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D2.6 – Conceptual model and Reference architecture - III

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Versioning and contribution history

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0.5	26.06.2020	Dimosthenis Kyriazis (UPRC)	Version after internal review
1.0	30.06.2020	Dimosthenis Kyriazis (UPRC)	Final version

Table of Contents

List of tables

List of figures

1. Executive Summary

BigDataStack aims to deliver a complete stack including an infrastructure management solution that drives decisions according to live and historical data, thus being fully scalable, runtime adaptable and highly performant. The overall objective is for BigDataStack to address the emerging needs of big data operations and data-intensive applications. The solution will base all infrastructure management decisions on data aspects (for example the estimation and provision of resources for each data service based on the corresponding data loads), monitoring data from deployments and logic derived from data operations that govern and affect storage, compute and network resources. On top of the infrastructure management solution, "Data as a Service" will be offered to data providers, decision-makers, private and public organisations. Approaches for data quality assessment, data skipping and efficient storage, combined with seamless data analytics will be realised holistically across multiple data stores and locations.

To provide the required information towards enhanced infrastructure management BigDataStack will provide a range of services, such as the application dimensioning workbench, which facilitates data-focused application analysis and dimensioning in terms of predicting the required data services, their interdependencies with the application micro-services and the necessary underlying resources. This will allow the identification of the applications data-related properties and their data needs, thereby enabling BigDataStack to provision deployment with specific performance and quality guarantees. Moreover, a data toolkit will enable data scientists to ingest their data analytics functions and to specify their preferences and constraints, which will be exploited by the infrastructure management system for resources and data management. Finally, a process modelling framework will be delivered, to enable functionality-based modelling of processes, which will be mapped in an automated way to concrete technical-level data analytics tasks.

The key outcomes of BigDataStack are reflected in a set of main building blocks in the corresponding overall architecture of the stack. This deliverable reflects the final version of the key functionalities of the overall architecture, the interactions between the main building blocks and their components. Comparing to the previous version of the architecture, several changes have been introduced referring both to the overall architecture (Section 5) as well as to the description of the main components of the architecture: the orchestration approach and the interactions with the CEP and the database, the realization engine, the data quality assessment mechanism, and the real-time CEP. Moreover, a new chapter has been introduced for the adaptable distributed storage approach. Additional information has also been provided regarding the main interactions (Section 7), reflecting the data as a service adaptations and new functionalities, as well as the runtime adaptations for several BigDataStack components. It should be noted that further design details and evaluation results for all components of the architecture will be delivered in the corresponding follow-up (WP-specific) deliverables addressing the user interaction block, the data as a service block and the infrastructure management block.

2. Introduction

The new data-driven industrial revolution highlights the need for big data technologies, to unlock the potential in various application domains (e.g. transportation, healthcare, logistics, etc). In this context, big data analytics frameworks exploit several underlying infrastructure and cluster management systems. However, these systems have not been designed and implemented in a “big data context”. Instead, they emphasise and address the computational needs and aspects of applications and services to be deployed.

BigDataStack aims at addressing these challenges (depicted in Figure 1) through concrete offerings, that range from a scalable, runtime-adaptable infrastructure management system (that drives decisions according to data aspects), to techniques for dimensioning big data applications, modelling and analysing of processes, as well as provisioning data-as-a-service by exploiting a seamless analytics framework.

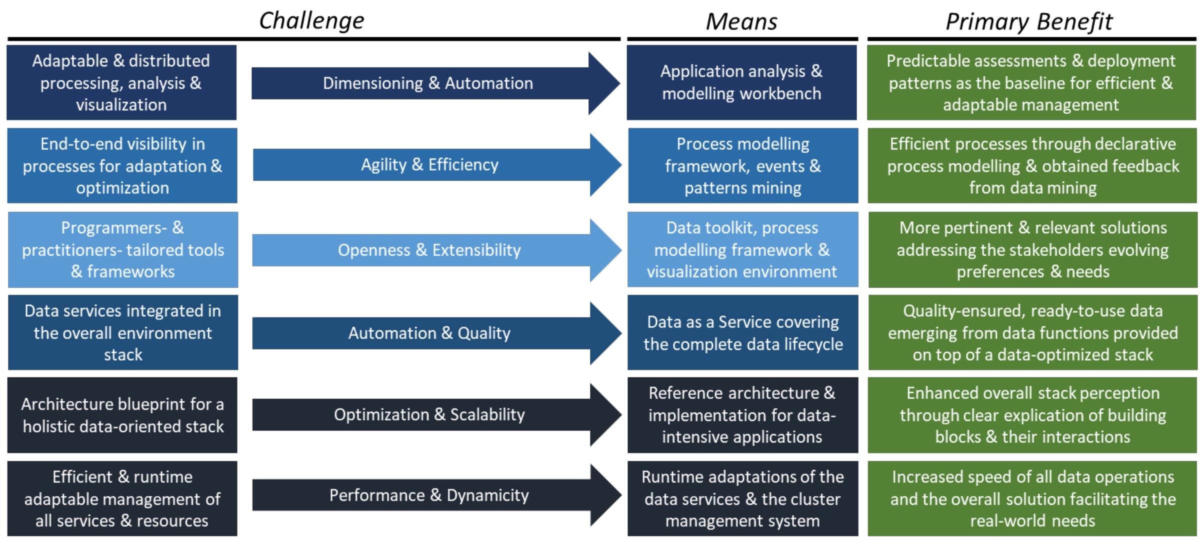

Challenge
Means
Primary Benefit
Adaptable & distributed processing, analysis & visualization
Dimensioning & Automation
Application analysis & modelling workbench
Predictable assessments & deployment patterns as the baseline for efficient & adaptable management
End-to-end visibility in processes for adaptation & optimization
Agility & Efficiency
Process modelling framework, events & patterns mining
Efficient processes through declarative process modelling & obtained feedback from data mining
Programmers- & practitioners- tailored tools & frameworks
Openness & Extensibility
Data toolkit, process modelling framework & visualization environment
More pertinent & relevant solutions addressing the stakeholders evolving preferences & needs
Data services integrated in the overall environment stack
Automation & Quality
Data as a Service covering the complete data lifecycle
Quality-ensured, ready-to-use data emerging from data functions provided on top of a data-optimized stack
Architecture blueprint for a holistic data-oriented stack
Optimization & Scalability
Reference architecture & implementation for data-intensive applications
Enhanced overall stack perception through clear explication of building blocks & their interactions
Efficient & runtime adaptable management of all services & resources
Performance & Dynamicity
Runtime adaptations of the data services & the cluster management system
Increased speed of all data operations and the overall solution facilitating the real-world needs

Figure 1 - Technical challenges

2.1. Terminology

The following table summarises a set of key terms used in BigDataStack, not regarding acronyms but regarding actual usage, given the large number of concepts and technologies addressed by the envisioned stack.

Term	Description
Application services	Components/micro-services of a user’s application
Data services	“Generic” services such as cleaning, aggregation, etc.
Dimensioning	Analysis of a user’s application services to identify the data and resources needs/requirements
Toolkit	Mechanism enabling ingest of data analytics tasks & setting of requirements (from an end-user point of view)
Graph	An overall graph including the application services and the data services
Process modelling	“Workflow” modelling regarding business processes
Process mining	Analytics tasks per process of the “workflow”
Process mapping	Mapping of business processes to analytics tasks to be executed

Interdependencies between application / data services	Data flows between application components and data services

Table 1 - Terminology

2.2. Document structure

The document is structured as follows:

- Section 3 provides an overview of the capabilities offered by the BigDataStack environment, including the key offerings and the main stakeholders addressed by each offering.
- Section 4 introduces the identified main phases, to showcase the interactions between different key blocks and offerings of the stack.
- Section 5 presents the overall project architecture.
- Section 6 provides descriptions of the main architecture components.
- Finally, in Section 7, a detailed sequence of events depicting the information flows is provided. It should be noted that these sequence diagrams capture the interactions on the overall architecture level and are not supposed to provide details of the interactions on lower levels given that these are provided by the corresponding design and specification reports of the work package deliverables.

3. BigDataStack Capabilities

This section provides an overview of the capabilities that will be offered by BigDataStack, in terms of offerings towards an extensive set of stakeholders. The goal is to present a set of "desired" capabilities as the key goals of BigDataStack. The components providing and realising these capabilities are thereafter described in the overall architecture.

3.1. Key offerings

BigDataStack offerings are depicted through a full "stack", that aims not only to facilitate the needs of data operations and applications (all of which tend to be data-intensive), but also promote these needs in an optimized way.

As depicted in Figure 2, BigDataStack will provide a *complete infrastructure management system*, which will base the management and deployment decisions on data from current and past application and infrastructure deployments. A representative example would be that of a service-defined deployment decision by a human expert (current approach), where he chooses to deploy VMs on the same physical host, to reduce data transfer latencies over the network (e.g. for real-time stream processing). On the other hand, the BigDataStack approach instead will base the decision making according to information from current and past deployments (e.g. generation rates, transfer bottlenecks, etc.), which may result in a superior deployment configuration. To this end, the BigDataStack infrastructure management system would propose a data-driven deployment decision resulting in containers/VMs placed within geographically distributed physical hosts. This simple case shows that the trade-off between service and data-based decisions on the management layer should be re-examined nowadays, due to the increasing volumes and complexity of data. The envisioned "stack" is depicted in Figure 2, which captures the key offerings of BigDataStack.

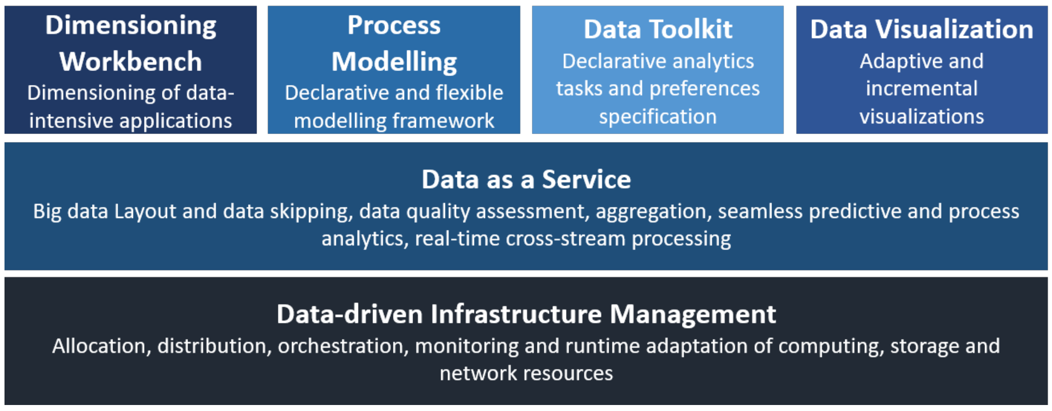

Dimensioning Workbench
Dimensioning of data-intensive applications
Process Modelling
Declarative and flexible modelling framework
Data Toolkit
Declarative analytics tasks and preferences specification
Data Visualization
Adaptive and incremental visualizations
Data as a Service
Big data Layout and data skipping, data quality assessment, aggregation, seamless predictive and process analytics, real-time cross-stream processing
Data-driven Infrastructure Management
Allocation, distribution, orchestration, monitoring and runtime adaptation of computing, storage and network resources

Figure 2 - Key offerings

The first core offering of BigDataStack is *efficient and optimised infrastructure management,* including all aspects of management for the computing, storage and networking resources, as described before.

The second core offering of BigDataStack exploits the underlying data-driven infrastructure management system, to provide *Data as a Service in a performant, efficient and scalable way*. Data as a Service incorporates a set of technologies addressing the complete data path: data quality assessment, aggregation, and data processing (including seamless analytics, real-time Complex Event Processing - CEP, and process mining). *Distributed storage* is realised through a layer, enabling data to be fragmented/stored according to different access patterns in different underlying data stores. A *big data layout and data skipping* approach is used to minimize the data that should be read from the underlying object store to perform the corresponding analytics. The *seamless data analytics framework* analyses data in a holistic fashion across multiple data stores and locations and operates on data irrespective of where and when it arrives at the framework. A *cross-stream processing engine* is also included in the architecture to enable distributed processing of data streams. The engine considers the latencies across data centres, the locality of data sources and data sinks, and produces a partitioned topology that will maximise the performance.

The third core offering of BigDataStack refers to *Data Visualization*, going beyond the presentation of data and analytics outcomes to *adaptable visualisations in an automated way*. Visualizations cover a wide range of aspects (interlinked if required) besides *data analytics*, such as *computing, storage and networking infrastructure data*, *data sources* information, and *data operations* outcomes (e.g. data quality assessment outcomes, application analytics outcomes, etc.). Moreover, the BigDataStack *visualisations will be incremental*, thus providing data analytics results as they are produced.

The fourth core offering of BigDataStack, the *Data Toolkit, aims at openness and extensibility*. The toolkit allows the *ingestion of data analytics functions* and the *definition of analytics*, providing at the same time *"hints" towards the infrastructure/cluster management system for the optimised management* of these analytics tasks. Furthermore, the toolkit allows data scientists to *specify requirements and preferences* as service level objectives (e.g. regarding the response time of analytics tasks), which are considered by *infrastructure management* both during deployment time and during runtime (i.e. triggering adaptations in an automated way).

The *Process Modelling* offering provides a *framework allowing for flexible modelling of process analytics* to enable their execution. Process chains (as workflows) can be specified through the framework, along with overall workflow objectives (e.g. accuracy of predictions, overall time for the whole workflow, etc) that are considered by mechanisms mapping the aforementioned processes to data analytics that can be executed directly on the BigDataStack infrastructure. Moreover, process mining tasks realize a feedback loop towards overall process optimisation and adaptation.

Finally, the sixth offering of BigDataStack, the *Dimensioning Workbench* aims at enabling the dimensioning of applications in terms of predicting the required data services, their interdependencies with the application micro-services and the necessary underlying resources.

3.2. Stakeholders addressed

BigDataStack provides a set of endpoints to address the needs of different stakeholders as described below:

1. *Data Owners:* BigDataStack allows to obtain both streaming and stored data from data owners and record them in its underlying storage infrastructure that supports SQL and NoSQL data stores.
2. *Data Scientists:* BigDataStack offers the *Data Toolkit* to enable data scientists both to easily ingest their analytics tasks and to specify their preferences and constraints to be exploited during the dimensioning phase regarding the data services that will be used (for example response time of a specific analytics task).
3. *Business Analysts:* BigDataStack offers the *Process Modelling Framework* allowing business users to define their functionality-based business processes and optimise them based on the outcomes of process analytics that will be triggered by BigDataStack. Mapping to specific process analytics tasks will be performed in an automated way.
4. *Application Engineers and Developers:* BigDataStack offers the *Application Dimensioning Workbench* to enable application owners and engineers to experiment with their application and obtain dimensioning outcomes regarding the required resources for specific data needs and data-related properties.

These actors interact with the corresponding offerings and provide information that is exploited thereafter by the infrastructure/cluster management system of BigDataStack. It should be noted that on top of these offerings, the *Visualization Environment* is also an interaction point with end users, providing the outcomes of analytics as well as the monitoring results of all infrastructure and data-related operations.

4. Main phases

The envisioned operation of BigDataStack is reflected in four main phases as depicted in Figure 3 (and further detailed in the following sub-sections): Entry, Dimensioning, Deployment and Operation.

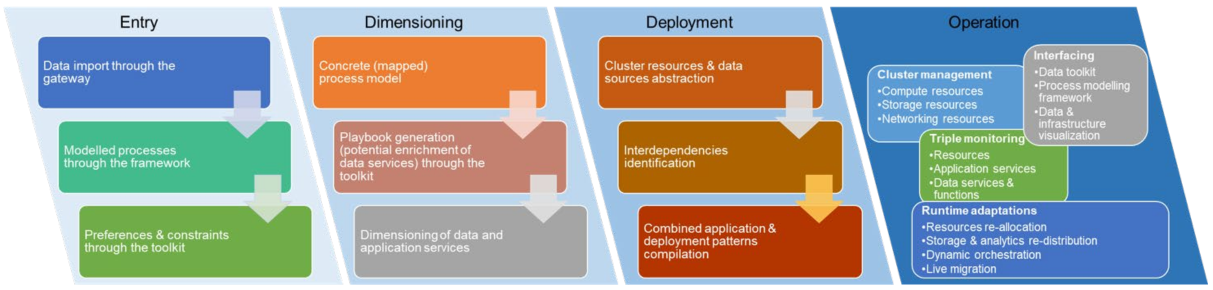

Entry
Data import through the gateway
Modelled processes through the framework
Preferences & constraints through the toolkit
Dimensioning
Concrete (mapped) process model
Playbook generation (potential enrichment of data services) through the toolkit
Dimensioning of data and application services
Deployment
Cluster resources & data sources abstraction
Interdependencies identification
Combined application & deployment patterns compilation
Operation
Cluster management
•Compute resources
•Storage resources
•Networking resources
Interfacing
•Data toolkit
•Process modelling framework
•Data & infrastructure visualization
Triple monitoring
•Resources
•Application services
•Data services & functions
Runtime adaptations
•Resources re-allocation
•Storage & analytics re-distribution
•Dynamic orchestration
•Live migration

Figure 3 - BigDataStack Main Phases

During the entry phase, data owners ingest their data. Analysts design business processes by utilising the functionalities of the Process Modelling framework in order to describe the overall business workflows, while data scientists can specify their preferences and pose their constraints through the Data Toolkit.

During the dimensioning phase, the individual processes / steps of the overall process model (i.e. workflow) are mapped to analytics tasks, and the graph is concretized (including specific analytics tasks and application services to be deployed). The whole workflow is modelled as a playbook descriptor and is passed to the Dimensioning Workbench. In turn, the Dimensioning Workbench provides insights regarding the required infrastructure resources, for the data services and application components, through an envisioned elasticity model that includes estimates for different Quality of Service (QoS) requirements and Key Performance Indicators (KPIs).

The goal of the deployment phase is to deliver the optimum deployment patterns for the data and application services, by considering the resources and the interdependencies between application components and data services (based on the dimensioning phase outcomes).

Finally, the operation phase facilitates the provision of data services including technologies for resource management, monitoring and evaluation towards runtime adaptations.

4.1. Entry phase

During the entry phase, data is introduced into the system, the Business Analysts design and evaluate their business processes, and the Data Scientists specify their preferences and constraints through the Data Toolkit. Thus, the Entry Phase consists of three discrete steps:

- Data owners ingest their data in the BigDataStack-supported data stores, through a unified gateway. They can directly choose if they want to store (non-) relational data or use the BigDataStack's object storage offering. The seamless analytics framework brings together the LeanXcale database and the Object Store into a new entity, permitting the definition of rules for automatic balancing of datasets between these two basic data storage components (e.g. data older than 3 months should be moved to the object store), as well as to describe and use a dataset, which may be spread over the two data storage components seamlessly. Streaming data can also be processed, leveraging the BigDataStack's CEP implementation.

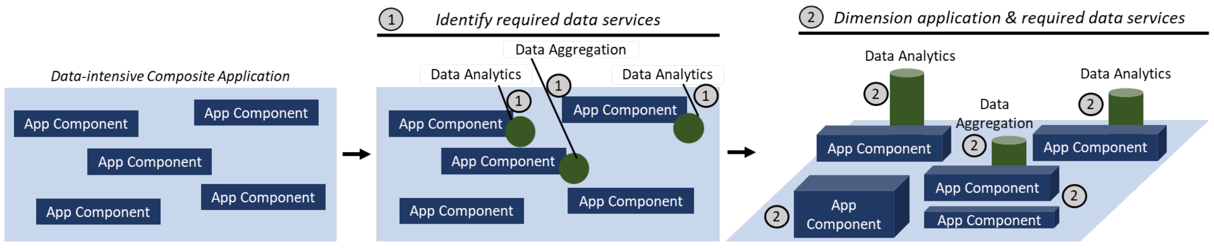
- Given the stored data, Business Analysts can design processes utilising the intuitive graphical user interface provided by the Process Modelling framework, and the available list of "generic" processes (e.g. customer segmentation process). Overall, they compile a business workflow, ready to be mapped to concrete executable tasks. These mappings are performed by a mechanism incorporated in the Process Modelling framework, the Process Mapping component.
- Based on the outcomes of process mapping, the graph of services (representing the corresponding business workflow) is made available to the Data Scientists through the Toolkit. The scientists can specify preferences for specific tasks, for example, what the response time of a recommendation algorithm should be or ingest a new executable in case a task has not been successfully mapped by the Process Mapping mechanism.

The output of the Entry Phase is a Kubernetes-like configuration template file describing the graph/workflow (which includes all relevant information for the application graph with concrete "executable" services). We refer to this as a *BigDataStack Playbook*. This is passed to the dimensioning phase in order to identify the resource needs for the contained services.

4.2. Dimensioning phase

The dimensioning phase of BigDataStack aims to optimize the provision of data services and data-intensive applications, by understanding not only their data-related requirements (e.g. related data sources, storage needs, etc.) but also the data services requirements across the data path (e.g. the resources needed for effective data storage, analytics, etc.), and the interdependencies when moving from an atomic / single service to an application graph. In this context, dimensioning includes a two-step approach that is realised through the BigDataStack Application Dimensioning Workbench:

- In the first step, the input from the Data Toolkit is used to define the composite application (consisting of a set of micro-services) needs with relation to the required data services. The example illustrated in Figure 4 shows that 3 out of the 5 application components require specific data services for aggregation and analytics.
- The second step is to dimension these identified/required data services, as well as all the application components, regarding their infrastructure resource needs. That is achieved by exploiting load injectors generating different loads, to benchmark the services and analyse their resources and data requirements (e.g. volume, generation rate, legal constraints, etc.).


Data-intensive Composite Application
App Component
1 Identify required data services
Data Aggregation
Data Analytics
2 Dimension application & required data services
Data Aggregation
Figure 4 - Dimensioning phase

The output of the dimensioning phase is an elasticity model, i.e., a mathematical function that describes the mapping of the input parameters (such as workload and Quality of Service - QoS) to needed resource parameters (such as the bandwidth, latency etc.).

4.3. Deployment phase

The deployment phase of BigDataStack aims at determining the optimum deployment configuration and deployment resources for the application and data services in terms of cluster resources. The need for such configuration emerges from the fact that to deploy the application and data services in a way such that it will meet the user's needs, BigDataStack needs to account for the application and data services complexity/efficiency, the workload (e.g. requests per second) and the user-defined quality of service requirements/preferences (e.g. <100ms response time).

To this end, the deployment phase of BigDataStack includes a four-step process:

- In a first step of the deployment phase, the application and data services compositions (as represented by a BigDataStack playbook) is analysed, and the independent sub-structures comprised of application and data services are identified. Structures that require non-negligible resources are selected, i.e. those that generate Kubernetes "pods". These are stored separately as service templates.
- Second, a set of resource templates are used to convert each service template into a series of candidate deployment patterns (CDPs), where each CDP is comprised of a service and resource template pair.
- Third, for each CDP, performance estimations are obtained from the Dimensioning phase (based on prior application benchmarking and analysis) given expected data and application workload or workloads.
- Finally, each CDP is scored with respect to the user's quality of service requirements and/or preferences to determine the suitability of each. The best configuration for each service template is then selected and stored with it, enabling subsequent deployments using that service template with the specified resources.

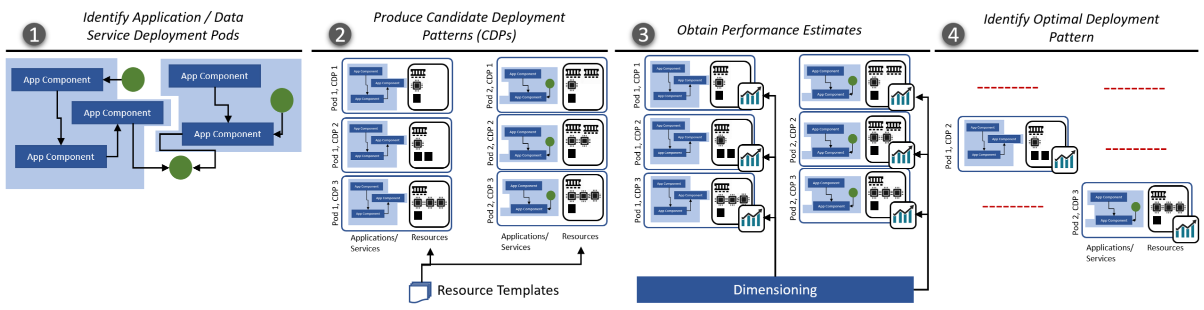


Figure 5 - Deployment phase

4.4. Operations phase

The operation phase of BigDataStack is realised through different components of the BigDataStack infrastructure management system and aims at the management of the complete physical infrastructure resources, in an optimised way for data-intensive applications.

The operation phase includes a seven-step process as depicted in Figure 6:

- Based on the deployment phase, each service template that is part of the deployment is used to reserve and allocate computing resources (based on the resource configuration contained within).
- According to the allocated computing resources, storage resources are also reserved and allocated. It should be noted that storage resources are distributed.
- Data-driven networking functions are compiled and deployed to facilitate the diverse networking needs between different computing and storage resources.
- The application components and data services are deployed and orchestrated based on “combined” data and application-aware instantiations of the aforementioned service templates. An envisioned orchestrator mechanism compiles the corresponding orchestration rules according to each service instantiation, as well as the associated reserved compute, storage and network resources.
- Data analytics tasks will be distributed across the different data stores to perform the corresponding analytics, while analytics on top of these stores is performed through the seamless analytics framework.
- Monitoring data is collected and evaluated for the resources (computing, storage and network), application components and data services and functions (e.g. query execution status).
- Runtime adaptations take place for all elements of the environment, to address possible QoS violations. These include resource re-allocation, storage and analytics re-distribution, re-compilation of network functions and deployment patterns.

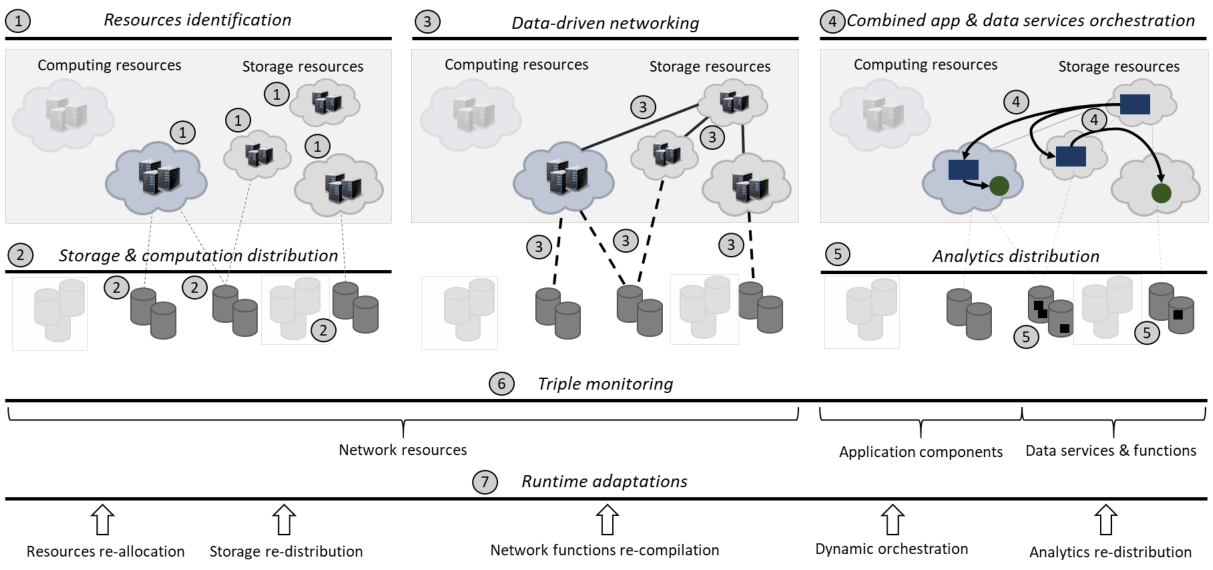


Figure 6 - Operations phase

5. Architecture

The following figure presents the overall conceptual architecture of BigDataStack, including the main information flows and interactions between the key components.

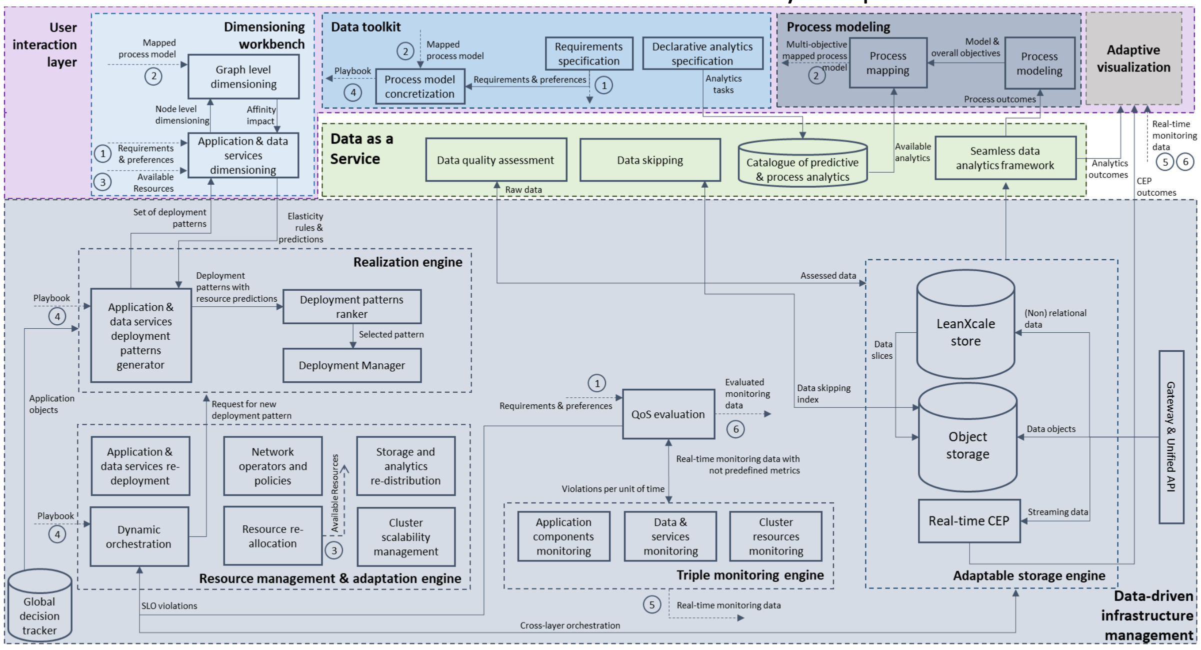

User interaction layer
Dimensioning workbench
Mapped process model
Graph level dimensioning
Node level dimensioning
Affinity impact
Requirements & preferences
Application & data services dimensioning
Available Resources
Data toolkit
Mapped process model
Requirements specification
Declarative analytics specification
Playbook
Process model concretization
Requirements & preferences
Analytics tasks
Process modeling
Multi-objective mapped process model
Process mapping
Model & overall objectives
Process modeling
Process outcomes
Adaptive visualization
Data as a Service
Data quality assessment
Data skipping
Catalogue of predictive & process analytics
Available analytics
Seamless data analytics framework
Analytics outcomes
Real-time monitoring data
CEP outcomes
Raw data
Set of deployment patterns
Elasticity rules & predictions
Realization engine
Deployment patterns with resource predictions
Deployment patterns ranker
Selected pattern
Deployment Manager
Playbook
Application & data services deployment patterns generator
Application objects
Request for new deployment pattern
Assessed data
LeanXcale store
(Non) relational data
Data slices
Data skipping index
Object storage
Data objects
Real-time CEP
Streaming data
Gateway & Unified API
Requirements & preferences
QoS evaluation
Evaluated monitoring data
Real-time monitoring data with not predefined metrics
Violations per unit of time
Application & data services re-deployment
Network operators and policies
Storage and analytics re-distribution
Available Resources
Playbook
Dynamic orchestration
Resource re-allocation
Cluster scalability management
Resource management & adaptation engine
Application components monitoring
Data & services monitoring
Cluster resources monitoring
Triple monitoring engine
Adaptable storage engine
Global decision tracker
SLO violations
Real-time monitoring data
Cross-layer orchestration
Data-driven infrastructure management

Figure 7 - BigDataStack architecture model

First, raw data are ingested through the *Gateway & Unified API* component to the *Storage* engine of BigDataStack, which enables storage and data migration across different resources. The engine offers solutions both for relational and non-relational data, an *Object Store* to manage data as objects, and a CEP engine to deal with streaming data processing. The raw data are then processed by the *Data Quality Assessment* component, which enhances the data schema in terms of accuracy and veracity and provides an estimation for the corresponding datasets in terms of their quality. Data stored in the *Object Store* are also enhanced with relevant metadata, to track information about objects and their dataset columns. Those metadata can be used to show that an object is not relevant to a query, and therefore does not need to be accessed from storage or sent through the network. The defined metadata are also indexed, so that during query execution objects that are irrelevant to the query can be quickly filtered out from the list of objects to be retrieved for the query processing. This functionality is achieved through the *Data skipping* component of BigDataStack providing the relevant data skipping objects. Moreover, slices of historical data are periodically transferred from the *LeanXcale* database to the *Object Store,* to free-up space for fresh tuples. Furthermore, during the last period of the project, the overall storage engine of BigDataStack has been enhanced to enable adaptations during runtime (i.e. self-scaling) based on the corresponding loads.

Given the stored data, decision-makers can model their business workflows through the *Process Modelling framework* that incorporates two main components: the first component is *Process modelling*, which provides an interface for business process modelling and the specification of end-to-end optimisation goals for the overall process (e.g. accuracy, overall completion time, etc). The second component refers to *Process Mapping.* Based on the analytics tasks available in the *Catalogue of Predictive and Process Analytics* and the specified overall goals, the mapping component identifies analytics algorithms that can realise the corresponding business processes. The outcome of the component is a model in a structural representation e.g. a JSON file that includes the overall workflow, and the mapped business processes to specific analytics tasks by considering several (potentially concurrent) overall objectives for the business workflow.

Following, through the *Data Toolkit*, data scientists design, develop and ingest analytic processes/tasks to the *Catalogue of Predictive and Process Analytics*. This is achieved by combining a set of available or under development analytic functions into a high-level definition of the user's application. For instance, they define executables/scripts to run, as well as the execution endpoints per workflow step. Data scientists can also declare input/output data parameters, analysis configuration hyper-parameters (e.g. the *k* in a *k*-means algorithm), execution substrate requirements (e.g. CPU, memory limits etc.) as service level objectives (SLOs), as well as potential software packages / dependencies (e.g. Apache Spark, Flink etc.). The output of the *Data Toolkit* component enriches the output of the previous step (i.e. *Process Modelling*) and defines a BigDataStack Playbook.

The generated playbook is sent to the *Realization Engine*, and more specifically the *Realization API* for persistent storage (backed by the *Realization State DB*). At this step, the playbook is deconstructed to form a series of templates that can be used to deploy each application or data service, as well as extract other definitions that are relevant to those services like metrics or service level objectives. In the case where a service template lacks a resource definition then the *Deployment Pattern Recommender* can be utilised to rectify this. This component creates different arrangements (i.e. patterns / configurations) of deployment resources for a service (template) and produces a recommended configuration based on available past performance data about that service. In particular, upon triggering of the deployment pattern recommender, a set of candidate deployment patterns (CDPs) are generated and passed to the *Application Dimensioning Workbench,* along with an end-to-end optimization objective and the information on the available resources. The application dimensioning workbench then produces an estimate for resource usage and QoS performance using an elasticity model, which defines the mapping of the input QoS parameters to the concrete resource needed (such as the number of replicas, bandwidth, latency etc.). These decisions depend on data-defined models. Finally, based on the obtained dimensioning outcomes, deployment patterns are ranked by the *Deployment Patterns Recommender* and the optimum pattern is selected and stored along with the associated service template, making the concluding arrangement of that service data-centric. Once configured, service templates can be directly instantiated to form a physical deployment either via the *Realization API*, *Realization UI* or *Realization Command-Line Client*. Additionally, instantiation and configuration of multiple service templates can be grouped together into sequence templates, enabling complex applications to be deployed with a single command.

During runtime, the *Triple Monitoring engine* collects data regarding resources, application components (e.g. application metrics, data flows across application components, etc.) and data operations (e.g. analytics / query progress, storage distribution, etc.). An advancement comparing to the previous version of the architecture is that these metrics are not predefined, and instead are identified during runtime so as to optimize which metrics should be collected and thereafter their evaluation. The collected data are evaluated through the *QoS Evaluation* component to identify events / facts that affect the overall quality of service (in comparison with the SLOs set in the toolkit). The evaluation outcomes are utilised by the *Runtime adaptation engine*, which includes a set of components (i.e. cluster resources re-allocation, storage and analytics re-distribution, network operators and policies enforcement, application and data services re-deployment, and dynamic orchestration patterns), to trigger the corresponding runtime adaptations needed for all infrastructure elements to maintain QoS. It should be noted that the dynamic orchestration employs a reinforcement-based logic that leads to cross-layer orchestration and optimization addressing both the resources and the data services.

Moreover, run-time monitoring also utilises several functions of the *Realization Engine*. In particular, all application and service state changes, as well as manually or automatically orchestrated alterations are stored centrally in the *Realization State DB*. In particular, application alteration requests are processed centrally by the *Realization API* service, which performs record keeping for those changes. Meanwhile, individual service state tracking for an application is enabled through the *Realization Monitoring* service. Other optional realization services can also be enabled if needed. For instance, the *Realization Events* service provides a way for other BigDataStack components or user services to stream events into the *Realization State DB*, while the *Realization Cost Estimator* can produce monetary costs for active services in cases where cost is a desired service level objective.

Finally, the architecture includes the *Adaptive Visualisation* environment, which provides a complete view of all information, including raw monitoring data (for resource, application and data operations) and evaluated data (in terms of SLOs, thresholds and the evaluation of monitoring in relation to these thresholds). Moreover, the visualization environment acts as a unique point for BigDataStack for different stakeholders, actors, thus, incorporating the process modelling environment, the data toolkit and the dimensioning workbench. These accompany the views for infrastructure operators (e.g. regarding service templates).

6. Main architectural components

Based on the overall architecture presented in the previous chapter, this chapter provides additional information regarding the individual components of the BigDataStack architecture.

6.1. Resources Management

The Resource Management sub-system provides an Enterprise grade platform which manages Container-based and Virtual Machine-based applications consistently on cloud and on-premise infrastructures. This sub-system makes the physical resources (e.g. CPUs, NICs and Storage devices) transparent to the applications. The application's requirements will be computed based on the input from the Realisation Engine and by a constant monitoring using the Triple Monitoring Engine. The applications' required resources are automatically allocated from the available existing infrastructures and will be dismissed upon execution completion. Thus, the Resource Management sub-system serves as an abstraction layer over today's infrastructures, physical hardware, virtual hardware, as well as private and public clouds. This abstraction allows the developing of compute, networking and storage management algorithms which can work on a unified system, rather than dealing with the complexity of a distributed system.

BigDataStack will build on top of the open source OpenShift Kubernetes Distribution (OKD) project [1] for its Resource Management sub-system. The OKD project is an upstream project used in Red Hat's various OpenShift products. It is based and built around Kubernetes and operators and is enhanced with features requested by commercial customers and Enterprise level requirements. According to Duncan et al. [2] ODK is "an application platform that uses containers to build, deploy, serve, and orchestrate the applications running inside it". OKD simplifies the whole process [3] of the deployment of a "fine-grained management over common user applications" and management of the containerized software (the lifecycle of the applications). Since its initial release in 2011, it has been adopted by multiple organizations and has grown to represent a large percentage of the market. According to IDC [4], OKD aims at accelerating the application delivery with "agile and DevOps methodologies"; moving the application architectures toward micro-services; and adopting a consistent application platform for hybrid cloud deployments.

As a base technology, OKD uses CRI-O for containerization and Kubernetes [5] for the core pods orchestration. It also includes packaging, instantiation and running the containerized applications. On top of the above described technologies, OKD adds [8]:

- Source code management, builds, and deployments for developers
- Managing and promoting images at scale as they flow through your system
- Application management at scale
- Team and user tracking for organizing a large developer organization
- Networking infrastructure that supports the cluster

OKD integrates in the DevOps and users' operation following a hierarchical structure, as shown in Figure 8. A master node centralizes the API/authentication, data storage, scheduling, and management/replication operations, while applications are run on Pods (following the Kubernetes philosophy).

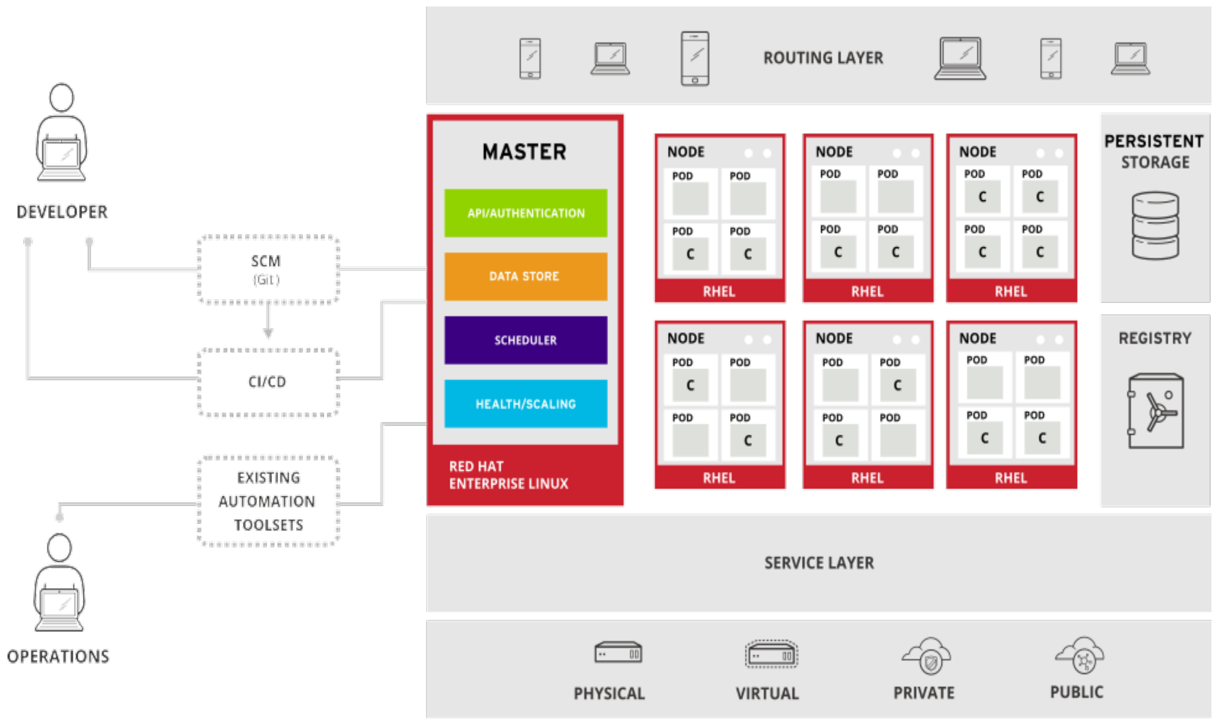


Figure 8 - OKD architecture overview inside the DevOps operation [8]

Following this layered architecture, users access the API, web-services and command line directly from the master node, while the applications and data services are accessed through the routing layer where the services are located, that is, in the physical machine the pod was deployed. Finally, the integrated container registry includes the set of container images which can be deployed in the system.

Another important point for the project is the protection of security and privacy of the user. On top of the security provided by Kubernetes, OKD also offers granular control on the security of the cluster. As shown in [4], users can choose a whitelist of cipher suites to meet security policies; and share PID between containers to control the cooperation of containers.

