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A Personalized Decision Support System forHealth care Applications

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ABSTRACT: We recommend to significantly take a look at encouraged remedy suggestions and compare historic treatment data for selected rare and persistentillnesses. As consultant sicknesses we take a look at Glioblastoma Multiforme(mind cancer) which is classified as an extraordinary disorder, and Diabetes Mellitus, that is a nationally and globally large persistent sickness. Agraph model is designed to seize the data bearing on the remedyalternatives and actual treatments administered and in addition analyzed to discover sequential remedy styles based on unique final results class122esprimarily based on durability, complications and many others. The belief of 'Patient Similarity' might be explored to form cohorts of clinically similar patients. Thetreatment patterns might be ranked, and noticeably ranked patterns mightbe ordered depending on anticipated results before being assigned tocohorts of patients. A prototype decision guide machine is planned forrecommending remedy alternatives based totally on a patients clinical and possibly genomic data while available.

KEYWORDS-Graph Data, Sequential Pattern Mining, Patient Similarity.

I. INTRODUCTION

In medical science, decision making is a complextask as it depends on variety of interrelated functions. We are concentrating not only on theaccuracy and prediction of the result, but also onthe interoperability of the result from thephysicians who use Decision Support System(DSS). Making the right decision at right time isthe most important factor in healthcare systems,especially in medical diagnosis systems. The phenomenal growth of technologicaldevelopment in healthcare systems, forces theknowledge corresponding to the diagnosis andadaptation of treatment flow to be recorded by avariety of methods such as Clinical pathways,DSS, Guideline based DSS and so on.

The decisionsupport system is one of the methods widely usedin healthcare systems.Classification plays a vital role in decisionmaking. Decision trees are among theclassification techniques that solve large complexproblems by providing rules in an understandable form. But the rules generated from decision treesdo not work well with continuous attributes.Fuzzy logic system supports uncertain boundaries. The main difficulty arises with aslight change in attribute values, which in turnchanges the sensitivity of decision tree. Crisp setcomprises a function with 0(false) and 1(true),whereas fuzzy set theory contains the elementswith unsharp boundaries, that is, it handles uncertain information.

In order to handle theaforementioned issues, it is necessary to move tofuzzy decision trees.Personalized treatment is an important factorin healthcare systems. The term personalizationrefers to the delivery of right diagnosis andtreatment for every individual patient. Traditional healthcare decision support systemsdo not provide reasoning and mainly focused onintegration of data and knowledge. In order toimprove knowledge representation and reasoningfacility, the ontologies acts as a stepping stone toimprove the healthcare systems.

II. BACKGROUND WORKS

Some work has been executed in the vicinity of developing fashions for predicting remedy plans for patients. Research companies have advanced models to are expecting thevarious drug interventions in addition to tablets coupled with lab interventions that might work nice for a specific ailment. These models do no longer include vital parameters like signs and symptoms, outcomes of investigations, laboratory take a look at results,and so forth and are simplest constrained to predicticting drugs that may be effective [15]. Werecall a completely complete definition of a treatment plan and the methodoutlined formerly would rank the remedy patterns for a given patient, whichimplies selection of medication/interventions, their dosages, their ordering, etc. Basedat the fashions built by way of Kim. Et al (2004) [7] for continual coronary heart failure (CHF)remedy, considerable factors improving the plasma BNP stages had been determined,which were established by way of massive-scale trials. Similar work has been finished in thelocation of heart disease analysis reporting fairly appropriate accuracy [19]. Neuvirth etal (2011) [11] present a prototype for a information-pushed chance evaluation machine forDiabetes patients and claim to become aware of physicians who can supply best careto such sufferers and also pick out sufferers requiring emergency care offerings.

The selection support model evolved via Chen et al(2012) for Diabetes [5] makes use ofa case primarily based reasoning approach to locate affected person cases similar to the only queriedand isn't always very robust for the reason that approach used by authors to find comparable instancesisn't always very granular and in the end the identical line of treatment which is given tothose comparable instances is recommended for the brand new affected person. In our method we willthink about all of the cohorts of patients just like the check affected person after which assign weights to the treatment sample in each cohort, which we trustmight be greater correct than the case primarily based reasoning technique. We considerablytease out the different remedy styles which might be function of a particularoutcome and plan to come up with a significant measure of affected person similarity to construct patient profiles primarily based on scientific and possibly behavioral variables,specifically for diabetes.

Since a well-defined data model is important forthe execution of treatment flow and for thesuccess of semantic web technologies inhealthcare systems, the ontology is used toconstruct the decision support systems. Theterm ontology is taken from philosophy and it isthe knowledge of formal explicit specification witha sharing facility of aggregation. Ontology isconstructed to define properties, attributes andrestrictions corresponding to the concepts. Eachand every entity can be called a class. An attributeof ontology refers to a characteristic of concept orrelationships between concepts. An instance ofontology implies a case of concept.

