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Architecture for Intensive Care Data Processing and Visualization in Real-time

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Abstract

Clinical data is growing every day. Ergo, to treat, store and publish such data is an emergent task. Furthermore, analysing data in real-time using streaming and processing technologies and methods, in order to obtain quality data, prepared to support decision making is of extreme value. Big Data emerged with the introduction of real-time processing, thus revolutionizing traditional technologies and techniques through the ability to deal with the volume, speed and variety of data. Countless studies have been proposed in the healthcare domain in search of solutions that allow the flow of data in real-time. However, the work presented hereby is distinguished by allowing the collection, processing, storage and analysis of Intensive Care Units (ICU) data, both collected in real-time from bedside monitors but also stored in a historical repository. The architecture proposed makes use of current technologies, like Nextgen Connector as message supplier and integrator, Elasticsearch as a search index, Kibana for viewing stored data and Grafana for real-time streaming. This article is part of the ICDS4IM project - Intelligent Clinical Decision Support in Intensive Care Medicine to support the experimentation of data processing techniques and technologies, based in HL7 format and collected in real-time so that it can be made available through Health Information Systems across the healthcare institutions.

Keywords: Real-time data processing; Real-time data Visualization; Decision Support Systems; Big Data

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1. Introduction

The task of analysing data that arises from UCI bedside monitors is of vital interest, not only for real-time decision making but also to support a wide variety of medical and health functions, including support for disease surveillance and health management of the unities [1]. However, with the current bloom in healthcare devices and information systems, made healthcare data not only much larger, but also much more difficult to manipulate and process. In addition, as data is created from a variety of devices in a short time, the characteristics of that data are stored in different formats and created quickly, which can, to a large extent, be considered a large volume problem of data [2].

ICDS4IM - Intelligent Clinical Decision Support System for Intensive Medicine is a global multidisciplinary project which aims to extend the actual state of the art to support clinical decision-making. Indeed, it is intended to use intelligent agents to perform several tasks automatically and add the usage of Data Mining techniques to make predictions and assist health care providers in the process of decision-making [3]. This work is based on the architecture proposed before by Peixoto et al in [3]. One of the most remarked advantages of Decision Support Systems, undeniably, is turning the decision-making process faster and more accurate, leading to less mistakes and better decisions [4]. In many clinical information systems today, semantically normalized and aggregated clinical data is not available and/or is not uniform enough to allow sharing across platforms or networks. This can result in medical errors, diagnoses and treatments based on incomplete knowledge of patient histories or vital data, harmful drug interactions, redundant tests, and other unnecessary admissions. The motivation to provide real-time information on the status of patients increases the quality and efficiency of care is one of the bases of this project.

This work presents an architectural sketch based on Nextgen Connector, Elasticsearch, Kibana, Grafana, communication and containerization standards. More specifically, the integration of data from bedside monitors, which are the source of architectural information, which serves as the basis for the Knowledge Discovery and Decision Support System developed, which can assist Intensive Care professionals in making decision-making, based on more reliable information [3]. The purpose of this solution is to use technologies that allow visualization of data in real-time through a simple interface, responding to the need for health professionals to obtain updated data, prepared to support immediate decision making. This manuscript is divided into five sections, beginning with this introduction, followed by the approach to Health Information Systems and to Big Data in healthcare domain, since they are two themes inherent to this area of activity due to the variety and quantity of data. Section three describes the main tools used and their part in the overall process. Subsequently, section four, entitled ICDS4IM, presents the technical description of the project, and the proposed architecture. Moreover, a SWOT analysis is used to present the strengths, weakness, opportunities and threats. The manuscript ends with the main conclusions and future work.

2. Background

2.1. Health Information Systems

Healthcare is turning into a science based on information and reputation [4]. In the last decade, information systems in healthcare have gained great importance and have grown in quality and in quantity [5]. Information demands within the healthcare industry range from clinically valuable patient-specific information to a variety of aggregation levels for statistical and/or quantifiable monitoring and reporting. Gathering this information and presenting it in a legible way to doctors is an interesting task [6]. Health information systems are increasingly their potential and becoming an instrument of fundamental importance for the development of health information strategies, both from the point of view of institutions but more important for citizens. This importance reaches different perspectives, assuming responsibility for the provision of health care and for the governance of health systems, for health promotion and disease prevention, as well as for those who interact with the system within the scope of its dynamics [7]. Nowadays, institution's information systems fluctuate from departmental solutions that cover the main goals of a single department to cross domain institution Patient Health Records [5].

2.2. Big Data in the healthcare domain

With the exponential increase in the volume of data, the Big Data concept appears to describe large data sets. The volume and variety of data (structured, semi-structured or unstructured) and complex associated with the Big Data phenomenon poses new challenges, as they result from the widespread use of sensors, smart devices and other technologies [8]. This data requires the use of powerful computational technologies and techniques to unravel trends and patterns [9]. While the Big Data theme is predominantly practice-oriented, organizations are exploring how a large volume of data can be useful in creating and capturing value for individuals, communities, communities and governments [10].