By building on top of OpenShift, we ensure that BigDataStack components are easily portable to different cloud offerings, such as Amazon, Google Compute Engine, Azure, or any On-Premise deployment based on OpenStack, since OpenShift can easily be installed in any of those platforms – for instance, Amazon will soon offer "Amazon Red Hat OpenShift", a fully supported Red Hat OpenShift natively integrated with AWS services: https://www.openshift.com/products/amazon-openshift/faq

In the BigDataStack context, and to ensure a more transparent and simple resource management we are working on several fronts that will be developed/integrated on our architecture:

- ***Kuryr**:* Network speed up by better integrating OpenShift on top of OpenStack cloud deployments. Working on Kuryr OpenStack upstream project to integrate OpenShift SDN networking into OpenStack SDN networking, simplifying the operations, as well as achieving remarkable performance boost (up to 9x better). By using Kuryr at the

OpenShift level we connect the containers directly into the OpenStack networks, instead of having 2 different SDNs and the performance problem of double encapsulation. In addition, it allows the connectivity between VMs and Containers, enabling extra options for deploying applications – in case not all the components can/should be containerized or if specific VMs functions must be used

- ***Ovn loadbalancer integration into OpenShift through Kuryr and Octavia***: When using Kuryr, Kubernetes services are implemented through Octavia LoadBalancers (instead of kube-proxy and iptables rules). However, the only Octavia provider existing was the "Amphora" provider. This means that for each service an amphora VM needed to be created, with the consequent resource consumption problem as well as delay in terms of provisioning services. To overcome these problems we have worked on the ***integration of the distributed ovn loadbalancer*** (fully managed by OpenFlow rules instead of VMs running ha-proxies) ***both in Octavia and Kuryr upstream projects***. By doing this, there is no need to create a VM per Kubernetes/OpenShift service, and there creation time is much faster (from minute(s) to second(s)). In addition, the data plane performance is also boosted due to not having to do an extra hop in the network to reach the loadbalancer VM when accessing the services endpoints.
- ***NVMe Kernel Driver:*** New (NVMe) Kernel driver that speeds up access to NVMe devices from VMs without guest image modification, achieving up to 95% of native performance – compared to standard 30% with existing VirtIO drivers.
- ***Kuryr Network Policies:*** Network Management through declarative API. As part of the ***Kuryr upstream work***, we have also extended its functionality to support Kubernetes Network Policies, which allows a user to define the access control to the different components of their applications in a fine grained manner. These policies are defined in a declarative way, i.e., by stating the desired status, rather than the steps to accomplish it. Then Kuryr will make sure that the isolation level desired at the OpenShift (pods) level is translated and enforced through OpenStack Security Group rules.
- ***Operators:*** Development of operators for easy life cycle management of infrastructure and applications. In addition to the performance improvements, we are also pursuing the use of the operators design pattern. This entails the use and development of certain operators (containers) which have their business logic integrated and react to the current status of the system/applications until they match the desired status. This helps to install the applications in an easy/reproducible manner, as well as to deal with day two operations, such as scaling or upgrades. In this regard we worked on:
    - ***Kuryr SDN operator*** (as part of the Cluster Network Operator) that allows easy installation and scaling of the OpenShift cluster on top of OpenStack environments. This network operator takes care of creating everything needed on the OpenStack side, as well as installing anything required by Kuryr both at the initial deployment time and upon OpenShift cluster scaling actions. In addition, it enables transparent upgrades, allowing the use of newly added Kuryr functionality. For instance, making use of the ovn-octavia benefits.
    - **Manilla Operator**: another problem of supporting OpenShift on OpenStack was the lack of standard write/read many option for volumes. In OpenStack, the Cinder component is the one in charge of providing volumes to VMs. However, if used for

pods, depending on the Cinder backend, attaching the same volume to different pods is not allowed. In order to have a solution for it, the Manila OpenStack component may be used instead (enabling a shared file system as a service). We have worked to integrate the usage of Manila at OpenShift as a new option for volume sharing between different pods. Additionally, we have built the needed operators so that installation and usage of the new Manila volumes is easy to consume.

   - **Spark Operator**: Another example of operators being used are the Spark Operator and the Cluster Monitoring Operator. We are not developing those operators, but we are making use of them and extending then with the required functionality for BigDataStack components. For instance, Spark clusters scaling operations may be decided by editing the proper ConfigMaps, as well as the Spark cluster is made reachable from outside the OpenShift cluster by creation of OpenShift resources (such as NodePort services).

- **OpenShift on OpenStack integration (with Kuryr):** We have worked on the installer as well as a few OpenShift operators to enable OpenShift Clusters on top of OpenStack Clouds. This includes work on the networking (Kuryr) and storage (Manila, Cinder, Swift) but also in automation (operators), security (certificates management) or testing (ensuring CD/CI). As a result of the work, we also published a guide with the best practices/recommendations for such types of environments: https://www.openshift.com/blog/ocp-4-on-osp-ra-blog-post
- ***Infrastructure API:*** Unified API for infrastructure resources to make infrastructure management easy, and abstracted from the real infrastructure. To achieve this, the upstream community created the Kubernetes Cluster API project. We have been working on the support for the OpenStack abstraction together with its operator/actuator: Cluster API Provider OpenStack. This allows us to automate the creation/scaling actions regarding OpenShift nodes when running on top of OpenStack too. Thus, we can easily extend an OpenShift cluster as needed, just by modifying an object in *Kubernetes/OpenShift:* Similarly, this gives us further advantages regarding resource management, e.g., if any of the VMs where our OpenShift is running dies (or the physical server that has it dies), the developed operator/actuator will automatically recreate the needed Nodes/VMs in a different compute node, automatically recovering the system until it maps the desired status. In addition, thanks to managing the infrastructure through declarative APIs, automatic auto-scaling of the cluster may be enabled by setting desired CPU/memory thresholds by using this Cluster/Machine API implemented for OpenStack. We have implemented and tested that for the OpenShift on OpenStack use case that BigDataStack relies on: https://www.openshift.com/blog/autoscaling-with-openshift-on-openstack

Note that while the first three points are related to infrastructure performance, the rest are key points for managing infrastructure as code, as well as to enable easy configuration/adaptation by upper layers, such as the Data-Driver Network Management or the Deployment Orchestration components.

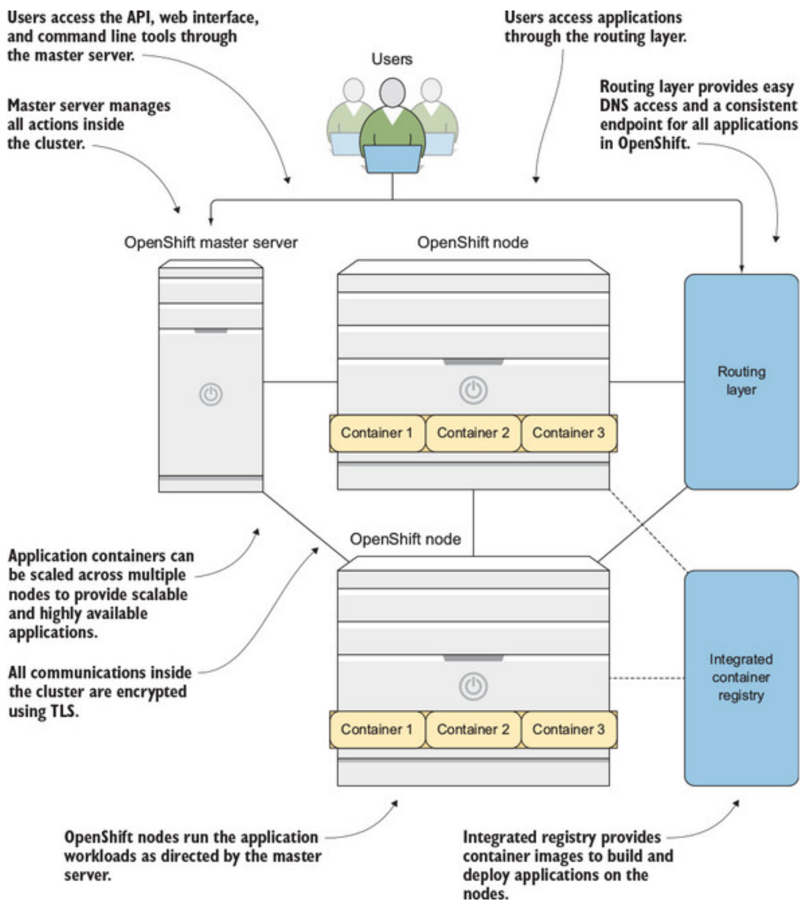

Users access the API, web interface, and command line tools through the master server.
Users
Users access applications through the routing layer.
Master server manages all actions inside the cluster.
Routing layer provides easy DNS access and a consistent endpoint for all applications in OpenShift.
OpenShift master server
OpenShift node
Container 1
Container 2
Container 3
Routing layer
OpenShift node
Application containers can be scaled across multiple nodes to provide scalable and highly available applications.
All communications inside the cluster are encrypted using TLS.
Container 1
Container 2
Container 3
Integrated container registry
OpenShift nodes run the application workloads as directed by the master server.
Integrated registry provides container images to build and deploy applications on the nodes.

Figure 9 - OKD architecture overview in the users operations

6.2. Data-Driven Network Management

The Data-Driven Network Management component will efficiently handle network management and routing introspection, computing and storage resources, by collectively building intelligence through analytics capabilities. The motivation is to optimise computing and storage mechanisms to improve network performance. This component can obtain data from different BigDataStack layers (i.e. from storage layer to applications layer) and will be used to extract knowledge out of the large volumes of data to facilitate intelligent decision making and what-if analysis. For example, with big data analysis, the data-driven network management will know which storage or computing resource has high popularity. Based on the analysis result, the component will be able to produce insights on how to redistribute storage and/or computing resources to reduce network latency, improve throughput and satisfy access load and thus response time.

Monitoring mechanisms over the storage layer will provide information to adjust the network parameters (e.g. by enforcing policies to achieve a significant reduction in data retrieval and response time). Also, monitoring mechanisms over the computing layer will enable the development of functionalities and trigger policies that will satisfy users' requirements regarding runtime and performance.

To serve data-driven network management, we will analyse the data coming from storage and computing resources within a workflow which is depicted in Figure 10. The workflow is composed of three components namely: *ingest*, which consumes network data, *process*, which computes network metrics and *analyse*, which produces network insights. The lifecycle of the analysis task includes a set of algorithms which enable computational analytics over the data, conduct a set of control mechanisms and infer knowledge related to resources optimisation. Taking advantage of data-driven network management, big data applications will be able to access the global network view and programmatically implement strategies to leverage the full potential of the physical storage and computing resources.

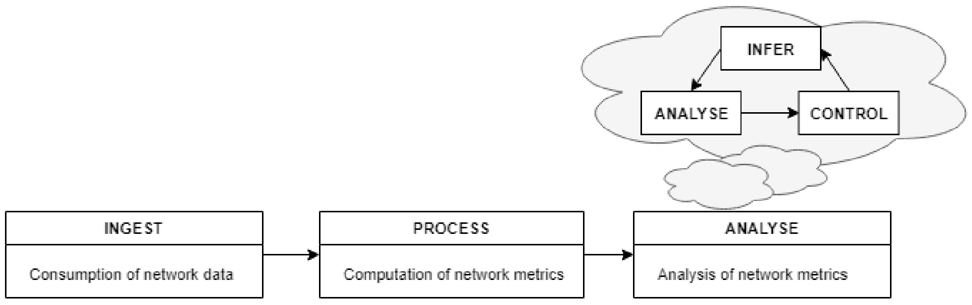

INFER
ANALYSE
CONTROL
INGEST
Consumption of network data
PROCESS
Computation of network metrics
ANALYSE
Analysis of network metrics

Figure 10 - Data-Driven Network Management components

6.3. Dynamic Orchestrator

The Dynamic Orchestrator (DO) assures that scheduled applications conform to their Service Level Objectives (SLOs). Such SLOs reflect Quality of Service (QoS) parameters and might be related to throughput, latency, cost or accuracy targets of the application. For example, to generate recommendations for online customers of an e-commerce website, the recommender has to analyse the customer profile and provide the recommendation in a limited amount of time (e.g., 1 sec.), otherwise, the page load will be too slow and customers might leave the website. If the number of online customers increases, then the recommender will need to improve its recommendations throughput in order to keep up serving the recommendations in less than 1 second. The DO will then modify the deployment in order to improve throughput, so that the recommender does not violate the corresponding SLO.
The DO assures conformation to SLOs by applying various dynamic optimisation techniques throughout the runtime of an application at multiple layers across various components of the data-driven infrastructure management system. As such, the DO knows about the changes in the deployment that can be carried out for an application and when these changes should be carried out, i.e. what changes will affect each SLO.

Figure 11 depicts the high-level interactions of the DO with other components. Newly scheduled applications are deployed through the components of the Realization Engine. In particular, the user's playbook is registered with the Realization API, which decomposes and stores it. The user may then opt to deploy that application, which will in turn create an Operation or Operation Sequence pod on the cluster that operationalizes that deployment. This process may include other BigDataStack services as required, such as ADS-Ranking, which scores different possible deployment patterns/configurations (CDPs) and selects the one which it predicts to best satisfy the application SLOs. After an application is deployed, the DO monitors its performance through the Triple Monitoring Engine (TME). In case any SLO violations occur, the QoS component sends a message with the violation to the DO, which has two choices: (i) Initiate a re-deployment of the application through the Realization API (this choice will be made when SLOs can only be reached with *major deployment changes*, e.g., selecting another ADS ranking option), (ii) Performing more *fine-grained adaptations* at different components of the system via the ADS-Deployment (e.g., the DO might perform "small" changes in the deployment configuration such as the number of replicas).

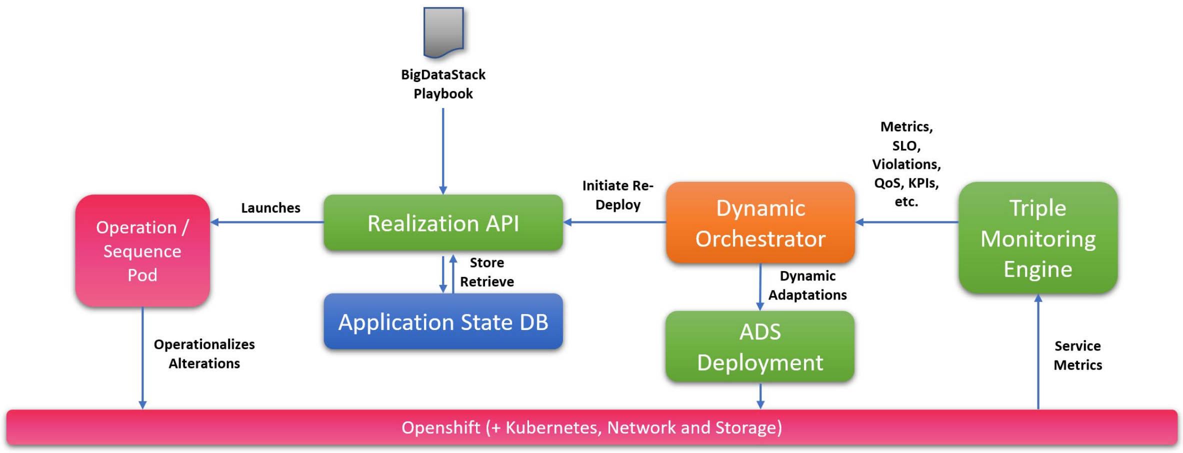


Figure 11 - High-Level Interaction with other Components

Note, that each of the other components also have their internal control loop and their internal logic for performing (high-responsive) actions, independently of the DO or any of the other components. The primary challenge of the DO is to reach a (close-to) optimal adaptation decision in little time for a newly deployed application. This is a difficult goal, because application tasks will be distributed and adaptation can be achieved through different components (application, platform, network). The relationship between an adaptation technique and how it affects an SLO is not clear in advance and two adaptation techniques at different components might lead both to conformation of an SLO. Likewise, two adaptations at two components, might also conflict with each other. As such, the main challenges of the dynamic orchestrator are:

- Balancing conflicting adaptations in different components
- Overhead of adaptation decisions in terms of computation resources and time
- Finding the optimal adaptation for a given SLO and application

6.3.1. Orchestration Logic

We have implemented the orchestration logic using a novel approach based on Reinforcement Learning (RL) we have called Tutor for Reinforcement Learning (T4RL). RL allows the DO to dynamically change its adaptation logic over time based on the outcome (feedback) from previous decisions, while being "guided" by general heuristics and safety constrains provided by the Tutor, that improve performance and robustness when compared to a plain RL approach. We describe T4RL in detail in deliverable 3.2: WP 3 Scientific Report and Prototype Description.

In RL, an agent interacts with an environment in discrete time (i.e., steps), in each step the agent observes the state of the environment, executes an action that affects the environment and receives a reward that tells the agent if that action was "good" or "bad". In our setting we define the RL elements as:

- *Environment:* the BigDataStack platform and the current application, which state is represented by its system and application metrics (e.g., CPU usage, throughput, response time) and SLOs metrics.
- Agent: the Dynamic Orchestrator.
- *Actions:* changes in deployment (e.g., add/remove a replica).
- *Reward:* a value that is positive and inversely proportional to resource utilization if SLOs are met, negative otherwise. With this reward function we aim to avoid overprovisioning of resources so when as the resource utilization grows, the positive reward decreases and vice versa. The agent, will then try to satisfy all the SLOs using as little resources as possible.

Figure 12 depicts a more detailed view of the DO and its functioning. Each application has its own BigDataStack application, RL Agent, RL Environment and set of guide and constrain functions; while the Manager is unique for all applications. The Manager is in charge of the communication with other components, receiving the Playbook, receiving the monitoring data and passing them to the corresponding BigDataStack application, and receiving the action to be taken from the RL Agent and sending it to the Realization API or the ADS-Deploy.

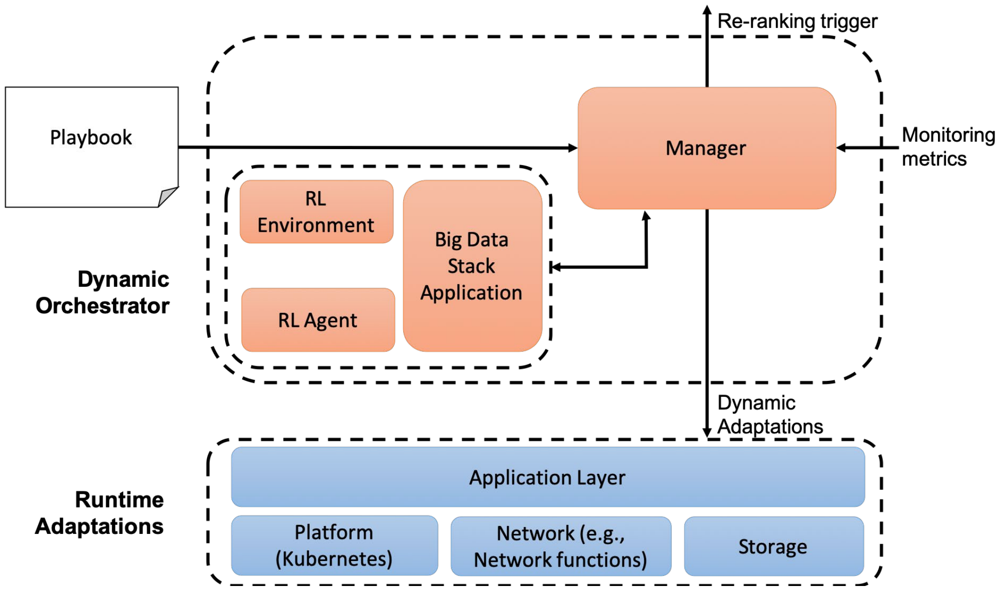


Figure 12 - Dynamic Orchestrator Detailed View

Moreover, Figure 13 depicts the different classes of the DO. Their inner working, step by step, is the following:

1. The Manager handles the communication with all the other components, using RabbitMQ and creates one instance of BigDataStackApplication for each application to be monitored.
2. The BigDataStackApplication creates the RLEnvironment, with its actions and state spaces, and the RLAgent that will be in charge of learning and deciding the best adaptation actions to take when an SLO is violated.

3. Each time a new message comes in, the Manager sends the information to the corresponding BigDataStackApplication, which updates the RLEnvironment state.
4. If a message with an SLO violation comes in, the Manager triggers the RLAgent, to decide which action should be taken according to the current RLEnvironment state.
    1. The RL Agent interacts with the RL Tutor for deciding the best action. If uncertainty is high, i.e., the Agent is still inexperienced, the Agent queries the Tutor by sending the state of the RLEnvironment and its reward.
    2. The Tutor feeds the state and reward to all of its guide functions and combines the output of the functions in an array ensemble with a value for each action. The higher the value, the higher certainty that the action in that position should be executed.
    3. Whether the Tutor was queried or the Agent used its internal policy to generate the action vector, the Agent sends the action vector to the Tutor so the Tutor applies a mask on the action vector, produced by the ensemble of the constrain functions. This mask disables actions that must not be taken and therefore add a layer of safety to the DO.
    4. Finally, the Tutor returns this action vector to the Agent that chooses the best action to perform by applying an argmax operation to it.
5. Then, the Manager sends a message to the Realization API requesting the identification of a new deployment configuration or to ADS-Deploy to directly change the deployment.

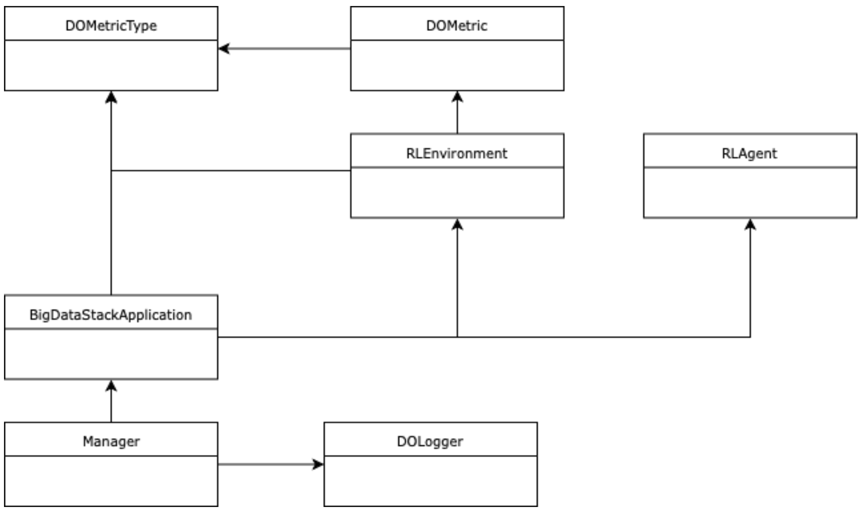


Figure 13 - High-level class diagram of the Dynamic Orchestrator

6.3.2. Interactions with other components: CEP and LXS

The DO also monitors the performance and alters the deployment and configuration of two components from the BigDataStack platform: the real-time CEP and LeanXcale (LXS). These two components are important for the performance of applications that depend on them and can also be dynamically scaled when necessary, therefore, the interaction between these components and the DO offers several benefits to the platform and its users.

LXS has already implemented scaling mechanisms as described in the section Adaptable Distributed Storage, but works with the DO to improve even further its decisions. While LXS already counts with its internal knowledge and data, the DO has a global view of resources, applications and components in the platform. As such, LXS provides information to the DO that are included in its GRL approach as guide and constrain functions, guiding the DO decisions in situations when uncertainty is high (i.e., states that have not been seen before by the DO) and avoiding decisions that might be harmful to the performance of LXS. As the DO gathers more experience, it will improve upon these guides provided by LXS, optimizing the scaling decisions by considering a broader view of the resources, components and applications currently running in the platform.
The CEP can also scale up when a sub-query experiences a high memory or CPU usage or when its queue is chronically growing due to a high rate of incoming messages, in this case, the CEP scales up the sub-queries relieving the bottleneck in any of the three previously described situations. The DO will monitor the CEP metrics as well as the application metrics and SLOs that use the CEP to decide when scaling up or down can be beneficial for the performance of the applications in the case of scaling up decisions, or beneficial towards resource utilization in the case of scaling down decisions when this scaling down does not impact on the application SLOs fulfilment.

6.4. Triple Monitoring and QoS Evaluation

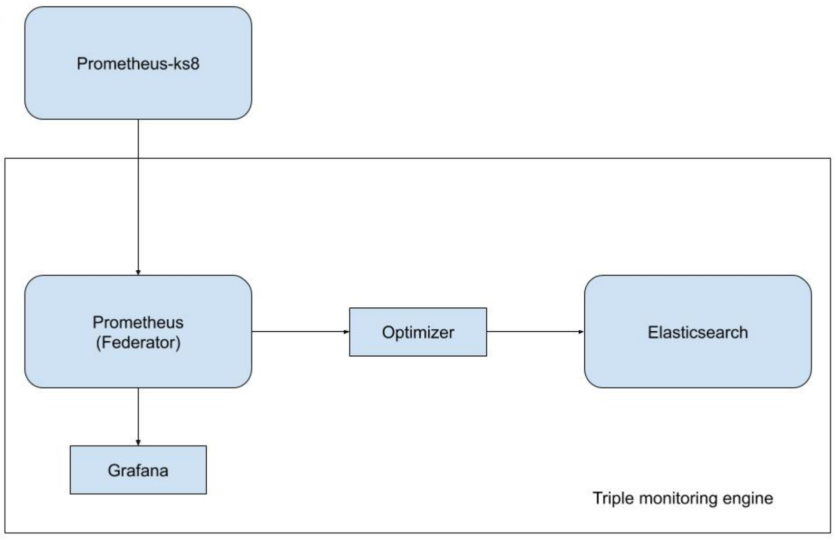
The *Triple Monitoring* and *QoS Evaluation* are two closely related components with clearly separated responsibilities:

- The objective of the Triple Monitoring is to collect, store and serve metrics at three levels of the platform: application, data services and infrastructure (cluster) resources.
- The goal of the QoS Evaluation is to continuously evaluate those metrics against constraints (thresholds) or objectives imposed by certain BigDataStack platform users.

6.4.1. Triple Monitoring

The monitoring engine manages and correlates/aggregates monitoring data from different levels to provide a better analysis of the environment, the application and data; allowing the orchestrator to take informed decisions in the adaptation engine. The engine collects data from three different sources:

- Infrastructure resources of the compute clusters such as resource utilisation (CPU, RAM, services and nodes), availability of the hosts, data sources generation rates and windows. This information allows the taking of decisions at a low level. These metrics are directly provided by the infrastructure owner or through specific probes, which track the quality of the available infrastructures. In the context of BigDataStack, the infrastructure's metrics are collected by Kubernetes. Those metrics will be ingested to the triple monitoring engine by federating Prometheus instances.



- Application components such as application metrics, data flows across application components, availability of the applications etc. This information is related directly to the data-driven services, which are deployed in the infrastructure. These metrics are associated with each application, and they should be provided by those applications. For applications related to BigDataStack infrastructure, the most suitable method is to embed a Prometheus exporter into each of those applications. In this case, use case metrics for an application are exposed via an http end-point.

- Data functions/operations such as data analytics, query progress tracking, storage distribution, etc. This is a mix of data and storage infrastructure information providing additional information for the "data-oriented" infrastructure resources.

The component will cover both raw metrics (direct measurements provided by the infrastructure deployed sensors or external measurement systems like the status of infrastructure) and aggregated metrics (formulas to exploit metrics already collected and produce the respective aggregated measurements that can be more easily used for QoS tracking). The collection of metrics will be based on both solutions: the direct probes in the system that should be monitored and the direct collection of the data from the monitoring engine.

- The probe approach will cover the information systems, where the platform will be able to deploy and collect direct information. In this case, the orchestration engine must manage the deployment of the necessary probes. This approach can cover other cases, where the probe is included directly in the application, and the orchestration only needs to deploy the associated application, which can provide the metric information to the monitoring engine.
- The direct collection will cover the scenarios where the platform cannot deploy any probe, but the infrastructures or the applications expose some information regarding these metrics. In this case, the monitoring engine will be responsible for collecting the metrics data that are exposed by a third party via a REST_API (Exporter).

After collecting and processing the data, the monitoring engine will be responsible for notifying other components when an event happens based on the metrics that it is tracking and specific attributes such as computing, network, storage or application level. Moreover, it will expose an interface to manage and query the content. This functionality is implemented in the QoS Evaluator (SLA Manager). Figure 14 depicts the Triple Monitoring Engine and their components.

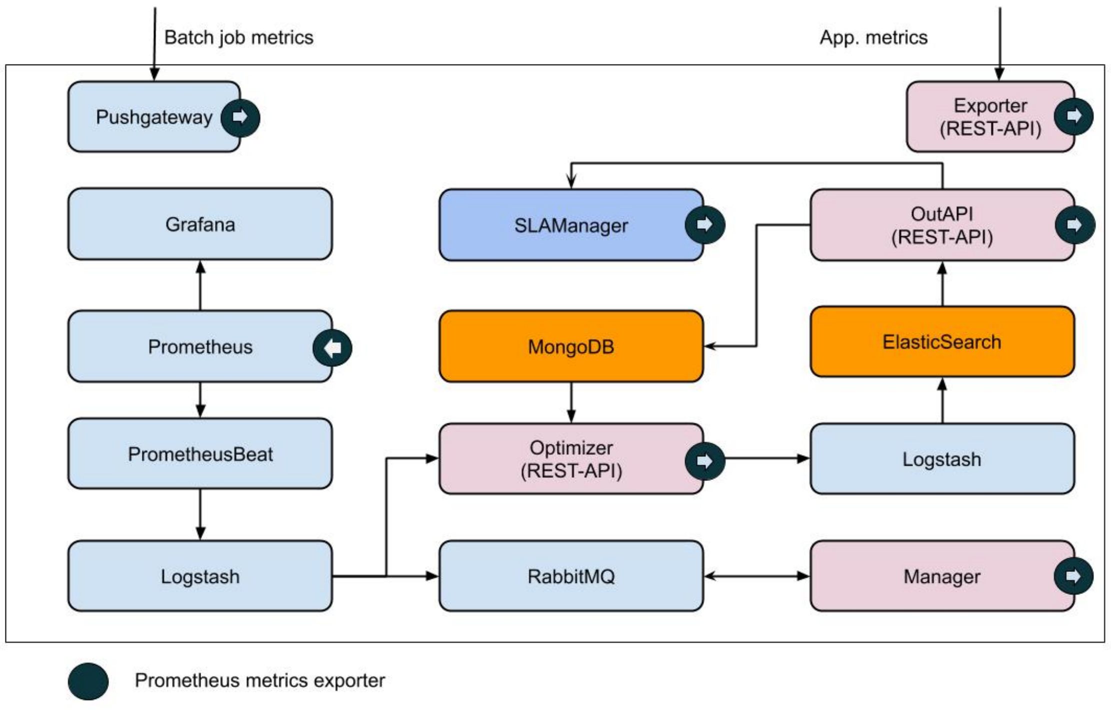


Figure 14 - Triple Monitoring Engine architecture diagram

The Triple Monitoring Engine will be based on the Prometheus monitoring solution (see [9] for more details) and is composed of the following components:

- Monitoring Interface: This is responsible for exposing the interface to allow other components to communicate. The interface will manage two ways of interaction with other components: i) exposing a REST API (outAPI, Figure 14) that will enable other components to know specific information, for example, if another component wants to know more details about one violation, to take the correct decision, or if they need to configure new metrics to collect directly by the monitoring engine. Therefore, the interface will consist of both a REST interface and a publish/subscribe notification interface. The publish/subscribe mechanism is implemented with RabbitMQ. This allows any components to consume in real-time information.
- Monitoring Manager: This component handles subscriptions by storing the queue, the list of metrics and metadata related to the subscription. The manager consumes all metrics collected by Prometheus. Based on the subscriptions list, they are redirected to the component subscribed by the queue declared.
- Monitoring Databases: ElasticSearch is currently used as the metrics database. MongoDB is also used to store all metrics requested via the outAPI in order to keep a track of metrics' utilization.

- PrometheusBeat: Since Prometheus has a small retention period, BigDataStack optimization loops in various components (e.g. deployment patterns generation) raised the need for a solution that would allow accessing and holding the collected metrics. To this end, this component receives the metrics collected by Prometheus, and ingests them to a pipeline (Logstash) for being stored.
- Optimizer: Since the Triple Monitoring Engine of BigDataStack collects monitoring data from different sources and all those data are utilized at specific time periods by different BigDataStack architecture components, storage optimization is required. Based on the information stored in the MongoDB (metrics utilization) this component decides about the time period for which the monitoring data should be kept.
- Push gateway: The push gateway is a Prometheus exporter. It is used in BigDataStack specially for collecting monitoring data obtained after each Spark driver execution.
- Collector Layer: This component is responsible for obtaining the data to be moved to the Monitoring manager. There are two ways to collect the data, either through a probe or through direct collection:
    - Probe API exposes an interface to allow different kinds of probes to send the monitoring data to the monitoring engine.
    - Direct collection is realized through a component that collects directly the monitoring data, by invoking other systems or components. For example, it receives the data directly from the Resource management engine or invoke the third-party libraries to obtain the state of the application and data services.

Integration with resource management engines

The Triple Monitoring Engine provides APIs for receiving metrics from different sources (infrastructure, application and data services) and exposes them for consumption. Although different APIs will be available due to the great diversity of monitoring data sources, the recommended API is the "Prometheus exporters" model. Some of the technologies that are being considered for BigDataStack are already integrated within Prometheus, as shown in Table 2.

Technology component	Monitoring aspect	Prometheus exporter availability	Method
Kubernetes	Computing infrastructure	Yes	Federation
OpenStack	Computing infrastructure	Yes	Exporter
Spark/Spark SQL	Data functions/operations	Yes	Exporter (SparkMeasure)
IBM COS (Cloud Object Store)	Data infrastructure	No	
LeanXcale database	Data infrastructure	For some metrics	Federation
CEP	Data Infrastructure	Yes	Federation

Table 2 - Prometheus integration

Federation of Prometheus instances

Federation is used to pull monitoring data from another Prometheus instance. This model is introduced in the BigDataStack Triple Monitoring Engine for two main reasons. Firstly, the platform uses Kubernetes as the container orchestrator, which has embedded by default in it a Prometheus (prometheus-ks8) instance. This instance collects monitoring data related to the cluster, nodes and services running. For security reasons it is not efficient to use this prometheus-k8s for collecting application- and data- related monitoring data. Instead, it is envisioned that users will have a Prometheus instance serving as the metric store for each namespace/project they own, thereby isolating metrics by owner and project. Secondly, the LeanXcale database and the CEP are independent systems and have their own Prometheus instances. For reusability reasons and improvement (e.g. to collect only monitoring data directly used by BigDataStack components) the proposed federation model is the most suitable method to achieve this requirement.

In the federation mode, the master instance should be configured appropriately by specifying the interval of time where metrics will be collected, the source job also if needed, and the metrics to collect.

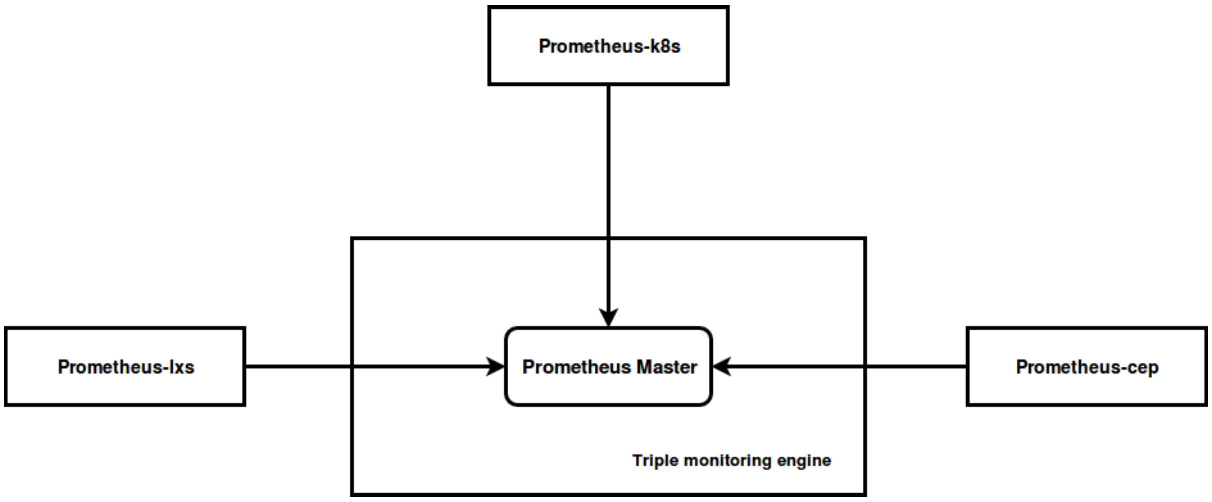


Figure 15 - Triple Monitoring Engine Federation Model

6.4.2. QoS Evaluation

The Quality of Service (QoS) Evaluation component uses data from the Triple Monitoring Engine to evaluate the quality of the application and data services deployed on the platform. To do so, it compares multiple service metrics (key performance indicators) with the objectives set by the owner of the service and thus imposed over the BigDataStack platform when this was deployed. The QoS Evaluation component is also responsible for notifying if the quality objectives are not met during the service lifetime. Therefore, the component is not responsible for obtaining the metrics (delegated to the monitoring engine), but to apply evaluation rules upon those metrics and notify when quality of service failures occur.

The main entities within the QoS Evaluation are the following:

- *Agreement*: it is a description of the QoS requirements of a specific service. It describes the lifecycle of the task, the provider and consumer of the service, and the list of QoS constraints or guarantees to be evaluated.
- *SLO* (Service Level Objective) or QoS *guarantee*: it represents a high level view of the requirements of a service, representing, for each requirement, different levels of criticality. A given requirement shall always be met to its expected level of service but, upon a violation of such a requirement, different levels can be set according to their

definition. The last threshold is always the last limit or final objective to be met. The other thresholds are used as checkpoints to better understand and control the dynamics of the indicator.
- *Violation*: it is generated when the value of a the QoS metric trespasses any of the SLO thresholds. The QoS Evaluation component notifies each violation to other components of the platform subscribed to the event; perhaps the most important of the subscribers is the Dynamic Orchestrator, which is responsible for the service deployment adaptation decisions and uses such violations as adaptation triggers.

The QoS Evaluation is made of the following components:
- *Interface component* (REST API): It is used to feed agreements into the QoS Evaluation component. The Dynamic Orchestrator is the main client of this API, as this component determines the lifecycle of the services.
- *QoS databases:* They are responsible for storing all the relevant QoS information in the system. On the one hand, the QoS evaluator uses an internal database to store its active agreements. In parallel, the violations are stored in the Realization State DB.
- *Evaluator:* it is responsible for performing QoS evaluation. A periodic thread is started to check the expiration date of agreements. For each enabled agreement, it starts a task to check each active agreement, using the metrics gathered from the adapter.
- *Adapter:* it is responsible for retrieving the metrics provided by the Triple Monitoring Engine.
- *Notifier:* It is responsible for notifying to third parties, namely the Dynamic Orchestrator and the Realization Events service, whenever something happens in the defined agreements, so that corrective actions can be taken.

In the BigDataStack platform, application and data services' QoS constraints (are specified by the ***Data Scientist*** through the ***Data Toolkit*** (see Section 6.13) together with the rest of the information describing the application to be deployed. This is compiled in the so-called BigDataStack *Playbook*, which serves as the specification for the BigDataStack platform to deploy and operate the application. The following table shows an example of the QoS constraints imposed over the response time of an online service called "recommendation-provider". Notice that the Data Scientist can specify not only required response times but also describe a recommended response time[1]:

```
- name: recommendation-provider
  metadata:
    qosRequirements:
    - name: "response_time"
      type: "maximum"
      typeLimit: null
      value: 900
      higherIsBetter: false
      unit: "miliseconds"
    qosPreferences:
    - name: " response_time"
```

[1] Notice this is an extract of a v1 format playbook showing just one of the QoS constraints imposed on one service. The playbook may define QoS constraints on any DeploymentConfig, Job or Pod object defined by an application.

```
       type: "maximum"
       typeLimit: null
       value: 300
       higherIsBetter: false
       unit: "miliseconds"
```

When a service deployment is requested, The Dynamic Orchestrator (i.e. the component in charge of making deployment adaptation decisions which satisfy the QoS constraints) breaks down the QoS objective into thresholds of increasing levels of criticality. Depending on the nature of the QoS metric (indicator) to control both the recommended and required values, the Dynamic Orchestrator may produce a number of thresholds between the first (related to recommended value) and last (related to the required value) thresholds.

With every deployment, the Dynamic Orchestrator will provide the QoS Evaluation component with a description of the service, that includes the QoS thresholds, using the interface component. In the previous example, the Dynamic Orchestrator may send a service description including the following message to the QoS Evaluation[2]:

```
"qosIntervals": {
  "reponse_time": [
    ">300",
    ">500",
    ">700",
    ">900"
  ]
}
```

The QoS Evaluation component incorporates the thresholds or intervals to be monitored (requested by the Dynamic Orchestrator) as a *guarantee* object in the *agreement* for the actual service deployment. In that way, all the QoS constraints to be evaluated and guaranteed for the same service deployment are maintained together. In the previous example, the *agreement* and *guarantee* created from the Dynamic Orchestrator request may resemble the following:

```
{
  "id": "TEST-ATOSWL-NormServ-19022019-1",
  "name": "TEST-ATOSWL-NormServ-19022019-1_agreement",
  "details": {
    "id": "TEST-ATOSWL-NormServ-19022019-1",
    "type": "agreement",
    "name": "TEST-ATOSWL-NormServ-19022019-1_agreement",
    "provider": {
      "id": "a-provider-01",
      "name": "ATOS Wordline"
    },
    "client": {
      "id": "a-client-01",
      "name": "Eroski"
    },
    "creation": "2019-05-30T07:59:27Z",
```

[2] Notice this is an extract of the *enhanced playbook* showing the QoS thresholds (intervals) for the evaluation of just one of the metrics (indicators) of one service.

```
     "expiration": "2020-01-17T17:09:45Z",
     "guarantees": [
     {
       "name": "response_time",
       "constraint": "[response_time>50]",
       "importance": [
       {
         "Name": "0",
         "Type": "warning",
         "Constraint": ">300"
       },
       {
         "Name": "1",
         "Type": "warning 2",
         "Constraint": ">500"
       },
       {
         "Name": "2",
         "Type": "warning 3",
         "Constraint": ">700"
       },
       {
         "Name": "3",
         "Type": "error",
         "Constraint": ">900"
       }
     ]}
   ]}
 }
```

The QoS Evaluation component will continuously assess all the guaranteed QoS attributes (metrics or indicators) and detect violations, that is, when the value trespasses the different thresholds that have been specified. QoS violations are notified to any interested component of the BigDataStack platform through a publisher/subscriber mechanism implemented as a topic within the RabbitMQ service (which acts as the message broker between BigDataStack components). Following the previous example, the following violation notifications may be published[3]:

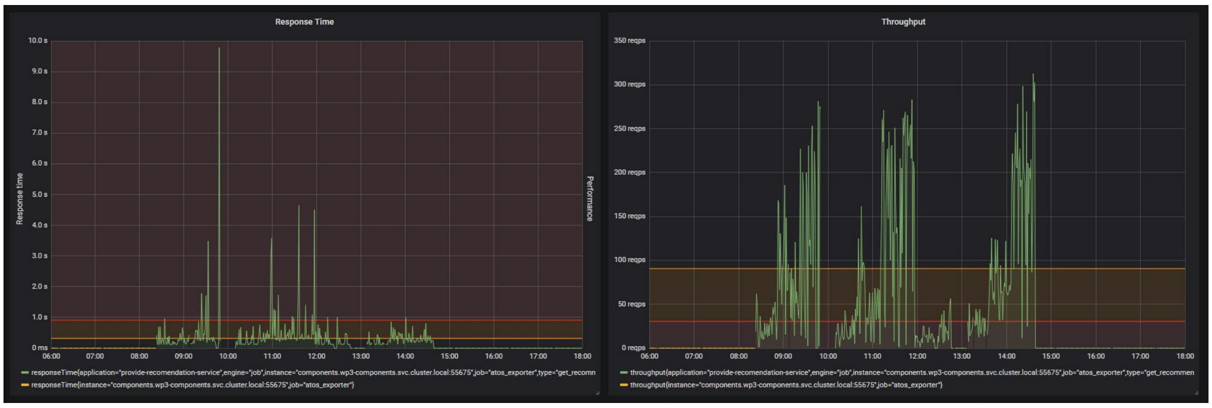
```
 {
   "Application": "TEST-ATOSWL-NormServ",
   "Message: "QoS_Violation",
   "Fields": {
     "IdAggrement": "TEST-ATOSWL-NormServ-19022019-1",
     "Guarantee": "response_time",
     "Value": "351",
     "ViolationType: {
       "Type": "warning",
       "Interval": "0"
     },
     "ViolationTime": {
       "ViolationDetected": "2019-06-30T07:59:27Z",
       "AppExpiration": "2020-01-17T17:09:45Z"
     }
   }
```

[3] Notice that the first violation notification example is that of the lowest level of criticality (meaning a simple warning) while the second example if that of the highest criticality (meaning an error).

```
}
{
  "Application": "TEST-ATOSWL-NormServ",
  "Message: "QoS_Violation",
  "Fields": {
    "IdAggrement": "TEST-ATOSWL-NormServ-19022019-1",
    "Guarantee": "response_time",
    "Value": "920",
    "ViolationType: {
      "Type": "error",
      "Interval": "3"
    },
    "ViolationTime": {
      "ViolationDetected": "2019-06-30T09:34:21Z",
      "AppExpiration": "2020-01-17T17:09:45Z"
    }
  }
}
```

Perhaps the most important of the subscribers is the Dynamic Orchestrator itself, which will respond to different violation alerts depending on the criticality of the threshold trespassed.

