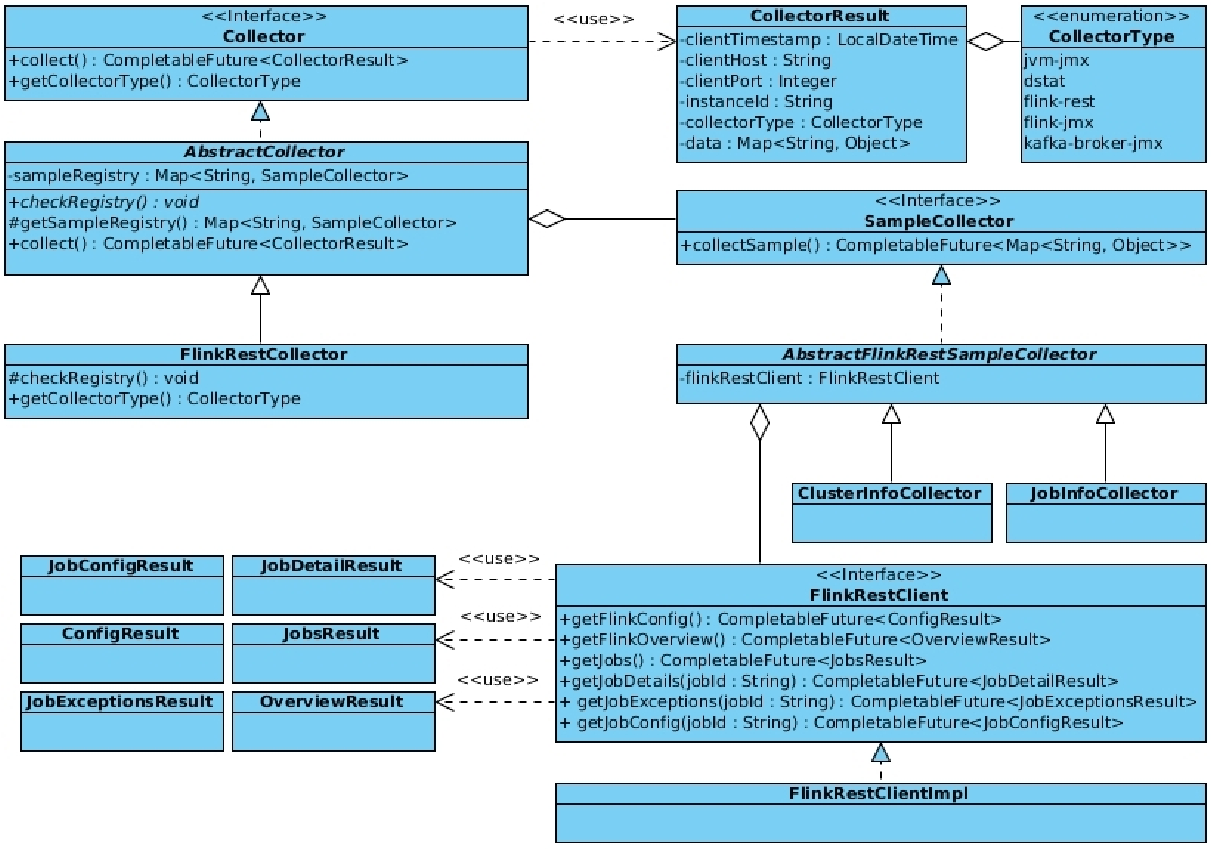
+getCollectorType() : CollectorType
<<use>>
ConversionUtil
+convertKilobytes(rawData : String) : Double
+convertThousand(rawData : String) : Double
CpuSampleCollector
AbstractDstatSampleCollector
-sampleRegistry : Map<String, AbstractDstatSampleCollector>
#createResultMap() : Map<String, Object>
#applyData() : Map<String, Object>
+apply(dstatData : String) : Map<String, Object>
MemorySampleCollector
DiskSampleCollector
IoSampleCollector
ProcessSampleCollector
SystemSampleCollector
NetSampleCollector

Figure A.3: Class diagram 'DStatCollector'