The health sector has historically generated a large amount of data, driven by record keeping, compliance, regulatory requirements, and patient care. Since most of the data was stored in hard copies, the trend now is to digitize most of the information. The health sector was driven by the potential to improve the quality of health care delivery, while addressing an economic perspective with reduced costs. Analysis of huge amounts of data are intended to support a wide variety of medical and health functions, including clinical decision support, disease surveillance and population health management [11]. The enormity and complexity of these data sets present great challenges in the analyses and applications after a practical clinical environment [12].

2.3. Case study – Sepsis Watch

Doctors seek to respond to changes in the user's condition through the information they receive. To help doctors make their decision, FHIR applications have been created that allow doctors to recognize a change in patient levels, such as the Sepsis Watch where predictive analysis is being used to help make the diagnosis earlier. FHIR is a standard for healthcare interoperability introduced by HL7 [13]. The need to have access to current and past clinical data of the user, through the electronic health record integrated in an FHIR application led to the creation of Sepsis Watch, an FHIR application that foresees changes through six variables that can be indicators of the beginning of Sepsis. The goal is a multiplatform in the Sepsis forecast that works with any integrated electronic health record activated by FHIR. With the critical importance of today, this FHIR application interfaces with the electronic health record in real-time with users, calculates the score in relation to Sepsis based on the machine learning algorithm, in order to alert the medical team through an interface interactive visual [13].

3. Technologies and Tools

Nextgen Connect - this integration mechanism uses a channel-based architecture, which allows connection to both sources and different destinations. Nextgen Connect has several types of inputs such as TCP channel, file read / write, database read/write and, most importantly, allows the use of JavaScript language not only in the input as in the output, but also in the intermediate transformations [14]. In this context, ICDS4IM explores the reception and sending features of TCP, where messages can be filtered, forwarded, or transformed based on predefined rules. Used as a specific layer in the new architecture presented in this work, it will be integrated with the Elasticsearch index to store data. The captured data stores messages with various information of the user and chosen, and it is in Mirth Connect where they are selected and transformed as desired variables. The data is captured quickly, with its original structure so that its format (HL7), subsequently requires the transformation of them to the JSON format, before sending to the target technology, in this case Elasticsearch.

Elasticsearch - has a comprehensive REST-based API that allows you to monitor and control all aspects of a cluster configuration. It provides endpoints to perform creation, retrieval, update and delete (CRUD) operations on data stored through HTTP API calls. To some extent, Elasticsearch can be used like any other NoSQL data store [15]. Elasticsearch is a document-oriented database, which means that it stores entire objects or documents. Not only does it serve as a data storage technology, it also indexes the content of each document to make it navigable. In Elasticsearch it is possible to index, search, classify and filter documents, so it uses a different way to think about the data and is one of the reasons that allows complex text searches [16]. With document-oriented databases like Elasticsearch, mappings and storage in documents are designed so that they are optimized for quick search and retrieval [17]. In this sense, this technology presents several advantages in its use within the scope of this project.

Elasticsearch through its search engine facilitates the collection of the index created in Mirth Connect. This index is an index per episode, that is, an Elasticsearch index is created where it is identified with the user's id, where each user has an id, making the episode unique and associated with each user. The index is created and sent to Elasticsearch, where each user's observations will be associated with their id. In this episode, all the variables measured to the user are found in that time stamp.

Kibana - is an open-source front-end application that works with Elastic Stack, providing search and visualization capabilities for indexed data in Elasticsearch. Known as the graphics tool for the Elastic Stack, Kibana acts as the user interface to monitor, manage and protect an Elastic Stack cluster, in addition to being the centralized hub for integrated solutions developed on the Elastic Stack. Kibana has grown to become the access window to the Elastic Stack itself, offering a portal for users [17]. Kibana's tight integration with Elasticsearch allows you to view indexed data in Elasticsearch and analyse the data by creating bar graphs, pie charts, tables, histograms, and maps. A dashboard view combines these visual elements to be shared via the browser and provide real-time analytical views of large volumes of data to support use cases [17]. Kibana was designed as a visualization platform for Elasticsearch providing a web-based interface for searching, viewing and analysing data stored in the Elasticsearch cluster [14]. Although Kibana allows the visualization of data in real-time, in this project it will be used to consult stored data where they can be performed in real-time.

Grafana - is an open-source visualization and analysis software that allows you to consult, visualize, alert and explore your metrics, regardless of where they are stored. It provides tools to transform data from the time series database into graphs and visualizations [18]. Grafana allows you to explore the data through ad-hoc queries and dynamic detail. Allows viewing and comparing different time intervals [18]. With Grafana it is also possible to send alerts through several different alert notifiers, including PagerDuty, SMS, e-mail, VictorOps, OpsGenie or Slack, and it is also possible to create different notifiers by visually defining the alert rules for the most important metrics [18]. The process after storing the index in Elasticsearch, with the array of user values goes through sending the index to Grafana, so that it is possible to view user data in real-time. Through the various options of data sources provided by Grafana, it is possible to add the source as the Elasticsearch index directly in Grafana, characterized by the ability to represent time series, a sequence of measurements, ordered by time.