The QoS Evaluation displays the warning (lowest criticality) and error (highest criticality) thresholds on the interface of the Triple Monitoring Engine, superimposed over the metrics evolution graphs. The following figure is an example of the *Response Time* evolution graph on the Triple Monitoring Engine.



responseTime{application="provide-recomendation-service",engine="job",instance="components.wp3-components.svc.cluster.local:55675",job="atos_exporter",type="get_recomn
responseTime{instance="components.wp3-components.svc.cluster.local:55675",job="atos_exporter"}
throughput{application="provide-recomendation-service",engine="job",instance="components.wp3-components.svc.cluster.local:55675",job="atos_exporter",type="get_recommen
throughput{instance="components.wp3-components.svc.cluster.local:55675",job="atos_exporter"}

Figure 16 - SLO thresholds over the *Response Time* (left) and Throughput (right) metrics graphs: warning (lowest criticality) and error (highest criticality) thresholds as orange and red lines

6.5. Applications & Data Services / Realization Engine

The Application and Data Services, or 'Realization Engine' is a grouping of components of the BigDataStack platform, as defined in the central architecture diagram (see Section 5). It is concerned with how best to deploy and manage the user's application in the cluster/cloud, based on information about the application and cluster characteristics. From a practical perspective, its role is to enable the transition of a user's application from a definition provided in a playbook into an actual running deployment and then provide the tools to manage it during operation. This involves the following functionality, which has been significantly expanded since the previous version:

- Registration of a user application and its internal components, as well as the persistent

storage of that information.
- In cases where required resource information is not provided for a service, the provision of this missing information based on available stated (hard) requirements and other desirable characteristics (e.g. low cost or high throughput).
- Operationalize the deployment of the user's application based on the selected option.
- Monitor the state of the application at run-time and persistently storing that state.
- Enable alterations to the application at run-time.
- Storage and linking of events generated by other BigDataStack or external components about an application to that application.
- Generation of run-time cost estimates for an application.
- Provision of a graphical user interface for monitoring and managing user applications.

Before discussing the components, it is important to highlight the core change to the design of the Realization Engine that has occurred since the previous version of this deliverable (D2.5). In particular, the original design of the Realization Engine included a component referred to as the *Global Decision Tracker*, which was envisioned as a central storage location for application-related information. However, based on subsequent analysis of usage patterns for the pilot use-cases and other applications deployed in our managed Openshift testbeds, it became clear that a more comprehensive centralised run-time application management solution was needed. As a result, the functionality previously provided by the Global Decision Tracker was separated into three services (the ADS-API, ADS-EventStreams and ADS-StateDB), meanwhile three additional components were added (ADS-Monitor, ADS-GUI and ADS-CostEstimator).

As a result, the current version of the Realization Engine is comprised of five main components, namely: ADS-API, ADS-Ranking; ADS-Deploy; ADS-Monitor; and ADS-GUI, as well as three support components, namely: the ADS-StateDB, ADS-EventStreams and ADS-CostEstimator. Note that elsewhere in this deliverable, for conciseness, we typically refer to these components under the 'Realization' heading rather than 'Application and Data Services'. For example, the *Application and Data Services API* is referred to as the *Realization API* elsewhere in this deliverable. We summarize each component below:

Primary Components:
- *Application and Data Services/**Realization API*** (ADS-API): This is the central management component of the Realization Engine. It enables programmatic access to storage of information about the different user applications, their running state and any run-time changes made about them. It also allows for both users and other components within BigDataStack to request alterations to the applications, i.e. acts as a control end-point.
- *Application and Data Services/**Realization Monitor*** (ADS-Monitor): This is a light-weight component that synchronises the state of running applications between Kubernetes/Openshift and the ADS-StateDB.
- *Application and Data Services/**Realization Ranking*** (ADS-Ranking): This is dedicated to the selection of the best deployment option. Note that this component is sometimes referred to as the 'deployment recommender service', as from the perspective of a BigDataStack Application Engineer, it produces a recommended

deployment configuration for them on-demand.

- *Application and Data Services/**Realization Deployment*** (ADS-Deploy): This is concerned with the physical scheduling/deployment of the application for the selected deployment option via Openshift.
- *Application and Data Services/**Realization GUI*** (ADS-GUI): This component provides a graphical user interface that exposes the functionality of the ADS-API to the user.

Support Components:

- *Application and Data Services/**Realization State DB*** (ADS-StateDB): This is the underlying service that provides the physical storage that backs the ADS-API. Any SQL database with a supported JDBC driver can be used for this.
- *Application and Data Services/**Realization Event Streams*** (ADS-EventStreams): This component is responsible for monitoring a RabbitMQ exchange server to collect events generated by other BigDataStack components or external services that are relevant to one or more of the user's applications. For example, this is used to collect QoS violations generated by the Triple Monitoring Engine and link them to the associated user applications.
- *Application and Data Services/**Realization Cost Estimator*** (ADS-CostEstimator): This component is responsible for monitoring running applications and producing cost over time estimates from them based upon their resource usage.

The interactions between these components are illustrated in Figure 17. Primary components are represented by green rectangles, while support components are represented by blue rectangles. In the remainder of this section we describe the primary components of the realization engine. Additional details on both the primary and support components can be found in the associated WP3 deliverables (D3.2 and D3.3).

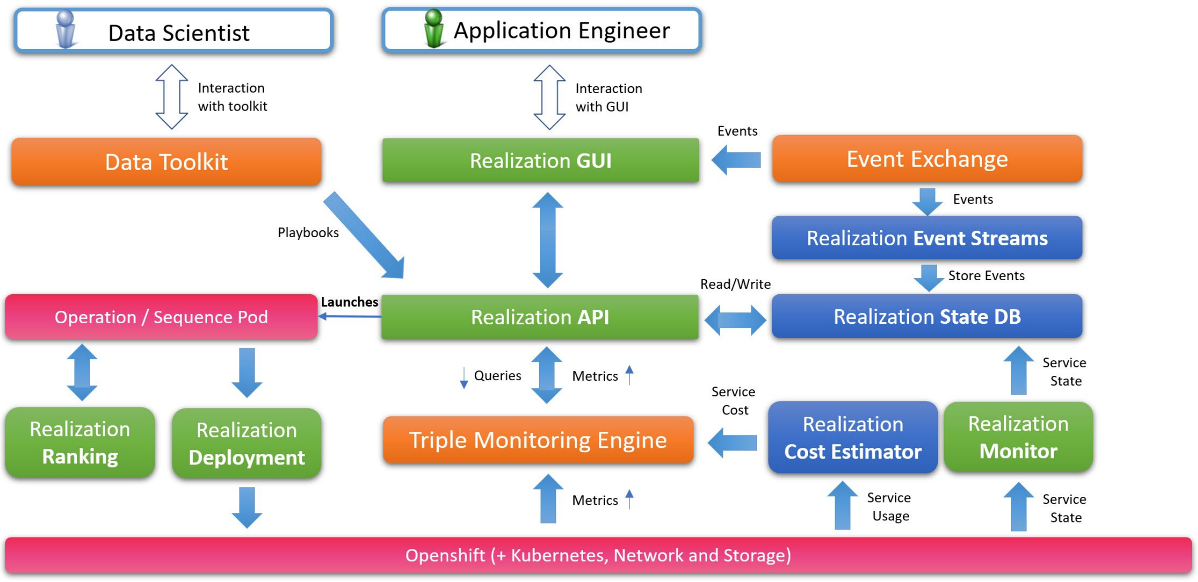


Figure 17 - Interactions between components within the Realization Engine

Application and Data Services/Realization Ranking (ADS-Ranking)

ADS-Ranking is considered an independent service that can be called by the user during the realization process (the steps the user takes to trigger application deployment). It is used in cases where the specification of resources for the different components within a user's application are incomplete. More precisely, any object definition that when instantiated would result in a physical pod being created (typically 'Job' or 'DeploymentConfig' objects) need to have resource requests (and possibly limits) given to enable the cluster/cloud to allocate the needed resources at deploy-time, as well as determine the deployment cost. However, BigDataStack Playbooks do not require that this information is provided. Hence, we need a mechanism to set this prior to deployment.

ADS-Ranking is related to another component of BigDataStack, namely the Application & Data Services Dimensioning (ADS-Dimensioning) component of BigDataStack that sits above it. The main output of ADS-Dimensioning is a series of candidate deployment patterns (ways that the user's application might be deployed) including resource usage and quality of service predictions. It is these deployment patterns that ADS-Ranking takes as input (see REQ-ADSR-01 [10]) and subsequently selects one or more 'good' options for the Application Engineer. Each candidate deployment pattern represents a possible configuration for one 'Pod' in the user's application (a logical grouping of containers, forming a micro-service) [11]. User applications may contain multiple pods.

ADS-Ranking is triggered after the 'Instantiate' operation of a typical deployment but prior to the 'Apply' operation (see ADS-API for more information on operations). It takes as input an instantiated object of type 'Job', 'DeploymentConfig' or 'Pod' and inserts a resource definition for that object. To achieve this a four-step process is followed:

1. The instantiated object is passed to the ADS Pattern Generation component to create a range of candidate deployment patterns for that object (representing the different ways it could be deployed).
2. Each of those patterns are passed to the ADS Dimensioning Core component that assigns estimated performances for each.
3. The resultant patterns are ranked based on estimated suitability with respect to the user's requirements and preferences. At this stage some patterns may also be filtered out that either do not meet the user's requirements, or that are otherwise predicted to provide unacceptable performance.
4. A single pattern is selected to return.

Figure 17 illustrates the data flow between the components around ADS-Ranking. As we can see, the data scientist first interacts with the Data Toolkit to create the BigDataStack Playbook, which is uploaded to the ADS-API (registering that application). The application engineer next interacts with the Realization GUI to instantiate a copy of the application (an application instance). If the resource definitions are missing at this point, then ADS-API will call ADS-Ranking to recommend a setting for the missing resource definitions within that instance. ADS-Ranking first contacts ADS Pattern Generation to produce the different candidate deployment patterns. Once those have been retrieved, they are forwarded to ADS-Dimensioning to add the performance estimates for each. Finally, ADS-Ranking ranks and filters those patterns, selecting one per-pod, which is predicted to efficiently and effectively satisfy the user's requirements. These top patterns are aggregated and sent back to the ADS-

API, where the application engineer can accept those patterns and use them directly for deployment, or otherwise customise them first. Once the application engineer is happy with the configuration of the instance, they can then trigger the sending of it to ADS-Deploy, which will schedule deployment on OpenShift.

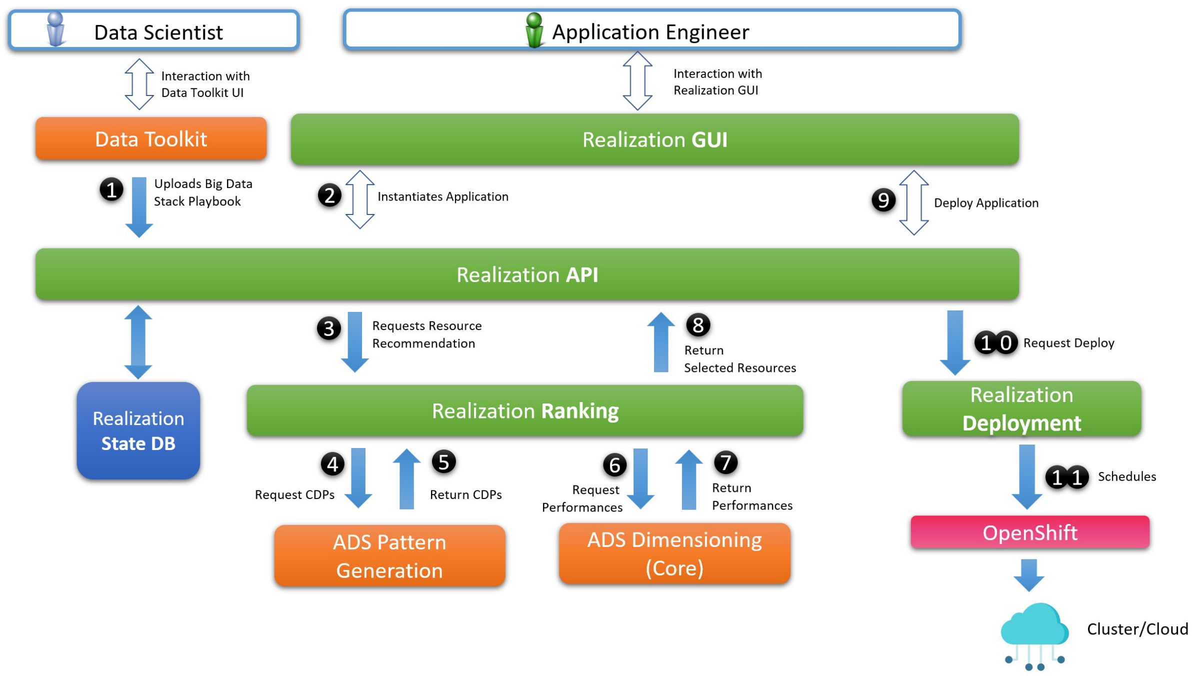


Figure 18 - Process Flow for the Realization Engine during First Time Deployment

Internally, ADS-Ranking supports two central operations: 1) the first-time ranking/filtering of CDPs; and 2) re-ranking of CDPs in scenarios where the previous deployment is deemed unsuitable. The first operation (CDP ranking and filtering) is comprised of three main processes. These three processes are:

- *Pod Feature Builder:* This takes as input a set of CDPs, and for each CDP in that package, it builds a single vector representation of that CDP, which combines all the information provided by dimensioning. It can also filter out CDPs that do not meet minimal Quality of Service (QoS) requirements, saving computation time later in the process. The output of this component is the (filtered) list of CDPs along with their new vector representations. This process targets REQ-ADSR-02 [10].
- *Pod Scoring:* This process takes the CDPs and vector representations as input and ranks those CDPs based on their predicted suitability, with respect to the user's desired quality of service. To achieve this, it uses either a rule-based model or a supervised model [12] trained on previous CDP deployments and their observed fitness. The output of this process is a ranking of scored CDPs. This process targets REQ-ADSR-03 and 04 [10].
- *Pod Selection:* This process takes as input the ranking of CDPs and selects one of these CDPs. This may be a simple process that takes the top CDP by score and filters out the rest. However, it may include more advanced techniques to better fit with user needs, such as making sure the selected CDP will provide sufficient extra processing capacity, in the case of applications that process data streams with fluctuating data rates. The

output of this process is a single CDP (per-pod), which is the recommended deployment that is shown to the user. This process targets REQ-ADSR-05 [10].

If the user's application is comprised of multiple pods, then the recommended CDP for each pod are then collected and aggregated together to form a recommendation for the entire application. The aforementioned processes are implemented using Apache Flink [13] to facilitate low-latency real-time processing. The overall flow for first-time ranking/filtering of CDPs is shown in Figure 18. In this simplified example, three CDPs are used as input for a single application (A1), which is comprised of two pods (P1 and P2). Pod 1 has two CDPs (A1-P1-1 and A1-P1-2), while Pod 2 has one CDP (A1-P2-1). As we can see from Figure 18, these CDPs are first grouped by pod, to create parallel processing streams for each. For each CDP, these are then subject to feature extraction, to create the representation vectors. In this case, features from the overall pod (e.g. total cost) and features from each container (e.g. container latency) are extracted here. These CDPs and feature vectors are sent to pod scoring, to produce a numerical estimate of overall suitability of the CDP. The best CDP per-pod (A1-P2-2 and A1-P2-1 here) are then grouped by application (A1) and then output (to the visualisation environment for viewing by the application engineer).

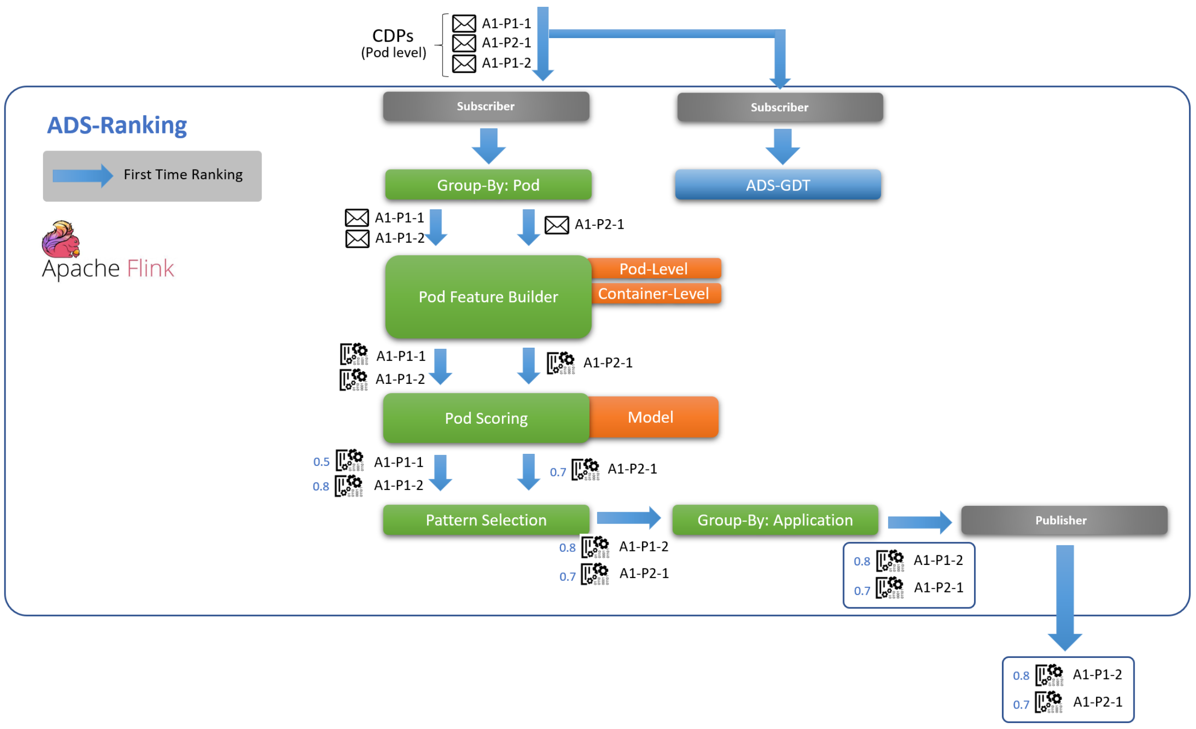


Figure 19 - ADS-Ranking, First Time Deployment Internal Process Flow

The second function (CDP Re-Ranking) is similar to the primary function, with the exception that it takes in a CDP that has been deemed to have failed the user in terms of quality of service along with context about that CDP (e.g. why it failed), and it introduces an additional 'Failure Encoding' process:

- *Failure Encoding:* This process examines the context of a failed CDP and encodes that failure into the CDP structure as features, such that they can be used by the Pod

Feature Builder when generating the CDP vectors. In this way, properties that promote other CDPs that will not suffer from the same issues as the failed CDP can be upweighted during ranking. This process targets REQ-ADSR-07 [10].

Figure 19 illustrates the main processes and data flow within ADS-Ranking. In this case, re-ranking is triggered by sending a set of CDPs representing a quality of service (QoS) failing user application deployment to ADS-Ranking. For this example, the application has two pods and hence two CDPs (A1-P2-2 and A1-P1-1), where a QoS failure has been detected for A1-P1-2 (denoted by ✗). The first step that ADS-Ranking takes is to collect all the alternative CDPs that were not selected from the user's application. These were stored in ADS-GDT (Global Decision Tracker), which will be described later. Once these CDPs have been collected, any CDPs for pods that were not subject to QoS failures are discarded, as these do not need to be considered for re-deployment (A1-P2-1). The remaining CDPs are then subject to failure encoding, which converts the failure information into a feature vector that can be used during ranking (<x>). The CDPs are then sent to the Pod Feature Builder in a similar manner to first-time ranking, where the normal process is followed, with the exception that the additional features obtained from the failure encoding are used to enhance ranking effectiveness.

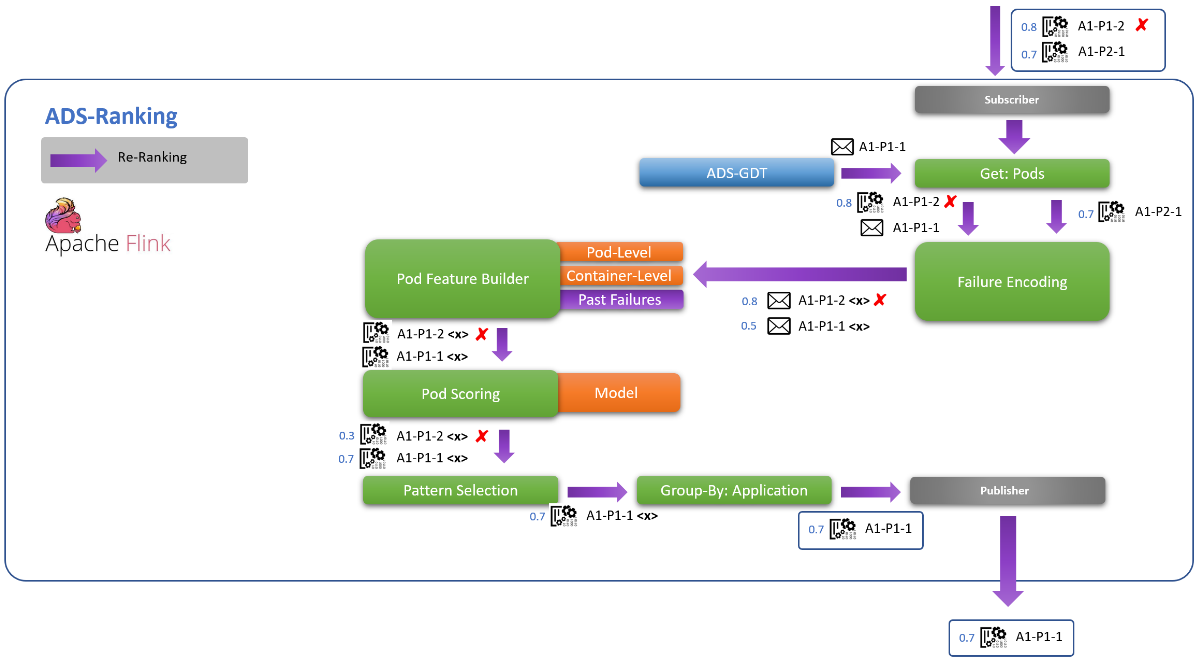


Figure 20 - ADS-Ranking, Re-Ranking Internal Process Flow

Application and Data Services/Realization Deployment (ADS-Deploy)

This component is triggered by ADS-GDT at the behest of the user as part of the 'Apply' operation, and takes as an input the selected CDP(s). The aim of this component is to use the given CDP(s) to launch the user's application pods on the cloud infrastructure. To achieve this, the ADS-Deploy component interacts with a container orchestration service (e.g. OpenShift), translating the CDP into a sequence of deployment instructions.

This task is divided into the following steps:

1. *Receive and check CDP.* The component checks that the CDP triggering the deployment process is structurally correct.

2. *Translate CDP.* The CDP is translated to an ontology that the orchestrator will understand.
3. *Interpretation and deployment.* The orchestrator interprets the file received and starts the containers and rules.

Application and Data Services/Realization API (ADS-API)
This component provides the functionality originally enabled by the Global Decision Tracker that came before it, i.e. it keeps track of any state or decisions made about a user's application related to its deployment or run-time performance. However, the ADS-API's remit is significantly larger, encompassing a wider range of application monitoring and management capabilities, as these were identified as a gap in the BigDataStack platform offering. Hence, the ADS-API currently has the following roles in the platform related to application realization:

- **Data Storage**
  - Stores each user's application definitions.
  - Stores supplementary configurations or definitions needed by the platform.
  - Stores definitions for non-atomic operations that can be triggered for a user application, referred to as Operation Sequences.
  - Stores the list of events associated to each application.
- **Logic**
  - Provides in-built logic for translating common tasks into re-usable operations, such as Instantiate, Apply, Wait-For, etc.
  - Provides the capability to deploy an Operation Sequence as an independent container, in a similar way to a Kubernetes Operator
  - Implements standardised data storage clients.
  - Implements a standardised event broadcast mechanism.
- **Interaction Mechanisms**
  - Hosts a REST API for retrieving information and state of applications.
  - Hosts a REST API for triggering operations/adaptations to applications.

Figure 20 shows the high-level architecture of the ADS-API before considering in-built operations (which are discussed later). Each box that is connected by arrows is a separate container. The arrows indicate communication flows. As we can see from Figure 20 the ADS-API itself is a container which has multiple sub-components within it. First, it has a database client (DB Client), this provides an abstraction layer for committing the definitions and state of the different user applications to persistent storage, as well as providing easy search operations over the stored data. Second, it contains an OpenShift Client, which is responsible for performing lower level operations on the cluster itself (this is used to launch other services or Operation Sequences). Third, it contains an Event Client, this provides a standard way for reporting/broadcasting information about changes in a user's application (either in its configuration or running state). When an event is generated, it is both persistently stored (via the DB Client) and broadcast on the Event Exchange (a publisher/subscriber service). Finally, it exposes a REST API that provides both data access to application state (i.e. querying upon the State Database) and the ability to trigger operations on each application, which is discussed next.

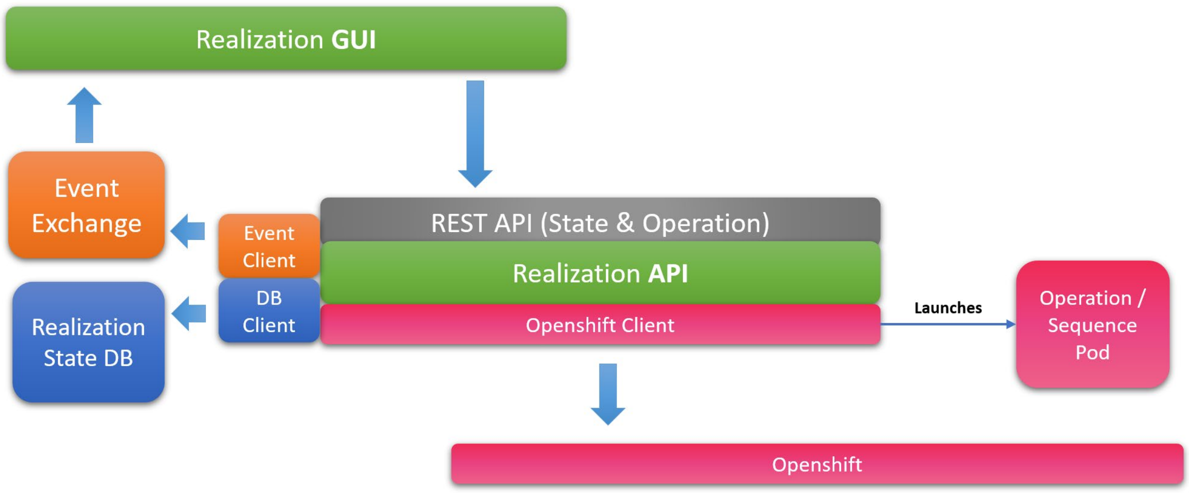


Figure 21 - Realization API (ADS-API) Architecture

One of the main functionalities provided by the ADS-API is the ability to trigger 'Operations' associated to the user's application, or in more advanced scenarios sequences of operations (known as Operation Sequences). To understand what an operation might consist of, we first must introduce how user applications are represented internally. A user 'Application' is now a high-level construct that can contain multiple 'Objects' (such as Jobs, DeploymentConfigs, Services, and so on). Objects can be either *templates* or *instances* (where instances are created from templates). When a user registers a new application via a playbook, internally it creates an application object and a series of object templates representing the different parts of the application. Object templates can be cloned/instantiated to form object instances. Operations are then actions that can be performed that interact with either an application's object templates or instances.

Example common Operations include:

- **Instantiate**: Takes an Object template and generates a corresponding Object instance.
- **SetParameters**: Alters an Object instance, replacing placeholder values with defined parameters.
- **RecommendResources**: Calls ADS-Ranking to produce resource request and limit information for an Object Instance.
- **Apply**: Uses either the Openshift Client or ADS-Deploy to deploy an Object instance.

Operations can be triggered individually for a user's application, however this can be unwieldy in practice and is not recommended. Instead the ADS-API provides the ability to pre-define sequences of operations that form a coherent task or alteration to a user's application, where the stages of that sequence can depend on the application state at evaluation time. For example, we might include a WaitFor operation in a sequence, which waits until an object reports 'Completed' state.

In a similar way to objects, operation sequences can then be either templates or instances. When first defined, an operation sequence is registered as a template with a unique id. A user can then trigger a sequence by id, which automatically instantiates the referenced template and begins processing each operation contained within. Note that sequence templates internally support parameterization, and there are also a range of supported operations that can alter the configuration of the sequence based on the application or cluster state. As a result, sequence templates can be a powerful and re-usable tool. It is also worth noting that sequence template instances are not run by the ADS-API itself. Instead, once the sequence template instance is created, a new container is launched (via the Openshift Client) that independently performs each stage defined within the sequence (while also reporting events as they are encountered).

A typical application deployment pattern is then to use a pre-defined operation sequence template to orchestrate the deployment (if it is suitably complex). In this case, the operation sequence template is used to create an operation sequence instance, which then runs in its own container. That operation sequence instance will then generate one or more object instances from the available templates and use those instances to create the associated objects on the cluster.

Application and Data Services/Realization Monitor (ADS-Monitor)
During the development of ADS-API, a need for a component to synchronise the state of a user's application between Kubernetes and the ADS-StateDB was identified. This involves first periodically looking-up the state of any object instance that can have an associated state in Kubernetes, e.g. DeploymentConfigs or Jobs, and updating the state field for those objects in the ADS-StateDB. Then, if associated Pods are detected for that object, then the state of those pods will also be retrieved and recorded within the ADS-StateDB. If any state changes are detected, then associated events should also be broadcast. Hence, a separate component named ADS-Monitor was created to achieve this.

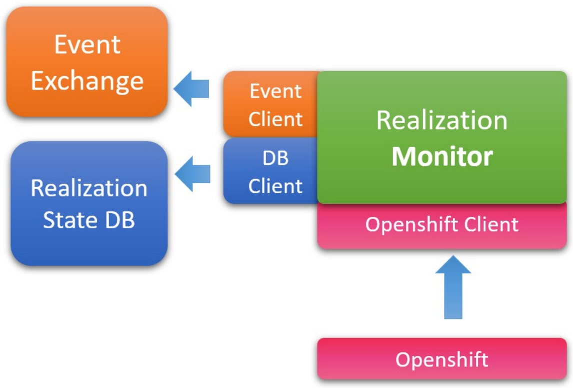


Figure 22 - Architecture of the Realization Monitor (ADS-Monitor)

Figure 21 illustrates the architecture of ADS-Monitor. As we can see from Figure 21, ADS-Monitor shares the support clients with ADS-API. The core difference is that instead of being responsible for exposing a REST API, ADS-Monitor is only responsible for updating the back-end state of the applications. ADS-Monitor is deployed automatically for a specified namespace by the ADS-API.

Application and Data Services/Realization GUI (ADS-GUI)
The ADS-GUI is a dashboard-style graphical user interface that aims to provide access to the functionality exposed by the ADS-API in a user-friendly manner. In particular, it provides visualizations for registered applications, their component object templates and instances, as well as associated metrics and service level objectives. It also allows the user to alter registered templates, enabling customisation directly prior to deployment. It also visualises pre-registered operation sequences for a user's application and enables users to construct new operation sequences using existing object templates and built-in operations. Users can also trigger application deployment and adaptation via this interface. Finally, for running applications, it provides a visualisation of the application state, associated events/alerts and tracked metrics.

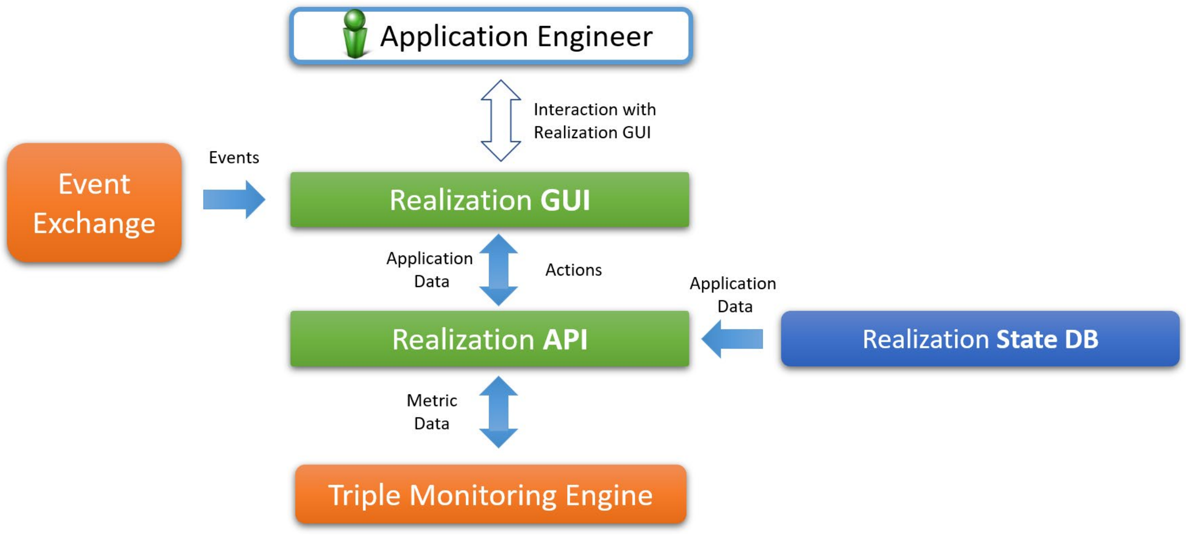


Figure 23 - Architecture of the Realization GUI (ADS-GUI)

Figure 22 illustrates the interactions around the ADS-GUI (Realization GUI). As we can see, the ADS-GUI sources data primarily from the ADS-API (Realization API), which itself sources data either from the ADS-StateDB (Realization State DB) in the case of application information, or from the Triple Monitoring Engine for run-time metrics. To provide push-based reporting of events associated to an application, the ADS-GUI can also subscribe to a RabbitMQ Event Exchange to receive events as they are published for display.

6.6. Data Quality Assessment

The data quality assessment mechanism aims at evaluating the quality of the data prior to any analysis, to ensure that analytics outcomes are based on datasets of specific quality. To this end, the BigDataStack architecture includes a component to assess the data quality as a service. The component incorporates a set of algorithms to enable domain-agnostic error detection. The domain-agnostic approach aims at facilitating the goals of data quality assessment without prior knowledge of the application domain / context, thus making it generalisable and applicable to different application domains, and, as a result, to different datasets.

While current solutions in data cleaning are quite efficient when considering domain knowledge (e.g., when functional dependencies are given), they provide limited results regarding data volatility, if such knowledge is not utilised. BigDataStack will provide a data quality assessment service that exploits Artificial Neural Networks (ANN) and Deep Learning (DL) techniques, to extract latent features that correlate pairs of attributes of a given dataset and identify possible defects in it. Furthermore, if discovering dependencies between pairs of attributes is not possible (e.g., due to heavy anonymization), the Data Quality Assessment component employs techniques that can detect errors within a single column.

The key issues that need to be handled by the Data Quality Assessment service are:

- Work in a context-aware but domain-agnostic fashion. The process should be adaptable to any dataset, learn the relationships between the data points and discover possible inconsistencies.
- Model the relationships between data points and reuse the learned patterns. The system should store the models learned by the machine learning algorithms, and reuse them through an optimisation component, which checks if the raw data have similar patterns, dataset structure or sources. In that case, already existing models should be activated, to complete the process in an efficient manner.
- Fall back to within-column error detection if discovering relationships between the data points is not possible for any reason.

6.6.1. Detecting Errors via Pairs of Attributes

The way to learn and predict the relationships between data points, to discover possible deviations, is to exploit the recent breakthroughs in Deep Learning, and the idea of an embedding space. Figure 22 depicts a serial architecture, which tries to predict if two entities are related to each other.

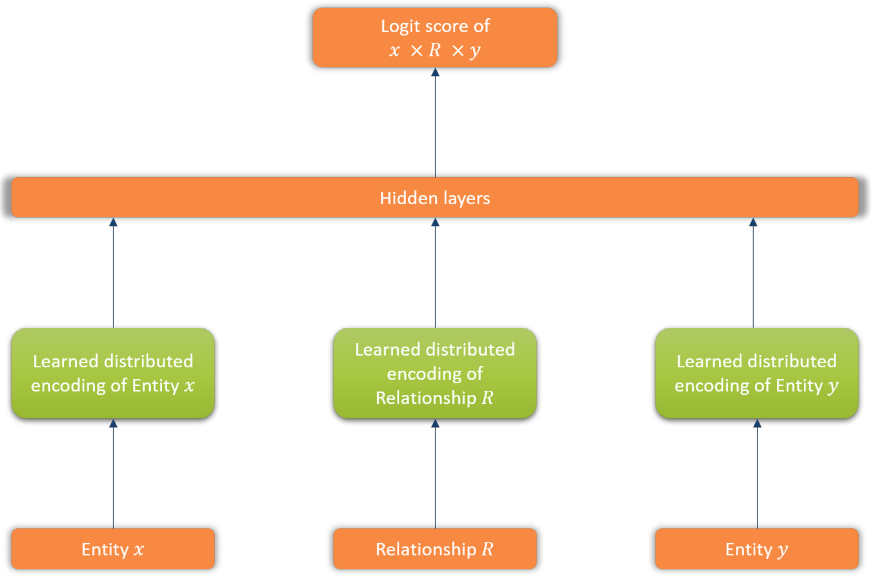

Logit score of $x \times R \times y$
Hidden layers
Learned distributed encoding of Entity x
Learned distributed encoding of Relationship R
Learned distributed encoding of Entity y
Entity x
Relationship R
Entity y

Figure 24 - Domain agnostic data cleaning model architecture

Given the learned distributed encodings of each entity x, y or, in our case any data point, we can discover if these two candidate entities or data points are related. Thus, considering the DANAOS use case, if the temperature sensor emits a value that is illogical given other rpm sensor readings, the relationship between these two data points would be associated with a low score (or probability). This could provide significant improvements in the results of an analytical task that the data scientist wants to execute, and is part of a general business process.

To optimize the data quality assessment process, we introduce a subcomponent that retrieves previously learned models, when a similar dataset structure arrives in the system, or the same data source sends new data.

Data quality assessment component inputs:

- The raw data ingested by the data owner through the Gateway & Unified API
- The data model provided by the optimizer if exists
- User preferences and specifications, ingested through the Data Toolkit

Data cleaning component outputs:

- Assessed data, establishing data veracity
  - A probability score for each tuple in the database column
- Trained, reusable ML models, stored in a repository for later use

The main structure of the Data Quality Assessment component is depicted in Figure 23.
Based on this figure the flow is as follows:

- The Data Pre-processing unit takes raw data and converts them in a form that the machine learning algorithms can work with
- The main pillar of the service is the data cleaning component, which takes the pre-processed data as input, trains a new model and stores it in the model repository
- During the assessment phase, a scheduler pulls newly ingested data to be assessed
- The data quality assessment module retrieves the learned model from the repository and makes the necessary predictions
- The assessed data are updated into the distributed storage

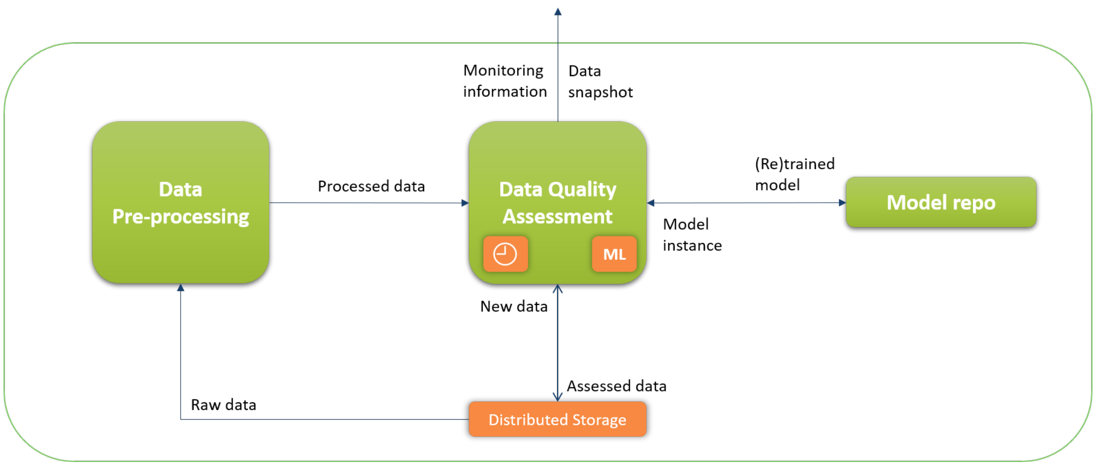


Figure 25 - Data Cleaning Module Architecture

6.6.2. Detecting Errors via n-gram Models

In order to use n-grams to detect format errors in tables, we need a way to generalize raw values to patterns. We could also train an n-gram model with the raw values, but the complexity of that approach introduces too many degrees of freedom, leading to high sparsity.

For example, let v_1 be a raw sequence of numbers expressing a zip code: 15122. Then, let v_2, v_3 signify two different codes: 345a7, 47592. Clearly, v_2 is erroneous, but if we pass the raw values in an n-gram model we will not get valuable information; see that $p(a|5) = p(1|5)$, thus we either miss the error or produce a false positive. But if we could generalize a raw value into a pattern, we could get more meaningful representations.

To this end, we use the notion of generalization trees and generalization languages. A generalization tree is just a hierarchy like the one in Figure 24, mapping raw values to a different representation.