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flink-rest
flink-jmx
kafka-broker-jmx
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+collect() : CompletableFuture<CollectorResult>
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FlinkRestCollector
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AbstractFlinkRestSampleCollector
-flinkRestClient : FlinkRestClient
ClusterInfoCollector
JobInfoCollector
JobConfigResult
JobDetailResult
ConfigResult
JobsResult
JobExceptionsResult
OverviewResult
<<use>>
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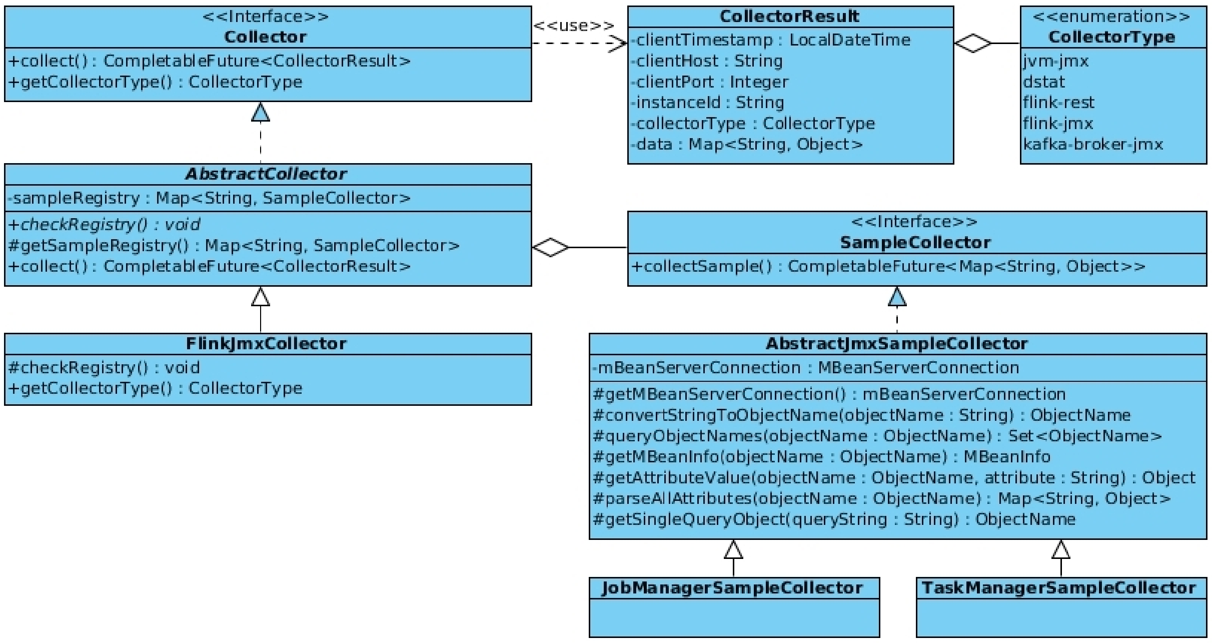
FlinkRestClient
+getFlinkConfig() : CompletableFuture<ConfigResult>
+getFlinkOverview() : CompletableFuture<OverviewResult>
+getJobs() : CompletableFuture<JobsResult>
+getJobDetails(jobId : String) : CompletableFuture<JobDetailResult>
+ getJobExceptions(jobId : String) : CompletableFuture<JobExceptionsResult>
+ getJobConfig(jobId : String) : CompletableFuture<JobConfigResult>
FlinkRestClientImpl

Figure A.4: Class diagram 'FlinkRestCollector'