4. ICDS4IM - Real-time visualization and processing architecture

In Figure 1, it is possible to see the proposed architecture with the technologies that integrate this project for the visualization of monitored data in real-time. This work presents the “Data Storage”, “Permanent Data Visualization” and Real-time Monitorization” blocks. The choices went through the Elasticsearch search index, and Kibana and Grafana, for viewing stored data and analysing data in real-time, respectively. All the components are held by containers inside a docker hub. The architecture defines the technologies that support the entire process, from data collection to its subsequent analysis and visualization.

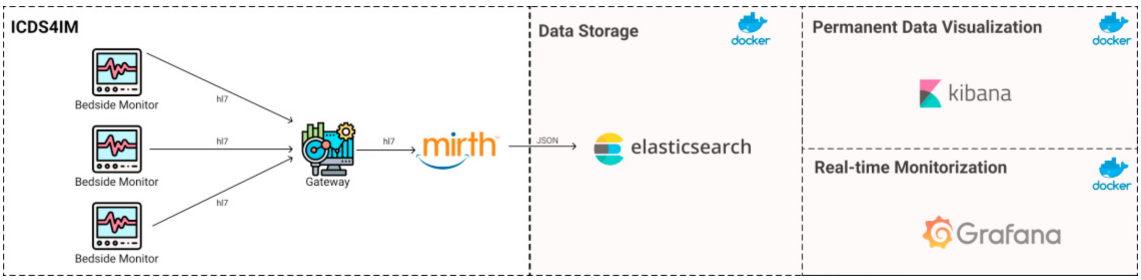

Fig. 1. Real-time monitorization architecture for ICDS4IM.

The data collection technology is Nextgen Mirth Connect, this integration mechanism uses a channel-based architecture, which allows connection to both sources and different destinations. The data, after being collected by the source of the Mirth Connect channel, is transformed into the destination and then sent to Elasticsearch. The use of Elasticsearch allows the creation of indexes in real-time, with possible visualization by Kibana that will be presented by Grafana. Kibana's tight integration with Elasticsearch allows you to view indexed data from Elasticsearch. With Grafana it is also possible to send alerts through several different alert notifiers, including PagerDuty, SMS, e-mail, VictorOps, OpsGenie or Slack, and it is also possible to create different notifiers by visually defining the alert rules for the most important metrics. The real-time monitorization dashboard can be observed in Figure 2. Here one can see measures from bedside monitors such as, blood pressure, systolic and diastolic, O2 saturation, and heart rate. In each chart, a threshold is present, enabling real-time alarms for physicians.

Fig. 2. Patient data visualization in real-time using Grafana

5. Discussion and Swot Analysis

The architecture proposed in this document serves to support the experimentation of data processing techniques and technologies in real-time so that they can be used by machine learning models in decision support, integrating a source of real-time data, collected and sent to the gateway of the ICDS4IM project. The collected data is sent to the gateway and sent to Mirth Connect which allows channelling and quick access to data. In this architecture the data source is through the bedside monitors that send data in HL7 to the gateway. For the visualization and analysis of data, the methods used show great results, and the visualization of data is done in real-time. At this point, a SWOT analysis will be developed in order to assess the use of technologies that allowed the visualization of data in real-time through a simple interface, responding to the need for health professionals to obtain updated data, prepared to support immediate decision-making.

Strengths:

- Easy installation: Easy installation of technologies on servers.
- Real-time: Ability to collect, visualize and analyse data in real-time to support decision making with real information in real-time.
- Flexible architecture: possibility to access a Rest API database and share graphics on web pages.
- Reliable: information is integrated and maintains quality from its source, due to its transparent collection and storage.
- Friendly interface: the solution has the ability to communicate with the user, using a language that is easy to understand.
- Alerts: Ability to alert users if patient measurements are not meeting the outlined requirements.

Weaknesses:

- The use of open-source software can lead to a dependence on the system in sharing and community knowledge.
- Non-automated graphing.

Opportunities:

- Add new features and alerts.

– Market with an increasing importance in support of decision-making in the field of intensive care.
– Possibility to implement the same solution in a different market.

Threats:

– Low adherence by health professionals due to their reticence in adopting decision support systems in their daily process.
– Decrease in investment in health services by the state.

6. Conclusion

The work presented herewith makes it possible to identify technologies that respond best to the communication of monitored signals in patients, to their processing and availability through Clinical Information Systems. Indeed, an architecture is proposed, which allows the processing, storage and availability of patient information through graphics that allow the visualization of data in real-time. Additionally, the proposed architecture enhances the quality of the decisions taken by physicians, which are made with updated information and as quickly as possible. Thresholds are defined and alerts are emitted when reached. The fact that the architecture is flexible and scalable, using a containerized approach, empowers a more complete solution for the context of real-time data visualization in the medical field. Using this architecture as a basis for the implementation of ICDS4IM, it contributes to make patient data available, but more important to serve as foundation for other health areas with real-time processing and visualization needs.

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