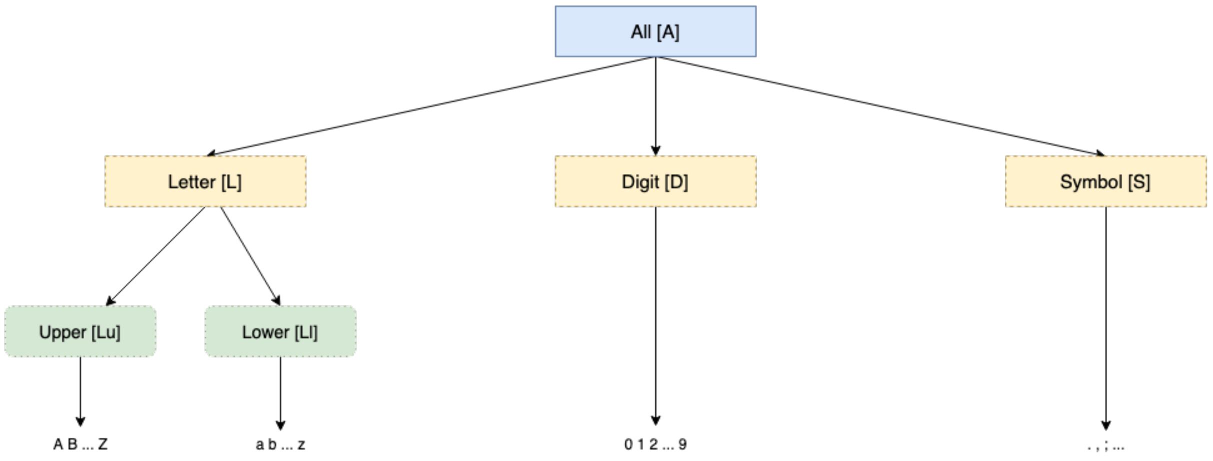


Figure 26 - A Generalization Tree

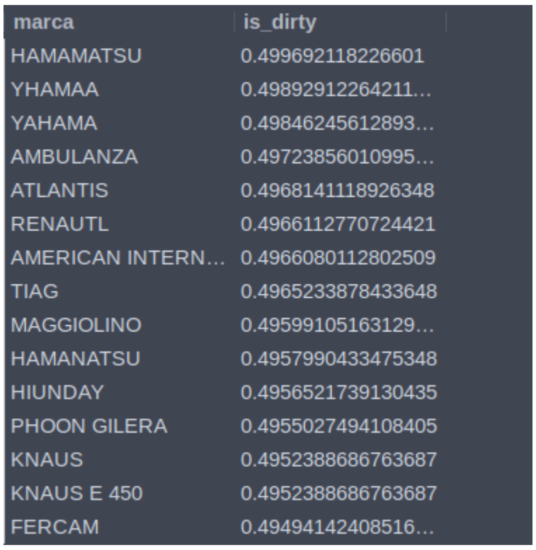
From that tree, we can derive many languages. An example is given in Figure 25.

$$L_1(x) = \begin{cases} \mathrm{L} & \text{if x is a letter} \\ \mathrm{D} & \text{if x is a digit} \\ \mathrm{S} & \text{if x is a symbol} \end{cases}$$

Figure 27 - A Generalization Language

Using L_1 we can transform v_1, v_2, v_3 into DDDDD, DDDLD, DDDDD. We could also compress that pattern to v_1 = D(5), v_2 = D(3)L(1)D(1), v_3 = D(5). Having this representation and a big enough dataset to train an n-gram model, we can get that the probability of having a letter L in a zip-code format is extremely low.

Using this technique, we introduced a new feature in the Data Quality Assessment component that can detect errors within a single column. When applying this technique to the GFT insurance data, we discovered several errors. For example, consider Figure 26.



marca	is_dirty
HAMAMATSU	0.499692118226601
YHAMAA	0.49892912264211…
YAHAMA	0.49846245612893…
AMBULANZA	0.49723856010995…
ATLANTIS	0.4968141118926348
RENAUTL	0.4966112770724421
AMERICAN INTERN…	0.4966080112802509
TIAG	0.4965233878433648
MAGGIOLINO	0.49599105163129…
HAMANATSU	0.4957990433475348
HIUNDAY	0.4956521739130435
PHOON GILERA	0.4955027494108405
KNAUS	0.4952388686763687
KNAUS E 450	0.4952388686763687
FERCAM	0.49494142408516…

Figure 28 - GFT Insurance Dataset

In this table we store the insurance vehicles brand and model. In the top-10 results with the highest probability of being “dirty” we come across errors like *YHAMAA* and *YAHAMA* instead of *YAMAHA,* or *RENAUTL* and *HIUNDAY* instead of *RENAULT* and *HYUNDAI*. Thus, a user could set a threshold and retrieve only the rows that have probability of being dirty below 0.49 and drop those rows. Alternatively, an expert could inspect those rows and correct the errors. This is now possible because the user will not have to go through the entire data set, which could be millions of rows.

6.7. Real-time CEP

Streaming engines are used for real-time analysis of data collected from heterogeneous data sources with very high rates. Given the amount of data to be processed in real-time (from thousands to millions of events per second), scalability is a fundamental feature for data streaming technologies. In the last decade, several data streaming systems have been released. StreamCloud [14], was the first system addressing the scalability problem allowing a parallel distributed processing of massive amounts of collected data. Apache Storm [15] and later Apache Flink [13] followed the same path providing commercial solutions able to distribute and parallelise the data processing over several machines to increase the system throughput in terms of number of events processed per second. Apache Spark [16] added streaming capability onto their product later. Spark’s approach is not purely streamed, it divides the data stream into a set of micro-batches and repeats the processing of these batches in a loop.

The complex event processing for the BigDataStack platform is a scalable complex event processing (CEP) engine able to run in federated environments with heterogeneous devices with different capabilities. The CEP can aggregate and correlate real-time events with structured information stored in the BigDataStack data stores. The CEP takes into account the resources of the hardware, the amount of data being produced and the bandwidth in order to deploy queries. The CEP also considers redeployment and migration of queries, if there are changes in the configuration, increase/decrease of data, changes in the number of queries running or failures.

Data enters the CEP engine as a continuous stream of events, and is processed by continuous queries. Continuous queries are modeled as an acyclic graph where nodes are streaming operators and edges are data streams connecting them. Streaming operators are computational units that perform operations over events from input streams and outputs resulting in events over its outgoing streams. Streaming operators are similar to relational algebra operators, and they are classified into three categories according with their nature, namely: stateless, stateful and data store.

- Stateless operators are used to filter and transform individual events. Output events, if any, only depend on the data contained in the current event.
- Stateful operators produce results based on state kept in a memory structure named sliding window. Sliding windows store tuples according to spatial or temporal conditions. The CEP provides aggregates and joins based on time windows (e.g., events received during the 20 seconds) and size windows (e.g. the last 20 events).
- User defined operators. They implement other user defined functions on streams of data.
- Data store operators are used to integrate the CEP with the BigDataStack data stores. These operators allow correlation among real time streaming data and data at rest.

The main components of BigDataStack CEP are:

- Orchestrator: It oversees the CEP. It registers and deploys the continuous queries in the engine. It monitors the performance metrics and decides reconfiguration actions.
- Instance Manager (IM): It is the component that runs a continuous query or a piece of it. They are single threaded and run in one core.
- Reliable Registry: It stores information related to query deployments and components status. It is implemented by Zookeeper.
- Metric Server: It handles all performance metrics of the CEP. The collected metrics are load, throughput, latency of queries, subqueries and operators, CPU, memory and IO usage of IMs. These metrics are handled by a Prometheus time series database.
- Driver: The interface between the CEP and other applications. Applications use the CEP driver to register/unregister or deploy/undeploy a continuous query, subscribe with the output streams of the queries to consume results and mainly to send events to the engine.

Figure 27 shows the different components of the CEP and their deployment in several nodes. Each node can run several Instance Managers (one per core). Instance Managers (IM) are single threaded and run in a single core. IMs are also assigned a fraction of the RAM at deployment time. The registry and metric server are deployed in different nodes although they can be collocated in the same node. The client and receiver applications are the ones producing and consuming the CEP data (shown as dashed black lines). The rest of the communication is internal to the CEP. The Orchestrator communicates with the IMs to deploy queries (configuration messages) and registers this information in Zookeeper (Zookeeper communication). All components send performance metrics to the metric server (yellow dashed lines).

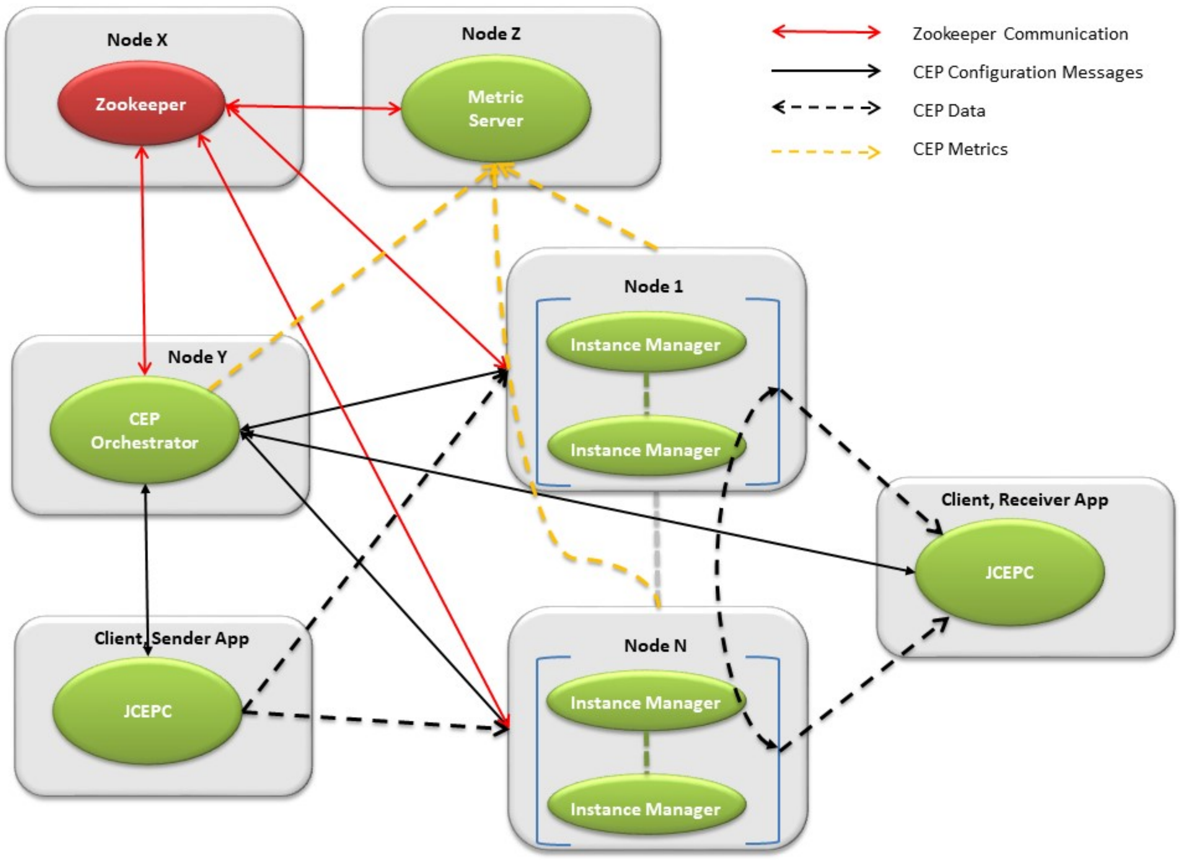


Figure 29 - CEP Components and Deployment

Given that the load is subject to changes due to temporal circumstances (e.g., the load is lower during night time and weekends) or bursts (e.g., a hot topic) or bandwidth changes (common in a wide-area network deployment), the CEP monitors the performance of the deployed queries and triggers self-configuration to cope with this type of dynamicity. The CEP can be used as a standalone component that reconfigures itself or with the BigDataStack Application Dimensioning Workbench. In the former case the performance metrics of the CEP are used to monitor the queries performance and trigger the adaptation actions. On the other hand, the CEP has built-in elasticity.

The elasticity in the CEP can be in the form of scale-up, scale-out or system reconfiguration. Figure 28 shows a query (SQ1) running at Edge Node 1. If the query is exhausting CPU or memory, the CEP will try to deploy a new Instance Manager (IM) at the same node (scale-up). If there are no more resources available at that node or the bottleneck is the bandwidth, a new IM will be deployed in a different node (scale-out).

The CEP monitors the resource usage at different levels and stores this information in the Metric Server. Table 3 summarizes the resource consumption metrics.

Table 3 - CEP resource usage

Metric Name	***Node***	***IM***	***Query***
Ingress network bandwidth (Mbps)		√	√

Egress network (Mbps)		√	√
Pairwise bandwidth (Mbps)	√		
Pairwise latency (ms)	√		
Memory usage (MB)	√	√	
CPU usage (%)			

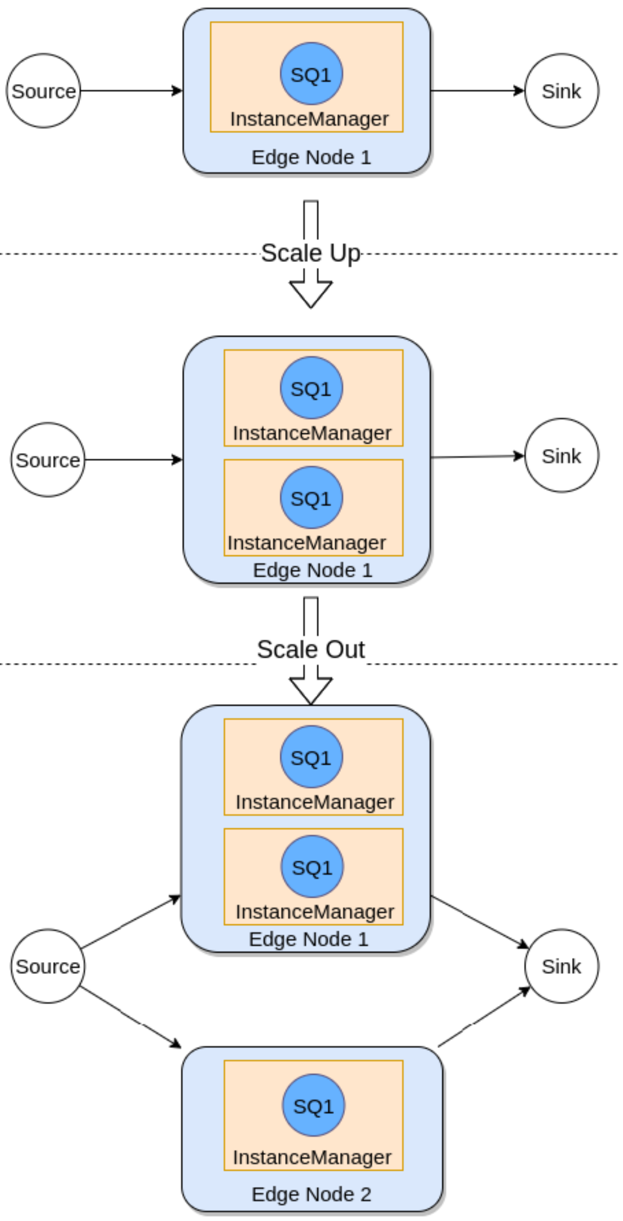


Figure 30 - Subquery scale-up, scale-out

Figure 29 shows the reconfiguration process. The reconfiguration may happen because there is a low resource usage (scale down) or the other way around; there is a high resource consumption. If the bandwidth is not fully utilized and the scarce resource is either memory or CPU assigned to an Instance Manager then, the system will scale up (if possible). The Orchestrator will create a new IM at that node and one of the queries will be migrated to that IM. We have implemented this as a first-fit descendent algorithm variant of the bin-packing problem. If the bandwidth is the bottleneck (i.e., the output rate of all queries running on a node consume all available bandwidth), scale up will not be possible. The Orchestrator will trigger a global reconfiguration in order to find an alternative deployment of the running queries. This is modelled as an integer linear programming problem (ILP) that assigns queries to IMs with the goal of minimizing latency across nodes. However, this may lead to a complete redeployment of the queries, which means stopping query processing and therefore, decrease system throughput and availability. The algorithm takes this into account and minimizes the number of queries that need to be migrated and the state to be transferred.

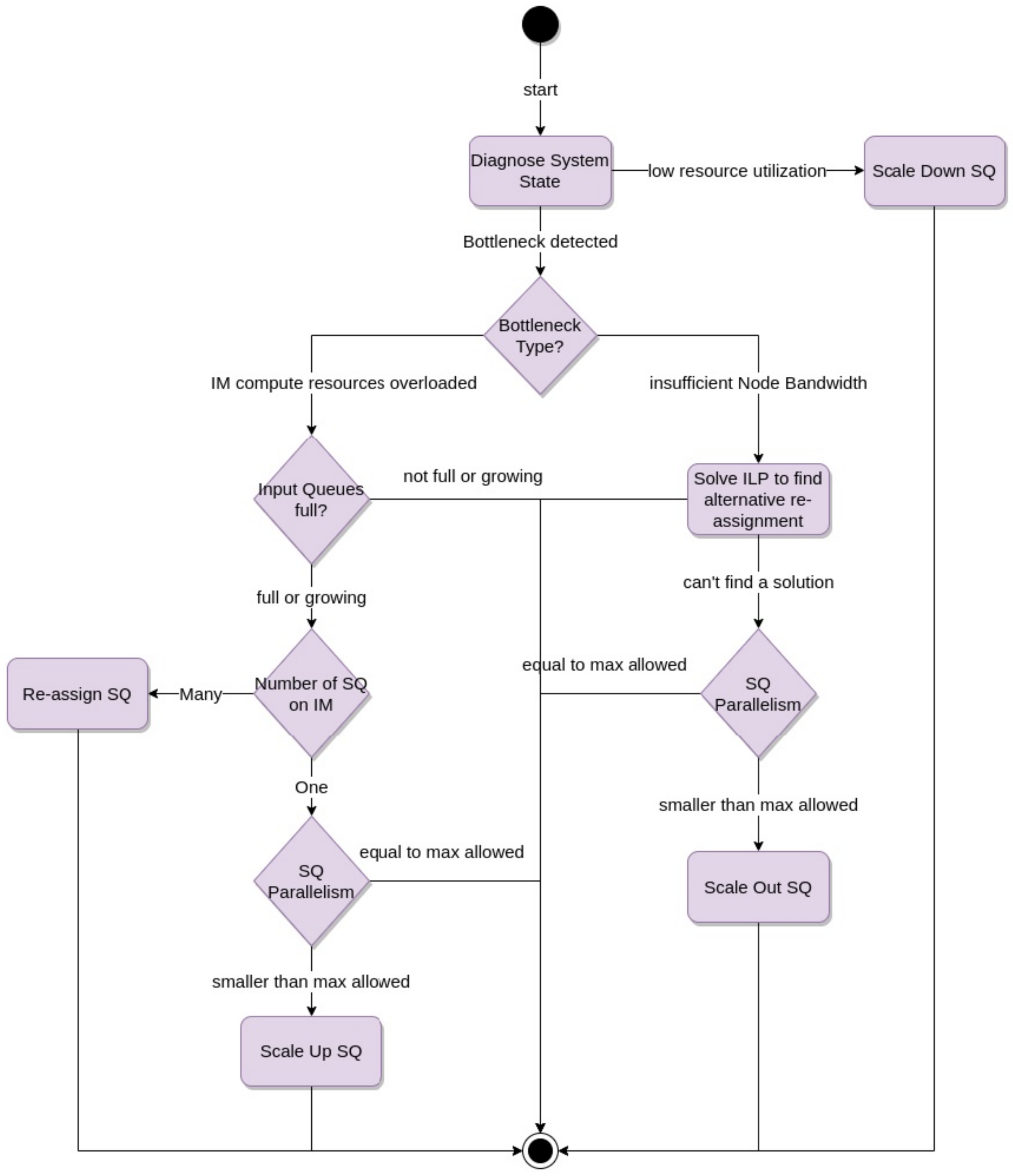


Figure 31 - CEP Reconfiguration

6.8. Process mapping and Analytics

The *Process mapping and analytics* component of the BigDataStack architecture consists of two separate sub-components: *Process Mapping* and *Process Analytics*.

- The objective of the Process Mapping sub-component is to predict the best algorithm from a set of algorithms available in the Predictive and Process Analytics Catalogue and provide a set of values for its respective input parameters given a specific dataset D and a specific analysis task T.
- The goal of the Process Analytics sub-component is to discover Processes from event logs and apply Process Analytics techniques to the discovered process models in order to optimize overall processes (i.e., workflows).

6.8.1. Process Mapping

The inputs of the Process Mapping sub-component consist of:

- The analysis task T (e.g., Regression, Classification, Clustering, Association Rule Learning, Reinforcement Learning, etc.) that the user wished to perform
- Additional information that is dependent on the analysis task T (e.g., the response – predictor variables in the case of Supervised Learning, the desired number of clusters in the case of Clustering, etc.).
- A dataset D that is subject to the analysis task T

The following table provides an overview of the main symbols used in the presentation of the Process Mapping sub-component.

Symbol	Description
T	An analysis task (e.g., clustering, classification…)
D	A dataset
T(D)	The analysis task T applied on dataset D
A(T)	An algorithm that solves the analysis task T (e.g., A(T)=K-means for T=Clustering)
Λ(A)	A set of values for the respective parameters of algorithm A
A(T,D)	An algorithm applied on D to solve the task T
M(D)	A model describing a dataset D
T	An analysis task (e.g., clustering, classification…)
D	A dataset
T(D)	The analysis task T applied on dataset D

Table 4 - Main symbols used in process mapping

The output of the Process Mapping sub-component is an algorithm A(T) along with a set of values for its respective parameters Λ(A) automatically selected as the best model for executing the data analysis task T at hand. The best algorithm can be based on various quantitative criteria, including result quality or execution time, and combinations thereof.

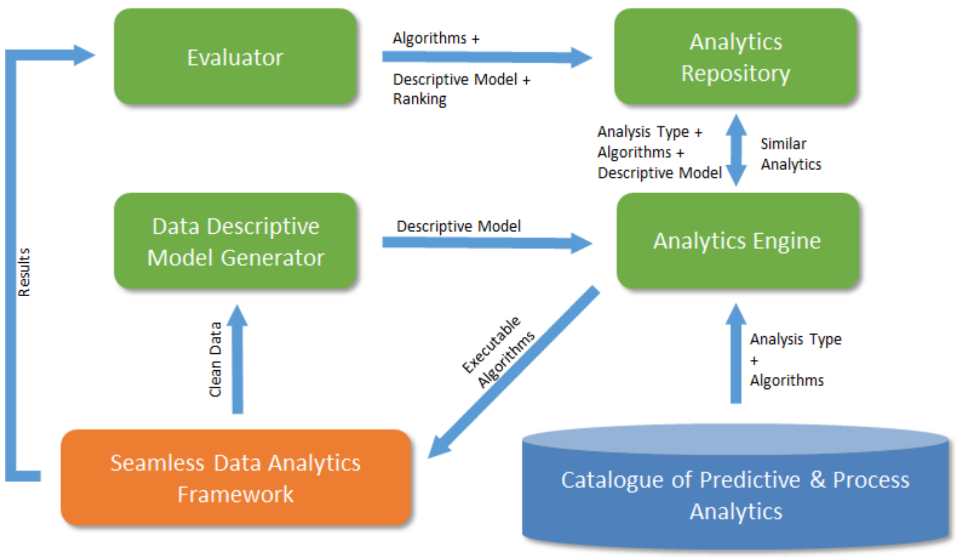


Figure 32 - High-level architecture of Process Mapping sub-component

High-level Architecture

Figure 30 provides an overview of the different modules and their interactions. The Process Mapping sub-component comprises the following four main modules:

- *Data Descriptive Model:* This module takes as input a dataset in a given input form and performs automatically various types of data analysis tests and computation of different statistical properties, in order to derive a model M(D) that describes the dataset D. Based on the relevant research literature, examples of information that is typically captured by the model M(D) include: dimensionality and the intrinsic (fractal) dimensionality, set of attributes, types of attributes, statistical distribution per numerical attribute (mean, median, standard deviation, quantiles), cardinality for categorical attributes, statistics indicating sparsity, correlation between dimensions, outliers, etc. The exact representation of the model M(D) is going to be presented in the following more concretely, but it can be considered as a feature vector. Thus, in the following, the terms model and feature vector are used interchangeably. Subsequently, the produced feature vector M(D) is going to be used in order to identify previously analysed datasets that have similarities with the given dataset. This is achieved by defining a similarity function *sim(M(D*$_1$*),M(D*$_2$*))* that operates at the level of feature vectors M(D$_1$) and M(D$_2$).
- *Analytics Engine:* The main role of this module is to provide an execution environment for analysis algorithms. Given a specific dataset D and a task T, the Analytics Engine can execute the available algorithms A(T) on the specific dataset, and obtain its result A(D,T). The available algorithms are retrieved from the Predictive and Process Analytics Catalogue for algorithms available in BigDataStack. In this way, evaluated results of analysis algorithms executed on datasets are kept along with the model description of the dataset. Separately, we implement in the analytics engine the functionality of computing similarities between models of datasets, thereby enabling the retrieval of the most similar datasets to the dataset at hand.

- *Analytics Repository:* The purpose of this repository is to store a history (log) of previous evaluated results of data analysis tasks on various datasets. Each record in this repository corresponds to one previous execution of a specific algorithm on a given dataset. It contains the model of dataset that has been analysed in the past, along with the algorithm executed, and its associated parameters. In addition, the record keeps one or more quality indicators, which are numerical quantities (evaluation metrics) that evaluate the performance of the specific algorithm when applied to the specific dataset.
- *Evaluator:* Its primary role is to evaluate the results of an algorithm that has been executed, and provide some numerical evaluations indicating how well the algorithm performed. For example, for clustering algorithms, several implementations of clustering validity measures can be used to evaluate the goodness of derived clusters. For classification algorithms, the accuracy of the algorithm can be computed. For regression algorithms, R-Squared, p-values, adjusted R-Squared and other metrics will be computed to evaluate the quality of the result. Apart from these quality metrics, performance-related metrics are also recorded, with execution time being the most representative such metric.

Once the Process Mapping sub-component has received the required inputs, the data is ingested into the Data Descriptive Model where characteristics and morphology aspects of the dataset D are analysed, in order to produce the model M(D). Then, together with user requirements are forwarded to the Analytics Engine. At this point a query is made from the Analytics Engine to the Analytics Repository, a storage of previously executed analysis models and the final algorithms that were executed in each case. We distinguish two cases:

- *No similar models can be found:* In this case, the available algorithms from the Predictive and Process Analytics Catalogue that match the user requirements are executed, and the results are returned and evaluated in the Evaluator (where quality metrics are computed for each run depending on its performance). The results are stored in the Analytics Repository.
- *A similar model can be found:* In this case, the corresponding algorithm (that performed well in the past on a similar dataset) is executed on the dataset at hand, and the results are again analysed in the Evaluator. The results are again stored in the Analytics Repository. In case the result is not satisfactory, the process can be repeated for the second most similar model, etc.

Example of Operation

The operation of Process Mapping entails two discrete phases: (a) the learning phase, and (b) the in-action phase.

In the learning phase, the system executes algorithms on datasets and records the evaluations of the results in the analytics repository. Essentially, the system learns from executions of algorithms of different datasets.

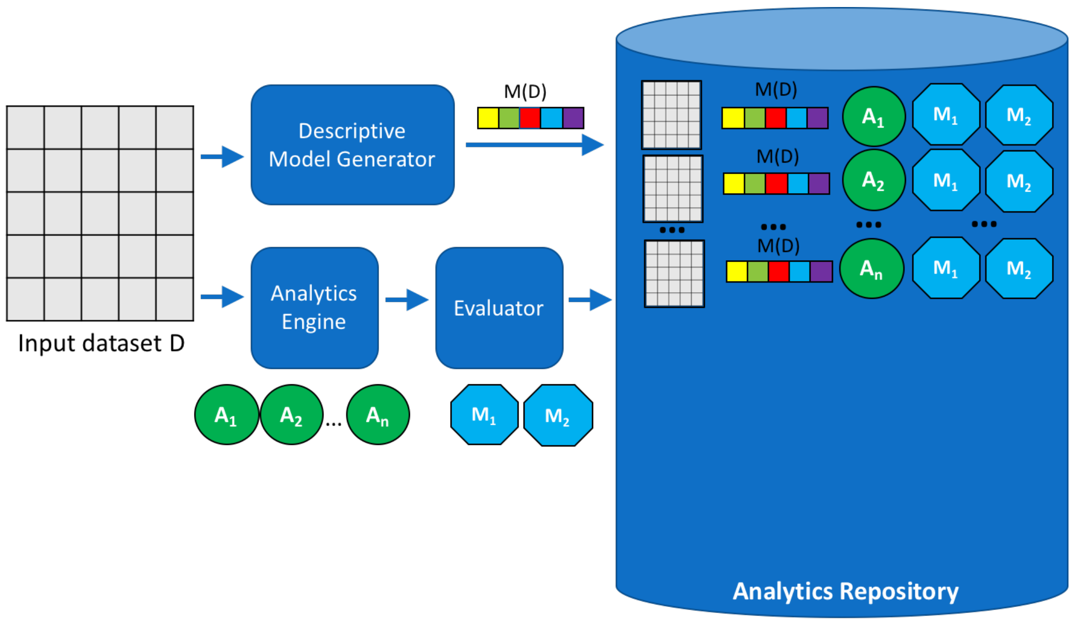


Figure 33 - Learning phase of Process Mapping: Processing the first dataset D

The learning phase starts without any evaluated results in the analytics repository. As shown in Figure 31, when the first dataset D is given as input, the Descriptive Model Generator produces the model M(D). In parallel, the available algorithms A_1, A_2, …, A_n are executed on D and their result is given to the Evaluator, which computes the available metrics M_1 and M_2. Examples of metrics could be accuracy and execution time. Then, this information is stored in the analytics repository: the model M(D), the algorithm A_i, and the values of metrics M_1 and M_2. Notice that the actual dataset is not stored, however it is shown in the figure just for illustration purposes.

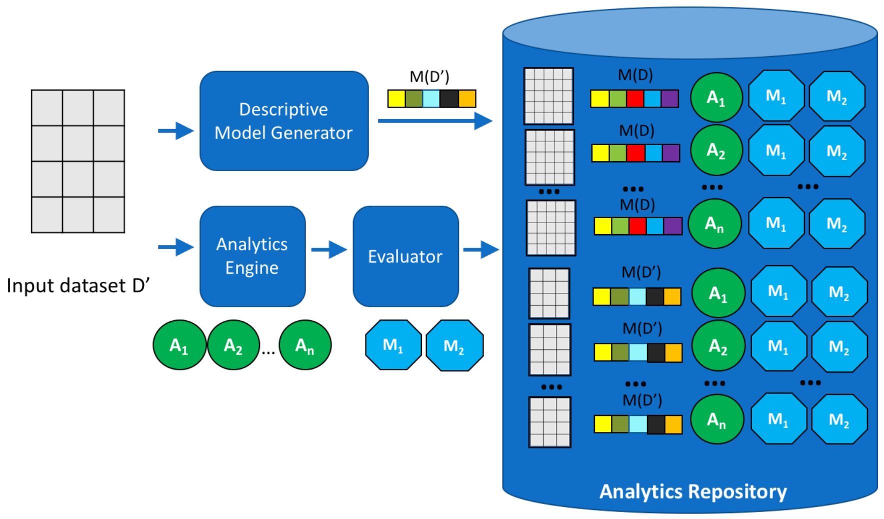


Figure 34 - Learning phase of Process Mapping: Processing the second dataset D'

Figure 32 shows the processing of a second dataset D’, still in the learning phase. The same procedure as described above is repeated, and the results are added to the Analytics Repository.

The in-action phase corresponds to the typical operation of Process Mapping in the context of BigDataStack, namely to perform the actual mapping from an abstract task T (which is present as a step of a process designed in the process modelling framework) to a concrete algorithm A(T) and a set of values for its parameters Λ(A) that can be executed on the dataset D at hand, i.e., A(T,D). The following example aims at clarifying the detailed operation.

Figure 33 shows a new dataset which is going to be processed based on the specification received from the process modelling framework. Next, the Process Mapping automatically suggests the best algorithm (A_*) from the pool of available algorithms A_1, A_2, …, A_n.

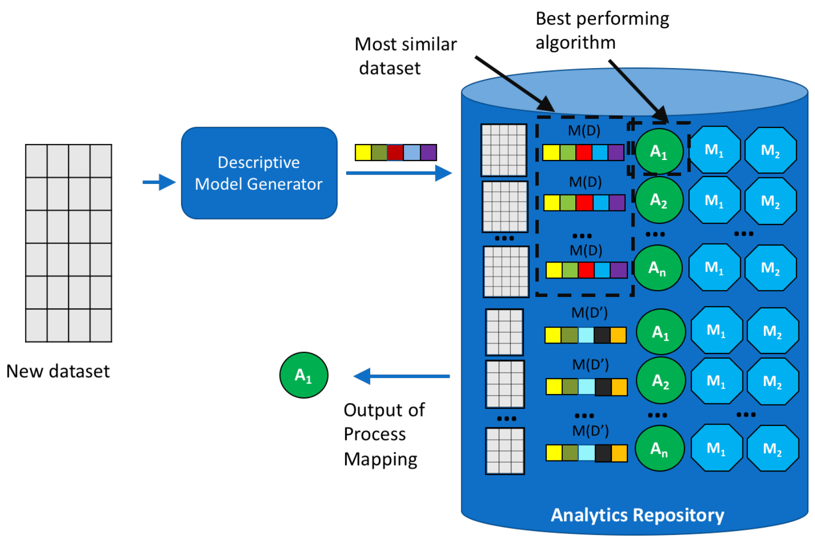


Figure 35 - The in-action phase of Process Mapping

As depicted in the figure above, the Descriptive Model Generator produces the model for the new dataset, and then this model is compared against all available models in the analytics repository in order to identify the most similar dataset. In this example, M(D) is the most similar model. Then, the best performing algorithm is selected from the results kept for M(D). The values of available metrics (M_1 and M_2) are used to identify the best algorithm based on an optimization goal, which could rely on one metric or a combination of metrics, according the needs of the application. In the example, the output of Process Mapping is depicted as algorithm A_1.

Technical Aspects of the Prototype Implementation

The prototype Implementation of Process Mapping covers two of the most known Machine Learning Tasks (T), namely Clustering and Classification. Below, we provide the technical details and individual techniques used by Process Mapping.

The Descriptive Model Generator computes and records a wide variety of state-of-the-art features used for Algorithm Selection, that can be distinguished into two categories depending on the analysis task they are to be used for (Classification or Clustering). All of them are presented accordingly in the following tables.

Meta Features Used for Classification	
General	• Ratio between the number attributes/ categoric and numeric features/ No instances and attributes • Relative frequency of each distinct class • Number of Numeric/Categorical/Binary Features • Number of Classes/instances
Information-theory	• Concentration Coefficient between each attribute and class • Concentration Coefficient between each pair of distinct attributes. • Joint Entropy between each attribute and class • Shannon's Entropy of target attribute
Statistical	• Harmonic Range/Mean/Mean/Median/Variance of each attribute • No distinct highly correlated pair of attributes • No attributes with at least one outlier value/ No outliers • Skewness/Kurtosis of each attribute • Eigenvalues of covariance matrix from data set

Table 5 - Features used for algorithm selection in classification

Meta Features Used for Clustering	
Information Theory	• Mean Entropy of Discrete Attributes • Mean Concentration between Discrete attributes
Statistics	• Mean absolute Correlation between attributes • Mean skewness/kurtosis of continuous attributes • Log of the number of Attributes/Objects
Distance Based	• Mean of distances vector • Variance of distances vector • Kurtosis of distances vector • Percentage of distance values in each of ten intervals that equally comprise range [0,1] • Percentage of distance values with absolute z-score in four intervals of range [0,inf)

Table 6 - Features used for algorithm selection in clustering

The Analytics Engine is implemented in Python 3, a popular selection of a programming language for the execution of machine learning tasks. At the time of writing the algorithms supported are listed per task as follows:

- **Clustering** (8): *Agglomerative Clustering, Birch, DBScan, Hierarchical Clustering, KMeans, MeanShift, OPTICS, Spectral Clustering*
- **Classification** (8): *AdaBoost (Ensemble Method), Decision Tree, Gaussian Process, Naïve Bayes, Nearest Neighbors, Neural Networks (MLP), Random Forest (Ensemble Method), SVM*

Last, but not least, the Evaluator uses metrics both for the quality of data analysis as well as for performance. The metrics used for evaluation depend on the Machine Learning Task that is executed. For clustering we opt to include six Indexes known as "Internal" (Silhouette, Calinski-Harabasz, Dunn, CDBW, SDbw, Davies-Bouldin) that base their scorings on aspects such as the inter and intra-cluster density and sparsity of a data set's records. As a default quality measure for indicating algorithm performance we conclude to Calinski-Harabasz due to empirical evidence we gained that suggested this index is the one with the best generalized applicability across problem instances. For Classification we use the mean Accuracy achieved during a 10-fold Cross Validation procedure, a method show to be less prone to overfitting. In terms of performance, the Evaluator records the execution time needed by the algorithm to produce the results. The application that runs in BigDataStack can select whether algorithm selection will be based on optimizing result quality, performance, or an arbitrary (application-defined) combination of these two.

6.8.2. Process Analytics

The Process Analytics sub-component comprises the following four main modules:

- *Discovery:* The main objective of this component is via a given event log to create a process model.
- *Conformance Checking/Enhancement:* This component's role is dual. Firstly, in the Conformance Checking Stage a process model is evaluated against an event log for missing steps, unnecessary steps, and many more (process model replay). Secondly, in the Enhancement Stage user input is considered (e.g. cost-effectiveness or time effectiveness of a process) to create an according model of a process. Also, in this stage dependency graphs will be created and through metrics, such as direct succession and dependency measures to be utilized by the Predictions component.
- *Log Repository:* A repository consisting of any changes to a model during the Conformance Checking/Enhancement stage.
- *Prediction:* Dependency graphs and weighted graphs of process models, created in the Enhancement phase will be used in collaboration with an active event log to predict behaviour of an active process.
- *Model Repository:* A storage unit of all process models, user-defined or created in the Discovery stage.

The input variables of this mechanism are:

- Event logs.
- Process models (not obligatory).

The output of the mechanism is as follows:

- Discovered process models.
- Enhanced process models.
- Diagnostics on process models.
- Predictions - Recommendations on events occurring in process models.

The main structure of the predictive component is depicted in Figure 34:

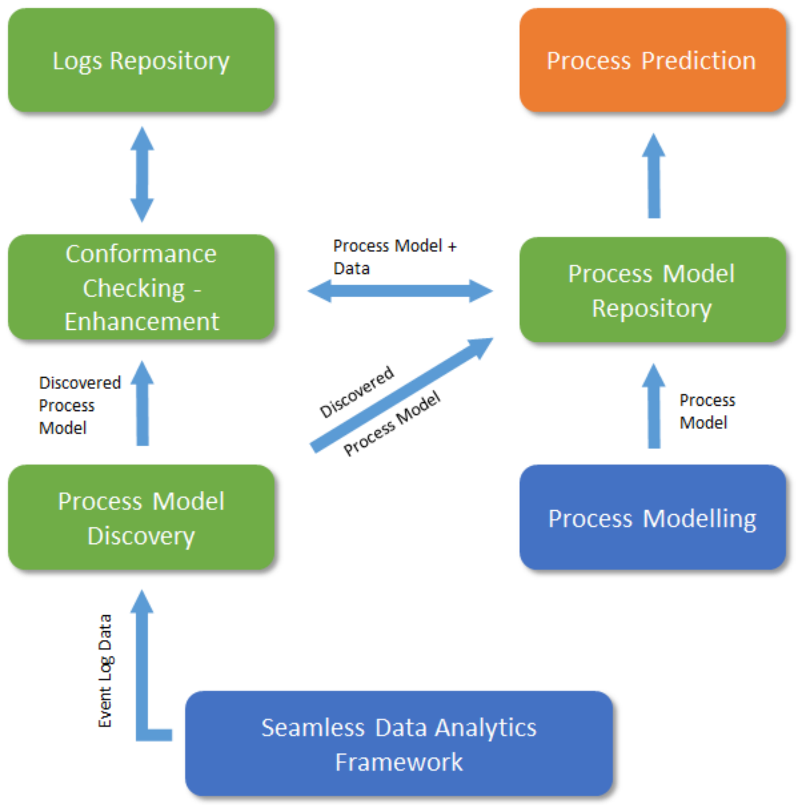


Figure 36 - Internal architecture of the Process Analytics sub-component

6.9. Seamless Analytics Framework

A single logical dataset can be stored physically in many different data stores and locations. For example, an IoT data pipeline may involve an ingestion phase from devices via a message bus to a database and after several months the data may be moved to object storage to achieve higher capacity and lower cost. Moreover, within each lifecycle phase, we may find multiple stores or locations for reasons such as compliance, disaster recovery, capacity or bandwidth limitations etc. Our goal is to enable seamless analytics over all data in a single logical dataset, no matter what the physical storage organization details are.

In the context of BigDataStack, we could imagine a scenario where data would stream from IoT devices such as DANAOS ship devices, via a CEP message bus, to a LeanXcale data base and eventually, under certain conditions be migrated to the IBM COS Object Store. This flow makes sense since LeanXcale provides transactional support and low latency but has capacity limits. Therefore, once the data is no longer fresh it could be moved to object storage to vacate space for newer incoming data. This approach is desirable when managing Big Data.

The seamless analytics framework aims to provide tools to analyse a logical dataset which may be stored in one or more underlying physical data stores, without requiring deep knowledge of the intricacies of each of the specific data stores, nor even awareness of where the data is exactly stored. Moreover, the framework provides the tools to automatically migrate data from the relational datastore to the object store, without the interference of a database administrator, with no downtime or expensive ETLs, ensuring data consistency during the migration process at the same time.

A given dataset may be stored within multiple data stores and the seamless analytics framework will permit analytics over it in a unified manner. The LXS Query Engine is extended in order to support queries over a logical database that might be split across different and heterogeneous datastores. This extended query engine will serve as the federator of the different datastores and will a) push down incoming queries to each datastore b) retrieve the intermediate results and merge them in order to return the unified answer to the caller. Therefore, the data user will have the impression of executing a query against a single datastore which hosts the logical dataset, without having to know how the dataset is fragmented and split within the different stores. Finally, the federator will provide a standard mechanism for retrieving data: JDBC, thus allowing for a variety of analytical frameworks such as Apache Spark to make use of the Seamless Analytical Framework to perform such tasks.

The data lifecycle is highlighted in the following figure:

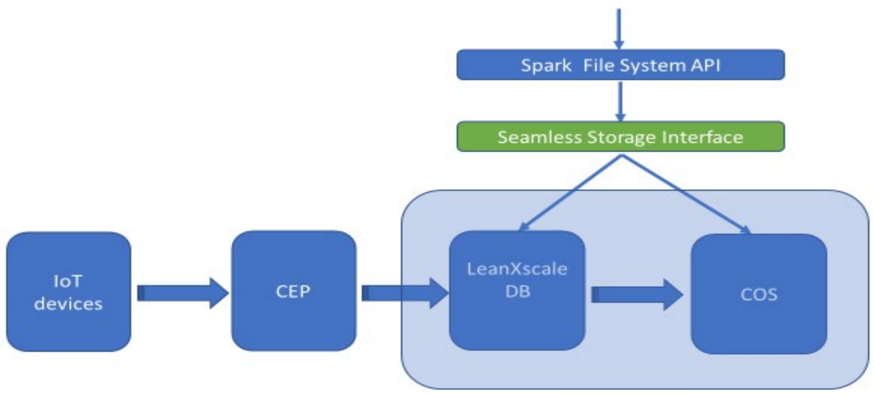


Figure 37 - Seamless Interface

Data is continuously produced in various IoT devices and forwarded to the CEP engine for an initial real-time analysis. This analysis might identify potential alerts or challenges which are triggered by submitting specific rules which use data coming from a combination of sources and are relevant under a specific time window. CEP later ingests data to the LeanXcale relational datastore, which is the first storage point due to its transactional semantics that ensure data consistency. After a period, data can be considered historical and are of no use for an application. However, they are still invaluable as they can participate in analytical queries that can reveal trends or customer behaviours. As a result, data are transferred to the Object Store that is the best candidate for such type of queries. Due to this, data is continuously migrating between stores, and the seamless interface provides the user with a holistic view, without needing to keep track of what was migrated when.

The *Seamless Analytical Framework* was successfully demonstrated in the scope of the DANAOS scenario; however, the scope of the framework was limited: it targeted cases where sensor IoT data are stored in data tables, which eventually become obsolete and are moved to the object store in order to exploit the capabilities of the latter to perform more efficiently analytical queries, by maintaining data consistency and transactional semantics due to the operational datastore. This implies that all operations and queries, even if they consist of complex analytical aggregations that have been re-designed in order to be executed in a distributed manner, they all involve single tables: *join* operations or queries that consist of nested statements were practically not supported, as this would have required for the whole result set of the operand to be fetched in the memory of the query federator. Such an implementation would have saturated the resources of the machine and the framework would have crashed. During the last phase of the project, we extended the functionalities of the *Seamless Analytical Framework* to support all SQL queries and widen its use. The *Connected Consumer* use case was found ideal to validate the novel functionalities.