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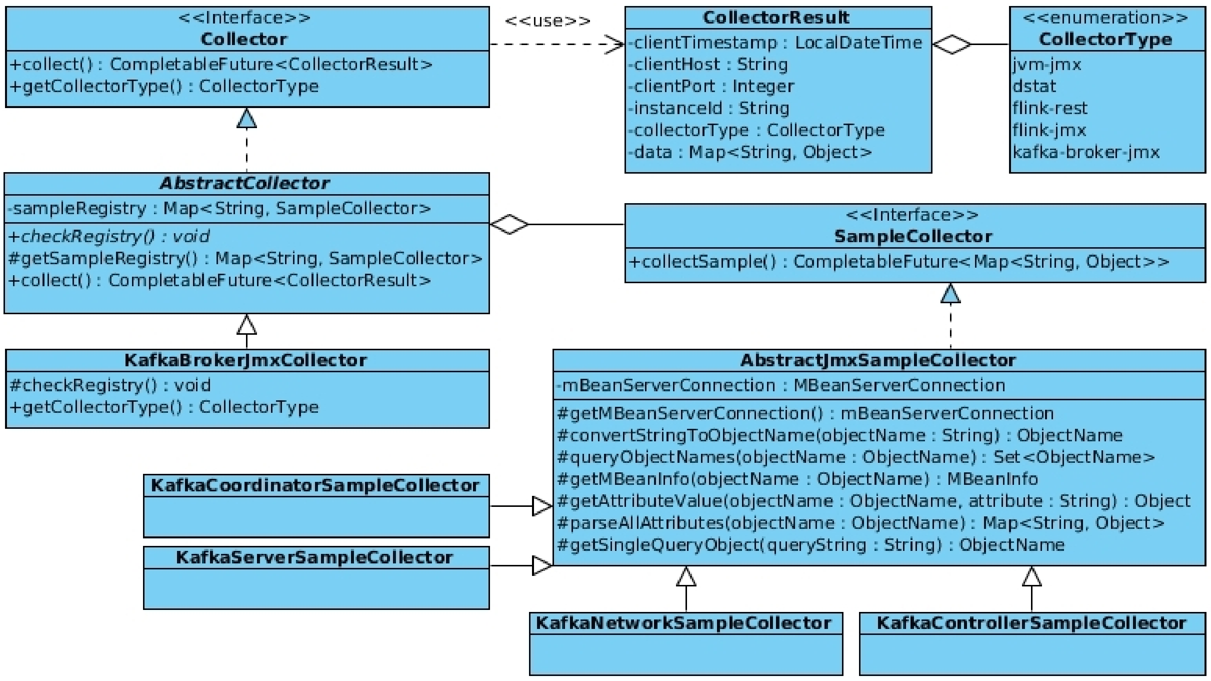
#queryObjectNames(objectName : ObjectName) : Set<ObjectName>
#getMBeanInfo(objectName : ObjectName) : MBeanInfo
#getAttributeValue(objectName : ObjectName, attribute : String) : Object
#parseAllAttributes(objectName : ObjectName) : Map<String, Object>
#getSingleQueryObject(queryString : String) : ObjectName
JobManagerSampleCollector
TaskManagerSampleCollector

Figure A.5: Class diagram 'FlinkJmxCollector'



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+getCollectorType() : CollectorType
AbstractJmxSampleCollector
-mBeanServerConnection : MBeanServerConnection
#getMBeanServerConnection() : mBeanServerConnection
#convertStringToObjectName(objectName : String) : ObjectName
#queryObjectNames(objectName : ObjectName) : Set<ObjectName>
#getMBeanInfo(objectName : ObjectName) : MBeanInfo
#getAttributeValue(objectName : ObjectName, attribute : String) : Object
#parseAllAttributes(objectName : ObjectName) : Map<String, Object>
#getSingleQueryObject(queryString : String) : ObjectName
KafkaCoordinatorSampleCollector
KafkaServerSampleCollector
KafkaNetworkSampleCollector
KafkaControllerSampleCollector

Figure A.6: Class diagram 'KafkaBrokerJmxCollector'

