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**INFO - H - 515**

2018 - 2019

3 May 2019

Big Data – Data Management Part

Project Assignment - Phase I

**Introduction**

The project for the course on Big Data is split into two parts. For this first part, students are required to design a Big Data Management Pipeline that is to be used for storage and management of sensor data as well as the computation of batch and streaming queries. The second phase will consist of applying Machine Learning methods on the collected data in order to build a predictive model.

**BDMA architecture**

Our smart city consists of a total of 10,000 locations in which 100,000 sensors were dispersed. As mentioned in the assignment, every sensor emits a reading approximately every 30 seconds. In other words, in a live context, the architecture should expect over 3,000 readings every second. Consequently, our use-case has immense data velocity. We assume our sensors are part of a very well-maintained network and do not emit faulty readings in such a way that previously recorded data is to be altered.

1. Characteristics of a BDS

As a refresher, here are the properties of a BDS (obtained from the course):

* Robust and fault-tolerance
* Scalable
* Low latency answering of pre-defined queries
* Support ad-hoc querying
* Low-latency updates
* Extensible/general
  1. Robustness and fault-tolerance

We mentioned previously that an assumption of our use-case is that our sensors are part of a well-maintained network. In case of any malfunction of a sensor, it is assumed to stop emitting data. If one was to assume that malfunctions would result in the emission of unprobeable readings, the system would compute wrong statistics about the network (robustness remains, but faults are introduced). All readings emerge from IoT devices that automatically measure and send the data. As this data is assumed to be correct and about a specific time, we are not confronted with possible mutability issues (data is immutable from start).

However, the sample of readings that was provided for this assignment shows that it is possible sensor-values are missing in the readings. In this case, the system avoids any errors by simply omitting these readings. By doing so, fault-tolerance is ensured.

* 1. Scalability

In any professional implementation project, it is important to consider possible scaling of the infrastructure and associated problem. From an external point of view, the use case can scale in several ways: more sensors could be fitted into spaces, more spaces could be added in our municipalities, the project could be extended to reach municipalities outside Brussels, etc.

Due to the fact that new spatial information can quickly be introduced into the system, structural issues are very small. Indeed, such operations solely require the assignment of new IDs to sensors and spaces, **a mapping between sensors and spaces** as well as a mapping between spaces and municipalities. If the project extends outside Brussels, more complicated modifications have to occur as the assumption that any municipality is located within Brussels will no longer hold.

From an architectural point of view, one should ensure new incoming data is handled adequately. As the format of information would not be altered by scaling the project, it all comes down to the frequency of incoming messages. Indeed, an increased frequency will increase the load on the system. Hence, one must assure computational power as well as data management techniques are suited to this frequency. By correctly constructing the original data architecture, scalability of this element should not be too complicated.

* 1. Low latency answering of pre-defined queries

The project describes three different queries that are to be implemented. These form the set of pre-defined queries of the system. As we assume the data comes in a streaming fashion, elements of the stream will be separated in several batches that are analyzed separately before storing the associated result. It comes without surprise that these results form the core of the dashboard and will need to be computed and displayed with low latency.

* 1. Ad-hoc querying

Our smart city project enables the user to consult data that was produced by the three queries that are to be implemented. However, the user might like to consult information according to a particular granularity in time and space. The rendering of these statistics relies on ad-hoc queries of previously computed data.

* 1. Low latency updates

Users that consult the dashboard will not want to wait an hour before having any information visible or obtain updates on related information. Consequently, the system must provide information on regular basis to update the data displayed in the dashboard. As the assignment mentions each sensor emits readings with averaged intervals of 30s, data of the dashboard will be updated following the same interval.

* 1. Extensible/General

Extensibility or generality of a project is related to the previously described structural scaling. Indeed, for the system to be as general as possible, assumptions that are made cannot be too closely related to the current state of the project. In our, this means a loss of generality exists when computations are specifically aimed towards a particular municipality for instance. Hence, the structure of the system should be such that adding sensors, spaces or maybe even additional municipalities would not impact the functionality of the system.

1. Finding a suitable architecture
   1. Broad description **(overall 1)**

As mentioned previously, we assumed incoming data is immutable. Consequently, the question of defining our architecture relies on what model would be most suitable for the tasks that we would like to perform. In the assignment, these tasks are described in the requirements section. In short, these refer to the possible queries that are to be implemented as well as their granularities in time and space. Additionally, we should consider that data arrives in streaming fashion and needs to be stored afterwards.

The system we have in mind consists of immutable data streaming in every **second**. Subsequently, this data is submitted to queries that will pre-compute useful information. For instance, statistics will be computed on batches and **stored every 30 seconds**. Using the information that was already stored, as well as newly computed information, the dashboard will be able to use precomputed batch views as well as precomputed (near) real-time views to execute the ad-hoc queries.

