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Integrating Healthcare Data for Enhanced Citizen-Centred Care and Analytics

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Abstract. The potential of healthcare systems worldwide is expanding as new medical devices and data sources are regularly presented to healthcare providers which could be used to personalise, improve and revise treatments further. However, there is presently a large gap between the data collected, the systems that store the data, and any ability to perform big data analytics to combinations of such data. This paper suggests a novel approach to integrate data from multiple sources and formats, by providing a uniform structure to the data in a healthcare data lake with multiple zones reflecting how refined the data is: from raw to curated when ready to be consumed or used for analysis. The integration further requires solutions that can be proven to be secure, such as patient-centric data sharing agreements (smart contracts) on a blockchain, and novel privacy-preserving methods for extracting metadata from data sources, originally derived from partially-structured or from completely unstructured data. Work presented here is being developed as part of an EU project with the ultimate aim to develop solutions for integrating healthcare data for enhanced citizen-centred care and analytics across Europe.

Keywords. healthcare, data lake, integration, blockchain, data analytics

1. Introduction

The EU project Serums² addresses a recently exacerbated need - in the presence of a global pandemic - of improving the coordination of healthcare provision across Europe and beyond. As citizens move between countries, their newly produced medical data, including data from personal devices, must be continuously integrated to complement medical records across the countries where they have lived or where they need to be treated. This is essential to guarantee that all required information on a patient is available, and can thus be used to improve the quality of the treatment they receive. This vision requires novel mechanisms to exchange confidential medical records to personalise clinical advice and enhance treatment plans, whilst enabling trust in data security and privacy at all times. In order to be able to integrate personal medical data from multiple sources such as personal healthcare devices, primary, secondary and/or tertiary care, we need a GDPR-compliant solution, which entails a coherent and unified notion of a smart patient health record (SPHR). The integration further requires solutions that can be demonstrated to be secure, including in cases of cross-border processing. This includes

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² For more information please see www.serums-h2020.org.

patient-centric data sharing agreements (smart contracts) on a blockchain, and novel privacy-preserving methods for extracting metadata from data sources, originally derived from partially-structured or from completely unstructured data. Some aspects of our work within Serums are described next.

2. Methods

A data lake is a universal data storage space which in our context is used for any healthcare data gathered from various healthcare providers and devices [6]. One advantage of a data lake is that it scales with ease, and its usage can range from simple storage, to a base from which to run analytics or big data processing, and machine learning (ML) at scale. A data lake consists of different zones (workspace, raw, structured, curated, consumer, analytic and trash) depending on the pre-processed state of the data it contains, and is responsible for carrying out data processing activities such as Retrieve, Assess, Process, Transform, Organise and Report (R·A·P·T·O·R). The R·A·P·T·O·R processing pipeline autocoder is scalable and a very efficient way of processing large amounts of data. It transforms the data according to a standard structure where data is classified into five groups: Time-Person-Object-Location-Event $(T \cdot P \cdot O \cdot L \cdot E)$, forming what is known as a data vault model within the curated data lake zone. This model enables the standardisation of all data into an expandable hyperscalable structure that can load any kind of health or social care related data. This makes the process of combining varied data sources easier as well as the ability to gain new insights from considerably more data through data analytics and machine learning (in the respective analytic zone).

To address security concerns, the Serums tool-chain [3] makes use of a blockchain to control data access through well defined rules. Rules can, for instance, limit what patient data can be seen by who and when, and encrypted logs are kept on every attempt to access patient records. Access within EU countries (Serums Use Cases [3]) is controlled under the General Data Protection Regulation (GDPR³) using smart contracts. For authenticated users, the blockchain controls the data that can be shown to the user, and the extraction is obtained from the $T \cdot P \cdot O \cdot L \cdot E$ data lake. User-friendly interfaces are coded to enable the security and data visualisation features with language translation based on the users' profile. The medical data is shown in its original language.

Figure 1 shows a general overview of the Serums project components [1]. Patients and healthcare providers interact with the system through the front end (Serums Web Interface) which communicates with a backend (Serums API) responsible for managing the integration of all components including authentication (refer to [2]), blockchain and data lake modules.