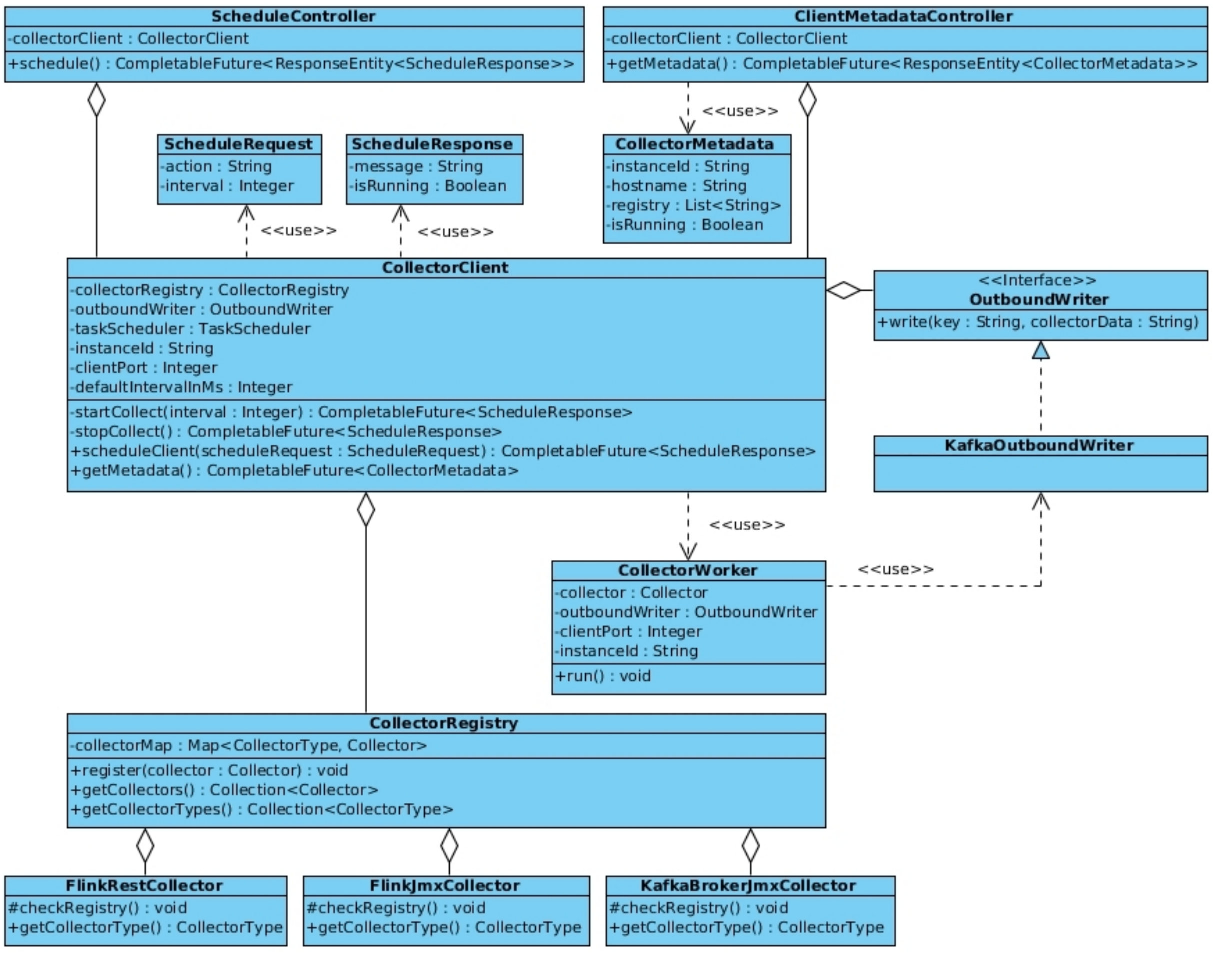
ScheduleController
-collectorClient : CollectorClient
+schedule() : CompletableFuture<ResponseEntity<ScheduleResponse>>
ClientMetadataController
-collectorClient : CollectorClient
+getMetadata() : CompletableFuture<ResponseEntity<CollectorMetadata>>
<<use>>
ScheduleRequest
-action : String
-interval : Integer
ScheduleResponse
-message : String
-isRunning : Boolean
CollectorMetadata
-instanceId : String
-hostname : String
-registry : List<String>
-isRunning : Boolean
<<use>>
<<use>>
CollectorClient
-collectorRegistry : CollectorRegistry
-outboundWriter : OutboundWriter
-taskScheduler : TaskScheduler
-instanceId : String
-clientPort : Integer
-defaultIntervalInMs : Integer
-startCollect(interval : Integer) : CompletableFuture<ScheduleResponse>
-stopCollect() : CompletableFuture<ScheduleResponse>
+scheduleClient(scheduleRequest : ScheduleRequest) : CompletableFuture<ScheduleResponse>
+getMetadata() : CompletableFuture<CollectorMetadata>
<<Interface>>
OutboundWriter
+write(key : String, collectorData : String)
KafkaOutboundWriter
<<use>>
<<use>>
CollectorWorker
-collector : Collector
-outboundWriter : OutboundWriter
-clientPort : Integer
-instanceId : String
+run() : void
CollectorRegistry
-collectorMap : Map<CollectorType, Collector>
+register(collector : Collector) : void
+getCollectors() : Collection<Collector>
+getCollectorTypes() : Collection<CollectorType>
FlinkRestCollector
#checkRegistry() : void
+getCollectorType() : CollectorType
FlinkJmxCollector
#checkRegistry() : void
+getCollectorType() : CollectorType
KafkaBrokerJmxCollector
#checkRegistry() : void
+getCollectorType() : CollectorType