The *Connected Consumer* use case is a typical scenario of an electronic store. It has several stores along Spain, that sell a variety of products, and its clients can submit online orders to buy specific goods. Moreover, a recommendation engine takes into account various parameters such as age, marital status and behavioural habits, in order to recommend new products that might be of the client's interest. The data schema of this application is relational and consists of various data tables of average size that are mostly read-only or expect update operations and rare inserts (i.e. the number of customers is being increased at low rate), thus are not expected to grow in a sense that will require a data warehouse. However, there is a specific data table that stores the results of the recommendation engine for all customers that is accepting new records at a high rate, and its size is typically higher than 95% of the whole database. This data table is only accepting insert operations and it takes part in complex analytical queries of the engine to create recommendations based on the historical data. Thus, it is a perfect example of a use case where a data table is accepting new records that become obsolete and are crucial for the analytical engine. However, the nature of the involved queries require *join* operations and nested SQL statements, thus were not supported by the *Seamless Analytical Framework* delivered in M18.

In order to support such scenarios, we extended the framework to provide these capabilities and to additionally increase the efficient execution of arbitrary query statements, without the need to pre-configure the object store for appropriate indexing in order to serve specific queries. The extensions mainly affected the *query federator* and the *data mover* of this framework. For the former, the whole engine was re-designed in order to be incorporated with the query engine of the operational datastore. Regarding the *join* operations, implementation now takes into account that one of the two operands is targeting a fragmented data table. This implementation retrieves the projection of the columns that need to be returned along with the columns that takes part in the *join* operation, and transforms the *join* instead into an *in clause* that is pushed down into the object store. This technique is widely known as *bind join*. Due to this, only close to the minimum amount of data is being transmitted across the network, and the *federator* retrieves only the data that need to be returned to the data user by the object store. Furthermore, all operations that require the retrieval of data of a fragmented dataset have been modified to allow *push down*s of other operations. Thanks to this, the query engine of the federator can incorporate all operations into its query planner, and the query optimizer can produce and reason about an alternative operation plan that is can deliver better performance. By doing so, now all types of queries can be supported, including nested statements that can involve join operations. Moreover, the *data mover* is now capable of retrieving statistical information about the submitted queries and the data distribution on the indexes, thus, can create on the fly appropriate partitioning on the object store side, that is capable of executing queries even faster.

6.10. Application Dimensioning Workbench

The goal of the dimensioning phase is to provide insights regarding the required infrastructure resources primarily for the data services components, linking the used resources with load and expected QoS levels. To this end, it needs to link between the application/service-related information (such as KPIs and workload, parameters of the data service etc.) and the used resources to be able to provide recommendations towards the deployment mechanisms, through e.g. prediction and correlation models. Benchmarking against these services is necessary in order to concentrate the original dataset that is needed in a variety of business scenarios, such as sizing the required infrastructure for private deployments of the data services or consulting deployment mechanisms in a shared multitenant environment where multiple instances of a data service offering may reside.

The main issues that need to be handled by the Dimensioning Workbench are:

- The target trade-off that needs to be achieved between a generic functionality and an adapted operation. For example, benchmarking for each individual application request would lead to very high and intolerable delays during the deployment process. Thus, one would need to abstract from the specifics of an application instance through the usage of suitable workload features, benchmark in advance for a variety of these workload features and thus only need to query for the most suitable results during the deployment stage. Thus, dual capabilities would need to exist, either benchmarking at the service level, ensuring a timely acquisition of a large number of samples, as well as benchmarking at the application entry point level, in order to understand how load propagates down the service graph and what input loads it generates at the data service input level.
- The achieved abstraction and automation for easily launching highly scalable and multi-parameter benchmarks against the data services, with minimal user interaction and need for involvement. This would require the rationale of a benchmarking framework inside ADW that will be able to capture the needed variations between the configuration parameters (workload, resource etc), adapt to the needed client types per data service as well as the target execution environment of the tests (e.g. different execution platforms such as OpenShift, Docker Swarm, external public Cloud offerings such as AWS, etc).
- The workflow/graph-based nature of the application, which implies that application (and data service) structure should be known and taken under consideration by the analysis. To this end, needed annotations are required so that the generic structure which is provided as input to the Workbench through the Data Toolkit contains all the necessary information such as expected QoS levels (potentially for different metrics), links between the service components etc. On top of this structure, the workbench can quantify the expected QoS per component and then propagate through the declared dependencies.
- While application structure is provided to the workbench, this will often not imply a particular deployment configuration for the application (e.g. what node types will be suitable for the user’s application). Multiple trade-offs in this domain could also be given to the users, enabling them to make a more informed final decision based on

cost or other parameters. For this reason, the dimensioning workbench needs to receive this input of available deployment patterns from the Pattern Generation in order to populate them with the expected QoS, information that is taken under consideration in the process for final ranking and selection.
- Adaptation of benchmarking tests in a dockerized manner in order to be launched through the framework in a coordinated and functional manner, based on each test's requirements and needed sequences.

Dependencies of the dimensioning component especially in the form of anticipated exchange of information (in type and form) are presented in the following bullets. Inputs include:

- Structure of the application along with the used data services is considered an input, as concretized by the Data Toolkit component (in the form of a playbook file, the BigDataStack Playbook) and passed on to the Dimensioning component, following its enrichment with various used resource types from the Pattern Generator, and including expected workload levels inserted by the user in the Data toolkit phase. This is the structure upon which the Dimensioning workbench needs to append information regarding expected QoS per component.
- Types of infrastructure resources available in terms of size, type, etc (referred to as resource templates). This information is necessary at the Pattern Generator side in order to create candidate deployments.
- Different types of Data Services will be provided by BigDataStack to the end users. Each of these services may have different characteristics and functionalities, affected in a different manner and quantity by the application input (such as the data schema used). Consideration of these features should be included in the benchmarking workload modelling of the specific service (e.g. number of columns in the schema tables, types of operations, frequency of them etc.), as well as inputs that may be received by the application developer/data scientist, such as needed quality parameters of the service (such as latency, throughput needed etc.) or other preferences declared through the Data Toolkit.
- Application related current workload and QoS values should be available to enable the final creation of the performance dataset, upon which any queries or modelling will be performed. This implies a collaboration and adaptation with the used benchmark tests and/or infrastructure monitoring components such as the Triple Monitoring Engine, in case the used benchmarks do not report on the needed metrics.
- Language and specification used by the Deployment component, or any other provisioned execution environment, given that ADW needs to submit such descriptors for launching the benchmarking tests.
- Exposure of the necessary information, such as endpoints, configuration, results etc to the Visualization components of the project, in order to be embedded and controlled from that side as well. Thus relevant APIs and JSON schemas need to be agreed and implemented based on this feature.

Necessary outputs:

- The most prominent output of the Dimensioning phase is the concretized (in terms of expected QoS) playbook for a candidate deployment structure for the used data services in the format needed by the ADS-Ranking component that utilizes the dimensioning outcomes. This implies that the format used by Dimensioning to describe these aspects should be understood by the respective components and thus was agreed in collaboration, defined currently as a Kubernetes configuration template type of file structure called a BigDataStack Playbook. More concretely, this is operationalized as a series of candidate deployment patterns (CDPs), which describe the different ways that the user's application might be deployed along with the expected QoS levels per defined metric. CDPs are provided in the respective file format, such that they can be easily used to perform subsequent application deployment. The Dimensioning phase will augment each CDP with estimated performance metrics and/or quality of service metrics, providing a series of indicators that can be used to judge the potential suitability of each CDP. These estimates are used later to select the CDP that will best satisfy the user's deployment requirements/preferences.
- Intermediate results include the benchmarking results that are obtained through the benchmarking framework of ADW. These need to be exposed either to internal ADW components for subsequent stages (e.g. modelling or population of the playbook) or external such as Visualization panels towards the users for informative purposes.

The main structure of the Dimensioning is depicted in Figure 36. The component list is as follows:

- *Pattern Generation:* The role of pattern generation is to define the different ways that a user's application might be deployed. In particular, given the broad structure of a user's application provided by the Data Toolkit, there are typically many ways that this application might be deployed, e.g. using different node types or utilizing different replication levels. We refer to these different ways that a user's application might be deployed as 'candidate deployment patterns' (CDPs). CDPs are generated automatically through analysis of the user's application structure provided in the form of a 'BigDataStack Playbook' file from the Data Toolkit, as well as the available cloud infrastructure. Some CDPs will be more suitable than others once we consider the user's requirements and preferences, such as desired throughput or maximum cost. Hence, different CDPs will encode various performance/cost trade-offs. These CDPs define the configurations that are used as filters for retrieving the most relevant benchmarking results during the Dimensioning phase, producing predicted performance and quality of service estimations for each. Even though Pattern Generation is part of Dimensioning, it is portrayed as an external component given that for each CDP the core Dimensioning block will be invoked.
- *ADW Core:* The ADW Core is the overall component that is responsible for the main functionalities of Dimensioning. It is split into two main parts, the ADW Core Benchmarking, which is responsible for implementing and storing benchmarking runs with various setups, and the ADW Core Runtime that is used during the assisted deployment phase of BigDataStack in order to populate the produced CDPs with the

predicted QoS levels. Following, a highlight of the various functionalities of each element is described, split into more fine-grained parts.

- *Bench UI:* The Bench UI is used by the Data Service owner or the Application Owner in order to define the parameters of the benchmarking process, which is performed "offline", thus not in direct relationship to a given application deployment during runtime. It is necessary for these user to investigate the performance considerations of their service and proceed with this stage, during the incorporation of their data service or application in the BigDataStack ecosystem, in order to have gathered the necessary data a priori and not need to benchmark during the actual application deployment. The latter would create serious timing considerations and limitations that would not be tolerated by the end users. Through the Bench UI, multiple parameters can be defined, leading to a type of parameter sweep execution of a test, in order to automate and enable an easier result gathering process. The UI includes a visual element for selection of the parameters (many of which are obtained through a link to an external repository (Gitlab), as well as a relevant REST endpoint in which the user can submit a JSON description of the test (thus enabling further automation through multiple REST submissions). It can also be used to monitor the progress of the test. Result viewing and relevant queries can also be performed via the central visualization component of BigDataStack. In Y3 the process has been enriched through the incorporation of the Jmeter generic load injector, which enables also the execution of the overall application graph and the inclusion of application specific workload files. This enables to obtain a more generic view of the overall application graph and the stress it creates at a given point of the application structure (e.g. the linked data service).
- *Test Control:* Test control is used in order to prepare, synchronize and configure test execution. A number of steps are needed for this process based on the user's selected options, such as running tests in a serial or parallel manner, preparing shared volumes and networks and so on. Test control in Y3 is enriched with two more features, the ability to include whether the test should be run in isolation or can be run in parallel with other tests and the ability to launch trace driven simulations. The latter is necessary in order to include a variable load graph that may be used to compress a series of experiments in one description fiile and include a sequential process including spike testing, endurance testing etc, breaking point testing etc.
- *Deployment Description Adapter:* In order to enable launching of the defined tests in an execution platform (such as Openshift, Docker Swarm, external Clouds etc), relevant deployment descriptors should be created. For example, for Openshift a relevant playbook file needs to be created and populated with the parameters selected for the benchmark tests, such as input arguments, selected resources etc and then forwarded to ADS Deploy. A playbook template structure is created beforehand for each bench test type based on the execution needs of each test (e.g. number and type of containers, needed shared volumes and networks etc), necessary included data service etc, that is then populated with the specific instantiation's details. Different execution platforms can be supported through the inclusion of relevant plugins that implement the according formats of that platform or the

relevant API calls to setup the environment (a Docker Swarm version is already supported at this time). Through this setup the system under stress (data service) is automatically deployed, as well as the necessary number of bench test clients in order to cover the desired load levels.

- *Image repository:* While this refers to the main image repository across the project, its inclusion here is used to indicate the necessary inclusion of the bench tests images, appropriately adapted based on the benchmarking framework's needs, in terms of execution, configuration and result storing.
- *Configuration repository:* Existing external repository through which the Benchmarking process can be configured through varius means (e.g. workload files, startup scripts, settings files etc). This is necessary in order to include the dynamic nature of the benchmarking setup and execution, as well as create links between the Bench UI and the available options to the user (e.g. UI retrieves list of available workload types from respective configuration folder of the external repository).
- *Results/Model repository:* This component is intended to hold the benchmarking results obtained through the test execution process as well as hold the created regression models used during the Result Retrieval queries in the Runtime phase (Y3).
- *Structure Translator:* This component acts as an abstraction layer and is responsible for obtaining the output of the Data Toolkit containing the application structure in the format this is expressed (e.g. playbook service structure) and extracting the parameters that are needed in order to instantiate the query towards the result retrieval phase. Furthermore, in cases of multi-level applications, it is responsible for propagating the process across the service graph.
- *Result Retrieval:* This component is responsible for obtaining the specified deployment options from the CDPs, the anticipated workload and produce the predicted QoS levels of the service. This may happen either through direct querying of the stored benchmarked results (y2) or through the creation and training of predictive regression models (Y3) that will also be able to interpolate for cases that have not been investigated, based on the training of the regressor and the depiction of the outputs (QoS) dependency from the predictor inputs (workload and h/w-s/w configuration used).
- *Output Adaptor:* This component acts as an abstraction layer and is responsible for generating the output format needed for the communication with ADS Ranking (in the particular case enriching the inputed playbook file with the extra QoS metrics).

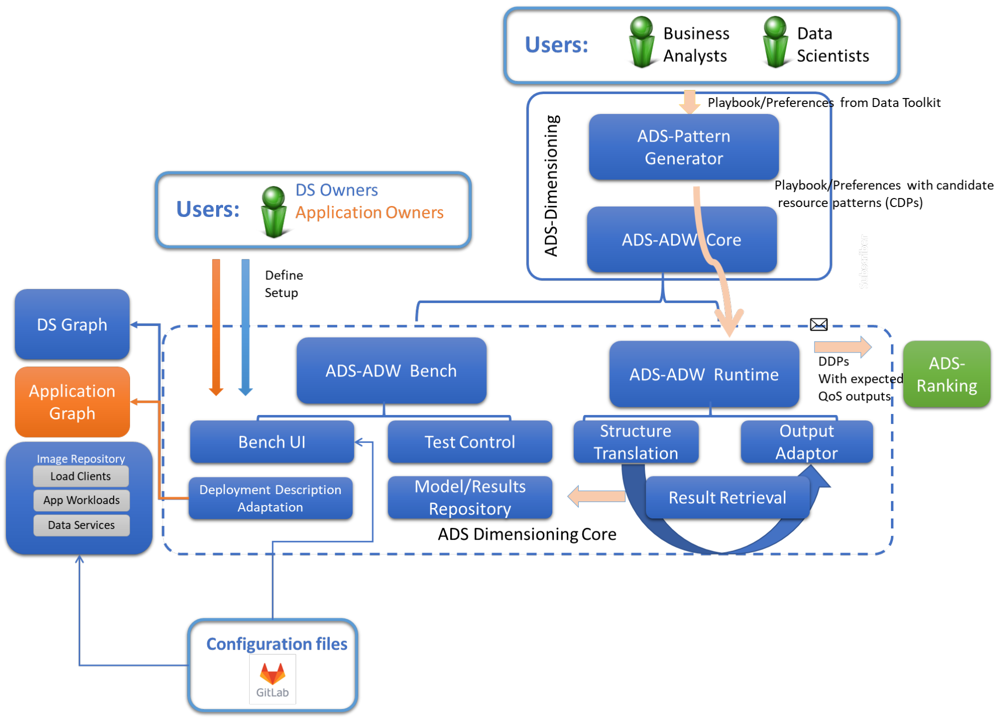


Figure 38 - Application dimensioning internal structure and link with external components

6.11. Big Data Layout and Data Skipping

Here we focus on how to best run analytics on Big Data in the cloud. Today's best practices to deploy and manage cloud compute and storage services independently leaves us with a problem: it means that potentially huge datasets need to be shipped from the storage service to the micro-service to analyse data. If this data needs to be sent across the WAN then this is even more critical. Therefore, it becomes of ultimate importance to minimize the amount of data sent across the network, since this is the key factor affecting cost and performance in this context.

We refer the reader to the BigData Layout section (8.10) of the D2.1 BigDataStack deliverable which surveys the main three approaches to minimize data read from Object Storage and sent across the network. We augmented these approaches with a technique called Data Skipping, which allows the platform to avoid reading unnecessary objects from Object Storage as well as avoiding sending them across the network (also described in D2.1). As explained there, in order to get good data skipping it is necessary to pay attention to the Data Layout.

In BigDataStack data skipping provides the following added-value functionalities:

1. Handle a wider variety of datasets, go beyond geospatial data
2. Allow developers to define their own data skipping metadata types using a flexible API.
3. Natively support arbitrary data types and data skipping for queries with UDFs (User Defined Functions)
4. Handle continuous streaming data that is appended to an existing logical dataset.
5. Continuously assess the properties of the streaming data to possibly adapt the partitioning scheme as needed

6. Handle general query workloads. This is significant because often different queries have different, even conflicting, requirements for data layout.
7. Handle query workloads which change over time.
8. Build a benefit/cost model to evaluate whether parts of the dataset should be partitioned anew (thus rewritten) to adapt to significant workload changes.
9. Implementation of additional ready indexes types such as the Bloom-filter index
10. We found out a serious performance problem with Apache Spark SQL which is that it requires for each SQL query to discover the dataset schema. This demands a repeated full read of the dataset. We fixed this with a "database catalogue" which stores the data schema and is used as an indirection between SQL queries and the dataset thus suppressing this performance problem.
11. Numerous functional and performance improvements so that this technology can be included into IBM products.

Previous research focused on the HDFS, whereas we plan to focus on Object Storage, which is of critical importance in an industrial context. Object Storage adds constraints of its own: once an object has been put in the Object Store, it cannot be modified, where even appending to an existing object is not possible, neither can it be renamed. This means that it is important to get the layout right as soon as possible and avoid unnecessary changes. Moreover, it is important for objects to have roughly equal sizes (see our recent blog on best practices [17]), and we are researching the optimal object size and how it depends on other factors such as data format. Moreover, the cost model for reorganizing the data layout is likely to be different for Object Storage than for other storage systems such as HDFS.

6.12. Process modelling framework

Process modelling provides an interface to business users (e.g. business analysts) to model their business processes and workflows as well as to obtain recommendations for their optimization following the execution of process mining tasks on the BigDataStack analytics framework. The outcome of the component is a model in a structural representation – a JSON formatted file. The latter is actually a descriptor of the overall graph reflecting the application and data services mapped to specific executables that will be deployed to the BigDataStack infrastructure. To this end, the descriptor is passed to the Data Toolkit component and then to the *Application Dimensioning Workbench* to identify their resource requirements prior to execution.

The main issues that need to be handled by the Process modeling framework are:

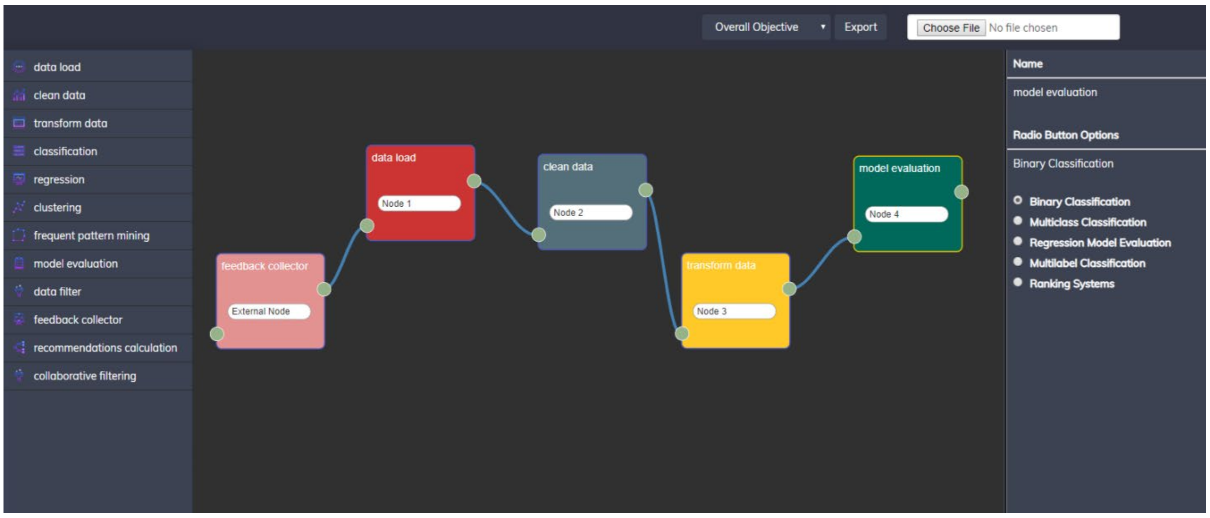
- *Declarative process modelling approach*: Processes may be distinguished in Routine (Strict) and Agile. Routine processes are modelled with the imperative method that corresponds to imperative or procedural programming, where every possible path must be foreseen at design time and encoded explicitly. If a path is missing, then it is considered not allowed. Classic approaches like the BPEL or BPMN follow the imperative style and are therefore limited to the automation type of processes. The metaphor employed is the flow chart. Agile processes are modeled with the declarative method according to which declarative models concentrate on describing what must be done and the exact step-by-step execution order is not directly prescribed; only the undesired paths and constellations are excluded so that all remaining paths are potentially allowed and do not have to be foreseen individually. The metaphor employed is rules/constraints. Agility at the process level, entails "the ability to redesign and reconfigure Individual business process components, combining individual tasks and capabilities in response to the environment" [18]. Declarative process modeling or a mixed approach seems to fit well in our environment providing the necessary flexibility in process modelling, mapping and optimization.

- *Structure to output to the Data Toolkit and subsequently to the application dimensioning framework, workflow/reference to executables/execution logic:* The output of the process modeling framework should be a structure to feed the Data Toolkit and later on the dimensioning framework. The structure should provide for reproducing the process graph, the tasks mapping to executables and the logic in terms of rules/constraints that govern the execution flow and the execution of the process tasks. Process Modelling outputs the structure of the developed process model to Data Toolkit component.

The main structure of the Process modelling framework is described below. The component list is as follows:

- *Modeling toolkit:* This component provides the *interface for business analysts* to design their processes in a non-expert way, the *interface for developers* to provide in an easy way predefined tasks and relationship types as selectable and configurable tools for business analysts and *the core engine* to communicate with all the involved components towards *design, concretization, evaluation, simulation, output and optimization of a business process*.
- *Rules engine:* The engine *provides all the logic for defining rules and constraints, evaluating and executing* them. The aim is the business analyst to be provided with a predefined set of rules offered as a choice through the tasks and relations toolbox.
- *ProcessModel2Structure Translator:* This component generates the structure from the developed model that will feed the Data Toolkit and subsequently the dimensioning framework. This structure must be able to instantiate and run as an application. It will include the *workflow*, *the logic* in terms of relationships and rules regarding the execution of process tasks, *reference and configuration* of the *involved analytics tasks* (contained in the catalogue) and reference to *other application tasks and services* (which are not contained in any catalogue) (i.e. a task that generates a report from collected values, a task that finds the maximum value of a set of values, or a task that when triggered communicates using an API and turns off a machine (if we consider a process that controls the operation of machines).

Process Modelling Framework Capabilities



Name
model evaluation

Radio Button Options
Binary Classification

- Binary Classification
- Multiclass Classification
- Regression Model Evaluation
- Multilabel Classification
- Ranking Systems

Figure 39 - Process modeling framework

The Process Modeler component is the first link in the chain. The Business Analysts have the ability to design their processes in a straightforward graphical way by using a visual editor. The user can create a graph containing nodes from a list provided and assign options to each node. In detail these nodes and their respective options are:

- Data Load
  - Distributed Store
  - Object Store
- Clean Data
  - Yes
  - No
- Transform Data
  - Normalizer
  - Standard Scaler
  - Imputer
- Classification
  - Binomial Logistic Regression
  - Multinomial Logistic Regression
  - Random Forest Regression
- Regression
  - Linear Regression
  - Generalized Linear Regression
  - Random Forest Regression
- Clustering
  - K Means
  - LDA
  - GMM
- Frequent Pattern Mining
  - FP Growth
- Model Evaluation
  - Binary Classification

  - Multiclass Classification
  - Regression Model Evaluation
  - Multilabel Classification
  - Ranking Systems
- Data Filter
  - Yes
  - No
- Feedback Collector (External Service)
- Recommendations Calculation (External Service)
- Collaborative Filtering
  - ALS
- Update Model

Additionally, the business analyst can define multiple overall objectives of the graph which can be an aggregation of the following:

- Cost
- Response Time
- Accuracy
- Throughput

Finally, the Process Modeller Component provides the capability to import, export, save and edit the generated graphs.

6.13. Data Toolkit

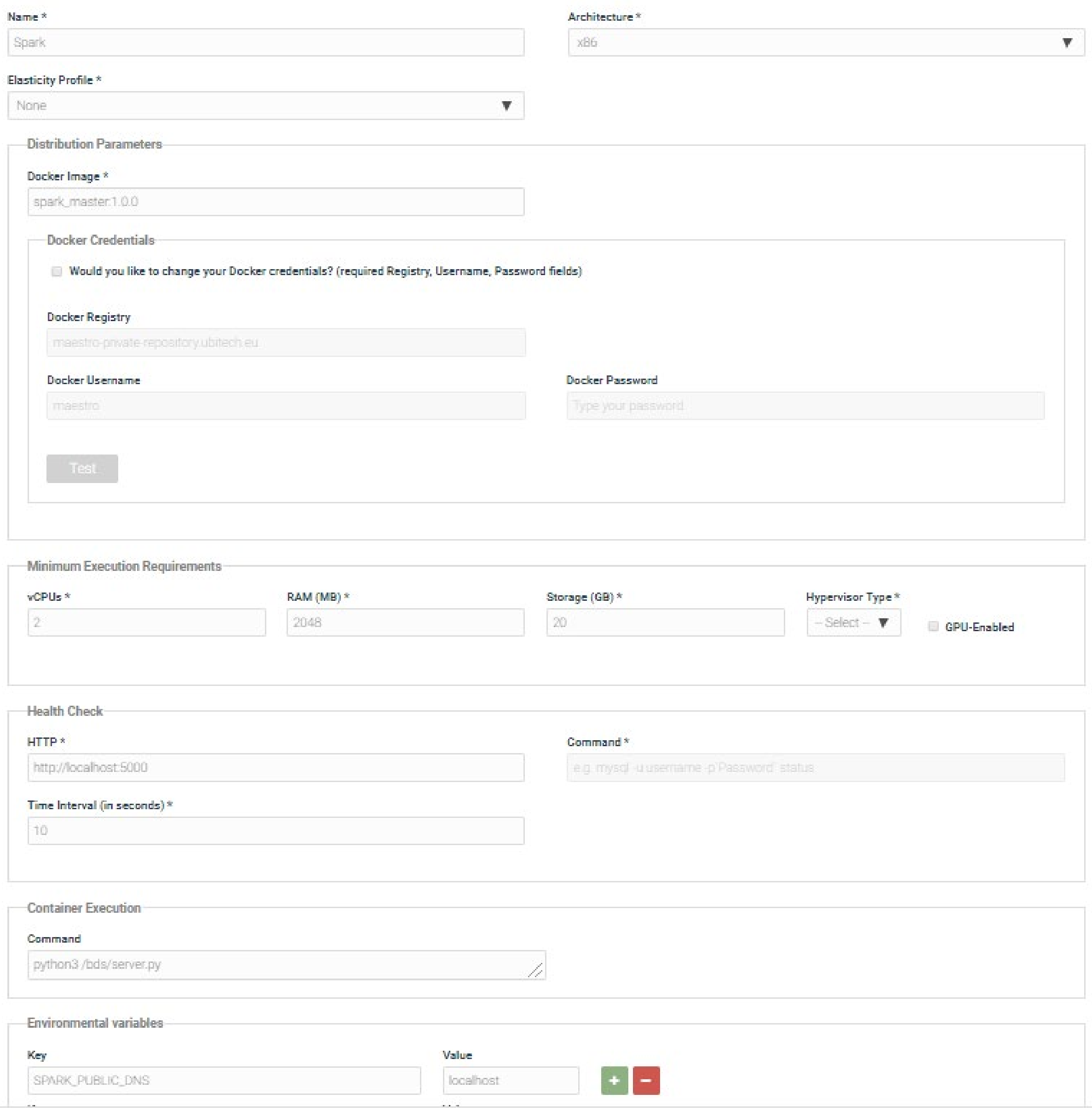
The main objective of the data toolkit is to design and support data analysis workflows. An analysis workflow consists of a set of data mining and analysis processes, interconnected among each other in terms of input/output data streams or batch objects. The objective is to support data analysts and/or data scientists to concretize the business process workflows created through the *process modelling framework*. This can be done by considering the outputs of the *process mapping* component or choosing among a set of available or under development analytic functions, while parametrizing them with respect to the service-level objectives defined in the corresponding process. A strict requirement regards the capacity to support various technologies/programming languages for development of analytic processes, given the existence and dominance of set of them (e.g. R, Python, Java, etc).

Towards this direction, the data toolkit is going to be modelled in a way that will enable data scientists to declare and parametrize the data mining/analytics algorithms, as well as the required runtime adaptations (CPUs, RAM, etc.), data curation operations associated with the high-level workflow steps of the business process model.

At its core, the data toolkit will incorporate an environment which supports the design of *graph-based workflows*, and the ability to annotate/enrich each workflow step with algorithm or process specific parameters and metadata, while respecting a predefined set of rules to which workflows must conform on in order to guarantee their validity.

There is a wide range of versatile flow-based programming tools that fit well the requirements for constituting the basis for the data toolkit, such as Node-Red [19]. Also a custom workflow-design environment tailored for the specific needs of the data toolkit could be developed, supported by libraries such as D3.js [20] and NoFlo [21], which will allow for fine-grained control over all the elements associated with the data analytics workflow.

Figure 38 depicts the core configuration user interface per functional component and/or service in the BigDataStack context. Therefore, the Data Scientist can parameterise her components providing details on the elasticity profile, the Docker images, the minimum execution requirements, the required environmental variables, the exposed interfaces and required interfaces (if any), existing attributes (i.e. lambda functions, etc.) and the corresponding health checks regarding the services.


Name *: Spark
Architecture *: x86
Elasticity Profile *: None

Distribution Parameters
Docker Image *: spark_master:1.0.0

Docker Credentials
☐ Would you like to change your Docker credentials? (required Registry, Username, Password fields)
Docker Registry: maestro-private-repository.ubitech.eu
Docker Username: maestro
Docker Password: Type your password

Minimum Execution Requirements
vCPUs *: 2
RAM (MB) *: 2048
Storage (GB) *: 20
Hypervisor Type *: -- Select --
☐ GPU-Enabled

Health Check
HTTP *: http://localhost:5000
Command *: e.g. mysql -u username -p'Password' status
Time Interval (in seconds) *: 10

Container Execution
Command: python3 /bds/server.py

Environmental variables
Key: SPARK_PUBLIC_DNS
Value: localhost

Figure 40 - Application configuration per graph components

6.14. Adaptable Visualizations

The adaptable visualization layer has multiple purposes: (i) to support the visualization of data analytics for the applications deployed in BigDataStack, (ii) to provide a visual application performance monitoring dashboard of the data operations and the applications during benchmarking, dimensioning workbench and during operation and (iii) to integrate and facilitate various components such as the Process Modeller, Data Toolkit, Benchmarking, Dimensioning Workbench, Triple Monitoring Engine, Data Quality Assesment and Predictive Maintenance. Importantly, the dashboard will be able to monitor the application deployed over the infrastructure. For the visualization of data analytics, it will provide a reporting tool that will enable users to build visual analytical reports. The reporting will be produced from analytical queries and will include summary tables as well as graphical charts.

The main issues that need to be handled by the adaptable visualizations framework are:

- User authentication
- KPIs definition and integration: Definition of a KPI must be possible through the framework if not supported elsewhere in the architecture
- Triggering of events and production of visual notifications. Event handling and triggering of alarms or responses to the event must be supported.
- Different views of the UI platform depending on the user role. 4 roles are defined:
    - Administrator (full UI View)
    - Business Analyst (Process Modeller View)
    - Data Analyst (Data Toolkit View)
    - Application Owner/Engineer (BenchMarking, Dimensioning Workbench, Analytics View)
- Integration of Process Modeller, Data Toolkit and Benchmarking Components.
- Deployment of playbooks towards the Dimensioning Workbench Component, visualization of the configurations recommended and deployment of the selected application.
- Management of the Deployed Applications and handling of the Deployment Adaptation Decisions. Decisions are managed via the Realization API.
- Ability to redeploy applications when QoS Warnings are received and Deployment Alterations are considered.
- Visualisation of the Predictive maintenance for both cases of full datasets and exclusively quality assessed data.
- Visualisation of the Data Quality Assessments in summary customizable tables.
- Integration of 3rd party generated application monitoring graphs.
- Visualization of real-time analytics data through graphs and charts responsively.

The foreseen I/O and the structure of the visualization framework in terms of definition of the subcomponents and their interactions are listed in the following bullets.

Necessary inputs:

- Analytic outcomes as input from the seamless data analytics framework

- Real-time monitoring data as input from the triple monitoring engine. Data will refer Application components monitoring, to Data & Services monitoring and to Cluster resources monitoring
- CEP outcomes as input from the real-time CEP of the Storage engine
- Input from exposed data sources to facilitate KPIs definitions and event triggering rules.

Necessary Outputs:

- Output of visual reports

The main structure of the Adaptable visualizations framework is depicted in Figure 39. The component list is as follows:

- *Visualization toolkit:* this component connects all the components (Process Modeller, Data Toolkit, Benchmarking, Dimensioning Workbench) and makes available a tool set of offered capabilities (e.g. types of graphs, reports, tables)
- *Rights management module (Admin Panel):* this component handles the permissions to modify views to components, editors and event triggers
- *Data connector:* this component makes possible to retrieve data schemas and data from the exposed data sources to assist in defining KPIs and set event triggers. Furthermore, it could provide in the same way access to historical data or reports
- *Events processing:* this component makes it possible to define event triggers that will produce visual notifications, warnings or generation of specific reports

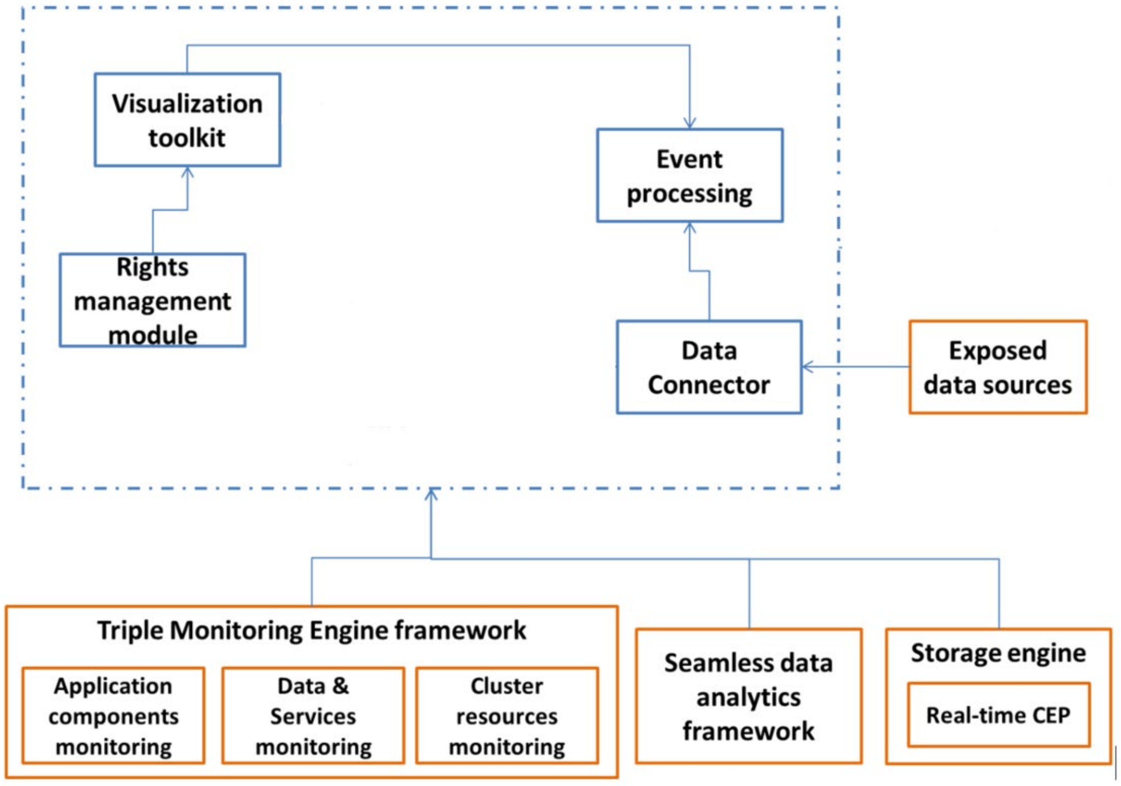

Visualization toolkit
Event processing
Rights management module
Data Connector
Exposed data sources
Triple Monitoring Engine framework
Application components monitoring
Data & Services monitoring
Cluster resources monitoring
Seamless data analytics framework
Storage engine
Real-time CEP

Figure 41 - Visualization framework building blocks

6.15. Adaptable Distributed Storage

In modern cloud applications, it is expected that they can scale out dynamically in order to serve diverse workloads. During the last years, various patterns have been proposed that can identify which part of the solution is becoming the bottleneck in terms of performance or is close to saturating the resources of the machine that will cause the whole solution to collapse. Modern applications consist of a variety of software components and the current trend is the use of microservices: small pieces of code that execute one task independently and they are usually stateless. However, scaling a stateless component is an easy task: one has to deploy an additional instance and balance the incoming workload to all available instances. Scaling a stateful component is far more complicated, as the state has to be preserved. Scaling a data base, which actually stores data items into the storage, is even more difficult.

During the last decade, novel data store solutions, usually known as NoSQL started to replace traditional relational database in cloud environments and multi-tenant applications, due to their ability to scale out easily during the runtime. A new data node is being added, and the data is being balanced by moving data regions from one node to the other in order to balance the data load. During this process however, the data consistency is lost. NoSQL solutions sacrifice the consistency for the need of the scalability on the runtime. In other words, they switch for the A (Availability) and P (Partition tolerance) of the famous CAP theorem and they never promised to provide transactional semantics. On the other hand, traditional relational databases ensure the ACID properties for the sake of online scalability. They sacrifice the P (partition tolerance) in the CAP theorem in order to ensure C (Consistency). Scaling out needs to be offline (by sacrificing the A-availability- of the CAP theorem) in order to ensure data consistency, or in solutions that do support online scalability, the performance is reduced to so low levels that the behaviour of the overall system is problematic while the scaling action takes place.

In BigDataStack, we developed a novel storage solution that allows for dynamic scalability with online data load balancing, where data consistency is ensured and the overall performance is not experiencing significant variations. The distributed storage provides its own monitoring mechanism that can identify both if the latency of the queries is exceeding some thresholds while the workload is being increased due to potential saturation of the available resources, or the disk storage will soon run out of space and the overall application will be blocked. When this happens, it can request from the infrastructure additional resources, and when the latter is granted, it starts the dynamic data load balancing. Data tables are being fragmented to regions, and it is an internal monitoring mechanism that characterizes them according to the amount of resources they require. By doing this, a knapsack-like non polynomial algorithm decides about a solution and redistributes the data in that sense that the overall workload will require an equal amount of resources in each machine. It is important to highlight here that the mechanism that ensures transactions in the data store is lock-free, and isolation is achieved by implementing the snapshot isolation paradigm. Due to this, there is no need to hold the locks of a transaction, that will cost the block of the data movement while the transaction is still open, rather it can just leave the data items in place, while creating replicas in the new machine, and remove them, once all transactions are closed. In other words, the adaptable distributed storage can achieve where current solutions fail: dynamically move data in order to scale out, without the need to sacrifice data consistency by not having transactions, neither sacrifice availability when aborting transactions in order to move a data region.

In the scope of the project, the importance of this mechanism can be validated by the DANAOS scenario. In the latter, IoT sensor data coming from the various vessels of the organization are being ingested to the data storage via the CEP deployment. As times goes, the storage space becomes saturated and additional node must be deployed. This is relevant in cases there the deployment of the database is taking place on physical machines that comes with their own disks, and the placement of a new disk will require the availability of a new machine. Moreover, we'll increase the number of the vessels that are ingesting data in order to increase the incoming workload. This is a valid scenario, as it is common for organizations to buy new vessels as they grow and need to serve a bigger market. The constant increase of the workload will stress the data store, and will saturate the available resources. Its internal monitoring mechanism will identify this and will request from the infrastructure additional resources and then dynamically distribute its data load, in order to self-adapt. Finally, we will reduce the number of vessels, so that the workload can be decreased as well. Again, the monitoring mechanism will identify such constant change, and will decide to scale-in, only if the overall data can fit to lesser machines, in order to prevent data losses.

7. Key interactions

7.1. User Interaction Layer

User Interaction within the BigDataStack ecosystem plays an important role in the entire lifecycle of a big data application / operation. There exist the following user roles: Business Analysts, Data Analysts and/or Data Scientists.

First, the *Business Analyst* uses the *Process Modelling Framework* to define the *business processes and associated objectives* and accordingly design a BPMN-like workflow for the actualization of the business-oriented objectives and the required analytic tasks to accomplish. The analyst is able to design, model and characterize each step in the workflow according to a list of predefined rules encapsulated by a *rules engine* component of the modelling framework. The output of this process is a graph-like output (i.e. in JSON format) with a high-level description of the workflow from the business analyst's perspective along with the related end-to-end business objectives. The sequence diagram of Process Modelling is depicted in Figure 40.

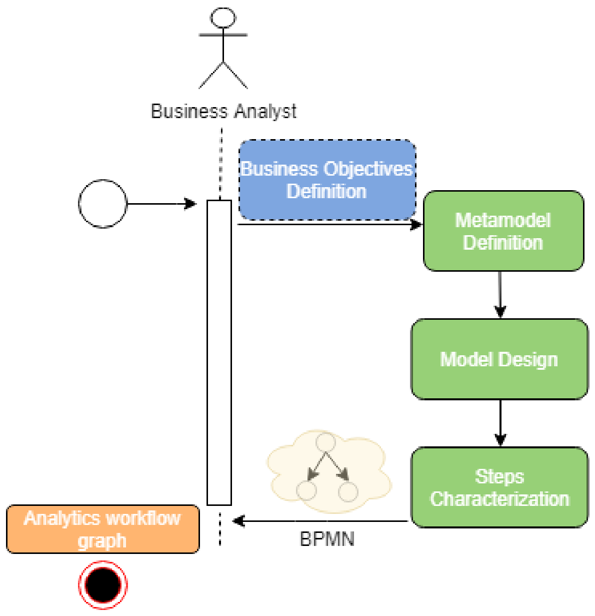


Figure 42 - Information flows in Process Modelling

Figure 41 depicts a high-level application graph designed by the Business Analyst by indicatively incorporating within the data workflow four (4) processing steps with editable fields by means of drop-down lists, namely data load, data clean, perform analytic task and evaluate result.

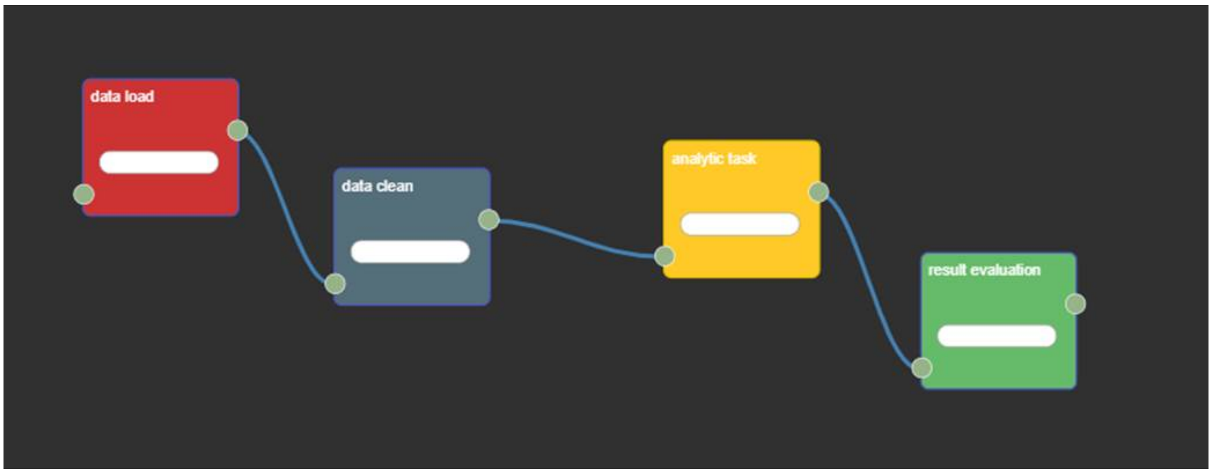


Figure 43 - Example of a high level BRMN-like application graph

Next, the *Process Mapping* component provides an association of the process steps modeled by the Business Analyst with specific analytic tasks, following a set of criteria related to each process task, while considering any constraints defined in the business objectives. These criteria may contain the characterization of required data, time, resources and/or performance parameters need to be concretized to perform the analytic tasks. The output of this step is a workflow graph (i.e. in JSON format) enriched with the mappings of the business process steps grounded to algorithms, runtime and performance parameters.