³ Information on GDPR can be found at https://gdpr-info.eu/

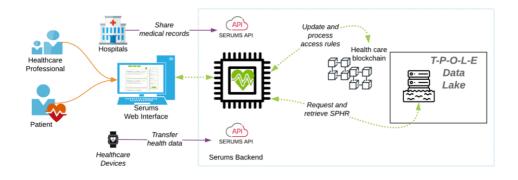




Figure 2 shows how the $T \cdot P \cdot O \cdot L \cdot E$ data lake expands to hubs, links and satellites to enable the effective and efficient storage of the health and social care data into a globally universal data storage. The $T \cdot P \cdot O \cdot L \cdot E$ model has the potential to resolve many challenges including the one identified in [4] on bringing together multiple sources of information on medications to provide a so-called My Medication Passport (MMP) for patients. Studies have shown that MMPs help patients understand their medications and promote adherence [5] contributing to an improved quality of life. The flexibility of the $R \cdot A \cdot P \cdot T \cdot O \cdot R$ processing on healthcare data lakes and the $T \cdot P \cdot O \cdot L \cdot E$ data vault means that we can combine varied data for a single patient more easily, and we can extract knowledge through analytics which is currently not directly possible. A further benefit is that we are able to bring new data sources into the data lake at all times without conflicting with existing data, as the data within the lake is split into zones.

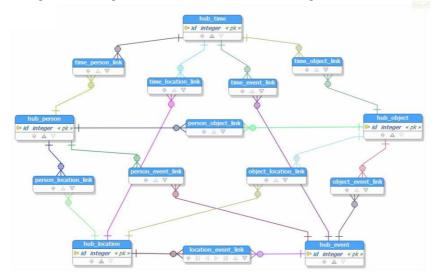


Figure 2. The $T \cdot P \cdot O \cdot L \cdot E$ structure within a data lake

3. Results and Discussion

The integration result is a data lake with advanced analytic capabilities that can handle the complexities of new global healthcare requirements. Data from various data sources enter the $R \cdot A \cdot P \cdot T \cdot O \cdot R$ processing ecosystem and is structured following the $T \cdot P \cdot O \cdot L \cdot E$ model. Within Serums we explore three use cases provided by hospitals in the Netherlands (sensor information on patient mobility for patients that have received a hip replacement), Catalonia (device information to monitor elderly patients with diabetes and cardiovascular disease from home) and Scotland (cancer patients that report daily on their symptoms in between chemotherapy treatments) [3]. The data is stored in a Linux shared file system within the proof-of-concept. The data processing is done using custom Python code. The production grade solution will be secure to deal with personal healthcare data, since each hospital is set up with their own data lake acting as an intermediary between their source systems and the outside world, with only data that the healthcare provider allowed access to being shared with the data lake. Whether, in the future, hospitals adopt cloud based or a physical on-site system depends on both local legislation and hospitals own guidelines. Whichever solution was applied, the repositories would be similarly accessed by the Serums API relying on the authentication module, the blockchain rules, and the basic access controls. In addition, the data lake can grow and further adapt to new health and social care data that is added to it enhancing the information we may have on individual patients, on general cohorts of patients (e.g., cancer patients) and on novel treatments, further improving knowledge we can gain through ML and data analytics. Figure 3 shows the steps in which the data lake interacts with the Serums API to connect and process the data into a SPHR.

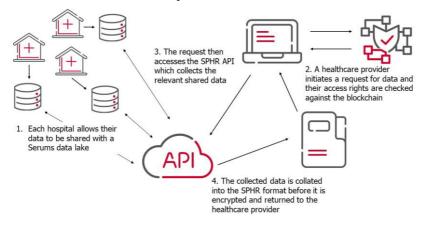


Figure 3. $T \cdot P \cdot O \cdot L \cdot E$ connections

Health and social care providers, in our case three hospitals, share their data with the data lake via a Serums API gateway that was custom build for the proof-of-concept. The providers use a Web Interface (cf. Figure 1) to request the data in accordance with an underlying agreed smart contract data request from the health care blockchain. The $T \cdot P \cdot O \cdot L \cdot E$ data factory then prepares the data and places an encrypted version in the consumer and analytics zone of the data lake ready for the SPHR API gateway to process.

The health and social care providers collect the data via the API gateway after it has been decrypted internally with the keys they receive from the blockchain.

Most healthcare systems today consist of distributed heterogeneous systems that do not necessarily communicate with each other making it very challenging, if not impossible, to readily integrate data from medical practices, hospitals, medical devices, and so on, in real-time and in a straightforward manner. The approach followed in Serums with a healthcare data lake allows us to combine different data sources because they are pre-processed in the same way through the $T \cdot P \cdot O \cdot L \cdot E$ model. The data lake concept thus removes the complexities of healthcare systems while opening novel and unprecedented capabilities to deploy any $T \cdot P \cdot O \cdot L \cdot E$ compliant analytics and ML algorithms to process the data lake at scale.

4. Conclusion

Serums comes with a methodology that can easily be expanded into a global health and social care data model to address current and future requirements to support near-realtime analytics on all citizens. Serums will supply a base model for a selected set of healthcare providers initially (cf. [3] for further details), however, it is not limited to this selection. The vision of Serums is to provide flexible structures which can be expanded to a European-wide solution for integrated medical records accessible anywhere in Europe.

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