Figure A.7: Class diagram 'CollectorClient'

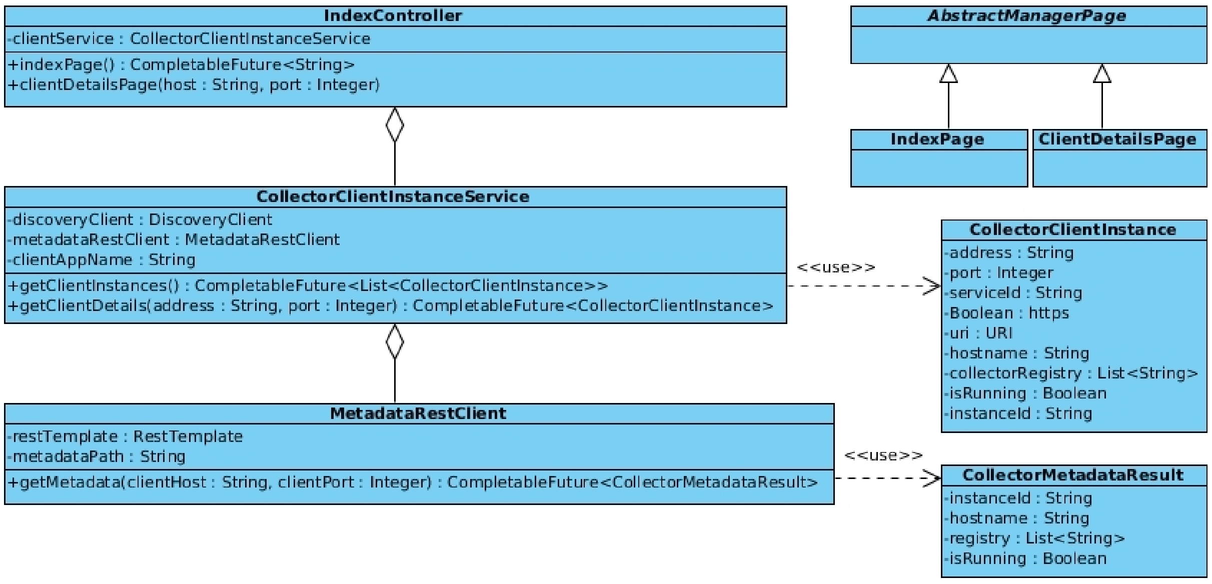
IndexController
-clientService : CollectorClientInstanceService
+indexPage() : CompletableFuture<String>
+clientDetailsPage(host : String, port : Integer)
AbstractManagerPage
IndexPage
ClientDetailsPage
CollectorClientInstanceService
-discoveryClient : DiscoveryClient
-metadataRestClient : MetadataRestClient
-clientAppName : String
+getClientInstances() : CompletableFuture<List<CollectorClientInstance>>
+getClientDetails(address : String, port : Integer) : CompletableFuture<CollectorClientInstance>
<<use>>
CollectorClientInstance
-address : String
-port : Integer
-serviceId : String
-Boolean : https
-uri : URI
-hostname : String
-collectorRegistry : List<String>
-isRunning : Boolean
-instanceId : String
MetadataRestClient
-restTemplate : RestTemplate
-metadataPath : String
+getMetadata(clientHost : String, clientPort : Integer) : CompletableFuture<CollectorMetadataResult>
<<use>>
CollectorMetadataResult
-instanceId : String
-hostname : String
-registry : List<String>
-isRunning : Boolean

Figure A.8: Class diagram 'CollectorManager'