Then, the *Data Analyst* and/or the *Data Scientist* uses the *Data Toolkit*, to perform a series of tasks related to the concretization of the analytics process workflow graph produced in the process mapping step, as depicted in Figure 42, such as:

- Concretizing the business objectives in terms of selecting lower bounds for hardware, runtime adaptations, performance for which the selected algorithms perform sufficiently well.
- Defining the data source bindings from where the datasets related to the task will be ingested.
- Defining any data curation tasks (i.e. data cleaning, feature extraction, data enrichment, data sampling, data aggregation, Extract-Transform-Load (ETL) operations) necessary for the algorithms and the related steps.
- Configuring and parametrizing the data analytics tasks returned (i.e. selected) by the Processes Mapping component, and additionally providing the functionality to design and tune new algorithms and analysis tasks, which are then stored to the Catalogue of Predictive and Process Analytics and can be re-used in the future.
- Selecting and defining performance metrics for the algorithms, along with the acceptable ranges with respect to the business objectives and service-level objectives, used to evaluate the algorithm/model and resources configurations.

At the end, a *Playbook* (i.e. in YAML format) representing the grounded workflow for each business process will be generated, in the format that further feeds the *Dimensioning workbench* in order to provide the corresponding resource estimates for each node of the graph.

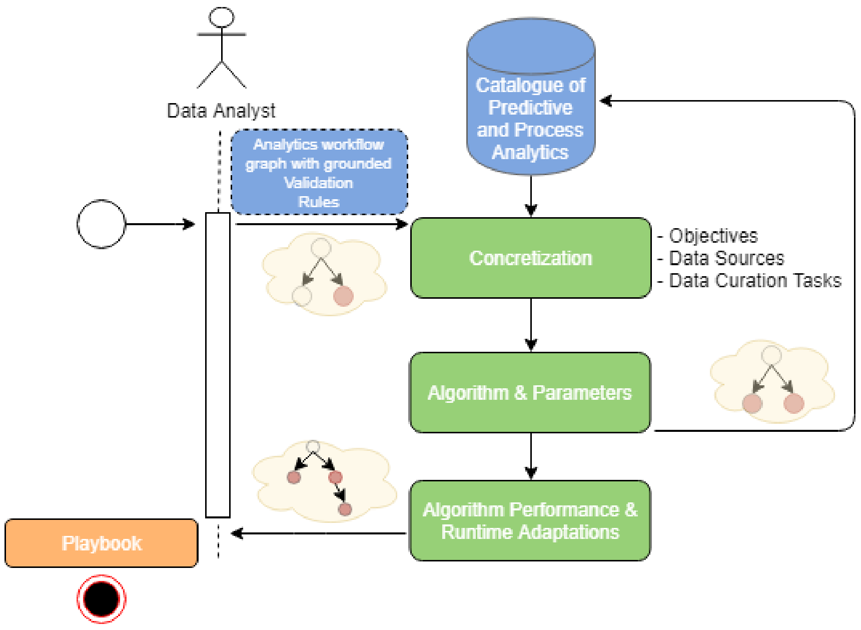

Data Analyst
Catalogue of Predictive and Process Analytics
Analytics workflow graph with grounded Validation Rules
Concretization
- Objectives
- Data Sources
- Data Curation Tasks
Algorithm & Parameters
Algorithm Performance & Runtime Adaptations
Playbook

Figure 44 - Information flows in Process Mapping

The following figure (Figure 43) presents the sequence diagram, which depicts the main information flows for the User Interaction Layer of the BigDataStack architecture.

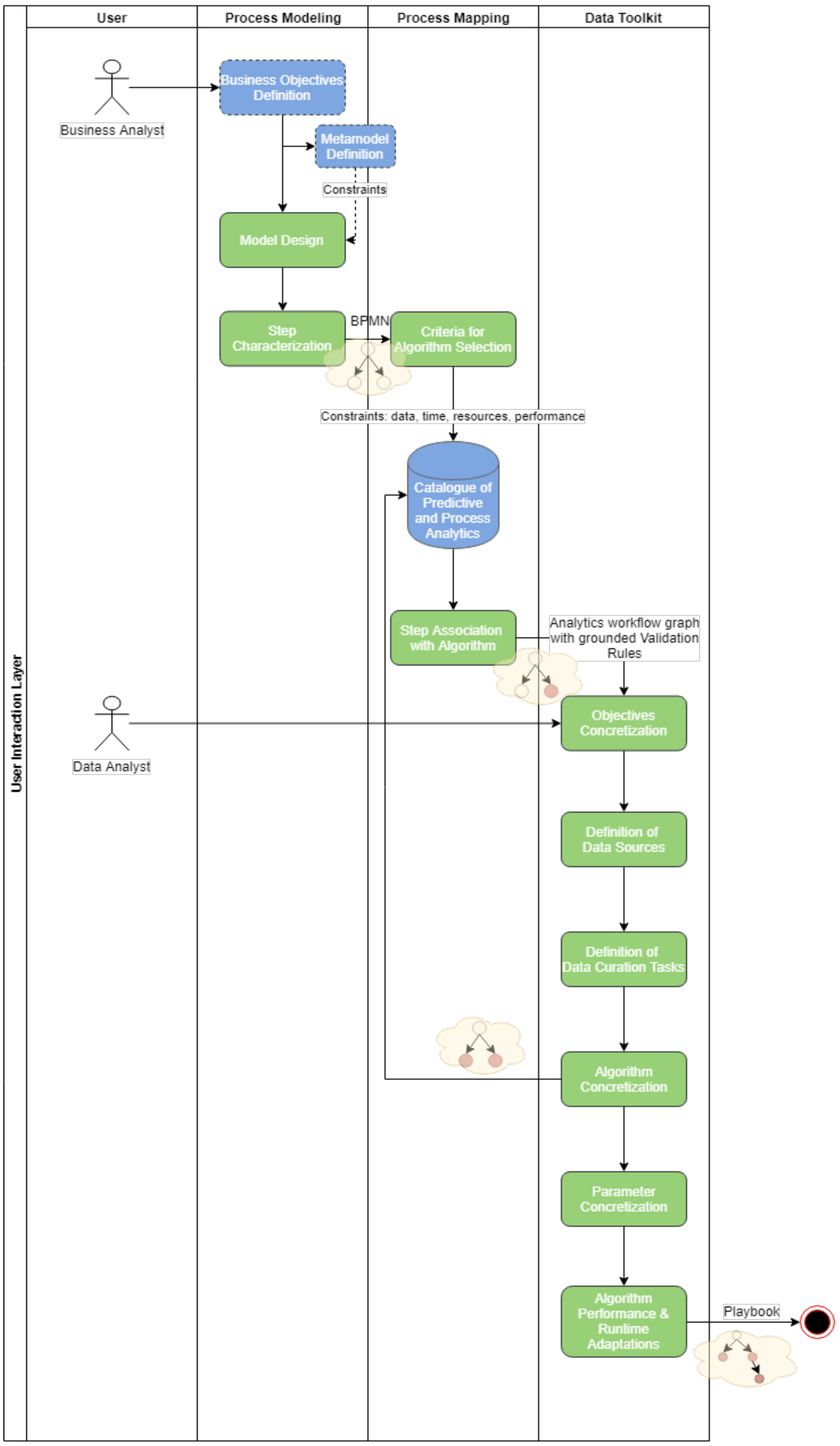

User Interaction Layer
User
Process Modeling
Process Mapping
Data Toolkit
Business Analyst
Business Objectives Definition
Metamodel Definition
Constraints
Model Design
Step Characterization
BPMN
Criteria for Algorithm Selection
Constraints: data, time, resources, performance
Catalogue of Predictive and Process Analytics
Step Association with Algorithm
Analytics workflow graph with grounded Validation Rules
Data Analyst
Objectives Concretization
Definition of Data Sources
Definition of Data Curation Tasks
Algorithm Concretization
Parameter Concretization
Algorithm Performance & Runtime Adaptations
Playbook

Figure 45 - User Interaction Layer Sequence Diagram

Example Use Case: Predictive Maintenance
Regarding the entry phase described above, an example is presented in the following sections to link the functionalities of different components to an actual use case.

Business Analyst’s View
The following figure (Figure 37) shows the perspective of a business analyst in terms of Process Modelling, which treats Real-time ship monitoring (RTSM) as a whole. This is expected to be the view (not in terms of user interface but in terms of processes and abstraction of information) of the Process Modelling Framework. Moreover, through the framework, the business analyst will be able to specify constraints (as noted with red fonts in the figure).
Overall, separate processes, actions and data required to perform RTSM. As shown, the first step is the vessel and weather data acquisition. That includes a dataset with granularity down to a minute and 2 years timespan for vessel data, along with weather data as provided by the National Oceanic and Atmospheric Administration (NOAA), i.e., granularity of weather reports up to 3 hours for every 30 minutes of a degree. Past this, given that there are plenty of attributes within both datasets, there has to be some attribute selection rule. For example, only 190 approximately are required from both datasets, because these are the most reliable and important. Following this, the data are imported into two different components. The first is the monitoring tool, which simulates and enhances the on-board tools of the Alarm Monitoring System (AMS). Given that, if an anomaly occurs a rule-based alert has to be produced close-to or in real time. The second component is the Predictive Maintenance Alert. This informs the end user that the current data under examination pinpoint a malfunction that has occurred in the past. Again, this should work close-to or even better in real-time. Consecutively, given that identifying an upcoming malfunction is achieved, spare part ordering follows. The ordered spare part has to be delivered at least 1 day before the estimated time of arrival, while ordering of spare parts should be performed only by suppliers that are to be trusted. Quality of service should not be neglected while cost criteria are also taken into account. Finally, given the delivery port of the spare part, re-routing of the vessel takes place, where the estimated time of arrival to the closest port is less than 12 hours.

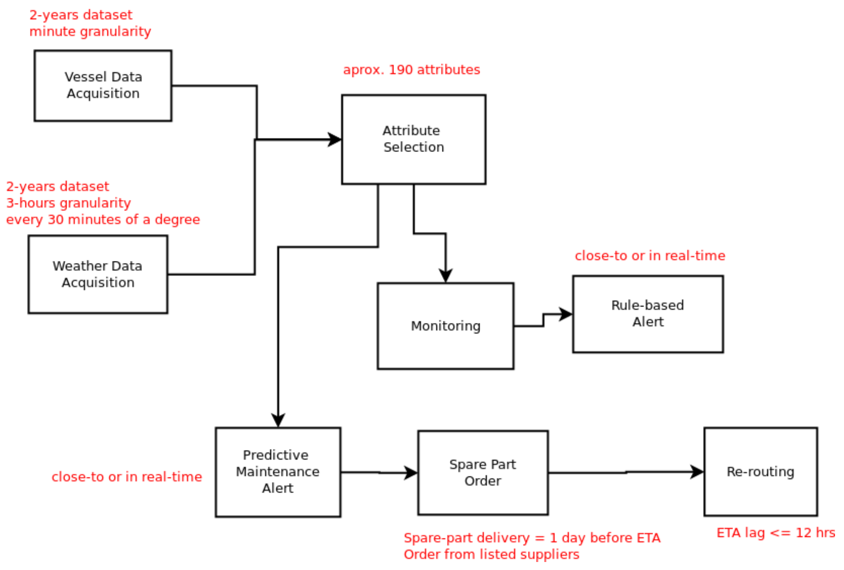


Figure 46 - Business analyst view

Data Analyst’s View

Following the outcome of the process modelling (previous view), Figure 45 depicts the view for the data analyst, that is the view in the Data Toolkit. As shown in the figure, the view is different with components that have been mapped automatically from the Process Mapping mechanism of BigDataStack (e.g. “CEP monitoring” to enable the “Rule-based alert” process).

Overall the data analyst’s view is a set of system components, in-house or out-sourced processes and/or systems, actions and data required to perform RTSM. The Vessel data acquisition process is fed from an in-house database (DB) that contains vessel data (power consumption related and main engine data) along with Telegrams and past maintenance events. Given a total of 10 vessels, this requires up to 40 GB of hard disk storage. Weather data are imported from NOAA via FTP, by a weather service that loads hindcasts in GRIB format for the whole earth with a 3-hour granularity for every 30 minutes of a degree. GRIB files are parsed and stored in a database that requires up to 2.1 TB storage. Given that any trajectory of a vessel can be joined with weather data via a REST API that the weather service provides. Past this, given that there are plenty of attributes within both datasets, i.e., weather and vessel data, there has to be some attribute selection rule. For example, only 190 approximately are required from both datasets, because these are the most reliable and important such as the consumed power (kW), the rotations per minute of the main shaft (RPM) etc. In order to avoid feeding the algorithmic components of this architecture with false or null data values, a filtering component is in charge of removing null values, preferably with average values, smoothing-out the effect of data-loss. Next, given a set of defined rules, such as “if the power consumption exceeds a limit and the fuel-oil inlet pressure drops below a threshold” the CEP component is in charge to produce an alert, close-to or in-real time. In parallel, a pattern recognition algorithm tries to identify patterns on the data that looks like a past case where a malfunction occurred in the main engine. If this happens, an alert is produced, and given the upcoming malfunction that has been identified a spare-part suggestion is made. Given the Danaos-ONE platform, where orders of spare parts are placed via a REST API, the order of the suggested spare-part is placed and is accessible from the suppliers that are preferred. So, once the order is made to a supplier, a suggested place and time are provided, and given this re-routing of the vessel takes place via an external REST service provided at a specific IP address and port.

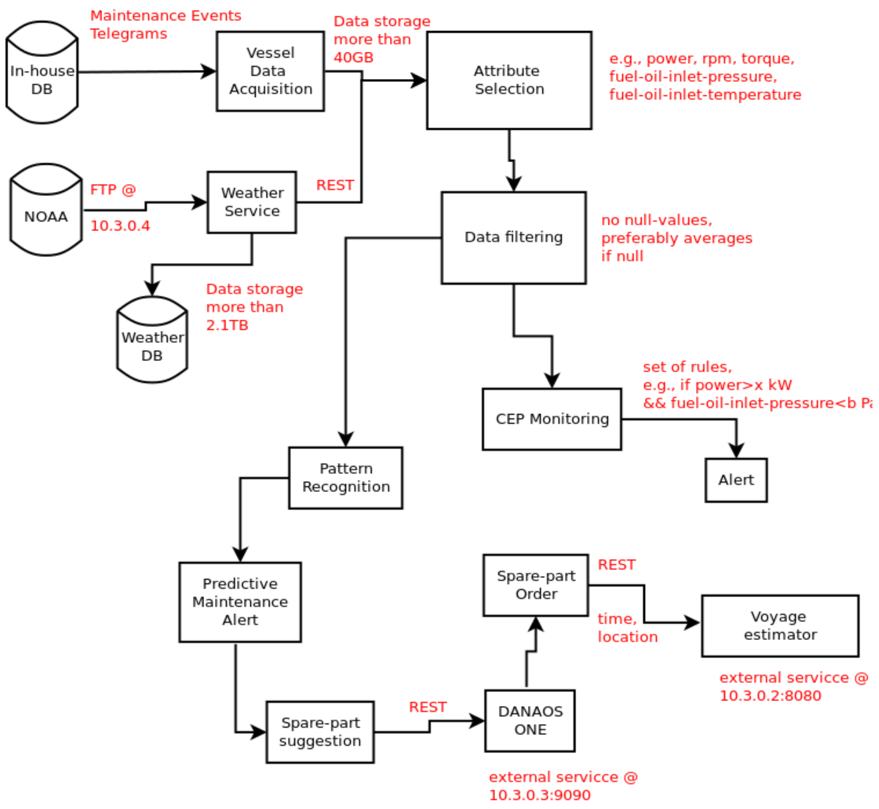

In-house DB
Maintenance Events Telegrams
Vessel Data Acquisition
Data storage more than 40GB
Attribute Selection
e.g., power, rpm, torque, fuel-oil-inlet-pressure, fuel-oil-inlet-temperature
NOAA
FTP @ 10.3.0.4
Weather Service
REST
Data filtering
no null-values, preferably averages if null
Weather DB
Data storage more than 2.1TB
set of rules, e.g., if power>x kW && fuel-oil-inlet-pressure<b Pa
CEP Monitoring
Alert
Pattern Recognition
Predictive Maintenance Alert
Spare-part Order
REST
time, location
Voyage estimator
external servicce @ 10.3.0.2:8080
Spare-part suggestion
REST
DANAOS ONE
external servicce @ 10.3.0.3:9090

Figure 47 - Data analyst's view

7.2. Realization & Deployment

Within the Realization module, there is a series of operationalizable tasks related to transitioning an application from a BigDataStack Playbook defined in the Data Toolkit to a running series of containers on the cloud/cluster infrastructure. There are four main tasks of interest when realizing an application's deployment:

- **Namespace/Project Initialization**: This involves the initialization of the Realization API (ADS-API), Realization Monitor (ADS-Monitor), Realization State DB (ADS-StateDB), Realization GUI (ADS-GUI) and Realization Deployment (ADS-Deploy) services at minimum for a specified Namespace/Project where user application(s) will later be deployed. Although this will also likely include deployment of other useful services such as the Realization Ranking (ADS-Ranking), Realization Event Streams (ADS-EventStreams) and/or Realization Cost Estimator (ADS-CostEstimator) services. This is accomplished via a command-line tool that bootstraps these services.
- **Registration of a new Application**: This involves the registration of an application and its contained object definitions with ADS-API. Applications will typically be registered by the Data Toolkit, but can be programmatically loaded from other services or from a file.
- **First-Time Ranking of Candidate Deployment Patterns**: This task aims to select the most suitable candidate deployment pattern from a set that has previously been generated when the user first requests deployment of their application. This task is operationalized in scenarios where a object template does not have a complete resource definition and relies on an available ADS-Ranking instance.
- **Application Deployment**: This task involves the practical deployment of the user

application on the cloud through interaction with Openshift via an instance of ADS-Deploy.

Below we discuss each of these tasks in more detail and provide an interaction sequence diagram for each. For legibility of the interaction diagrams, we use short names for each component. A mapping between components and their short names are shown in the following table:

Full name	Sub-component	Short name (interaction diagrams)
Application and Data Services Dimensioning	Benchmarking/Core	Dimensioning
Application and Data Services Dimensioning	Pattern Generation	Pattern Generation
Realization Ranking	Pod Feature Builder	ADS-R Feature Builder
Realization Ranking	Pod Scoring	ADS-R Scoring
Realization Ranking	Model	ADS-R Model
Realization Ranking	Pattern Selector	ADS-R Pattern Selector
Realization Deploy	N/A	ADS-Deploy
Realization Bootstrap Tool	N/A	CLI
Dynamic Orchestrator	N/A	Orchestrator
Realization API	N/A	ADS-API
Realization Monitor	N/A	ADS-Monitor
Realization State DB	N/A	State DB
Event Exchange	N/A	Exchange
Data Toolkit	N/A	Data Toolkit

Table 7 - Short-name component mapping table

Namespace/Project Initialization

The first task is concerned with the preparation of a namespace for deployment of BigDataStack Applications. In effect, this involves the deployment of the realization engine components into the target namespace/project, enabling monitoring and management of that namespace by the engine. The first component launched is ADS-StateDB as this is a core dependency for the Realization Engine (to store application data and state). Following this, to enable the tracking of application state within the namespace project ADS-Monitor will be deployed. Next, to enable user management, the end-points ADS-API and ADS-GUI are deployed in addition to ADS-Deploy. Finally, optional services may be added based on whether their functionality is needed (at the time of writing, these are ADS-Ranking, ADS-EventStreams and ADS-CostEstimator). This is triggered by the Application Engineer, or potentially some other member of the team responsible for managing the cluster, via the Openshift OC tool and a provided command line tool. In particular, they first need to use the Openshift OC tool to bring ADS-StateDB to a running state as follows:

- oc apply -f ads-statedb.yaml

Once these have reached a running state, the user can then use a provided command line tool for BigDataStack to bootstrap the remaining components into the namespace project as follows:

- java -jar BigDataStack-Realization.jar register namespace <namespaceID>
- java -jar BigDataStack-Realization.jar bootstrap <owner> <namespaceID>

Here namespace registration simply enables that namespace to be a valid target for subsequent deployment. Meanwhile, the bootstrap process incrementally launches the remaining Realization Engine components. Internally, each Realization Engine component is defined within its own BigDataStack Playbook, the bootstrap process then is simply registering each playbook and triggering it's in built deployment Operation Sequence, which is executed in the background.

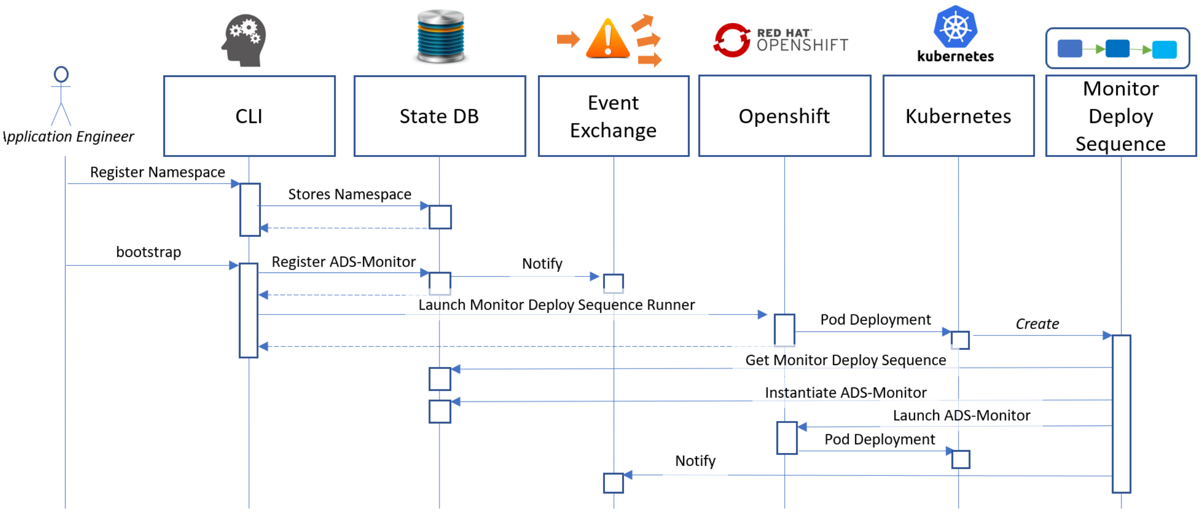


Figure 48 - Namespace Initialization Sequence Diagram

Figure 46 illustrates the initialization of a namespace where only ADS-Monitor is deployed (the underlying process would be repeated for each component to be launched). In this case, when bootstrap is called, the CLI will load predefined default templates for the ADS-Monitor and register them in the State DB. This includes both the ADS-Monitor Deployment Config and an Operation Sequence for configuring and launching that Deployment Config (denoted Monitor Deploy Sequence). Once registered, this will generate an event, reporting the creation of these objects. Next, the CLI will request that Openshift create a new pod to execute the monitor deploy sequence, which in-turn calls Kubernetes to set up the pod and containers. From the user perspective, the request ends at this point. However, once the pod executing the monitor deploy sequence starts, it will retrieve the definition of the monitor deploy sequence from the State DB, and will start executing the operations. This involves instantiating a new copy of GDT-Monitor and executing the Apply operation to launch it on the cluster/cloud. Apply calls Openshift, which in-turn calls Kubernetes. The last action of the monitor deploy sequence is to notify the Event Exchange of the success of the deployment.

Registration of a new Application

Once a namespace has been initialized, user applications can then be registered targeting that namespace. This is performed by calling the ADS-API, sending the BigDataStack playbook. Upon receiving the playbook, the ADS-API will store the application and associated object templates found within the playbook within the State DB, and then notify the Event Exchange of the creation of the new application. This is illustrated as a sequence diagram in Figure 47.

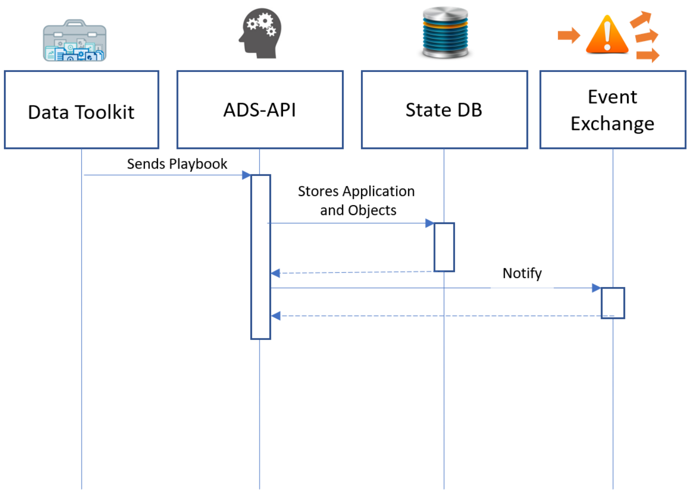


Figure 49 - Application Registration Sequence Diagram

First-Time Ranking of Candidate Deployment Patterns

For some applications, the user will not have provided resource specifications for some or all of their object templates (representing the application components that can be deployed). Hence, for these applications, before deployment, we need to obtain this information. This can be performed using ADS-Ranking to produce a recommended resource definition. In this case, the ADS-API requests a resource definition for a specified object instance, by sending that object instance to ADS-Ranking. ADS-Ranking then requests a set of candidate deployment patterns (CDPs) for that object instance from ADS Pattern Generation. Once retrieved, ADS-Ranking sends these CDPs to ADS Dimensioning, such that performance estimations can be attached, which will subsequently be used to estimate pattern suitability. Within ADS-Ranking, the Feature Builder analyses and aggregates the different quality of service estimations into a form that can be used for ranking (referred to as features). Once this transformation is complete, the CDPs and aggregated features are sent to the Scoring sub-component, which uses a ranking model to score and hence rank each CDP based on its suitability with respect to the user's requirements. Once the CDPs have been ranked, that ranking is sent to the Pattern Selection sub-component, which selects the most suitable one. This selected CDP is then returned to the ADS-API such that the object instance can be updated with the new resource specification (i.e. written to the State DB).

Figure 48 illustrates the first time ranking of candidate deployment patterns as a sequence diagram. Note that we omit the event reporting that occurs at each stage to avoid further complicating the diagram.

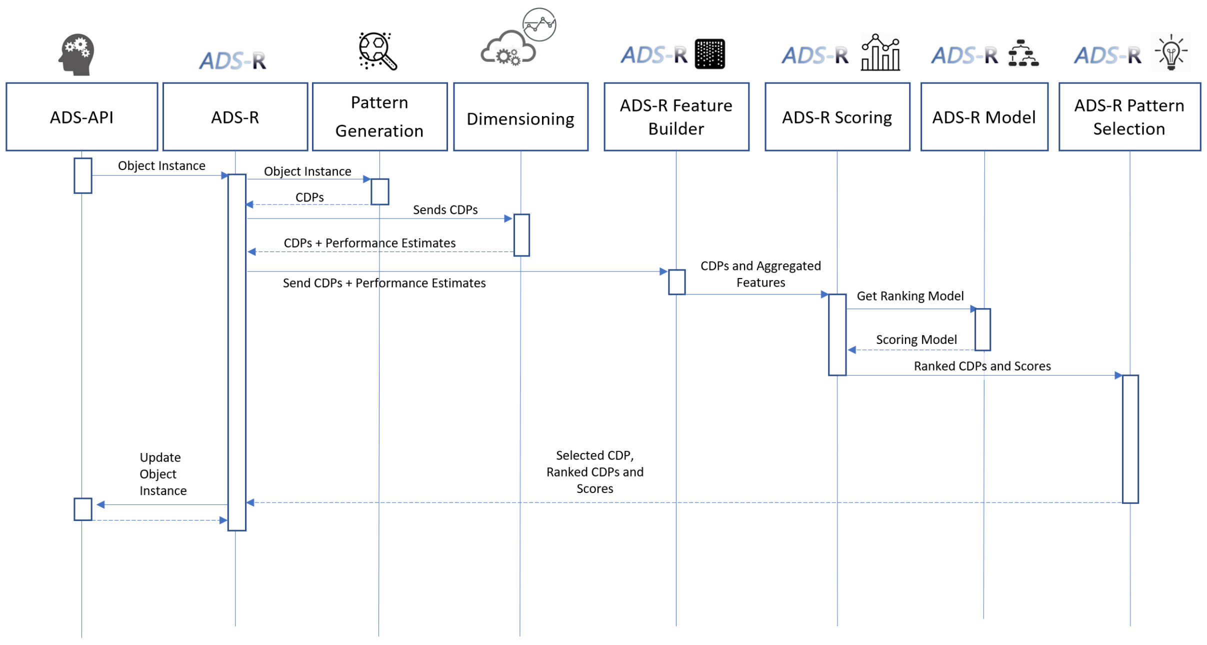


Figure 50 - Interaction Diagram for First-Time Ranking

Application Deployment

The ADS-Deploy component interacts with Openshift through Kubernetes' OpenAPI v1 [1]. Once an object instance has been selected for deployment, it is sent to ADS-Deploy, which generates a series of independent Openshift-managed objects. These objects are grouped into a single logical application, in order to maintain the internal coherence and keep relations between the objects. Supported objects include:

- Pods: A Pod represents an atomic object in Openshift, and includes one or more containers. Each pod can be replicated according to the configuration values or due to Quality-of-Service requirements. Pods have been represented as DeploymentConfig objects in BigDataStack. [11]
- Services: A Service provides access to a pod from the outside, and is in charge of vital actions such as load balancing. Services can also be replicated, so that they are scaled in/out independently or together with the pods. ADS-Deploy, creates a configuration file for each service and sends it to Openshift.
- Routes: A route gives a service a hostname that is reachable from outside the cluster. Routes are not replicable, but they are closely related with the services. In BigDataStack, a configuration file is created for each route, and information on the service and application to which they relate is contained in there.

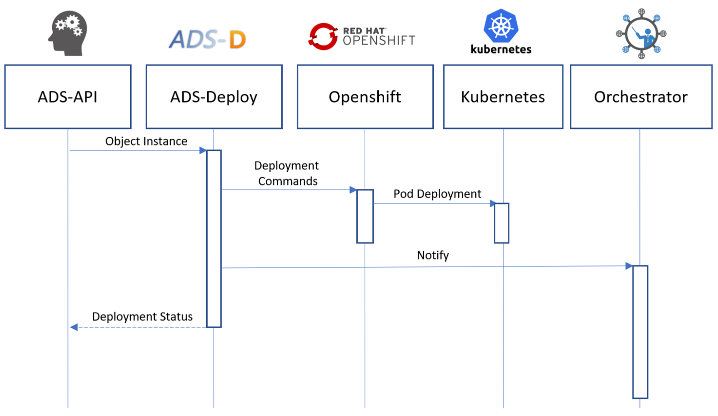


Figure 51 - Interaction Diagram for Application Deployment

7.3. Data as a Service & Storage

The Data as a Service and the Storage offerings of BigDataStack cover different cases. As base data stores, the LeanXcale data store and the Cloud Object Storage (COS) are considered as depicted in the following figure (Figure 38).

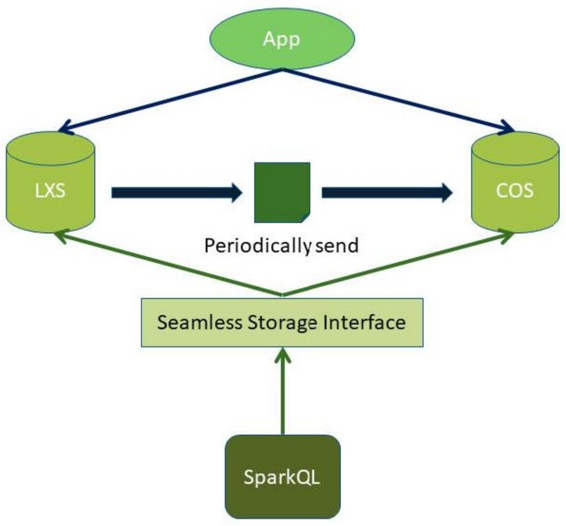


Figure 52 - Architecture of data stores

Note that the IBM COS is only taken as an example of an Object Storage, any Object Storage implementing the S3 protocol could fit within the seamless architecture. From the above, it can be considered that the two components that are able to persistently store data are: LeanXcale's relational data store, and IBM's Cloud Object Store. The former is a fully transactional database which will serve operational workloads, while in the meantime can execute analytical operations on the runtime, providing a JDBC implementation, thus being able to execute SQL compliant queries. The latter is a cloud Object Store capable of storing numerous terabytes of data but lacking transactional nor SQL capabilities. Fresh data will be first inserted in the LeanXcale database (LXS) in order to benefit from its transactional capabilities. Once data is no longer considered as fresh, (e.g. several months have passed), data will be moved to the Cloud Object Store (COS) while analytical processing over COS is provided by Apache Spark.

On top of the datastores the Seamless Storage Interface (SSI) provides an entry point for seamlessly executing queries over a logical dataset that can be distributed over different datastores which themselves may provide different interfaces. The SSI provides a common JDBC interface and is capable of executing standard SQL statements. The SQL queries will be pushed down to both stores, and retrieved intermediate results will be merged and returned. Offering a JDBC interface, SSI can be exploited by data scientists through the usage of well-known analytical tools such as SparkSQL. As a result, the end-user can write SparkSQL queries and have the SSI locate the various parts of the dataset and retrieve the results. Direct execution of the queries to a specific data store is also permitted. As a result, we have the following five scenarios:

- Direct access to the LeanXcale database
- Direct access the Cloud Object Store (COS)
- Request data using a simple SparkSQL query
- Insert data to BigDataStack
- Insert streaming data to BigDataStack

Direct access the LeanXcale (LXS) database

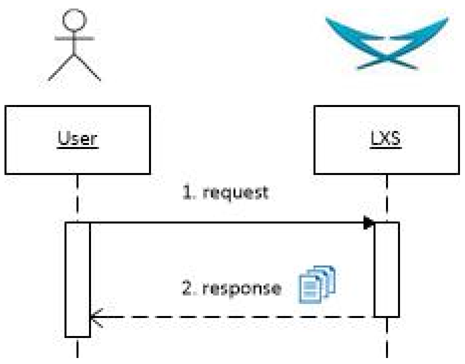


Figure 53 - Direct access the LXS

User executes an SQL query, requesting data directly from LXS using a standard JDBC interface, and the latter returns the resultSet as the response.

Direct access the Cloud Object Store (COS)

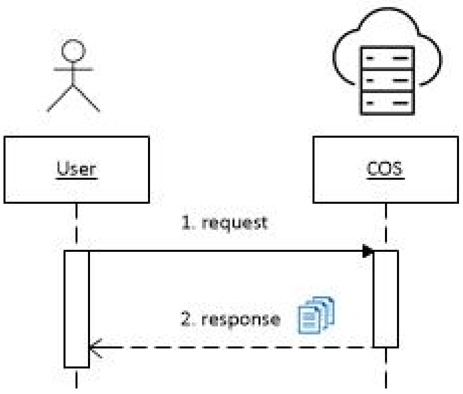


Figure 54 - Direct access the COS

User executes a query from Apache Spark, requesting data directly from COS, using the *stocator* open source connector which permits the connection of Object stores to Spark, and the COS returns back the result as the response.

Request data using a simple SparkSQL query

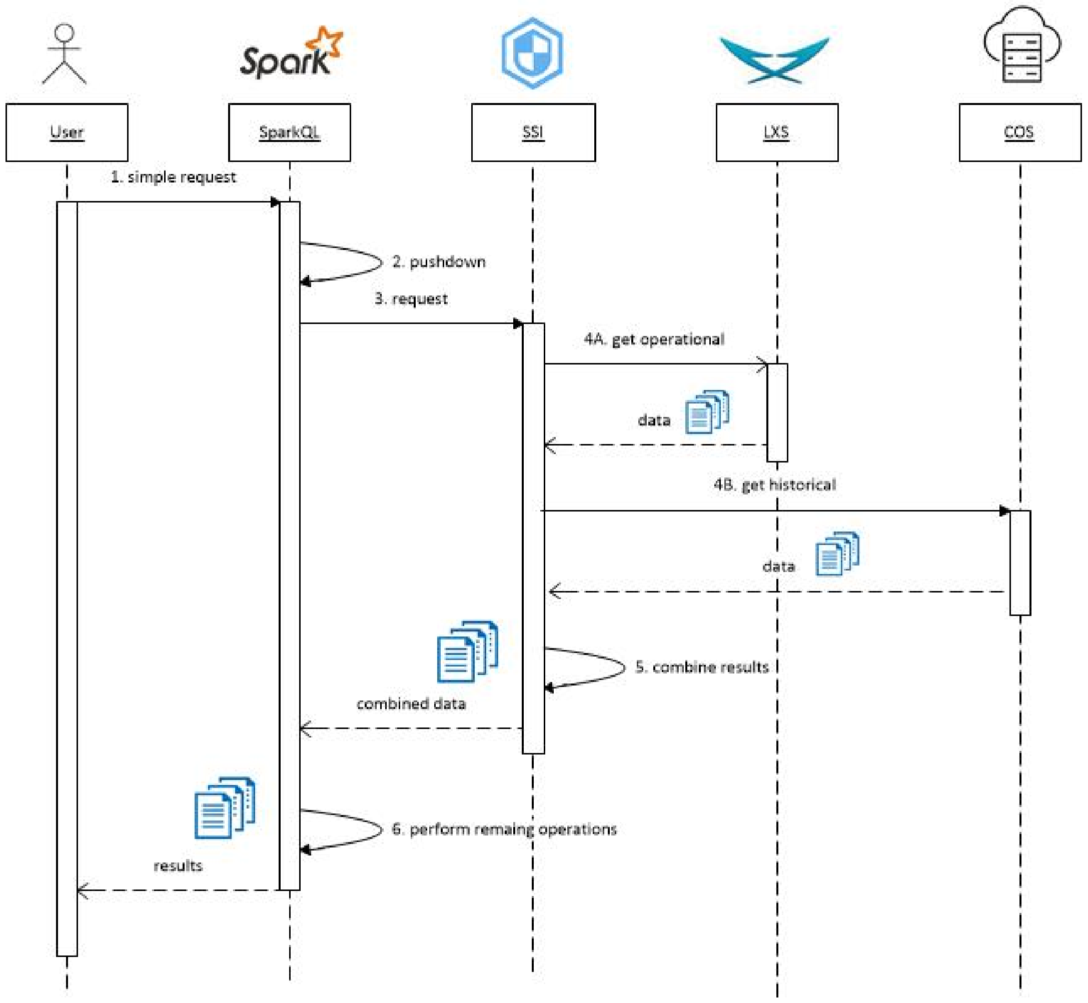


Figure 55 - Request data using a simple SparkSQL query

User sends a request for executing an analytical task by writing a SparkSQL query. The SSI, which is an extension of the LXS Query Engine provides a JDCB functionality, and as a result, is already integrated with SparkSQL. Due to this, SparkSQL will *pushdown* all operations to be executed by the SSI itself. The SSI is aware of the location of the data over the distributed dataset that is split into the two different datastores and is integrated with both of them. As a result, it translates the query to each data store's internal language and requests the data from both of them. It finally aggregates the results and returns the data back to SparkSQL, which returns the results to the user. It is important to notice that the SSI supports various query operations such as table scans, table selections, projections, ordered results, data aggregations (min, max, count, sum, avg) either grouping them by specific fields or not. From the above figure it can be also noticed that steps 4A and 4B might be in parallel according to the type of the query operators.

The architecture of the seamless analytical framework and the main interactions between its components can be shown in Figure 54:

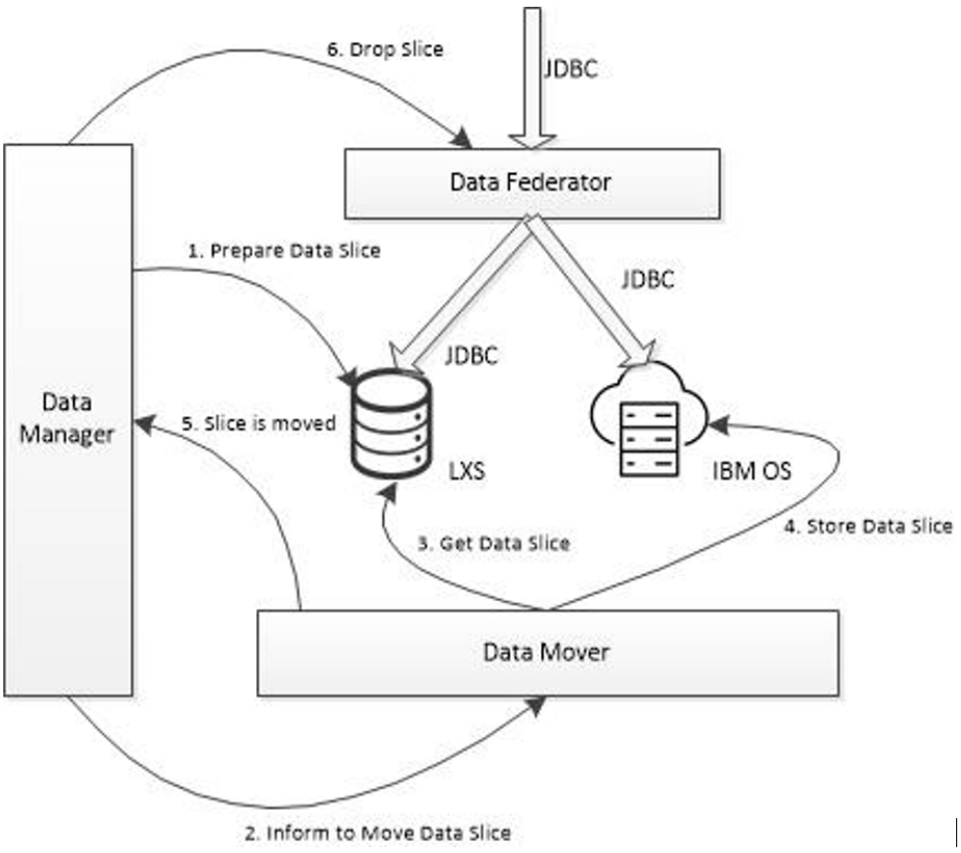


Figure 56 - Seamless Analytical Framework

The Data Manager component, as shown in Figure 54, keeps track of the data ingested in the framework. For each dataset the data user can configure the period of time after which data can be considered as historical and can safely be moved to a data warehouse such as the Object Store. When a data movement action is triggered, it first informs the relational database that a data slice should be moved to the COS. At this point, LXS gets prepared to drop that slice (internally it marks it as read-only and splits it to a data region that can be easily dropped later on). The Data Manager then informs the Data Mover to move the slice. The latter requests the data slice by executing one or many standard JDCB statements to LXS and then uploads the data slice as one or many objects into the objects store. When the whole slice is eventually persisted into the Object Store, it informs the Data Manager which forwards this acknowledgment to the data Federator. The data Federator internally keeps track of a timestamp which records the latest successful data movement. When a query is submitted for data retrieval, it creates the query tree and pushes down a selection based on this timestamp on each operation for a table scan. Then it rebuilds the query by interpreting it according to the target datastore and retrieves the results. Finally, in accordance with the query operation, it merges the results and builds the result set. When the Data Manager acknowledges a data movement and informs the Data Federator, the Data Federator will move accordingly the internal timestamp (the splitting point). At this point, the data corresponding to the moved data slice co-exists in both stores. However, the Data Federator thanks to the timestamp will hide the replicated data first at the Object Store and after the timestamp is updated at the relational store. When it receives the acknowledgement, it updates this timestamp (split point) so that the next transactions can scan the tables accordingly. Pending transactions however will continue to scan the tables based on the value that they received when the transaction first started. The transactional semantics of LXS ensure the data consistency when the split point is updated. When this happens, the Data Federator can order the LXS to safely drop the data slice that has now been moved to the object store. However, it will wait until all pending transactions have been finished, and thus, no scan operation is performed on the data slice that is about to be dropped. By doing so, the Data Federator ensures data consistency and the validation of the results during the process of data movement: Data will exist either on LXS or the COS, or both, but they will be always scanned only once.

