RESEARCH

A sample article title

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Abstract

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Introduction

Data and Information modeling in the healthcare domain have witnessed significant improvements in the last decade owing to advances in the development of state-of-the-art information and communication technologies (ICT) and formalization of storage and messaging standards. Subsequently, the scope of Healthcare Management Information Systems (HMIS), medical ontologies, and Clinical Decision Support Systems (CDSS) has broadened, beyond the operational capabilities of traditional rule based systems. One of the major reasons behind this limitation is due to the numerous heterogeneities in healthcare at data, knowledge, and process level. Thus, healthcare interoperability which aims to provide a solution to this problem, can be compartmentalized into data interoperability, process interoperability, and knowledge interoperability. Data interoperability resolves the heterogeneity between data artifacts, to enable, seamless and interpretable communcation among source and target organizations, while preserving the data's original intention during storage, communication, and usage (as defined by IEEE 610.12 [1], Health Level Seven International HL7, and Healthcare Information and Management Systems Society HIMSS [2]). On the other hand, process interoperability regulates the communication among organizational processes to provide compatability between process artifacts within and seamless transformations across different organizations[3]. Lastly, knowledge interoperability provides a sharing mechanism for reusing interpretable medical knowledge, acquired through expert intervention and other mechanisms, across decision support systems [4].

In more tangible terms, healthcare interoperability at data, process, and knowledge level can be exemplified within the healthcare constraints experienced due to the emergence of Covid 19. The operational capabilities of the current healthcare service delivery infrastructure has gone under tremendous stress due to Covid 19. World over, large primary healthcare units have managed to create separate units for managing patients, suffering from extreme cases of the novel coronavirus. For secondary and tertiary care units, government involvement has become necessary to filter coronavirus patients and adhering to a national pandemic response policy. These complex circumstances have enhanced the need for sharing patient data and state-of-the-art medical knowledge in real-time, to provide the medical experts with

a tool to make accurate and timely decisions. Data interoperability can enable the front line medical workers to fetch, understand, and use patient data, especially co-morbidities, across organizational and physical boundaries, without suffering from societal taboos that may prevent the patient from sharing their complete and accurate medical histories. Knowledge interoperability can improve the knowledge acquisition and sharing protocols to provide the medical experts such as epidieo-mologists and vaccinologist, with latest information on affected population trends, disease diagnosis, treatment, and followup procedures, and interpretable decisions leading to positive or negative outcomes. Process interoperability can help reduce and in some cases remove the operational redundancies between health centers. In this way, successive healthcare treatments can take benefit from earlier diagnosis, treatment, and followup procedures, thereby reducing the stress on healthcare experts and systems.

Standards such as HL7 and openEHR provide the foundations for storing and communicating medical data, through the use of well defined protocols such as HL7-FHIR, or the older HL7v2 HL7 v3. While Snomed-CT and LOINC provide a standard definition for clinical terminologies and lab tests, respectively. Similarly Medical Logic Module (MLM) provides a standardized way for expressing medical knowledge. However, the plethora of standards,n necessitates the creation of bridging standards, that can resolve the heterogeniety between medical standards. In this regard, CIMI has

Cimi and Yosemite

Uhp, previous paper

pharmacists and vaccinologists Under these complex circumstances, a technical solution for healthcare interoperability, has become all the more necessary. While the standardization efforts by CIMI, SNOMED-CT, LOINC, yosemite group

Related Work

Althubait et al. [5] proposed an ontology expansion methodology that identifies and extracts new class from text articles using word embedding and machine learning techniques. The authors identified the similarity of tokens and phrases of the text articles with the exiting classes of the ontology. The target ontology is expanded with classes from text articles having greater similarity with that of already added classes. A similar word embedding technique was also used by Nozaki et al. [6], where the authors used instance based schema matching technique to identify the semantic similarity between two instances. The results of the study showed the possibility of detecting similar string attributes of different schemas. Yousfi et al. [7] also utilized semantic base techniques and proposed xMatcher XML schemas matching approach. xMatcher transforms schemas into a set of words, followed by measuring words context, and relatedness score using WordNet. The terms from different schemas having similarities greater or equal to 0.8 are considered similar. Bylygin et al. [8] devised an ontology and schema matching approach by combining lexical and semantic similarity with machine learning approaches. The authors used lexical and semantic measures as features and trained various machine learning algorithms including Naive Bayes, logistic regression, and gradient boosted tree. The result achieved showed that the combination of algorithms outperformed the single modal.

Kersloot et al. [9] performed a comprehensive systematic review to evaluate natural language processing (NLP) algorithms used for clinical text mapping onto ontological concepts. The findings of the studies were evaluated with respect to five categories; use of NLP algorithms, data used, validation and evaluation performed, result presentation, and generalization of results. The authors revealed that over one-fourth of the NLP algorithms used were not evaluated and have no validation. The systems that claimed generalization, were self evaluated and having no external validation.

Content

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In this section we examine the growth rate of the mean of Z_0, Z_1 and Z_2. In addition, we examine a common modeling assumption and note the importance of considering the tails of the extinction time T_x in studies of escape dynamics. We will first consider the expected resistant population at vT_x for some $v > 0$, (and temporarily assume $\alpha = 0$)

$$E\big[Z_1(vT_x)\big] = \int_0^{v \wedge 1} Z_0(uT_x) \exp(\lambda_1)\, du.$$

If we assume that sensitive cells follow a deterministic decay $Z_0(t) = xe^{\lambda_0 t}$ and approximate their extinction time as $T_x \approx -\frac{1}{\lambda_0} \log x$, then we can heuristically estimate the expected value as

$$
\begin{aligned}
& E\big[Z_1(vT_x)\big] \\
&= \frac{\mu}{r} \log x \int_0^{v \wedge 1} x^{1-u} x^{(\lambda_1/r)(v-u)}\, du.
\end{aligned}
\tag{1}
$$

Thus we observe that this expected value is finite for all $v > 0$ (also see [10, 11, 12, 13, 14, 15]).

Appendix

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Acknowledgements
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Abbreviations
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Ethics approval and consent to participate
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Competing interests
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Figures

Figure 1 Sample figure title

Figure 2 Sample figure title

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Tables
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