A.1.3 Sequence diagrams

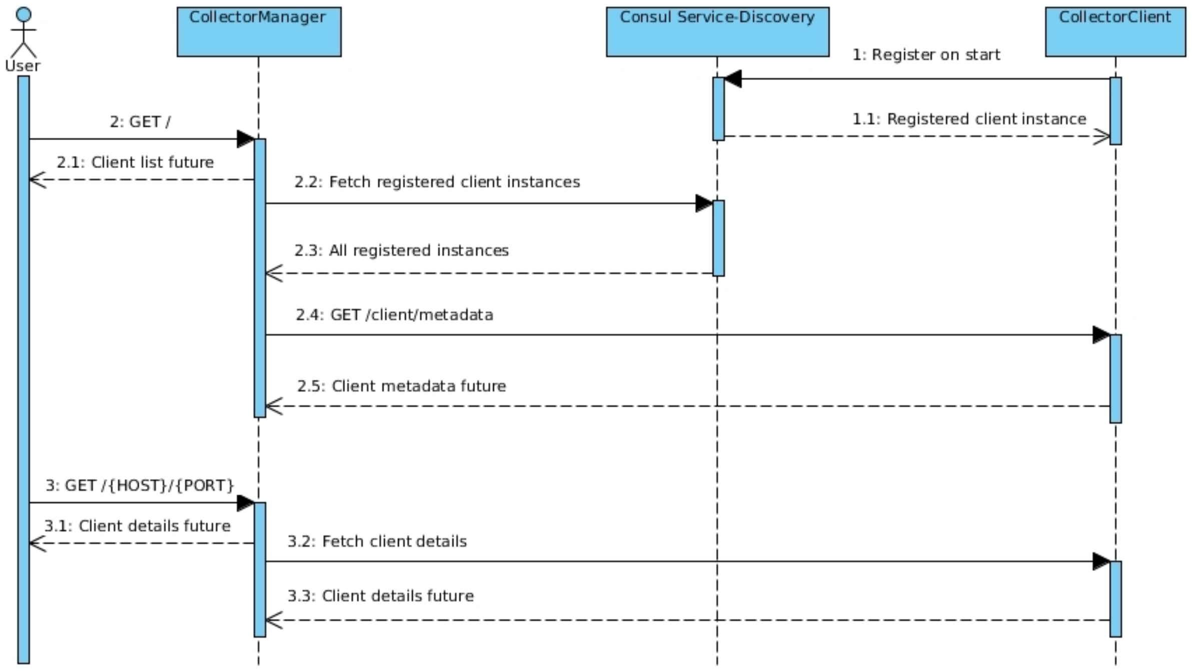
User
CollectorManager
Consul Service-Discovery
CollectorClient
1: Register on start
1.1: Registered client instance
2: GET /
2.1: Client list future
2.2: Fetch registered client instances
2.3: All registered instances
2.4: GET /client/metadata
2.5: Client metadata future
3: GET /{HOST}/{PORT}
3.1: Client details future
3.2: Fetch client details
3.3: Client details future

Figure A.9: Sequence diagram 'Client discovery'