Insert data to BigDataStack

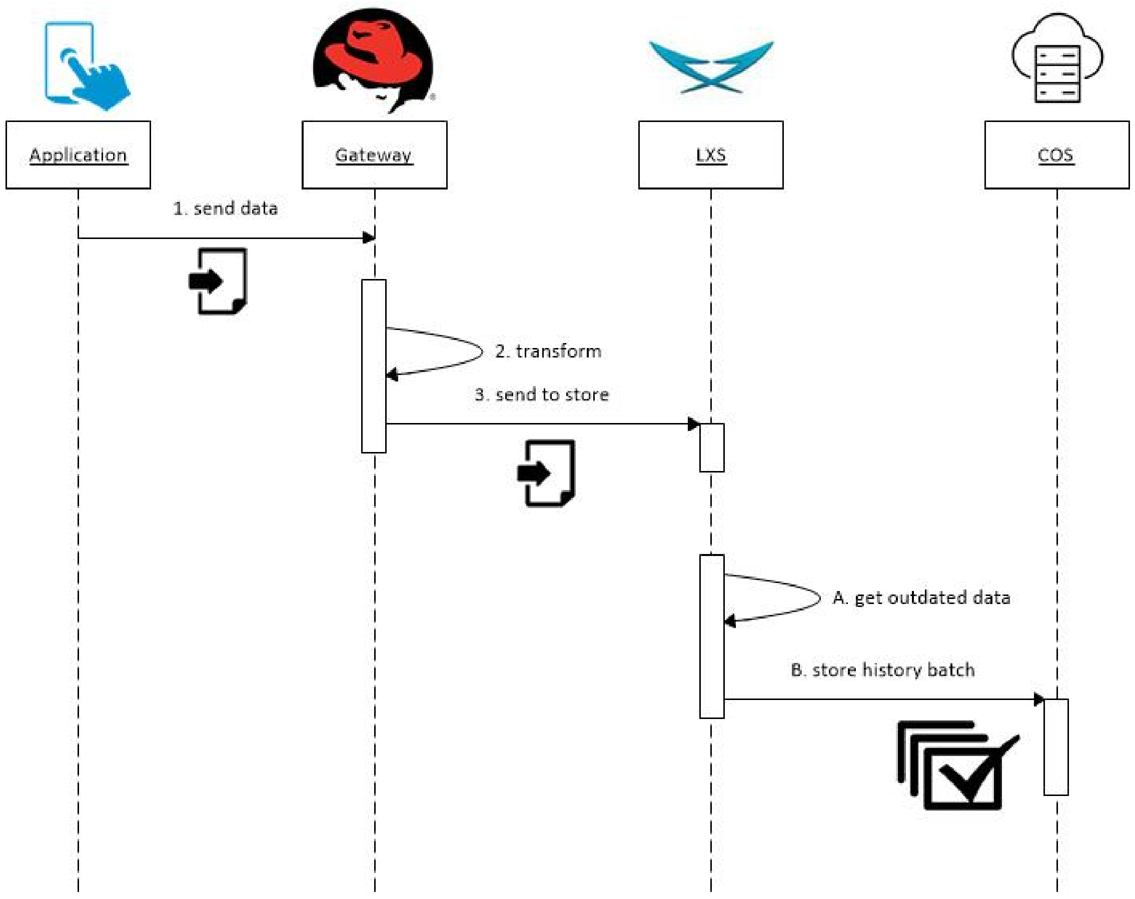


Figure 57 - Inserting data

An integrated application produces data to be stored in the BigDataStack platform. The data are being sent to the *Gateway*: the entry point of the platform. Its responsibility is to transform data coming from external sources in various formats, to the platform's internal schema. Then, it forwards the data to the operational data store to permanently store them. The latter periodically moves data that has been inserted from more than a constant period of time, to the COS.

Insert streaming data to BigDataStack

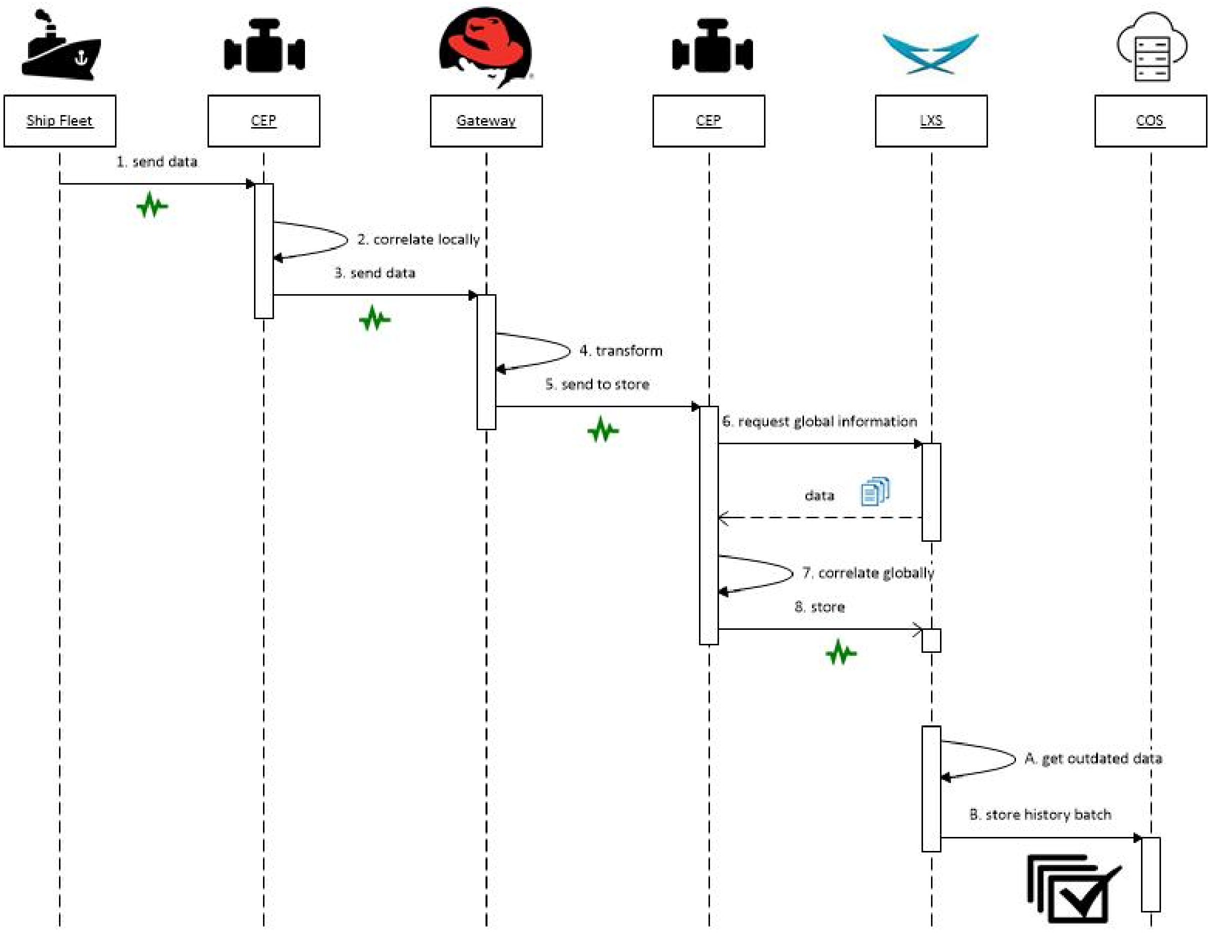


Figure 58 - Inserting streaming data

In this specific use case, a ship from the DANAOS fleet streams data coming from one of its sensors. Data is being first sent to a local installation of the CEP which correlates them and identifies possible threats, producing alerts. Then, data is sent to the platform´s Gateway which is responsible of transforming the data to the platform’s internal format. A CEP cluster inside the platform receives data from the Gateway. It further analyses data to detect possible rules infringement. Data coming from all the fleet vessels is merged. This second CEP cluster processing involves querying LXS to retrieve data in rest that has been already been stored in the data store. Finally, it stores the incoming data to the relational datastore which eventually will move the data to the Object Store.

7.4. Monitoring & Runtime Adaptations

When considering the process of monitoring and adapting user applications on the cloud, it is useful to divide the discussion into three parts: 1) the interactions required to perform the actual monitoring of a running application; 2) how this monitoring process can be used to track quality of service; and 3) the interactions needed to adapt the user’s application to some new configuration when a quality of service deficiency is identified or predicted. We summarize each below.

7.4.1. Triple Monitoring Engine

The triple monitoring system provides APIs for receiving metrics from different sources and exposes them for consumption. Metrics are obtained mainly by exporters and federation. In the case of the deployment of an exporter is impossible for some reason, the monitoring engine implements a system that can receive metrics by get and post methods and exposes them to Prometheus. This component of the triple monitoring engine is expected to behave as a REST API and Prometheus exporter. The following diagram describes its functionality.

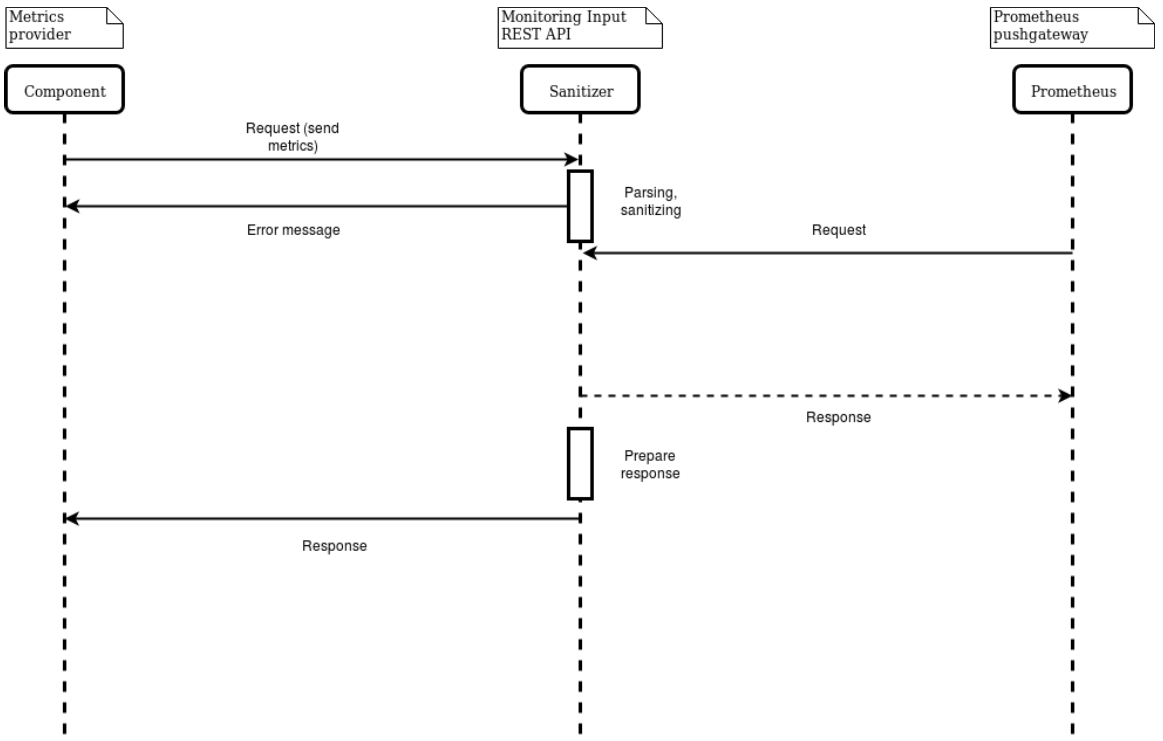


Figure 59 - Prometheus exporters

An application provider sends its metrics in JSON format by http get or post, the API parses the json structure, sanitizes metrics to convert them to Prometheus's format and saves them in a temporary list. A response is then returned to the application provider. The Prometheus engine scrapes the REST API by http get metrics, to get available metrics. This scraping operation is iteratively performed at intervals based on the amount of time specified in the Prometheus configuration.

The triple monitoring engine implements two different exposition system methods. The first is a REST API where applications consumers ask for a metric, the REST API translates this request to an Elasticsearch query and returns a result. The following sequence describes this process.

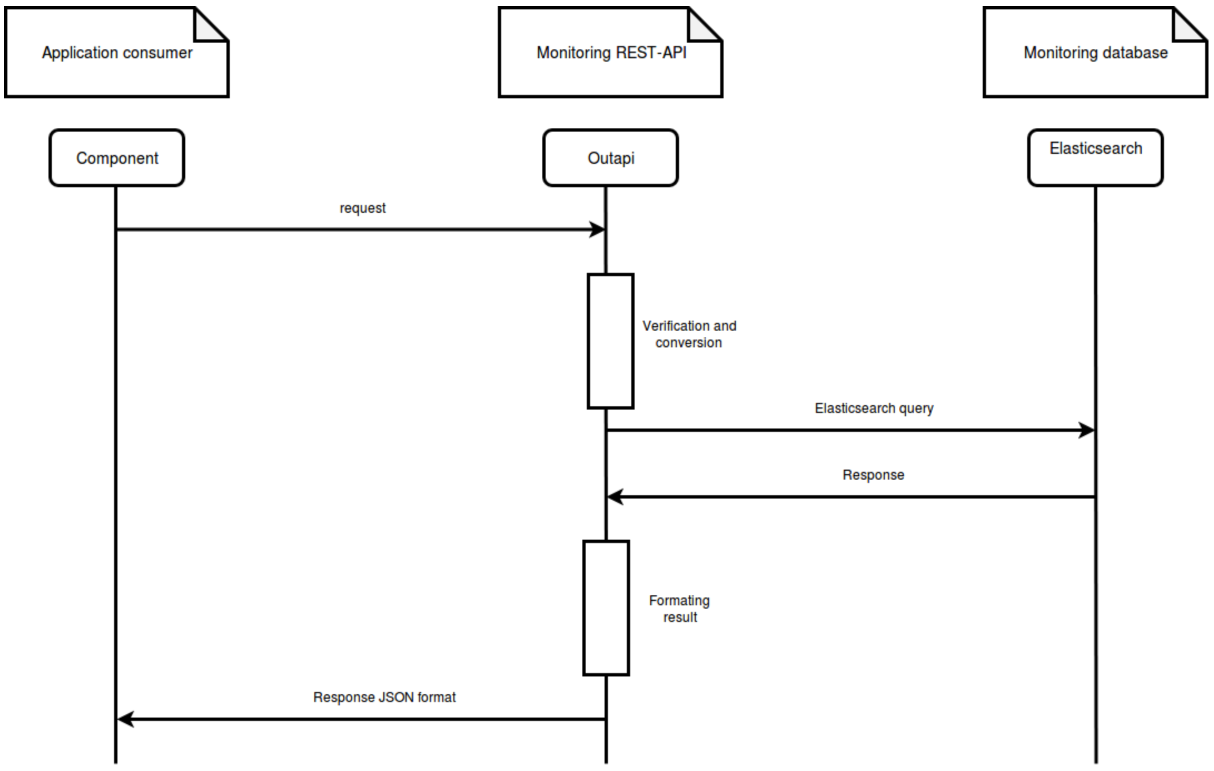


Figure 60 - Prometheus REST API

The second output interface implemented in the triple monitoring system is the publish/subscription mechanism.

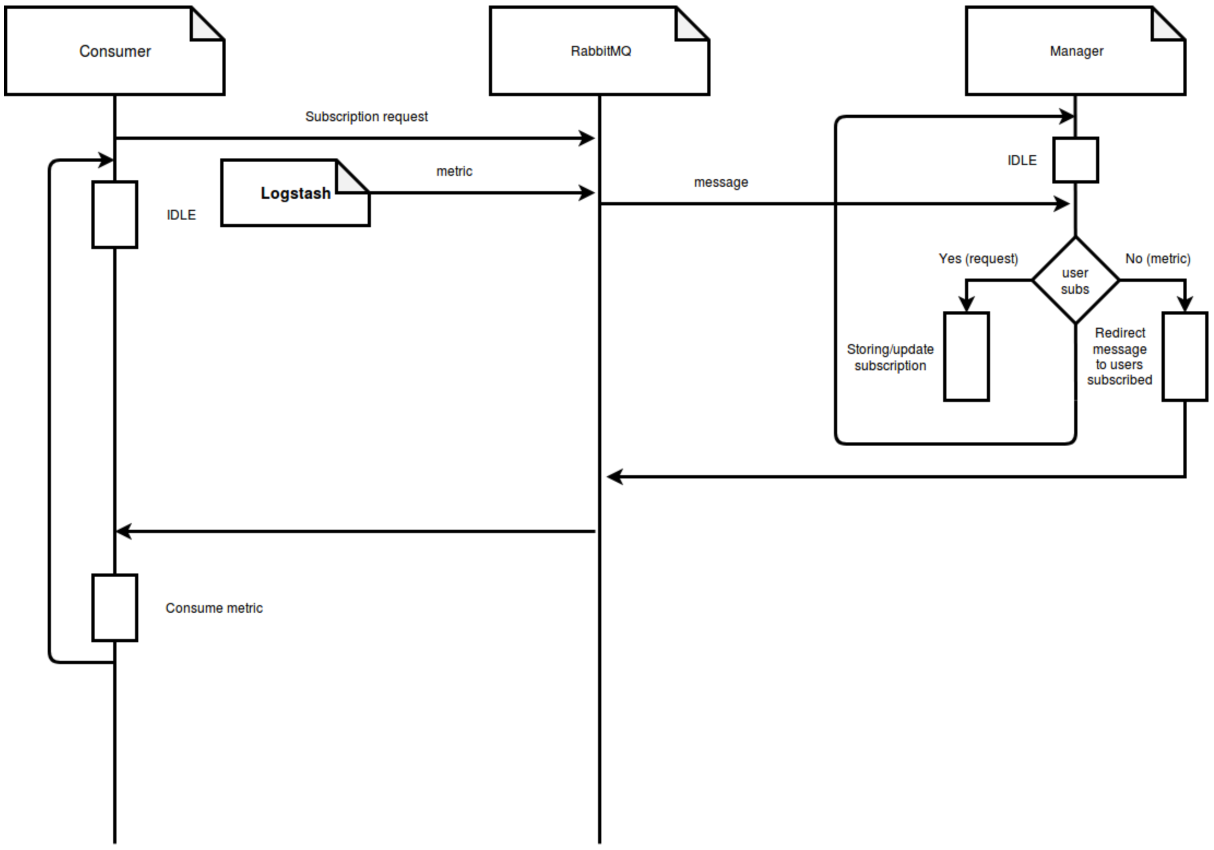


Figure 61 - Publish/subscription mechanism

An application that needs streaming data can through this component subscribe and receive metrics in real-time. Four different types of requests are available.

- The first request type is the “subscription”, the consumer after having created its queue will send to the pub/sub system a subscription request that contains the name of its queue, its name (application name) and a list a metrics. The consumer sends its request in the “manager” queue so that to be consumed by the manager of the triple monitoring system. The manager receives the subscription request, creates a subscription object and adds it into the subscription list. A confirmation message is then returned to the consumer. The manager reads the subscription list each time it receives a metric from its queue, it redirects this metric to the declared queue.
- The second request is the “add_metrics” request type, the consumer sends a message that contains its name, queue name and a metric to add to its subscription list, the manager verifies the request, updates the subscription and returns a message.
- The third request type is “my_subscription”, the consumer sends its name and queue name. The manager returns the corresponding subscription list.
- The last request is the heart_beat, the manager has no way to detect disconnection by a consumer. The consumer should confirm its presence each specific interval of time. The heart_beat interval is declared in the subscription request.

7.4.2. Quality of Service (QoS) Evaluation

QoS properties (parameters) to be evaluated by the QoS Evaluation component should correspond to the kind of quality of service (QoS) requirements coming from the Application Dimensioning Workbench and defined within the BigDataStack Playbook.

- An example of a QoS requirement is the "throughput."
- There should be a trivial mapping between Playbooks' KPIs and the "guaranteed" of "agreements".

The QoS Evaluation component will be responsible for translating the Playbooks' QoS requirements into SLOs (Service Level Objectives).

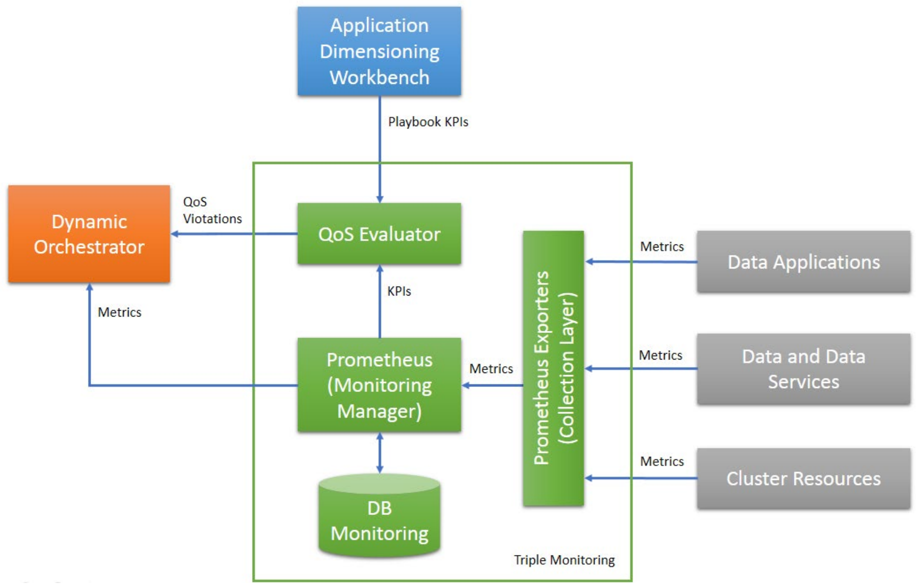


Figure 62 - QoS Evaluation component

The QoS Evaluation component will periodically query the Triple Monitoring Engine (based on Kubernetes) to recover the metrics related to the monitored QoS parameters.

Once a violation of a given SLO is detected, a notification is sent to the Dynamic Orchestrator to trigger the data-driven orchestration of application components and data services. The standard sequence of interactions will be the following:

- Evaluator calls the Adapter to recover a certain set of QoS metrics from Prometheus.
- The Evaluator calls the Notifier when an SLO violation is detected.
- Notifier calls the Dynamic Orchestrator passing a message describing the violation through the publisher/subscriber mechanism implemented as a topic within the RabbitMQ service (which acts as the message broker between BigDataStack components)

The Dynamic Orchestrator communicates with the ADS-Ranking component to trigger the dynamic adaptation (re-configuration) of the application or data service deployment patterns.

Adapting at Runtime

If a user's application is identified or predicted to have some deficiency with respect to the quality of service targets, then that application's configuration needs to be altered to correct for this. For instance, this might involve moving data closer to the machines performing the computation to reduce IO latency, or in more extreme cases it might require the complete re-deployment of the user's application on new more suitable hardware. BigDataStack supports a range of adaptations that might be performed , such as Pattern Re-Deployment, where the goal is to select an alternative candidate deployment pattern (hardware configuration) after the user's application has been deployed. This is used in cases where the original deployment pattern was deemed unsuitable and this could not be rectified without changing the deployment infrastructure. In this case, a new candidate deployment pattern will be chosen, and the application services will be transitioned to this new configuration. This may result in application down-time as services are moved.

The components involved for this adaptation are the Dynamic Orchestrator (DO) and the Triple Monitoring Engine. When a new application is deployed, the Playbook is sent to the DO on the queue OrchestratorPlaybook. The DO reads the playbook and enriches it, adding more information about the SLOs: it splits the values of the metrics related to SLOs in different intervals that the QoS component will monitor, e.g. response time can be divided in the intervals 0.5-1s, 1-1.5s, etc. In addition, the DO subscribes to the Triple Monitoring Engine and creates a new queue, using which it will consume the metrics from the application.

The Enriched Playbook is sent to the QoS Evaluator on the queue EnrichedPlaybook. The QoS registers this and will start monitoring the application to detect when an SLO is violated, and in this case, a message will be sent to the DO on the queue OrchestratorQOSFeed. The DO will read this message and based on the current state (as defined by the metrics consumed from the Triple Monitoring Engine, the QoS information and its experience), will decide what is the most likely action to resolve the violation is and subsequently send it to the Realization API (ADS-API), which will manage the alteration action.

In the remainder of this section we provide more detail on how Pattern Re-Deployment is operationalized within BigDataStack.

Pattern Re-Deployment

The aim of the pattern re-deployment task is to facilitate the selection of a new candidate deployment pattern (CDP) if a previously selected CDP is no longer considered viable. This might occur if a deployed application fails to meet minimum service requirements and this cannot be resolved through data service manipulation. In this case, the Realization Ranking component (ADS-Ranking) needs to take into account why the current pattern is failing and based on that information, re-rank the CDPs for the user application and select a new alternative that will provide better performance. This new CDP can then be used to transition the user's application to the new configuration by the Realization Deployment component (ADS-Deploy).

This task is triggered by the Dynamic Orchestrator when the orchestrator detects that an application deployment is failing. It sends a notification to the Realization API. At this point, if the Dynamic Orchestrator has specified a particular action to be performed, then the

Realization API has the power to directly implement that action, so long as that change does not violate any pre-defined requirements set by the user. On the other hand, in cases where a change request is made, but no rectifying action is specified, then the Realization API will contact the Realization Ranking component for a solution. More precisely, this notification is processed by the Failure Encoder sub-component. This component first contacts the Realization State DB (ADS-StateDB) to retrieve the other CDPs that were not selected for the failing user's application (as it is from these that a new pattern will be selected). These patterns are then sent into the same process pipeline as for first-time ranking (see Section 6.5), with the exception that the previously selected deployment is excluded (we know that it is insufficient) and the Pattern Selector sub-component will also consider the reason that the previously selected CDP failed.

When the ADS-Selector chooses the new CDP, this information is sent to the ADS-Deploy, together with the instruction to redeploy. Then, the deployment component translates the CDP, and communicates it to the container orchestrator using the same process as defined in Section 6.5. The orchestrator will then start a re-dimensioning process. If the process is successful, then the user's process continues normally. However, if the re-dimensioning was unsuccessful, then the container orchestrator needs to destroy the current deployment, stopping the processes and starting a new deployment from scratch. This situation has the setback that users have their processes interrupted and/or restarted and ultimately impair the availability of application and data services (downtimes).

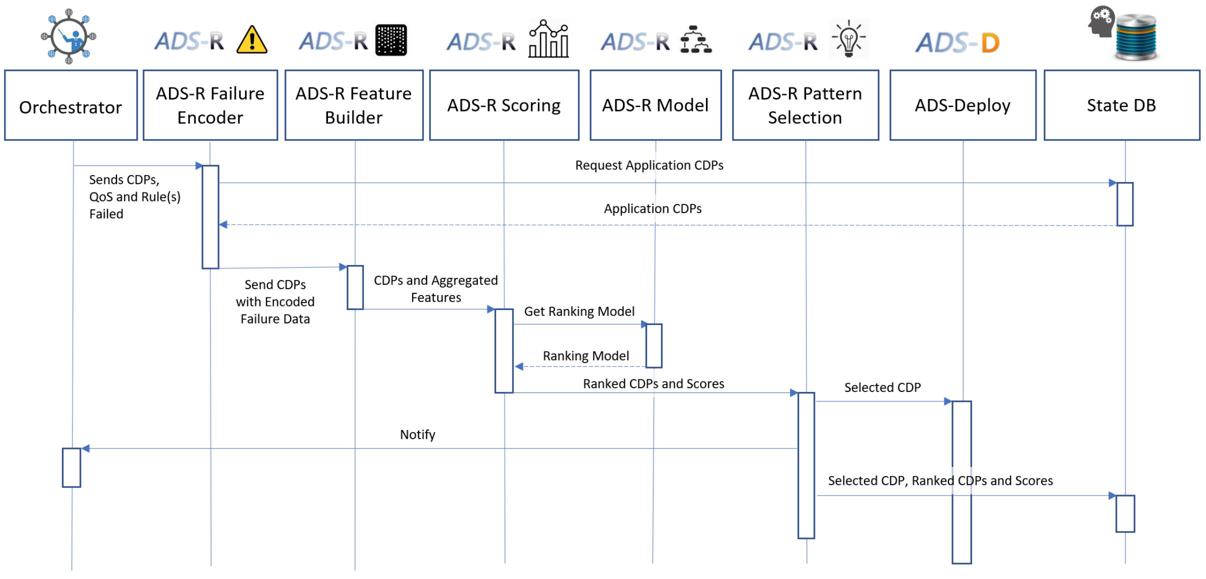


Figure 63 - Interaction Diagram for CDP Re-Ranking

Data Service Re-Deployment

The re-deployment process of the data services are handled separately to application redeployment inside the BigDataStack platform. These services are stateful, meaning that given a re-deployment, they might be inside a transaction. If the re-deployment of a data service is forced during a transaction, this may lead into an unstable situation. Thus, BigDataStack incorporates a mechanism to ensure that the transactions of data services are stopped before starting a re-deployment, as shown in Figure 62.

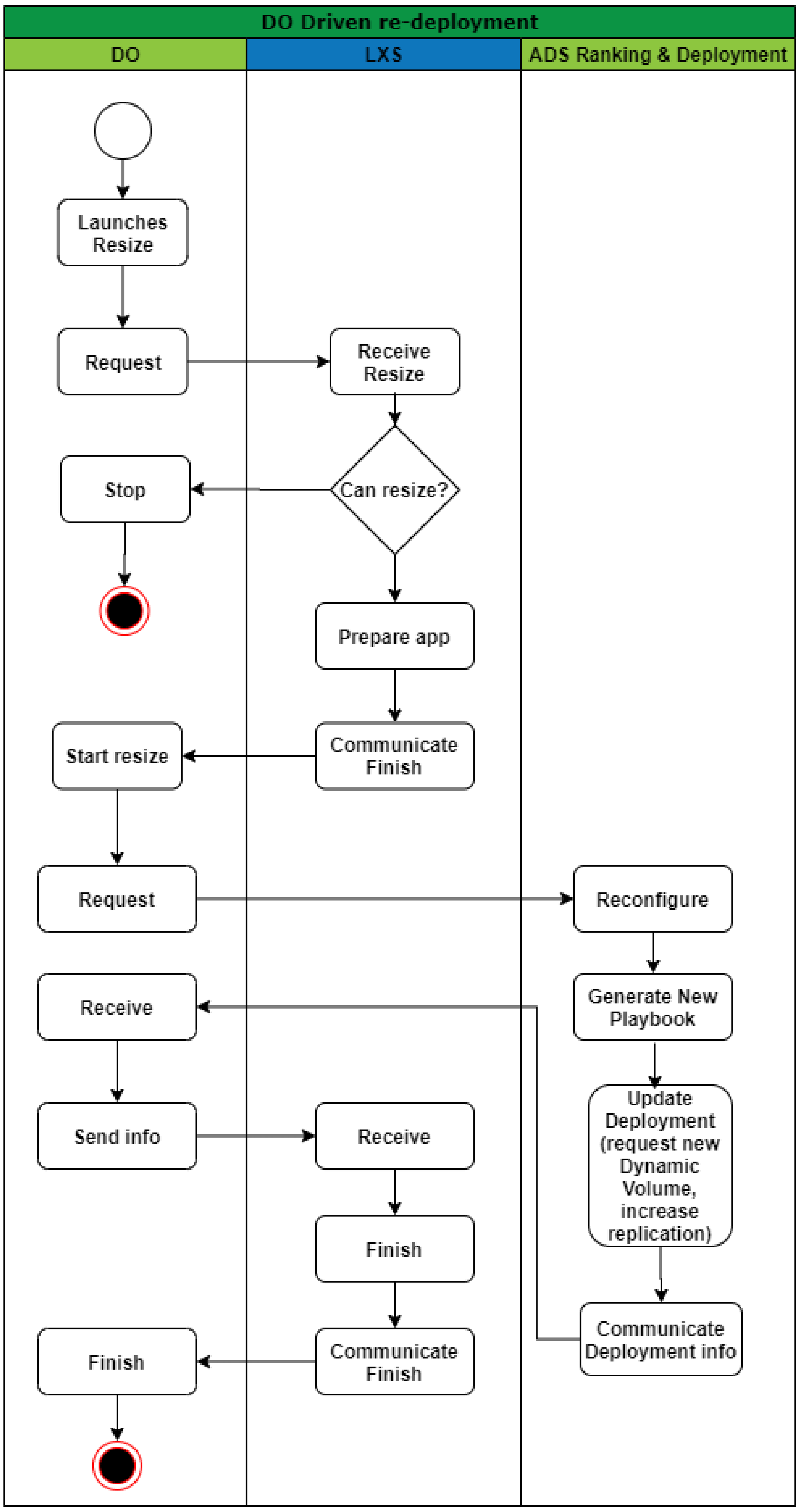


Figure 64 - Data-Service Redeployment triggered from the Data Service

Furthermore, data services can trigger their own re-deployment. As shown in Figure 63, this process requires for the data service (in the example LXS) to communicate this change to the Dynamic Orchestrator, which then starts the process of creating a CDP and communicating it to the ADS-Deploy.

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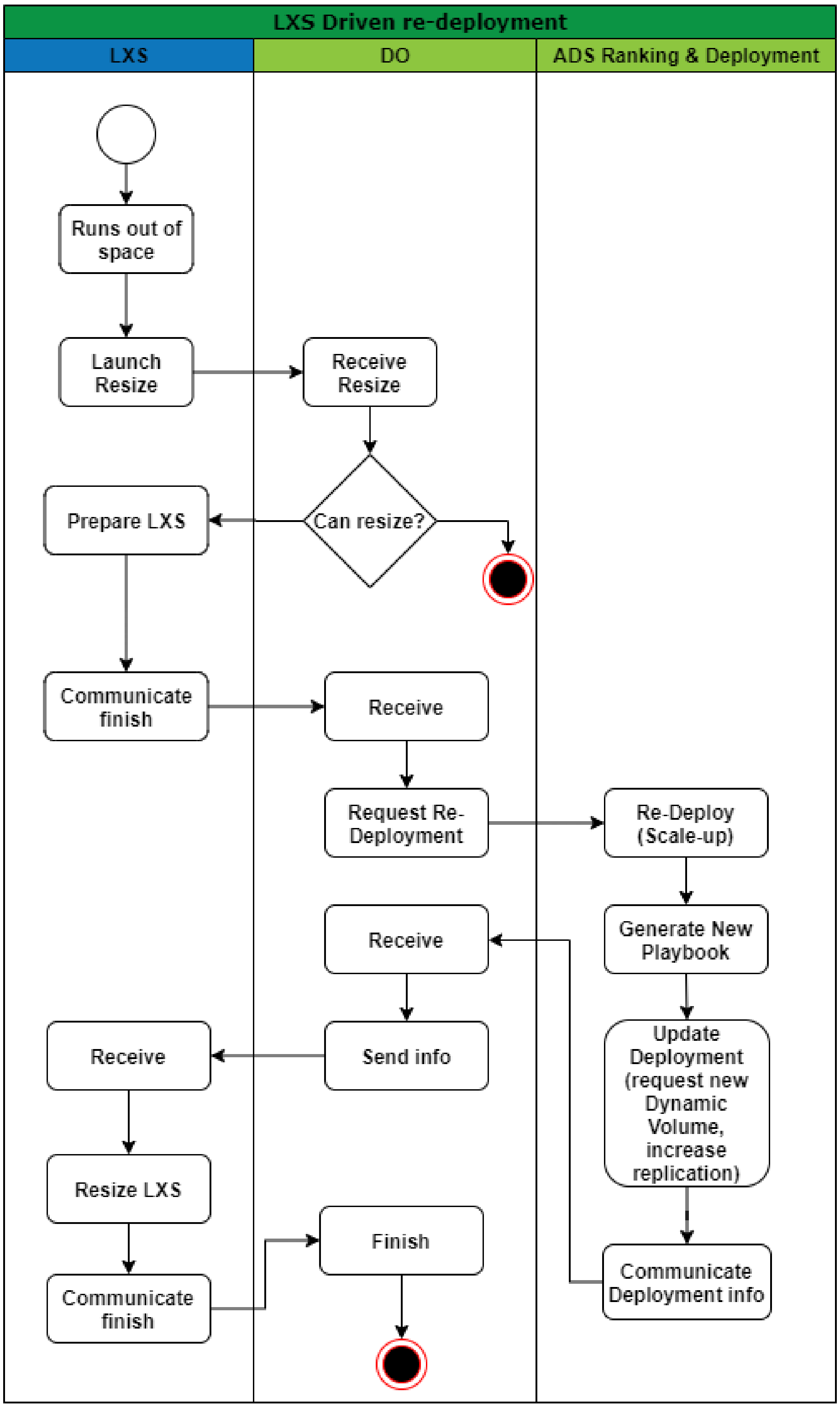

Figure 65 - Data-Service Redeployment triggered from the Data Service

CEP Re-deployment

As described in section 6.3.2, the real-time CEP will interact with the DO for its dynamic re-deployment, that will allow the CEP to scale up and down during runtime to improve performance of its queries while optimizing the use of resources in the BigDataStack platform. The interaction between the CEP and DO will be structured as shown in the figure below.

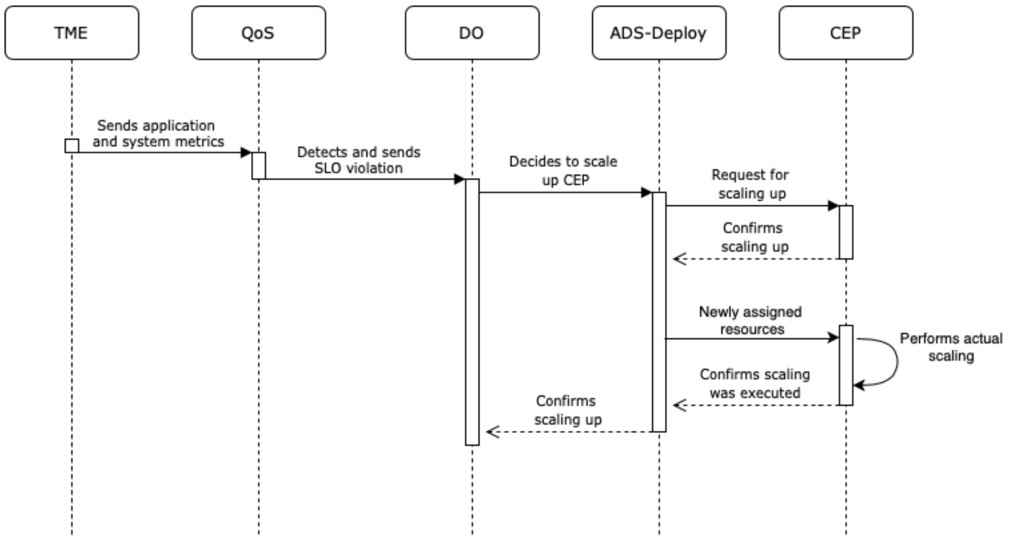

Figure 66 - Dynamic scaling for CEP

Each query in the CEP can be defined along with SLOs that will be monitored during runtime. As for user applications, the TME will periodically inform the QoS about metrics for the CEP and the system. Once the QoS detects an SLO is violated, it will trigger the DO, which will decide if a re-deployment is necessary for the CEP. If so, the DO will communicate this to the ADS-Deploy that will in turn send a request to scale up/down to the CEP. The CEP can reply to this request accepting or denying the re-deployment if its affected sub-query cannot be re-deployed. The ADS-Deploy receives the reply and if the CEP accepted the re-deployment, the ADS-Deploy will modify the resources assignment for the CEP and communicate the newly assigned resources to the CEP if any, so it performs the actual scaling up. In the end, the CEP will confirm the operation to the ADS-Deploy, the ADS-Deploy will forward the message to the DO so it updates its internal state and learns from this experience.

LXS Re-deployment

Apart from the scenarios where the WP3 components take the decision that an application component should be scaled, in the case of WP4 components and more precisely the LXS datastore and the CEP, they also have their own internal monitoring mechanism and decision making and can also request for a scalability action. In general, WP4 components are all stateful and their treatment is different from traditional stateless application components and microservices. This is due to the fact that they store date and state, so any scalability action must take this into consideration. For instance, even if WP3 components might identify small peaks of workload that lead to increased resource consumption for a couple of minutes, it is not advisable to scale out the database, as this will require moving data from one node to the other in order to achieve data load balancing. If the dataset is very big, this action might take more than the time that the peak is observed, so it might be better to scale out a different component. Moreover, it might be impossible for the WP4 components to scale out at that time, as another action might be occurring at the same time, e.g. online data redistribution among the data nodes in order to establish better load balancing. When this action happens underneath, LXS datastore will have to reject any actions coming from the infrastructure level to scale out, until the data redistribution has been finished. Another common scenario is when the infrastructure requests for the data components to scale in, thus shrinking in size and releasing resources. This also might be impossible, and the data components must reject this request in case the release of a data node will lead to data loss. Finally, as the data components have their own monitoring mechanisms, they can decide on their own when might be best to scale out.

For all these reasons, in BigDataStack there has been a vice-versa protocol that allows for the data repository to request for a scalability action. The sequence diagram of these interactions is depicted in Figure 65.

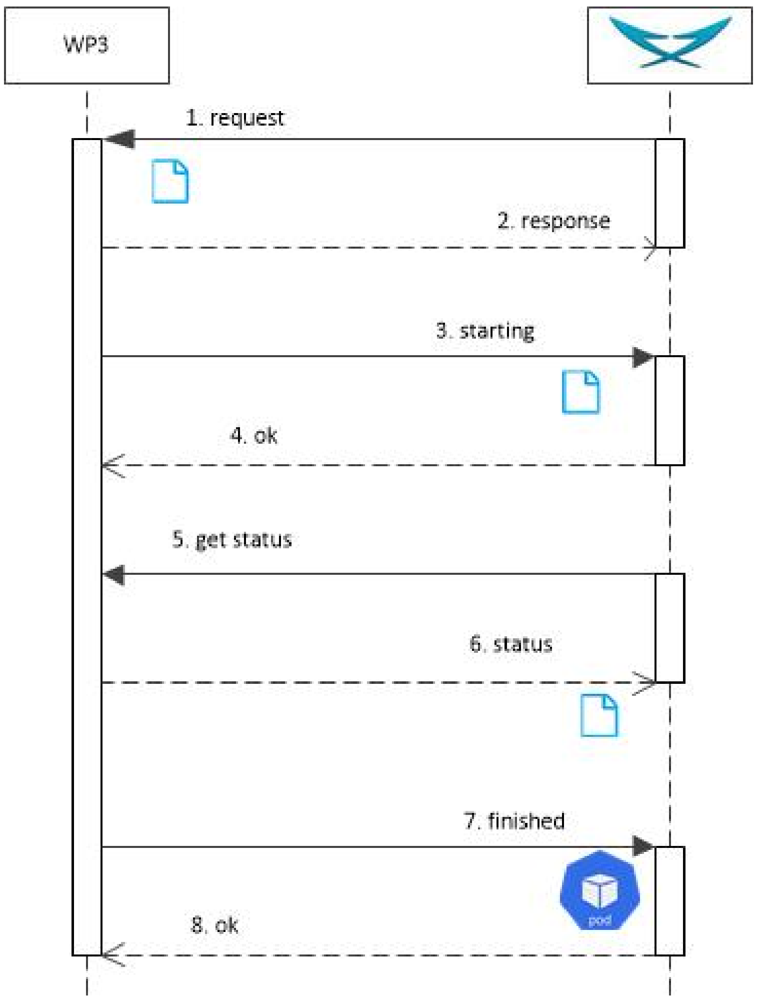

Figure 67 - LXS requests to scale out

After LXS identifies the need to scale out, either due to computational resource saturation or due to lack of storage, it sends a request to the WP3 components with the amount of additional nodes it requires. At this point the infrastructure might reject this request due to lack of resources, or can confirm it. Upon confirmation, LXS puts this request into a waiting state, while WP3 is performing all actions in order to create a new instance, as described in the aforementioned sections. It firstly informs LXS that it has started creating the new instances. In parallel, LXS can periodically ask for the status of this process. At the end of the process, the WP3 components sends a message to LXS that the new pod has been successfully created, along with the information that describes that pod, like pod or domain name, etc, or an error notification that the creation of the new instance has failed. If everything goes well, then LXS confirms to the WP3, and the latter finishes its flow, while LXS start deploying its internal components to the newly created instance, while also performing re-distribution of the stored data for load balancing. However, there might be a rejection of LXS, even if the pod has been created from the infrastructure. Due to the asynchronous nature of communication, the creation of the new instance might take some time. LXS, as an operational datastore, cannot freeze all its internal process and wait for WP3 to respond. Moreover, there might be a failure in some of the WP3 components, which will cause the whole process to stall. For all these reasons, LXS will continue proceeding with its internal actions. This might have as effect that when the new node is available to the datastore, a data redistribution, or the building of a new index might take place by a manual administrative operation of the data user. These actions forbid the scaling of LXS in parallel. In order to avoid putting requests in a queue, and execute them one by one, LXS will inform the WP3 components that rejects the new node and WP3 must release these resources. After the completion of these actions by LXS, the latter might identify that there is still the need to scale out and will send a new request to the infrastructure components, repeating this flow.