In more precise terms, incoming data should be stored alongside all other data that will be handled by system. In terms of architecture, this forms the batch layer. Additionally, we want to extract useful information from readings that come streaming in and provide them as support for queries on already collected data. This forms our architectural speed layer. Finally, we would like to gather a series of precomputed views (query results on batches) to ensure disposal over data that can be displayed in the dashboard. This type of mechanism corresponds to a serving layer. Hence, the obtained model can be formalized as a lamda-architecure.

* 1. Why lambda? **(overall 2)**

We are aware of the fact that lambda-architectures are not the only BDMA architectures that exist. In fact, we briefly considered the implementation of a Kappa architecture. Indeed, Kappa architectures essentially function in the same manner Lamba architectures do. The key difference lies within the fact that Kappa architectures omit the batch layer. If our dashboard was not required to be able to access earlier computations (e.g. 10 years back), the Kappa architecture would have been sufficient. Unfortunately, our need for storage and more complete views over the data directed us towards an architecture with batch layer, namely the Lambda-architecture.

Our research has also shown that data lake architectures exist. Contrarily to the currently discussed solutions, data lakes allow storage of structured, semi-structured, and unstructured data. Additionally, data lakes do not use conventional ways of storing data: usually data is stored in files and folders, whereas data lakes provide a flat hierarchy where different records essentially share a common space. Though the principle of these kinds of architecture seems very interesting, we know our data is very structured and, hence, systems designed to store structured data are more suited to our architecture.

* 1. Architecture specificities **(components)**

Data that is transmitted from our sensors to the dashboard is formatted in a particular way (described in the assignment). We assume that sensors will not emit faulty data (such as empty readings) and that data will be sent in chronological order.

The fact that our BDM should be scalable and generalizable will have to be translated into our specificities. Indeed, if one would assume a single ‘client’ could be able to manage all sensor information, the system would suffer when the load increases. Hence, we know that multiple client type workers are required. As we dispose over several types of sensors, we choose to assign one worker to each sensor category. By doing so, we know the model will withstand possible increased loads. Additionally, generalization and scalability are maintained as an increase (decrease) in sensor types can be managed by adding (removing) associated workers. Also, if the load was to increase dramatically, assigning multiple workers to each sensor type would make the overload manageable. All in all, the system would remain scalable.

In terms of implementation, we have opted for Apache Kafka. Indeed, Kafka gives us the possibility to create consumers that obey the “publish-subscribe” message queue paradigm. More precisely, for each sensor type we can instantiate a consumer that will solely consume messages of that type (topic = sensor id). However, dramatical increase in load could result in paradigm shift to a hybrid consumption model (with consumer groups). If this is the case, some modifications in implementation will have to be carried out.

Scalability is enforced by Kafka through partitioning of topics. Aside from a scalability, opting for Kafka also makes querying lighter: most queries will not require data from all types of sensors, but rather only a given sensor type. Consequently, having access to consumption per sensor type is very advantageous in such conditions. Kafka’s implementation is also very beneficial to increase fault-tolerance. Indeed, as partitions can be replicated, the probability of faults occurring diminishes. Topics themselves are not fully managed by Kafka. In reality, Kafka builds on Apache Zookeeper that essentially acts as a centralized service that provides all necessary operations to manage our topics as well as their distribution and synchronization.

Managing streaming data will be done using the Spark Streaming framework. This framework will enable us to collect short-span data to subsequently produce RDDs. A great advantage of using this mini-batch method is that we can handle multiple data instances simultaneously, as opposed to one-by-one management.

There does exist alternatives to Spark Streaming to handle incoming data streams. For instance, the same company created Apache Storm. The main difference between the two frameworks is that the latter processes data in real-time, whereas the former introduces a small delay between arrival and processing of data. However, it is precisely that delay that makes it possible for Spark Streaming to satisfy the *exactly once* in normal conditions and *at least once* conditions in less favorable conditions.

**Queries**

1. Basic statistics

The first query requires computation of basic statistics about the sensor readings (per type of sensor). These basic statistics are the minimal reading, the maximal reading and the average reading. As the smart city that yields readings is hierarchical (space < municipality < city), the computed statistics are to be made available for each element of each level of the hierarchy. Additionally, these should be computed for several granularities in time.

* 1. Implementation

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1. Characterization of temperature timeslots

For every temperature sensor, the second query should characterize every 15-minute timeslot into daytime and nighttime temperature. The former is described as an average temperature starting from 19,5°C, whereas the latter is described by any average temperature below this number. Again, characterization of timeslots is to be executed for all possible granularities in space as well as several granularities in time.

* 1. Implementation

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1. Frequent readings in sliding window

The last query computes readings that are frequent on a sliding window of one hour, as well as an estimate of their frequency. For this query, students are allowed to choose their own threshold of what is considered to be frequent. Additionally, the result of the query is allowed to be approximate.

* 1. Implementation

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