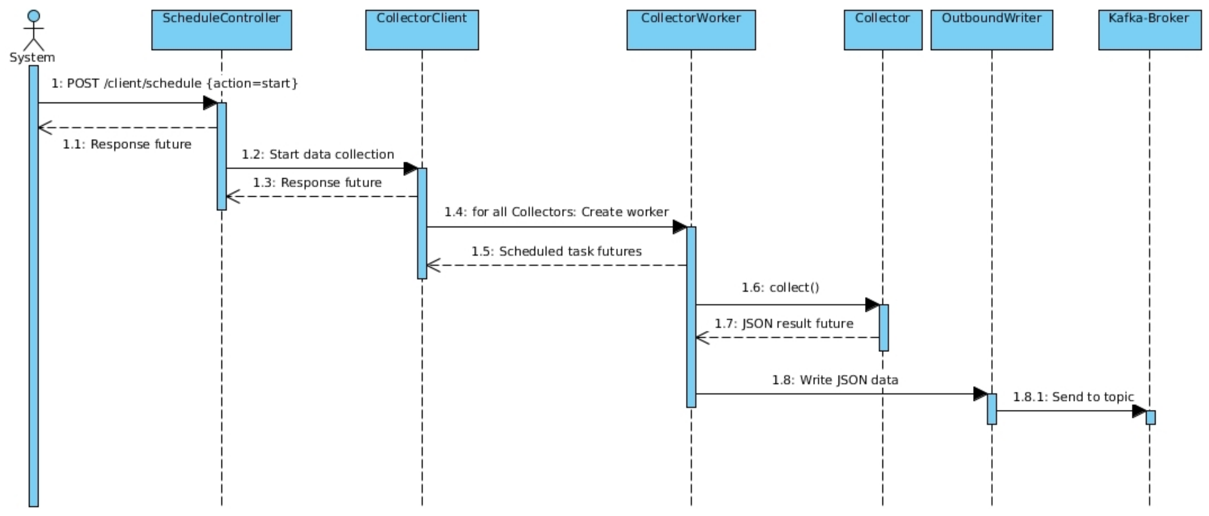

Figure A.10: Sequence diagram 'Client scheduling'

A.1.4 Component diagram

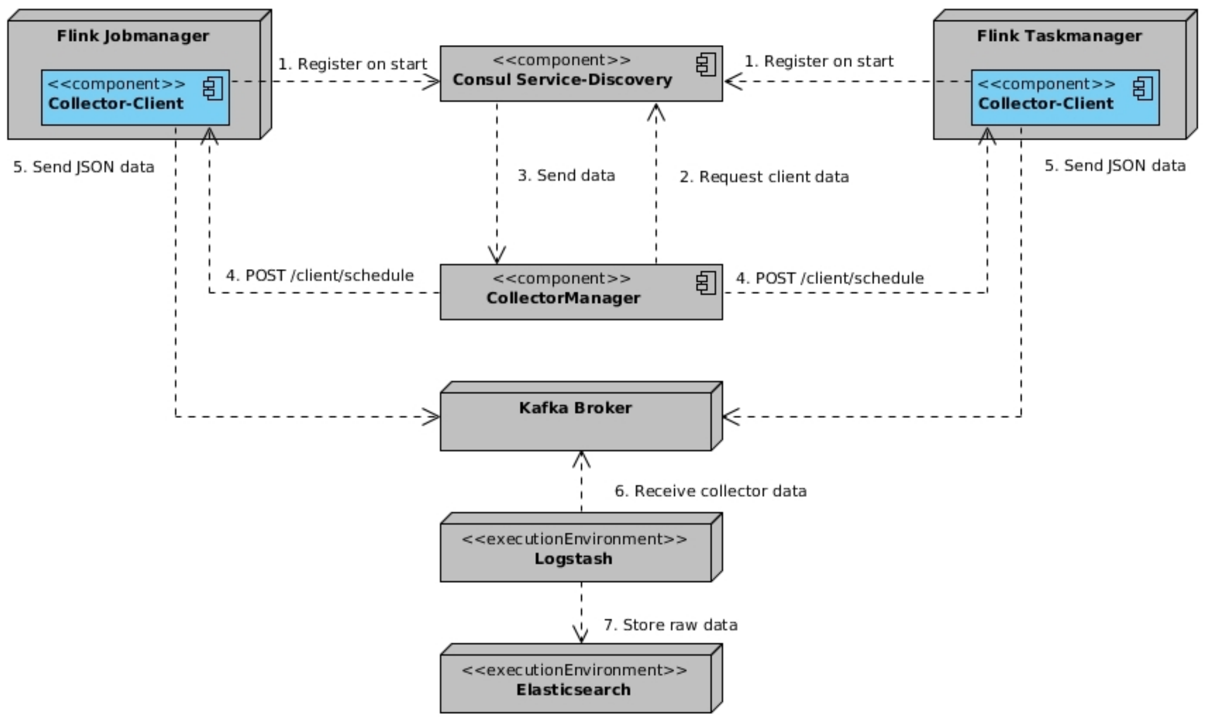
Flink Jobmanager
<<component>> Collector-Client
1. Register on start
<<component>> Consul Service-Discovery
1. Register on start
Flink Taskmanager
<<component>> Collector-Client
5. Send JSON data
3. Send data
2. Request client data
5. Send JSON data
4. POST /client/schedule
<<component>> CollectorManager
4. POST /client/schedule
Kafka Broker
6. Receive collector data
<<executionEnvironment>> Logstash
7. Store raw data
<<executionEnvironment>> Elasticsearch