8. Conclusions

This document provides the final version of the BigDataStack architecture following the previous releases in deliverables D2.4 and D2.5 - Conceptual model and Reference architecture I and II. It captures the final version of the overall conceptual architecture in terms of information flows and capabilities provided by each one of the main building blocks. Additional information for each component is also detailed on the corresponding sections, as well as the changes in the interactions between them and the overall flows depicted in Section 7.

This report serves as a design documentation for the individual components of the architecture (which are further specified and detailed in the corresponding WP-level scientific reports) and presents the outcomes (in terms of design) of the final integrated prototypes and the obtained experimentation and validation results.

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Appendix 1 – Real-time Ship Management use case dataset structure and description

It should be noted that given the data schemas described below, the DANAOS datasets do not have any GDPR-related aspect.

TELEGRAMS table structure (14 attributes)

id: Telegram id,

vessel_code: The id of the vessel,

telegram_date: Telegram timestamp (UTC),

type: Telegram type: D:Departure, A:Arrival, N:Noon-telegram,

total_teus: Total Twenty-foot Equivalent Unit (TEU) (# of containers)

total_feus: Total Fourty-foot Equivalent Unit (FEU) (# of containers)

cons_ifo_static_counter: sensor-based measurement TEUs

cons_ifo_static1_counter: sensor-based measurement of FEUs,

draft_aft: Vessel draft at stern (m),

draft_fore: Vessel draft at fore (m),

sea_temperature: Sea temperature (°C),

port_name: Current port name,

next_port: The name of the next port,

eta_next_port: ETA to the next port

VESSEL_DATA table structure (23 attributes)

vessel_code: Vessel id,

datetime: Timestamp of the measurement (UTC),

power: Consumed power (kW),

apparent_wind_speed: Wind-speed (kn),

speed_overground: GPS speed (kn),

stw_long double precision: Speed through water – longitudinal (kn),

stw_trans double precision: Speed through water – transverse (kn),

rpm: rotations per minute of the main shaft,

apparent_wind_angle: Wind angle (0-359.99 degrees), total_teus: Total Twenty-foot Equivalent Unit (TEU) (# of containers),

total_feus: Total Fourty-foot Equivalent Unit (FEU) (# of containers),

cons_ifo_static_counter: Low-sulfur fuel oil consumption (metric tones),

cons_ifo_static1_counter: High-sulfur fuel oil consumption (metric tones),

port_mid_draft: Vessel draft at port-side (left-side looking to the fore) (m),

stbd_mid_draft: Vessel draft at starboard-side (right-side looking to the fore) (m),

draft_aft: Vessel draft at stern (m),

draft_fore: Vessel draft at fore (m),

stw: Speed through water – calculated by stw_trans and stw_lon (kn),

equivalent_teus: Total number of containers,

mid_draft: Vessel draft at mid-line (m),

trim: The trim of the vessel, calculated by draft_aft and draft_fore,

latitude: The latitude of the vessel's position,

longitude: The longitude of the vessel's position,

MAIN_ENGINE_DATA table structure (102 attributes)

vessel_code: The id of the vessel,

datetime: Timestamp of measurement in UTC,

airCoolerCWInLETPress: Air Cooler Cooling Water Inlet Pressure (Pa)

scavAirFireDetTempNo1: Cyllinder #1 Scavenge Air Fire Detection Temperature (°C),

scavAirFireDetTempNo2: Cyllinder #2 Scavenge Air Fire Detection Temperature (°C),

scavAirFireDetTempNo3: Cyllinder #3 Scavenge Air Fire Detection Temperature (°C),

scavAirFireDetTempNo4: Cyllinder #4 Scavenge Air Fire Detection Temperature (°C),

scavAirFireDetTempNo5: Cyllinder #5 Scavenge Air Fire Detection Temperature (°C),

scavAirFireDetTempNo6: Cyllinder #6 Scavenge Air Fire Detection Temperature (°C),

scavAirFireDetTempNo7: Cyllinder #7 Scavenge Air Fire Detection Temperature (°C),

scavAirFireDetTempNo8: Cyllinder #8 Scavenge Air Fire Detection Temperature (°C),

scavAirFireDetTempNo9: Cyllinder #9 Scavenge Air Fire Detection Temperature (°C),

scavAirFireDetTempNo10: Cyllinder #10 Scavenge Air Fire Detection Temperature (°C),

scavAirFireDetTempNo11: Cyllinder #11 Scavenge Air Fire Detection Temperature (°C),

scavAirFireDetTempNo12: Cyllinder #12 Scavenge Air Fire Detection Temperature (°C),

coolerCWinTemp: Air Cooler Cooling Water Inlet Temperature (°C)

cfWInPress: Cooling Fresh Water Inlet Pressure (Pa), controlAirPress: Control Air Pressure (Pa),

cylLoTemp: Cylinder Lube Oil Temperature (°C)

exhVVSpringAirInPress: Exhaust Valve Spring Air Inlet Pressure (Pa)

foFlow: Fuel Oil Flowrate (lt),

foInPress: Fuel Oil Inlet Pressure (Pa),

foInTemp: Fuel Oil Inlet Temperature (°C),

hfoViscocityHighLow: Heavey Fuel Oil Viscosity High Low (mm2/s)

hpsBearingTemp: HPS Bearing Temperature (°C),

jcfWInTempLow: Jacket Cooling Fresh Water Inlet Temperature Low (°C)

cylExhGasOutTempNo1: Cyllinder #1 Exhaust Gas Out Temperature (°C),

cylExhGasOutTempNo2: Cyllinder #2 Exhaust Gas Out Temperature (°C),

cylExhGasOutTempNo3: Cyllinder #3 Exhaust Gas Out Temperature (°C),

cylExhGasOutTempNo4: Cyllinder #4 Exhaust Gas Out Temperature (°C),

cylExhGasOutTempNo5: Cyllinder #5 Exhaust Gas Out Temperature (°C),

cylExhGasOutTempNo6: Cyllinder #6 Exhaust Gas Out Temperature (°C),

cylExhGasOutTempNo7: Cyllinder #7 Exhaust Gas Out Temperature (°C),

cylExhGasOutTempNo8: Cyllinder #8 Exhaust Gas Out Temperature (°C),

cylExhGasOutTempNo9: Cyllinder #9 Exhaust Gas Out Temperature (°C),

cylExhGasOutTempNo10: Cyllinder #10 Exhaust Gas Out Temperature (°C),

cylExhGasOutTempNo11: Cyllinder #11 Exhaust Gas Out Temperature (°C),

cylExhGasOutTempNo12: Cyllinder #12 Exhaust Gas Out Temperature (°C),

cylJCFWOutTempNo1: Cyllinder #1 Jacket Cooling Fresh Water Outlet Temperature (°C),

cylJCFWOutTempNo2: Cyllinder #2 Jacket Cooling Fresh Water Outlet Temperature (°C),

cylJCFWOutTempNo3: Cyllinder #3 Jacket Cooling Fresh Water Outlet Temperature (°C),

cylJCFWOutTempNo4: Cyllinder #4 Jacket Cooling Fresh Water Outlet Temperature (°C),

cylJCFWOutTempNo5: Cyllinder #5 Jacket Cooling Fresh Water Outlet Temperature (°C),

cylJCFWOutTempNo6: Cyllinder #6 Jacket Cooling Fresh Water Outlet Temperature (°C),

cylJCFWOutTempNo7: Cyllinder #7 Jacket Cooling Fresh Water Outlet Temperature (°C),

cylJCFWOutTempNo8: Cyllinder #8 Jacket Cooling Fresh Water Outlet Temperature (°C),

cylJCFWOutTempNo9: Cyllinder #9 Jacket Cooling Fresh Water Outlet Temperature (°C),

cylJCFWOutTempNo10: Cyllinder #10 Jacket Cooling Fresh Water Outlet Temperature (°C),

cylJCFWOutTempNo11: Cyllinder #11 Jacket Cooling Fresh Water Outlet Temperature (°C),

cylJCFWOutTempNo12: Cyllinder #12 Jacket Cooling Fresh Water Outlet Temperature (°C), cylPistonCOOutTempNo1: Cyllinder #1 Piston Cooling Outlet Temperature (°C),

cylPistonCOOutTempNo2: Cyllinder #2 Piston Cooling Outlet Temperature (°C),

cylPistonCOOutTempNo3: Cyllinder #3 Piston Cooling Outlet Temperature (°C),

cylPistonCOOutTempNo4: Cyllinder #4 Piston Cooling Outlet Temperature (°C),

cylPistonCOOutTempNo5: Cyllinder #5 Piston Cooling Outlet Temperature (°C),

cylPistonCOOutTempNo6: Cyllinder #6 Piston Cooling Outlet Temperature (°C),

cylPistonCOOutTempNo7: Cyllinder #7 Piston Cooling Outlet Temperature (°C),

cylPistonCOOutTempNo8: Cyllinder #8 Piston Cooling Outlet Temperature (°C),

cylPistonCOOutTempNo9: Cyllinder #9 Piston Cooling Outlet Temperature (°C),

cylPistonCOOutTempNo10: Cyllinder #10 Piston Cooling Outlet Temperature (°C),

cylPistonCOOutTempNo11: Cyllinder #11 Piston Cooling Outlet Temperature (°C),

cylPistonCOOutTempNo12: Cyllinder #12 Piston Cooling Outlet Temperature (°C),

tcExhGasInTempNo1: Turbo-Charger #1 Exhaust Gas Inlet Temperature (°C)

tcExhGasInTempNo2: Turbo-Charger #2 Exhaust Gas Inlet Temperature (°C),

tcExhGasInTempNo3: Turbo-Charger #3 Exhaust Gas Inlet Temperature (°C),

tcExhGasInTempNo4: Turbo-Charger #4 Exhaust Gas Inlet Temperature (°C),

tcExhGasOutTempNo1: Turbo-Charger #1 Exhaust Gas Outlet Temperature (°C),

tcExhGasOutTempNo2: Turbo-Charger #2 Exhaust Gas Outlet Temperature (°C),

tcExhGasOutTempNo3: : Turbo-Charger #3 Exhaust Gas Outlet Temperature (°C)

tcExhGasOutTempNo4: Turbo-Charger #4 Exhaust Gas Outlet Temperature (°C)

tcLOInLETPressNo1: Turbo-Charger #1 Lube Oil Inlet Pressure (Pa),

tcLOInLETPressNo2: Turbo-Charger #2 Lube Oil Inlet Pressure (Pa),

tcLOInLETPressNo3: Turbo-Charger #3 Lube Oil Inlet Pressure (Pa),

tcLOInLETPressNo4: Turbo-Charger #4 Lube Oil Inlet Pressure (Pa),

tcLOOutLETTempNo1: Turbo-Charger #1 Lube Oil Outlet Pressure (Pa),

tcLOOutLETTempNo2: Turbo-Charger #2 Lube Oil Outlet Pressure (Pa),

tcLOOutLETTempNo3: Turbo-Charger #3 Lube Oil Outlet Pressure (Pa),

tcLOOutLETTempNo4: Turbo-Charger #4 Lube Oil Outlet Pressure (Pa),

tcRPMNo1: Turbo-Charger #1 RPMs,

tcRPMNo2: Turbo-Charger #2 RPMs,

tcRPMNo3: Turbo-Charger #3 RPMs,

tcRPMNo4: Turbo-Charger #4 RPMs,

orderRPMBridgeLeverer: Order RPM (Bridge Lever) rpm: Rotations per minute of the main shaft

scavAirInLetPress: Scavenge Air Inlet Pressure (Pa),

scavAirReceiverTemp: Scavenge Air Receiver Temperature (°C),

startAirPress: Starting Air Pressure (Pa),

thrustPadTemp: Thrust Pad Temperature (°C),

mainLOInLetPress: Main Lube Oil Inlet Pressure (Pa),

mainLOInTemp: Main Lube Oil Inlet Temperature (°C)

foTemperature: Fuel Oil Temperature (°C)

foTotVolume: Fuel Oil Total Volume (lt)

power: Consumed power (kW),

scavengeAirPressure: Scavenge Air Pressure (Pa)

torque: Torque of the main shaft (N/m),

coolingWOutLETTempNo1: Turbo-Charger #1 Air Cooler Cooling Water Outlet Temperature (°C),

coolingWOutLETTempNo2: Turbo-Charger #2 Air Cooler Cooling Water Outlet Temperature (°C),

coolingWOutLETTempNo3: Turbo-Charger #3 Air Cooler Cooling Water Outlet Temperature (°C),

coolingWOutLETTempNo4: Turbo-Charger #4 Air Cooler Cooling Water Outlet Temperature (°C),

foVolConsumption: Fuel Oil Consumption (lt/min)

VESSEL_DAMAGES table structure (5 attributes)

vessel_code: The id of the vessel,

defect_type: Type of damage (Main Bearing, Crosshead Bearing, Crankpin Bearing)

defect_details: Short description of damage

date_of_damage: Date of damage

cause_of_damage: Short description for cause of damage

Appendix 2 – Connected Consumer use case dataset structure and description

Introduction

This document aims at describing the main entities to be used in the implementation of the recommender system that is going to be developed in the retailer use-case of the project BigDataStack.

Having pre-analysed a sample of raw data coming from our partner Eroski, a selection of the most relevant attributes that are candidates to be used during the build of the predictive model has been done. These selected attributes are the ones contained in this document.

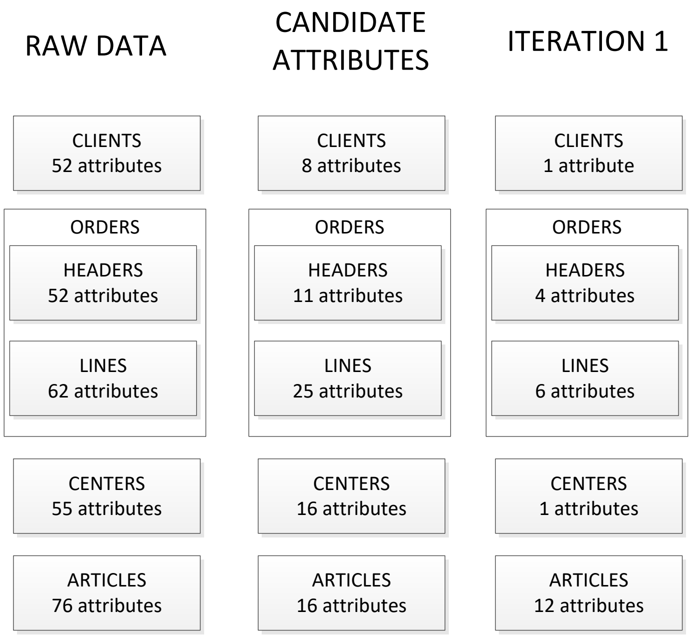

Figure 68 - Dataset structure and description

The dataset contains information about EROSKI clients. However, GDPR aspects have been taken into account before sharing the data with the consortium. Concretely:

- The only data that could be used to uniquely identify a person related to the field "ID_CLIENTE".
- ID_CLIENTE is an internal identifier of the database of EROSKI that is not known by the customers. I.e. only a person with access to the database of EROSKI could identify the customer from ID_CLIENTE.
- ID_CLIENTE has been encrypted by EROSKI with an SHA-1 algorithm. Encryption has been done before providing the dataset to BigDataStack consortium. A SHA-1 (168 bits) algorithm has been used for encryption of ID_CLIENTE.
- For each ID_CLIENTE, SHA-1 has been applied to "string_1"+ID_CLIENTE+"string_2". String_1 and string_2 are alphanumeric that contain capital and non-capital letters, numbers and special characters. These 2 values are only known by EROSKI.

The attributes for each entity have been included in this section.

CLIENTS table structure (21 attributes)

ID_CLIENTE: Client id,

TIPO_CLIENTE_ORO: Type of gold client

FLG_CLIENTE_APP: Flag if the client is an app client or not,

FLG_CLIENTE_WEB: Flag if the client is a web client or not,

FLG_CLIENTE_NUTRICIONAL: Customer shows interest in healthy products

FRANJA_GASTO_ORO_INICIAL: Initial Range of expenditure

POSIBLE_VALOR_ORO: Percentage indicating the discount given to the customer for being a gold customer

CLIENTE_1000_ORO: Flag indicating whether the client is 1000 Oro or not

FRANJA_GASTO_ORO_ACTUAL: Current Range of expenditure

TIPO_MADUREZ: Type of maturity of the client

DESC_SEG_C_CLIENTE: Description of the type of maturity of the client

DESC_SEG_G_FIDELIDAD: Segmentation of the customer according to his loyalty

DESC_INTERES_AHORRO: Segmentation of the customer according to his interest in promotions

DESC_INTERES_FRESCOS: Segmentation of the customer according to his interest in fresh food

DESC_INTERES_LOCAL: Segmentation of the customer according to his interest in local food

DESC_INTERES_SALUD: Segmentation of the customer according to his interest in healthy food

DESC_INTERES_SALUD_DETALLE: additional detail on which type of healthy food the customer is interested in

DESC_MISION_COMPRA: description of the purchase mission of the customer

DESC_SEG_SEC: segment description

DESC_SEG_SOCIODEMO: Socio-demographic segment of the client.

COD_LOC: preferred store

TICKETS (36 attributes)

ID_CLIENTE: Client id,

COD_LOC: Store's localization id,

DIA: Day,

COD_CAJA: Till id,

NUM_TICKET: Ticket number (id),

NUM_LINEA: Line number (id),

COD_TIPO_MOVIM: Movement type,

HORA_EMISION: Timestamp of tickets emission,

COD_TIPOMARCA_HIST: Type of brand of the product

COD_F_PAGO_DET -> M_FORMA_PAGO: Type of payment procedure,

UNID_VENTA_TARIFA: Total amount of items sold in tariff's type,

UNID _VENTA_OFERTA: Total amount of items sold in offer's type,

UNID _VENTA_COMPETE: Total amount of items sold in competence's type,

UNID _VENTA_LIQUID: Total amount of items sold in liquidation's type,

UNID _VENTA_CAMPANA: Total amount of items sold in campaign's type,

IMP_VENTA_TARIFA: Total economic amount of the items sold by tariff's type,

IMP_VENTA_OFERTA: Total economic amount of the items sold by offer's type,

IMP_VENTA_COMPETE: Total economic amount of the items sold by competence's type,

IMP_VENTA_LIQUID: Total economic amount of the items sold by liquidation's type,

IMP_VENTA_CAMPANA: Total economic amount of the items sold by campaign's type,

IMP_DTO_CONSUMER: Discount amount applied for using VISA Eroski,

IMP_DTO_TRAVEL: Discount amount applied for using loyalty card Travel Club,

IMP_DTO_COUPON: Discount amount applied for the usage of coupons,

IMP_DTO_CUOTA: Discount amount applied for being member of EROSKI Club,

IMP_DTO_ONSITE: Discount amount applied after redemption of loyalty Travel points,

IMP_DTO_OTROS: Other discounts,

IMP_DTO_VALE: Amount of discounts coming from the redemption of a supplier coupon,

IMP_CONSUMO_RAP: Special discount applied in the shop,

COD_ART: Article's id,

FLG_TECLA: information about whether the product has been sold by a direct key or not

ANO_OFERTA: year of the offers applied to the order

COD_OFERTA: offer code

COD_TIPO_CENTRO: type of shop (primary/secundary)

FLG_SCANNER: has the product been scanned during the purchase (Y/N)

IMP_PVP_TARIFA: amount of the order if all of the items had been charged to the customer with catalogue prices

CENTERS structure (55 attributes)

COD_LOC: Store's localization id,

COD_PROVIN: Province id,

DESC_LOC: Center's description,

DESC_PROVIN: Province's name,

FLG_PLATAF : Indicator of distribution platform,

FEC_MODIF: Date of last modification,

COD_ZONA: Zone id,

DESC_ZONA: Zone description,

COD_REGION: Region id,

DESC_REGION: Region description,

COD_AREA: Area id,

DESC_AREA: Area's description,

COD_ENSENA: Type of center id,

DESC_ENSENA: Type of center description (Eroski City, Eroski Center…),

COD_NEGOCIO: Store's id,

DESC_NEGOCIO: Store's type,

COD_SOCIEDAD: Type of company,

DESC_SOCIEDAD: Company's description,

COD_GAMA_OBLIG: Code of mandatory catalogue,

COD_FINANZIA: financing code,

DESC_DIRECCION: address,

DESC_POBLACION: location,

FLAG_CUOTA: quota flag,

FEC_INI_LOC: opening date,

FEC_FIN_LOC: closing date,

NUM_CAJAS: number of boxes,

NUM_M2: squared meters of the store,

NUM_M_LINEA: linear meters,

COD_LOC_AME: store code in AME system,

COD_TP_LOC: type of location,

DESC_TP_LOC: description of the type of location,

COD_LOC_PADRE: father location code,

COD_MUNICIPIO: location code,

COD_TP_POTENCIAL: type of potential code,

FEC_ULT_APERTURA : last opening date,

COD_POSTAL: zip code,

COD_AGR_IMP: grouping code,

FLG_CECO_MODELO_COSTES: cost model flag,

LATITUD: latitude,

LONGITUD: longitude,

COD_ISLA: ISLA code,

FLG_LEAN: lean flag,

FLG_TRANSFORMADO: transformed flag,

FLG_PUESTA_PUNTO_PLUS: tunning flag,

COD_NIVEL_ESTR_LOC: code of local structure of sales of the center,

COD_N1: code of the level 1 of the structure of sales of the center,

DES_N1: description of the level 1 of the structure of sales of the center,

COD_N2: code of the level 2 of the structure of sales of the center,

DES_N2: description of the level 2 of the structure of sales of the center,

COD_N3: code of the level 3 of the structure of sales of the center,

DES_N3: description of the level 3 of the structure of sales of the center,

COD_N4: code of the level 4 of the structure of sales of the center,

DES_N4: description of the level 4 of the structure of sales of the center,

COD_N5: code of the level 5 of the structure of sales of the center,

DES_N5: description of the level 5 of the structure of sales of the center,

PRODUCTS structure (79 attributes)

COD_ART: product id,

DESC_ART: product description,

FLG_TECLA: exists a direct key to sell the product or not,

COD_TIPOMARCA: type of brand code,

DESC_TIPOMARCA: description of the type of brand code,

COD_N1_PPAL: Area’s id,

DESC_N1: Area’s description,

COD_N2_PPAL: Section’s id,

DESC_N2: Section’s description,

COD_N3_PPAL: Category's id,

DESC_N3: Category's description,

COD_N4_PPAL: Subcategory's id,

DESC_N4: Subcategory's description,

COD_N5_PPAL: Segment's id,

DESC_N5: Segment's description,

FEC_INI_ART: Article start time,

FEC_FIN_ART: Article finishes time,

COD_FORMATO: Format id (KG, Gr, Unities...),

COD_MARCA: Brand's id,

COD_EAN: EAN code,

COD_TALLA: Size code,

DESC_TALLA: Size code description,

COD_COLOR: Colour code,

DESC_COLOR: Colour code description,

COD_PACK : Number of items per pack,

COD_BLOQUEO: has the product blocked for the sales?,

COD_ENS_EROSKI: commercial codification in the Hypermarket,

COD_ENS_CONSUM: commercial codification in the SUPERmarket,

COD_TIPO_FORMATO: unit of measurement (related to COD_FORMATO),

COD_ART_PRIM: father product code,

COD_TIPO_MARCA2: code of EROSKI Brand (only for products belonging to a EROSKI brand)),

DESC_TIPO_MARCA2: description of EROSKI Brand (only for products belonging to a EROSKI brand)),

FEC_ULT_BLOQ: date on which the product was blocked for the sales,

COD_PORCI_CONS: product has info for the consumer related to the number of portions,

DESC_PORCI_CONS: indicator about whether the product has a description for the portions,

CC_CAPRABO: Comercial code of CAPRABO,

COD_CATEGORI_HIP: Category code hypermarket,

DESC_CATEGORI_HIP: Description of the Hypermarket Category,

COD_CATEGORI_SUP: Category code supermarket,

DESC_CATEGORI_SUP: Description of the supermarket Category,

COD_SENSIBI_HIP: SENSIBI code hypermarket, DESC_ SENSIBI HIP: Description of the SENSIBIcode of the hypermarket,

COD_ SENSIBI SUP: Category code supermarket,

DESC_ SENSIBI SUP: Description of the SENSIBIcode of the supermarket,

FLG_COMPRA: indicator about whether the product is for purchasing,

FLG_VENTA: indicator about whether the product is for sales,

COD_FAMILIA: family of the product,

DESC_FAMILIA: description of the family of the product,

COD_AMBITO_EROSKI: Scope code of the product in the hypermarkets,

DESC_AMBITO_EROSKI: Description of the scope of the product in the hypermarkets,

COD_AMBITO_CONSUM: Scope code of the product in the supermarkets,

DESC_AMBITO_CONSUM: Description of the scope of the product in the supermarkets,

COD_CODMARCA: brand code (related to COD_MARCA)

FLG_MMPP: Does the product belong to a EROSKI brand?,

COD_POSICION_MARCA: Maker brand / EROSKI Brand code,

DESC_POSICION_MARCA: Description of the code of maker Brand / EROSKI Brand code,

FLG_SALUD_BIENESTAR: health indicator,

FLG_INNOVACION: innovation indicator,

FLG_GAMA_TURISTICA: tourism product,

FLG_PODER_ADQUISITIVO: indicator about product for customer with a high purchasing power,

FLG_BLOQ_DEFINITIVO: Product definitely blocked,

COD_SUBMARCA: sub-brand code,

DESC_SUBMARCA: sub-brand description

FLG_GAMA_LOCAL: local product,

FLG_GAMA_REGIONAL: regional product,

FLG_PESO_SGA: flag product by weight,

FLG_LIQUIDABLE: flag payable,

FLG_EXDEPRECIACION: depreciation flag,

COD_TP_ART: product type,

DESC TIPO_ARTICULO: description of the product type,

CANTIDAD: number of ítems per lot,

FEC_LANZAM: launch date,

PORC_IVA: VAT rate,

COD_PROVR_GEN: code of generic supplier,

COD_PROVR_TRABAJO: code of work supplier,

NOMBRE: name of the work supplier,

PESO: weight (in grams),

PESO_NETO: net weight (in grams),

VOLUMEN: volume (in cm3)

Appendix 3 – Smart Insurance use case dataset structure and description

The datasets provided by the Insurance Company (customer of GFT) are described in the following in terms of tables and records structure and description.

Following the GDPR directive, all sensitive information of the datasets have been anonymized. For the encryption, we used a cryptographic hash function, the MD5 algorithm. It is a unidirectional function different from coding and encryption because it is irreversible. The spread of this encryption algorithm is still widespread (just think that the most frequent integrity check on file is based on MD5). This function takes as input an arbitrary length string and outputs another 128 bit output. The process happens very quickly and the output (also known as "MD5 Checksum" or "MD5 Hash") returned is such that it is highly unlikely to obtain the same hash value in output with two different input strings.

We have modeled the length of the encrypted string, based on the length of the field to be encrypted. For example, for the tax code the encrypted string is 16 characters, while for the license plate it is 8 characters. This eliminates the possibility of tracing back to the initial value. We have performed several decrypting tests present on numerous online sites and no one has been able to decrypt the string entered.

Furthermore, we have carried out a univocal check of all the encrypted keys, so that the possibility of two different string yielding identical encrypted strings is excluded.

In the following, the datasets tables and records are described. The fields highlighted in blue have been anonymized as explained above.

ana

****

id_univoco_anagrafica	string	Flow unique identifier: REGISTRY
id_univoco_master	string	
codice_fiscale	string	Subject unique identifier
tipo_anagrafica	string	Registry type (P = person, N = company)
cognome	string	Surname / company name
nome	string	Name
sesso	string	Gender (M=male, F=female, N=company)
pubblica_amministrazione	string	Public Administration (YES/NO)

ana_ptf

****

codice_fiscale	string	Subject unique identifier
idpolizza	string	Policy unique identifier
ruolo	string	Subject role
cognome	string	Surname / company name
nome	string	Name

ana_sin

****

id_univoco_anagrafica	string	Flow unique identifier: REGISTRY
id_univoco_master	string	
codice_fiscale	string	Subject unique identifier
idsinistro	string	Claim unique identifier
ruolo	string	Subject role
cognome	string	Surname / company name
nome	string	Name

ana_vei

****

codice_fiscale	string	Subject unique identifier
targa	string	License plate
cognome	string	Surname / company name
nome	string	Name

anaage

****

codice_fiscale	string	Subject unique identifier
agenzia	string	Agency ID
descrizione	string	Description

anaaia

****

codice_fiscale	string	Subject unique identifier
codice_anomalia	string	Anomaly identifier

anabds

****

codice_fiscale	string	Subject unique identifier
bds	bigint	
p1	bigint	
p2	bigint	
p3	bigint	
p4	bigint	
p5	bigint	
p6	bigint	

anacci

****

codice_fiscale	string	Subject unique identifier
tipo_assicurazione	string	Insurance type
ente_comunicante	string	Communicating entity
data_infortunio	string	Accident date
luogo_infortunio	string	Accident place
lesione_1	string	Injury nr 1
lesione_2	string	Injury nr 2
lesione_3	string	Injury nr 3
lesioni_ulteriori	string	Other Injuries
percentuale_inabilita	double	Disability percentage
data_decesso	string	Date of death

anacnt

****

codice_fiscale	string	Subject unique identifier

tipo_contatto	string	Contact type
contatto	string	Contact

anacontatori

****

codice_fiscale	string	Subject unique identifier
portafoglio	bigint	Total insurance policies number
portafoglio_auto	bigint	Auto insurance policies number
portafoglio_re	bigint	Elementary branches insurance policies number
portafoglio_vita	bigint	Life insurance policies number
portafoglio_cauzioni	bigint	Deposits policies number
sinistri_aperti	bigint	Open claims number
veicoli_attivi	bigint	Insured vehicles number

anafid

****

codice_fiscale	string	Subject unique identifier
tipo_soggetto	string	Subject type

anaind

****

codice_fiscale	string	Subject unique identifier
comune	string	Subject main address, city
provincia	string	Subject main address, province
nazione	string	Subject main address, country
flag_principale	string	

analnkcnt

****

tipo_contatto	string	Contact type
contatto	string	Contact
codice_fiscale_a	string	Subject unique identifier a
codice_fiscale_b	string	Subject unique identifier b

crvdlnk

****

partita_iva	string	VAT number
codice_fiscale	string	Subject unique identifier
denominazione	string	Subject / company name
cognome	string	Surname / company name
nome	string	Name

crvdsem

****

codice_fiscale	string	Subject unique identifier
semaforo	string	Traffic light

ptf

****

idpolizza	string	Policy unique identifier
agenzia	string	Agency ID
descrizione_agenzia	string	Agency description
provincia_agenzia	string	Province of the agency
ramo	string	Policy branch
tipo_polizza	string	Policy type (Individual / Collective)
stato_polizza	string	Policy state (Active/ Canceled / Suspended)
stato_coass	string	No coinsurance / Our delegation / Delegation
codice_prodotto	string	Product Code-Product Description
prodotto	string	Product
data_effetto	string	Policy effective date
data_scadenza	string	Policy effective deadline
premio	double	Policy premium

ptf_gar

****

idpolizza	string	Policy unique identifier
codice_prodotto	string	Product Code-Product Description

prodotto	string	Product
desurec	string	Insurance guarantee description
garanzia	string	Insurance guarantee code

sin

****

idsinistro	string	Claim unique identifier
idpolizza	string	Policy unique identifier
data_sinistro	string	Claim occurrence date (Format: YYYY-MM-DD)
ora_sinistro	string	Claim occurrence time (Format: HH: MM)
tipo_sinistro	string	Accident type (RCA / ARD / RE)
tipo_danno	string	Damage reported type (1 = THINGS / 2 = PEOPLE / 3 = MIXED)
tipo_gestione	string	Claim management type
flag_autorita_presenti	string	Authority flag present (S - Yes, N - No)
stato_sinistro	string	Accident status
data_definizione_sinistro	string	Claim closing date (Format: YYYY-MM-DD)
numero_veicoli	bigint	Vehicles involved number
comune	string	Claim occurrence address, city
provincia	string	Claim occurrence address, province
pagato	double	Paid
riservato	double	Reserved
data_denuncia	string	Claim complaint date (YYYY-MM-DD)

sinantifrode

****

idsinistro	string	Claim unique identifier
semaforo	string	Traffic light
verifica	string	Verification
note_verifica	string	Verification notes
approfondimento	string	Deepening
note_approfondimento	string	Deepening notes
antifrode	string	Anti fraud

sinantifrodectl

****

idsinistro	string	Claim unique identifier
controllo	string	Check

vei

****

targa	string	License plate
marca	string	Vehicle brand
modello	string	vehicle model
tipo_veicolo	string	Vehicle type
tipo_targa	string	License plate type
data_immatricolazione	string	Matriculation date

vei_ptf

****

targa	string	Vehicle identifier
idpolizza	string	Policy unique identifier

vei_sin

****

targa	string	Vehicle identifier
idsinistro	string	Claim unique identifier

Open datasets

OD_Caratt_Geo_Morf_Comuni (OD Geo Morphological Municipalities Features)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
comune	nvarchar	city

aree a pericolosità idraulica bassa (kmq)	float	low hydraulic hazard areas
aree a pericolosità idraulica media (kmq)	float	medium hydraulic hazard areas
aree a pericolosità idraulica elevata (kmq)	float	high hydraulic hazard areas
area di attenzione pai - aa (kmq)	float	attention area PAI
area a pericolosità da frana pai moderata - p1 (kmq)	float	moderate landslide hazard area PAI - p1
area a pericolosità da frana pai media - p2 (kmq)	float	medium landslide hazard area PAI - p2
area a pericolosità da frana pai elevata - p3 (kmq)	float	high landslide hazard area PAI - p3
area a pericolosità da frana pai molto elevata - p4 (kmq)	float	very high landslide hazard area PAI - p4
provincia	nchar	province

OD_Classificazione_Sismica_Province (OD Province Seismic Classification)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
Regione	nvarchar	region
Province	nvarchar	province
CodiceIstat	float	Istat code
Denominazione	nvarchar	name
Classificazione2015	int	classification 2015

OD_Codifica_Comuni_Province (OD Coding Municipalities Provinces)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
comune	nvarchar	city
provincia	nvarchar	province
sigla	nvarchar	acronym

OD_Elenco_Cod_Province (OD Province Codes List)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
codreg	float	region code
regione	nvarchar	region
codice	float	code
sigla	nvarchar	acronym
provincia	nvarchar	province

OD_Immatricolazioni_Auto (OD Car registrations)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
Provincia	varchar	province
Regione	varchar	region
Classe di cilindrata	varchar	displacement class
Numero veicoli	varchar	number of vehicles

OD_Inail_Dati_Infortuni (OD Inail Accident Data)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
DataRilevazione	varchar	Detection Date
DataProtocollo	varchar	Protocol date
DataAccadimento	varchar	Occurrence date
DataDefinizione	varchar	Definition date
DataMorte	varchar	Death date
LuogoAccadimento	varchar	Occurrence place
IdentificativoInfortunato	varchar	Injured ID
Genere	varchar	Gender
Eta	varchar	Age
LuogoNascita	varchar	Place of birth
ModalitaAccadimento	varchar	Happening mode
ConSenzaMezzoTrasporto	varchar	With Without Means Of Transport
IdentificativoCaso	varchar	Case ID
DefinizioneAmministrativa	varchar	Administrative Definition
DefinizioneAmministrativaEsitoMortale	varchar	Administrative Definition Mortal Outcome
Indennizzo	varchar	Compensation
DecisioneIstruttoriaEsitoMortale	varchar	Investigative Decision Mortal Outcome
GradoMenomazione	varchar	Degree of impairment
GiorniIndennizzati	varchar	Compensation Days
IdentificativoDatoreLavoro	varchar	Employer ID
PosizioneAssicurativaTerritoriale	varchar	Territorial Insurance Position
SettoreAttivitaEconomica	varchar	Economic Activity Sector
Gestione	varchar	Management
GestioneTariffaria	varchar	Tariff management
GrandeGruppoTariffario	varchar	Large Tariff Group

OD_Istat_Dati_Incidenti_Stradali (OD Istat Road Accident Data)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
Provincia	nvarchar	province
conducente morto	float	dead driver
passeggero morto	float	dead passenger
pedone morto	float	dead pedestrian
totale morto	float	total dead
conducente ferito	float	injured driver
passeggero ferito	float	injured passenger
pedone ferito	float	injured pedestrian
totale ferito	float	total injured
conducente totale	float	total driver
passeggero totale	float	total passenger
pedone totale	float	total pedestrian
totale totale	float	total total

OD_Precipitazioni_Medie_Ultimi_10_anni (OD Average Precipitation Last 10 years)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
Provincia	varchar	province
2009	varchar	year 2009
2010	varchar	year 2010
2011	varchar	year 2011
2012	varchar	year 2012
2013	varchar	year 2013
2014	varchar	year 2014
2015	varchar	year 2015
2016	varchar	year 2016
2017	varchar	year 2017
2018	varchar	year 2018

OD_Reati (OD Crimes)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
POS#	float	pos#
PROVINCIA	nvarchar	province
NUMERO REATI	float	number of crimes
OGNI 100mila ABITANTI	float	every 100000 inhabitants
VAR# % ANNUA	float	annual percentage change

OD_Reati_altri_delitti (OD other crimes)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
POS#	float	pos#
PROVINCIA	nvarchar	province
NUMERO REATI	float	number of crimes
OGNI 100mila ABITANTI	float	every 100000 inhabitants
VAR# % ANNUA	float	annual percentage change

OD_Reati_Associazione_per_delinquere (OD Criminal association)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
POS#	float	pos#
PROVINCIA	nvarchar	province
NUMERO REATI	float	number of crimes
OGNI 100mila ABITANTI	float	every 100000 inhabitants
VAR# % ANNUA	float	annual percentage change

OD_Reati_Associazione_tipo_mafioso (OD Mafia type association)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
POS#	float	pos#
PROVINCIA	nvarchar	province
NUMERO REATI	float	number of crimes
OGNI 100mila ABITANTI	float	every 100000 inhabitants
VAR# % ANNUA	float	annual percentage change

OD_Reati_Furti (OD theft crimes)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
POS#	float	pos#
PROVINCIA	nvarchar	province
NUMERO REATI	float	number of crimes
OGNI 100mila ABITANTI	float	every 100000 inhabitants

VAR# % ANNUA	float	annual percentage change

OD_Reati_Furti_Autovetture (OD car theft offenses)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
POS#	float	pos#
PROVINCIA	nvarchar	province
NUMERO REATI	float	number of crimes
OGNI 100mila ABITANTI	float	every 100000 inhabitants
VAR# % ANNUA	float	annual percentage change

OD_Reati_Furti_Con_Strappo (OD Theft Crimes With Tear)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
POS#	float	pos#
PROVINCIA	nvarchar	province
NUMERO REATI	float	number of crimes
OGNI 100mila ABITANTI	float	every 100000 inhabitants
VAR# % ANNUA	float	annual percentage change

OD_Reati_Furti_in_abitazioni (OD Thefts in homes)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
POS#	float	pos#
PROVINCIA	nvarchar	province
NUMERO REATI	float	number of crimes
OGNI 100mila ABITANTI	float	every 100000 inhabitants
VAR# % ANNUA	float	annual percentage change

OD_Reati_Furti_in_esercizi_commerciali (OD Thefts in commercial establishments)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION

POS#	float	pos#
PROVINCIA	nvarchar	province
NUMERO REATI	float	number of crimes
OGNI 100mila ABITANTI	float	every 100000 inhabitants
VAR# % ANNUA	float	annual percentage change

OD_Reati_Furto_con_destrezza (OD Theft With Dexterity)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
POS#	float	pos#
PROVINCIA	nvarchar	province
NUMERO REATI	float	number of crimes
OGNI 100mila ABITANTI	float	every 100000 inhabitants
VAR# % ANNUA	float	annual percentage change

OD_Reati_Incendi (OD fire crimes)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
POS#	float	pos#
PROVINCIA	nvarchar	province
NUMERO REATI	float	number of crimes
OGNI 100mila ABITANTI	float	every 100000 inhabitants
VAR# % ANNUA	float	annual percentage change

OD_Reati_omicidi (OD homicidal offenses)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
POS#	Float	pos#
PROVINCIA	Nvarchar	province
NUMERO REATI	Float	number of crimes
OGNI 100mila ABITANTI	Float	every 100000 inhabitants
VAR# % ANNUA	Float	annual percentage change

OD_Reati_omicidi_consumati (OD homicidal crimes committed)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
POS#	float	pos#
PROVINCIA	nvarchar	province
NUMERO REATI	float	number of crimes
OGNI 100mila ABITANTI	float	every 100000 inhabitants
VAR# % ANNUA	float	annual percentage change

OD_Reati_rapine (OD robbery crimes)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
POS#	float	pos#
PROVINCIA	nvarchar	province
NUMERO REATI	float	number of crimes
OGNI 100mila ABITANTI	float	every 100000 inhabitants
VAR# % ANNUA	float	annual percentage change

OD_Reati_Reciclaggio_impiego_denaro (OD Money laundering crimes)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
POS#	float	pos#
PROVINCIA	nvarchar	province
NUMERO REATI	float	number of crimes
OGNI 100mila ABITANTI	float	every 100000 inhabitants
VAR# % ANNUA	float	annual percentage change

OD_Reati_Stupefacenti (OD Narcotic offenses)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
POS#	float	pos#
PROVINCIA	nvarchar	province
NUMERO REATI	float	number of crimes
OGNI 100mila ABITANTI	float	every 100000 inhabitants
VAR# % ANNUA	float	annual percentage change

OD_Reati_Tentati_Omicidi (OD Murder Attempted Offenses)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
POS#	float	pos#
PROVINCIA	nvarchar	province
NUMERO REATI	float	number of crimes
OGNI 100mila ABITANTI	float	every 100000 inhabitants
VAR# % ANNUA	float	annual percentage change

OD_Reati_Truffe_frodi_informatiche (OD Computer fraud scams)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
POS#	float	pos#
PROVINCIA	nvarchar	province
NUMERO REATI	float	number of crimes
OGNI 100mila ABITANTI	float	every 100000 inhabitants
VAR# % ANNUA	float	annual percentage change

OD_Reati_Usura (OD Wear offenses)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
POS#	float	pos#
PROVINCIA	nvarchar	province
NUMERO REATI	float	number of crimes
OGNI 100mila ABITANTI	float	every 100000 inhabitants
VAR# % ANNUA	float	annual percentage change

OD_Reati_Violenze_sessuali (OD Sexual Violence Offenses)

****

COLUMN_NAME	DATA_TYPE	DESCRIPTION
POS#	float	pos#
PROVINCIA	nvarchar	province
NUMERO REATI	float	number of crimes
OGNI 100mila ABITANTI	float	every 100000 inhabitants
VAR# % ANNUA	float	annual percentage change