The SWRL is one of the standard rulelanguages of semantic web, which contributes tothe ability to write Horn-like rules with respect toWeb Ontology Language (OWL) concepts. SWRLrules make three-fold use of the vocabulary ofontology syntactically, semantically andinferentially. SWRL is a combination of RuleMLand OWL ontology and at present it is one of thespecifications of W3C. The rules are used toderive new knowledge from OWL knowledgebases by using inference engine. The Java ExpertSystem Shell (JESS) is a forward chaining inferenceengine developed under Java language at SandiaNational Laboratories, New Mexico. JESS uses thevery efficient Rete algorithm to match the SWRLrules.

III. PROPOSEDWORK

A prototype of the tool is being developed for GBM patients using clinical andgenomic data from a public portal called 'The Cancer Genome Atlas Portal' [10]and cBioPortal [3]. The clinical domain includes demographic information aboutthe patient along with some basic clinical features, e.g Karnofsky performancescore, histological type, survival duration, prior glioma information and most importantly the vital status of the patient (Living / Dead). Studies show thatGBM patients can be classified into four subtypes namely Classical, Mesenchymal, Proneural and Neural based on the expression levels of a particular setof genes [6, 22]. For our study we considered these set of genes and used theirmRNA expression levels, copy number varation data and methylation status. Additional information includes drugs prescribed along with their dosage, therapytype, radiation type, radiation dosage, and start and end dates for the treatment.We model this data as a graph where nodes are of two types: 'patient node' &'treatment type node' and edges are also of two types: 'prescription edge' &'sequence edge'.

A graph offers a much richer picture of a network, and relationships of several types. The majority of

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path-based graph database operationsare highly aligned with the way in which the data is laid out hence increasingthe efficiency [16]. Figure 1 shows a graph consisting of two patients just for illustrative purposes. In the graph patient nodes have properties such as 'patientid', 'age', etc. Drugs and radiation prescribed are represented as treatment typenodes with properties such as 'drug name' and 'radiation type' respectively. The'prescription edge' signifies the prescription of treatment with properties such as'start date of prescription', 'end date of prescription', 'dosage', etc. The 'sequenceedge' signifies the sequence in which drugs or radiation were prescribed. E.g.,The edge labeled 'Prescribed' between the patient node with 'id = Patient 1'and the drug node with 'drugName = Drug A' signifies that 'Patient 1' wasprescribed 200 mg/day of 'Drug A' on 05/21/2007 till 06/22/2007. The othertype of edge labeled 'Followed by' would always be between two drugs or twotypes of radiation or between a radiation type and a drug signifying the sequenceof the prescription. E.g., the 'Followed by' edge between source node 'Drug A'and target node 'Drug B' with properties 'patient' and 'overlap' signifies thatfor 'Patient 1', Drug A was followed by Drug B and there was an overlap of24 days. The graph shown in the above figure is based on the data available forGBM patients.

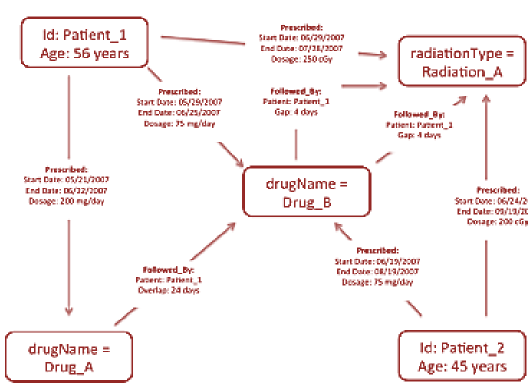

Fig. 1. Data represented as a graph

The objective is to upsurge the survival period of the patient as much as possible. For GBM patientswe analyze the treatment data of patients and recognize treatment patterns, which are characteristic of survival for a certain range of time (e.g., 6-12 months). Theperception of 'affected person similarity' would be explored to both use present similaritymeasures or develop a brand new metric for the motive of figuring out similar patients,which would play a significant position in recommending remedy for a cohort ofpatients. Significant work has been carried out on the Healthcare Systems and Analytics Research department of IBM inside the region of affected person similarity regarding doctor comments as an critical parameter to organization similar patients [21].

Chan et al.(2010) [4] have proposed a new affected person similarity set of rules namedSimSVM, which does a binary type and outputs the expected classthat is survival more than twelve months or much less than one year and diplomaof similarity or dissimilarity. Their method only considers a single outcomeand a few similarity measures as arrive. We consider that our technique could bea substantial development because we plan to recollect multiple outcomes collectivelyas we believe that a single outcome based totally technique will be misleading. Forevery man or woman affected person we would rank the treatment styles primarily based on ancient revel in with comparable patients. Heuristics would be evolved to do the ranking.

IV. CONCLUSION

Most of the paintings stated underneath will feed into the prototype improvementpaintings In the paper we suppliedthe first step in mining massive sequential treatment patterns and correlatingthe styles with survival length of patients. From a clinical angle, it offersan insight to the scientific practitioner about the importance of prescribing a hard and fastof drugs in a specific series. The contribution of the thesis will be the following like the treatment selection problem would be modeled the use of a graph formalism. Enhancements could be made to sequential mining set of rules/

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