Figure A.11: Component diagram

A.1.5 Deployment diagram

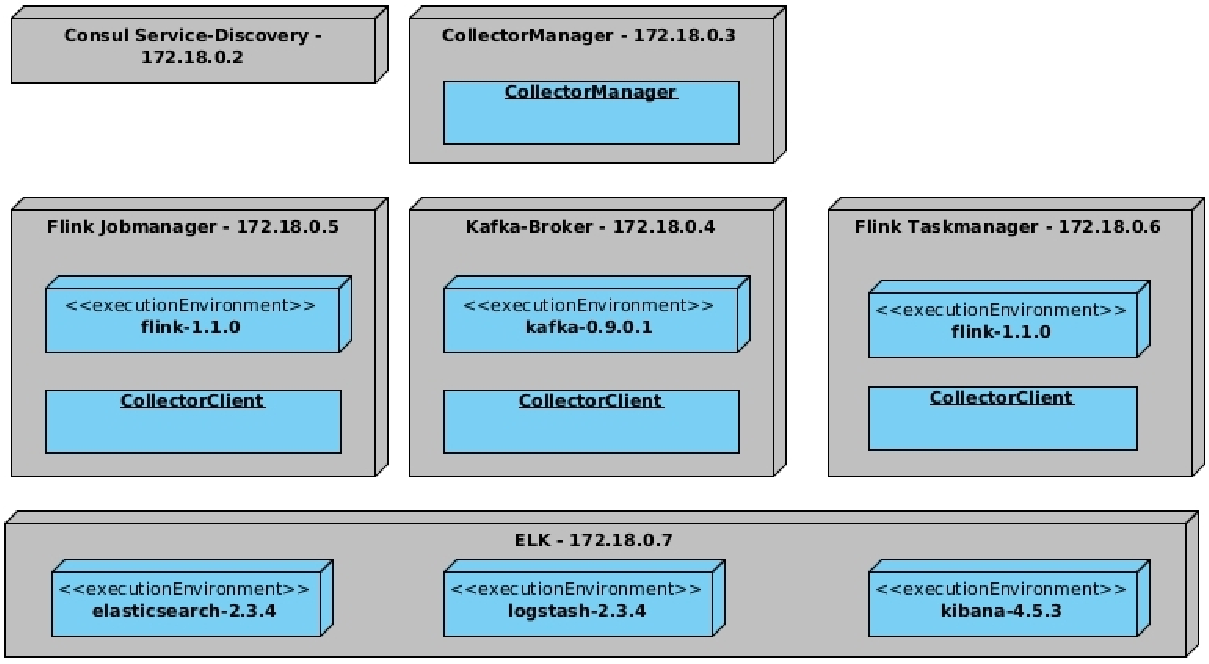
Consul Service-Discovery - 172.18.0.2
CollectorManager - 172.18.0.3
CollectorManager
Flink Jobmanager - 172.18.0.5
<<executionEnvironment>> flink-1.1.0
CollectorClient
Kafka-Broker - 172.18.0.4
<<executionEnvironment>> kafka-0.9.0.1
CollectorClient
Flink Taskmanager - 172.18.0.6
<<executionEnvironment>> flink-1.1.0
CollectorClient
ELK - 172.18.0.7
<<executionEnvironment>> elasticsearch-2.3.4
<<executionEnvironment>> logstash-2.3.4
<<executionEnvironment>> kibana-4.5.3

Figure A.12: Deployment diagram

A.2 Tabelle

A.3 Screenshot

A.4 Graph

Eigenständigkeitserklärung

Hiermit versichere ich, dass ich die vorliegende Masterarbeit selbstständig und nur unter Verwendung der angegebenen Quellen und Hilfsmittel verfasst habe. Die Arbeit wurde bisher in gleicher oder ähnlicher Form keiner anderen Prüfungsbehörde vorgelegt.

Stadt, den xx.xx.xxxx

Max Mustermann